

# Predicting short-term stock fluctuations by using processing fluency

Adam L. Alter\* and Daniel M. Oppenheimer

Department of Psychology, Princeton University, Princeton, NJ 08540

Edited by Dale Purves, Duke University Medical Center, Durham, NC, and approved May 2, 2006 (received for review February 9, 2006)

**Three studies investigated the impact of the psychological principle of fluency (that people tend to prefer easily processed information) on short-term share price movements. In both a laboratory study and two analyses of naturalistic real-world stock market data, fluently named stocks robustly outperformed stocks with disfluent names in the short term. For example, in one study, an initial investment of \$1,000 yielded a profit of \$112 more after 1 day of trading for a basket of fluently named shares than for a basket of disfluently named shares. These results imply that simple, cognitive approaches to modeling human behavior sometimes outperform more typical, complex alternatives.**

heuristic reasoning | psychology | stock market

Short-term fluctuations in stock prices are notoriously difficult to predict (1, 2). For decades, economists have created complicated mathematical models that ultimately fail to describe short-term share price movements (3). Indeed, the range of factors that influence share prices is so broad that many eminent scholars describe short-term price changes as “random” (3–5). Some economists have even suggested that a monkey throwing darts at a dartboard of stocks is as likely as a seasoned financial analyst to select immediately profitable stocks (3).

If stock market analysis were solely the province of economists and financial analysts, one might accept their robust failure to predict short-term stock prices as an indication that stock prices are only predictable in the long term. However, as the advent of behavioral economics demonstrated in the 1970s (6, 7), psychological theory has the potential to inform economic thought. Researchers have recently begun to consider the influence of incidental variables on stock market investment. Consistent with the finding that people are more optimistic when in a good mood (8), markets are more likely to appreciate on sunny rather than rainy days (9, 10). Similarly, behavioral finance researchers have found a so-called “home bias,” in which people prefer to invest in local as opposed to international markets (11). Although investors stand to benefit from diversifying their portfolios, they might prefer the familiarity of domestic stocks, avoiding the lack of information associated with foreign markets. Inspired by the success of these psychological approaches to economic analysis, we sought to develop a straightforward alternative to complex economic models in the quest to predict short-term stock price movements.

When people attempt to understand complicated information, they tend to simplify the task by relying on mental shortcuts, or heuristics (12). For example, people tend to judge stimuli that are fluent, or easy to process, more positively on a range of evaluative dimensions. Studies have shown that people believe fluent stimuli are more frequent (13), true (14), famous (15), likeable (16), familiar (17), and intelligent (18) than similar but less-fluent stimuli. Perhaps most relevant to investment behavior, fluency gives rise to feelings of familiarity and a positive affective response, resulting in higher judgments of preference (19, 20). People are also more inclined to believe aphorisms that rhyme (e.g., woe unite foes)

than similar aphorisms that do not rhyme (e.g., woe unite enemies), suggesting that the fluency effect extends to the domain of language processing (21). Because people respond positively to easily processed information, it seems plausible that they might prefer stocks with simpler names relative to those with complex names.

Surprisingly, the literature has been devoid of demonstrations that fluency influences investors' selection among a set of stocks (22). The only related study we located demonstrated a correlation between stock performance and the likelihood of that stock being recognized (23). The researchers measured the performance of stocks that were already on the market, so recognition might have merely reflected a stock's previous success. However, because recognized objects tend to be more fluent (24), it is possible that the results could be interpreted as evidence that fluency affects stock price. Unfortunately, the design of that study makes it impossible to determine whether success led to recognition or whether recognition caused success.

## Study 1

**Description.** To ensure that our studies measured the causal effect of fluency on stock performance, we began by systematically manipulating the fluency of fabricated stocks. One group of participants rated these stocks on ease of pronunciation, as a proxy for fluency. A second group of participants estimated the future performance of fabricated stocks that had been prejudged as having simple or complex names (for a full list of stock names and their fluency ratings, see Data Set 1, which is published as supporting information on the PNAS web site).

**Results.** As we anticipated, participants expected fluently named stocks ( $M = 3.90\%$  appreciation,  $SD = 6.46$ ) to outperform disfluently named stocks ( $M = 3.86\%$  depreciation,  $SD = 6.54$ ),  $t(n = 29) = 4.14, P < 0.0001, \eta^2 = 0.39$  during a year of trading. Furthermore, both predicted values differed from zero, implying that people expected fluently named shares to appreciate in value,  $t(n = 29) = 3.20, P < 0.01, \eta^2 = 0.28$ , whereas they expected disfluently named shares to depreciate in value,  $t(n = 29) = -3.12, P < 0.01, \eta^2 = 0.27$ .

