The ‘Ostrich Effect’:

Selective Exposure to Information About Investments

Niklas Karlsson, George Loewenstein and Duane Seppi

November 4, 2004

**** Very Preliminary ****

The 'Ostrich Effect': Selective exposure to information about investments

The observation that people derive utility not only from outcomes but also from beliefs, though once heretical in economics, is now commonplace and relatively uncontroversial. In the last few decades, economic models have been developed that incorporate utility from anticipation (Caplin and Leahy, 2001; Loewenstein, 1987) and from self-image or "ego" (Bodner and Prelec, 2001; Koscegi, 1999), as well as work on 'psychological games' in which utility depends directly on beliefs about the beliefs of other players (Geanakoplos, Pearce and Stacccetti, 1989; Rabin, 1993). 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 both happier (Diener and Diener, 1995; Scheier, Carver and Bridges, 2001; Petersen and Bossio, 2001) and healthier (Baumeister, Campbell, Krueger and Vohs, 2003:28-32), if not necessarily wiser (Alloy and Abramson, 1979).

The insight that people derive utility from beliefs has also enriched the field of finance. Traditional finance theory assumes that people care only about the value of their assets at the point when they liquidate them – e.g., upon retirement – but people clearly derive pleasure and pain directly from shifts in the value of their portfolios prior to consuming the actual underlying cash flows. Barberis, Huang, and Santos (2001) show that a model of investor behavior which incorporates utility from changes in value of financial wealth provides an intuitive and parsimonious explanation for the equity premium puzzle as well as the low correlation between stock market returns and consumption growth (for an earlier treatment, see Bernartzi & Thaler, 1995; Gneezy & Potter, 1997).

Incorporating beliefs directly into the utility function has diverse ramifications. Utility from anticipation can diminish or even reverse time discounting, resulting in patterns of behavior that resemble negative time discounting (Loewenstein, 1987), and can affect an individual's level of risk-aversion (Caplin and Leahy, 2000). Ego utility can cause people to take actions that they otherwise wouldn't to signal that they are of a particular type (Bodner and Prelec, 2001), and utility derived from beliefs about others can influence behavior in games in a variety of different ways (Geanakoplos, Pearce and Stacchetti, 1989; Rabin, 1993).

One of the most novel, and potentially controversial, ramifications of the idea that people derive utility from beliefs is that they may have an incentive to control or even *manipulate* those beliefs. There is, in fact, ample evidence from psychology that desires can exert a powerful influence on beliefs, a phenomenon that psychologists call 'motivated reasoning' (Kruglanski, 1996; Kunda, 1990; Babad, 1995; Babad and Katz, 1991).

Despite the plethora of evidence for self-manipulation of beliefs and the naturalness of the step from allowing beliefs to enter into utility to assuming that people manipulate their beliefs, there has, however, been little work in economics on self-manipulation of beliefs. Akerlof and Dickens (1982) examined one type of belief-manipulation in which cognitive dissonance causes workers in dangerous work environments to downplay the severity of the risks they face. Koszegi (1999) and Bodner and Prelec (2001) have examined forms of belief manipulation in which people take actions to persuade themselves that they are a particular type of person (even when they are not). Benabou and Tirole (2000) propose a model of belief-distortion in which people exaggerate their own likelihood of succeeding at a task so as to counteract the inertia-inducing effects of hyperbolic time discounting. Brunnermeier and Parker (2002) propose a model in which agents maximize total well-being over time by balancing the benefits of holding optimistic beliefs and the costs of basing actions on distorted expectations. The resulting optimal expectations cause agents to overestimate returns, to underdiversify in their portfolio choice problem, to consume more than implied by rational beliefs in early life due to over-optimism and overconfidence, and to procrastinate in certain situations. Karlsson, Loewenstein and Patty (2003) likewise develop a theoretical model in which people derive utility from beliefs and have some capacity to manipulate those beliefs dynamically over time. The model predicts that people awaiting news about uncertain outcomes they care about will tend to begin with high expectations (*how* high depends positively on the length of the waiting period) but then lower their expectations as the 'moment of truth' draws near. Numerous studies by psychologists document exactly such a pattern.

Most models that permit self-manipulation of beliefs assume that there are some limits to feasible self-deception. Brunnermeier and Parker (2002) assume that people trade off the benefits of optimism against the negative effects that biased expectations have on the quality of their decision-making. Karlsson, Loewenstein and Patty (2003) assume that people can only change their beliefs by a limited amount in a specified amount of time. Rabin and Shrag (1999), in a somewhat different context, assume that people cannot simply believe whatever they want, but that they can interpret evidence in a biased fashion that responds more strongly to information consistent with what they are motivated to believe.

Our paper presents a theory of belief manipulation in terms of "bundles" of multiple interrelated psychological phenomena. These bundles differ along three dimensions. The first is *selective attention*. This is the idea that individuals consciously decide what information to expose themselves to and what information to avoid. The second is *impact regulation*. This is the idea that individuals consciously decide, within limits, how intensely their sense of well-being (i.e., utility) is affected by their environment. The third building block is *benchmark dynamics.* In prospect theory, the utility of an outcome is defined in terms of the outcome's deviation from a pre-specified benchmark. We argue that the dynamics of how these benchmarks evolve over time may be affected by how intensely individuals experience prior outcomes.

In our model, individuals choose between two composite psychological states when responding to an event that changes their environment. One possibility is to be psychologically *attentive*. In this case people experience the event intensely, they actively seek out additional information about the event, and their benchmark for future utility is strongly updated. The alternative response is to be psychologically *inattentive*. In this case people experience the event less intensely, they avoid learning additional information, and their benchmark for future utility is comparatively unaffected.

Under reasonable parameter values, individuals in this framework exhibit behavior that we call the "ostrich effect." Given bad news about their environment, they optimally choose to be psychologically inattentive and, in particular, avoid collecting additional information. They "put their heads in the sand" to shield themselves from bad news. This is the ostrich effect. In contrast, given favorable news, individuals should choose to be psychologically attentive and, in particular, seek out additional information about their environment. We validate this predicted asymmetry using Scandinavian data about investor decisions to check their portfolio value. Consistent with the ostrich effect, investors check their portfolio value more frequently in rising bull markets than in falling bear markets.

Most readers, if they self-introspect about their personal behavior during the bull market of the late 1990s and the subsequent meltdown, will not be surprised by this empirical result. One attraction of our theoretical model, however, is that it allows us to link observable behavior (i.e., information collection decisions) with internal psychological covariates that, while not directly observable, are important for the dynamics of changing investor preferences in rising and falling markets. Thus, investor decisions to update information about their portfolio are, our model, a proxy that can be used to identify unobservable investor preference parameters. This is important because earlier models with similar psychological considerations (e.g., Barberis, Huang and Santos, 2001; Routledge and Zin, 2004) have only been tested with price data. Our approach provides additional potentially testable over-identifying restrictions on the joint behavior of prices with observable non-price variables that are correlated with the unobservable psychological phenomena.

