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Predicting the Presidential Election Cycle in US Stock Prices: Guinea Pigs versus the Pros

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Abstract

The notion that US stock prices follow a pattern that is synchronized with the rhythm of presidential elections has been a topic among financial investors for a long time. Academic work exists that supports this idea, quantifies the pattern, and has demonstrated its robustness over several decades and across parties in power. This paper takes the existence and robustness of this presidential election cycle for granted and asks whether individuals exploit it when asked to predict stock prices. It considers and contrasts two types of such forecasts: Those made by professionals included in the Livingston survey; and those made by students in a laboratory experiment. One key result is that neither group fares particularly well, though participants in the lab experiment clearly outperformed the professionals.

Keywords

Livingston survey, experiment, expectations, forecast, presidential election cycle, stock prices

JEL Classification

C91, D84, G12, G14

1. Introduction

While academic economists continue to entertain disparate views on many crucial issues, these days a vast majority subscribes to the desirability of building economic models and analyses on explicit microfoundations. However, with the host of "anomalies" that went on record during the last two decades, it has become less and less obvious which specific model of economic man or woman economists should employ when constructing such microfoundations.[1] Generating a rather bewildering picture, research findings have claimed on the one extreme that even birds, rats and ants are capable of making rational choices.[2] On the other extreme, serious doubts are entertained as to whether highly trained specialists in foreign exchange and equity markets process information rationally.[3]

This paper elaborates on the rationality of economic man by observing, evaluating, and comparing the forecasting skills of trained economists in real-world stock markets with those of undergraduate students in a laboratory environment that mimics real-world scenarios. In doing so, it draws on and is related to three particular strands of research: (i) the empirical literature on election-related patterns in US stock prices;[4] (ii) the vast amount of work on the nature and rationality of forecasts (or expectations) reported by respondents in the Livingston surveys;[5] and (iii) the investigation of expectation formation in experimental sessions conducted in computer laboratories.[6]

The paper is organized as follows: Section 2 introduces the empirical backdrop for this

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[1] A good entry point into this literature is provided by a string of papers published in the Journal of Economic Perspectives since 1987. See, in particular, Thaler (1987a, 1987b) on seasonal movements in stock prices, and De Bondt and Thaler (1989) on mean reversion. More recent examples are the contributions to the symposium on behavioural finance published in the Journal of Economic Perspectives by Hong and Stein (2007) and Baker and Wurgler (2007).

[2] See Tullock (1971) for one of the pioneering works in this field of research. Tullock's later insights on the subject and results with a wider range of animals are included in (Rowley (2006), chapter 3, which covers bioeconomics. However, in biology also the rationality of various species has been questioned by a number of authors. See Schuck-Paim, Pompilio and Kacelnik (2004) for a recent contribution.

[3] See Fama (1991). In the current paper's it is important to stress that one should not confuse predictability with inefficiency. See Balvers, Cosimano and MacDonald (1990).

[4] Examples of academic work in this area of research are the papers by Umstead (1977), Allivine and O'Neill (1980), Huang (1985), Gärtner and Wellershoff (1995) Hensel and Ziemba (1995), Booth and Booth (2003) and Wong and McAleer (2007).

[5] A classic in this area of research is Dokko and Edelstein (1989). A more recent effort is Söderlind (2007)

[6] See Haruvy, Lahav and Noussair (2007).

paper's statistical analysis – the cycle in US stock returns that is related to the timing of presidential elections – which had already been noed decades ago and apparently has remained a robust phenomenon since. Section 3 subjects individual stock return forecasts volunteered by Wall Street professionals and reported in the Livingston surveys to empirical scrutiny, with a special eye for whether they include the previously established presidential election pattern in the movement of stock prices. Section 4 analyzed results from a laboratory experiment that exposed students to real-world data on US stock prices and challenged them to come up with the best possible ex ante forecasts. Again, we search for a four-year election cycle in this data. The results presented in sections 3 and 4 underscore the limited rationality of decision makers and provide another, important and certainly surprising piece in the puzzle of how to picture individual behaviour in real-world situations. Section 5 offers interpretations of the obtained results and concludes. The data is being described as we go along, with details and sources available in an appendix.

2. A Random Walk Down Wall Street – Or a Stroll Around the White House?

This section establishes the empirical patterns in US stock prices that we will look for in the real-world and experimental forecasts scrutinized in sections 3 and 4. Our focus is on the long-run trend or drift and, in particular, on the election pattern that synchronizes the movement in stock prices with the rhythm of federal elections in the United States.