Assuming that investors seek gains and avoid losses, these results imply that people without additional knowledge will invest in companies with fluent rather than complex names. However, it is difficult to generalize these results to real stock behavior because judgments were made on fabricated stocks in the absence of any other information about stock performance. It was therefore important to replicate these findings in an ecologically valid domain, where competing sources of information have the potential to eliminate the effects of name complexity on performance. Thus, in a second study, we sought to

Conflict of interest statement: No conflicts declared.

This paper was submitted directly (Track II) to the PNAS office.

Abbreviations: AMEX, American Stock Exchange; NYSE, New York Stock Exchange.

\*To whom correspondence should be addressed at: Department of Psychology, Green Hall, Princeton University, Princeton, NJ 08544. E-mail: aalter@princeton.edu.

© 2006 by The National Academy of Sciences of the USA

show that the fluency of a share's name predicts its early performance in the stock market.<sup>†</sup>

## Study 2

**Description.** When a company first releases shares, investors are unlikely to have much additional diagnostic information about the company's performance. Consequently, incidental factors like the complexity of the share's name may influence the share's performance shortly after its release onto the stock exchange. Over time, however, other factors are more likely to influence the share's price, introducing noise that might occlude name-complexity effects. As a result, fluency of a share's name might influence its performance in the short term, whereas such effects might be diminished in the long term.

**Results.** To explore the effects of name complexity on stock performance, we examined the relationship between participants' ratings of stock name complexity and the actual performance of those shares after they had been on the NYSE for 1 day, 1 week, 6 months, and 1 year (for a list of randomly selected stocks, see List 1, which is published as supporting information on the PNAS web site). As we expected, the more complex a share's name, the more poorly it performed after 1 day of trading [ $\beta = -0.23$ ,  $t(n = 89) = -2.17$ ,  $P < 0.05$ ] and after 1 week of trading [ $\beta = -0.21$ ,  $t(n = 89) = -1.96$ ,  $P = 0.05$ ].<sup>‡</sup> However, as predicted, the complexity of a share's name did not reliably predict its performance at 6 months [ $\beta = -0.05$ ,  $t(n = 89) = -0.47$ ,  $P = 0.64$ ] or 1 year [ $\beta = -0.08$ ,  $t(n = 89) = -0.77$ ,  $P = 0.47$ ] after it first began trading, although the direction of the effect was consistent across all time periods.

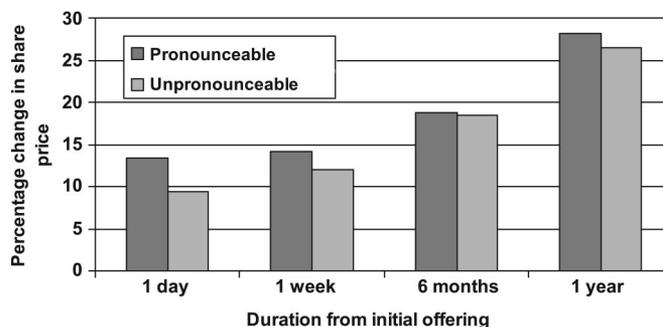
To emphasize just how successful investing in fluently named stocks would be, we calculated how much a \$1,000 investment would yield when invested in a basket of the 10 most fluently named shares and the 10 most disfluently named shares. The fluent basket would have yielded a significantly greater profit at all four time periods: \$112 after 1 day, \$118 after 1 week, \$277 after 6 months (all  $P$ s  $< 0.05$ ), and \$333 after 1 year ( $P < 0.10$ ) (see Table 1, which is published as supporting information on the PNAS web site).

We were concerned that two alternative factors may have driven these results. First, it was possible that larger companies had greater access to marketing resources, which might have led them to select catchier names that are easier to pronounce. If this were true, it could be that company size rather than name fluency influenced share price. To eliminate this possibility, we conducted a mediational analysis using the total value of shares offered by each company as a proxy for company size. We found that, although larger companies had names that were marginally easier to pronounce,  $r(n = 89) = -0.19$ ,  $P = 0.08$ , company size was not related to share performance,  $r(n = 89) = 0.14$ ,  $P = 0.33$ . Thus, company size did not mediate the effect of name complexity on share performance (25).<sup>§</sup>

<sup>†</sup>All stock performance data in this study are from the Global New Issues Database. We searched for data on all stocks that began trading between 1990 and 2004 on the NYSE and AMEX stock markets.