II. Literature Review

One important avenue people use to manipulate their own beliefs is by selectively attending (exposing themselves) to information. An extensive body of empirical research in psychology supports what is sometimes referred to as the 'selective exposure' hypothesis. Ehrilch, Guttman, Schonbach and Mills (1957), for example, found that new car owners paid more attention to advertisements for the model they purchased than for models they had considered but did not end up buying. Brock and Balloun (1967) demonstrated that smokers attended more to prosmoking messages and non-smokers attended more to antismoking messages. Although some other studies produced more equivocal findings (Cotton, 1985; Festinger, 1964), casting some doubt on the phenomenon (e.g., Freedman and Sears, 1965), the most recent research has provided quite strong support for the selective exposure hypothesis (e.g., Jonas et al., 2001; see Frey, 1986 for a review). The research on selective attention has mainly focused on the idea that people search selectively for information that conveys good news or that reinforces their pre-existing beliefs. There has been less research on whether people avoid information that conveys bad news or conflicts with prior beliefs (Frey and Wicklund, 1978).

The selective exposure hypothesis has also made its way into economics. Caplin (2003), building on earlier ideas proposed earlier by Witte (1992), assumes that people have some ability to choose how much to *attend* to information. He 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 this one step further by examining the differential degree to which people expose themselves to positive versus negative information. Specifically, we test whether investors who own risky assets are more inclined to check on their portfolio value at times when they have reason to suspect that the performance has been positive than at times when they have reason to suspect it has been negative.

A conceptually tricky issue with selective exposure to information (and self-deception more generally) is that, to avoid receiving adverse information one needs to know, or at least suspect, that it is bad. This raises the question of whether one can really shield oneself from negative information. In fact, true self-deception has been argued to be logically impossible (see, e.g., Sartre 1953) since it involves simultaneously knowing something and willfully not knowing it. But, this argument assumes that there is only one way to ’know’ something. In fact, recent work by psychologists (e.g., Sloman, 1996; Epstein, 1992) suggests that people may hold beliefs at different levels.[1]

We address this concern in several ways. We allow individuals to condition their decisions on imperfect prior information that may be positive or negative. Given that knowledge, they then decide how much they will allow that information to affect them. They can choose behaviors to intensify their enjoyment of good news (celebrating) or behaviors to distract themselves from unpleasantness. Thus, how intensely knowledge affects one’s sense of well-being is, at least partially, under one’s conscious control. We call this impact regulation. People, in addition, can decide whether to collect additional information to update their initial imperfect information. This is selective attention.

Selective attention and impact regulation are closely related. Prior research shows that people’s beliefs often lack precision – i.e., are “fuzzy” (Schneider, 2001) – which may provide some leeway for self-manipulation of expectations in relation to knowledge. Whether this should be labeled self-deception depends on one’s definition of the term, but knowing that information is bad is quite different from only suspecting that it is bad (and vice versa). When, for example, the market is down on a particular day, one might be able to anticipate with great likelihood that one's own portfolio will have declined in value, but that is not guaranteed. It is always possible that the specific stocks in one's own portfolio have risen even when the market has declined. If

[1] When presented with two jars, one containing one blue and nine red beans, and the other containing ten blue and ninety red beans, most people state that the probability of drawing blue is the same with either jar; yet most people prefer to bet on the jar with the larger number of blue beans (and many are willing to pay a premium to do so).

knowing definitively that one's portfolio has declined in value is worse than simply suspecting that it has, then people will have an incentive to shield themselves from receiving adverse information definitively when they only suspect that the news is bad. On the basis of this logic, we predict that people will check the value of their risky investments more often when the stock market has gone up than when it has gone down.

Prospect theory predicts that utility depends on how outcomes deviate from a pre-specified benchmark. Psychological and economic research suggests that “kinks” in investor preferences have important consequences for individual behavior and for market equilibrium. We argue here that it is plausible to suppose that individual’s decisions about the intensity with which they experience events affects the evolution of their benchmark in the future.

III. A Model of Selective Attention

We illustrate the interactions between selective attention, impact regulation, and benchmark dynamics using a stylized decision-theoretic model for a single investor. The investor has some control over both the timing of information she receives about her personal wealth and about how this information affects her utility. In particular, the investor can choose to be psychologically attentive or inattentive to information about her wealth. Being attentive, which in the context of this specific application means actively checking the value of one's portfolio, has two main consequences: (1) it increases the impact of information about wealth on utility, and (2) it accelerates updating of the individual’s benchmark (reference point). Being inattentive means that she does not check the value of her portfolio, in which case current wealth news has a smaller impact on her utility, and her benchmark adjusts more slowly.

For simplicity, assume there are two dates, t = 1 and 2. At date 1 there is an innovation to the investor’s wealth. Let W_0 be the investor’s incoming wealth at the start of date 1 and let $W_1 = W_0 + \varepsilon_1$ denote her new exact wealth at the end of date 1. The date 1 innovation consists of two components $\varepsilon_1 = c_a + c_d$. The investor learns the first component c_a automatically but can decide at date 1 whether she wants to learn the second component. For example, the first component c_a might be a market index return that is regularly reported in the public news media (e.g., the ‘Dow’) while the discretionary information c_d could depend on the specific holdings in the investor’s portfolio. We assume $c_a \in \{-e, 0, +e)$ so the public/automatically known innovation represents good, neutral, or bad news about her wealth. For simplicity we assume that the discretionary information is of the same magnitude as the public innovation, but can only take two states, $c_d \in \{-e, +e\}$, which correspond to good or bad news relative to c_a. At date 2 there is one further innovation to the investor's wealth so that her final wealth is $W_2 = W_1 + \varepsilon_2$. Again, for simplicity, the final wealth innovation, $\varepsilon_2 \in \{-e, +e\}$, is simply good or bad news relative to W_1. We assume that good and bad realizations for c_d and ε_2 are equally likely.

There is no direct cost to the investor if she chooses to learn c_d at date 1. For example, investors in our empirical database can log on to a web page and review their account balances at no cost except for a trivial investment of time. However, the investor does have the option of "burying her head in the sand" at date 1 – i.e., delaying learning about the additional component c_d of her wealth until date 2. This is our "ostrich effect."

A key assumption is that the investor can condition her decision at date 1 about whether to be psychologically attentive or inattentive on her wealth $W_1^* = W_0 + c_a$ after learning the automatic public component. Given her decision, her perceived wealth W_1^p at date 1 is either W_1 (if she chooses to be attentive and learn c_d) or W_1^* (if she does not). At date 2, the investor learns all available information (i.e., this is not a choice). Consequently, her perceived wealth equals her actual wealth $W_2^p = W_2$. We also assume that she is psychologically attentive at date 2.