Classical efficient market theory maintains that stock market prices follow a random walk with drift,

(1) $$s_t = s_{t-1} + d + \varepsilon_t$$

where s is the natural logarithm of stock prices, d is a constant drift parameter, and $\varepsilon \sim N(0,\sigma_\varepsilon)$. By backward substitution equation (1) can be rearranged to yield

(2) $$s_t = s_0 + d \times t + \sum_1^t \varepsilon_i,$$

which states that, starting at s_0, s_t is driven by a trend and keeps a perfect memory of all random disturbances that occurred to date. Given the white-noise property of ε each historical episode of stock price movements is unique and without any systematic link to the past.

Chartist or technical theories, on the other hand, are based on the notion that history repeats itself and, thus, challenge the random walk hypothesis. But the random walk hypothesis and its underlying perfect-memory notion has also been challenged in academic research, the foremost examples being the mean-reversion literature and, more specifically, the literature that claims to detect patterns in the daily, weekly, monthly, or even longer-term movements of stock prices. One such claim is that stock price indices in the United States exhibit a pattern that is linked to the rhythm of presidential elections.

The idea that movements in stock prices reflect political events such as major elections has been part of investors' folklore for a long time, and it remains no puzzle why this is so when we add a grid of election dates to plots of popular stock market indexes, as done in Figure 1 for the Standard & Poor's 400 industrial shares price index. Still the origins of the terms election cycle or presidential cycle, as the phenomenon is more often referred to among Wall Street pundits, are not readily identified.[7] It seems though, that after predecessors on time patterns in equity prices and other economic variables, such as Kitchin (1923), the phenomenon of the presidential election cycle was described in serious print for the first time by Yale Hirsch (1967) in his first annual compilation of stock market time patterns and trends for the average investor. Financial economists and investment advisors have never lost interest since as documented by the many mentions in investment letters and pertinent blogs found on the internet.[8]

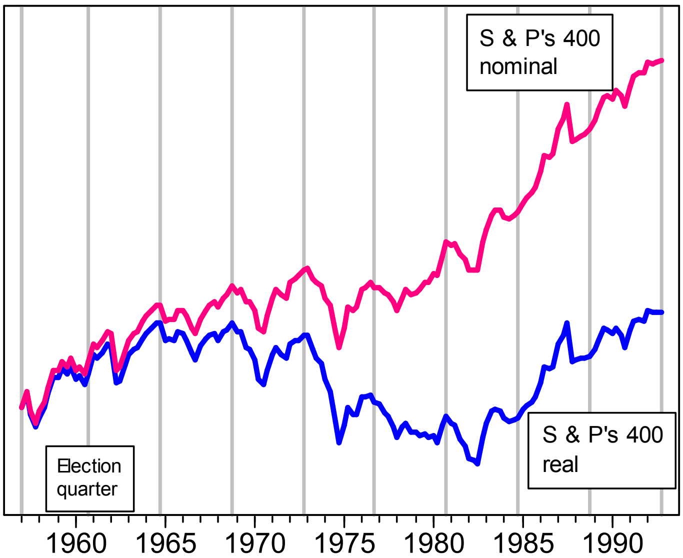

Figure 1. Standard & Poor's 400 stock market price index. Adapted from Gärtner and Wellershoff (1995), p. 388. Data source: IMF, International Financial Statistics.

[7] Oftentimes investors choose to call it the four-year US presidential cycle in order to set it apart from the mid-term presidential election cycle that also appears to exist.

[8] Examples of recent investment letters that feature the presidential cycle are Nickles (2004), BTR Capital Management (2005) and Carey (2005).

Web blogs that discuss the phenomenon can be found at http://attheselevels.com/archives/243-About-That-Presidential-Cycle.html, http://www.hussmanfunds.com/rsi/prescycle.htm or http://bigpicture.typepad.com/comments/2006/06/4_year_presiden.html

The first academic study of the phenomenon and the first thorough statistical backing of this postulate in a major academic journal occurs in Umstead (1977). After identifying a sixteen-quarter seasonal structure in stock prices, that paper hypothesizes that this structure may be related to the presidential election cycle. For statistical support, it is demonstrated that between 1927 and 1974, average stock returns during the eight quarters immediately prior to a presidential election were significantly higher than average returns during the eight quarters immediately following. These results have been substantiated and refined in later works that include Allivine and O'Neill (1980), Huang (1985), Gärtner and Wellershoff (1995) and Hensel and Ziemba (1995). More recently, Wong and McAleer (2007) showed that the election pattern stands up to the use of spectral analysis and the EGARCH intervention model. Of particular interest for the purposes of this paper is the study by Booth and Booth (2003). In an elaborate piece of statistical work, these authors find evidence for the presidential election cycle in stock prices in data reaching back as far as 1803.

