Charting from Past to Future: Frames, Graphs and Forecasts

By

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Abstract

Changes in judgments or decisions resulting from different ways of presenting information are called *framing effects*. The primary purpose of this dissertation was to determine if different ways of showing the same information in graphs or charts could produce framing effects similar to those previously shown to result from different verbal descriptions. Three experiments investigated how different ways of showing stock price information influenced stock price forecasting and share trading. In Experiment 1, 30 Introductory Psychology students at Carleton University were each shown 30 stock charts which systematically varied in time scale (X-axis = one week, one month or one year of previous share prices), price scale (Y-axis = \$0 to \$100 or lowest price to highest price), and price trends (year trend = up, down, flat, up-down or down-up). Participants were asked to forecast the next five days stock prices after viewing each chart. Participants increased the uncertainty in their forecasts (e.g., higher variability, weaker correlation, and larger subjective confidence interval) as the amount of historical price data increased. They also produced consistent asymmetry in their price forecasts, showing higher standard deviations and subjective confidence when forecasting from a year-long up price trend than from the mirror-image year-long down price trend.

Experiment 2 examined the influence of chart framing effects on forecasts in more detail, and also explored the influence of chart framing on share trading. Forty eight undergraduate students participated in this study. As in Experiment 1, they were asked to forecast the next five days of stock prices and to trade shares after seeing stock price charts that varied in time scale, price scale, and price trend. They were also asked

to assume they owned shares and cash, and told the price they bought each stock they held (the entry price). Forecasting results largely replicated those of Experiment 1, again showing history and asymmetry effects. Share trading was also influenced by time scale. Participants bought more shares when they saw an up trend, sold more shares when they saw a down trend, and held more shares when they saw a flat trend. They also showed a consistent asymmetry in share trading, selling more shares when they saw a down trend than buying shares when they saw the mirror-image up trend. Trading was influenced by entry price when participants saw a downward trend, but not when they saw a mirror-image upward trend.

Experiment 3, a partial replication of Experiment 2, examined whether experienced traders performed differently than the undergraduate students in forecasting stock prices and shares trading. Twelve traders with at least one year experience participated in the study, undertaking the same forecasting and trading tasks as did the undergraduates in Experiment 2. There was no significant difference between experienced traders and naïve students in forecasting stock prices or in share trading.

The results of all three experiments are interpreted from the perspective of Prospect Theory, and their implications discussed.

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Introduction

Just as picture frames can influence people's impressions of a picture, people's judgments and decisions can be influenced by the way information is framed or presented. These *framing effects* often have important consequences. Judgments of insurgents, for example, vary depending on whether they are framed as terrorists or freedom fighters. Research demonstrating framing effects vary the frame by changing the words used to describe a judgment or decision situation (see, for example, Fischhoff, 1983; Kuhberger, 1997; Roszkowski & Snelbecker, 1990; Tversky & Kahneman, 1981). Changing the pictures used to describe a judgment or decision situation might also induce framing effects. Software such as Microsoft PowerPoint allows people to chart the same data in different ways using, for example, bar, line, pie, scatter, and other type of charts. It is possible that variations of these charts induce framing effects, by influencing judgments and decisions based on the data displayed. My dissertation attempts to determine whether variations in charts influence predictions and decisions based on the chart data.

There are many situations in which judgments and decision are made on the basis of charts or graphs. I have chosen to examine how different charts of historical data influence forecasts of future trends. Many people claim to use historical trends to forecast the future. One example can be seen in weather forecasts. Meteorologists use historical data as well as other information in forecasting weather for the near future. In addition, many stock market analysts use historical data about share prices to forecast future changes of share price, an activity called *technical analysis*. Charts of share price fluctuations over time have become icons of the stock market. I have chosen to examine

possible framing effects of various stock charts on forecasting share prices and trading shares by using a simulated stock market judgment and decision making in a laboratory setting.

Forecasting share prices and trading shares are two central activities in the stock market. Accurate forecasts of share prices and correct decisions about trading shares may help people obtain high profits or avoid large losses. Traders, analysts, and researchers frequently seek charts of past share prices before making forecasts and trading decisions. Their desire for stock chart information suggests that these charts are valuable and important in stock prediction and trading processes. How do they use stock chart data to forecast share prices and trade stocks? More specifically, how do charts displaying past share prices influence their judgments and decisions about stocks? The present research attempts to determine how features of stock chart influence people's price prediction and trading behaviour.

Attempts have been made for predicting stock prices and trading stocks from both the academic and financial domains. Relevant studies can be found in the literature on technical analysis, fundamental analysis, artificial intelligence (AI), judgment and decision making, as well as in behavioural finance (Santillan, 2001).

Technical analysis involves using historical data such as past stock prices, volumes, and trend lines to forecast future stock prices. Technical analysis generally uses stock price indices such as opening price, closing price, and 52-week high/low prices to represent the movement of stock prices. The stock price indices in turn are generated from statistical formulas by using various stock data such as moving averages and oscillators. Technical analysis is also based upon recognition and interpretation of chart

patterns. Many traders claim to rely on technical analysis to forecast future stock prices and trade stocks (Murphy, 1998).

Fundamental analysis seeks to judge future stock prices by understanding and measuring a company's financial data such as revenue, expense, annual reports, and financial statements. Analysts weigh and evaluate these data to forecast a fair price or value of a stock. By doing that, investors forecast the stock price will decline when above fair value, and rise if below, and make decisions to buy or sell stocks (Reed, 1997).

Artificial Intelligence techniques have been applied in the forecasts of stock prices since the late 1980s. The studies in AI techniques are generally divided into four approaches: neural network analysis, genetic algorithms, fuzzy logic, and expert systems (Lee & Jo, 1999). Neural network analysis focuses on the intrinsic dynamics and complexity of the stock market. Various approaches to neural network modeling such as multivariate time series, nonlinear statistical models, and network topology have been used for stock market predictions (Azoff, 1994; Kamijo & Tanigawa, 1990; White, 1988, 1994). Genetic algorithms have also been used as an approach that seems appropriate for forecasting a complex, fluctuating system. They have been applied in stock market predictions using approaches with names such as search, optimization, and machine learning (Goldberg, 1989; Mahfoud & Mani, 1995). Fuzzy logic is an approach to forecasting stock prices based upon deriving a set of fuzzy logic rules. These rules allow a focused search of a stock price database and are then applied to make judgments about stock price changes (Leigh, Modani, Purvis & Roberts, 2002; Wang, 2002). An expert system attempts to forecast stock prices using a computer model of human experts' knowledge and experience. It can be used to interpret stocks' past price patterns and their

future price movements. Such an expert system is generally suitable to handle complex but specific problems in stock market such as simulations to forecast stock prices for a specific company (Lee & Jo, 1999; Yamaguchi & Tachibana, 1991).

Technical analysis, fundamental analysis, and AI techniques have revealed some valuable results, but have overlooked many situations important to individual investors. Studies in technical analysis, fundamental analysis, and AI techniques have mainly focused on the measurement of the entire stock market based on very large samples of experimental and real stock data (Chou et al., 1997; Murphy, 1998; Schwager, 1995). Most individual investors in the stock market, however, pay more attention to one or several stocks they own or are considering, and do not have enough money or interest to pay for consulting with professional, customized analysis, technical, fundamental or AI (Mowen & Brewer, 1984; O'Neil, 1995). Technical analysis, fundamental analysis, and AI have also ignored some human elements of investment such as individual preferences, risk aversion, heuristics and biases. These human elements influence investors' market behaviour (Coval & Shumway, 2001). Moreover, although various models, algorithms, formulas, and statistics have been used to improve forecasting, they are still not very accurate; investors need not depend upon them, and instead may use their own psychological rules and biases to make their judgments and decision to forecast stock prices and trade stocks (Mowen & Brewer, 1984).

Most technical and fundamental analysts and AI experts would argue that traders should use their tools because the tools would improve traders' predictions. Yet there is little evidence of this improvement (Fama, 1965; Malkiel, 1973; Mowen & Brewer, 1984). Perhaps when all investors use their tools, stock prices will be predictable. In the

meantime, human tendencies will continue to influence the market. The market is, after all, nothing more than the collective consequences of these tendencies. So even if the tendencies are sometimes irrational, they deserve to be understood.

Finally, the human tendencies are also discovered in investors' interactive processes about stock prices. It is assumed that if a stock price is too high, investors (sellers) will drive the price down, if the stock price is too low, investors (buyers) will push the price up. By doing that, investors' judgments for stock price changes and their interactive (i.e., trade stocks) behaviour makes up a dynamic stock price movement. Even though technical analysis, fundamental analysis, and AI techniques are considered useful methods, human tendencies ultimately determine stock prices.

Theoretical Background

Judgment and decision making research and Behavioural finance research attempt to link technical analysis, fundamental analysis, and AI techniques to human behaviour by using psychological principles to study and understand people's investment behaviour in the stock market. They focus on how and why people make their judgments and decisions, and much behavioural finance research focuses specifically on investment decision making (Kahneman & Tversky, 1974, 1979, 2000, Slovic, 2001). Below I briefly review relevant research on judgment and decision making and behavioural finance, particularly discussions of cognitive heuristics and biases, framing effects, and Prospect Theory in the domain of investment decision making.

A brief review of judgment and decision making research

Judgments versus decisions. People make decisions in everyday life. What is decision making? A decision is a choice of action - of what to do or not do. Decision

making is considered as a process by which a person, group, or organization identifies a choice to be made, gathers and evaluates information about alternatives, and selects one or more of them (Carroll & Johnson, 1990). In a decision, one or more alternatives are selected from a set of alternatives. A typical example in the stock market is that of an investor choosing to trade (i.e., buy, sell, or hold stock shares) from a list of stocks. In contrast to decisions, a judgment involves the evaluation of features of alternatives. A broker rating a stock is an example of a judgment. Although the two examples illustrate distinctions between judgments and decisions, it is not always as clear, and often is also not necessary. For example, ranking alternatives involves an evaluation of each alternative (as does a judgment), but so does identification of the most preferred alternative (which is a decision). Rather than discussing how judgments and decisions differ, this paper focuses on both.

Prescriptive versus descriptive. Generally, researchers think about judgment and decision making from two traditional approaches: prescriptive (also called normative) and descriptive (Bell, Raiffa, & Tversky, 1988, Kahneman & Tversky, 2000, Lipshitz, 1994). How “rational” people should make decisions is a domain of judgment and decision making from the normative perspective. A normative theory is developed to build these norms or rules for making judgment and decisions by rational people. Axioms, basic principles, and fundamental desiderata are concerned with logical, rational, and intelligent behaviour in a normative theory. Such a normative theory ignores the behaviour of real people with their limited rationality, cognitive biases, anxieties and disappointments, internal turmoil, and shifting values.

How people do make decisions is the general topic of decision making from a descriptive perspective. Descriptive decision making research seeks to discover how and why people make the decisions they do. The main topics of this research include perception of uncertainty or risk, cognitive biases, internal conflicts, heuristics or strategies for decision making. The descriptive approach may involve mathematical modeling and statistical analysis to summarize actual decision making behaviour.

Linking how people should make decisions and how they do is often the focus of decision making from the prescriptive perspective. Prescriptive decision making concentrates on motivating people to make good decisions and training them to make better ones. Prescriptions may be based on a normative theory, but might also be influenced by findings from descriptive decision making research. Prescriptive decision making concentrates on the practical significance of research. Prescriptive (or normative) and descriptive decision making approaches play an important role as theoretical frameworks in the research on human judgment and decision making.

Normative decision models. The earliest mathematical study of a normative model, the expected utility (EU) model, can be traced to Bernoulli (1738). In order to explain the St. Petersburg paradox, Bernoulli suggested that people maximize moral expectation (or the utility of wealth) rather than expected monetary value. He believed that moral expectation shows diminishing marginal utility (Bernoulli, 1738); the utility of the difference between \$100 and \$101 is assumed, for example, to be less than between \$10 and \$11. After more than 200 years, von Neumann and Morgenstern (1947) developed expected utility theory as an underpinning of normative models in the domain of decision making. Their theory embodies the essence of rational decision making under

risk and it has become the predominant economic choice model during the past several decades. Unlike the Bernoullian model, von Neumann and Morgenstern's theory offers an extended mathematical formulation of expected utility, and has been considered as the theoretical framework for normative approaches (Schoemaker, 1980).

Based on von Neumann and Morgenstern's theory, studies were undertaken to offer evidence for normative models. Examples include observing and constructing the utility function in a laboratory situation (Mosteller & Nogee, 1951), measuring utility for small amounts of money losses (Davidson, Suppes & Siegel, 1957), plotting a utility curve in risk-taking situations (Friedman & Savage, 1948), discovering a general psychological law for probabilities of overestimating and underestimating (Yaari, 1965), and conducting experiments about probability perception (Rosett, 1971).

Although von Neumann and Morgenstern's theory of rational choice was mathematically elegant, it was soon shown to produce unwanted paradoxes such as Allais paradox and Ellsberg's paradox (see Plous, 1993). The *Allais paradox* is the most prominent example for behavioural inconsistencies related to the independence axiom of von Neumann and Morgenstern's theory. This paradox shows that most decision makers prefer risky prospects to uncertain ones, although the uncertain prospects are rationally the better choices from the point of view of von Neumann and Morgenstern's theory. In the other words, the Allais paradox as a stronger violation provides no evidence for the independence axiom of von Neumann and Morgenstern's theory (Allais, 1953). Ellsberg's paradox is another example of behavioural inconsistencies to disprove the independence assumption of von Neumann and Morgenstern's theory. This paradox arises from a series of games involving colored balls in urns. For example, there are two

urns, each of which contains a hundred balls, which are either red or black color. One urn contains fifty red balls and fifty black balls. The proportion of red and black balls in the other urn is unknown. You can draw one from an urn without looking, and if you draw a red ball you win a hundred dollars. Which urn will you choose? Ellsberg found that people strongly prefer chose the urn known to have fifty balls of each color to the unknown urn (Ellsberg, 1961). These violations of rationality indicated that the normative models cannot always be used to prescribe how people should behave in judgment and decision making, and they stimulated interest in describing how people do behave.

Decision making: a descriptive perspective. In response to the limitations of rationality, descriptive models have been developed over the last several decades, intended to understand people's actual judgment and decision making behaviour (Beach & Mitchell, 1978; Hogarth, 1980, Kahneman & Tversky, 1979, 1981, 2000). Simon (1957), for example, proposed the idea of *bounded rationality* to understand how people make decisions. The term bounded rationality is used to designate rational choice that takes into account the limitations of both knowledge and cognitive capacity. It is concerned with the ways in which the actual decision-making process influences decisions. Simon believed that human judgment and decision making is bounded by these limitations. He suggested that it is better to understand decision making by explaining actual, rather than normative, decision processes. Based on the idea of bounded rationality, Simon (1957) suggested a *satisficing* model to describe people's decision processes. Simon assumed that, because decision makers have only bounded rationality, and often make decisions by satisficing instead of maximizing or optimizing. To

satisfice, a decision maker first sets up an aspiration level. If the aspiration level is achieved, the decision maker will be happy with his/her decision. If not, the decision maker will try to change either the aspiration level or the decision. By doing that, Simon's satisficing model may help us to understand people's decision behaviour in the bounded, uncertain, and real world.

Many empirical studies have been undertaken to examine behavioural violations of normative rationality in the domain of decision making. Wason (1965) provided empirical evidence of inferential irrationality (e.g., biases and illogical errors) in a study of human reasoning, and emphasized the importance of human experience, particularly recent experience, in decision processes. Tversky (1972) proposed that many people violate normative predictions because they make choices with an "Elimination by Aspects" rule. Tversky describes how decision makers select alternatives by examining them lexicographically, one aspect at a time. Epstein, Pacini, Denes-Raj, and Heier (1996) investigated how people interpret information in making a decision. They argue that decision making involves interaction between human rationality and irrationality. Hardman and Harries (2002) demonstrated that in order to avoid a certain loss, people often take a gamble that could lead to an even bigger loss. They agreed with Tversky & Kahneman (1974) that people employ heuristics to make judgments, particularly in the face of risk and uncertainty.

For the past 30 years, descriptive models have been developed to understand human judgment and decision making. One of the most important descriptive models is Prospect Theory developed by Kahneman and Tversky beginning in the 1970s. They employed the concept of a prospect to describe people's actual judgment and decision

making under risk (Tversky & Kahneman, 1979, 1981, 1986, 2000). According to Prospect Theory, a prospect is defined as the possibility of outcomes, or a finite distribution of outcomes. A positive prospect involves no losses in making a decision. A negative prospect contains risks of losses in making a decision. Prospect Theory hypothesizes a choice process for selecting prospects to describe decision making which can be divided into two phases: editing and evaluation. Editing is considered as an early phase, and evaluation is thought of as a subsequent phase. In the editing phase, a simple representation of prospects is offered for preliminary analysis and evaluation. In the evaluation phase, the edited prospects are assessed and the prospect with higher value is chosen. In doing so, these two choice phases can be used to describe people's decision processes (Kahneman & Tversky, 1979).

Kahneman and Tversky (1979, 1981) found that people often make decisions by using a reference point. The reference point is a value defined over gains and losses of alternatives rather than over a decision maker's wealth (Kahneman & Tversky, 1979; Kahneman, 1992). The reference point may shift in such a way that it will affect people's decisions. The concept of reference point may explain why the same situation can often generate different decision results when framed as a gain, than when framed as a loss. In other words, the reference point may vary as a function of problem presentation (Schoemaker, 1980).

An asymmetric and nonlinear value function is employed to describe the subjective values of gains and losses and loss aversion in Prospect Theory. Prospect Theory assumes people treat gains differently to losses. Except for very small probabilities, risk seeking is observed for losses while risk aversion is observed for gains.

Loss aversion implies that the subjective value of losses is more extreme than the subjective value of equivalent gains. According to Prospect Theory, the slope of the value function is steeper in the negative (loss) than in the positive (gain) side. Benartzi and Thaler (1995) estimated the disutility of losses to be twice as great as the utility of equivalent gains.

Prospect Theory has come to play an important role as a descriptive theoretical framework in judgment and decision making. A more detailed discussion of Prospect Theory will be given later. Prospect Theory has stimulated many psychologists, economists, and other researchers to understand better people's decision behaviour. For example, behavioral Finance is a new hybrid of economics and psychology based on Prospect Theory.

A framework for behavioural finance

Behavioural finance is considered one of the most active domains in economics, finance, judgment and decision making, as well as in psychology. It is gaining wider attention from financial analysts, economists, decision experts, and psychologists both academically and professionally. Behavioural finance attempts to understand and explain how psychological processes such as cognitive biases influence people's financial decision behaviour. Many researchers (for example, Campbell, Lo, & MacKinlay, 1996; Shefrin, 2000; Shiller, 2000; Thaler, 2003) believe that the study of psychology and other social sciences can shed considerable light on the efficiency of financial markets as well as explain many stock market anomalies, market bubbles, and crashes.

Studies of behavioural finance may generally be divided into two areas. One has used insights from research on how cognitive processes, especially heuristics and biases,

influence people's judgments that may lead to various stock market anomalies. Another area has examined the impact of beliefs about risk on people's investment decision making that may also result in fluctuation of the stock market. These studies of judgment and decision making in behavioural finance help us better understand how and why people predict, interpret, and react to stock information.

Cognitive heuristics, biases, and investment judgments. In psychology, a cognitive heuristic is a simple mental rule used to solve a problem or to make a judgment or decision. A cognitive bias is a mental distortion or error, usually caused by the use of a cognitive heuristic. Several cognitive heuristics and biases have been documented in the judgment and decision making literature. Cognitive heuristics usually involve availability, representativeness, the law of small numbers, and anchoring. Cognitive biases include overconfidence, hindsight bias, misattribution, and perseverance. It is helpful to understand people's investment judgments by exploring these cognitive heuristics and biases.

Availability is defined as the ease of retrieving or readily imaging salient information from memory to make judgments (Kahneman & Womack, 2001; Mowen & Brewer, 1984). People are often faced with an overwhelming amount of information when they seek to make judgments and decisions. They have a tendency to use availability heuristics as shortcuts to limit the amount of information they must process. When forecasting future stock prices, for example, some traders might match stock chart shapes or patterns with shapes or patterns easily available in memory to make their judgments of share prices.

Representativeness is a heuristic that is employed to attempt to categorize information. Categorization is a cognitive process that people use to understand objects based on characteristic features of the objects. Some studies (Olsen, 1998; Shefrin, 2000), for example, illustrate that traders' judgments for stock price might be influenced by the representativeness heuristic. For example, most traders (De Bondt, Werner & Thaler, 1985) tend to overreact to unexpected and dramatic news, both bad and good. The overreaction leads losers to become underpriced and winners to become overpriced. Their behaviour tendencies in turn affect the fluctuation of stock prices.

The law of small numbers was first labeled and documented by Tversky and Kahneman (1971). They used the term to describe how people exaggerate the degree to which the probability distribution in a small group will closely resemble the probability distribution in the overall population. One of their studies (Tversky & Kahneman, 1971, 1982) showed that people generally do not realize how fast the variance of the sample mean of a random variable decreases with increased sample size. In the gambler's fallacy, for example, if a few early tosses of a fair coin give disproportionately many heads, many people believe that the next flip is more likely to be tails, even if the flips are statistically independent. The gambler's fallacy is also found in predicting the sequence of stock prices (Warneryd, 2001). It suggests that traders might often be less likely to predict a stock price will go up the more the stock continues to rise.