We model the investor as having disappointment-averse preferences. When she is attentive (designated as 'A', with inattentive designated as 'IA') her utility per period,

$$u_t(A_t, W, b_{t-1}) = \begin{cases} u_{t-1} + a(W_t^p - b_{t-1}) & \text{if } W_t^p > b_{t-1} \\ u_{t-1} + a(1+\delta)(W_t^p - b_{t-1}) & \text{if } W_t^p < b_{t-1} \end{cases}$$

At each date the investor's utility is centered at the level of her previous utility. Her utility is then perturbed by the deviation of her perceived wealth from a previously determined disappointment threshold b_{t-1}. The parameter $\delta > 0$ captures that idea that the investor is disappointment-averse. Her marginal utility of wealth is greater when her perceived wealth W_t^p is less than a disappointment threshold b_{t-1}. The disappointment threshold changes over time depending on the evolution of the investor's perceived wealth and on how psychologically attentive or inattentive the investor is in response to changes to her wealth:

$b_0 = W_0$

$b(W_1, A) = W_1^P$

$b(W_1, IA) = \theta\, W_1^P + (1\text{-}\theta)\, W_0 = W_0 + \theta\, [W_1^p - W_0]$

$= W_0 + \theta\, c_a.$

When the investor is inattentive, her utility per period is:

$$u_t(IA_t, W, b_{t-1}) = \begin{cases} u_{t-1} + a\lambda\, (W_t^p - b_{t-1}) & \text{if } W_t^p > b_{t-1} \\ u_{t-1} + a\lambda\, (1 + \delta)(W_t^p - b_{t-1}) & \text{if } W_t^p < b_{t-1} \end{cases}$$

The parameter λ, with $0 < \lambda < 1$, captures the idea of impact regulation in that the utility impact of wealth when the investor is inattentive is muted relative to when she is actively paying attention.

The investor's decision at date 1 is to choose whether to be psychologically attentive, which means collecting additional information, experiencing the utility-consequences of attending to her wealth, and accepting the active benchmark updating dynamics – or to be psychologically inattentive – by waiting until date 2 to concentrate on to her wealth, not collecting additional news, and accepting the passive benchmark updating dynamics. We consider how her decision depends on the automatic news she receives at date 1 about the public component c_a.

Good news case: First, consider that case in which the investor receives a positive signal $W_1^* = W_0+e$. If she is psychologically attentive, then her cumulative expected utility,

$$\begin{aligned} J(A,W_0+e, b_0) = {} & \tfrac{1}{2}\, u_1(A, W_0+2e, b_0) + \tfrac{1}{2}\, u_1(A, W_0, b_0) \\ & + \tfrac{1}{2}\, [\tfrac{1}{2}\, u_2(W_0+3e, b(A, W_0+2e)) + \tfrac{1}{2}\, u_2(W_0+e, b(A, W_0+2e))] \\ & + \tfrac{1}{2}\, [\tfrac{1}{2}\, u_2(W_0+e, b(A, W_0)) + \tfrac{1}{2}\, u_2(W_0\text{-}e, b(A,W_0))] \end{aligned}$$

$$\begin{aligned} = {} & u_0 + \tfrac{1}{2}\, a\, 2e + \tfrac{1}{2}\, 0 \\ & + \tfrac{1}{4}\, [u_0 + a\, 2e + a\, e] + \tfrac{1}{4}\, [u_0 + a\, 2e - a(1 + \delta)\, e] \\ & + \tfrac{1}{4}\, [u_0 + 0 + a\, e] + \tfrac{1}{4}\, [u_0 + 0 - a(1 + \delta)\, e]. \end{aligned}$$

If she instead decides to be inattentive, then her cumulative expected utility is

$$J(IA, W_0+e, b_0) = u_1(IA, W_0+e, b_0)$$
$$+ \tfrac{1}{2} [\tfrac{1}{2} u_2(W_0+3e, b(IA, W_0+e)) + \tfrac{1}{2} u_2(W_0+e, b(IA, W_0+e))]$$
$$+ \tfrac{1}{2} [\tfrac{1}{2} u_2(W_0+e, b(IA, W_0+e)) + \tfrac{1}{2} u_2(W_0-e, b(IA, W_0+e))]$$

$$= u_0 + a\lambda e$$
$$+ \tfrac{1}{4} [u_0 + a\lambda e + a (3e - \theta e)] + \tfrac{1}{4} [u_0 + a\lambda e + a (e - \theta e)]$$
$$+ \tfrac{1}{4} [u_0 + a\lambda e + a (e - \theta e)] + \tfrac{1}{4} [u_0 + a\lambda e + a(1 + \delta) (-e- \theta e)]$$

Comparing the alternatives of being attentive or inattentive, gives:

$$J(A, W_0+e, b_0) - J(IA, W_0+e, b_0) = [a - a\lambda] e + [a - a\lambda] e$$
$$+ [\tfrac{1}{2} a – \tfrac{1}{2} a(1 + \delta)] e$$
$$- [\tfrac{1}{4} a (3 - \theta) + \tfrac{1}{2} a (1 - \theta) + \tfrac{1}{4} a(1 + \delta) (-1- \theta)] e$$

$$= 2 a [1 - \lambda] e$$
$$- [\tfrac{1}{4} a (1 - \theta) + \tfrac{1}{2} a (1 - \theta) + \tfrac{1}{4} a(1 + \delta) (1- \theta)] e$$

$$= 2 a [1 - \lambda] e - (1 - \theta) a [1 + \tfrac{1}{4} \delta] e.$$

The optimal decision about whether to attend to her portfolio in period 1, therefore, depends on a trade-off between the advantages of actively enjoying good news and the advantages of slow benchmark updating. Clearly, actively enjoying good news increases the psychological utility derived from the good news. However, if $\theta < 1$, this current active enjoyment comes at the cost of raising future anticipations (i.e., her disappointment benchmark) for date 2. In contrast, being less attentive reduces the impact of the good news on next period's benchmark. This makes it easier to avoid disappointment at date 2. Given good news at date 1, the investors will choose to be attentive if:

- The initial impact regulation effect is strong in that λ is sufficiently small
- The inattentive benchmark revision, θ, is sufficiently large.

In the absence of both the impact regulation effect and delayed benchmark updating, $\lambda = \theta = 1$, the investor is indifferent between learning c_d at date 1 or at date 2. If $\lambda = 1$ (i.e., no utility difference between being attentive or inattentive), then any lag in the benchmark updating, $\theta < 1$, causes the investor to be inattentive and not look. Some amount of impact regulation is necessary to get active "looking" at c_d following good news. If $\theta = 1$ so the delayed benchmark effect is absent, then any impact regulation $\lambda < 1$ causes the investor to be attentive and look. A natural intermediate case is $\theta = \lambda$. This means that whatever portion of the date 1 wealth innovations is "enjoyed" at date 1 is also "booked" into the future benchmark for date 2. In this case the attentive/inattentive comparison simplifies further to

$$J(A,W_0+e, b_0) - J(IA,W_0+e, b_0) = [1 - \lambda]\, a\, [1 - \tfrac{1}{4}\delta]\, e$$

Thus, given $\lambda = \theta < 1$, the investor optimally chooses to be psychologically attentive and collect additional information provided she is not too disappointment averse: $\delta < 4$.

