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The ostrich effect: Selective attention to information

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Abstract We develop and test a model which links information acquisition decisions to the hedonic utility of information. Acquiring and attending to information increases the psychological impact of information (an *impact effect*), increases the speed of adjustment for a utility reference-point (a *reference-point updating effect*), and affects the degree of risk aversion towards randomness in news (a *risk aversion effect*). Given plausible parameter values, the model predicts asymmetric preferences for the timing of resolution of uncertainty: Individuals should monitor and attend to information more actively given preliminary good news but "put their heads in the sand" by avoiding additional information given adverse prior news. We test for such an "ostrich effect" in a finance context, examining the account monitoring behavior of Scandinavian and American investors in two datasets. In both datasets, investors monitor their portfolios more frequently in rising markets than when markets are flat or falling.

Keywords Selective exposure · Attention · Investor behavior

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The observation that people derive utility from information and beliefs, though once heretical in economics, is now commonplace and relatively uncontroversial. A novel, and potentially more controversial, ramification of the idea that people derive utility directly from beliefs is, however, that they may have an incentive to control or

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regulate those beliefs. One specific way in which individuals can control their beliefs is via decisions about whether or not to acquire information. We argue that information acquisition decisions are likely to be linked with the internal psychological processing of information and the hedonic impact of information on utility.

An extensive body of empirical research in psychology supports the idea that people have some capacity to attend to or not to attend to—i.e., ignore—information. This is sometimes called the *selective exposure hypothesis*. Selective exposure has made its way into economics. Caplin (2003), building on earlier ideas in Witte (1992), develops a model in which people respond to health warnings either by adopting behaviors consistent with those beliefs, or, if the warnings are too threatening, by willfully ignoring them. We take Caplin's analysis a step further by examining the degree to which people choose to expose themselves differentially to additional information after conditioning on prior positive and negative news.

We develop a model of selective attention in which individuals receive preliminary but incomplete information and then decide whether to acquire and attend to definitive information. The intuition is that individuals regulate the impact of good and bad news on their utility by how intently they attend to the news. If knowing definitively that an outcome is negative is worse than merely suspecting it is likely to be bad, then people may try to shield themselves from receiving definitive information when they suspect the news may be adverse. For reasonable parameter values, our model predicts that people will exhibit an *ostrich effect*—a term coined by Galai and Sade (2003). They defined the ostrich effect as "avoiding apparently risky financial situations by pretending they do not exist." We use the term in a related, but expanded sense, as avoiding exposing oneself to information that one fears will cause psychological discomfort. Given preliminary bad news—or, as it turns out in our model, ambiguous news—people may optimally choose to avoid collecting additional information: They "put their heads in the sand" to shield themselves from further news.[1] In contrast, given favorable news, individuals seek out definitive information.

The exposition of our model and the associated empirical work are in a finance context. When the aggregate market is down, investors may reasonably forecast that their personal portfolios are *likely* to have declined in value, but it is still *possible* that the specific stocks they own may have risen even when the overall market has declined. The ostrich effect predicts that investor account monitoring decisions may, therefore, be asymmetric in up and down markets. Our empirical work finds support for such an asymmetry in information monitoring using Scandinavian and American data on investor logins to personal portfolio accounts.

Our intuitions about the psychology of information and the possibility of an ostrich effect in information acquisition decisions, although tested in a financial context, have far broader applications. They can apply, for example, to people's decisions about when to seek formal medical diagnoses for worrisome health

[1] The idea that ostriches hide their head in the sand is a myth. According to the Canadian Museum of Nature (http://www.nature.ca/notebooks/english/ostrich.htm): "If threatened while sitting on the nest, which is simply a cavity scooped in the earth, the hen presses her long neck flat along the ground, blending with the background. Ostriches, contrary to popular belief, do not bury their heads in the sand."

symptoms, to when parents will seek testing for a child who is having trouble in school, to an academic's decision of when and whether to pursue doubts about the integrity of a student, or to a business executive's decision to investigate—i.e., perform due diligence—when there are warning signs relating to a prospective deal. In particular, the ostrich effect predicts that people may delay acquiring information, even when doing so degrades the quality of decision making, if knowing the information forces them to confront and internalize possible disappointments they would mentally prefer to avoid.

The paper is organized as follows. Section 1 briefly reviews the related literature. In Section 2 we present a model of selective attention that predicts an asymmetry in the attention paid to bad or ambiguous news compared to good news. Section 3 validates this predicted asymmetry using data on Scandinavian and American investors' decisions to check the value of their portfolios on-line. Consistent with the predictions of our model, investors check their portfolio value less frequently in falling or flat markets than in rising markets. Section 4 considers alternative explanations of the observed ostrich effect. In Sections 5 and 6 we discuss additional implications of the ostrich effect and the rationality of selective attention. Section 7 concludes.

1 Related literature

Economic models commonly assume that information affects utility indirectly as an input in decision making. Recent economic models also incorporate information and beliefs directly in utility via anticipation (Köszegi and Rabin 2007; Caplin and Leahy 2001; Loewenstein 1987), self-image or ego (Benabou and Tirole 2006; Bodner and Prelec 2001; Köszegi 1999), and recursive preferences that depend on beliefs about future utility (Epstein and Zin 1989; Kreps and Porteus 1978). Incorporating beliefs into the utility function has ramifications for time discounting, the effective level of risk-aversion, and preferences about the timing of the resolution of uncertainty.[2]

The insight that people derive utility from information has also enriched finance. Traditional finance theory assumes that investors only derive utility from their assets at the time they liquidate and consume them—e.g., upon retirement—but people clearly derive pleasure and pain directly from changes in their wealth prior to consuming the underlying cash flows. Barberis, Huang, and Santos (2001) show that a model in which investor utility depends directly on the value of their financial wealth can explain the equity premium puzzle as well as the low correlation between stock market returns and consumption growth (for earlier treatments, see Gneezy and Potter 1997; Benartzi and Thaler 1995).

Research in psychology bolsters the work in economics by showing that people who hold optimistic beliefs about the future and positive views of themselves are happier (Scheier, Carver and Bridges 2001; Diener and Diener 1995) and healthier (Baumeister, Campbell, Krueger and Vohs 2003; Peterson and Bossio 2001), if not necessarily wiser (Alloy and Abramson 1979). There is also ample evidence from

[2] Benabou and Tirole (2006); Bodner and Prelec (2001); Geanakoplos, Pearce and Stacchetti (1989); and Rabin (1993) provide other examples of how information-dependent utility changes people's behavior.

psychology that desires exert a powerful influence on beliefs, a phenomenon that psychologists call "motivated reasoning" (Kruglanski 1996; Babad 1995; Babad and Katz 1991; Kunda 1990). Economists, too, have been interested in motivated formation of beliefs, but have focused more on modeling the phenomenon than on studying it empirically.[3]

Empirical support for the selective exposure hypothesis can be found in diverse research conducted by psychologists. Ehrilch, Guttman, Schonbach and Mills (1957) found that new car owners pay more attention to advertisements for the model they purchased than for models they had considered but did not buy. Brock and Balloun (1967) observed that smokers attend more to pro-smoking messages and that non-smokers attended more to anti-smoking messages. Although some studies have equivocal findings (Cotton 1985; Festinger 1964; Freedman and Sears 1965), the most recent research provides quite strong support for the selective exposure hypothesis (e.g., Jonas, Schulz-Hardt, Frey and Thelen 2001; Frey and Stahlberg 1986).