For reasons that will become obvious in a moment, our analysis of the forecasting behavior of stock market participants draws on Gärtner and Wellershoff (1995), who employ an unrestricted dummy variable approach to demonstrate that US stock prices follow a four-year cycle overlaying equation (2), thus demonstrating the robustness of the election cycle over time and identifying the details of the election pattern in US stock market prices. According to their results, stock prices fall relative to trend growth after the inauguration of a new president, begin to recover around mid-term, and peak just before the next election. This cycle was also found to be robust to the use of different stock price indexes, nominal or real, and across parties in power. In fact, it occurred during each and every presidency from John F. Kennedy to George Bush.[9] Attached to the identified trend, the election cycle looks like the dashed pattern shown in Figure 2.

It turned out that a parsimonious and handy way to represent this cycle, which did not violate the unrestricted estimates, was to augment equation (2) by a single dummy variable *ELDUM* instead of the 15 quarterly dummy variables necessary in the estimation of the unconstrained cycle. *ELDUM* follows the symmetrical pattern 0, 1, 2, 3, 4, 5, 6, 7, 7, 6, 5, 4, 3, 2, 1, and 0 during each 16-quarter election term, beginning with the quarter in which a presidential election takes place.

Adding $ELDUM^a$ to the right-hand side of equation (2), with $a \neq 1$ allowing nonlinear patterns, using an on/off dummy variable *CRASH* to neutralize the stock market crash of October 1987, permitting the error term to follow an ARMA process instead of assuming it to be white noise, and finally, taking first differences on both sides in order to make the endogenous variable stationary, the general estimation equation becomes.

$$\Delta s_t = d_0 + d_1 \Delta ELDUM^i + d_2 \Delta CRASH + \text{ARMA}$$

[9] During the Bush presidency, examined in isolation, the pattern proved significant only when the stock market crash of October 1987 was neutralized by means of a dummy variable.

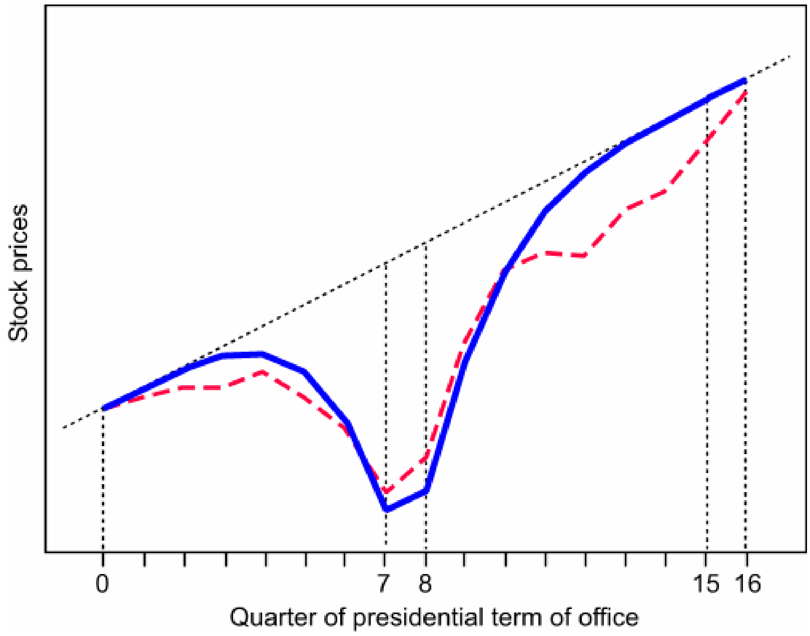

Figure 2. The graph visualizes the constrained (solid line) and the unconstrained (dashed line) estimate of the election cycle in US stock prices reported in Gärtner and Wellershoff (1995). Elections are held in quarters 0 and 16.

Table 1 shows a number of estimates based on permutations of this equation that signal the robustness of the election pattern embedded in stock price movements.

Table 1. Election Cycles in US Stock Returns

Eq. #	Constant	$\Delta ELDUM$	$\Delta ELDUM^4$	$\Delta CRASH$	Error term	R^2_{adj}	Box-Pierce
1	0.44 (0.74)	−2.58 (5.17)	–	−24.63 (6.24)	ARMA	0.41	10.49
2	0.40 (0.72)	–	−0.0063 (6.69)	–	ARMA	0.31	9.72
3	0.56 (1.00)	–	−0.0066 (7.83)	−24.91 (5.20)	ARMA	0.45	10.06
4	0.66 (1.36)	–	−0.0064 (6.41)	−26.64 (4.87)	White noise	0.32	29.91
5*	1.81 (3.34)	–	−0.0064 (7.87)	−24.90 (5.42)	ARMA	0.45	11.68

Notes: Results are from Gärtner and Wellershoff (1995), Table 1. Endogenous variable: *real* returns on industrial share prices over the previous quarter, in percent. Parentheses contain absolute *t* values. Box-Pierce is the χ^2 statistic for the first 16 sample autocorrelations. OLS and GLS estimates. 128 quarterly observations 1961:I – 1992:IV.
* The endogenous variable in equation 5 is *nominal* returns on industrial share prices.

