

Detecting Anchoring in Financial Markets

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Anchoring is a term used in psychology to describe the common human tendency to rely too heavily (anchor) on one piece of information when making decisions. Here a trading algorithm inspired by biological motors, introduced by L. Gil [2007], is suggested as a testing ground for anchoring in financial markets. An exact solution of the algorithm is presented for arbitrary price distributions. Furthermore the algorithm is extended to cover the case of a market neutral portfolio, revealing additional evidence that anchoring is involved in the decision making of market participants. The exposure of arbitrage possibilities created by anchoring gives yet another illustration on the difficulty proving market efficiency by only considering lower order correlations in past price time series.

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Having a background in physics but working in the field of finance for the last decade, it is sometimes hard not to notice how much the field of finance has been influenced by the “exact” sciences in terms of both methods on ideas but also on the mathematical notations in which ideas are presented. Somewhere along this road, however, it is often forgotten that sciences such as physics were founded on empirical observations on which theories were then build, rejected, or accepted based on comparison with observations of data. Unfortunately, far too often in finance there seems to be a “detachment” between what the reality tells in form of empirical data and the wishful theoretical thinking of what should be the origin in creating that data. In that sense, behavioral finance stands out since it actually stresses the empirical side by taking seriously how human and social emotional biases can affect market prices. The field adapts a more pragmatic and complex view on financial markets, in contrast to standard finance theory where people rationally and independently on the basis of full information try to maximize utility. The more realistic view comes at a cost, however, since a multifactorial world is captured mainly via observations or postulates about human behavior.

One of the first observations of anchoring was reported in the now classical experiment by Tversky and Kahneman

[1974]. Two groups of test persons were shown to give different mean estimates of the percentage of African nations in the United Nations, depending on the specific anchor of percentage suggested by the experimenters to the two groups. Evidence for human anchoring has since been reported in many different domains such as customer inertia in brand switching (Ye [2004]), on-line auctions (Dodonova and Khoroshilov [2004]), and real estate pricing (Northcraft and Neale [1987]). In the context of financial markets, anchoring has been observed via the so-called “disposition effect” (Shefrin and Statman [2000], Khoroshilov and Dodonova [2007]), which is the tendency for people to sell assets that have gained value and keep assets that have lost value. In that case the *buying price* acts as an anchor. This is different from the anchoring discussed in the following where a recent *price level* instead acts as an anchor. As noted in Weber and Camerer [1998], conclusive tests using real market data are usually difficult because investors’ expectations and individual decisions cannot be controlled or easily observed. In experimental security trading, however, subjects were observed to sell winners and keep losers (Weber and Camerer [1998]).

The problem addressed in this article relates to the general question of whether it is possible to put on a more solid ground the impact of human emotional and social cognitive biases on the pricing in financial markets. The particular question posed here is if anchoring occurs in financial markets, how will it manifest itself and how can one in a controlled way detect this? Typically such biases, put forward as postulates in the field of behavioral finance, have been

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tested in well-controlled laboratory experiments. However, the impact they could have in the financial markets is still disputed. Critics argue that experimentally observed behavior is inapplicable to market situations, since learning and competition will ensure at least a close approximation of rational behavior. To probe what could be the impact and signature of behavioral biases in financial markets, it is therefore important to suggest tests and tools that apply directly to financial market data.

To get a better understanding of how aggregation of individual behavior can give rise to measurable effects in a population in general and financial markets in particular, it would be interesting to model specific human traits on a micro scale and study the emergence of a dynamics with observable or even predictable effects on a macro scale. The hope would be to reproduce in models many of the mechanisms reported at work in behavioral finance. One step in this direction was done in Anderson and Sornette [2005], where it was shown how consensus (called “decoupling”) and thereby predictability could emerge at certain special “pockets of time” due to mutual influence on the price in a commonly traded asset, among a group of agents who had initially different opinions. This idea in turn was applied as a tool to understand speculative bubble formation in an experiment with human subjects that traded an asset (Roszczynska et al. [2009]). The study was done by first generating trading data in the experiments with humans, and the data were then used for computer simulations of agent-based models. Roszczynska et al. [2009] illustrated that as the agents tried to maximize their profit using the market data created by humans, certain moments of decoupling happened, where the decision of an agent would become independent of the next outcome of the human experiment. Such moments of decoupling (or consensus) were shown to lead to pockets of deterministic price actions of the agents and were simultaneously found to be the moments when the humans entered a moment of consensus. It coincided with the entrance point of a speculative price bubble.