While not focusing specifically on selective exposure, research in behavioral finance, like that of psychologists, highlights the importance of attention for investor behavior. DellaVigna and Pollet (2005), for example, show that earnings announcements have a more gradual impact on stock prices when they occur on a Friday (when investors are likely to be inattentive) than when they occur on other days of the week. Barber and Odean (2008) predict and find that individual investors, as compared with institutional investors, tend to be net buyers of attention-grabbing stocks—e.g., those that receive special news coverage.

2 Model of selective attention

We propose a stylized decision-theoretic model to develop predictions about selective attention. The model applies generically to situations in which an individual derives utility from information and has some control over the timing of information acquisition. For purposes of exposition, we focus on a financial application in which an investor decides the timing of information she receives about her portfolio. The investor decides whether or not to acquire and attend to information about her wealth, conditional on prior public information.

Our definition of attention encompasses both external behavior and internal psychological processes. The most obvious external manifestation of attention is actively seeking additional information. In the context of investing, a natural first step when acquiring additional information is to check the current value of one's portfolio. This is psychologically important because having definitive information about a portfolio's exact

[3] In Akerlof and Dickens (1982), workers in dangerous work environments downplay the severity of unavoidable risks. In Köszegi (1999), Bodner and Prelec (2001), and Benabou and Tirole (2006), people take actions to persuade themselves, as well as others, that they have desirable personal characteristics that they may not have. In Benabou and Tirole (2002), people exaggerate their likelihood of succeeding at a task to counteract inertia-inducing effects of hyperbolic time discounting. In Brunnermeier and Parker (2002) and Loewenstein (1985, chapter 3), agents maximize total well-being by balancing the benefits of holding optimistic beliefs and the costs of basing actions on distorted expectations. In Rabin and Shrag (1999), people interpret evidence in a biased fashion that responds more strongly to information consistent with what they are motivated to believe.

value is likely to be more salient than having an estimate of its value (with estimation error) based on public index returns (if the portfolio is not fully indexed).

Our model allows for three pathways through which attention can affect utility. The first is an *impact effect*. Previous research suggests that the impact of news on utility depends not just on the objective content of the information (i.e., good or bad) but also on psychological and context factors. For example, people appear to derive greater utility from positive outcomes, and greater disutility from negative outcomes, when they feel personally responsible for the outcomes (Kahneman and Tversky 1982; Shefrin and Statman 1984; Loewenstein and Issacharoff 1994), when the outcomes are unexpected (Kahneman and Miller 1986; Loomes and Sugden 1986; Mellers et al. 1997; Delquié and Cillo 2006), and when the outcomes are not traded in markets, as is true of health (Horowitz and McConnell 2002). We add attention to the short list of factors that influence the steepness of the utility function. We posit, hopefully uncontroversially, that definitive knowledge has a greater psychological impact on utility than simply suspecting something (in an expected value sense).

The second consequence of attention is a *reference point updating effect*. Prospect theory and models of loss aversion and habit formation all posit that utility depends on how outcomes deviate from pre-specified reference points (see Zeelenberg et al. 2000, Gul 1991; Constantinides 1990; Loomes and Sugden 1986; Bell 1985). Our model recognizes that attention and information acquisition can affect the dynamics of future reference points. We assume that attention to definitive information accelerates the updating of one's reference point. In contrast, inattention causes the reference point to adjust more slowly. This is consistent with empirical evidence that reference points are less responsive to probabilistic than to deterministic information (see Loewenstein and Adler 1995).

The third consequence of attention is a *risk aversion effect*. Risk aversion and prospect theory both suggest that negative departures from a reference point have a greater negative impact on utility than the positive impact of positive departures (Kahneman and Tversky 1982; Brooks and Zank 2005). The intensity of informational risk (or loss) aversion depends, in principle, on where the probability distribution of informational shocks is located along the utility function. Since attention moves the location of the reference point around which the utility function is centered, this can affect the relevant utility curvature over time. The resulting predictable intertemporal variation in risk aversion can affect the preferred timing of when individuals want to learn information and be exposed to the associated informational risk.

By linking discretionary information acquisition with the hedonic impact of attention on utility, we implicitly assume certain inherent constraints on investor psychology. For example, investors cannot distract themselves from bad news (or celebrate good news) independently of how much they pay attention to news. Given these linkages, selective attention is consistent with investor rationality if it maximizes utility subject to the operative psychological impact, updating and risk aversion effects.

Consider the decision problem of an investor who potentially receives information at two points in time, t=1 and 2, about the past realized return $r = r_p + r_d$ on her portfolio over some prior holding period. The investor learns the first component r_p automatically at date 1 but can decide whether to learn the second component r_d either at date 1 or 2. We call r_p *preliminary* information. In an investments context, this might be an investor's estimated return based on a market index that is widely reported in the public news media (e.g., the Dow). We call the second component, r_{d}, *discretionary* information. This could be the investor's personal idiosyncratic return given the specific holdings in her portfolio. Information about r_{d} is discretionary in the sense that it cannot be inferred from the public index return, but must be actively sought out. We assume that, conditional on the preliminary information r_{p}, the expected value of the discretionary part, $E\left[r_{\mathrm{d}}\middle|r_{\mathrm{p}}\right]$, is mean zero. In other words, the investor's ex ante expectations about r_{d} are rational.

There is no direct cost to the investor if she chooses to learn r_{d} at date 1. Investors in our empirical data, for example, can log on to a web page and review their account balances at no cost except for a trivial amount of time. However, the investor does have the option of "burying her head in the sand" at date 1 by delaying learning r_{d} until date 2. This is the *ostrich effect*. We use an indicator A_1=1 to denote attention and A_1=0 to denote inattention at date 1.

A key assumption is that the investor can condition her decision at date 1 about whether to pay attention to her total return r after first learning the preliminary component r_{p}. Given her decision, her *perceived* return r_1^* at date 1 is either $r_1^* = r = r_{\mathrm{p}} + r_{\mathrm{d}}$ (if she is attentive) or $r_1^* = \mathrm{E}\left[r\middle|r_{\mathrm{p}}\right] = r_{\mathrm{p}}$ (if she is inattentive). At date 2, the investor automatically learns any remaining information. This is not a choice. The investor can only decide the timing of when she learns r_{d}, not her final knowledge at date 2.

We model the investor as having preferences over information about her return. At date 1, her utility is a function $(1+\alpha(A_1))u\left(r_1^* - b_0\right)$ of the deviation of her perceived return r_1^* from a previously determined benchmark reference point b_0. At date 2, we assume her informational utility is just $u(r-b_1)$. We assume the function $u(\ )$ is increasing, concave, and continuous in perceived performance relative to the benchmark. We normalize utility so that $u(0)$=0. In the special case in which the investor is loss averse, there is a "kink" at 0. Otherwise, u is twice continuously differentiable.