An *anchor* is a cognitive reference point that tends to influence people's judgments. The reference point for stock prices can be a historical price or a round value of a stock market index (for example, 10,000 for the Dow Jones Industries, 2,000 for NASDAQ). Psychologists (Fiske & Taylor, 1991; Kahneman, Slovic, & Tversky, 1982)

have demonstrated that, when people make quantitative estimates, their judgments may be influenced by the reference point of a previous value. For example, the 10,000 level of Dow Jones Industries, a round or memorable value, has acted as a type of anchor that is highly recognizable and salient by some traders and brokers. Slovic and Lichtenstein (1971) demonstrated that some investors overestimate a recently quoted price level which serves as an anchor for further probability assessments.

Overconfidence is a bias that results from people overestimating their abilities and knowledge. Some traders may believe they have the ability and knowledge to predict stock prices, particularly experienced traders and financial professionals and, as a result, they are often surprised by unfolding events in the stock market. Barber and Odean (2001) studied the trading activities of people who have discount brokerage accounts. They found that men tend to be more overconfident than women and, on average, men traded more and did worse in the market than women. Glaser, Langer, and Weber (2002) studied price trend recognition ability. They found that financial professionals are more overconfident than novices.

Hindsight bias often happens when people reveal their prior estimate of the probability of an event. This bias leads people to exaggerate their predictive accuracy after the fact. Fischhoff (1975) found that, after an event occurs, people overestimate the degree to which they could have predicted the event, as if whatever happened is bound to happen. The hindsight bias also can be seen in prediction of stock market prices (Shefrin, 2000). For example, if stock prices in the market decline after a prolonged rise, people may say that “trees don’t grow to the sky”, as if they have known all along, and if the

stock market prices continue to rise, people may say “the trend is your friend”, as if they have known all along.

Attribution bias refers to people’s tendency to assign certain causes for an event or action and ignore others. A trader, for example, might ascribe the cause of his or her predictions to skill, and blame his or her failures on bad luck. Daniel, Hirshleifer, and Subrahmanyam (1998) found that traders tend to attribute their ability for successful price prediction, even through their successful records differ little from ones that could be expected by pure chance.

Perseverance bias occurs when people maintain prior beliefs in the face of contrary evidence. In a perseverance study, Anderson, Lepper, and Lee (1980) demonstrated that people with different prior beliefs interpret the same information differently. Typically, people who believe something is true are more inclined to interpret information as consistent with their belief. With the perseverance bias, for example, traders often believe a prior statistical result for the patterns of a stock price, and ignore a consistent change of the stock price (Mowen & Brewer, 1984).

As described above, people’s judgments often use cognitive heuristics that lead to biases which, in turn, can lead them to make bad predictions and decisions (Kahneman & Tversky, 1974). They are likely to show these heuristics and biases when predicting stock market prices (Fisher & Statman, 2000). To the extent that people base their decisions on these predictions, the heuristics and biases will influence their investments. In terms of the studies of behavioural finance, these heuristics and biases lead to systematic and predictable errors. If we can better understand the cognitive heuristics and biases of traders, perhaps we could decrease their negative effects, and help explain why people

are not always successful traders, even if they are knowledgeable traders or financial professionals.

Risk, framing effects, and Prospect Theory

Stock prices often fluctuate dramatically in the stock market. The fluctuation shows that the past performance of a stock is not necessarily indicative of its future performance (Zuckerman & Karmin, 2002). Stock trading is risky, and traders respond to risk in different ways. Some shy away from risky trades, but others seem to embrace them. For many years, rational choice theory has been used in economics, finance, and marketing to explain people's judgment and decision making under risk from a normative perspective. Axioms and basic principles are concerned with logical, rational, and intelligent behaviour in a normative theory (Arrow, 1990). However, abundant evidence has been found that people's choice behaviour often violates the rationality assumption of rational choice theory (Bell, Raiffa, & Tversky, 1988; Carroll & Johnson, 1990). Why do many people fail to minimize losses and maximize profits? How do people respond to risk in the stock market? Tversky and Kahneman, (1979, 1981, 1986) examined *framing effects* as one aspect of Prospect Theory related to risk and decision making to answer the questions.

Framing effects refer to the changes in judgment and decision making as a result of how information is presented, or framed. Many early studies in psychology illustrate framing effects in human perception (Coren & Miller, 1974; Sherif, Taub, & Hovland, 1958). A good example is the well-known Müller-Lyer illusion: the top line appears longer than the bottom line, although it is same length as the bottom line, because of the "frame" of arrows at the ends.

In the domain of judgment and decision making, many examples of framing effects have been found in a variety of task and procedures. Thaler (1980) drew attention to the framing effect in consumers' choices on a difference between two prices as a surcharge or a discount. Fischhoff (1983) explored different ways of predicting frame choice by individuals and groups. Bazerman, Magliozzi, and Neal (1985) observed framing effects of risk seeking in bargaining behaviour. Roszkowski and Snelbecker (1990) measured a framing effect of risk tolerance in money management. Johnson, Hershey, Meszaros, and Kunreuther (1993) showed that preferences for insurance coverage can vary, depending on whether premiums are "framed" as rebates or deductibles. Ginyard (2001) found framing effects in traders' performance from experimental research on money management.

A classical example to illustrate framing effects is the "Asian disease" problem (Tversky & Kahneman, 1981). Below is the description of the framing effect in their study. "Problem 1: Imagine that the US is preparing for the outbreak of an unusual Asian disease, which is expected to kill 600 people. Two alternative programs to combat the disease have been proposed. Assume that the exact scientific estimates of the consequences of the programs are as follows:

If Program A is adopted, 200 people will be saved.

If Program B is adopted, there is 1/3 probability that 600 people will be saved, and 2/3 probability that no people will be saved.

Which of the two programs would you favor?" (Tversky & Kahneman, 1981, p. 453) It was found that 72% of 152 respondents chose risk averse, Program A. That is, the prospect of saving 200 lives with certainty was generally preferred to the probability of a

one-in-three chance of saving 600 lives, although this risky prospect B was of equal expected value as the first prospect A. To illustrate the framing effects, Tversky and Kahneman rebuilt the Asian disease problem with a different frame: “A second group of respondents was given the cover story of problem 1 with a different formulation of the alternative programs, as follows:

Problem 2:

If Program C is adopted 400 people will die.

If Program D is adopted there is 1/3 probability that nobody will die, and 2/3 probability that 600 people will die.

Which of the two programs would you favor?” Tversky and Kahneman (1981) found that 72% of 155 respondents in the second problem chose the more risk D alternative. That is, the certain death of 400 people is less acceptable than the two-in-three chance that 600 people will die. They concluded that “choices involving gains are often risk averse and choices involving losses are often risk taking” (Tversky & Kahneman, 1981, p. 453). In fact, problem 1 and 2 are identical, the only difference is that they are framed in different ways.

How about people’s financial behaviour? Is a \$1 loss more painful than the pleasure of a \$1 gain? How do questions affect answers? Kahneman and Tversky (1979) examined the effect of framing on people’s financial behaviour. In this study, the participants were required to choose one of two situations.

A: 80% possibility to win \$4,000 and 20% risk of not winning anything;

B: 100% possibility to win \$3000.

Eighty percent participants chose B, a safe \$3000. However, when Tversky and Kahneman (1979) reversed the two situations as the following:

C: 80% possibility to lose \$4000 and 20% risk of not losing anything;

D: 100% possibility to lose \$3000.

They found that 92% participants picked C, the gambling alternative. Obviously, the framing effect illustrates the asymmetry between loss and gain occurred in decision making.

Framing affects people's risk behaviour such as risk seeking and risk aversion. Risk seeking occurred in the preferences between negative prospects (i.e., losses). Risking aversion occurred in the preferences between positive prospects (i.e., gains). In other words, "the same psychological principles - the overweighing of certainty - favors risk aversion in the domain of gains and risk seeking in the domain of losses." (Kahneman & Tversky, 1979, p. 266) and "it is easy to think of decision problems that are most naturally represented in one of the forms above rather than in the other" (Kahneman & Tversky, 1979, p. 272).

To understand how framing effects influence decision behaviour, Kahneman and Tversky (1979) developed Prospect Theory. Prospect Theory considers three components of a decision: the choice process, the value function, and the weighting function. The choice process has two phases, an early editing phase and a subsequent evaluation phase. In the editing phase, a simplified representation of alternatives (also called prospects in Prospect Theory) is developed for analysis of evaluation. In the evaluation phase, the edited prospects are compared and the prospect with the highest value is chosen. The two

phase choice process can be used to describe people's choice behaviour under risk (see Markowitz, 1952; Edwards, 1962; Fellner, 1965; Coombs, 1975; Fishburn, 1977).

The value function in Prospect Theory is considered to be an S-shaped function relating objective measures (often expected value of money) to subjectively expected utility (SEU) of decision making under uncertainty. It measures the subjective value of an outcome regarding the reference point of no gain or loss. The value function is a negatively accelerated function for all amounts of gain and loss, but slopes more rapidly for losses than gains. The S-shaped value function reflects the psychological phenomenon of diminishing sensitivity as one side (i.e., gains or losses) moves away from a reference point that divides gains from losses, usually taken to be zero by default. Three basic assumptions are central to the value function. First, the value function assumes that the value depends upon the evaluation of relative changes or differences instead of the evaluation of absolute magnitudes. Second, in terms of the definition of the value function, it is assumed that losses hurt more than gains feel good. Third, it assumes that the degree of steepness for losses and gains is different, and that the function is steeper for losses than for gains (Kahneman & Tversky, 1979).

The weighting function refers to a function that maps mathematical probabilities of events into decision weights. According to Prospect Theory, the weight function is not a linear mapping of probability. For very small probabilities, for example, people are not very sensitive to the difference between a probability of 0.001% and 0.002%. They weigh or classify such probabilities as an impossible event (i.e., treat such low probabilities as zero). For an extremely high probability such as 0.999%, on the other hand, people weigh

or classify such a probability as a certain event (deal with such high probability as one) (Kahneman & Tversky, 1979).

Taken together, the assumptions of Prospect Theory explain how people make decisions under risk. Particularly, its asymmetric S-shaped value function implies more impact of losses than gains (i.e., loss aversion). In stock market research, the way people make their decisions with risk (e.g., risk aversion or risk seeking) in case of gains or losses can be explained by Prospect Theory (Brown, Smith, & Wilkie, 2001; Shefrin & Statman, 1985; Weber & Camerer, 1998).

Implications of Prospect Theory for Investment Decision Making

Prospect Theory is becoming increasingly popular as a theoretical framework in the domain of behavioural finance. Prospect Theory accounts for a number of behavioural anomalies in the stock market. Examples of anomalies are: the endowment effect, sunk cost effect, house money effect, mental accounting, myopic loss aversion, and the disposition effect (Shefrin, 2000).

Endowment effect. The endowment effect occurs when people place an extra value on things they already own. With the endowment effect, people demand more to give up the things than they would be willing to pay to acquire them. In an earlier study, Thaler (1980) found an endowment effect in goods held for sale. He employed the concept of loss aversion from Prospect Theory to explain the difference between the willingness-to-pay and willingness-to-accept in the endowment effect. Kahneman, Knetsch, and Thaler (1990) exploited the impact of the endowment effect on people's trade behaviour in a simulated laboratory market. In their first study, undergraduates registered in an economics class participated in a series of market trades, some playing

the role of seller and some the role of buyer. Kahneman, Knetsch, and Thaler found that, on average, the sellers' asking price is about twice the buyers' bid price. The sellers were unwilling to sell for less than the price they asked; the buyers were unwilling to pay more than the price they bid. In the second study, the participants were randomly assigned to one of three groups: seller, buyer, and chooser. The choosers were asked either to buy or sell by choosing a price ranging between sellers and buyers prices. It was found that the choosers behaved more like buyers than sellers (Kahneman, Knetsch, & Thaler, 1990).

Sunk cost effect. If an investment starts to fail, do you to stick with it? Perhaps you feel your investment is too much to quit. The scenario is a good example of the sunk cost effect. Arkes and Blumer (1985) describe the sunk cost effect as “manifested in a greater tendency to continue an endeavor once an investment in money, effect, or time has been made. The prior investment, which is motivating the present decision to continue, does so despite the fact that it objectively should not influence the decision” (Arkes & Blumer, 1985, p. 127). Some studies (Arkes & Blumer, 1985; Laughhunn & Payne, 1984; Thaler, 1980), however, showed that many decision makers attend to sunk costs and are reluctant to cut their losses. These decision makers believe that they have to continue to make the same investments, “throwing good money after bad,” in hopes of recovering previous losses (Bazerman, 2002; Plous, 1993).

House money effect. People may take more risks when they make investments with surplus money or money that is not their own. This scenario is described as the house money effect. Thaler and Johnson (1990) examined how individual behaviour is affected by prior gains and losses in their experiments. An initial loss can increase risk aversion, reducing risk-taking behaviour. In contrast, after a prior gain people are more

risk seeking (i.e., a house money effect; Thaler & Johnson, 1990). Barberis, Hvary, and Santos (1999) also demonstrated a strong house money effect: when endowed with house money, people became more risk taking (Barberis, Hvary, & Santos, 1999). Furthermore, Ackert, Charupat, Church, and Deaves (2006) exploited a house money effect by observing how people use different amounts of cash endowment. They concluded that traders' bids and predictions are influenced by the amounts of money that are provided prior to trading (Ackert, Charupat, Church, & Deaves, 2006).

Mental account. Tversky and Kahneman (1981) define a mental account as “an outcome frame which specifies (i) the set of elementary outcomes that are evaluated jointly and the manner in which they are combined, and (ii) a reference outcome that is considered neutral or normal” (Tversky & Kahneman, 1981, p. 456). Based on the sources and purposes of money, for example, people have a tendency to separate their money into several “mental accounts”, such as the children’s education account. According to the concept of mental account, the value that people assign to one dollar in one mental account can differ from that of one dollar in other mental accounts. Shefrin and Thaler (1988) used the concept of mental account to describe how people tend to decompose and evaluate their financial transactions such as salary, asset, and future incomes. In investment decision making, the mental accounting is often observed in the construction of portfolios (Fisher & Statman, 1997). According to Prospect Theory, the mental accounting may be used to understand how traders make small decisions sequentially. When a stock is added to a trader’s portfolio, he or she opens a new mental account with a reference point of the purchase price per share. The trader makes a trade (e.g., sells a stock) based on his or her mental account of the stock. With such mental

accounting, the trader creates a personal trading history with every investment in his or her portfolio (Tversky & Kahneman, 1981).

Myopic loss aversion & the equity premium puzzle. In financial economics, the equity premium refers to the chances that risky stocks will be better performers than safe, fixed income investments, such as bonds or treasury bills, particular in the long term. Many people believe less risky investments (e.g., bonds) should perform better than risky investments (e.g., stocks) (Siegel & Thaler, 1997). Bernarzi and Thaler (1995) combined loss aversion with mental accounting to create a concept labeled myopic loss aversion to explain the equity premium puzzle. They argue that traders often make judgments myopically, in the short-term, when they evaluate sequences of investment opportunities, particularly loss aversion traders. Such myopic loss aversion let the decision maker reject the chance of an investment that would be accepted from a less myopic more long-term view (Bernarzi & Thaler, 1995).

Disposition effect. The disposition effect refers to the tendency to sell winning stocks too soon and hold losing stocks too long (Shefrin & Statman, 1985). Often, traders, including the less experienced, prefer to sell winners than losers. They don't like to sell stock losing money, preferring to keep it and taking a risk that its price will fall even more. Some research on the disposition effect points to Prospect Theory as an explanation. In terms of Prospect Theory, the researchers believed that traders' loss aversion is strongly related to the disposition effect (Odean, 1998; Weber & Camerer, 1998).

As described above, these studies have provided evidence that Prospect Theory is a useful tool to understand many observed behaviors of investment decision making.

Prospect Theory is an important theoretical framework that encourages more psychologists and economists to focus on behavioural anomalies in the domain of investment decision making (Kahneman & Tversky, 2000; Shefrin, 2000; Wakker & Zank, 2002).

Related Research on Stock Market Behaviour

Research about stock market dynamics (e.g., Fama, 1965; Malkiel, 1973; Bass, 1999) showed that the movement of the stock market is likely a random walk and that is very difficult to predict. Even so, many efforts have been made to understand stock market behaviour (Bernstein, 1992). Studies have been conducted from various research perspectives as reviewed below. These studies range over topics such as the movement of stock price changes, traders' cognitive biases and heuristics, news and rumor influence, predicting stock prices under risk, overconfidence, goal setting and strategy using, information and its predictive value, as well as impact of stock charts on market behaviour.

Do stock prices walk randomly? The Random Walk Theory of stock market price movement (see Malkiel, 1973) assumes that stock price changes from one day to next are similar to a random walk. As a result, the past movement of stock prices cannot be used to predict their future movement in market. Fama (1965) used the random walk theory to explain the behaviour of stock price changes in market. He provided empirical evidence to support the two basic assumptions of Random Walk Theory: (1) that the price changes conform to some probability distribution such as normal distribution, and (2) that successive price changes are independent. Financial people have generally assumed a Gaussian or normal distribution as the general shape of the distribution of stock price

changes. Fama doubted the validity of the Gaussian hypothesis for the distribution of stock price changes. He believed that Mandelbrot Benoit's hypothesis is better at describing the distribution of stock price changes. Fama's results more closely approximated Mandelbrot's hypothesis from two points of view, economic and statistical analysis. In order to test the validity of the independence assumption of the Random Walk Theory, Fama used a serial correlation model, runs analysis, and filter techniques. He concluded that the independence assumption of the Random Walk Theory seems to be an adequate description of stock market fluctuations.

Although Fama concluded that the Random Walk Theory could account for the behaviour of stock prices, he did not deny that the movement of stock prices may be influenced by psychological, economic and political factors that are considered as random noise in the Random Walk Theory. Many investors seem to base their actions in the stock market on the evaluations of economic and political situations. They believe that stock price changes depend on economic and political factors which affect companies' prospects. For example, news, either economic or political, plays an important role as a signal in stock trade. Some investors may be more sensitive to news as a signal to buy or sell stocks. Fama also conceded that some sophisticated technical analysts may be able to improve the short-run predictions for stock price changes with their strong statistical background.

Trade heuristics: a non random walk of stock prices. In contrast to Random Walk Theory, Kumar and Dhar (2002) studied the impact of stock price trends on people's trading behaviour as a non random walk in market prices. They thought that traders' behaviour may be driven by changes in their beliefs about future stock prices, and these

beliefs are likely to be influenced by past price trends. Kumar and Dhar believed that traders used different heuristics in their stock market behaviour. Two main heuristics were considered in their study: momentum and contrarian. Momentum traders expect price continuations and hence they buy on an upward stock trend and sell on a downward stock trend. Contrarian traders, on the other hand, anticipate price reversals and thus they buy on a downward stock trend and sell on an upward stock trend. Other experimental research (Tversky & Kahneman, 1971) has shown that people often use these two heuristics as predicting signals in short sequences that may be random. They believed that the biases may result from the representativeness heuristic. That is, people forecast future outcomes in terms of the most representative value of the past evidence (Tversky & Kahneman, 1973). Barber and Odean (1999) found that traders' overconfidence may result in the persistent momentum pattern. For example, the traders' overconfidence may be exacerbated in a bullish market where traders are likely to attribute their success to their own predictive skill instead of the nature of the market.

In their studies, Kumar and Dhar (2002) examined whether there are underlying differences across individuals who expect continuations as opposed to those who expect reversals. They selected more than 40,000 traders who had accounts with common stocks that trade on the main stock markets such as NYSE, AMEX, and NASDAQ. Based on their trading performance, these traders in the research were divided into four groups: 1) momentum buy; 2) momentum sell; 3) contrarian buy; and 4) contrarian sell. The results of the study reveal that contrarian traders are more sophisticated than momentum traders. The contrarian buy traders, for example, are more likely to buy near recent low prices, and the contrarian sell type traders are likely to sell near the recent high prices. In

contrast, the momentum traders do not exhibit such trading behaviour. By analyzing the traders' portfolio characteristics, Kumar and Dhar found that contrarian and momentum traders have different perceptions of market characteristics. The contrarian traders have a lower portfolio turnover and longer stock holding periods compared with momentum traders.

Kumar and Dhar (2002) also studied the impact of reference points and disposition effect across contrarian and momentum traders. The reference points may be the current price, high or low prices of the day, month, or year. While buying or selling stocks, traders are likely to use one or more past or current prices as reference points to make a trade. They found that contrarian traders are likely more sensitive to these reference points than momentum traders. Contrarian traders are more likely to buy at lower prices, and sell at high prices during a period such as three months trading activities. Momentum traders, on the other hand, expect continuation of past price trends in such a way that short term price highs and lows do not influence their trading behaviour.

The disposition effect describes the tendency of people to hold their losing investments (e.g., stocks) too long and sell their winning investments too soon. It may result from different expectations about future stock prices. In general, contrarian traders expect price trend reversals and are more likely to hold a losing stock. Momentum traders, on the other hand, believe that a downward price trend is likely to continue and are more likely to sell now rather than later. Kumar and Dhar (2002) measured the disposition effect in their study, and found that the disposition effect is stronger among

contrarian traders who expect price trend reversals and weaker among momentum traders who expect price trend continuation.