Neutral news case: If the public news at date 1 is neutral, $W_1^* = W_0$, then the investor's cumulative expected utility from being psychologically attentive at date 1 is

$$\begin{aligned} J(A,W_0, b_0) = {} & \tfrac{1}{2} u_1(A, W_0+e, b_0) + \tfrac{1}{2} u_1(A, W_0-e, b_0) \\ & + \tfrac{1}{2} [\tfrac{1}{2} u_2(W_0+2e, b(A, W_0+e)) + \tfrac{1}{2} u_2(W_0, b(A, W_0+e))] \\ & + \tfrac{1}{2} [\tfrac{1}{2} u_2(W_0, b(A, W_0-e)) + \tfrac{1}{2} u_2(W_0-2e, b(A, W_0-e))] \end{aligned}$$

$$\begin{aligned} = {} & u_0 + \tfrac{1}{2} a e - \tfrac{1}{2} a(1 + \delta) e \\ & + \tfrac{1}{4} [u_0 + a e + a e] + \tfrac{1}{4} [u_0 + a e - a(1 + \delta) e] \\ & + \tfrac{1}{4} [u_0 - a(1 + \delta) e + a e] + \tfrac{1}{4} [u_0 - a(1 + \delta) e - a(1 + \delta) e] \end{aligned}$$

If she is instead inattentive, then her value function is

$$J(IA, W_0, b_0) = u_1(IA, W_0, b_0) + ½ [½ u_2(W_0+2e, b(IA, W_0)) + ½ u_2(W_0, b(IA, W_0))] + ½ [½ u_2(W_0, b(IA, W_0)) + ½ u_2(W_0-2e, b(IA, W_0))]$$

$$= u_0 + ¼ [u_0 + a\ 2e] + ¼ [u_0] + ¼ [u_0] + ¼ [u_0 – a(1 + \delta)\ 2e]$$

Comparing the two alternatives, we see that the investor is strictly better off being inattentive at date 1 and waiting until date 2 to learn the non-public component c_d.

$$J(A, W_0, b_0) - J(IA, W_0, b_0) = - ½ a\delta e - ½ a\delta e + [½ a - ½ a(1 + \delta)] e - [½ a - ½ a(1 + \delta)] e = - a\delta e < 0$$

This is entirely due to the impact of checking on date 1 utility given disappointment aversion. In particular, the expected utility perturbations at date 2 are identical irrespective of whether the investor is attentive or passive at date 1.

Bad news case: If the public news at date 1 is negative, $W_1^* = W_0$-e, then the investor's cumulative expected utility from being psychologically attentive at date 1 is

$$J(A, W_0-e, b_0) = ½ u_1(A, W_0, b_0) + ½ u_1(A, W_0-2e, b_0) + ½ [½ u_2(W_0+e, b(A, W_0)) + ½ u_2(W_0-e, b(A, W_0))] + ½ [½ u_2(W_0-e, b(A, W_0-2e)) + ½ u_2(W_0-3e, b(A, W_0-2e))]$$

$$= u_0 + ½\ 0 - ½ a(1 + \delta)\ 2e + ¼ [u_0 + a\ e] + ¼ [u_0 – a(1 + \delta)\ e] + ¼ [u_0 - a(1 + \delta)\ 2e + a\ e] + ¼ [u_0 - a(1 + \delta)\ 2e – a(1 + \delta)\ e]$$

The corresponding value function if the investor is inattentive is:

$$J(IA,W_0\text{-}e, b_0) = u_1(IA, W_0\text{-}e, b_0)$$
$$+ ½ [½ u_2(W_0+e, b(IA, W_0\text{-}e)) + ½ u_2(W_0\text{-}e, b(IA, W_0\text{-}e))]$$
$$+ ½ [½ u_2(W_0\text{-}e, b(IA, W_0\text{-}e)) + ½ u_2(W_0\text{-}3e, b(IA, W_0\text{-}e))]$$

$$= u_0 – a(1 + \delta) e$$
$$+ ¼ [u_0 – a(1 + \delta) e + a (e + \theta e)]$$
$$+ ¼ [u_0 – a(1 + \delta) e + a(1 + \delta)(-e + \theta e)]$$
$$+ ¼ [u_0 – a(1 + \delta) e + a(1 + \delta)(-e + \theta e)]$$
$$+ ¼ [u_0 – a(1 + \delta) e + a(1 + \delta)(-3e + \theta e)]$$

Comparing the two options conditional on bad public news gives:

$$J(A,W_0\text{-}e, b_0) - J(IA,W_0\text{-}e, b_0) = [a\lambda (1 + \delta) – a (1 + \delta)] e + [a\lambda (1 + \delta) – a (1 + \delta)] e$$
$$+ [½ a - ½ a(1 + \delta)] e$$
$$- [¼ a (1+ \theta) + ½ a(1 + \delta)(-1 + \theta) + ¼ a(1 + \delta)(-3+ \theta)] e$$

$$= [\lambda –1] a (1 + \delta) e + [\lambda –1] a (1 + \delta) e$$
$$- [¼ a (\theta\text{-}1) + ½ a(1 + \delta)(\theta\text{-}1) + ¼ a(1 + \delta)(\theta\text{-}1)] e$$

$$= 2 [\lambda –1] (1 + \delta) a e + (1\text{-}\theta) [1 + ¾ \delta] a e$$

With bad news, the inattention effect now works in the direction of the investor being inattentive to wealth. The benchmark delay effect works in the direction of being attentive so as to have a lower benchmark at date 2. On balance, the investor is inattentive and does not collect additional information if:

- The initial impact regulation effect is strong in that λ is sufficiently small
- The inattentive benchmark updating is not too slow (θ is sufficiently large)

As with good news, the absence of both an impact regulation effect and delayed benchmark updating, $\lambda = \theta = 1$, makes the investor indifferent between when she learns c_d. If $\lambda = 1$ (no utility difference between being attentive or inattentive), then any benchmark updating lag $\theta < 1$ causes the investor to be attentive and collect additional information. Some impact regulation is again necessary to get "not looking" given good news. If $\theta = 1$ (no delayed benchmark effect), then any inattention $\lambda < 1$ causes the investor to be attentive and look. In the natural intermediate case of $\theta = \lambda$, the comparison simplifies further to

$$J(A,W_0\text{-}e, b_0) - J(IA,W_0\text{-}e, b_0) = [\lambda - 1]\,[2\,(1+\delta) - (1 + \tfrac{3}{4}\,\delta)]\;a\;e$$

$$= [\lambda - 1]\,[1 + \tfrac{1}{4}\,\delta]\;a\;e \;<\; 0$$

In this case, given $\lambda = \theta < 1$ and bad news, the investor is optimally never attentive.

Comparing bad news to neutral news: Our intuition is that investors are more likely to closely monitor their portfolios when the market is up than when it is neutral. As will be evident in the following section, the data weakly support this prediction. The implications just discussed seem superficially to conflict with this intuiton since the model predicts that people will *never* monitor their portfolios when the market is flat and also predicts that for some parameter values investors *will* monitor their portfolios when the market news is positive. Yet, as the following analysis shows, there is a wide range of parameter values at which the disincentive for looking is greater when the market is down than when it is neutral. Finding those parameter values involves looking for a situation in which:

$$J(A,W_0, b_0) - J(IA,W_0, b_0) > J(A,W_0\text{-}e, b_0) - J(IA,W_0\text{-}e, b_0)$$

Substituting terms from earlier derivations gives:

$$- a\delta e > [\lambda - 1]\,[1 + \tfrac{1}{4}\,\delta]\;a\;e$$

Which simplifies to:

$$\delta < 4[1 - \lambda] /[3 - \lambda]$$

Reasonable parameter values for λ lie between zero and one. Values greater than one would imply that information has a greater impact on utility when one doesn't pay attention than when one does. Values lower than zero would imply that bad news can actually make one feel *better* if one isn't paying attention. Thus, at one extreme, if $\lambda=0$, investors will be more motivated to avoid bad news when the market is down rather than when it is flat as long as δ is less than 4/3. At the other extreme, when $\lambda=1$, then investors will be more motivated to avoid bad news when the market is down rather than when it is flat as long as δ is less than 8. Even the first, less stringent, of these conditions seems quite plausible. Empirical studies of disappointment aversion (which is generally termed loss aversion in the decision-making literature) typically estimate values of loss aversion for money that are around 2 to 2.5. For $\delta=4/3$, loss aversion is equal to 2.33. Thus, for virtually the entire range of plausible parameter values, our model predicts that people will be less motivated to look when information is bad than when it is neutral.