<sup>‡</sup>To ensure that these effects were not driven by outliers, we ran two additional analyses. The effects replicated when the data were log-transformed and also replicated after the removal of all data  $> 3.5$  SD from the mean. Thus, we replicated the original findings when we dealt with outliers using two common methods, demonstrating that these findings were not driven by extreme data.

<sup>§</sup>According to this multistage mediational procedure, a variable cannot be said to mediate the relationship between a predictor and a dependent measure unless three steps are satisfied: the predictor is significantly correlated with the dependent variable, the mediator is significantly correlated with the dependent variable, and the mediator affects the relationship between the predictor and the dependent measure by suppressing the effect of the predictor on the dependent measure when both the mediator and predictor are regressed on the dependent measure. In our analysis, the second step was not satisfied, which obviated the need to carry out the third step.



**Fig. 1.** Actual performance of shares with pronounceable and unpronounceable ticker codes in the NYSE 1 day, 1 week, 6 months, and 1 year after entry into the market from 1990–2004. Although the difference in performance between the pronounceable and unpronounceable stocks was not significant beyond 1 day, the trend persists at 1 week, 6 months, and 1 year. Although the effect size associated with this pronounceability effect is small, the practical consequences, given the amount of money invested in the NYSE, are considerable.

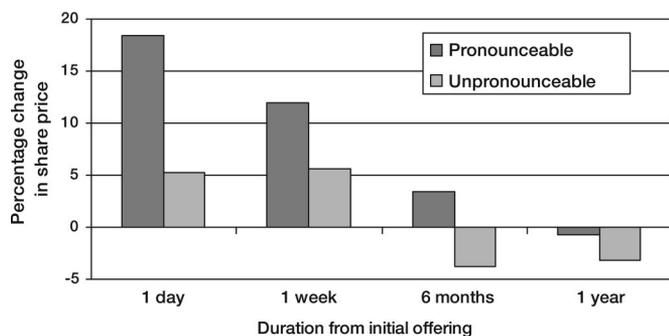
It was also possible that companies in certain industries tended to have more fluent names. If this were true, it could be industry rather than name fluency influencing share price. However, a series of pair-wise comparisons did not reveal any differences in company name complexity across the various industries, mean pair-wise  $P = 0.97$ . A similar set of tests showed no evidence of differential performance across the industries, mean pair-wise  $P = 0.91$ . Thus, differential naming trends across industries did not explain the relationship between name complexity and stock performance.

## Study 3

**Description.** The first two studies suggested that the fluency of a share's name influences both people's predictions about the share's performance and its actual performance. One concern with the second study is that investors may have derived useful semantic information from company names. For example, companies that included the term "tronic" in their titles in the 1960s experienced short-term gains relative to similar companies that failed to include the buzzword in their title (3). Similarly, foreign company names might be more disfluent, leading investors to prefer fluent stocks not because of the complexity of their names, *per se*, but because of their country of origin. Indeed, the home bias suggests that people are reluctant to invest in foreign stocks because they feel better informed about the factors that influence local stock prices.

To investigate this possibility, we conducted a third study examining the effects of fluency on stock performance in a semantically impoverished context: by using the pronounceability of each company's three-letter stock ticker code as a predictor of performance. Ticker codes often replace share names on scrolling displays on television, in public venues, and on web sites. Accordingly, it is plausible that ticker codes, like stock names, might influence short-term share prices. In this study, we compared the performance of shares with pronounceable ticker codes (e.g., KAR) to those with unpronounceable ticker codes (e.g., RDO). As in the previous study, we expected shares with pronounceable ticker codes to experience a boost in performance in the short term. To rule out the possibility that this effect was limited to one particular stock market, we conducted the same analysis using data from two distinct markets.

**Results.** As we expected, shares with pronounceable ticker codes outperformed those with unpronounceable ticker codes after 1 day of trading in both the New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) (see Figs. 1 and 2).



**Fig. 2.** Actual performance of shares with pronounceable and unpronounceable ticker codes in the AMEX market 1 day, 1 week, 6 months, and 1 year after entry into the market, from 1990–2004. Although the trend appears to continue beyond one day of trading, the small sample size of shares in the AMEX ( $n = 116$ ) meant that the probability of detecting a significant effect, assuming one existed, ranged between 6% and 24%. Thus, with a larger sample size, we might have expected the discrepancy in performance between the pronounceable and unpronounceable stocks to maintain significance beyond 1 day of trading.

Although pronounceable shares outperformed unpronounceable shares after 1 day of trading in both markets [ $t(n = 665) = 2.40, P < 0.05, \eta^2 = .01$  and  $t(n = 116) = 1.74, P = 0.09, \eta^2 = .03$ ], this trend diminished over time, such that the difference in performance between the two groups did not reach significance beyond 1 day of trading (all  $P$ s  $> 0.20$ ).