The results show that while a linear specification generates highly significant results already, a non-linear specification of the election cycle dummy variable yields a somewhat better fit Moreover, the coefficient of the cycle dummy, and hence, the estimate of the election cycle in stock prices, is completely insensitive to whether the stock market crash of 1987 is treated as an outlier and thus neutralized or not, and is also not sensitive to which statistical properties are being assigned to the error term. The solid line in Figure 2 visualizes the election pattern in stock prices estimated via equation (4). The estimates suggest that the Standard & Poor's 400 index loses more than 15 percent of its value relative to its trend during the first half of a presidential term, but regains those losses at a decelerating pace during the second half of the term.

3. The Election Cycle and the Livingston Surveys

Probing into the question of whether stock market participants did exploit this election-related pattern when anticipating future movements in stock prices, Gärtner and Wellershoff (1999) find that *aggregate* stock price forecasts given by the Wall Street professionals included in the Livingston surveys are ignorant of this four-year cycle. This need not really challenge the view that the stock market is efficient, however. From a Darwinian perspective, rational expectation formation by a reasonably potent subgroup of investors may well suffice to provide for market efficiency.

To deal with this possibility, we need to go down to the micro level and analyze the forecasts of *individual* respondents. Before we look at results, however, we need to note some of the peculiarities of the Livingston data and report how we dealt with the issues arising in this context.

3.1 The Livingston Data

Started by columnist Joseph Livingston right after the end of World War II, the Livingston survey, currently conducted and published by the Federal Reserve Bank of Philadelphia, is the oldest continuous survey of economists' expectations. It summarizes the forecasts of economists from industry, government, banking, and academia, and is published twice a year, in June and December. Forecasts on stock prices began in June 1952 and were given for 6- and 12-month horizons. Livingston's original series focused on the Standard & Poor's Industrial Stock Price Index 400 and was discontinued after December 1989.[10] This paper's empirical work focuses on the time period for which the estimates reported in Gärtner and Wellershoff (1995) and the Livingston survey's S&P 400 forecasts overlap,

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[10] While this is the information provided by the Federal Reserve Bank of Philadelphia in early documentation after it took over conducting and administering the Livingston surveys, it later on felt compelled to caution users, stating that "that description was a bit too general". For details see the online documentation provided at http://www.philadelphiafed.org/files/liv/NewFilesJun04/SPI/Old_Stock_Price_Web_Doc.pdf.

which leaves us with thirty years of biannual observations from June 1961 through December 1989.

Each release of the Livingston survey reports the forecasts of some 20 to 40 individuals. Over the years that are included in our sample, almost 500 individuals have participated in the survey. Some only for brief spells, others for decades. For this section's statistical analyses, we selected those ten individuals who, beginning in June 1961, had the longest uninterrupted streak of participation in the survey. This does not generate a random sample, of course, and this is intended. In the spirit of the above Darwinian argument against judging market efficiency from means or medians of pooled individual forecasts, this sample is deliberately biased towards incorporating those individuals with the best staying power – which should include those with the most convincing predictive skills.

Our analysis focuses on the expected returns implied by the S&P index predictions of the Livingston survey respondents. Since respondents are not being asked for these values directly, but rather for predicted *levels* of the index, expected returns need to be computed. Problems occur, here, because we do not know exactly when the prediction had been made and, thus, what information respondents had at the time. There are several options to solve or avoid this problem: One option would be to use Livingston's own base values as communicated to forecasters on the survey questionnaire. Unfortunately, this information could be weeks off from the information that respondents actually had, and its timing is highly unstable. For instance, in Livingston's original work, base values supplied with the summer questionnaire were dated anywhere between May 11 and May 31, and forecasters had weeks to respond by mail. The Philadelphia Fed runs a tighter ship, it seems. In the December 2007 survey, it reports that data listed as "actual" are the "data that were available to the forecasters when they were sent the survey questionnaire on November 20." And that "(a)ll forecasts were received on or before November 30." A second option is to assume that forecasters were aware of the end of December or end of May S&P values, respectively, when the winter and summer surveys where conducted. This certainly adds noise to the data and may assume a few days or even a week more of information than respondents actually had. This may not be a high price to pay in light of the 7-month forecast horizon. A third option, which avoids the inherently unsolvable problem of guessing what respondents know, exploits the fact that respondent always predict stock prices at a 6-month and a 12-month horizon. These two level forecasts always imply a forecast of stock returns that accrue between 6 and 12 months into the future. We will present and discuss our results based on this third approach.[11]

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[11] Others who opted for this approach include Dokko and Edelstein (1989) and Söderlind (2007). The statistical analyses reported in table 2 have also been conducted based on the second approach, with qualitatively identical results.