Of course, how motivated people are to look is irrelevant if everyone in the neutral information situation is looking. However, the model, as laid out above, leaves out some important factors that will generally tend to favor looking. These include curiosity, and the desire for information in order to make sensible investment decisions. Once these are incorporated into the model, as we plan to do in a future version of this paper, then the strength of motivation to look will become critical.

IV. An Empirical Investigation of Selective Attention to Investments

The key prediction of our model is that is that investors are more likely to look up their portfolio's value when the stock market is up than when it is down. To test this hypothesis we examined three separate data sets about investor decisions to check the value of their personal portfolios. The first date set gives the daily number of separate investors at a major Swedish bank who logged in to a page displaying personal mutual fund value data. The second data set gives the daily number of separate investors who looked up their personal pension fund value with the Swedish Premium Pension Authority. The third data set reports the daily number of separate investor account look-ups at a large Norwegian investment company.

We follow the same estimation strategy for all three datasets: We regress the numbers of look-ups on each day on the value of the relevant index on that day, the average value of the index during the prior 6 days (i.e., the remainder of the week), and the average of the index over the 24 days before that (i.e., the remainder of the month). This lag structure provides a compromise between examining day-to-day changes and examining longer-term trends. It removes, however, the impact of any secular drift in both variables – in look-ups and market trends. In addition to these basic regressions, we also run regressions with added controls for day of the week, and time trend. Finally, when the data set permits it, we attempt to control for (cancel out) cases in which individuals logged on for the purpose of transaction.

Data set 1: Swedish mutual funds. Our first data set was provided by one of the major Swedish banks and mutual fund managers. The data include information about the number of individual logins each day during 90-day period extending from June 30 to October 10, 2003. The logins recorded were to a page, personalized for each investor, which displayed information about the current value and performances of their mutual fund holdings. To reach this page, investors must first enter their personal bank page, which included general account and transaction information.

Since some investors may log in to their personal bank page specifically to check their mutual funds, while others may log in for other reasons and then decide to check their mutual funds once they are there, the number of checks of mutual funds will be dependent on the number of logins on the personal bank page. As dependent measures we therefore use both the number of logins to the page displaying information about mutual funds and the proportion of logins to this page by people who had logged in to their personal bank page.

During the sample period there were an average of 57,513 logins into personal bank pages per day, and an average of 11,602 logins to the page displaying mutual fund information. Hence, on average, people checked the values of their mutual funds 20% of the times that they logged in to their personal bank pages.

Figure 1 displays standardized values of the Swedish all shares stock exchange index (SAX), the number of mutual fund checks (Fund check) and the proportion mutual fund checks of the total number of log ins (Fund check (prop)) for each day over the period. As may be seen, the overall pattern over the period and the short-term variations both suggest that the total fund-checks and the proportion of logins to personal bank pages that led to checking of mutual fund information are positively related to changes in the level of the SAX index.

Figure 1 here

Casual inspection of the figure suggests that there is a positive relationship between fund checks and the overall value of the SAX both at the daily level and over broader spans of time. To capture these short- and long-term relationships, we ran two sets of regressions. The dependent variable in one set (columns 1 and 2) is the absolute number of fund checks on any given day, and the dependent variable in the other (columns 3 and 4) is the proportion of website logins that led to fund checks. All regressions include the level of the SAX on the day in question, the average level of the SAX for the prior 6 days, and the average level of the SAX during the 23 days prior to that as dependent variables. We include the two different lagged averages to let the data determine the relevant window for investor to accumulate conditioning information. In the regressions in columns two and four, we also include four weekday dummy variables (WD1 to WD4) and a linear time term (TIMELINE), to control for seasonalities and temporal drifts in logins over time. Table 1 presents the regression results. Only days when the stock exchange was open were included in the regression.

Table 1 here

We note that the sum of the negative coefficients on the two lagged SAX averages is close to the same magnitude as the positive sign on the current value of the SAX. This is consistent with the “ostrich effect” which predicts that the number of look-ups is positively related to the change in the SAX (our proxy for public/automatic news) over the past six- and 30-day time windows.

To link this empirical analysis more closely to the three cases discussed in the model section – where market news is positive, neutral or negative – we also calculated daily changes in the SAX and divided them into three equal groups (triciles) consisting of the third of days following the biggest daily increases, third of days following the biggest daily decreases and third of days lying in between these two extremes (i.e., with relatively small increases or decreases in the SAX). Figure 2a shows the daily change in the number of portfolio look-ups, and figure 2b shows the ratio of lookups to logins, in each case broken down by triciles of changes in the SAX. Both of these graphs show a very substantial difference in look-ups between days following large increases in the SAX and those following decreases or a lack of change. This is exactly the pattern predicted by our model given, we argued, plausible parameter values.

Figures 2a and 2b here

Data set 2: Swedish Premium Pension Authority. Our second data set is from the Swedish Premium Pension Authority. It is the longest and broadest sample. In the Swedish premium pension scheme (introduced the year 2000), Swedish citizens choose how to invest 2.5% of their before tax income in equity and interest bearing funds as part of their state pension savings. In 2003, 5.2 millions of Sweden's 8.9 million citizens were included in this new premium pension system. The data we obtained included information about the number of people who checked the value of their portfolio on each day between January 7, 2002 and October 12, 2003. In addition, the data set includes the number of changes (reallocations) made to portfolios (either on the web or through an automatic telephone service) for each day. The data on fund changes give us a better opportunity to look at when people check the value of their investments since people only log in to check the value of their premium pension funds or to make changes in their portfolio. As a dependent measure we use number of logins minus the number of changes made each day (on the web or an automatic telephone service). For the entire period investigated, the average number of logins each day is 6,807. Of these, 755 also involved a change to investment allocation.

Figure 3 presents the standardized values of the Swedish all shares stock exchange index (SAX) and the number of logins to check the value of funds for each day of the period. As in our first data set, the number of logins follows the SAX index reasonably closely. The number of logins is higher when the SAX index is higher, and vice versa.

Figure 3 here

To test whether people look up the value of their investments more frequently after the stock market has gone up than when it has fallen, we ran four regressions, parallel to those conducted on the previous data set. The first column of Table 2 presents a regression of logins on the current value of the SAX, lagged averages, the number of transactions and various weekday dummy variables and time trends.

Table 2 here

Once again, the number of fund-checks is increasing in the current SAX level and decreasing in lagged SAX values. This is true, moreover, even after controlling for the number of transactions on the day. Thus, this second data set also supports the "ostrich effect."

Figure 4 investigates triciles based on the previous daily change for the Swedish pension data. Clearly the number of fund-checks increases dramatically following good news. However, there is no support for the prediction of fewer fund checks following bad news than neutral news.