Again, we calculated the bonus in profit that a \$1,000 investment would yield from investing in a basket of all shares with pronounceable ticker codes, equally split across the NYSE and AMEX markets. The pronounceable basket yielded a profit \$85.35 in excess of the unpronounceable basket after 1 day, \$42.40 after 1 week, \$37.10 after 6 months, and \$20.25 after 1 year. Given that investors traded shares valued at roughly \$2 billion on the average day in 2006 (26), these differences have dramatic practical consequences.

As in our second study, we sought to rule out the alternative possibility that company size accounted for the relationship between ticker pronounceability and share performance. Again, the total value of shares offered served as a proxy for company size. Given that companies with pronounceable ticker codes ( $M = 278.21, SD = 661.19$ ) did not significantly differ in size from companies with unpronounceable ticker codes ( $M = 232.00, SD = 468.94$ ),  $t(663) < 1$ , we concluded that company size did not explain the relationship between ticker pronounceability and share performance.

We also considered the possibility that companies in certain industries might systematically select ticker codes that are pronounceable, suggesting that the pronounceability effect is an artifact of performance differences across industries. To rule out this possibility, we conducted a  $\chi^2$  analysis to determine whether the proportion of pronounceable ticker codes differed by industry. Across the industries considered (insurance, investment funds, manufacturing, personal and business service, and real estate investment funds), the proportion of pronounceable ticker codes ranged narrowly from 20% to 29%. Not surprisingly, then, a  $\chi^2$  test did not reveal a significant effect of industry on ticker code pronounceability,  $\chi^2(n = 422) = 2.55, P = 0.64$ . Thus, differential performance across industries was not an alternative explanation for the effect of ticker name pronounceability on share performance.

Finally, we were concerned that ticker code pronounceability might not be independent of stock name pronounceability. In other words, we were concerned that any semantic information contained in the stock names might also influence the pro-

nounceability of the stock ticker codes. We addressed this possibility by conducting an analysis of covariance using the 89 NYSE stocks from Study 2, in which we examined the effect of ticker code pronounceability on stock performance while controlling for any variance in performance also explained by stock name pronounceability. Again, stocks with pronounceable ticker codes (adjusted  $M = 13.45\%$ ,  $SD = 24.80$ ) significantly outperformed stocks with unpronounceable ticker codes (adjusted  $M = 9.67\%$ ,  $SD = 14.15$ ) after 1 day of trading,  $P < 0.05, \eta^2 = 0.07$ .

## Discussion

The three studies reported demonstrated that the fluency of a share's label, in both the form of company name and ticker code, influences its early performance on the stock exchange. The first study established a causal chain by showing that, in a fully controlled laboratory experiment, people expected fluently named stocks to outperform stocks with more complex names. The second and third studies showed that shares with fluent names actually experienced an early boost in performance across two large U.S. stock markets, using the pronounceability of company name and stock ticker codes as predictors of success.

This simple three-study demonstration is particularly powerful in light of economists' many failed attempts to predict short-term share movement using often complex and unwieldy mathematical models. Whereas financial analysts delve into the differential performance of industries and market sectors, a straightforward psychological principle cuts across these categories and predicts, quite simply and robustly, that companies with names like Barnings Incorporated will initially outperform companies with names like Aegeadux Incorporated. More broadly, our findings suggest that researchers' intuitive attempts to understand complex real-world phenomena with equally complex models may not always be the best approach. Keeping in mind that humans are forced to seek a simple thread of understanding when bombarded with excessive information, sometimes a surprisingly simple theory is a successful predictor of human behavior.

## Methods

**Study 1.** Twenty nine Princeton University undergraduates (14 females) participated in this study for partial course credit. The study was a two-level single-factor within-subjects experiment, in which participants estimated the future performance of 30 stocks with names that were either easy to pronounce (simple) or difficult to pronounce (complex). Before the main study, 10 pilot participants rated an initial pool of 60 fictional stock names according to how easy or difficult they were to pronounce. Fifteen stock names rated as difficult to pronounce (mean rating of 3.1 or higher on a four-point scale) and 15 rated as easy to pronounce (mean rating of 1.7 or lower on a four-point scale) were used in the main study. Participants estimated the performance of each stock after 1 year of trading using a nine-point scale. The scale progressed in increments of 10% from "40% loss in value" to "40% gain in value."