Can news make stock prices go up or down? Stock prices reflect many market influences such as economic reports, political news, and technical analysis. Zielonka (2004) studied how financial professionals use these real market variables to estimate the future behaviour of stock prices. Forty financial professionals were invited to participate in his study. A questionnaire of 60 items, derived from a financial newspaper, was presented to these participants. All items in the questionnaire were divided into three: economic news, political news, and technical analysis. The participants were asked to use the questionnaire to estimate the impact of these items on stock prices. In Zielonka's study, the news are grouped into four: 1) the growth of foreign and domestic investments in the stock market; 2) the withdrawal of foreign and domestic investments from the stock market; 3) unfavorable economic, financial and political news, negative technical analysis; and 4) favorable economic, financial and political news, positive technical analysis. Most participants regarded technical analysis and news as valid for predicting stock price changes, and believed them to have predictive value.

Why do well-educated financial experts use economic news, political news, and technical analysis to predict stock price changes? Zielonka suggests three answers. First, these financial professionals were taught to believe that economic news, political news and technical analysis can improve stock price predictions. Second, the professionals, according to Cognitive Dissonance Theory (Festinger, 1957), strive to have consistent attitudes, beliefs, and behaviors. If a financial professional believes he or she has the ability to predict stock prices, even the stock prices are random, the professional still

believes the stock prices are predictable (Worchel & Shebilske, 1995). Finally, the professionals' cognitive biases might influence their judgments. Zielonka does not give more detailed discussions of his suggestions.

Do rumors influence stock price changes? Unlike news, rumor is colored by various shades of doubt and always unconfirmed. Even so, it can be a powerful influence on the market. "Buy the rumor, sell the news" is a popular aphorism on Wall Street. Rumors have long been implicated in stock price changes (Koenig, 1985), often by introducing uncertainty. Reasons for the influence of rumor can be found in a variety of cognitive tendencies. For example, people seek information such as rumor, associated with causality and often pay more attention to this information than non-causal information that has better predictive validity (Holland, 1986; King, Keohane & Verba, 1994). To examine the rumors' influence on market behaviour, DiFonzo and Bordia (1997) studied the relationship between rumor and stock price predictions. In DiFonzo and Bordia's experiments, participants were divided into two groups. One group of participants was presented news. Another group was presented published and unpublished rumors. A computer stock trading game simulated a consecutive series of 60 trading days. The price change series was obtained by historical price data of a company. Participants in the experiments claimed that rumor sources were non-credible and that they were not influenced by rumor in their prediction. However, they made their predictions on rumor as though it was news. DiFonzo and Bordia (1997) conclude that, despite rumor having less credibility than news, if the same causal information is embedded in a rumor, it would yield similar effect to that of news in the prediction of

stock prices. Rumors do not have to be believed or trusted to influence predictions.

Rumors simply have to make sense.

Does loss aversion affect trading stocks? As economic news, political news, and rumor influence stock prices, so to do traders' loss aversion tendencies. Coval and Shumway (2001) studied the impact of loss aversion behaviour on stock prices. Recall that loss aversion describes why traders don't like to sell a stock when it is losing money and prefer to keep the stock, taking a risk that its price will fall even more. Coval and Shumway focused their study on the trading behaviour of financial professionals who are the members of the Chicago Board of Trade (CBOT). These experts were full-time brokers whose livelihood depended entirely on their ability to trade effectively. To examine the cause and effect of loss aversion, Coval and Shumway examined a trading day in the morning and again in the afternoon to determine whether traders with profitable mornings increase or reduce their afternoon risk taking. Two major findings emerged. First, they found that CBOT traders exhibited a loss aversion in trades. They were highly loss-averse if they were losers in the morning trading period. That is, they were more likely to take on additional loss risk on the afternoons following morning losses than morning gains. Second, the loss aversion of CBOT traders influenced stock prices, because their losses resulted in buying at a higher price or selling at lower price following their morning losses. The researchers believed that the loss aversion behaviour helps account for stock volatility, that is, the fluctuations in the stock prices (De Long et al., 1990; Coval & Shumway, 2001).

As described above, Coval and Shumway (2001) showed that financial professionals exhibit afternoon loss-averse behaviour according to losses in the morning.

However, their study has some limitations. For example, the financial professionals employed in the study were stock brokers. Their loss aversion behaviors might be different than common traders. A broker, for example, spends other people's money and may share risk with his or her colleagues who work in the same investment company. An individual trader has to take all the risk him or her self, and is the only person who has all responsibility for his or her stock trades. Moreover, in Coval and Shumway's study, the loss aversion behaviour was only measured in a day trade rather than the trade of week, month, or year. Financial professionals generally focus on long term investments in the market (O'Neil, 1995). Perhaps such a day trader's behaviour cannot be generalized to the professionals' long term investment behaviour.

Overconfidence. Overconfidence also affects a stock's trading activity, volatility, and price change. Odean (1998) divided market traders into three groups: price-takers, insiders, and market makers. In Odean's studies, price-takers are traders who have to take the market price in order to sell their stocks. They are unable to sell their stocks at the prices higher than the market prices. Insiders are directors or senior officers of a corporation who have access to inside information about a company. Market makers are brokerages who maintain clients' stocks, make price quotes, and so on. Odean discovered that the three traders all exhibit overconfidence in the value of stock information. The traders believe their knowledge is more precise than it really is; they rate their own abilities more highly than the abilities of common traders, and they are excessively optimistic or overconfidence (Odean, 1998).

Are financial professionals more overconfident than novices when forecasting stock prices? Glaser, Langer, and Weber (2002) studied financial professionals'

overconfidence in experiments on stock trend prediction. The participants in the experiments were divided into two groups. One group had 31 financial professionals who worked in banks for many years. Another group contained 64 undergraduate students studying banking and finance in university. Two related tasks were involved in the experiments. The first task was called “trend prediction by probability estimates”. The second was labeled “trend prediction by confidence intervals”. In the first task, two samples of distributions of price changes with different probabilities were displayed graphically and numerically to the participants. They were informed that one of the two distributions was randomly picked to generate a price movement. After observing the price movement, the participants were asked to provide their subjective probability (i.e., a personal judgment or belief) that either a positive trend or negative trend was driving the price movement. In the second task, the participants were asked to make a prediction about the range of price changes, a confidence interval which they believed the real price would be 90% of the time, an estimated range with an upper and lower limit.

Glaser, Langer, and Weber (2002) employed subjective probability and confidence intervals to measure participants’ overconfidence. They found that both financial professionals and novices showed overconfidence when they forecasted stock trend in the experiments. The financial professionals, however, showed more overconfidence than the novices, and did not always perform better or worse than the novices.

Glaser, Langer, and Weber’s (2002) study is a good example of the financial professionals’ performance in a task of predicting stock price changes. However, they used only two distributions of price changes to help the subjects make their forecasts

either positive or negative trends. Glaser, Langer, and Weber did not mention what type of distribution they used, not where their price data came from. Different distribution types might have different effects on the subjects' forecasts of price changes.

Working smarter rather than working harder? In stock market studies, researchers recognize that using a trading strategy can enhance performance in forecasting prices and trading shares (Ball, Kothari & Wasley, 1995; Harrington, 1983; Kahneman & Tversky, 1982). Earley, Connolly, and Lee (1989) examined the effects of employing a trading strategy on the task of predicting stock prices in a laboratory study. The participants in Earley et al.'s experiments were divided into three groups: No Strategy, Search Restriction, and Search Training. Participants in No Strategies condition were asked to perform the task of predicting stock prices in any way they wished. Participants in the Search Restriction group were provided with a list of alternative strategies, selected from some common and successful strategies. One such strategy, for example, is to calculate average stock price by close/open, or high/low prices, and use the average price to estimate the actual stock price. Participants in the Search Restriction group were required to select the strategies, and use them in the task of predicting stock prices. The Search Training participants were offered by a step by step training for developing their own strategies to predict stock prices in the experimental task.

Ninety four undergraduate students participated in Earley et al.'s (1989) study. The participants were asked to play the role of stock brokers to make judgments of stock prices for individual companies. Earley et al. found a strong relationship between using strategies and task performance. Participants who used a strategy performed better than did the participants who did not use a strategy. Moreover, Earley et al. found that

participants who received Search Training made significantly better price predictions than participants in the Search Restriction group. Also, participants in these two groups, improved their performance with experience of applying their strategies. Earley et al.'s (1989) study is a good example of research to help us to better understand the influence of using strategy on the performance of predicting stock prices.

What information has more predictive value? Zielonka (2004) studied the impact of cognitive biases on forecasting stock prices. The three cognitive biases examined in Zielonka's study are: gambler's fallacy, ignoring the principle of regression to the mean, and anchoring and adjustment. The gambler's fallacy is often observed in a casino where, if black has not occurred for a long run, the roulette player is inclined to believe that the black will be occur next. In stock markets the gambler's fallacy manifests itself in predicting a trend reversal. For example, if a stock increases for a long period, traders are more likely to believe that it will begin to decline very soon. Regression to the mean refers to the statistical phenomenon that the lowest values are usually followed by higher ones, and highest values followed by lower. Most traders, including experts, however, are not aware of the principles of regression to the mean in stock market (Bernstein, 1992). The anchoring and adjustment refers to such a cognitive bias that most traders tend to make their judgments based on a salient reference point (anchor). Traders, for example, overestimate the importance of a recent stock price that may be considered as an anchor for predicting future stock prices.

Twenty four financial professionals were invited to participate in Zielonka's (2004) study. They were presented a questionnaire with 24 questions about stock information, and were asked to rate the predict importance of stock information for

predicting stock prices. The more important a stock information, the higher predictive value it has. Examples of stock information about technical analysis are the following.

- Rising stock index breaks its main trend line;
- After a big rise, stock index creates a “head and shoulders” formation;
- Stock index’s increase accompanied by a drop of the unemployment rate;
- Rising stock index creates longer and longer horizontal shelves;
- The fall of stock index accompanied by a government crisis.

Zielonka (2004) found that different stock information has different value for predicting stock prices. However, the more predictive value the information has, the easier the information produces the cognitive biases (e.g., gambler’s fallacy, anchoring and adjustment).

Only financial professionals were employed in Zielonka’s (2004) study. They are more familiar with the information of technical analysis than common traders. How do common traders use the same information of technical analysis as the financial professionals in their trade processes? Zielonka did not look at the difference between financial professionals and common traders.

How do charts affect traders to buy and sell stocks? Stock chart plays an important role to help traders forecast future stock prices and trading stocks, even though efficient markets theory (Fama, 1965; Malkiel, 1973) suggests that the movement of prices is random. Prices have no memory, but perhaps traders do. How do charts influence traders’ market behaviour? Mussweiler and Schneller (2003) studied the impact of stock charts depicting past prices on traders’ decisions of buying and selling stocks.

They used two stock charts in the experiments. One chart had what they called a *clear high price change*, meaning that the prices increase first and then decrease; another one had what they called a *clear low price change*, meaning that the prices decrease first and then increase after (see Figure 1a and 1b).

Figure 1a. Example of one chart with a clear high price change
 1b. Example of one chart with a clear low price change

One hundred and two students of business or economics at the University of Würzburg, with at least one year of investment experience, were employed in Mussweiler & Schneller's (2003) experiments. Participants forecasted a higher future price when they saw the clear high stock chart than when they saw the clear low stock chart. They were less likely to sell and more likely to buy stocks when saw a clear high price than when saw a clear low price showing on chart. Mussweiler and Schneller (2003) noted that much richer information (i.e., company profile, news, financial reports, and competitors, etc.) about a stock likely reduce the influence of stock chart on the participants' trading behaviour. Still, participants' trading behaviour was influenced by stock charts depicting past prices, even though they were provided by much richer information of the stock. In a follow-up study, Mussweiler and Schneller (2003) employed twenty financial

professionals as participants. All worked for German bank. Their trade decisions also seemed to be strongly influenced by the charts.

Mussweiler and Schneller's (2003) study is a good example to help us better understand traders' decisions to buy or sell stocks by the stock charts. However, their study has several limitations. First, participants made their trade decision only based on a clear high or low price change; no other price trends were shown. Second, Mussweiler and Schneller only presented the stock charts associated with one year's prices. Stock charts associated with shorter durations such as a month or a week was not shown. Finally, they didn't compare the financial professionals' trade behaviour with students', even though Mussweiler and Schneller investigated the trade behaviour of both.

Mussweiler and Schneller's findings are similar to other research on the effects of time series data on trade decisions. De Bondt & Werner (1993), for example, demonstrated that traders tend to expect recent trends in the market to continue, so they predict higher stock prices in a rising (bull) market than in a falling (bear) market.

In summary, Random Walk theory assumes that stock price changes are random and thus it is impossible to predict price movement. However, this theory also accepts that stock price changes are influenced by human factors such as heuristics and biases. Related research on the impact of human factors on predicting stock prices and trading stocks has been undertaken from various points of view.

First, stock price trends have been shown to influence traders' market behaviour. Traders usually employ heuristics such as availability, representativeness, the law of small numbers, and anchoring in their trade judgments and decisions.

Second, traders generally exhibit overconfidence in their stock prices judgments and trade decisions. Financial professionals have more experience in the stock market, but they still demonstrate the overconfidence in their trading processes.

Third, risk affects traders' judgments and decisions in their investments. Loss aversion, for example, can be found in financial professionals who are engaged in a trade task during a short period.

Fourth, using strategies enhances performance in the task of prediction of stock prices, especially for traders who acquire the strategies by learning. The stock information may have different predictive values for stock prices from the point of view of traders. However, it was found that the stock information with more predictive values almost always is related to cognitive biases such as regression to the mean. In addition, news and rumor affect people's trade behaviour. Some individual traders believe the words, "Buy on the rumor, sell on the news", when they make their trade decisions.

Finally, stock charts are widely viewed as a useful graphic tool to analyze price changes in the market, particularly in the domain of technical analysis. Research on charted stock trends indicates that charts do influence people's trading behaviour.

Charts, frames, and biases

As noted previously, behavioural finance is a new approach to financial market behaviour that has emerged, at least partially, in response to criticisms of "rationality" faced by traditional economic and finance approaches. Some behavioural phenomena in the financial market can be better understood using theories of behavioural finance. The theories help to explain what happens when people make judgments and decisions in their investment behaviour.

A major theoretical framework of behavioural finance, Prospect Theory, makes use of research on cognitive heuristics and biases. In some research, the cognitive heuristics and biases have been examined to determine how they influence various market phenomena. In other studies, the Prospect Theory has been used to account for people's risk behaviour, and to explain the implications of framing effects on trading judgments and decisions in the financial market. Based on Prospect Theory, researchers have conducted various studies to explore people's market behaviour. Mussweiler and Schneller's (2003) study is a good example. Their study help us better understand traders' decisions to buy or sell stocks by the stock charts. Mussweiler and Schneller, however, didn't study the influence of framing effects of chart features such as price scale and time scale on trading behaviour in their experiments, nor did they explore influences on trading behaviour of more than two trends displayed on chart. Even though Mussweiler and Schneller investigated the trade behaviour of financial professionals, they didn't compare their trade behaviour with that of novices. Considered these limitations in previous studies, the current study extended research on framing effects noted in Prospect Theory to a visual display of price information, a stock chart, and consider the implications of stock chart framing effects on people's market behaviour.

In today's internet-accessible stock market, traders may obtain real-time stock data displayed on a computer screen. Much of these data are summarized in stock charts that provide a history at a glance of the trading in stocks, reveling general trends, and showing how many shares were traded, at what price and when. Judging from the popularity of stock charts, traders consider them an important analysis tool in making their investment judgments and decisions. For example, they use stock charts to predict

the probable direction a stock will move, because they believe that the stock charts provide clues about future stock prices (Jiler, 2003). Stock charts are often considered the most effective way to describe, explore, and summarize a set of stock data such as price information, even a very large set, because they allow the eye to detect trends and patterns (Tufte, 1997).

For the past 30 years, various studies of framing effects have focused on stock market behaviour (Bazerman et al, 1985, Fischhoff, 1983; Ginyard, 2001; Johnson et al, 1993; Kirchler et al, 2004; Roszkowski & Snelbecker, 1990; Thaler, 1980; Tversky & Kahneman, 1979, 1981; Weber et al, 2000). Most framing effects, however, have been found only with verbal descriptions or instructions. Yet charts can be manipulated as easily as words (Brown, 2003), the same stock data may be displayed in very different ways. Yesterday's stock price, for example, may be shown in either a weekly chart or a monthly chart or a yearly chart. Stock price changes may be displayed in a chart showing real price movement or a chart showing rate of change. Many financial advisors try to calm nervous clients who react to sudden market changes by showing them stock charts plotting long term trends. In doing so, the advisors reveal their intuition that different charts make a difference. So it is easy to imagine that variations in stock charts can produce their own framing effects, influencing what the predictions and trading decisions of investors.

The Present Research

The primary purpose of the present research is to examine the effects of different stock charting styles on two aspects of peoples' stock market behaviour: 1) predictions of future stock prices, and 2) decisions about trading (buy, sell, and hold) stocks. I will test the hypothesis that people's stock market behaviour depends on the way the data are shown or displayed in the stock chart. I predict that the way data are presented in a stock chart influences both people's predictions of stock prices and their trading behaviour.

What is a stock chart? What are its components? A chart is a visual display of information (see Webster's online dictionary), or a graphic representation of data. Almost all stock charts illustrate the relationships between time (X-axis) and stock trading price (Y-axis). A stock chart is a line graph that provides graphical representations of a stock's price changes over time. The data in a stock chart include the stock symbol, chart type (e.g., bar, line, and candlestick chart), and past prices (e.g., weekly, monthly, and yearly). The chart title usually displays a company's name and stock symbol. The Y axis is used to represent the price of one share; most stock prices are less than \$100.00 dollars. The X axis is used to denote a time period such as an hour, day, week, or month. The pairs of X and Y values are composed of stock data points. To display the movement of stock price a line is drawn linking these data points. Figure 2 illustrates an example of a yearly stock chart of a company called Volt Information Sciences Inc. VOL is the company's stock symbol. Its share prices change between \$10.00 and \$ 25.00 over the past trading year (252 days). The pairs of time and price scale (the pairs of X and Y) represent the movement of price over past year.

Figure 2. A yearly stock price changes of Volt Information Sciences Inc.

Guided by the concept of frames and the verbal frames studied by Tversky and Kahneman (1981, 1982), I wanted to see if visual frames defining charts could also affect predictions of future stock prices, or affect trading behaviour. I was especially interested in the frames of stock charts provided by their two axes: the X-axis and the Y-axis.

The same stock prices can be represented by different X and Y axes. These X and Y axes together define a *chart frame*. It is often possible to frame the same stock price data in more than one way. Stock price data, for example, can not only be displayed in a weekly chart, but also in an hourly or a yearly chart. To perform a technical analysis, traders may seek more information about the movement of stock price in a yearly chart than that in a weekly chart.

Two main chart frame effects are examined: time scale (X axis), price scale (Y axis). Price trend (pairs of X and Y) is also considered in the present research. I examined time scale and price scale effects on stock price predictions and stock trades across different kinds of price trends such as up, down, flat, down and up, up and down. The *time scale frame* refers to how much price history is displayed (weekly, monthly, and

yearly) in a stock chart. In terms of technical analysis (Brown, 2003), recent prices can be displayed by different time periods. Display of a long price history (e.g., one year) can reveal any wave-shaped, periodic movement of stock prices, and reveal long-term trends. Display of a short-term price history can “zoom in” on recent price fluctuations but do not reveal long-term trends. Figure 3a, 3b, and 3c illustrate different time periods used to display five days of share prices. The five prices of 3c are shown as the rightmost five days in charts 3b and 3a.

Figure 3a. One year's stock price changes of Yahoo! Inc.

Figure 3b. One month's stock price changes of Yahoo! Inc.

Figure 3c. One week's stock price changes of Yahoo! Inc.

As illustrated in the Figure 3a, 3b and 3c, the same recent 5-day prices can appear quite different, even though these three stock charts have same price scale (Y-axis). The 5-day prices in the yearly chart appear to show a recent history of a sharp up turn (see Figure 3a); the same 5-day prices in the monthly and weekly chart display a flat line (see Figure 3b and 3c). Such a difference in the time scale may influence people's stock predictions and trades. Based on the explanation of framing effects of Prospect Theory (Kahneman & Tversky, 1979), traders probably make different judgments when same stock prices are presented in different chart frames. I predict that traders will show less variation and be more confident in their price predictions when shown a yearly chart than shown a weekly chart, since the yearly chart provides more historical context than does a monthly or weekly chart. For the same reason, I also predict that the traders will trade more shares of stock when shown a yearly chart than shown a monthly or weekly chart.

A *price scale frame* refers to how the stock price (Y-axis) is displayed in a stock chart. For a given period of time, the changes of a stock price can be represented by its previous open, close, high and low prices, price-earnings ratio (P/E), rate of change

(ROC), and so forth. Only previous closing price is selected for study in the present research, since the closing price is the most common price indicator used in the everyday stock market. In terms of technical analysis, the closing price is the last price traded on the previous day. The closing prices showing on chart reveal the movement of stock price from day to day.