Figure 4 here

Data set 3: Norwegian bank/mutual fund company. Our third data was obtained from a major Norwegian bank and mutual fund. It included both logins and transactions during the three and a half months period from October 2, 2003 to January 17, 2004. While the logins were registered the day they were performed on the web, the transactions were registered and carried out by the bank the day after it was actually made by the customer. As a consequence transactions that were actually made by the customer on the web on a Friday, Saturday, or Sunday, were all registered and carried out by the bank on Monday. Since the number of transactions limits the number of observations substantially, we looked at two different dependent measures of number of checks of mutual fund values: one in which we subtract the number of transactions made that same day on the web, and one that don't.

Figure 5 displays for each day the standardized values of the Norwegian all-share stock exchange index (OSBEX), the number of log ins in total (LOGIN_Z), and the number of log ins minus number of transactions (LOGINC_Z). The average number of logins on the web per day was 937 and the average number of transactions was 97. As may be seen, again, the number of logins each day follows the national index quite closely.

Figure 5 here

To test the hypothesis that people log in to check the value of their funds more often when the stock market has gone up than when it has going down, we regressed the current day's price of the OSBEX index, the average price from the day before to 7 days before (AVP2_7), the average price from 8 days before to 30 days before (AVP8_30), and four week day dummies (WD1 to WD4). The regression results are very different depending on whether or not a time trend is included. These results, thus, are the weakest support for the "ostrich effect." The triciles in Figure 6 are similar to those for the Swedish pension data.

Table 3 here

Figure 6 here

V. Conclusion

This paper has presented a decision theoretic model in which information collection is linked to investor psychology. For a wide range of plausible parameter values, the model predict that investor should collect additional information conditional on favorable news and avoid information following bad news. We call this the ostrich effect. Empirical evidence from Scandinavian investors supports the existence of the ostrich effect in financial markets.

Our analysis is important because it links observable investor behavior (information collection decisions) with psychological phenomena which current research by Barberis, Huang and Santos (2001) and Routledge and Zin (2004) suggests is important for asset pricing. Most theoretical models of investor behavior have been tested and parameterized purely on the basis of time series data on asset prices. Whether people attend to their portfolios provides a new form of observable investor behavior that can be used to test models and estimate parameter values.

An interesting twist is that although selective exposure can distort decision-making, given that people are generally risk aversive, it may actually be a way to live with risky investments, and to reduce the immediate worries about the risks in order to obtain the potential long-term benefits of such investments. In fact, indicating that people may reduce their worries by selective exposure, research suggest that the selective exposure to positive information is especially pronounced for pessimistic people and people in a negative mood (Aspinwall et al, 2001; Raghunathan and Trope, 2002).)

References

Akerlof, George A., and William T. Dickens. "The Economic Consequences of Cognitive Dissonance." *American Economic Review*, 72 (1982), 307–319.

Alloy, Lauren B. and Lyn Y. Abramson. "Judgment of Contingency in Depressed and Nondepressed Students: Sadder but wiser?" Journal of Experimental Psychology: General, 108(4) (Dec 1979), 441-485.

Aspinwall et al (2001).

Badad (1995)

Badad & Katz (1991)

Barberis, Nicholas, Ming Huang, and Tano Santos, "Prospect Theory and Asset Prices," *Quarterly Journal of Economics*, 116, (2001), 1-53.

Baumeister, Roy F., J.D. Campbell, J.I. Krueger, and K.D. Vohs. "Does High Self-esteem Cause Better Performance, Interpersonal Success, Happiness, or Healthier Lifestyles?" *Psychological Science in the Public Interest*, 4(1) (2003), 1-44 (whole issue).

Benabou, Roland and Jean Tirole. "Self-confidence and Social Interactions," NBER Working Paper 7585, 2000.

Benartzi, Shlomo and Richard Thaler. Myopic Loss Aversion and the Equity Premium Puzzle. Quarterly Journal of Economics 110(1) (1995), 73-92.

Bodner, Ronit, and Drazen Prelec. "Self-signaling and Dagnostic Utility in Everyday Decisionmaking," in Collected Essays in Psychology and Economics, Isabelle Brocas and Juan D. Carrillo, editors (Oxford: Oxford University Press, 2001).

Brunnermeier, Markus K. and Jonathan A. Parker. "Optimal Expectations." Princeton University, Working Paper, 2002.

Brock & Balloun (1967)

Caplin, Andrew, "Fear as a Policy Instrument," in Time and decision, George Loewenstein, Daniel Read, and Roy Baumeister, editors (New York: Russell Sage, 2003).

Caplin, Andrew, and John Leahy Psychological expected utility theory and anticipatory feelings *Quarterly Journal of Economics*, 116, (2001), 51-80.

Cotton (1985)

Diener, E., and M. Diener, “Cross-cultureal Correlates of Life Satisfaction and Self-esteem. *Journal of Personality and Social Psychology*, 68 (1995), 653-663.

Ehrilch, guttman, Schonback & Mills 1957.

Epstein 1992

Festinger, Leon, *Conflict, Decision, and Dissonance* (Stanford, CA: Stanford University Press, 1964).

Freedom & Sears 1965

Frey 1986

Frey & Wicklund 1978

Geanakoplos, John David Pearce, and Ennio Stacchetti. *Psychological games and sequential rationality. Games and Economic Behavior*, 1(1) (1989), 60–79.

Gneezy, Uri and Jan Potters. An Experiment on Risk Taking and Evaluation Periods," Quarterly Journal of Economics, 112, (1997), 631-645.

Jonas et al. 2001

Karlsson, Niklas, George Loewenstein & John W. Patty. A dynamic model of optimism. Working paper, Department of Social and Decision Sciences.

Koszegi, Botond, “Self-image and Economic Behavior,” Mimeo, Massachusetts Institute of Technology, 1999.

Kruglanski (1996)

Kunda, 1990

Loewenstein, George , “Anticipation and the Valuation of Delayed Consumption.” *Economic Journal*, 97 (1987), 666–684.

Peterson, Christopher, and Lisa M. Bossio, “Optimism and Physical Well-being,” in *Optimism & Pessimism: Implications for Theory, Research, and Practice*, Edward C. Change, editor (Washington, DC: American Psychological Association, 2001).

Rabin, Matthew, "Incorporating Fairness into Game Theory and Economics." *American Economic Review* 83 (1993), 1281-1302.

Rabin, Matthew, and Joel L. Schrag, “First Impressions Matter: A Model of Confirmatory Bias. *Quarterly Journal of Economics*, 114(1) (1999), 37–82.

Raghunathan & Trope 2002

Routledge, Bryan & Stanley Zin 2004, “Generalized Disappointment Aversion and Asset Prices,” NBER working paper w8683.

Sartre, Jean-Paul, *The Existential Psychoanalysis (H.E. Barnes, trans.)* (New York: Philosophical Library, 1953).

Scheier, Michael F., Charles S. Carver, and Michael W. Bridges, “Optimism, Pessimism, and Psychological Well-being,” in *Optimism & Pessimism: Implications for Theory, Research, and Practice*, Edward C. Chang, editor (Washington, DC: American Psychological Association, 2001).

Schneider, Sandra L. “In Search for Realistic Optimism: Meaning, Knowledge, and Warm Fuzziness.” *American Psychologist*, 56 (2001), 250–263.