3.2. Empirical Results

Table 2 reports the results from evaluating the stock price forecasts of 10 individual respondents included in the Livingston survey. Respondents are kept anonymous, identified only by numbers in the Livingston data sheets. These numbers are reported in the second column. The number of observations that are available in each case, given in the first column, varies between 37 and 57. So given that our reference sample spans 60 releases of the Livingston survey, the individuals included in our groups participated in 62 to 95 percent of the conducted surveys.

Table 2. Standard & Poor's Index Forecasts by Individual Participants in Livingston Survey
Biannual data; Reference period: 1961:July – 1989:December

		Endogenous variable: forecast error			Endogenous variable: forecasted return		
Number of observations	Respon-dent #	Constant	$\Delta ELDUM^4$	R^2 D.W.	Constant	$\Delta ELDUM^4$	R^2 D.W.
47	#14	−0.04 (0.05)	0.0050 (4.48)	0.31 2.77	1.34 (6.21)	−0.0001 (0.45)	0.01 2.32
34	#27	0.77 (0.86)	0.0049 (4.19)	0.35 2.49	2.05 (8.14)	−0.0002 (0.54)	0.01 1.82
57	#28	−0.66 (0.79)	0.0033 (2.68)	0.12 1.78	1.24 (3.10)	−0.0004 (0.77)	0.01 0.47
44	#75	0.15 (0.17)	0.0045 (3.52)	0.23 2.51	1.44 (3.22)	−0.0005 (0.88)	0.02 1.63
41	#87	0.88 (1.07)	0.0050 (4.41)	0.33 2.81	1.85 (5.47)	−0.0000 (0.01)	0.00 1.19
33	#101	0.86 (0.94)	0.0048 (3.72)	0.31 2.30	2.21 (6.33)	−0.0010 (1.98)	0.12 1.20
37	#106	1.17 (1.43)	0.0044 (3.66)	0.28 2.56	2.28 (4.60)	−0.0005 (0.71)	0.02 1.73
44	#116	0.28 (1.02)	0.0049 (4.01)	0.28 2.44	2.33 (6.06)	−0.0003 (0.51)	0.01 1.17
48	#118	−0.77 (0.92)	0.0043 (3.68)	0.23 2.48	0.72 (1.58)	−0.0006 (0.88)	0.02 2.19
31	#119	2.41 (2.05)	0.0042 (2.66)	0.20 0.95	3.01 (4.27)	0.0002 (0.16)	0.01 0.68
58	Mean	−0.29 (0.38)	0.0039 (3.52)	0.18 2.31	1.49 (7.47)	−0.0003 (1.02)	0.02 0.55
58	Median	0.33 (0−.44)	0.0038 (3.50)	0.18 2.30	1.46 (8.18)	−0.0004 (1.42)	0.04 0.81
					Endogenous variable: Actual stock return		
58					1.78 (2.48)	−0.0041 (4.03)	0.22 2.44

Notes: OLS estimates. Absolute *t* statistics are given in parantheses. Actual and expected returns over 6 months are expressed as quarterly rates of change in order to facilitate comparisons with the results presented in Tables 1 and 3, where quarterly observations are being used.

There are two ways to assess the rationality of the stock return forecasts submitted by the ten selected respondents: One is by checking whether regularities that are found in actual stock returns are also detected in forecasted returns. As the last regression shows, the biannual end-of-period index values for our reference period 1961:July – 1989:December contain two such regularities that are in line with the results reported in Gärtner and Wellershoff (1995): Actual returns feature a significant constant term – signalling a *trend* in stock *prices* of 1.78 percent per quarter – and a significant four-year cycle that drives stock prices below their trend path by almost 10 percent. This equation explains 22 percent of the variation in nominal stock returns.

To what extent individuals and the group included in the Livingston surveys made use of the pattern reported in the bottom equation is explored in the remaining equations in the right-hand part of Table 2. The results are quite sobering. While most of the Livingston survey's experts seem to make use of the long-run trend in stock prices when making their predictions, there is hardly any evidence of the election pattern. Respondent #101 comes closest to making use of the election cycle in a statistically significant fashion. But even there the coefficient of -0.001 is less than one fourth of what it is in actual stock returns.

One might argue that since no respondent participated throughout the entire reference period, the regularities detected in actual stock returns on the basis of all 58 observations may not be equally strong or even present in (much) smaller and in many cases interrupted subsamples.[12] Therefore, caution may be called for when comparing constant terms and presidential election cycle coefficients found in individual forecasts with those found in actual stock returns. In order to check this potentially valid argument, the estimates reported in the left-hand part of Table 2 regress the committed forecast error on the election dummy variable, asking the question whether the individual under consideration could have reduced his or her prediction error by drawing on the election pattern.

There is no ambiguity in these results. Every single series of individual forecast errors contains a highly significant election pattern, with t statistics that range from 2.66 to 4.48. Up to a third of the committed forecast errors could have been prevented had the election pattern been taken into account. This result is also found in the index of all Livingston respondents' predictions, no matter whether we are using mean or median values.