I predict that closing price scale will also show a framing effect and influence stock price predictions and stock trades. The price scale of a chart usually refers to price range, minimum and maximum prices shown at the bottom and top of the Y-axis. There are two main kinds of price scales: truncated and absolute. A *truncated scale* sets the Y-axis end points to the values that are close to the lowest and highest prices for a given time period (see Y-axis of Figure 4a). If a stock price, for example, changes from \$15.78 to \$45.15 in the past 52 weeks, then its truncated scale may be displayed from \$10.00 (minimum value) to \$50.00 (maximum value) on the Y-axis. An *absolute scale* refers to such a scale whose price range is between \$0.00 and some stated maximum (usually \$100.00) in a given time period. An example is shown in Figure 4b, below. Here, the \$0.00 is the minimum price value, and \$100.00 is the maximum value (since most stock prices are less than \$100.00 a share). Only truncated scales are shown in typical stock charts in market; I use both truncated and absolute scales to see if they influence traders' predictions and trading behaviour.

Figure 4a. One year's stock chart of Yahoo! Inc. (truncated price range: \$10.00-\$50.00)

Figure 4b. Same year's stock chart of Yahoo! Inc. (absolute price range: \$0.00-\$100.00)

Notice that the price movement displayed in the Figure 4b appears flatter, smaller, less volatile than one in the Figure 4a. I predict that the difference in these appearances will affect people's stock predictions and trades. In particular, I predict that the "flatter" or "less volatile" appearance of absolute scales (as in Figure 4b) will produce flatter or less variable predictions of future stock prices than will its truncated counterpart, and will also produce fewer share trades (buy , sell) and more shares hold.

Because a stock chart provides a visual representation of past prices, it allows the eye to detect historical trends or patterns. According to technical analysis, a price trend represents the general direction of stock price movement in a given time period. Many traders prefer to use the price trend as a primary consideration in their trades (i.e., buy, sell or hold stocks) (Kaufman, 1995).

Do the time frame or price frame influence predictions and trades for all charts, or only for those of a certain shape or trend? In order to examine the generality of any time frame and price frame effects, I examined them for five common stock price trends: up, down, flat, down-up, and up-down trend. In a given time period, an up trend shows a generally rising direction of price movement; a down trend displays a generally falling direction of price movement; a flat trend exhibits a generally horizontal direction of price movement; a down-up trend has a “U” direction of price movement; and an up-down trend indicates in inverted “U” direction of price movement. Figure 5 (a), (b), (c), (d), and (e) illustrate the five price trends.

Figure 5a. An up price trend of Safenet Inc.

Figure 5b. A down price trend of MI Developments Inc.

Figure 5c. A flat price trend of Wolseley PLC

Figure 5d. A down-up price trend of A.C. Moore Arts & Crafts Inc.

Figure 5e. An up-down price trend of j2 Global Communications Inc.

As shown in Figures 5a, 5b, 5c, 5d, and 5e, charts of stock prices may reveal different trends, although these charts are composed of almost same time and price scales. Not surprisingly, I predict that if people are shown an up trend, they will predict that the stock price will continue to rise. If people are shown a down trend, they will predict the stock price will continue to fall. If they are shown a flat trend, they will predict the stock price will remain flat. It is more difficult to predict what people will do if shown a down-up or an up-down trend. But I predict that if they see charts with enough history (e.g., a year) to reveal the trend, they will make different predictions than if they see only the last sequence of the trend (e.g., the last week).

To test these predictions and answer the above questions about influences of time frame and price frame on predictions and trading, I conducted three experiments. The purpose of the first experiment was to examine the chart framing effects of time scales (X-axis), price scales (Y-axis) on people's predictions of future stock prices for the five price trends. The second experiment was to study the influence of time scales and price scales on forecasting future stock prices and trading stocks (e.g., buy, sell, and hold

stocks). The third experiment was a partial replication of the second experiment using experienced traders rather than undergraduates and undertaken to determine if trading experience makes a difference in framing effects.

Experiment 1

The purpose of Experiment 1 was to determine if time scale (X axis), price scale (Y axis), and price trend (the shape of the price plot) influence participants' prediction of future stock prices. Each participant was shown several stock charts taken from real, publicly traded companies and asked to predict the next five days of prices for each stock shown in a chart. The charts were systematically varied in three ways: time scale, price scale and price trend. To vary time scale, some charts showed only the previous week (five trading days) of closing prices for each of a set of publicly traded companies. Others showed the previous month (21 trading days = the previous week + the three weeks previous to that) of the prices for the same set of companies. And others showed the previous year (252 trading days = the previous month + 11 months previous to that) of stock prices for the same set of companies. Thus, participants saw the same previous week data of a stock chart three times: once with no historical context, once in the previous month's historical context, and once in the previous year's historical context. In this way, I could determine if the addition of more historical data would change the nature of the predictions that participants made.

Two price scales, one absolute and one truncated, were also used in the experiment. The absolute scale charts showed prices on a Y-axis that ranged from \$0 to the price that was double the maximum price (e.g., if the maximum price is \$50, then the top of the Y-axis showed \$100), and the truncated scale charts showed prices that ranged from just below the minimum price to just above the maximum.

Finally, five year-long price trends were selected: up, down, flat, down-up, and up-down (for example, see Figures 5a-5e). Based on different combinations of time scale

and price scale, the stock price data showing on the chart were thus “framed”. For example, a participant would predict the next five days of Yahoo stock prices based on the year-long chart shown in Figure 3a. The same participant would also predict the next five days of Yahoo stock prices based on a chart showing the most recent 21 days (trading month) of the prices in Figure 3b. And the participant would predict the next five days of Yahoo stock prices based on a chart showing only the most recent 5 days (trading week) of prices in Figure 3c. A comparison of the participant’s three sets of five-day predictions would reveal any time scale influences. Half the participants saw these data on charts with an absolute scale Y-axis; the remaining half of the participants saw the same data on a truncated scale Y-axis. Comparisons of their results could reveal if the price scale frame (Y-axis) influenced their five-day price forecasts.

Three questions were addressed. First, does the prediction of stock prices vary with different time scales? Second, does the prediction of stock prices vary with different price scales? Third, does the prediction of stock prices vary with different price trends? To answer the three questions, I needed indicators of prediction characteristics that would reflect psychologically meaningful phenomena. I chose three such indicators. The first was the standard deviation (SD) of the five predictions a participant made of a stock’s next five days of share prices. A participant who predicted the next five days of a stock’s price would be \$23, \$23, \$23, \$23, and \$23 would have an SD of 0.0. A participant who predicted the next five days of a stock’s price would be \$23, \$27, \$34, \$20, and \$41 would have a relatively large SD. If a participant was using all historical information in the chart provided (a week, a month or a year), then, as the amount of information increased, I would expect the SD to decline simply because predictions should be more

stable as the sample used to derive them increases. I would also predict the SD to increase with the perceived variability (volatility) of stock prices. Because the perceived variability would increase from an absolute to a truncated frame, I hypothesize more variability in the five predictions when a stock chart was shown in a truncated price frame than in an absolute price frame.

The second indicator of prediction characteristics was the linear correlation of the five predictions. If, for example, the predictions went up from tomorrow (day 1), the day after tomorrow (day 2), ... to four days after tomorrow (day 5) in a linear progression (for example, \$5, \$7, \$9, \$11, \$13) the correlation would be $r = +1.0$ and indicate that the participant was predicting an upward trend. A similar downward trend might occur (for example, \$31, \$27, \$23, \$19, \$15), or no trend (\$4, \$6, \$2, \$3, \$5). I predicted that charts showing an uptrend would produce a positive correlation of these predictions, charts showing a down trend would show a negative correlation, and charts with no trend would show no correlation. If participants were using year-long information in down-up and up-down charts, then their correlations should change when they saw only the right-hand part of the curve in the month and week charts.

The third indicator of prediction characteristics was generated by the participants themselves. In addition to asking them for price predictions in the five days following, I also asked them to give a range of prices for each of the five days that they believed with 95% confidence the real price would fall within. The resulting subjective confidence interval (high minus low in the stated range) was examined for several differences. Because subjective confidence tends to decline as we predict further into the future, I hypothesized that the subjective confidence interval would increase (indicating a decrease

in prediction confidence) from the Day 1 prediction to the Day 5 prediction, just as the confidence of meteorologists declines as they make longer range weather forecasts. Because subjective confidence tends to increase as more information is examined (e.g., see Oskamp, 1965), I also predicted that the five subjective confidence intervals would decline, indicating greater subjective confidence, with increasing amounts of chart data; so subjective confidence intervals would be smaller when yearly charts were seen than when monthly charts were seen, and smaller still when weekly charts were seen. Finally, I predicted that subjective confidence intervals would be smaller when participants saw charts in absolute price frames than in truncated price frames, simply because absolute frames reduce the perception of price volatility (compare Figures 4a and 4b).

As described as above, I summarized these hypotheses in Table 1. The left and middle columns were hypothesis ID and its description. The right column was used to describe the variable to be test in the experiment.

Table 1. Summary of the hypotheses of forecasting future prices

Hypothesis	Description	Variable to be tested
1.1	Participants will show less variability in their five-day price forecasts when viewing stock charts showing long-term price data than when viewing stock charts showing short-term price data.	time scale (variability)
1.2	Participants will show less variability in their five-day price forecasts when viewing stock charts showing an absolute price scale than when viewing stock charts showing a truncated scale.	price scale (variability)
1.3	Participants will show more of a linear trend in their forecasts when viewing stock charts showing a linear yearly trend than when viewing stock charts showing a non-linear trend.	price trend (correlation)
1.4	Participants will show more confidence in their five-day forecasts, and thus show narrower subjective confidence intervals in their predictions, the more historical data they see.	time scale (confidence)
1.5	Participants will show more confidence, and thus show narrower subjective confidence intervals in their predictions when viewing charts showing an absolute price scale than when viewing charts showing a truncated scale.	price scale (confidence)
1.6	The further in the future forecasts are made the wider the subjective confidence interval will be.	predicted days (1-5) (confidence)

Method

Experimental Design

A 3 x 2 x 5 (3 time scales, 2 price scales, and 5 price trends) mixed repeated factorial design was employed in the experiment. Time scale and price trend were within-subject variables. Price scale was a between-subject variable. Half the participants saw a truncated price scale (e.g., \$10.00-\$50.00 on the Y-axis), the one normally used in commercial stock charts. The remaining participants saw an absolute price scale (e.g., \$0.00-\$100.00 on the Y-axis) for research comparisons. Price scale was chosen as a

between-subject variable to minimize the confusion participants were likely to experience seeing the Y-axis shift from the absolute to the truncated scale from one trial to the next.

Five year-long price trends were shown: (1) up, (2) down, (3) flat, (4) down-up, and (5) up-down. Two examples of each trend were shown to each participant. Three time scales were employed: (1) last week, (2) last month, and (3) last year. Considering weekends and holidays each weekly stock chart showed the previous 5 days of stock prices, each monthly chart showed the previous 21 days of stock prices, and each yearly chart showed the previous 252 days of stock prices. The absolute scale showed dollars on the Y-axis ranging from \$0 to the price that was double the highest stock price on the chart. The truncated scale showed the price range covering \$5.00-\$10.00 lower than the lowest price and \$5.00-\$10.00 higher than the highest price of the stock depicted in a chart. The research design is summarized in Table 2.

Table 2. Research design of Experiment 1

Participants	Price scale (Y-axis)	Time scale (X-axis)		
		last week	last month	last year
1-15	absolute	5 trends x	5 trends x	5 trends x
		2 examples =	2 examples =	2 examples =
		10 charts	10 charts	10 charts
16-30	truncated	5 trends x	5 trends x	5 trends x
		2 examples =	2 examples =	2 examples =
		10 charts	10 charts	10 charts

After examining each of the 30 assigned charts, a participant was asked to predict its stock prices for each of the next five days (the five-day forecast). These five predicted prices were the five primary dependent variables of the experimental design. Participants were also asked to give the high & low prices on either side of these five predictions

within which they felt 95% confident each day's price would fall. The ranges of these five high-low sets were used to calculate subjective confidence intervals.

Participants

Thirty undergraduate students taking Introductory Psychology at Carleton University participated in the experiment. Their average age was 22 years. Thirteen were female students; and seventeen were males. All participants reported that they learned a little about stock market as part of a high school class, but were otherwise naïve about the stock market. They were given experimental participation credit to fulfill course requirements for Introductory Psychology. Fifteen of the participants were randomly assigned to the absolute scale condition; the remaining 15 were randomly assigned to the truncated scale condition (see Table 2).

Materials

The materials in the experiment were the task instructions (Appendix A), two sets of 30 stock charts, and one short questionnaire. Two sets of charts, one set for participants 1-15, the other set for participants 16-30, showed the 30 combinations of different stocks, trends, and historical prices. A sample of stock chart showing truncated price scale is shown in Appendix B. A sample of stock chart showing absolute price scale is shown in Appendix C. The questionnaire required each participant to indicate his/her stock trading background (Appendix D).

The Stock Charts. The price data used to construct the stock charts were chosen from a database of real stocks. A week chart showed the most recent five trading days of a stock's closing prices. A month chart showed these same five days plus 16 additional trading days = the 21 most recent trading days of a stock's closing prices. A year chart

showed these 21 trading days plus 231 additional trading days = the 252 most recent trading days of a stock's closing prices. In this experiment, the five trends were depicted only in the yearly chart; thus, it happened that a yearly up trend might be flat in the most recent month and even a down trend in the most recent week. My decision to employ real stock data increased the ecological validity of the experiment and allowed me to see if predictions based on a short-term trend (e.g., a week) might change when seen in a long-term, historical context. However, the decision reduced the experimental control that could come from showing a trend as year long, and as month-long, and as week-long. This control was added in Experiments 2 and 3. All stock charts were shown in the same font, color, style, and size. Thirty charts were randomly printed on 10 separate sheets of paper; three charts per sheet. The order of the charts was randomized by shuffling the 10 sheets before each participant arrived.

Procedure

Upon arriving at the testing room, each participant was asked to sign the informed consent form, provided in Appendix E. Then he/she was asked to complete the short questionnaire regarding to his/her stock market experience. After completing the questionnaire, the participant was told how the experiment would proceed. He/she was asked to forecast a stock's prices for the next five days after examining each chart. The participant was also assured that the purpose of the experiment was to evaluate how stock charts affect predictions rather than to test his/her ability to make these predictions.

A stack of the 30 charts, displayed three per sheet on ten shuffled sheets, was placed on the table in front of each participant. The participant was asked to look at each stock chart until he/she felt ready to forecast its price and ranges for the next five days.

The participant was then shown how to write down his/her predictions (prices and their ranges) to the right of the stock chart (see Appendices B and C for a typical sheet).

He/she performed the task in this manner for 30 charts, each chart representing one of the 3 x 2 x 5 combinations of trend examples (two exemplars of each of the five trends) and time scales (3). Each participant was then thanked for participating, given a debriefing sheet (Appendix F) and excused.

Results

As previously noted, I employed three derived measures in the data analysis: standard deviation (SD), correlation coefficient (r), and subjective confidence interval (SCI). The SD measures the variability of the five predicted prices and was used as an indicator of variable or changing predictions. The correlation coefficient, r , measures the degree to which predicted prices are a linear extrapolation of historical prices. The subjective confidence interval, SCI, reflects participants' uncertainty of his/her price predictions. These derived measures are helpful in understanding how the three variables, time scale, price scale, and price trend, might be influencing price predictions.

Variability Measure (SD)

In order to examine how time scale, price scale, and price trend influenced the variability of predicted price data, I used a mixed model (3 x 2 x 5) ANOVA to analyze the SDs of predicted price data. There were two significant main effects, one for time scale, $F(2, 56) = 11.014, p < .001$ and one for price trend, $F(4, 112) = 14.326, p < .001$. There was no significant main effect for price scale (Y-axis), nor was there any

significant interaction effect, so Hypothesis 1.2 was not supported. The two significant main effects, time scale and price trend, are displayed in Figure 6.

Figure 6. Means of SD for time scales and price trends

The main effect of time scale indicates that the forecast increased in variability as more historical data were shown (see Figure 6). On average, participants made more variable five-day forecasts after seeing a long history than after seeing a short history. Significant pairwise differences existed among all three mean differences of SD for the time scale (see Table 3). This is contrary to hypothesis 1.1 that forecast variability would decline as more historical data were added. There are at least two possible reasons for this reversal. First, the historical data might simply confuse participants. Second, historical data might allow participants to make linear extrapolations (rather than, say, forecasting the same share price for the next five days) more easily and the extrapolations might account for the increase in SDs. This can be tested, of course, by examining the effects of historical trend information on the correlation coefficient, which I report in Table 3.

(Note: All pairwise comparisons in Experiment 1 are based on the Least Significant Difference test.).

Table 3. Pairwise comparisons of mean difference of SD for time scale

	SD	year	month	week
year	.078			
month	.042	.159**		
week	.037	.261*	.102**	

* $p < .001$ ** $p < .05$

The simple main effect of price trend indicated that different trends displayed on charts produced different variability in five-day forecast. Pairwise comparisons were applied to examine the mean difference among the five different trends. The differences between the means of SD are listed in Table 4.

Table 4. Pairwise comparisons of mean difference of SD for price trends

	SD	up	down	flat	down-up	up-down
up	.048					
down	.060	-.076				
flat	.028	.198*	.275*			
down-up	.069	-.004	.072	-.203*		
up-down	.056	-.140**	-.064	-.338*	-.136**	

* $p < .001$ ** $p < .05$

As plotted in Figure 6, the chart showing a flat trend produced less variability in predicted price than the two other linear trends (i.e., up trend and down trend). There was no significant difference between the up trend and the down trend in the variability of five-day forecast. A significant difference was found between down-up and up-down trend. Only the chart showing a flat trend showed less variability than all others in forecasting future stock prices.

Correlation Coefficient (r)

The Person correlation coefficient, r , was employed to measure the extent to which participants were making a linear extrapolation in their five-day forecasts. I used a mixed (3 x 2 x 5) ANOVA to analyze how price scale, time scale, and trend influenced the forecasted trends. The values of r at first were transformed to Z scores using the following standard formula.

$$Z = \frac{\ln[(r + 1)/(r - 1)]}{2}$$

There was no significant main effect of price scale, but there was a significant main effect for time scale, $F(2, 56) = 5.421, p < .05$. There was also one significant interaction between time scale and price trend, $F(8, 224) = 4.584, p < .001$. The results are shown in Figure 7; I converted the Z scores back to r values to illustrate the differences more clearly. Because the five price trends were defined only in yearly charts, trends for month and week were not always consistent with the yearly trends, and it was thus not possible to give a clear interpretation of the significant time-by-trend interaction. Figure 7 shows the mean r of each price trend in yearly charts.

Figure 7. Mean of r of each trend for the two price scales in yearly charts

The results shown in Figure 7 suggest that, when participants saw linear trends (i.e., up, flat, and down trends), they made their 5-day forecasts by extrapolating from what they saw. The average r values for forecasts based upon up, flat, and down trends of both groups were respectively 0.54, 0.03, and -0.39, which parallel the three trends. However, two other features of these results are noteworthy. First, the correlations for up and down forecasts are noticeably weaker than the correlations of the trends that produced them (r for up trend = +0.95; r for down trend = -0.93), suggesting a degree of caution, timidity or confusion in forecasting. Second, there is a noticeable asymmetry between the correlation of forecasts from the up trend and the correlation of the forecasts from the down trend. The asymmetry in average r values between forecasts based on the yearly up trend and the yearly down trend could not be explained by differences in the historical trend correlations because their r values were virtually identical. The asymmetry principle of Prospect Theory addresses asymmetric values of gains and losses. My results indicate that asymmetry may also extend to judgments of the possibilities of

gains and losses. Participants seemed more cautious or timid about forecasting continued losses based on a year-long trend of losses than about forecasting continued gains based on a year-long trend of gains. I was not able to find a simple cognitive explanation for this asymmetry. Perhaps the explanation lies in wishful thinking.

The forecasts based on the two non-linear yearly trends (down-up and up-down) were more puzzling. As shown in Figure 7, the average r values for down-up and up-down trend were respectively 0.17, and 0.10, indicating that participants made almost no linear extrapolation from the two non-linear trends. It is likely that non-linear trends are more difficult for participants to employ in forecasting share prices than are linear trends. In response to the added difficulty, many participants might ignore recent and previous trends, instead making the safe prediction that tomorrow's price will be the same as today's. I have no good explanation for the r values of non-linear trends. But the forecasting inconsistencies suggest that participants are not consistent in their interpretation of non-linear trends, and that historical data might only be useful when they show a simple, linear trend.

To help understand the degree of statistical relationship between the historical prices showing on charts and predicted prices, I summarize the r values of historical prices shown on yearly chart and the r values of the forecasted 5-day prices in Table 5.

Table 5. Relation between r of historical prices and r of predicted prices (yearly chart only)

Trend type		Historical prices showing on chart		Predicted prices (Average)
Linear	up	0.95		0.54
	down	-0.93		-0.39
	flat	-0.14		0.03
Non-linear	down-up	-0.79	0.83	0.17
		(down)	(up)	
	up-down	0.85	-0.81	0.10
		(up)	(down)	

As described above, the results support the hypothesis 1.3, participants made more consistent linear extrapolations when viewing stock charts showing a linear yearly trend than when viewing stock charts showing a non-linear trend.