Attention affects both the current impact of information on utility at date 1 and the dynamics of the future benchmark at date 2. The term $\alpha(A_1)$ denotes a boost in the utility impact when the investor actively attends to information, $\alpha(A_1 = 1) = \alpha \geq 0$, relative to when she is inattentive, $\alpha(A_1 = 0) = 0$. For simplicity, we assume the initial benchmark at date 1 is b_0=0. The reference point at date 2 depends on both the investor's prior perceived return and on how attentive she was at date 1:

$$b_1(r_1^*, A_1) = \begin{cases} r_p + r_d & \text{if} \quad A_1 = 1 \\ (1-\theta)r_p + \theta b_0 = (1-\theta)r_p & \text{if} \quad A_1 = 0 \end{cases} \tag{1}$$

The parameter θ, where $0 \leq \theta \leq 1$, represents the reference-point updating effect. It allows the reference point to respond more slowly to changes in wealth when the investor is inattentive. A higher value of θ thus means that an inattentive investor updates her reference point more slowly.

The investor decides whether to be attentive at date 1 so as to maximize the cumulative utility from the flow of information about her return over dates 1 and 2.

$$\max_{A_1 \varepsilon \{0,1\}} \quad J(A_1, r_{\mathrm{p}}) = \mathrm{E}\left[(1+\alpha(A_1))u\left(r_1^* - b_0\right) + u\left(r - b_1\left(r_1^*, A_1\right)\right)\middle|r_p\right] \tag{2}$$

In particular, this means choosing whether to learn the discretionary (investor-specific) return r_{d} at time 1 (by being attentive) or to wait until time 2 (by being inattentive at time 1) and accepting the psychological consequences for her date 1 marginal utility and the reference point dynamics that accompany this decision. The investor conditions her decision on whatever she automatically learns at time 1 about the preliminary (public) information r_p about her return.

If full information about the past return r is useful in making future investment decisions, this simply biases the investor's decision towards information acquisition and attention. We consider this aspect of the problem more fully after first analyzing the purely psychological consequences of attention.

Given a preliminary news realization $r_p=p$, the expected informational utility from attending is $(1+\alpha)\mathrm{E}[u(p+r_d)]+u(0)$. The expected utility from being passive and not attending is $u(p)+\mathrm{E}[u(\theta p+r_d)]$. Comparing the two expected utilities gives the differential utility from attention conditional on the preliminary news p

$$\begin{aligned}\Delta J(p) &= J(A_1=1,p)-J(A_1=0,p)\\ &= (1+\alpha)\mathrm{E}[u(p+r_d)]+u(0)-[u(p)+\mathrm{E}[u(\theta p+r_d)]]\end{aligned} \tag{3}$$

The concavity of u and the fact that the random return r_d is mean-zero implies that $\mathrm{E}[u(p+r_d)]<u(p)$ and $u(0)>\mathrm{E}[u(r_d)]$. Thus, the optimal decision depends on two considerations: First, there is a trade-off between the impact boost to utility α from attending at date 1 given that the expected deviation is $E[r|r_p]-b_0=p$ versus the additional expected utility experienced at date 2 given incomplete reference point updating following inattention at date 1. Second, predictable differences in the investor's risk/loss aversion towards a random deviation $r-b_0$ with an expected value p at date 1 (in the case of attention) versus a random deviation $r-b_1$ centered at θp at date 2 (in the case of inattention) can create incentives to shift the informational risk from learning r_d between the two dates. In combination, these two effects lead to the following result.

Proposition 1 *Attention to positive news $p>0$ (and inattention to negative news $p<0$) is optimal at date 1 given a sufficiently large impact effect $\alpha>0$, sufficiently rapid inattentive reference point updating (i.e., θ close enough to 0), and utility curvature that is not too large and that decreases sufficiently quickly in expected wealth.*

Proof If $\mathrm{SD}(r_d)=0$, then $\Delta J(p)$ given $p>0$ is increasing in α and decreasing in θ. As long as the $\mathrm{SD}(r_d)>0$ is not too large given the curvature in u so that $\mathrm{E}[u(p+r_d)]>0$ when $p>0$, the differential $\Delta J(p)$ is again increasing in α and decreasing in θ. Greater curvature in u around the expected value θp at date 2 than around the expected value $p>0$ at date 1 increases $\Delta J(p)$. The arguments when $p<0$ are similar except that $\Delta(p)$ will be decreasing in α and increasing in θ.

To see the curvature intuition more explicitly, suppose there is no kink at 0 so that u is everywhere twice continuously differentiable (i.e., risk aversion but no loss aversion). Using Taylor representations for $\mathrm{E}[u(p+r_d)]$, $u(p)$, and $\mathrm{E}[u(\theta p+r_d)]$ we can rewrite the utility differential as

$$\begin{aligned}\Delta J(p) = u'(0)(\alpha-\theta)p &+ 1/2\mathrm{E}\left[(1+\alpha)u''(x_1)-u''(x_2)-u''(x_3)\theta^2\right]p^2\\ &+1/2\mathrm{E}\left[[(1+\alpha)u''(x_1)-u''(x_3)]r_d^2\right]\end{aligned} \tag{4}$$

where $x_1 = x_1(r_\mathrm{p})\, \varepsilon\, [0, p + r_\mathrm{d}]$, $x_2 = x_2(r_\mathrm{p})\, \varepsilon\, [0, p]$, and $x_3 = x_3(r_\mathrm{p})\, \varepsilon\, [0, \theta p + r_\mathrm{d}]$ are functions giving the residual coefficients for the exact second-order Taylor representations of $\mathrm{E}[u(p + r_\mathrm{d})]$, $u(p)$, and $\mathrm{E}[u(r_\mathrm{d} + \theta p)]$ for each possible realization of r_d. The first term on the RHS of Eq. (4) captures the direct trade-off between the impact and updating effects. The second term captures the effect of differential curvature on the utility experienced from the preliminary news p at date 1 (given attention) and at dates 1 and 2 (given inattention). The third term of Eq. (4) reflects differential risk aversion towards bearing the informational risk associated with the news r_d given the utility function's curvature around an expected deviation $\mathrm{E}[r|r_\mathrm{p}] - b_0 = p$ at date 1 (given attention) versus the risk when the deviation is centered at $\mathrm{E}[r|r_\mathrm{p}] - b_1 = \theta p$ at date 2 (given inattention).

A few special cases convey some intuition for the preference parameter combinations that lead to ostrich effect behavior. First, consider the case of risk neutrality. Since all of the u''s in Eq. (4) are 0, the optimal attention decision is driven solely by the sign of $\alpha - \theta$ (i.e., on whether the impact or delayed updating effect is dominant) and the sign of p. If $\alpha - \theta > 0$, then attention is optimal given good preliminary news, $p > 0$, and inattention is optimal given bad news, $p < 0$. This is an example of the ostrich effect. If, however, $\alpha - \theta < 0$, we would have an *anti-ostrich* effect with the opposite decisions. To see the differential risk aversion effect as it relates to the third term in Eq. (4), consider the special case of neutral preliminary news, $p = 0$. In this case, $x_1 = x_3$ so that $\Delta J(0) = 1/2\mathrm{E}[\alpha u''(x_1) r_\mathrm{d}^2] < 0$. Inattention is unambiguously optimal in "flat" markets given any impact effect $\alpha > 0$ and any concavity $u'' < 0$.[4] The reason is that the impact effect magnifies the curvature at date 1, thereby making it preferable to defer learning r_d until date 2 when the investor is less sensitive to news.