Respondent #119 stands out from the others. First, because his or her prediction error features a significant constant term. And second, because there is clear evidence that the prediction errors contain an unexploited serial correlation. Since serial correlation may be a potential, though minor, issue in the estimates for other repondents as well, it may be instructive to take a second look at respondent #119's predition errors, permitting first-order autocorrelation of the error term. This specification yields

[12] Even here we should note, though, that individuals observe the stock market even when they do not participate in the Livingston survey. So their real-world experience reaches far beyond the sample of predictions each one contributes to the survey.

$$\underset{}{\text{forecast error}_t} = \underset{(3.59)}{1.92} + \underset{(5.67)}{0.0048}\,\Delta ELDUM^4 - \underset{(1.94)}{0.39}\,\nu_{t-1} + \varepsilon_t$$

$$R^2 = 0.56 \quad p \text{ value of Breusch-Godfrey LM test (2 lags)} = 0.73$$

where ν denotes the autoregressive error term driven by the white noise disturbance ε.

This result makes things look worse for this respondent. Now there is a highly significant forecast error of almost 2 percent per quarter, the election cycle stands out stronger and is more significant than before, and there is serial correlation in the errors. Had he or she taken all this into account, more than half of the variation in forecasting errors could have been eliminated.[13]

Drawing all this together, it appears that the ten Livingston respondents we picked out here displayed some basic rationality when generating their predictions, and weak-form rationality regarding such simple regularities as trends or first-order autocorrelation in errors. Such basic violations of rationality are not present in the forecast errors. As soon as regularities are of a slightly more complex mould, however, respondents fail badly. Since the detection of a simple four-year cycle is light-years less demanding than what rational-expectations or perfect-foresight economics presumes homo oeconomicus to know (or to have learned), it seems worthwhile and necessary to give this result a second look from a different angle.

4. Guinea Pigs on Wall Street

We now turn to a second set of data bearing on expectation formation and how to perceive economic man. These stem from the following simple forecasting experiment that confronts participants with the task of predicting stock price movements.

4.1. Setup of the Experiment

The data were collected in a single experiment conducted at the computer laboratory of the University of St. Gallen, Switzerland. Ten participants were recruited from 3rd and 4th year economics and political science classes at the University of St. Gallen. During recruitment, students were told that they had the opportunity to participate in a scientific experiment for a fee of 20 Swiss francs (approximately 14 U.S. dollars) each, and that this experiment would take about one hour. The only further information provided at this stage was that the expected (or average) payoff for each participant in the experiment was 40 francs, and that the minimum payoff was zero francs.

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[13] One should note, however, that some data points were lost with this new specification, bringing the number of observations down to 25.

A more detailed briefing took place just prior to the actual experiment in the computer lab. At this stage, the following information was given:

Participants would be given a series of numbers, in one step increments. After a number had been supplied, students would be asked to predict the next number and enter the prediction via their keyboard. After the end of the experiment, each participant's performance would be evaluated and participants would be ranked on the basis of each person's total summed-up absolute forecasting errors. Starting with the winner, progressive payoffs were announced to follow 120, 90, 65, 45, 30, 20, 15, 10, 5 and 0 Swiss francs. Participants were not given any information as to the nature of the supplied series of data.

During the experiment, each participant sat in front of a personal computer. At the start, the computer screen showed a graphical display of the first ten observations for the S&P 400 stock price index shown in Figure 2 above. No information whatsoever as to the nature of the data was provided. Then students were asked to predict the next value. After having entered their forecasts, they were provided with the actual observation and asked for another one-period forecast. In this way each participant provided a total of 120 one-period forecasts. Throughout the experiment participants could switch between two screens, one featuring a graph of actual data revealed up to that point, the second displaying the individuals forecast errors made to date. Forecasts had to be entered within 30 seconds. Each period's true value was only supplied after all participants had entered their prediction. Participants were not informed about the true nature of the employed data. Periods were numbered 0 through 130.

4.2. Experimental Results

Table 3 gives the results obtained from regressing each of the ten individual return forecasts and forecast errors, respectively, and the group's aggregated data, on a constant and the cycle dummy variable *ELDUM*.

Again, we start by looking at forecasted returns which are analyzed in the right-hand section of Table 3. As a reference, the pattern found in the employed actual stock returns is shown as equation 12 at the bottom of the table: During the sample period 1961:I – 1990:III stock prices exhibit a drift parameter of 1.86 percent per quarter, and there is an election pattern in stock prices, represented by $-0.0065 \times \Delta ELDUM$. Both estimates are highly significant, with absolute t values of 3.49 and 5.85, respectively. The coefficient of determination is 0.23, and the Durbin-Watson statistic of 1.57 is no cause for worry, in particular since we know from the results presented in Gärtner and Wellershoff (1995) that giving the error term a more refined ARMA treatment does not really affect coefficient estimates.