Subjective *confidence interval* (SCI)

Participants were asked to not only forecast the next five days of prices, but also to estimate a range of the predicted prices, high and low prices for each of the five days, in which they felt 95% confident that the price would fall. The resulting five high minus low prices for each of the five days of forecasts were employed to measure the subjective confidence interval of each participant. Participants with low ranges were defined as those who had more confidence in their predictions than participants with high ranges. To normalize the SCI, the following formula is employed in the data analysis.

$$SCI = (\text{predicted high price} - \text{predicted low price}) / \text{current predicted price}$$

I use the range of predicted high price and low price divided by current predicted price rather than the range only in order to control the difference in the current predicted price. Here is an example. The predicted price is \$31.25, the predicted high price is \$32.50, and the predicted low price is \$31.00. Its SCI is equal to $(\$32.50 - \$31.00) / \$31.25 = 0.05$. In

this way, I calculated the five SCIs and average of them for each participant. The SCIs for each predicted day (from day 1 to day 5) also were calculated to see if there were differences of SCI values from first day, second day, ... fifth day in participants' forecasted price data.

A mixed model (3 x 2 x 5) ANOVA was employed to analyze the average SCIs for the five-day predicted price data. Two significant simple main effects were found, one for time scale, $F(2, 56) = 13.458, p < .001$ and one for price trend, $F(4, 112) = 7.109, p < .01$. There was no significant difference for price scale and no significant interactions were found in the results. Hypothesis 1.5 thus was not supported. The two main effects of both time scale and price trend are displayed in Figure 8.

Figure 8. Mean of SCI for time scale and price trend

Table 6 lists the tests for pairwise differences among the three time scales. And Table 7 shows the pairwise differences among the five trends.

Table 6. Pairwise comparisons of mean difference of SCI for time scale

Time scale	Average SCI	year	month	week
year	.059			
month	.044	.016*		
week	.042	.017**	.002	

* $p < .001$ ** $p < .05$

Table 7. Pairwise comparisons of mean difference of SCI for price trend

Price trend	Average SCI	up	down	flat	down-up	up-down
up	.038					
down	.060	-.022*				
flat	.045	-.007**	.016**			
down-up	.046	-.009**	.014**	-.002		
up-down	.052	-.014**	.008**	-.007	-.005	

* $p < .001$ ** $p < .05$

According to the statistical analysis, the charts showing a year of price data had a significantly larger average SCI value than the charts showing a month or a week of price data (see Figure 8). This suggests that participants felt less certain about forecasting share price when shown long-term prices than when shown short-term prices. The result didn't support hypothesis 1.4. One possible reason is that participants perceived more variability (volatility) of share prices showing in a yearly chart than those showing in a monthly or weekly chart. As a result, perhaps they felt more uncertainty in their forecasts when saw a yearly chart than when saw a month or weekly chart.

Pairwise comparisons also indicate significant trend differences in the SCI. Up trends showed significantly lower SCI, and down trends showed significantly higher SCI than the remaining three price trends. The asymmetry parallels that found with correlation coefficients, above, and suggests again that the gain/loss asymmetry assumption of Prospect Theory can perhaps be extended to include forecasts as well as values.

I was also interested to see if the SCI values increased as the forecasts went further into the future. I therefore conducted a 5 x 2 repeated measure ANOVA (five days of forecasts and two price scales) to see if there was a significant forecast effect. The statistical results indicated that there was a small but significant increase in SCI values from the first forecast to the last, an increase shown in Figure 9. The finding supported hypothesis 1.6.

Figure 9. Mean of SCI values for prediction of next 5-day stock price

Discussion

The primary purpose of Experiment 1 was to determine if time scale, price scale, and price trend influence participants' forecast of future stock prices. Price scale did not appear to influence forecasts, but time scale and yearly trend did. Four principal influences were found. First, participants increased the uncertainty of their price forecasts, indicated by higher SDs and by SCIs, as the amount of historical price data increased. Second, participants made linear extrapolations in their price predictions when they saw linear trends, but they made inconsistent extrapolations when they saw non-linear trends. Third, day-by-price correlations of five-day forecasts based on viewing

linear up and down trends were weaker than the correlations of the trends themselves.

Finally, participants showed consistent asymmetry in their price forecasts, showing lower SDs and SCIs when forecasting from a year-long up trend than from an equivalent year-long down trend.

The increased uncertainty and lower confidence in forecasts made with more historical data are contrary to previous research (for example, see Oskamp, 1965), indicating that subjective confidence increases as more information is obtained. Perhaps the reason for this contradiction is related to the character of the research task. A “bigger picture” revealed by charting greater amounts of historical information exposed participants in my experiment to wider variation or more volatility in share prices. This increase in variation may have led participants to be more uncertainty or less confidence about predicting the future.

It is comforting to show that, when participants saw linear yearly trends (up, down, and flat), their forecasts were approximate linear extrapolations of these trends. This confirmed hypothesis 1.3. It remains puzzling why participants did not do the same for the two nonlinear trends. The up-down and the down-up trends bent in the middle of the past year; the most recent six months were consistently down or consistently up. If participants ignored the most ancient six months, their forecasts should have extrapolated the most recent six-month trend and their subjective confidence intervals should have been smaller. This did not happen, suggesting that participants did notice the nonlinear pattern across the whole year, but did not know what to do with this pattern in making forecasts.

Why might the correlations found in the five-day forecasts of linear trends be weaker than the trends producing them? Perhaps the weakness reflects some variation of a regression effect – correlations regressing toward zero. On the other hand, SD and SCI results suggest that the weaker correlations reflected a form of forecasting timidity or caution. This, in turn, may be the result of using inexperienced participants for the study. More experienced participants were used in Experiment 3.

Why did roughly symmetrical up and down trends produce asymmetrical price forecasts? According to Prospect Theory (Kahneman & Tversky, 1979), the negative value of a loss is greater than the positive value of an equivalent gain. In my experiment, however, the asymmetry was found in price forecasts, not in value assessments. Perhaps participants thought of up trends as gains and down trends as losses, and somehow transferred asymmetrical values to asymmetrical beliefs. If so, the result may extend Prospect Theory to include beliefs, as well as values, about gains and losses. The result seems important and worthy of replication attempts. I attempt to replicate the asymmetry in Experiments 2 and 3.

The results of Experiment 1 are helpful to understand participants' forecasting behaviour. There are, however, limitations to the experiment. Because I wanted my first experiment to have ecological validity, I selected real stock data. But this allowed me only to manipulate yearly trends reliably; the most-recent month and most-recent week trends in the data I selected could not be controlled. To overcome this limitation, the data for charts in Experiments 2 and 3 were artificially created. This allowed me to manipulate and control weekly and monthly trends as well as yearly trends.

In the real stock market, people not only forecast future share prices, but they also buy and sell shares. Different from simply forecasting behaviour, a trader also must deal with his/her possible gains and losses by buying or selling shares. I designed Experiment 2 to explore forecasting further, and to explore trading behaviour as well.

Experiment 2

There were two purposes of Experiment 2: (1) to further investigate framing effects on share price predictions by controlling more trend variables than those controlled in Experiment 1, and (2) to examine how framing effects might influence trading behaviour. The first purpose led me to design a variation of Experiment 1, asking participants to make five-day forecasts after seeing year, month and week-long trends equated for their strength (correlation). The second purpose led me to ask the participants also to buy, sell, or hold shares either before or after they made their forecasts.

My research design was partly guided by the results of Experiment 1. I continued to use the three indices of forecasts: SD, r , and SCI. However, because price scale seemed to make no difference in forecasts, I chose not to manipulate it in Experiment 2; instead I showed all charts using a truncated price scale (Y-axis). Similarly, because the up-down and down-up trends produced ambiguous forecasts in Experiment 1, I chose for Experiment 2 to concentrate only on linear price trends: up, down, and flat. Rather than using price data from real stocks, as I had in Experiment 1, I generated realistic looking price charts by adding different amounts of random variation to linear price trends. The results were price charts that looked similar to scatter plots of days against prices; manipulating the amount of random variation effectively changed the correlation between time and price. This allowed me the benefit of showing equivalent up trends, down trends or flat trends for the past week, the past month, and the past year of trading. As a result, I could address questions about forecasts based on, say, the past week of trading showing a day/price correlation of +0.65, the past month of trading showing a day/price correlation

of +0.65, and the past month of trading showing a day/price correlation of +0.65.

Examples of these charts are shown in Figures 10a, b, and c below.

Figure 10a. One year's stock chart of Par Technology Corp. ($r = +0.65$)

Figure 10b. One month's stock chart of A C M Managed Inc. ($r = +0.65$)

Figure 10c. One week's stock chart of W-H Energy Services Inc. ($r = +0.65$)

In order to vary the price trends and their consistency, I generated five data sets that varied in their day-price correlations. Each data set was represented by six charts: two showing the previous week of share prices, two showing the previous month of share prices, and two showing the previous year. One data set produced a day-price correlation of about $r = +0.9$ for all six charts; a second data set produced a day-price correlation of about $r = +0.6$ for all six charts; and a third data set had a day-price correlation of about $r = +0.0$ for all six charts. The remaining two data sets had negative correlations of about $r = -0.6$ and $r = -0.9$ for their six charts. These were generated simply by turning the data sets with positive correlations upside down. I called these five trends, strong up, moderate up, flat, moderate down and strong down.

Hypotheses of price forecasts

My hypotheses about forecasts were also guided in part by the results of Experiment 1. For example, Experiment 1 indicated that including more historical price data increased the variability (SD) of five-day forecasts. I therefore predicted that year-long stock charts would produce more variation over the five forecasted prices than

would the equivalent month-long and week long charts, and that month-long charts would produce more forecast variation than would week-long charts (Hypothesis 2.1)

The results of Experiment 1 showed that the price trend did influence five-day forecasts of share prices. I reasoned that a strong price trend would show more influence than a moderate one, and a moderate trend would show more influence than a flat one. As a result, I predicted that the day-price correlations of the forecasts based on strong up and strong down trends would be larger (in absolute value) than those based on moderate up and moderate down trends, and that all would be larger than those based on a flat trend (Hypothesis 2.2)

As noted above, the same strong, moderate and flat trends were shown in year, month and week share price charts. If participants were making use of most of the chart information, then the longer a linear trend was shown on a chart, the more linear should be the five-day forecasts. I therefore predicted that the five-day forecast r -values for year charts would be higher than the five-day forecast r -values for month charts, and that both would be higher than the five-day forecast r -values for week charts (Hypothesis 2.3)

Subjective confidence intervals should also be affected by the length and strength of the trend. Charts showing longer term prices provide more historical data to confirm a trend than do charts showing shorter term prices. Hence, I predict that stock charts showing long-term prices will produce smaller subjective confidence intervals than stock charts showing short-term prices (Hypothesis 2.4). Similarly, the stronger the linear trend shown in a chart, the more confident participants should be in their five-day forecasts. I therefore predict that strong up and down trends will produce smaller subjective

confidence intervals in forecasts than will moderate up and down trends, which will, in turn, produce smaller subjective confidence intervals than flat trends (Hypothesis 2.5).

According to Prospect Theory (Kahneman & Tversky, 1979), people perceive gains differently than losses. Experiment 1 showed an asymmetry in the correlation and confidence intervals of five-day forecasts based on year-long up and down trends; up trends had higher correlations than did down trends (see Table 5) and had smaller subjective confidence intervals (see Figure 8). I predicted that the same would occur in Experiment 2. Specifically, I predicted that strong and moderate up trends would generate higher r -values (Hypothesis 2.6) and smaller subjective confidence intervals (Hypothesis 2.7) than would the equivalent down trends. Finally, as predicted and modestly confirmed in Experiment 1, I also predicted that subjective confidence intervals would increase from Day 1 forecasts to Day 5 forecasts (Hypothesis 2.8). Hypotheses 2.1 to 2.8 are summarized in Table 8.

Table 8. Summary of the hypotheses of forecasting future prices

Hypothesis	Description	Variable to be tested
2.1	Participants will show more variability in their five-day price forecasts when viewing a chart showing long-term price data than when viewing a chart showing short-term price data.	time scale (variability)
2.2	Participants will show higher r value in their five-day price forecasts when viewing stock charts showing strong trends than when viewing stock charts showing moderate trends, and the both will generate higher r values than flat trends.	price trend (correlation)
2.3	Participants will show higher r values in their five-day price forecasts when viewing a yearly stock chart than when viewing a monthly chart, and the both will generate higher r value than a weekly chart.	time scale (correlation)
2.4	Stock charts showing long-term price data will produce smaller subjective confidence intervals than stock charts showing short-term price data.	time scale (confidence)
2.5	Stock charts showing strong up and down trends will produce smaller subjective confidence intervals in forecasts than stock charts showing moderate up and down trends, which will, in turn, produce smaller subjective confidence intervals than flat trends.	price trend (confidence)
2.6	Stock charts showing strong and moderate up trends will generate higher r values than stock charts showing the equivalent down trends.	price trend (correlation, asymmetry)
2.7	Stock charts showing strong and moderate up trends will generate smaller subjective confidence intervals than stock charts showing the equivalent down trends.	price trend (confidence, asymmetry)
2.8	Participants' subjective confidence intervals will increase from day 1 forecasts to day 5 forecasts.	predicted days (1-5) (confidence)

Hypotheses about trading behaviour

Just as chart framing can influence forecasts, it is also likely to influence share trading, because it is commonly assumed that forecasts mediate trading decisions. The

relationship between forecasting and trading is probably more complex than assumed by simple stock market adages such as “buy low and sell high”. Even so, links between forecasting and trading suggest that trading behaviour will likely change with time scale and with the strength and direction of price trend. Trading behaviour might also change when forecasts must be made before trading, rather than after, and when the forecasted price rises above or falls below the entry (original buying) price. All of these possible changes will be explored in the present experiment.

If the simple adage in the previous paragraph is correct, then participants should buy more shares when they see an up trend, sell more shares when they see a down trend, and hold more shares when they see a flat trend (Hypothesis 2.9). Participants should also buy more shares when they see a strong up trend than when they see a moderate up trend, and sell more shares when they see a strong down trend than when they see a moderate down trend (Hypothesis 2.10).

Trend information may be obtained from charts showing prices for a year, month, and week. A long time period, by definition, reveals more of a consistent trend than does a short time period. For example, price trend information in a yearly chart (252 days of price data) more clearly shows a long-term trend than does a weekly chart (5 days of price data). I hypothesize that, as the price goes up, participants seeing a long-term price chart will buy more shares than when they see a short-term price chart (Hypothesis 2.11). Inversely, as a stock share price goes down, I predict that the stock chart showing long-term price data will lead participants to sell more shares than the stock chart showing short-term price data (Hypothesis 2.12).

To balance the order of predicting and trading stocks, half of the participants forecasted prices first, and then traded stocks; the other half traded stocks first, and then forecasted prices. Decision making researchers usually assume that predictions are made before making decisions (Carroll & Johnson, 1990), but there is reason to believe that the reverse can happen as well. Some decisions might be made from immediate preferences or gut feelings, and later rationalized by predictions (for example, see Gladwell, 2005). The predict-before/after-trading manipulation served primarily as an experimental control, but also allowed me to test for order effects of the manipulation. I hypothesized that participants who are required to forecast first and trade after will show a stronger relationship between forecasts and trading than the ones who are required to trade first and forecast after (Hypothesis 2.13).

Finally, entry price is also likely to influence how many shares participants will buy, sell, or hold, and when they will make trades. The entry price is the share price at which a stock was purchased. The entry price might be considered as a reference point used by participants to judge how much their shares have gained or lost. Suppose a trader, for example, has 100 shares of a stock, and perceives an up trend of the stock showing on the chart. Suppose today's price of the stock is \$32.00 a share, the entry price the trader bought one week ago is \$30.00 a share. Knowing the entry price, the trader can calculate that he/she would receive a profit of \$200.00 dollars by selling the 100 shares of stock. Inversely, if the trader observes a down trend of the stock showing on chart from his/her entry price of \$32 to today's \$30.00 a share, then the trader can calculate that he/she may lose \$200.00 dollars if he/she sells the 100 shares of the stock. Because only linear trends such as up, down, and flat were employed in the present experiment, the

entry price is lower than the current price in an up trend, and is higher than the current price in a down trend.

To explore the influence of entry price, I told half of the participants to assume for each stock that they bought shares one week ago. The other half of participants were also told to assume they had bought shares, but were told neither when nor how much each share had cost them. I hypothesized that the participants who knew their entry price would trade more (more buying + selling) than participants not told their entry price (Hypothesis 2.14), simply because they had a reference point for profit/loss comparisons.

Table 9 summarizes the trading hypotheses.

Table 9. Summary of the hypotheses of trading stocks

Hypothesis	Description	Variable to be tested
2.9	Participants will buy more shares when viewing an up trend, sell more shares when viewing a down trend, and hold more shares when viewing a flat trend.	price trend (trade stocks)
2.10	Participants will buy more shares when viewing a strong up trend than when viewing a moderate up trend, and sell more shares when viewing a strong down trend than when viewing a moderate down trend.	price trend (correlation, trade stocks)
2.11	As stock price goes up, participants seeing a long-term price chart will buy more shares than seeing a short-term price chart.	time scale, price trend (buy stocks)
2.12	As a stock price goes down, participants seeing a long-term price chart will sell more shares than seeing a short-term price chart.	time scale, price trend (sell stocks)
2.13	Participants who are required to forecast first and trade after will show a stronger relationship between forecasts and trading than the ones who are required to trade first and forecast after.	order of forecast and trade
2.14	Participants who knew their entry price will trade more shares than participants not shown their entry price.	entry price (trade stocks)

*Method**Experimental Design*

A 2 x 2 x 5 x 3 (2 entry prices, 2 orders of predicting and trading, 5 price trends, and 3 time scales) mixed repeat factorial design was employed for this experiment. There were two between-subject variables: (1) entry price and (2) the order of predicting and trading. The two within-subject variables were price trend and time scale. The entry prices were divided into two groups: with and without entry price. The “with entry price” participants were told their entry price was the price one week ago, and could see that price on each stock chart; the “without entry price” participants were not told their entry price. Both groups were given the same stock charts associated with different historical price data. As in Experiment 1, three time scales were employed: last week’s, last month’s, and last year’s historical price data. Five linear price trends were used: strong up, moderate up, flat, moderate down, and strong down. To counter balance the order of trading stocks and predicting prices, half the participants predicted prices first and traded stocks next; the other half traded stock first and then predicted prices. A summary of the design is shown in Table 10.

Table 10 Research design of Experiment 2

Participants	Trade/predict	Entry price	Time scale		
			last week	last month	last year
1-24	trade/predict	with	5 trends x	5 trends x	5 trends x
		without	2 examples = 10 charts	2 examples = 10 charts	2 examples = 10 charts
25-48	predict/trade	with	5 trends x	5 trends x	5 trends x
		without	2 examples = 10 charts	2 examples = 10 charts	2 examples = 10 charts

Participants

Forty eight undergraduate students registered in Introductory Psychology at Carleton University participated in this study. Their average age was 22 years. Twenty seven participants were female and 21 were male. All indicated on a background questionnaire that they had never traded stocks, and had only had little knowledge of stock market learned from high school. Participants obtained two experimental participation credits towards their course requirements for their efforts. The participants were randomly assigned to the experimental conditions.

Materials

As in Experiment 1, the research materials included task instructions, a set of 10 pages of stock charts (three charts per page) and a short background questionnaire. The task instructions set the stages for the experiment (Appendix G). The stock charts, as noted above, were artificially constructed to show share price information to the participants. Next to each stock chart, two text areas were used to record the participant's responses. One text area, called the "prediction area", was used to write down forecasts for the next 5 days of share prices in the same manner as Experiment 1. The other text area, labeled the "trade area", was used to record share trades (i.e., how many shares the participant wished to buy, sell, or hold). To control for and examine order effects of prediction and trading, half participants did the "prediction area" first then the "trade area", indicating that they should answer prediction questions first. The other half of the participants did the "trade area" first and the "prediction area" later, indicating that they should answer trading questions first. A sample stock chart and related prediction and trade areas are shown in Appendix H. The 10 pages of stock charts, three charts per page,

were shown in a different random order for each participant. A questionnaire, designed to investigate participants' introspections about their forecasts and trades, was also used (see Appendix I).

The Stock Charts. The linear trends showing on charts were associated with different correlation coefficients. Two exemplars of each of the five trends (strong up, moderate up, flat, moderate down and strong down) were shown in year-long charts, and in month-long charts, and in week-long charts, for a total of 30 charts. As previously noted, the two showing a strong up trend had a day-by-price correlation of $r = +0.9$, and the two showing a strong down trend had a correlation of $r = -0.9$. The two showing a moderate up trend had a day-by-price correlation of $r = +0.6$, and the two showing a moderate down trend had a correlation of $r = -0.6$. This symmetry was accomplished by constructing the down trends as a mirror image of the up trends. Finally, the two showing a flat trend had a day-by-price correlation of $r = 0.0$.

Procedure

Upon arriving at the experiment, each participant first was asked to fill out an informed consent form (Appendix E). Next, the participant was required to complete a background questionnaire about his/her stock market experience. He/she was then asked to read the task instructions and to ask for clarification if needed. When all questions were answered, he/she was asked start the experiment. The participant was assured that the purpose of the experiment was to understand how people use stock trend charts rather than to test his/her ability to perform the tasks.