Thus, ostrich effect behavior is optimal if the impact effect α is large relative to the delayed updating effect θ and if the curvature of the investor's utility function u is sufficiently decreasing in the realized deviation (e.g., if $u''(x)$ is a small enough negative number as x increases). It is the asymmetry of the preference for the timing of resolution of uncertainty conditional on past information which distinguishes the ostrich effect and our theory of selective attention from the timing preferences in recursive utility models (see Epstein and Zin 1989.; Kreps and Porteus 1978). Of course, whether investor preferences about the timing of the resolution of uncertainty in the real world are asymmetric is an empirical question. We document this asymmetry empirically in the next section.

The model is admittedly stylized in its assumptions of only two periods, no time discounting, and that the investor automatically learns all remaining information in the second period rather than being able to defer information acquisition for an extended period of time. However, the basic intuitions for how attention affects the

[4] Our intuition a priori is that investors are more likely to monitor their portfolios when the market is neutral than when it is sharply down. As will be evident in the following section, the data provide mixed support for this prediction. The prior analysis may seem to be at odds with this intuition since the model says that people will *never* monitor their portfolios when the market is flat but that, for some parameter values, investors *will* monitor when the market news is negative. However, the *magnitude* of the disincentive for attention can be greater when the market is down than when it is flat if α is large and θ is close to 0.

information acquisition decision are likely to be robust. For example, if investors discount future utility, this only increases the attractiveness of attention to positive news at date 1 and deferring attention to negative news to date 2. Moreover, introducing an additional mean-zero shock to returns between dates 1 and 2 complicates the differential risk aversion effect but does not alter the model's basic predictions.[5]

Other motives for information In the standard economic model of information acquisition, investors have an indirect demand for information as an input into their trading decisions. They need to know their current financial situation in order to make informed decisions about whether to trade. Our analysis easily accommodates an indirect demand for information. Let $v(A_1 = 1, r) \geq 0$ denote the expected "option value" of potential trades that the investor may identify at time 1 provided that she is actively attending to her portfolio. The investor then compares the combined direct and indirect expected utility from being informed, $J(A_1 = 1, r_\mathrm{p})+$ $\mathrm{E}[v(A_1 = 1, r)|r_\mathrm{p}]$, with the expected utility from being less informed and forgoing any potential trading opportunities, $J(A_1 = 0, r_\mathrm{p})$ when deciding whether to monitor her portfolio at date 1.

If investors only have a transactional demand for information then, since $E[v(A_1 = 1, r)|r_\mathrm{p}] \geq 0$, it is plausible to conjecture that they are equally likely to collect information in up markets as in down markets. Moreover, the potential trading benefit from information is likely to increase as market conditions become more extreme in either direction. If so, investors should monitor their portfolios most actively following extreme up-markets and also following extreme market downturns. For investors not to attend to their portfolios, there must be some cost to attention. A direct hedonic disutility from negative information endogenously provides such a cost.

Empirical hypothesis The empirical tests for ostrich effect behavior in Section 3 use data about information monitoring decisions for cross-sections of investors. In doing so, we interpret the ostrich effect to mean that investors are simply *less likely* to check their portfolios in down and flat markets than in up markets; not that *no* investor will check. The possibility of an indirect demand for information as an input to trading justifies this interpretation. Whether investors attend to their financial situation in down and flat markets depends on the relative magnitude of the disutility of attending to bad and neutral news and the positive option value of trading. If investors are heterogeneous, then some may attend while others may not. In up markets, however, investors will have a stronger incentive to attend both because of the direct utility from good news and also because of the option value of possible trades.

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[5] If r_2 is an independently distributed, mean-zero shock that is realized and automatically learned at date 2, then the attention differential is $\Delta J(p) = (1+\alpha)\mathrm{E}[u(p+r_\mathrm{d})] + \mathrm{E}[u(r_2)] - [u(p) + \mathrm{E}[u(\theta p + r_\mathrm{d} + r_2)]]$. In this case, $\mathrm{E}[u(p+r_\mathrm{d})] < u(p)$ and $\mathrm{E}[u(r_2)] > \mathrm{E}[u(r_\mathrm{d} + r_2)]$ where the later inequality follows because r_2 second-order stochastic dominates $r_\mathrm{d} + r_2$.

3 Empirical investigation of the ostrich effect

If investors exhibit ostrich effect behavior, they will monitor their portfolios more frequently when the aggregate stock market is up than when it is down. We test for this asymmetry in two different data sets, one from Sweden and the other from the US, each containing data about investor decisions to monitor the value of their personal portfolios on-line. Table 1 presents some basic information about these data sets.

The first data set is from the Swedish Premium Pension Authority. Beginning in 2000, the Swedish premium pension system allows Swedish citizens to choose how to invest 2.5% of their before-tax income in equity and interest-bearing funds as part of their state pension. By 2004, 5.3 million of Sweden's 9 million citizens were in this new pension system. Our data include the total number of people who logged in to check the value of their portfolio on each day between January 7, 2002 and October 13, 2004. In addition, the data include the number of reallocations (transactions) made to investor portfolios each day (either on the web or through an automatic telephone service). The average number of logins each day is 10,903. Of these, 1,142 involved changes to investment allocations. Since people only log in either to check the value of their premium pension portfolio or to reallocate their portfolio holdings, we can use the number of account logins less the number of portfolio reallocations (on the web or via an automatic telephone service) to measure the daily number of informational account *look-ups*.

The second data set is from the Vanguard Group. The data give the daily number of times Vanguard clients accessed their Vanguard accounts on-line between January 2, 2006 and June 30, 2008. In 2007, approximately 21 million investors had accounts at Vanguard. Since the Vanguard data do not include the number of transactions, we use aggregate S&P 500 trading volume as a proxy to control in our regression analysis for transactional, as opposed to informational, logins.