**Study 2.** Sixteen Princeton University undergraduates participated in this study for partial course credit. We randomly selected 89 shares that began trading on the NYSE between 1990 and 2004. Participants rated each share according to how difficult the company's name would be to pronounce if they were asked to do so at an awards ceremony (1, very easy to pronounce; 6, very difficult to pronounce). These ratings formed a continuous independent measure of stock name complexity. The four dependent measures were the percentage change in share price after trading for 1 day, 1 week, 6 months, and 1 year.

**Study 3.** Two coders classified 665 NYSE shares according to whether their ticker codes were pronounceable according to the laws of English pronunciation. They made this decision on the

basis of their subjective impression of whether the code was pronounceable. These shares were drawn from a total of 1,388 shares that began trading on the NYSE between 1990 and 2004, and they were included on the basis that the data set recorded their performance across all four time periods. This procedure was repeated for the AMEX, which yielded 116 shares with complete information.

The raters, who disagreed on the classification of <10 share names, resolved discrepancies by discussing and reaching consensus on the appropriate categorization of those shares.

1. Samuelson, P. A. (1965) *Indust. Mgmt. Rev.* **6**, 41–49.
2. Cootner, P. (1964) *The Random Character of Stock Market Prices* (MIT Press, Cambridge, MA).
3. Malkiel, B. G. (2003) *A Random Walk Down Wall Street* (Norton, New York).
4. Black, F. (1971) *Fin. Anal. J.* **Mar–Apr**, 16–22.
5. Fluck, Z., Malkiel, B. G. & Quandt, R. E. (1997) *Rev. Econ. Stat.* **79**, 176–183.
6. Tversky, A. & Kahneman, D. (1974) *Science* **185**, 1124–1131.
7. Kahneman, D. & Tversky, A. (1979) *Econometrica*, **47**, 313–327.
8. Schwarz, N. & Clore, G. L. (1996) in *Social Psychology: Handbook of Basic Principles*, eds. Higgins, E. T. & Kruglanski, A. (Guilford, New York), pp. 433–465.
9. Saunders, E. M. (1993) *Am. Econ. Rev.* **83**, 1337–1345.
10. Hirshleifer, D. & Shumway, T. (2001) *J. Finance* **58**, 1009–1032.
11. French, K. R. & Poterba, J. M. (1991) *Am. Econ. Rev.* **81**, 222–226.
12. Kahneman, D., Slovic, P. & Tversky, A. (1982) *Judgment Under Uncertainty: Heuristics and Biases* (Cambridge Univ. Press, Cambridge, U.K.).
13. Tversky, A. & Kahneman, D. (1973) *Cognit. Psychol.* **5**, 207–232.
14. Reber, R. & Schwarz, N. (1999) *Consc. Cognit.* **8**, 338–342.
15. Jacoby, L. L., Kelly, C. M., Brown, J. & Jascenko, J. (1989) *J. Pers. Soc. Psychol.* **56**, 326–338.
16. Reber, R., Winkelman, P. & Schwarz, N. (1998). *Psychol. Sci.* **9**, 45–48.
17. Whittlesea, B. W. A. & Williams, L. D. (1998) *Acta Psychol.* **98**, 141–166.
18. Oppenheimer, D. M. (2006) *Appl. Cognit. Psychol.* **20**, 139–156.
19. Reber, R., Schwarz, N., Winkelman, P. (2004) *Pers. Soc. Psych. Rev.* **8**, 364–382.
20. Schwarz, N. (2004) *J. Cons. Psychol.* **14**, 332–348.
21. McGlone, M. & Tofighbakhsh, J. (2000) *Psychol. Sci.* **11**, 424–428.
22. Hirshleifer, D. (2001) *J. Finance* **56**, 1533–1597.
23. Gigerenzer, G., Todd, P. M. & ABC Research Group (1999) *Simple Heuristics That Make Us Smart* (Oxford Univ. Press, New York).
24. Benjamin, A. S., Bjork, R. A. & Schwartz, B. L. (1998) *J. Exp. Psychol. Gen.* **127**, 55–68.
25. Baron, R. M. & Kenny, D. A. (1986). *J. Pers. Soc. Psychol.* **51**, 1173–1182.
26. www.NYSEData.com, accessed on 7 February 2006 (Official Web Site of the New York Stock Exchange).

Once the shares were divided according to whether their ticker codes were pronounceable or unpronounceable, we compared the mean performance of the shares in each group after 1 day, 1 week, 6 months, and 1 year. We conducted this procedure for both the NYSE and AMEX markets.

We thank S. Etchison, P. Forsberg, and G. Goodwin for their help with this project. This work was supported by National Science Foundation Grant 051811.