Each participant made price predictions and traded stocks (i.e., buy, sell, or hold stock shares) for 30 trials. On each trial, the participant looked at the stock chart until

he/she felt comfortable to forecast prices for the next 5 days and to decide on trading shares. The participant then wrote down his/her 5-day forecast in the prediction area beside the stock charts, and wrote down in the trading area how many shares he/she wanted to buy, sell or hold. In a typical trading session, participants were told, "Suppose you have 100 shares of this company bought at \$27.50 for a share one week ago. You also have enough cash to buy up to 100 shares stock if you wish. After examining the stock chart, do you want to buy more shares, sell some or all of your shares, or hold the stock?" After completing forecast and trade replies to all 30 stock charts, each participant was thanked for participating in the experiment and given a debriefing.

Results

Because each combination of five trends and three time scales had two exemplars, I first averaged the forecasts and trades of each exemplary pair. All analyses reported below are based on these averages.

Forecasting

As described above, half the participants made price forecasts before trading, and half traded before making forecasts. ANOVAs were conducted on all dependent variables (SD, r , SCI and trade indicators noted below) to determine if this order had any effect on forecasting or trading. There were no significant differences in any main effect or interaction. This finding suggests that neither forecasting nor trading was affected by the order of the two tasks.

The SD of the five forecasts given for each chart was used to measure the variability of the five-day predicted stock prices. Two main effects were statistically significant, one for trend $F(4, 176) = 9.753, p < .001$, and one for time scale, $F(2, 88) =$

31.271, $p < .001$. Their interaction was also statistically significant, $F(8, 352) = 2.966$, $p < .05$. Averages are shown in Figure 11 and statistically compared in Tables 11 and 12 (Note: All pairwise comparisons in Experiment 2 are based on the Least Significant Difference test).

Figure 11. Relation between price trend, time scale, and forecast SD

Table 11. Pairwise comparisons of mean difference of SD for time scale

	Mean	year	month	week
year	.520			
month	.431	.089**		
week	.322	.198*	.109*	

* $p < .001$ ** $p < .05$

Table 12. Pairwise comparisons of mean difference of SD for price trend

	Mean	strong up	moderate up	flat	moderate down	strong down
strong up	.449					
moderate up	.397	.052**				
flat	.360	.089**	.037			
moderate down	.393	.056**	.005	-.033		
strong down	.521	-.072**	-.124**	-.161*	-.129*	

* $p < .001$ ** $p < .05$

Considering the two significant main effects and their interaction, the results indicate that when participants forecasted future stock prices, yearly charts produced more variability than monthly charts, and monthly charts produced more than the weekly charts. This finding replicated the results of Experiment 1, and supported Hypothesis 2.1. As shown in Figure 11 and Table 12, moreover, strong up and strong down trends produced more forecasted variability than did moderate up and down trends, though the moderate trends produced no more variability than did the flat trend. Finally, the strong down trend produced more forecast variability than did the strong up trend – an equivalent asymmetric result to that found in Experiment 1 with year-long up and down trends. The asymmetry, however, did not appear with moderate up and down trends.

The correlation coefficient r was used to measure the extent to which five-day forecasts were linear extrapolations of the trends shown in the charts. As in Experiment 1, the r was calculated as an index of the linear regression between (x) days 1, 2, 3, 4, and 5 in the future, and (y) forecasted prices. Then, the r values were transformed to Z scores for the analysis of variance. Only the main effect of trend was statistically significant, $F(4, 176) = 23.319, p < .001$. The interaction between trend and time scale was also statistically significant, $F(8, 352) = 2.769, p < .05$. The relation between trend, time scale and correlations of forecasts is shown on Figure 12. Pairwise comparisons of the average correlations of the five trends are shown in Table 13.

Figure 12. Interaction between linear trends and time scale for r of forecasted prices

Table 13. Pairwise comparisons of mean difference of Z score for linear trend

	Mean r	strong up	moderate up	flat	moderate down	strong down
strong up	.74					
moderate up	.36	.567*				
flat	.02	.918*	.351**			
moderate down	-.22	1.165*	.598*	.247		
strong down	-.31	1.257*	.690*	.339**	.092	

* $p < .001$ ** $p < .05$

Several features of the results shown in Figure 12 and Table 13 are noteworthy.

First, strong up and down trends produced more highly correlated forecasts than did moderate up and down trends, and all four trends produced more than did the flat trend. This confirmed Hypothesis 2.2. Second, time scale made no significant difference in the average r of the forecasts; so Hypothesis 2.3 was not supported. Third, the price-over-days correlations of five-day forecasts were always weaker than the trends that produced them. For example, when participants saw a strong up trend ($r = +0.9$), they forecasted a

weaker up trend ($r = +0.74$), and when participants saw a moderate down trend ($r = -0.6$), they forecasted a much weaker down trend ($r = -0.22$).

Fourth, stocks showing strong and moderate up trends did produce significantly higher forecast correlations than did stocks showing strong and moderate down trends (see Table 13). This supports Hypothesis 2.6 and replicates the asymmetry of correlations found in Experiment 1. The length of the trend (week, month or year) had a noticeably greater influence on down trends than on up trends. Indeed, the short, week-long down trends produced weak up-trend forecasts! The asymmetry in forecast correlated with the length of trend. Together these results reinforce speculations of Experiment 1 that participants are conservative, cautious, confused or timid about forecasting, especially about forecasting the future of down trends.

The subjective confidence interval, SCI, was employed again to analyze the subjective uncertainty versus confidence that participants had in their forecasts. An analysis of variance on average SCIs revealed two significant main effects: one for trend, $F(4, 176) = 12.367, p < .001$, one for time scale, $F(2, 88) = 12.241, p < .01$. Their interaction was also significant, $F(8, 352) = 7.746, p < .001$. Figure 13 shows the relations found between linear trend, time scale, and average SCIs. Pairwise comparisons for trend and time scale are shown in Tables 14 and 15.

Figure 13. Relation between linear trend, time scale, and the SCI of forecasted prices

Table 14. Pairwise comparisons of mean difference of SCI for time scale

	Mean	year	month	week
year	.055			
month	.040	-.015**		
week	.034	-.021*	-.006**	

* $p < .001$ ** $p < .05$

Table 15. Pairwise comparisons of mean difference of SCI for linear trend

	Mean	strong up	moderate up	flat	moderate down	strong down
strong up	.036					
moderate up	.038	-.002				
flat	.041	-.006	-.003			
moderate down	.039	-.003	-.001	-.002		
strong down	.062	-.026*	-.024*	-.020*	-.023*	

* $p < .001$ ** $p < .05$

The results shown in Figure 13, Tables 14 and 15, reveal that the strong down trend, particular in the yearly charts, accounts for most of the main effects for SCI values. The larger SCI values for year-long down trends are consistent with the smaller r values reported above, indicating again that participants seemed less confident, more confused

or cautious, about forecasting down trends than about forecasting up trends – contrary to Hypothesis 2.5. The results do not support Hypothesis 2.4 that stock charts showing a long-term price data generate more confidence (smaller SCIs) than stock charts showing a short-term price data. The results also do not support Hypothesis 2.5 that strong trends will generate more confidence (smaller SCIs) in forecasts than will moderate trends. However, the results partially support the asymmetrical Hypothesis 2.7 that stocks charts showing up trends create more subjective confidence than the equivalent stock charts showing down trends; this is certainly true for strong trends, less so for moderate trends.

As in Experiment 1, I also examined whether the SCI values increased as forecasts extend into the future. A one-way ANOVA was performed on the five average SCIs across the five-day forecasts. The results indicate no significant difference in average SCIs across the five-day forecasts, $F(4, 184) = 2.4, p > .05$. Averages of SCIs across the five-day forecasts are: 0.043, 0.041, 0.041, 0.043, and 0.045. This finding paralleled the significant but tiny increase in SCI found in Experiment 1, and did not support Hypothesis 2.8 that participants' subjective confidence intervals would increase from day 1 forecasts to day 5 forecasts.

Trading I: buying shares

To determine whether trend, time scale, entry price, or prediction order influenced share buying behaviour, a mixed model (2 entry prices x 2 prediction orders x 5 linear trends x 3 time scales) ANOVA was employed to analyze the average number of shares bought. There was no significant main effect or interaction for time scale; thus Hypotheses 2.11 and 2.12 were not supported. Only the main effect of trend was significant, $F(4, 176) = 15.914, p < .001$. The main effect is shown in Figure 14. Pairwise

comparisons indicate that significant differences existed between most of the averages (see Table 16).

Figure 14. Effects of trend on number of shares bought

Table 16 Pairwise comparisons of mean difference of shares bought

	Mean	strong up	moderate up	flat	moderate down	strong down
strong up	37.4					
moderate up	21.8	14.486*				
flat	9.5	30.347*	15.861*			
moderate down	8.1	31.285*	16.799*	0.938		
strong down	15.6	23.750*	9.264	-6.597	-7.535**	

* $p < .001$ ** $p < .05$

The results above indicate that linear trends showing on charts influenced buying shares. As predicted by Hypothesis 2.10, participants bought more shares after viewing a strong up trend than after viewing a moderate up trend. Not surprisingly, participants bought more shares when they saw charts showing up trends than when they saw flat or down trends. Curiously, however, some participants did buy shares on down trends, and

significantly more shares were bought on a strong down trend than on a moderate down trend and a flat trend.

There was no significant difference between the “forecast first and trade after” and the “trade first and forecast after” condition, so Hypothesis 2.13 was not supported. In addition, there was no significant main effect or interaction between the participants who were told their entry price and those not told in the average number of shares they bought, so the “buy” portion of Hypothesis 2.14 was not supported.

Trading II: selling shares

The equivalent mixed model ($2 \times 2 \times 5 \times 3$) ANOVA was employed to analyze the effects of entry price, prediction order, trend, and time scale on selling stocks. Three significant main effects were found, one for trend, $F(4, 176) = 12.821, p < .001$, one for time scale, $F(2, 88) = 7.776, p < .001$, and the third for entry price, $F(1, 4) = 8.395, p < .05$. Also, there was a significant interaction between trend and time scale, $F(8, 352) = 2.709, p < .05$. The results are shown in Figure 15.

Figure 15. Effects of trend and time scale on number of shares sold

Again, pairwise comparisons were performed to examine how the linear trend and time scale influence the behaviour of selling stocks separately. The results demonstrate that selling was significantly higher when down trends were seen than when flat or up trends were seen (confirming Hypothesis 2.9), and that this difference was amplified as the length of the trend increased (see Tables 17 and 18). Contrary to Hypothesis 2.10, however, participants did not sell significantly more shares after seeing a strong down trend than after seeing a moderate down trend. Notably, participants were selling, on average, about 12-16 of their 100 shares on flat and up trends. It is another indication that participants were conservative, timid or confused about their trading strategies.

Table 17. Pairwise comparisons of mean difference of shares sold for linear trends

	Mean	strong up	moderate up	flat	moderate down	strong down
strong up	14.6					
moderate up	12.0	2.569				
flat	15.7	-1.146	-3.715			
moderate down	32.4	-17.813**	-20.382*	-16.667*		
strong down	37.8	-23.250*	-25.819*	-22.104*	-5.437	

* $p < .001$ ** $p < .05$

Table 18. Pairwise comparisons of mean difference of shares sold for time scale

	Mean	year	month	week
year	29.7			
month	19.8	9.971*		
week	18.1	11.658*	1.688	

* $p < .001$ ** $p < .05$

Results shown in Table 18 reveal that more shares were sold after seeing a year-long trend than after seeing a month- or week-long trend, partially confirming Hypothesis 2.12. But participants were as likely to sell on a month-long trend as they were a week-long trend, contrary to Hypothesis 2.12.

The main effect of entry price revealed that participants who knew their entry price sold more shares, on average, than participants who did not know their entry price. Figure 16 shows the means of shares sold associated with/without entry price for each linear trend on the yearly chart. The finding supported Hypothesis 2.14 that participants who knew their entry price would sell more shares than participants not shown their entry price. No significant difference between the “forecast first and trade after” and the “trade first and forecast after” was found, so Hypothesis 2.13 was not supported.

Figure 16. Means of shares sold for different linear trends on yearly chart

Trading III: holding shares

Finally, the same mixed model ($2 \times 2 \times 5 \times 3$) ANOVA was used to analyze the effects of prediction order, entry price, trend, and time scale on holding shares. One significant main effect of linear trend was found, $F(4, 176) = 9.903, p < .001$, and one significant interaction between linear trend and time scale was also found, $F(8, 352) = 3.007, p < .05$. Figure 17 shows the relations between linear trend, time scale, and shares held.

Figure 17. Effects of linear trend and time scale on share held

Pairwise comparisons, shown in Table 19, indicate that participants held significantly more shares when they saw a flat trend than when they saw an up trend or a down trend. This finding supports Hypothesis 2.9. The number of shares held when seeing strong or moderate up or down trends did not significantly differ (see Table 19).

Table 19 Pairwise comparisons of mean difference of shares held for linear trends

	Mean	strong up	moderate up	flat	moderate down	strong down
strong up	29.2					
moderate up	40.3	-11.111				
flat	68.8	-39.583*	-28.472*			
moderate down	50.0	-11.806	-.694	27.778*		
strong down	39.0	-9.772	1.389	29.861*	2.083	
* $p < .001$ ** $p < .05$						

Questionnaire

After completing the experiment, the participants were required to answer a questionnaire about what information they believed most influenced their trading behaviour (see Appendix I). Six questions were included in the questionnaire. These

questions were related to time scale and price trend which were displayed on stock charts in the experiment. Below are the main results.

Sixty-nine percent of the participants believed that price trend was most important in the decision making to trade stocks. Twenty-five percent of the participants thought that time scale was most important in their trading processes. These results roughly parallel the number and size of significant effects of trend and time scale on trading.

Forty-two percent of the participants thought that it was easiest to obtain trend information from the yearly charts. Thirty-three percent of the participants thought it was easiest to see a trend in monthly charts. And 25% believed that the weekly charts were easiest for seeing trends. This also roughly parallels the finding that forecasts showed stronger linear trends following a year-long chart than a month long-chart and that both had stronger correlations than a week-long chart.

When asked which part of yearly charts were most important in trading decisions, only 48% of the participants answered that the whole year was most important; 52% answered that the most recent month or week was most important. When asked which parts of monthly charts were most important, 69% answered that the whole month was, and 31% answered the most recent week. And when asked which part of weekly charts was most important, 75% answered the whole week. The results suggest a recency effect: recent price data were reported to be more important than previous data. It is another indication that older parts of long term data tend to be ignored.

Forecasting prices vs. trading stocks

What is the relation between price trends, price forecasts and stock trading behaviour? Table 20 summarizes previously reported results.

Table 20. Trends, forecasts and shares traded (yearly chart only)

Trend type (yearly chart)	Correlation coefficient r		Number of traded shares		
	historical trends	predicted prices	bought	held	Sold
strong up	0.93	0.74	37	35	15
moderate up	0.66	0.36	22	48	17
flat	0.02	0.02	9	56	21
moderate down	-0.66	-0.22	8	25	44
strong down	-0.93	-0.31	16	29	52

Table 20 reveals at least four interesting results. First, more trading (buying + selling) occurs when strong trends are seen than when moderate or flat trends are seen. Second, the number of shares bought on strong and moderate up trends is lower than the number of shares sold on equivalent down trends – a trading asymmetry. Third, the number of shares bought on forecasted up trends is much lower than the number of shares sold on forecasted down trends – an amplified trading asymmetry. Fourth, about 25% of all buys occurred on a down trend, and about 26% of all sells occurred on an up trend, indicating noticeable individual differences in trading strategies.

Discussion

The purpose of Experiment 2 was to investigate how time scale and price trends influence share price forecasts and share trading behaviour. The forecasting results, using artificially-generated price trends rather than the real share data employed in the first experiment, largely replicate the results of Experiment 1. This indicates that the results of Experiment 1 are relatively robust and replicable. As before, at least three important forecasting results emerged: (1) as the amount of historical price data increased, participants increased their uncertainty, indicated by higher SDs, weaker correlations, and larger SCIs in their forecasts; (2) extrapolations were more similar to historical data as the amount of historical data increased; (3) participants showed consistent asymmetry of

SD, r , and SCI their forecasts, generally showing lower SDs, higher r , and smaller SCIs when they saw up trends than when they saw down trends. These asymmetries became larger as the length of the trend increased.

Time scale and, more often, price trends also influenced share trading. Three main findings emerged in the experiment. First, participants bought more shares when they saw an up trend, sold more shares when saw a down trend, and held more shares when they saw a flat trend. Next, participants showed a consistent asymmetry in their trading stocks, selling more shares when they saw a down trend than when they saw an equivalent up trend. Finally, another consistent asymmetry was found, participants' trading behaviour was influenced by entry price when they saw a down trend, but entry price did not influence participants' trading behaviour when they saw an equivalent up trend.

Two of the non-significant differences in buying behaviour are, I believe, theoretically important. First, the average number of shares that participants bought was not influenced by the length of a trend. Second, participants were just as likely to buy shares on down trends as on a flat trend, and significantly more likely to buy shares on a strong down trend than on a moderate down trend. This pattern suggests that, even though predictions are influenced by time scale (noted in the predictions results, above), acquisitions are not, and that many participants are confused about the best trading strategy to follow in light of a down trend. Participants acted as though they believed a strong down trend would not last forever and, ever optimistic, decided to "buy in" when prices were low. Perhaps this is a result of being naïve about stock trading. Experiment 3, below, looks for the same effect in more experienced traders.

Why is share trading behaviour (i.e., shares bought, sold, and held) associated with the strength of linear trends? Buying shares increases potential gains if a trend goes up. Selling shares decreases potential losses if a trend goes down. And holding shares is better than buying or selling when a trend is flat. The higher a trend correlation, and the longer the trend, the more clearly the trend can be seen. As a result, participants' trading behaviour appeared to be associated with the correlations of linear trends. In addition, participants traded more shares as the amount of historical price data added in charts, specifically for shares sold and held.

Why did the equivalent up and down trends produce asymmetrical shares bought and sold? According to Prospect Theory (Kahneman & Tversky, 1979), the asymmetry of gains/losses produces different values; losses have a larger negative value than do equivalent gains. The asymmetry of shares bought and sold supports this asymmetric function of Prospect Theory. Just as a continued up trend would lead to greater gains if participants bought more shares, a continued down trend would lead to greater losses if participants did not sell their shares (loss aversion). Being more sensitive to losses, therefore, participants would sell more shares more quickly than they would buy shares on equivalent up trends.

Another asymmetry of shares bought and sold was produced by entry price. Participants who knew their entry price and saw a strong down trend sold more shares than did participants who did not know their entry price. There was, however, no equivalent entry-price effect for buying on a strong up trend. According to Prospect Theory (Kahneman & Tversky, 1979), a reference point determines how an outcome is perceived. The entry point perhaps is a reference point. The results suggest that

participants told their entry price did use it as a reference point, and were more inclined to sell shares when trends brought them below it.

Questionnaire responses generally paralleled the behavioural data, suggesting that participants had a rough understanding of what mattered in their decisions. But the questionnaire responses also indicated that, even though participants found yearly data were more useful than monthly or weekly data, they found the most recent weeks of yearly charts more important than older weeks. This is somewhat paradoxical because in both Experiment 1 and Experiment 2, week-long trends show smaller influences than month-long and year-long trends. Perhaps the paradox merely reflects flaws in the questionnaire. The parallels between many behavioural and questionnaire responses suggests that a refined questionnaire might be useful as an approximation to behavioural observations.

Taken together, the results of Experiment 1 and 2 lead to the impression that participants were timid, cautious, conservative or confused about what they were doing. Forecasts were in the right direction but did not match the strength of the historical trends on which they were based. Trading seemed cautious and often contradictory; few participants bought all they could or sold all they had, and selling was more pronounced than buying – an indicant of risk aversion that is explained by Prospect Theory (Kahneman & Tversky, 1979).

Such timidity or caution might reflect fundamental human orientations toward risk or trading, orientations in need of explanation. On the other hand, the timidity or caution might reflect inexperience. Would more experienced traders show the same results as the undergraduates in Experiments 1 and 2? In order to answer this question, I

conducted a partial replication of Experiment 2 with a new sample of participants, all of whom claimed to have at least one year of stock market trading experience.

Experiment 3

The participants in Experiments 1 and 2 were undergraduate students who were studying Introductory Psychology at Carleton University. They were relatively naïve and inexperienced about the stock market, about predicting stock prices and trading stocks. Can their experimental results be generalized to a more experienced sample of stock traders? Do experienced traders perform differently than undergraduates in forecasting prices and trading stocks? To answer these questions, Experiment 3 examined how time scale and price trend influence price forecasts and stock trades of more experienced traders, and how these influences compared with those of inexperienced undergraduate students who participated in Experiment 2.

Stock brokers are usually considered as experienced traders or experts in the stock market, but they often disagree in their share price forecasts and share trades because the future is uncertain (for example, see Slovic, 1969). Weiss & Shanteau (2003, 2004) recently developed discrimination and consistency indicators that could scale degrees of expertise (called CWS measures for Cochran-Weiss-Shanteau), but they have yet to be employed in assessing differences between naïve and self-proclaimed experts in stock market trading. Although my data did not allow me to employ CWS measures, Experiment 3 was inspired by them. I hypothesized that, in comparison with naïve students, experienced stock traders would produce different forecasting and trading behaviors than did the naïve participants in Experiment 2.