We follow the same estimation strategy for both datasets: We regress the daily number of account $LOOKUPS_t$ (or $LOGINS_t$) on several control variables and on an "averaged" prior log return, $RETURN_t$, computed as $\ln(INDEX_t/LAGAVERAGE_t)$

Table 1 Descriptive statistics

	Swedish Premium Pension Authority		Vanguard	
Sample period	Jan. 7, 2002–Oct. 13, 2004		Jan. 2, 2006–June 30, 2008	
	Mean	SD	Mean	SD
$LOGINS_t$	10,903	7,055	416,916	81,229
Number of transactions per day	1,142	878	na	na
$LOOKUPS_t$	9,761	6,392	na	na
Closing index level	184	28.87	1,387	88
$RETURN_t$	−0.0004	0.0203	0.00034	0.011
$VOLUME_t$ (in billions)	na	na	3.074	0.933

$LOOKUPS_t$ in the Swedish pension data are the daily number of account $LOGINS_t$ less the daily number of portfolio rebalancings. The Swedish stock index is the Stockholm All Shares (OMXSPI) index. The US index is the S&P 500. $RETURN_t$ is the averaged prior return defined as the log change in the index relative to the average index level over the previous 4 days. VOLUME_t in the US data is the S&P 500 trading volume where $INDEX_t$ is the index level on day t and $LAGAVERAGE_t$ is the average of lagged index levels from day t-4 through day t-1. Our central prediction is that the coefficient on $RETURN_t$ should be positive if investors exhibit the ostrich effect. That is to say, more investors should check the value of their portfolio in up markets than in down markets. We also allow for other factors that may affect account monitoring activity. In all specifications, we control for day-of-the-week effects via daily dummy variables ($DAY_{i,t}$). In some specifications we include a linear time trend and in others we include the lagged number of look-ups (or logins) from the prior day. Finally, we include the number of transactions, $TRANSACTIONS_t$, (in the Swedish regressions) and the aggregate market volume, $VOLUME_t$, (in the Vanguard regressions) to distinguish the ostrich effect from a transactional demand for account information. For example, people may transact more when the market is up than when it is down (i.e., as predicted by the disposition effect) and may check the value of their portfolio as an input into trading.

Results for Swedish Premium Pension Authority data Figure 1 plots the standardized daily level of the Stockholm All Shares stock index (OMXSPI) and the daily number of investor non-transactional account look-ups after controlling for day-of-the-week effects, trends, and also (for look-ups) the number of transactions.[6] As can be seen, the number of look-ups is generally higher when the OMXSPI index is higher, and vice versa.

Strictly speaking, however, the ostrich effect makes predictions about account look-ups and prior *changes* in the market index, not the *level* of the index per se. Figure 2 shows daily changes in the number of account look-ups for each of seven quantiles ("heptiles") based on the corresponding prior averaged returns for the OMXSPI index. Both the look-up changes and prior returns are again residuals from regressions controlling for day-of-the-week effects, a time trend, and (for the look-ups) the number of transactions. Here the positive relation is even more apparent. Clearly the number of look-ups is substantially higher following good news that the market index increased and lower after bad news.

To examine the specific impact of prior index returns on account look-ups, we estimate two regressions. The first column of Table 2 regresses account look-ups on the prior OMXSPI returns with day-of-the-week dummy variables, a linear time trend, and the daily number of portfolio reallocations (transactions) as additional control variables. The second column presents a parallel regression in which the trend variable is replaced with the one-day lagged look-ups.

In both regressions, the number of account look-ups is increasing in the prior index change. An additional 1% increase (i.e., 0.01) in $RETURN_t$ leads to 120 to 140 additional informational look-ups (i.e., just over 1% of the mean number of daily look-ups). The $RETURN_t$ coefficient is significant at the 10% level (in the trend specification) and at the 1% level (in the lagged variable specification). Although not reported in the table, our regression results are robust, and sometimes even stronger, in alternative specifications using simple lagged returns over 1-day and 5-day

[6] Although $LOOKUPS_t$ is defined as the number of logins less the number of portfolio rebalancing transactions, there may be look-ups motivated by a potential interest in trading which did not ultimately result in trades.

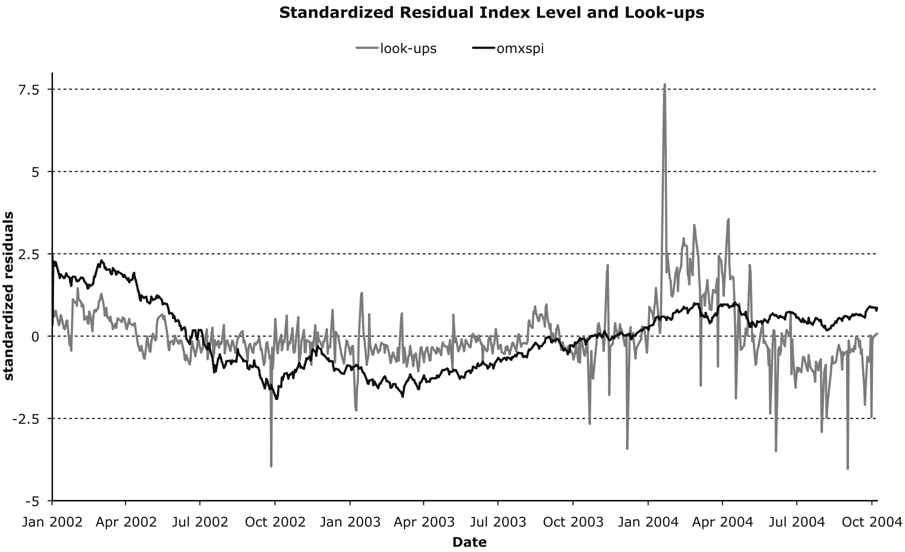

Fig. 1 Stockholm All Shares stock index and Swedish pension account look-ups. The figure plots standardized residuals from the following two regressions: $LOOKUPS_t = \alpha_0 + \Sigma_{i=\mathrm{TWRF}}\alpha_{1,i}DAY_{i,t} + \alpha_2 TREND_t + \alpha_3 TRANSACTIONS_t + e_t$ and $INDEX_t = b_0 + \Sigma_{i=\mathrm{TWRF}}b_{1,i}DAY_{i,t} + b_2 TREND_t + e_t$ where $LOOKUPS_t$ is the daily number of Swedish Premium Pension investor account logins less the daily number of account rebalancings, $DAY_{i,t}$ are day-of-the-week dummy variables, $TREND_t$ is a linear time trend, $TRANSACTIONS_t$ is the daily total number of Swedish pension investor transactions, and $INDEX_t$ is the level of the Stockholm All Shares (OMXSPI) stock index. The sample period is January 7, 2002 to October 13, 2004

horizons in place of the $RETURN_t$ variable with its averaged denominator. Thus, the Swedish investor data set strongly supports the ostrich effect.

The control variables are all statistically significant. In particular, the positive coefficient on contemporaneous $TRANSACTIONS_t$ is consistent with a transactional demand for account information. Time trends and positive autocorrelation in look-ups are also important. The Durbin–Watson statistics indicate some residual autocorrelation in the time trend specification which argues for the lagged look-up specification. The R^2s indicate that our model explains a substantial part of daily variation in investors' portfolio monitoring decisions.

Results for Vanguard data Figures 3 and 4 are time series and heptile plots for daily Vanguard logins and the S&P 500. The positive relation between the number of logins and the aggregate market is even stronger than in the Swedish data. Investors log in to their Vanguard accounts much more frequently in rising rather than in falling markets.