Table 3. Standard & Poor's index forecasts in an experimental setting
Quarterly data: 1961:I – 1990:III

		Endogenous variable: forecast errors			Endogenous variable: forecasted return		
Eq.	Parti-cipant	Constant	$\Delta ELDUM^4$	R^2 D.W.	Constant	$\Delta ELDUM^4$	R^2 D.W.
1	#1	−1.59 (2.53)	0.0045 (3.45)	0.09 1.83	−0.16 (0.54)	−0.0019 (3.19)	0.08 1.56
2	#2	−3.22 (5.75)	0.0054 (4.67)	0.16 1.84	−1.80 (6.25)	−0.0009 (1.57)	0.01 1.72
3	#3	−1.93 (2.39)	0.0042 (2.52)	0.05 1.21	−0.48 (0.77)	−0.0023 (1.80)	0.02 0.92
4	#4	−0.86 (1.16)	0.0045 (2.92)	0.07 2.06	0.59 (1.19)	−0.0022 (2.09)	0.04 1.61
5	#5	−1.74 (2.43)	0.0049 (3.29)	0.08 1.67	−0.32 (0.71)	−0.0017 (1.75)	0.03 1.19
6	#6	−0.62 (0.87)	0.0045 (3.01)	0.07 1.65	0.80 (1.89)	−0.0020 (2.25)	0.03 1.37
7	#7	−0.52 (0.83)	0.0043 (3.35)	0.09 1.90	0.94 (3.02)	−0.0021 (3.26)	0.08 1.35
8	#8	−0.56 (0.59)	0.0031 (2.17)	0.04 2.17	0.89 (2.13)	−0.0034 (3.91)	0.12 1.76
9	#9	−1.61 (2.40)	0.0044 (3.16)	0.08 2.00	−0.17 (0.40)	−0.0020 (2.34)	0.04 1.60
10	#10	−0.59 (0.90)	0.0038 (2.84)	0.06 2.02	0.87 (2.50)	−0.0026 (3.66)	0.10 1.79
11	Average	1.33 (2.21)	0.0044 (3.51)	0.10 1.95	0.12 (0.46)	−0.0021 (4.02)	0.12 1.55
					Endogenous variable: Actual stock return		
12					1.86 (3.49)	−0.0065 (5.85)	0.23 1.57

Notes: OLS estimates. Endogenous variable: Quarterly forecasts of Standard & Poor's industrial share prices 400, in percent. Parentheses show absolute *t* statistics.

Looking at the forecast performance collected by our laboratory experiment, on an individual basis and on average, as a group, provides a number of interesting results:

Facing very much the same task, the forecasting performance of the participants in our experiment differs in several respects from that of the individuals we lifted from the Livingston survey. Most importantly, the majority of participants made use of the election pattern embedded in the supplied S&P 400 series when making their predictions. In all cases the respective coefficient estimate is negative. In seven out of the ten cases the estimate is significant at the 95 percent level or better. The lowest *t* value obtained is 1.57 in the case of participant #2. Quite surprisingly, though, individuals appear to find it more difficult to identify the drift in stock prices and employ it for their forecasts. This is shown by the much too low and insignificant constant term in the average return predictions, and also when we look at individual predictions. None of the constant terms found there even comes close to the actual drift parameter of 1.86, with the highest estimate being 0.94. Furthermore, half of the participants even appear to have made forecasts on the assumption of a negative trend. Only one of these estimates, the one for participant #2, is significant, however, though with an absolute *t* value of 6.25, which is the highest of all. Fit levels remain modest, with coefficients of determination between 0.01 and 0.12 in the individual samples.

Since all individuals underestimate the strength of the election cycle, it does not come as a surprise that all forecast errors feature such a pattern: Forecast errors clearly peak towards the middle of a presidential term. Respective results do not seem to vary a lot between participants, with coefficient estimates remaining in the narrow zone between 0.0031 and 0.0051 and reaching confidence levels of 95 percent and above. As a second consequence of the constant term being too low in all return forecasts, forecast errors feature a negative constant term. Since participants do not appreciate the drift in stock prices to its full extent, index predictions tend to be too low, and this feature is even significant in half of the cases.

All this corroborates the key result from the previous section's scrutiny of Livingston data that individuals were able to churn out unbiased predictions of the election cycle neither in actual data, nor of the stock price series' inherent trend. Surprisingly, the forecasts of our guinea pigs compare quite favorably with those of Wall Street professionals. This is all the more puzzling given that forecasters in the experiment were on their own and had to churn out forecasts within 30 seconds, whereas Wall Street pros had several weeks and could tap the human and artificial intelligence of large firms or institutions.