It was no easy task to find experienced traders willing to participate in my experiment. Because I could find only 12, I decided that all of them would participate with no knowledge of entry price and by predicting before trading. I could then compare

their forecasts and trading behaviour with the 12 naïve participants in Experiment 2 who also participated with no knowledge of entry price and by predicting before trading.

Method

Experimental Design

A 2 x 3 x 5 (2 group of participants, 3 time scales, and 5 price trends) mixed, factorial design was employed in the experiment. As in Experiment 1 and 2, time scale and price trend were within-subject variables. The between-subject variable was the group of participants: 12 of the undergraduate students from Experiment 2 who had no stock trading experience; and 12 more experienced traders who had at least one year of stock trading experience. The experimental design is shown in Table 21.

Table 21. Research design of Experiment 3

Participants	Trade experience	Time scale		
		last week	last month	last year
1-12	yes	5 trends x	5 trends x	5 trends x
		2 examples =	2 examples =	2 examples =
		10 charts	10 charts	10 charts
13-24*	no	5 trends x	5 trends x	5 trends x
		2 examples =	2 examples =	2 examples =
		10 charts	10 charts	10 charts

**Note:* The 12 participants were undergraduate students who were chosen from Experiment 2. They performed the same tasks of forecasting prices and trading stocks in Experiment 2 as the experienced traders did in Experiment 3.

Participants

Twelve, self-proclaimed experienced traders, nine males and three females, participated in Experiment 3. I recruited them using friendship networks and snowball techniques. Their ages ranged from 30 to 65 years, and they had various work backgrounds such as administrator, teacher, and engineer. None of them were investment professionals such as stockbrokers, but were trading hobbyists with at least one year

experience of trading shares in stock market. The experienced traders participated voluntarily. All 12 experienced traders were given the 30 stock charts used in Experiment 2, were not given entry price, and were not asked to make a forecast of the next five days of share prices before making and trades. Twelve naïve traders who participated in Experiment 2 were selected for comparison: the twelve students who were not given entry price and who made each forecast before making each trade.

Materials and Procedure

The experimental materials and procedure were same as those in Experiment 2.

Data Analysis

As in the previous experiments, three derived measures: standard deviation (SD), correlation coefficient (r), and subjective confidence interval (SCI) were employed in data analysis of forecasting behaviour. As in Experiment 2, the numbers of shares bought, sold, and held were used in data analysis of trading behaviour. In addition, the same mixed model ANOVA were used in the data analyses, which were similar to the ones in Experiment 2.

Results

Forecasting stock prices

A 2 expertise x 3 time scales x 5 trends ANOVA of SDs for the five-day price forecasts showed no significant main effect of expertise, $F(1, 22) = 1.175, p > .05$, and no interaction between expertise and the other two independent variables. There was a significant main effect for price trend, $F(4, 176) = 11.471, p < .001$, and for time scale, $F(2, 88) = 17.615, p < .001$. In addition, there was a significant interaction between price trend and time scale, $F(8, 352) = 6.194, p < .001$. The results indicated that the both trend

and time scale influence the five-day forecast stock prices, and they replicated the results of Experiment 2. My exploratory hypothesis that experienced traders would have different forecast SDs than would naïve students was thus not supported. Table 22 displays means of SD of the 5-day price forecasts for experienced traders and naïve students. Though not significant, experienced traders did show a small but consistent tendency to generate larger SDs; this can be seen by comparing the five average SDs of experienced traders with the five corresponding average SDs of naïve traders. Addition of more participants might show this small difference to be statistically significant.

Table 22. Means of SD of 5-day price forecasts for experienced traders and naïve students

Trend type	Experienced traders (N=12)				Naïve students (N=12)			
	year	month	week	Average	year	month	week	Average
strong up	.741	.490	.360	.530	.637	.485	.349	.490
moderate up	.314	.430	.392	.379	.298	.368	.398	.354
flat	.592	.376	.181	.383	.530	.360	.186	.358
moderate down	.450	.374	.366	.397	.428	.350	.394	.390
strong down	.670	.630	.306	.535	.610	.574	.334	.506
Average	.553	.460	.321		.501	.427	.332	

As in Experiment 2, the chart showing longer-term price data produced significantly higher average SDs in forecasts than did the chart showing shorter-term price data. The strong trends (either up or down) produced significantly more average variability than did the moderate or flat trends in forecasts.

An equivalent ANOVA of the correlation coefficients also revealed that there was no significant difference between the experienced traders and naïve students, $F(1, 22) = .297, p > .05$, and no significant interaction involving experience. Two main effects were found, one for price trend, $F(4, 88) = 9.693, p < .001$, another for time scale, $F(2, 44) = 4.978, p < .01$. The price trend x time scale interaction was also significant, $F(8, 176) =$

4.258, $p < .05$. The results replicated those in Experiment 2, indicating the five-day forecasts were influenced by both price trend and time scale.

Table 23 lists the average r values of forecasted prices of the experienced and the naïve participants for each combination of trend and time scale. As shown in Table 23, the five-day price forecasts were generally consistent with the price trends showing on the charts. Both naïve and experienced traders gave weaker r values in their forecasts than they were shown in the charts. In addition, both the naïve and experienced participants showed asymmetry in their forecast correlations.

Table 23. r comparison between five-day price forecast and price trends showing on chart

Trend type	Time scale	Price trend (r)	Forecasted prices (r)	
			Experienced traders (N=12)	Naïve students (N=12)
strong up	year	.930	.606	.514
	month	.920	.634	.571
	week	.930	.467	.472
moderate up	year	.660	.389	.304
	month	.640	.359	.375
	week	.650	.258	.231
flat	year	.016	-.091	-.014
	month	.013	.159	.117
	week	.015	.077	-.015
moderate down	year	-.660	-.167	-.269
	month	-.640	-.184	-.150
	week	-.650	.069	-.124
strong down	year	-.930	-.459	-.491
	month	-.920	-.327	-.380
	week	-.930	-.166	-.223

Finally, an equivalent ANOVA of SCIs for price forecasts revealed that there was no significant difference between the experienced traders and naïve students, $F(1, 22) = 3.172$, $p > .05$, nor was there any significant interaction involving expertise. As in Experiment 2, two main effects were found: one for price trend, $F(4, 88) = 14.983$, $p <$

.001, one for time scale, $F(2, 44) = 8.099, p < .01$. Their interaction was also significant, $F(4, 88) = 7.289, p < .001$. Table 24 shows means of SCI of the five-day forecasts of the trend and time scale for the experienced traders and naïve students. As with SDs, the five average SCIs generated by experienced participants were all slightly higher than the corresponding five SCIs generated by naïve participants; additional data might show these differences to be significant, but still small.

Table 24. Means of SCI of five-day price forecasts for experienced traders and naïve students

Trend type	Experienced traders (N=12)				Naïve traders (N=12)			
	year	month	week	Average	year	month	week	Average
strong up	.048	.048	.034	.043	.041	.043	.028	.037
moderate up	.041	.045	.038	.041	.039	.042	.038	.039
flat	.037	.036	.035	.036	.037	.030	.032	.033
moderate down	.044	.036	.038	.039	.040	.036	.036	.037
strong down	.080	.065	.041	.062	.078	.062	.039	.059
Average	.050	.046	.037		.047	.043	.035	

In short, the experienced traders' forecasting behaviour was not significantly different from that of naïve students. The results thus did not support the hypothesis that there would be a difference between experienced traders and naïve students in five-day price forecasts.

CWS-inspired measure of expertise for forecasting stock prices

Although my research was completed before I learned of Shanteau and Weiss' CWS measures of expertise, I tried to adapt CWS (Cochran-Weiss-Shanteau) measures to investigate expertise of forecasting stock prices. Weiss & Shanteau (2003, 2004) define two important components of expertise: *discrimination* and *consistency*. Discrimination is the ability to differentiate between similar stimuli. Experts should make fine

discriminations, but novices probably do not. Consistency refers to the ability to repeat judgments for a stimulus when it was presented more than once. An expert should make the same responses for a repeated stimulus, but novices probably do not. Weiss & Shanteau (2003, 2004) employed variance, standard deviation (SD), or mean absolute deviation (MAD) to measure discrimination and consistency. According to their research, “we estimate discrimination as the variance between responses to different stimuli; larger variances imply greater discrimination. Similarly, we estimate consistency as the variance between responses to repeated stimuli; smaller variance imply greater consistency” (Weiss & Shanteau, 2003, p. 629).

I did not have the data to employ Weiss & Shanteau’s CWS indices of discrimination and consistency. I could, however, compare the expertise of experienced traders in price forecasts with that of naïve students in another way. I calculated the Standard Deviation of the average five-day forecasts across experienced participants for each of the 15 trend-by-time scale combinations; I did the same for naïve participants. In this way, SD became an index of inter-judge reliability. If the experienced traders had more forecasting expertise than the naïve participants, then they should agree more among themselves in their forecasts, and such increased agreement would be seen as lower Standard Deviations of average forecasts among experienced participants than among naïve participants. Table 25 shows the average SDs.

Table 25. Average SD of five day forecasted prices for stock charts among experienced traders and naïve students

Time scale	Group	Average SD of five forecasted stock prices					
		Day 1	Day 2	Day 3	Day 4	Day 5	Average
year	experienced	1.32	1.10	1.45	1.21	1.63	1.35
	Naïve	1.66	1.70	1.75	1.75	1.89	1.75
month	experienced	0.45	0.70	0.85	1.11	1.18	0.86
	Naïve	0.43	0.79	0.94	1.06	1.20	0.88
week	experienced	0.19	0.34	0.55	0.62	0.83	0.51
	Naïve	0.22	0.35	0.64	0.87	1.03	0.62
Average	experienced	0.65	0.72	0.95	0.98	1.21	
	Naïve	0.77	0.95	1.11	1.23	1.38	

There are 15 pairs of SDs of five day forecasted prices for both the experienced traders and naïve students shown in Table 24. Thirteen of these SDs of the experienced traders' were smaller than those of the naïve students = 87%. This finding partially supported the prediction that the experienced traders would produce smaller variability than naïve students in the task of forecasting future stock prices.

Trading stocks

As in Experiment 2, I analyzed the data of stock shares bought, held, and sold. Also, I compared the experienced traders' trading behaviour with the naïve students'.

A 2 x 3 x 5 ANOVA of shares bought indicated that there was no significant difference between the experienced traders and naïve students, $F(1, 2) = 0.00, p > .05$, but there was a marginally significant time-by-group interaction, $F(2, 44) = 3.17, p < .07$. The main effect of price trend was significant, $F(8, 352) = 24.732, p < .00$, as was the interaction between price trend and time scale, $F(8, 176) = 2.421, p < .05$.

Table 26 shows the means of stock shares bought for the both experienced traders and naïve students. As in Experiment 2, participants bought more shares when they saw an up

trend than when they saw a down trend. Participants also bought a few shares when they saw a flat trend. But experienced participants bought fewer shares when they saw long-term trends and more shares when they saw short-term trends. In contrast, naïve participants bought about as many shares for long-term trends as they did for short-term trends.

Table 26. Means of stock shares bought by experienced traders and naïve students

Trend type	Experienced traders (N=12)				Naïve students (N=12)			
	year	month	week	Average	year	month	week	Average
strong up	33.33	66.67	58.33	53.11	58.75	47.92	40.83	49.17
moderate up	12.50	29.17	62.50	34.72	6.25	37.92	32.08	25.42
flat	0.00	8.33	0.00	2.78	26.27	6.67	12.50	15.15
moderate down	4.17	0.00	12.50	5.56	21.67	2.08	5.42	9.72
strong down	16.67	8.33	25.00	16.67	8.75	10.00	19.17	12.64
Average	13.33	22.7	31.66		24.34	20.92	22.00	

A similar 2 x 3 x 5 ANOVA of shares *sold* confirmed that there was no significant difference between the experienced traders and naïve students, $F(1, 22) = 1.310, p > .05$, but the main effect for price trend was significant, $F(4, 88) = 7.430, p < .01$, and so was the main effect for time scale, $F(2, 44) = 5.586, p < .01$. Two interactions were also significant: the trend-by-time interaction, $F(8, 176) = 5.088, p < .001$, and the trend-by-time-by-experience interaction, $F(8, 176) = 2.989, p < .05$. As in Experiment 2, the results reveal that both price trend and time scale influenced the participants to sell stock shares. On average, they sold more shares on down trends than on flat or up trends. Moreover, the participants sold more shares when they saw a year-long chart than when they saw a month-long or a week-long chart.

Table 27 shows the means of stock shares sold for both experienced traders and naïve students. The three-way interaction is difficult to interpret, but it does indicate that experience has some kind of effect on the selling of shares.

Table 27. Means of stock shares sold by experienced traders and naïve students

Trend type	Experienced traders (N=12)				Naïve students (N=12)			
	year	month	week	Average	year	month	week	Average
strong up	29.17	8.33	20.83	19.44	24.17	12.50	4.17	13.61
moderate up	33.33	8.33	16.67	19.44	55.00	0.00	19.58	24.86
flat	50.00	25.00	41.67	38.89	20.83	28.33	36.67	28.61
moderate down	58.33	8.33	54.17	40.28	10.00	18.75	43.75	24.17
strong down	58.33	87.50	25.00	56.94	74.17	44.58	24.17	47.64
Average	45.83	27.50	31.67		36.83	20.83	25.67	

Finally, a 2 experiences x 3 time scales x 5 price trends ANOVA of shares *held* confirmed that there was no significant difference of shares held between the experienced traders and naïve students, $F(1, 22) = 2.468, p > .05$, but two main effects and their interaction were found to be significant. One main effect was price trend, $F(4, 88) = 8.012, p < .001$. Another one was time scale, $F(2, 44) = 4.058, p < .05$. Their interaction was significant, $F(8, 176) = 3.570, p < .05$. The results indicate that both the price trend and time scale influence the participants to hold stock shares, which replicated the results of Experiment 2. Table 28 lists the means of stock shares held for both the experienced traders and naïve students.

Table 28. Means of stock shares held by experienced traders and naïve students

Trend type	Experienced traders (N=12)				Naïve students (N=12)			
	year	month	week	Average	year	month	week	Average
strong up	33.33	16.67	16.67	22.22	0.00	16.67	25.00	13.89
moderate up	50.00	58.33	8.33	38.89	16.67	33.33	8.33	19.44
flat	41.67	66.67	58.33	55.56	41.67	58.33	33.33	44.44
moderate down	33.33	91.67	25.00	50.00	41.67	66.67	25.00	44.44
strong down	25.00	0.00	33.33	19.44	8.33	25.00	33.33	22.22
Average	36.67	46.67	28.33		21.67	40.00	25.00	

As noted above, there was no significant difference between the experienced traders and naïve students in stock shares bought, held, and sold, though experience did contribute to two interaction effects. As in Experiment 2, participants appeared to buy more shares while the stock trend went up than while it moved down. They had a tendency to sell more shares while the stock trend went down than while it moved up. Participants were likely to hold more shares when saw a flat trend than a strong up or down trend.

Comparing the results across Tables 26, 27 and 28, it seems that experienced traders had amplified tendencies than naïve students to buy more shares on up trends, sell more shares on down trends, and hold more shares on a flat trend. This suggests that, even though experienced and naïve participants did not show reliable differences in their forecasts, they did show reliable differences in their trading behaviour. Experienced participants tended to be more active or bold in their trading than naïve participants, a result consistent with the development of other skill such as driving a car or giving a speech.

CWS-inspired measure of expertise for trading stocks

Similar to the CWS-inspired measure of forecasting stock prices above, I also compared standard deviations (SDs) of shares bought, held, and sold across experienced participants to the SDs across naïve participants to measure the expertise of trade stocks for the both experienced traders and naïve students. According to Weiss & Shanteau (2003, 2004), experts should be display more consistency than naïves in response to repeated stimuli. If the experienced traders were also experts, then they should also agree with each other more than would non-experts. Therefore, I predicted that the experienced traders would produce smaller SDs in shares traded than would naïve students.

Forty-five pairs of SDs of shares bought, held, and sold were calculated for both experienced traders and naïve students. The results, shown in Tables 29, 30 and 31, indicate that experienced traders much more often than not had *larger* SDs in their trades than did naïve students, contrary to the prediction of smaller SDs based on the assumption that experienced traders would have more expertise.

Table 29. Average SD of shares bought for the experienced traders and naïve students

Time scale	Group	Trend type					Average
		strong up	moderate up	flat	moderate down	strong down	
year	experienced	49.24	31.10	0.00*	14.43	38.93	26.74
	naïve	45.83	15.54	41.41	32.71	22.58	31.61
month	experienced	44.38	45.02	28.87	0.00*	28.87	29.43
	naïve	43.56	36.27	23.09	7.22	28.92	27.81
week	experienced	51.49	48.27	0.00*	31.08	39.89	34.15
	naïve	40.78	37.02	29.27	13.05	36.30	31.28
Average	experienced	48.37	41.46	9.62	15.17	35.90	30.10
	naïve	43.39	29.61	31.26	17.66	29.26	30.23

*Note: no participants in this group bought shares of stock.

Table 30. Average SD of shares sold for the experienced traders and naïve students

Time scale	Group	Trend type					Average
		strong up	moderate up	flat	moderate down	strong down	
year	experienced	45.02	49.24	47.67	51.49	51.49	48.98
	naïve	38.25	41.51	39.65	28.92	44.81	38.63
month	experienced	28.87	28.87	45.23	28.87	31.08	32.58
	naïve	31.08	0.00*	44.69	37.06	45.00	31.57
week	experienced	39.65	32.57	51.49	49.81	45.23	43.75
	naïve	14.43	34.80	47.16	41.51	34.76	34.53
Average	experienced	37.85	36.89	48.13	43.39	42.60	41.77
	naïve	27.92	24.55	43.83	35.83	41.52	34.91

*Note: no participants in this group sold shares of stock.

Table 31. Average SD of shares held for the experienced traders and naïve students

Time scale	Group	Trend type					Average
		strong up	moderate up	flat	moderate down	strong down	
year	experienced	33.33	50.00	41.67	33.33	25.00	36.67
	naïve	0.00*	16.67	41.67	41.67	8.33	21.67
month	experienced	16.67	58.33	66.67	91.67	0.00*	46.67
	naïve	16.67	33.33	58.33	66.67	25.00	40.00
week	experienced	16.67	8.33	58.33	25.00	33.33	28.33
	naïve	25.00	8.33	33.33	25.00	33.33	25.00
Average	experienced	22.22	38.89	55.56	50.00	19.44	37.22
	naïve	13.89	19.44	44.44	44.45	22.22	28.89

*Note: no participants in this group held shares of stock.

Discussion

The main purpose of Experiment 3 was to examine if differences existed between experienced traders and naïve students in forecasting prices and trading stocks. The results showed no significant general differences (main effects) between the experienced traders and naïve students of forecasting future stock prices and trading stocks, but do indicate that experience does produce significant interaction effects with other variables.

The CWS (for Cochran-Weiss-Shanteau) approach to measuring expertise inspired me to use another measure of expertise more suitable to the data I collected for

my experiment: the agreement among experts. Einhorn (1974) and Ashton (1985) argue that the agreement between experts is a necessary condition for expertise. Shanteau et al. (2003) also believe that consistency between experts is one important property of expertise, since two or more experts should not disagree about a judgment or decision. Considering the limitations of my experiment, I used the idea of the consistency between experts to analyze the expertise of the experienced traders. The results indicated that experienced traders generally did not show more agreement among themselves than did naïve students in forecasting prices and trading stocks.

Why did the experienced traders show less consistency than naïve students? There are at least three possible reasons. One of the possible reasons was that experienced traders were not given the amount of price information they would normally use to analyze a stock, information such as trade volume, moving averages, price indicators, and annual reports which were omitted for the sake of developing a manageable research design.

Traders vary in their preferences for stock information and trading style (Schwager, 1989). Some traders, for example, prefer technical analysis to fundamental analysis. Some traders prefer the reverse. Others like to employ both in their trade activities. In addition, some traders prefer to trade several times a day, while others prefer to trade every week or month. The constraints of Experiment 3 might have thrown several experienced traders “off their game” and thus produced more disagreements than would otherwise occur.

I chose the experienced traders based on their self-report of at least one year experience trading shares and stocks in the stock market. Perhaps this is not enough.

Their years of experience may have varied greatly, and so too may have their trading success – an experienced trader is not necessarily a successful trader. Future studies of expertise should better control for these variables.

The amount of expertise of experts seems to depend on task difficulty. Shanteau et al. (2003), for example, found that the average correlation for weather forecasts is quite high at $r = +0.95$ and the average correlation for stockbrokers is low at $r = +0.32$.

Forecasting future prices and trading stocks are two of the most difficult tasks in life, since many factors such as economic environment and political issues influence the stock market. So we should not expect large amounts of expertise to develop with experience.

An expert is a person who has special skill or knowledge by training or experience in a particular domain such as a stockbroker. Experience may be necessary to become an expert, but it is not sufficient. The experienced traders in Experiment 3 were not experts such as stockbrokers; the degree of their expertise (Shanteau, 2000) was therefore unknown. Future research on stock market forecasting and trading should attempt to employ people certified as experts in addition to people who have various amounts of trading experience.

General Conclusions

Summary of main findings

The purpose of my dissertation was to explore possible framing effects of stock charts on people's market behaviour: forecasting future stock prices and trading stocks. I tried to answer three questions. First, does the form or the features of a stock chart influence stock market behaviour? If yes, what features of a chart influence stock market behaviour? Third, are experienced traders influenced differently by chart framing effects than naïve traders?