Table 3 reports the regression results for the Vanguard data. Once again, account logins are strongly increasing in prior returns. The positive coefficient on $RETURN_t$ indicates that a 1% increase in the *prior averaged* return (i.e., 0.01) is associated with between 18,000 and 23,000 additional account logins (i.e., 5–6% of the daily mean number of logins). In both specifications, the $RETURN_t$ coefficients are significant at the 1% level. This evidence clearly supports an ostrich effect in US investor behavior. The magnitudes of the coefficients using US data are different from those for the Swedish data, in part, because the number of Vanguard accounts

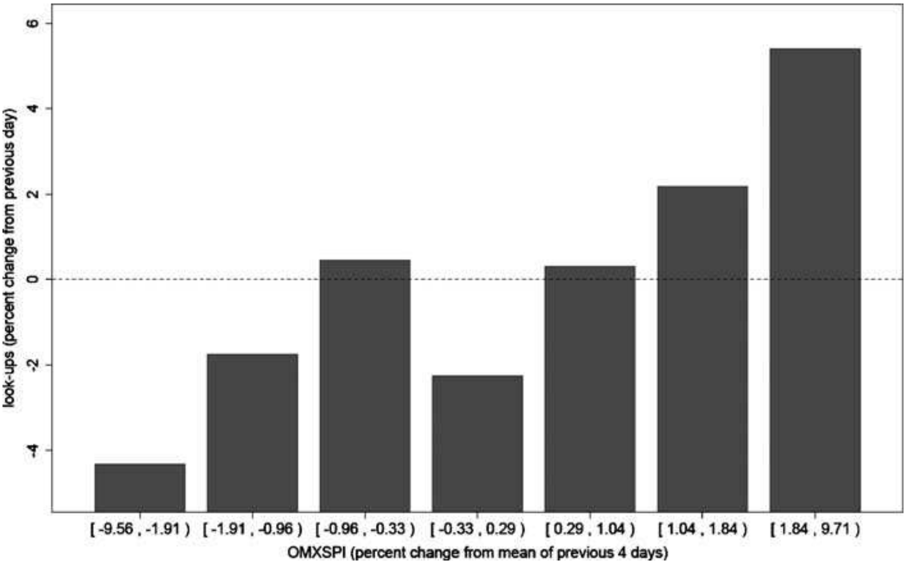

Fig. 2 Stockholm All Shares return heptiles and Swedish pension account look-ups. The figure plots average changes in Swedish investor pension account look-ups for heptiles of prior Stockholm All Shares index changes where both variables are residuals from regressions: $\Delta \ln(LOOKUPS_t) = \alpha_0 + \Sigma_{i=\mathrm{TWRF}}\alpha_{1,i}DAY_{i,t} + \alpha_2 TREND_t + \alpha_3 TRANSACTIONS_t + e_t$ and $RETURN_t = b_0 + \Sigma_{i=\mathrm{TWRF}}b_{1,i}DAY_{i,t} + b_2 TREND_t + e_t$ where $LOOKUPS_t$ is the daily number of Swedish Premium Pension investor account logins less the daily number of account rebalancings, $\Delta\ln(LOOKUPS_t)$ is the corresponding daily log change, $DAY_{i,t}$ are day-of-the-week dummy variables, $TREND_t$ is a linear time trend, $TRANSACTIONS_t$ is the daily total number of Swedish pension investor transactions, and $RETURN_t$ is the percentage change in the Stockholm All Shares (OMXSPI) stock index relative to the mean index level over the previous 4 days. The sample period is January 7, 2002 to October 13, 2004

Table 2 Regression results for Swedish Pension Authority data

	Model 1	Model 2
Intercept	2,656 (5.91)	2,010 (13.69)
$RETURN_t$	13,696 (1.76)	11,990 (4.34)
Tuesday	−133 (−0.27)	−1,514 (−8.59)
Wednesday	−865 (−1.76)	−2,280 (−12.90)
Thursday	−1,437 (−2.89)	−2,075 (−11.71)
Friday	−1,449 (−2.93)	−2,908 (−16.36)
$TREND_t$	8.4084 (9.42)	
Lagged *LOOKUPS*		0.9313 (73.56)
$TRANSACTIONS_t$	4.3501 (21.42)	0.3786 (4.11)
Adj. R^2	0.5880	0.9479
Durbin–Watson	0.5038	2.1564

Model 1: $LOOKUPS_t = \alpha_0 + \alpha_1 RETURN_t + \Sigma_{i=\mathrm{TWRF}}\alpha_{2,i}DAY_{i,t} + \alpha_3 TREND_t + \alpha_4 TRANSACTIONS_t + e_t$
Model 2: $LOOKUPS_t = b_0 + b_1 RETURN_t + \Sigma_{i=\mathrm{TWRF}}b_{2,i}DAY_{i,t} + b_3 LOOKUPS_{t-1} + b_4 TRANSACTIONS_t + e_t$
$LOOKUPS_t$ is the daily number of Swedish Premium Pension investor account logins less the daily number of account rebalancings, $DAY_{i,t}$ are day-of-the-week dummy variables, $TREND_t$ is a linear time trend, $TRANSACTIONS_t$ is the daily total number of Swedish pension account rebalancings, and $RETURN_t$ is the percentage change in the Stockholm All Shares (OMXSPI) index relative to the mean index level over the previous 4 days. *t*-statistics are in parentheses. The sample period is January 7, 2002 to October 13, 2004

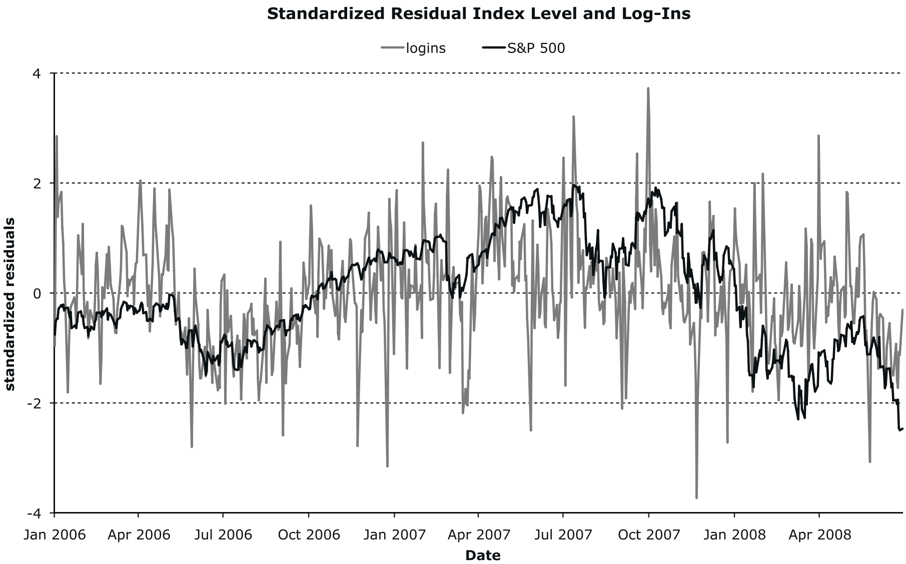

Fig. 3 S&P 500 index and Vanguard account logins. The figure plots standardized residuals from the following two regressions: $LOGINS_t = \alpha_0 + \Sigma_{i=\mathrm{TWRF}}\alpha_{1,i}DAY_{i,t} + \alpha_2 TREND_t + \alpha_3 VOLUME_t + e_t$ and $INDEX_t = b_0 + \Sigma_{i=\mathrm{TWRF}}b_{1,i}DAY_{i,t} + b_2 TREND_t + e_t$ where $LOGINS_t$ is the daily number of Vanguard investor account logins, $DAY_{i,t}$ are day-of-the-week dummy variables, $TREND_t$ is a linear time trend, $VOLUME_t$ is the S&P 500 trading volume, and $INDEX_t$ is the level of the S&P 500 stock index. The sample period is January 2, 2006 to June 30, 2008

is much larger. Once again, the control variables are all statistically significant. The volume coefficient is strongly positive which is again consistent with the transactions input hypothesis for account monitoring. The Durbin–Watson statistic again suggests that the model is better specified including lagged logins rather than the time trend.