5. Discussion and Outlook

We have examined two groups of forecasters, in two quite different settings, with the common task of predicting the S&P 400 stock price index. The focus was on whether individuals succeeded in exploiting the trend and, in particular, the four-year cycle embedded in targeted data series. The setting in which the two groups of individuals operated are so different in many respects that one should not make too much of the difference between the obtained results: One group had to come up with forecasts 7 and 12 months into the future, the other with forecasts 3 months into the future. One group knew that the numbers to forecast were stock prices, the other one did not. One group had weeks to respond, and a host of methods, variables, and models to ponder. The other one had to decide within 30 seconds, and the only resources to draw on were the history of the data series itself and a keen mind. Which group was at an advantage may be open to debate. As Söderlind (2008) argues, Livingston survey predictions of stock price movements "are very much like a 'too large' forecasting model: poor performance and too sensitive to irrelevant information" (p. 1). This may mean that too much information and knowledge may blur the view at the simple patterns buried in noisy-looking variables.

When we look beyond differences between the two groups and pool the insights generated by the study of both the Livingston respondents and the experimental forecasters, one very important point is made rather forcefully by the observations reported in this paper: There are clear and rather narrow limits to how rational expectations become even after long periods of learning. It appears safe to speculate that exactly where learning efforts eventually capitulate is determined by two major factors. One of these is the complexity of the underlying process. An ARIMA(4,2,12)-process or simultaneous-equations relationships are certainly more difficult to detect than, say, the mean value of a series. More important may be a second factor, however, namely the ratio of the variance generated by the process to unaccounted variance or noise. As this noise-to-pattern ratio rises, even extremely simple patterns tend to remain undetected. After only two completed cycles, any child would be able to forecast the pattern estimated for stock prices – if this core pattern was all that was presented and statistical noise was omitted. Garnished with a 4:1 noise-to-pattern ratio, however, apparently neither Wall Street pros nor prospective economics majors were able to detect the cycle – well not even the trend.

As such, economic forecasts tend to become more rational the more the generating process stands out relative to any accompanying noise. Given this, it makes a lot more sense to postulate rational expectations regarding building blocks of macroeconomic models that are robust and well-supported by empirical data. Other behavioral relationships with little explanatory power may be completely ignored or overlooked and may even be caricatured by market participants. Thus, for many policy applications, a different and not necessarily rational expectation-formation mechanism may be called for.

Without any question, analyses based on the assumption of complete rationality have provided and will continue to provide many important baseline results. The results presented in this paper, however, urgently call for a more moderate picture of economic man for analyzing acute policy dilemmas, given how little complexity or uncertainty is required to make even informed individuals discard all learning efforts.

Where do we go from here? As is often the case, our results raise a host of new questions. We found evidence that even straightforward relationships and patterns are easily overlooked when buried under a lot of noise. The question is, to what do individuals resort then? Do they retreat towards simplicity? If they don't see the trend, do they believe the variable is stationary? If they don't see the constant term around which a stationary variable fluctuates, do they trust that the constant is zero? Or is the pattern they fall back on path dependent, a reflection of history or recent personal experience in other areas? In a wider context, regarding the belief in or the use of models, similar questions arise. Such questions could be addressed in an appropriately designed experimental program. They are also linked to a strand of recent research on choosing and processing information [Abel, Eberly and Panageas (2007)]. This paper's results should feed into this line of work.

A. Data Appendix

All data on share prices used in this paper are the Standard & Poor's industrial share price index 400. The source is the International Monetary Fund's International Financial Statistics, line 62.
The election-cycle dummy variable ELDUM follows the four-year pattern 0, 1, 2, 3, 4, 5, 6, 7, 7, 6, 5, 4, 3, 2, 1 and 0, starting with the quarter during which a presidential election takes place.

Section 3. The source for the Livingston survey predictions is Ibbotson Associates (1994). The six-month returns and return forecasts employed in this section have been transformed to quarterly rates of change by means of the formulas $\left[\left(\frac{S_t}{S_{t-6}}\right)^{\frac{3}{6}} - 1\right] \times 100$ and $\left[\left(\frac{F_t}{F_{t-6}}\right)^{\frac{3}{6}} - 1\right] \times 100$, where S and F denote actual and forecasted end-of-period values of the S&P 400 index for time t, and t changes in monthly increments. Return forecast errors are defined as $\left[\left(\frac{F_t}{F_{t-6}}\right)^{\frac{3}{6}} - 1\right] \times 100$ - $\left[\left(\frac{S_t}{S_{t-6}}\right)^{\frac{3}{6}} - 1\right] \times 100$.

Section 4. Predictions of stock prices were collected in the experiment described in the text. Returns and return forecasts are percentage rates of change over the preceding quarter. Forecast errors are computed as $\frac{F_t - S_t}{S_t} \times 100$.

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