Sloman. Steven A., “The Empirical Case for Two Systems of Reasoning.” Psychological Bulletin, 119 (1996), 3–22.

Witte (1992). Putting the fear back into fear appeals: the extended parallel process model. Communication Monographs 59. Available at http://www.msu.edu/~wittek/fearback.htm

Table 1: Regressions with the Swedish bank data

The sample period is June 30, 2003 through October 7, 2003. Standard errors are in parentheses.

	Dependent variable: logins to mutual fund page		Dependent variable: logins to mutual fund page/logins to personal bank page	
	(1)	(2)	(3)	(4)
Intercept	-18857* (8190)	15469 (44573)	-.0061 (.042)	-.166 (.042)
SAX index	382.6** (140.6)	320.4* (137.8)	.00585*** (.001)	.00622*** (.001)
Ave(SAX_{t-1}-SAX_{t-7})	-169.7 (160.2)	-112.6 (154.4)	-.00207* (.001)	-.00248** (.001)
Ave(SAX_{t-8}-SAX_{t-30})	-26.9 (85.2)	-255.7 (288.7)	-.00264*** (.0001)	-.00161 (.002)
Day dummies and time trend?	no	yes	no	yes
Number of observations R-square	69 0.22	69 0.41	69 0.64	69 0.68

*** p<.001; **p<.01; *p<.05

Table 2: Regressions with the Swedish Pension Authority data

The sample period is January 7, 2002 and December 3, 2003. Standard errors are in parentheses.

	Dependent variable: logins to mutual fund page			Dependent variable: logins to mutual fund page – transactions	
	(1)	(2)	(3)	(4)	(5)
Intercept	-292 (743)	-401 (460)	-9062*** (505)	-12313*** (593)	-316 (645)
SAX index	126*** (36.4)	72.3*** (22.6)	77.6*** (15.6)	96.2*** (19.4)	114*** (31.6)
Ave(SAX_{t-1}-SAX_{t-7})	33.7 (42.7)	44.3 (26.4)	1.9 (18.3)	-19.6 (22.7)	36.1 (37.0)
Ave(SAX_{t-8}-SAX_{t-30})	-118*** (17.5)	-93.7*** (10.8)	-27.1*** (8.25)	-4.2 (10.2)	-112.6*** (15.1)
Transactions per day	---	4.4*** (0.13)	3.0*** (0.11)	---	---
Day, week and year dummies?	No	No	Yes	Yes	No
Number of observations R-square	693 0.18	693 0.69	693 0.85	693 0.71	693 0.20

*** p<.001; **p<.01; *p<.05

Table 3: Regressions with Norwegian bank data

The sample period is October 2, 2003 and January 17, 2004. Standard errors are in parentheses.

	Dependent variable: logins to mutual fund page		Dependent variable: logins to mutual fund page – transactions	
	(1)	(2)	(3)	(4)
Intercept	-2025*** (455)	-5522* (2191)	-2593*** (458)	-5324** (1981)
OSBEX2 index	602*** (13.5)	62.7*** (13.5)	47.6*** (12.4)	49.9*** (12.4)
Ave($OSBEX2_{t-1}$- $OSBEX2_{t-7}$)	-31.6* (14.1)	-24.4 (14.7)	-20.2 (13.1)	-15.7 (13.4)
Ave($OSBEX2_{t-8}$- $OSBEX2_{t-30}$)	-13.1 (6.6)	1.0 (10.9)	-9.1 (6.5)	2.8 (10.6)
Day dummies	yes	yes	yes	yes
Time trend?	no	yes	no	yes
Number of observations R-square	105 0.72	105 0.73	68 0.81	68 0.82

*** p<.001; **p<.01; *p<.05

Figure 1: The SAX and fund look-ups by investors at a large Swedish Bank

The sample period is June 30, 2003 through October 7, 2003.

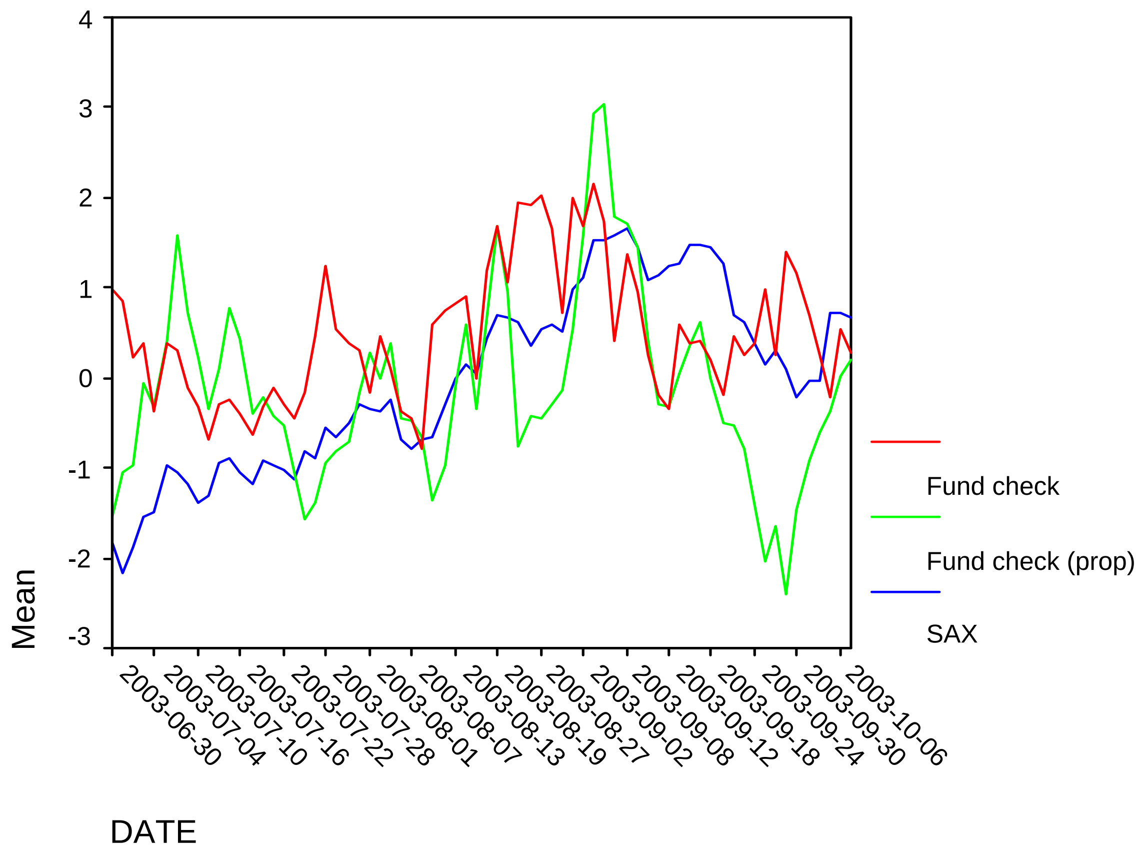


Figure 2a: Changes in the SAX and fund look-ups by investors at a large Swedish bank

The sample period is June 30, 2003 through October 7, 2003.