4 Alternative explanations

The results from both data sets strongly support the ostrich effect. There might, however, be alternative explanations. First, it could be that media coverage is asymmetric in a way that makes investors pay more attention to their portfolios in bull markets. If the media talks more about the stock market when the market is up than when it is down, this could stimulate attention and portfolio monitoring during up-markets. However, we know of no evidence that media coverage of the stock market is asymmetric in up and down markets. Furthermore, even if differences in media coverage could explain part of our empirical results, one would still need to explain why *the media* pays more attention when the market is up. One possible explanation is that, consistent with an ostrich effect, the demand for media coverage is greater in bull markets—i.e., people want more information when the market is up.

A second possible explanation for the observed asymmetry in portfolio monitoring and prior index returns builds on an inverse reasoning about the direction of causation. Suppose that retail investors' desire to transact depends on

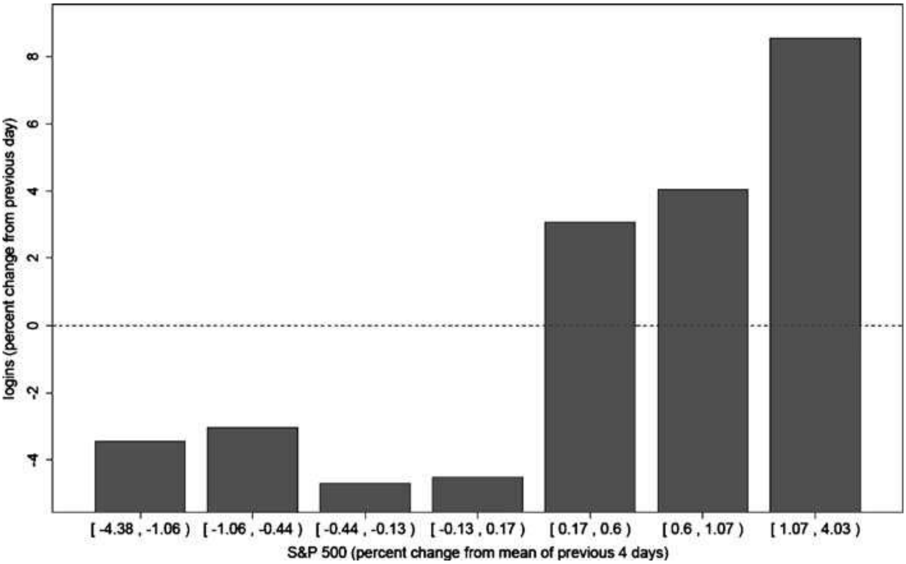

Fig. 4 S&P 500 return heptiles and Vanguard account logins. The figure plots average changes in Vanguard investor account logins for heptiles of lagged S&P 500 index changes where both variables are residuals from regressions: $\Delta \ln\,(LOGINS_t) = \alpha_0 + \Sigma_{i=\mathrm{TWRF}}\alpha_{1,i}DAY_{i,t} + \alpha_2 TREND_t + \alpha_3\ VOLUME_t + e_t$ and $RETURN_t = b_0 + \Sigma_{i=\mathrm{TWRF}}b_{1,i}DAY_{i,t} + b_2 TREND_t + e_t$ where $LOGINS_t$ is the daily number of Vanguard investor account logins, $\Delta\ln(LOGINS_t)$ is the corresponding daily log change, $DAY_{i,t}$ are day-of-the-week dummy variables, $TREND_t$ is a linear time trend, $VOLUME_t$ is the S&P 500 trading volume, and $RETURN_t$ is the percentage change in the S&P 500 stock index on day t relative to the mean index level over the previous 4 days. The sample period is January 2, 2006 to June 30, 2008

Table 3 Regression results for Vanguard data

	Model 1	Model 2
Intercept (in 000s)	281 (28.00)	79 (6.57)
$RETURN_t$ (in millions)	2.32 (10.03)	1.81 (9.82)
Tuesday (in 000s)	56 (6.90)	78 (11.97)
Wednesday (in 000s)	56 (6.83)	43 (6.60)
Thursday (in 000s)	44 (5.41)	28 (4.41)
Friday (in 000s)	35 (4.33)	25 (3.94)
$TREND_t$	118 (5.82)	
Lagged *LOGINS*		0.585 (20.91)
$VOLUME_t$	0.000019 (4.58)	0.000019 (8.06)
Adj. R^2	0.3567	0.5950
Durbin–Watson	0.7631	1.8546

Model 1: $LOGINS_t = \alpha_0 + \alpha_1 RETURN_t + \Sigma_{i=\mathrm{TWRF}}\alpha_{2,i}DAY_{i,t} + \alpha_3 TREND_t + \alpha_4 VOLUME_t + e_t$
Model 2: $LOGINS_t = b_0 + b_1 RETURN_t + \Sigma_{i=\mathrm{TWRF}}b_{2,i}DAY_{i,t} + b_3 LOGINS_{t-1} + b_4 VOLUME_t + e_t$
$LOGINS_t$ is the daily number of Vanguard account logins, $DAY_{i,t}$ are day-of-the-week dummy variables, $TREND_t$ is a linear time trend, $VOLUME_t$ is the daily S&P 500 trading volume, and $RETURN_t$ is the percentage change in the S&P 500 index relative to the mean index level over the previous 4 days. t-statistics are in parentheses. The sample period is January 2, 2006 to June 30, 2008

exogenous variables, including information gleaned from their own portfolio's value. If investors look at their portfolios to transact and if this willingness to transact is disproportionately an expression of a higher demand for stocks (perhaps due to the disposition effect), then market prices could go up when more investors log in to check the value of their funds. Although we control for the number of transactions and market volume to rule out this possibility, our controls may be insufficient because we do not know if a single investor logs in one or several times when transacting. However, note, first, that our return variable temporally precedes the account logins whereas the reverse causation story has them in the opposite order. Second, another contraindication to the inverse causal reasoning emerges from examining partial correlations in the Swedish premium pension sample in which we have the number of transactions registered. If lookups are driven by a willingness to transact, the partial correlation between transactions and the market index controlling for look-ups should be greater than the partial correlation between look-ups and the market index controlling for transactions, but this is not the case. When controlling for look-ups, the correlation between transactions and the OMXSPI index is weak and non significant ($correlation=0.04$, $p\text{-}value=0.34$). However, when controlling for transactions, the partial correlation between look-ups and the OMXSPI index is much greater and significant ($correlation=0.35$, $p\text{-}value<0.001$).