To answer these questions, three experiments were developed to explore the effects of stock charts as a cognitive frame on the prediction of stock price changes and on decisions about trading stock shares. Experiment 1 examined whether changes in the time frame (X-axis) and the price frame (Y-axis) of stock charts influenced students' predictions of future share prices of stocks that had different year-long price trajectories. Experiment 2 re-examined time frame influences using artificially constructed price trajectories that controlled for the strength of up and down price trends. It also examined the effects of time frame and price trajectory on trading behaviour. Finally, Experiment 3 examined whether experienced traders differed from naïve traders (students in Experiment 2) in how time frame and price trajectory influenced forecasting stock prices and trading stocks.

The results of Experiment 1 showed no reliable influences of price frame on forecasting, but did show reliable influences of time frame and price trend on forecasting. Three indices of five-day forecasts: their Standard Deviation, their day-by-price correlation, and their confidence intervals generated by the participants themselves,

revealed several interesting results about forecasts and what influences them. Among the most interesting were the following: (1) Forecasts tend to be weak linear extrapolations of linear trends and inconsistent extrapolations of nonlinear trends; (2) forecast uncertainties tend to increase, rather than decrease with the length of the trend shown; (3) linear up trends produce more consistent linear extrapolations than to corresponding linear down trends (asymmetric forecasting).

The forecasting results of Experiment 2 replicated those of Experiment 1 with strong and moderate year-long linear price trends and, to a lesser extent, strong and moderate month-long linear price trends. In general, influences of trends were amplified in the charts showing longer time frames. Trading results showed more buying on strong trends (both up and down) than on moderate or flat trends, regardless of the time scale. More shares were sold on down trends than bought on equivalent up trends, and this asymmetry was amplified as the time scale increased. Entry price had no reliable effect on buying, but did significantly affect selling; those who knew their buying price unloaded shares of falling stocks much faster than those who were ignorant of their buying price.

Though experienced traders in Experiment 3 did not differ significantly from equivalent naïve traders (students) from Experiment 2 in their forecasts, they did show a few interesting differences in their trading behaviour. Experienced traders, for example, tended to buy more shares after seeing charts showing short term (week-long) trends than did naïve traders, and experienced traders were somewhat more prone to sell shares than were naïve traders. Such differences suggest that experience makes traders bolder or less timid in their trading behaviors, though it does not suggest that experienced traders are

more successful than are naïve traders. Indeed, my explorations of expertise indicated no reliable differences in expertise between experienced and naïve traders.

Implications: theory and practice

The results of my studies have a number of theoretical implications. First, stock charts can produce the framing effects. Framing differences in stock charts, especially differences in time scale, influenced people's forecasts of future share prices and the number of shares they bought, sold, or held. Tversky & Kahneman (1981) demonstrated framing effects with a popular example called the "Asian disease" problem, and subsequent research has revealed many more (Fischhoff, 1983; Frisch, 1993; Levin et al., 2002, Shafir & Le Boeuf, 2002; Stanovich & West, 1998). These framing effects have been produced by variations of verbal or text descriptions or questions. In my studies, however, framing effects were produced by visual presentation. This is an important extension of the research on framing effects.

Second, the asymmetry of trading behaviour (i.e., buying versus selling) provides more evidence for a central tenant of Prospect Theory. According to Prospect Theory, the value function is an important implication of Prospect Theory. The results of my research support this value function of Prospect Theory, the asymmetry of buying/selling shares is similar to the asymmetry of gains/losses function in Prospect Theory. Yet I also found asymmetry in forecasting future prices, an asymmetry which is not addressed by Prospect Theory. It is an interesting important new finding that deserves further investigation

Finally, the results of the study also demonstrate anchoring and recency effects. In my research, the anchoring or reference point for forecasts appears to be the last day's price showing on stock chart. The results indicate that the participants forecasted future

prices and trading stocks close to the last day's price. The recency effect results from disproportionate salience of recent stimuli or observations. The questionnaires of Experiment 2 reveal that the participants preferred to use recent prices in their stock trades. Anchoring and recency effects are often called cognitive biases (Kahnemann, Slovic, & Tversky, 1982). However, in my experiments, they are arguably not biases at all, but instead are rational rules of inference about time series.

A picture can be worth a thousand words, but my research indicates that it can also distort predictions or other judgments and influence subsequent behaviour. As a result, it is advisable to pay attention to chart design. Understanding the influence of chart features on forecasts can be helpful for graphic designers in laying out good charts that will minimize biases – or that will produce biases that favor the designer.

Limitations

As in all research, there were a number of limitations associated with my experiments, including the following. First, the stock market is more complex than portrayed in my research. I tried my best to simulate the stock market in the experiments, but the tasks I chose for reasons of simplicity and experimental control were, as always, somewhat contrived. Information not in stock price charts is readily available to traders, and it probably influences forecasts and trading as much as price trends. Such information includes expectation of future corporate earnings, interest rates, inflation, economic growth, political issues, news, even rumors. According to a research on gambling decisions in a real casino in Las Vegas (Fryback, Goodman, and Edwards, 1973), however, there was no difference in gambling decisions made in the laboratory and in the casino. This suggests that the results of my laboratory simulations may be

generalizable beyond the lab. My research results, therefore, may help us to better understand people's stock market behaviour.

Technical analysis and fundamental analysis are the two main techniques of forecasting shares prices and trading stocks in the market. I only focused on a part of technical analysis and limited the research on the visual displaying of stock chart in the study. Various types of stock charts such as line, bar, pie, and candlestick are also used in today's stock market. I selected only line charts in my experiments, since they are simple yet popular in the financial world. I varied only time scale, price scale, and price trend. Hundreds of other features that might influence forecasting and trading behaviour were of necessity ignored. Even so, I found significant influences of the simple features I manipulated. This suggests that many other features of displaying share price or other stock data are likely to influence forecasts and trading as well.

Third, online trading is popular in today's stock market. Various stock charts are displayed on computer screens with a few clicks of a keyboard or mouse. In my experiments, however, only pen and paper were employed. It is possible that the medium changes the influence of several framing effects. This deserves further study.

Finally, most participants of the experiments were undergraduate students. None of them had stock market experience and most had only a little knowledge of the stock market learned from high school. The few trading differences I found between these students and experienced traders suggest that experience and expertise are likely to change the influence of various chart frames. Future research should recruit more experienced traders after evaluating their skills and background.

Future directions

My experiments have documented the existence of framing effects in simple stock charts that can influence price forecasting and share trading. My discussions have highlighted some possible reasons why stock chart frames affect the participants' forecasting and trading behaviour. Some possible limitations were listed in the paragraphs above. The results and limitations lead to several suggestions for future studies.

More studies should be done of forecasts based on various types of nonlinear trends. I explored only two simple nonlinear trends in Experiment one, and abandoned further studies of them for the sake of exploring linear trends. But nonlinear trends are ubiquitous and thus worthy of more detailed investigations. So too are displays of price ranges, candlestick displays and many other styles of presentation. Some of these may produce more accurate forecasts than others. I did not consider forecasting accuracy. The effects of chart frames, styles, and trends on forecasting accuracy also deserve study.

Finally, CWS provides a good method to measure expertise. It is important to evaluate the expertise of the experts in future studies. By designing experiments to derive CWS measures, we can better understand the nature and extent of expertise in the financial world, and perhaps classify professionals according to their level. If expertise can be learned, then there are surely variations in the effectiveness of methods to teach it to stock market traders. Stock charts and many other forms of data displays are likely important components of effective teaching. Future research could help to discover the best means of displaying data for effective teaching of expertise.

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Appendix A

Instruction

Thank you for participating in this experiment. The purpose of the experiment is to learn how people make predictions of future events. The experiment will take about 50 minutes to complete.

In a moment, I will ask you to make predictions about the prices of stocks bought and sold on the stock market after looking at stock charts. Some charts show prices for the past week. Some charts show prices for the past month. And some charts show the prices for the past year.

When you see a chart, you will also see an area below the chart where you will record your predictions. The area asks you to predict what the price of a stock will be tomorrow, the day after tomorrow, two days after tomorrow, three days after and four days after. So you will make predictions for the next five days.

Many people feel it is difficult to make a precise prediction, and easier to predict that a future price will be within a range of values. For example, you might guess that tomorrow's price of one share of Wal-Mart stock might be \$53.25 but not feel sure of your guess. You would, however, feel 95% sure that tomorrow's price would be between \$51.50 and \$55.00. I would like you to write down a range of prices in which you feel 95% sure the future price would fall. For each of your five predictions, it does not need to be the average of the price range. It should be the best single guess within the range of prices.

For practice, let us look at the example below.

YHOO – Yahoo! Inc.

Write down your predictions for next five days

1) Prices

_____	_____	_____	_____	_____
Day 1	Day 2	Day 3	Day 4	Day 5

2) Ranges of the price

Low

High _____	_____	_____	_____	_____
Day 1	Day 2	Day 3	Day 4	Day 5

At the left you will see one of the stock charts, this one showing the price of one share of Yahoo stock for the past year. On the right you will see the record area. Suppose you are 95% confident that tomorrow's price will be \$45.50 between \$44 and \$48. You would then write the predicted price and its range in here. Then you would make a price and its range to indicate your predictions for the day after tomorrow, and for the three subsequent days.

Do you understand what to do? Good! I will now give you 30 graphs in a random order. Please remember to look at the horizontal axis and note if the chart shows the price of a stock for a week, a month or a year.

Appendix B

A Sample of Stock Chart Showing a Truncated Price Scale

INTL – Inter-Tel Inc

Write down your predictions for next five days

1) Prices

_____	_____	_____	_____	_____
Day 1	Day 2	Day 3	Day 4	Day 5

2) Ranges of the price

Low				
High	_____	_____	_____	_____
	Day 1	Day 2	Day 3	Day 4
				Day 5

Appendix C

A Sample of Stock Chart Showing an Absolute Price Scale

INTL – Inter-Tel Inc

Write down your predictions for next five days

1) Prices

_____	_____	_____	_____	_____
Day 1	Day 2	Day 3	Day 4	Day 5

2) Ranges of the price

Low

High _____	_____	_____	_____	_____
Day 1	Day 2	Day 3	Day 4	Day 5

Appendix D

Stock Market Experience Questionnaire

The following is a list of questions regarding your stock market experience. Please read each question, and write down your answers. Thanks.

Question 1: What is your age? _____ years

Question 2: How knowledgeable are you about the stock market?

- ☐ I have no investment experience.
- ☐ I have a basic understanding about stock market, but have never invested.
- ☐ I have made some investments with my basic knowledge of the stock market.
- ☐ I am a knowledgeable investor.

Question 3: Which of the following statements would you feel best describes your investment philosophy?

- ☐ I cannot accept any loss of my stock investments.
- ☐ I may accept any loss of my stock investments, but only for small loss.
- ☐ I prefer to invest in safer, lower return than in risky, higher return investments.
- ☐ I am interested the high, long-term returns and not concerned about short-term decreases in my stock investments.

Question 4: If the stock market fell by 25% in one month, how would you react?

- ☐ I would sell some or all of my stock investments.
- ☐ I would maintain my current stock investments.
- ☐ I would buy more stocks.

Question 5: Most investment decisions involve both the possibility of making money and a chance of losing money. When making an important investment decision, which seems more significant for you?

- ☐ I would consider the potential loss money from my stock investments.
- ☐ I would consider the potential loss some money from my stock investments.
- ☐ I would consider the potential gain some money from my stock investments.
- ☐ I would consider the potential gain money from my stock investments.

Appendix E

Informed Consent Form

An Informed Consent Form is required by the Ethics Committee of the Psychology Department for all research projects conducted in Psychology Department at Carleton University. The purpose of the Informed Consent Form is to ensure that you, an experimental participant, understand the purpose of the study and the nature of your involvement. The informed consent must provide sufficient information such that you have the opportunity to determine whether you wish to participate in the study.

Study Title. Charting from Past to Future: Frames, Graphs and Forecasts

Principal Investigator. The principal investigator for this project is Jing Liu, Ph.D. candidate of Psychology Department, Carleton University, phone 520-2600, ext. 8478, e-mail, room in A404 Loeb Building, Carleton University. The project supervisor for this study is Professor Warren Thorngate, Psychology Department, Carleton University, phone 520-2600 ext. 2706, e-mail warren_thorngate@carleton.ca, room in A402 Loeb Building, Carleton University. If you have any questions about the experiment, you may contact them at any time. If you have any ethical concerns about this study, please contact Dr. Chris Davis (Chair of the Carleton University Research Ethics Committee for Psychological Research, 520-2600, ext. 2251).

Purpose and Task Requirements. The purpose of the study is to investigate how people judge stock price changes, and make decisions to trade stocks (i.e., buy or sell stocks), particularly how stock charts influence people's market behaviour.

The experiments will be run with pen and paper. The experiments will not take more than 50 minutes to complete, and will usually take much less time. The particular instructions for an experiment will be given to you at the beginning of experiment. You will be asked to complete a questionnaire concerning how you predict future stock prices and how you make decisions to trade stocks. You benefit from this study because you learn something about how people predict stock price changes and make decisions to trade stocks, what issues are of interest to psychologists, and what your own abilities of judgment and decision making are.

Potential Risk/Discomfort. There are no physical or psychological risks in this study.

Right to Withdraw and Anonymity/Confidentiality. Your participation in this study is entirely voluntary. At any point during the study you have the right to withdraw from the study or not answer certain questions that you feel uncomfortable or for any reason, with no penalty whatsoever. You may also stop participating at any time. Everything you write here is confidential. The experimental data will be made available only to persons conducting the study unless you specifically give permission in writing to do otherwise. No reference will be made in verbal or written form which could link your name to the study.

Signatures. I have read the above description of the study entitled “Charting from Past to Future: Frames, Graphs and forecasts” and understand the conditions and the tasks of my participation. The data collected will be used in research purpose. My signature indicates that **I ACKNOWLEDGE THAT I HAVE READ AND UNDERSTOOD THIS AGREEMENT, that I have executed this agreement voluntarily.**

Participant’s Name (please print): _____

Participant Signature: _____ Date (dd/mm/yy): ____/____/____

Witness’s Name (please print): _____

Witness’s Signature: _____ Date (dd/mm/yy): ____/____/____

Appendix F

Debriefing

Thank you for participating in this study. The purpose of the debriefing is to help you understand the nature of the study. As I described in the informed consent form, the purpose of this study is to investigate how people judge stock price changes, and make decisions to trade stocks (i.e., buy or sell stocks), particularly how stock charts influence people's market behaviour. Investors, financial experts, and academic researchers often employ stock charts to plot data, predict prices, and trade stocks. In the study, I will examine whether peoples' market behaviour depends on the way the data are shown or displayed in the stock chart. I predict that how data are presented in a stock chart will influence investors' predictions of stock prices and their trading behaviour.

If you have any questions or comments about this study, please feel free to contact Jing Liu, room in 214F SSRB (Social Science Research Building), Carleton University (520-2600 ext. 8478, jliu@ccs.carleton.ca). If you have any ethical or other concerns about this study, please contact Dr. C. Davis, Chair, Carleton University Research Ethics Committee for Psychological Research (520-2600 ext. 2251, cdavis@ccs.carleton.ca) or Dr. M. Gick (Chair of the Department of Psychology at Carleton University, 520-2600 ext. 2648, mary_gick@carleton.ca).

The experimenter's name is: _____ Date (DD/MM/YY): ____/____/____

Experiment Title: Stock charts & forecasts

Experiment Number: 04-074

The Participant's name is: _____ Date (DD/MM/YY): ____/____/____

The Participant's ID: _____

Appendix G

Instruction

Thank you for participating in this experiment. The purpose of the experiment is to learn how people to forecast future events and make decisions. The experiment will take maximum 90 minutes to complete.

In a moment, I will ask you to predict the change of stock price and make decision to buy or sell stocks after looking at stock charts. Some charts show prices for the past week. Some charts show prices for the past month. And some charts show the prices for the past year.

When you see a chart, you will also see two areas to the right of the stock chart. One area, prediction area, is the location where you will record your predictions. Another area, question area, is the location where you will write down your answers for a question. The prediction area asks you to predict what the price of a stock will be tomorrow, the day after tomorrow, two days after tomorrow, three days after and four days after. So you will make predictions for the next five days. The question area asks you to answer the question of buying, selling, or holding stocks.

Many people feel it is difficult to make a precise prediction, and easier to predict that a future price will be within a range of values. For example, you might guess that tomorrow's price of one share of Wal-Mart stock might be \$20.25 but not feel sure of your guess. You would, however, feel 95% sure that tomorrow's price would be between \$20.80 and \$19.35. I would like you to write down a range of prices in which you feel 90% sure the future price would fall. For each of your five predictions, it does not need to be the average of the price range. It should be the best single guess within the range of prices.

What is stock? How to buy or sell stocks? Stock represents ownership of a company. Stock is bought and sold as shares. Each share is one unit of ownership. Stock price is what an investor will pay to buy shares of stock or what he or she will sell shares of stock. For example, if the investor has bought shares at \$10 each and now sells them for \$20 each, that investor has clearly made money. If an investor has bought shares at \$20 each and now sells them for \$10 each, that investor has clearly loss money.

In general, Stock Price x Share Number = Your Money (to buy or sell stock). You have \$3000 dollars, for example, you want to buy a company's stock. The stock price is \$30 a share, you may buy a maximum of 100 shares stocks for the company, because $30(\text{price}) \times 100(\text{shares}) = \3000 (your money). Another example is to sell stocks. Support you have 100 shares of a company's stock. The stock price is \$30 a share. You may sell a maximum of 100 shares and you get \$3000 dollars cash.

For practice, let us look at the example on the next page.

YHOO – Yahoo! Inc.

Write down your predictions for next five days

1) Prices

_____	_____	_____	_____	_____
Day 1	Day 2	Day 3	Day 4	Day 5

2) Ranges of the price

Low

High _____	_____	_____	_____	_____
Day 1	Day 2	Day 3	Day 4	Day 5

Question

Suppose you have **100 shares** of this company' stock, which you bought at \$43.68 for a share one week ago. You also have enough cash to buy up to 100 shares stock if you wish. After examining the stock chart, do you want to buy more shares, sell some or all of your shares, or do nothing (hold the stock)?

- a. __Buy. How many shares do you want to buy? _____ .
- b. __Sell. How many shares do you want to sell? _____ .
- c. __Hold.

You will see one stock chart, showing the price of one share of Yahoo stock for the past year. On the right of the chart you will see the prediction and question areas. Suppose you are 95% confident that tomorrow's price will be \$45.50 between \$44 and \$48. You would

then write the predicted price and its range in the prediction area. Then you would make a price and its range to indicate your predictions for the day after tomorrow, and for the three subsequent days. In the question area, you will write down if you buy, sell or hold the company's stock. If you want to buy or sell the stocks, how many shares you want to buy or sell. If you don't want to buy or sell, you will mark for hold.

Appendix H

A Sample of Stock Chart and Question

KFX – K F X Inc.

Write down your predictions for next five days

1) Prices

_____	_____	_____	_____	_____
Day 1	Day 2	Day 3	Day 4	Day 5

2) Ranges of the price

Low

High _____	_____	_____	_____	_____
Day 1	Day 2	Day 3	Day 4	Day 5

Question

Suppose you have **100 shares** of this company' stock, which you bought at \$19.50 for a share one week ago. You also have enough cash to buy up to 100 shares stock if you wish. After examining the stock chart, do you want to buy more shares, sell some or all of your shares, or do nothing (hold the stock)?

- a. __Buy. How many shares do you want to buy? _____ .
- b. __Sell. How many shares do you want to sell? _____ .
- c. __Hold.

Appendix I

Questionnaire for Trading Stock Prices

The following is a list of questions regarding your shares trading. Think back to the experiment that how you make your decision to buy, sell, or hold stocks. Please read each question, and write down your answers. Thanks.

Question 1: What was the most important information on a stock chart that you used to trade stocks?

- ☐ Time series (weekly, monthly, or yearly, i.e., X axis)
☐ Price scale (Y axis)
☐ Price trend variation
☐ Gridlines

Question 2: Which time period of a stock chart was more useful for you to buy, sell, or hold stocks? (Please rank: 1 = most useful; 2 = 2nd most useful; 3 = least useful)

- ☐ Weekly ☐ Monthly ☐ Yearly

Question 3: Which time period of a stock chart is easier to obtain price trend? (Please rank: 1 = easiest; 2 = easier; 3 = least easy)

- ☐ Weekly ☐ Monthly ☐ Yearly

Question 4: When you saw a YEARLY stock chart to trade stocks, which part of the year was is the most useful? (Please rank: 1 = most useful; 2 = 2nd most useful; 3 = useful; 4 = least useful)

- ☐ Last month ☐ Last six months
☐ Last three months ☐ Whole year

Question 5: When you saw a MONTHLY stock chart to trade stocks, which part of the month was most useful? (Please rank: 1 = most useful; 2 = 2nd most useful; 3 = useful; 4 = least useful)

- ☐ Last 5 days ☐ Last three weeks
☐ Last two weeks ☐ Whole month

Question 6: When you saw a WEEKLY stock chart to trade stocks, which part of the week was most useful? (Please rank: 1 = most useful; 2 = 2nd most useful; 3 = useful; 4 = least useful)

- ☐ Yesterday ☐ Last three days
☐ Last two days ☐ Whole week