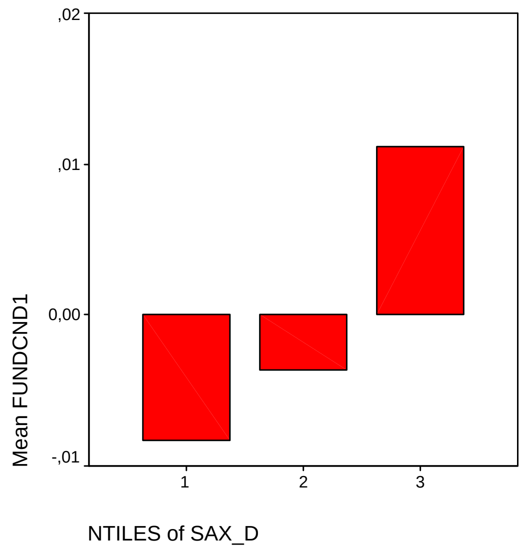
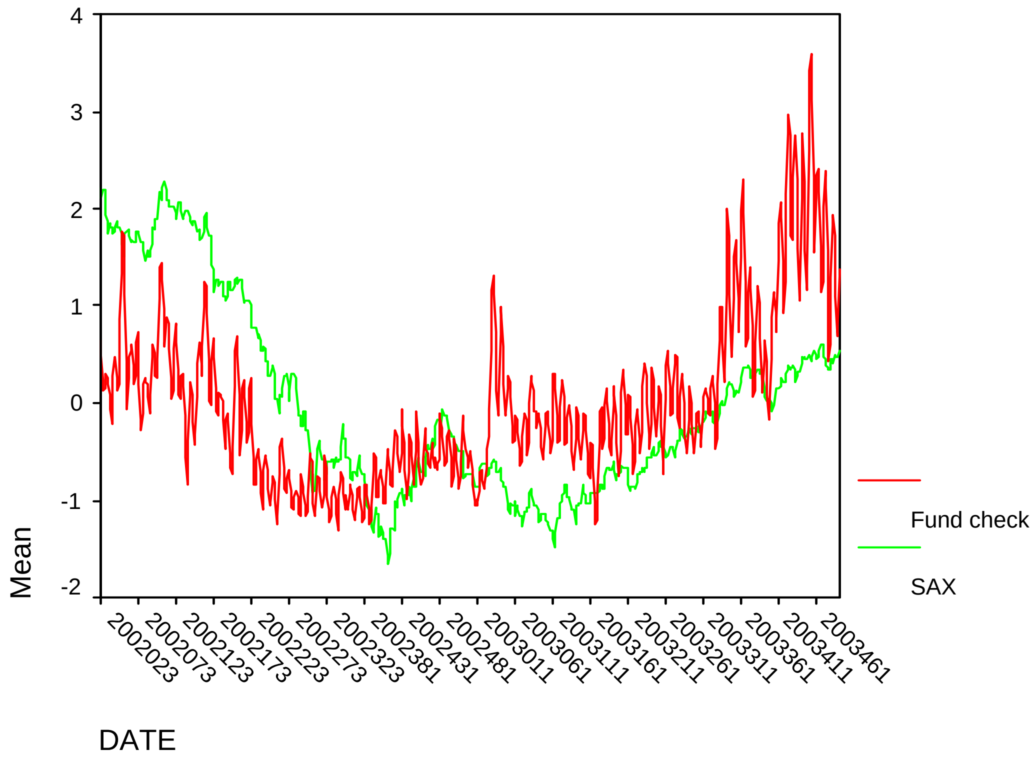


Figure 2b

Figure 3: SAX index and portfolio checks for Swedish pension data

The sample period is January 7, 2002 and October 12, 2003



Note: New people entered the system where the red line jump up in the middle of the figure.

Figure 4: Changes in the SAX and fund look-ups for Swedish pension data

The sample period is January 7, 2002 and October 12, 2003

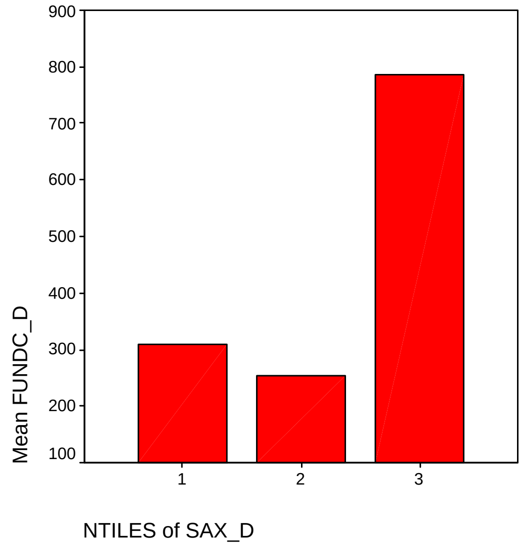


Figure 5: OSBEX index and logins by investors at Norwegian bank

The sample period is October 2, 2003 to January 17, 2004

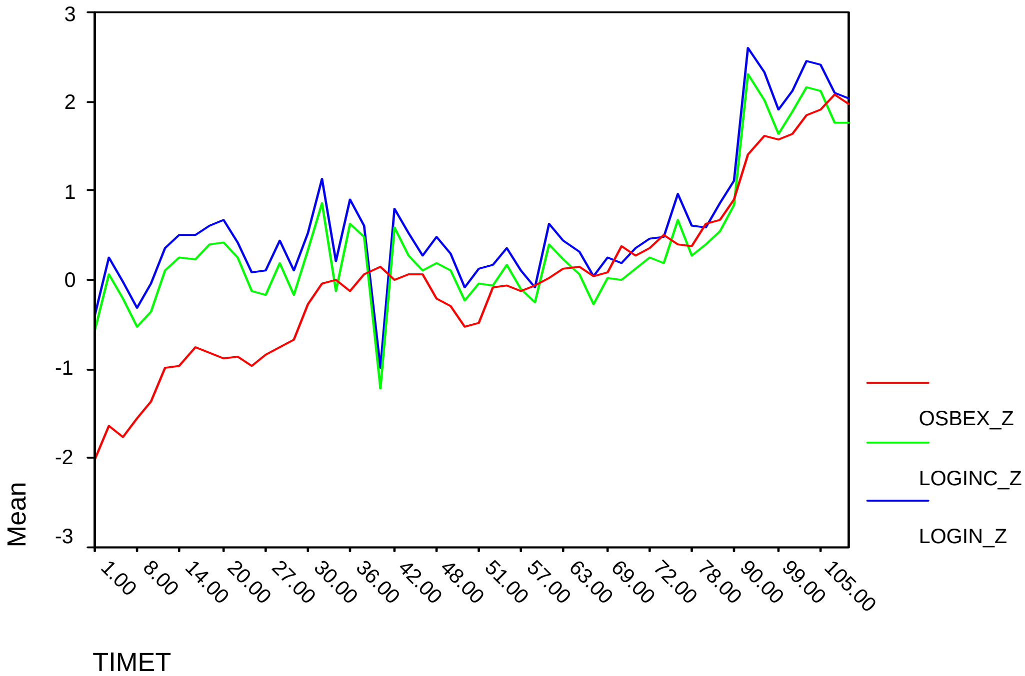


Figure 6: Changes in the OSBEX and fund look-ups by investors at Norwegian bank

The sample period is October 2, 2003 to January 17, 2004