5 Additional implications of the ostrich effect

We suspect most readers, who introspect about their own behavior during the bull market of the late 1990s and the subsequent meltdown, or on the behavior of those around them, will not be surprised by these results. An attraction of our model, however, is that it links observable behavior (i.e., information collection) with internal preferences. In particular, our empirical evidence of an ostrich effect implies that, consistent with Proposition 1, the impact effect of attention is large, that the lag in reference point updating given inattention is small, and that risk aversion is not too high and is decreasing (or not increasing too quickly) in the expected level of the informational shocks. Portfolio monitoring decisions are, thus, a window into investors' preferences for the timing of the resolution of uncertainty. In contrast, earlier models with similar psychological considerations (e.g., Backus, Routledge and Zin 2004; Barberis, Huang and Santos 2001) have only been tested with price data.

Our model also suggests other new testable restrictions. First, the ostrich effect implies that the loss aversion reference point should increase faster in bull markets than it falls in down markets. Since the "kink" in loss-averse utility functions induces first-order risk aversion at the reference point, the asymmetric reference point updating dynamics will lead to asymmetric dynamics in the market risk premium. In contrast, most prior models assume symmetric dynamics for risk premia associated with loss aversion in up- and down-markets.

Second, the ostrich effect has implications for trading volumes and market liquidity. For example, it may help explain the well-documented relationship between trading volume and market returns. Griffin, Nardari and Stulz (2004) examined market-wide trading activity and lagged returns in 46 markets and found that positive returns led to significant subsequent increases in volume 10 weeks later in 24 of 46 countries. In no country was there a significant decrease. After exploring liquidity effects, participation costs, over-confidence, disposition effects, and a variety of other possible explanations, the conclusion is that no single theory is consistent with all of the patterns observed in the data. The ostrich effect may play at least a contributory role since positive lagged returns reduce the cost of attending to the market and, thereby, reduce the cost of being available for trading.

Third, the ostrich effect may also induce differential returns to liquid and illiquid fixed-income investments, a hypothesis tested by Galai and Sade (2003) in their paper on a related type of ostrich effect. They argue that average returns on liquid fixed-income investments (such as treasury bills) are greater than on illiquid fixed-income investments (such as certificates of deposit) because investors are less likely to attend to the day-to-day fluctuations in the value of illiquid investments.

Fourth, it is a commonplace that liquidity dries up during major market downturns such as the Asian crisis of 1997, the Russian debt default in 1998, and the credit crunch of 2008. This is, again, consistent with retail investors temporarily ignoring their portfolios in downturns—so as to avoid coming to terms mentally with painful losses—and, thus, being unavailable to supply liquidity. During market rallies, the ostrich effect improves liquidity as more investors actively follow the market.

Fifth, the ostrich effect has social consequences for the transmission of information. As Robert Shiller documents in *Irrational Exuberance*, social factors play a critical role in financial markets, pumping up values when rising markets create a "buzz." If people do not pay attention to the market when prices fall, this could easily suppress such social transmission, exacerbating downturns. If investors obsessively track the value of their portfolios when market values are rising, it is likely that this would facilitate interpersonal communication and positive feedback effects.

Our model can, and should, be expanded to more than two periods. With multiple periods, investors have a richer decision about *when* to monitor and attend. In an up-market, attending early is, on the one hand, likely to provide an immediate burst of positive utility, but is also likely to diminish future utility. The reverse is true in a down-market. Not attending over a prolonged period of time in a down-market is the financial equivalent of "death by a thousand cuts." Failing to attend and come to terms with her losses after a market downturn means that the investor repeatedly evaluates her utility using an inflated benchmark due to slow benchmark updating. This suggests that people with high discount rates would be more likely to look frequently in up markets and infrequently in down markets.

6 Selective attention and rationality

Selective attention is fully rational given the premise that investors are psychologically affected by information about the world around them. There is no self-deception in the sense of simultaneously knowing something and willfully not knowing it (see, e.g., Sartre 1953). In our model, investors correctly interpret whatever information they have. Our argument that investors can regulate the impact of information on their utility instead relies on the idea that there are multiple ways to "experience" information. Recent work by psychologists (e.g., Sloman 1996; Epstein et al. 1992) suggests that people may hold beliefs at different levels. Prior research also shows that knowledge that is "fuzzy"—i.e., lacking in precision—is perceived as less salient or vivid and has greater leeway for self-manipulation of expectations in relation to knowledge (Schneider 2001). Thus, whether the ostrich effect is rational depends on the accuracy of people's assessments of how potential information will make them feel. Our model is exposited assuming these assessments are accurate, so our story does not require irrationality.[7]

Selective exposure may also play an evolutionary role in helping people live with risk and, thereby, obtain the potential long-term benefits of risk-taking. Thus, in a finance context, the ostrich effect may lower, to some extent, the required market equity premium. Prior work in behavioral economics has also shown, consistent with the theory of second best, that the introduction of new biases can have beneficial effects when they counteract the negative effects of existing biases. For example, overconfidence can mitigate extreme risk aversion induced by loss aversion (Kahneman and Lovallo 1993). However, the ostrich effect can also induce costs due to delays in information acquisition in adverse environments.

7 Conclusions

This paper has presented a decision-theoretic model in which information acquisition decisions are linked to investor psychology. For a range of plausible parameter values, the model predicts that individuals may collect additional information conditional on favorable news and avoid information following neutral or bad news. Empirical evidence from two large datasets for Swedish and American investor account login activity supports the existence of an "ostrich effect" in financial markets.

Possible applications of the ostrich effect are much broader than finance. Ostrich-like behavior should be observed in any situation in which people are emotionally invested in information and have some ability to shield themselves from it. For example, our two period model can be applied to the situation of parents of children with chronic problems, such as autism or mental retardation. In period 1 the parents receive public information (observations of the child's behavior) and must decide whether to seek early definitive medical tests. By period 2 the child's condition is clear regardless of whether they obtained the test results in period 1. Similar intuitions could apply in emotionally charged medical situations such as HIV testing.

The core ideas in this paper—that people derive direct utility from information and that, as a result, they pay selective attention to information—join an expanding body of research that can be labeled the *new* new economics of information (Loewenstein 2006). Whereas the new economics of information adhered to standard economic assumptions about the individual but showed how market-level information asymmetries can produce suboptimalities, the *new* new economics of information focuses on characteristics of how emotionally invested and computa-

[7] If ex ante utility forecasts are erroneous (see Loewenstein, O'Donoghue and Rabin 2003), then the ostrich effect could cause investors to pay attention too little or too much.

tionally bounded individuals process information. This work ranges from evidence that people do not use Bayes' Rule when updating expectations (e.g., Camerer 1987) to violations of the law of iterated expectations (Camerer, Loewenstein and Weber 1989) to demonstrations that personal experience is weighted more heavily than vicarious experience, even when both have equal information value (Simonsohn et al. 2008). Our observation that people derive utility directly from information—and are, therefore, motivated to attend to it selectively as part of utility maximization—is just the latest in an ongoing effort to map out a more realistic account of how people mentally process and respond to information.

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