Here another method is suggested which rigorously test for a different human trait introduced by behavioral finance, namely anchoring. The algorithm used was introduced by L. Gil [2007] and is inspired from the way biological motors work by exploiting favorable Brownian fluctuations to generate directed forces and move. Similar ideas were also introduced in Sornette and Andersen [2006], where it was shown how increments of uncorrelated time series can be predicted with a universal 75% probability of success.

The idea behind the method can be resumed as follows. Assume anchoring is present in financial markets because of “sticky” price movements with recent prices used by market participants as anchor in determination of whether an asset is over- or undervalued. Such irrational behavior would in principle open up for arbitrage possibilities for speculators buying when an asset is conceived undervalued and selling when overvalued. As will be seen, just like in biological motors where a move is performed when a favorable fluctuation

occurs, so can a patient trader wait and act when the right price fluctuation happens. However, one would only be able to settle the question whether such strategy is profitable and how risky it would be, knowing three things:

- (1) One would need to know the probability for finding the price of the asset having a given value A . The method assumes the price evolution to be “sticky” (quasi-stationary) so that at any given time t , a market participant has a notion of the likelihood of a certain price value A at that very moment of time. It would be natural that this probability changes over time, but to keep the illustration of the method simple it will in the following be assumed time independent. Generalization to a time dependent probability distribution is straightforward. One needs to know the price probability distribution function $P(A)$.
- (2) The probability $P(A \rightarrow B)$ to go from one quasi-stationary price A to another quasi-stationary price B , and
- (3) The transaction costs C .

The method is described in detail in the Appendix and quantifies under which circumstances the presence of anchoring in financial markets would be detectable in terms of a profitable investment strategy that speculates on this particular cognitive bias. In the following the method will first be illustrated in the case where an exact solution is available before applying the algorithm to real financial data.

To check the algorithm (7) with the expressions (9), (10) random price time series $P(A_i) = A_i \pm dA_i$ (with the randomness stemming from the sign of dA_i) were generated with fixed values of A_i, dA_i . Figure 1 shows the average return obtained using the algorithm as a function of time. To make the classification as indicated in Table 1, the averaged value of A_i was estimated as in Gil [2007] using an average over

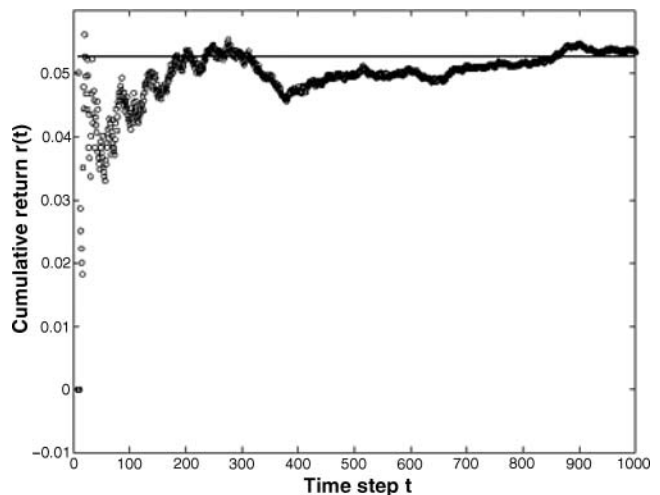


FIGURE 1 Averaged return $r(t)$ as a function of time t . Circles represent the result obtained by using the algorithm (9) with ($A_1 = A_2 = 1.0$, $dA_1 = dA_2 = 0.11$), and memory $m = 5$. Solid line represents the analytical expression (11).

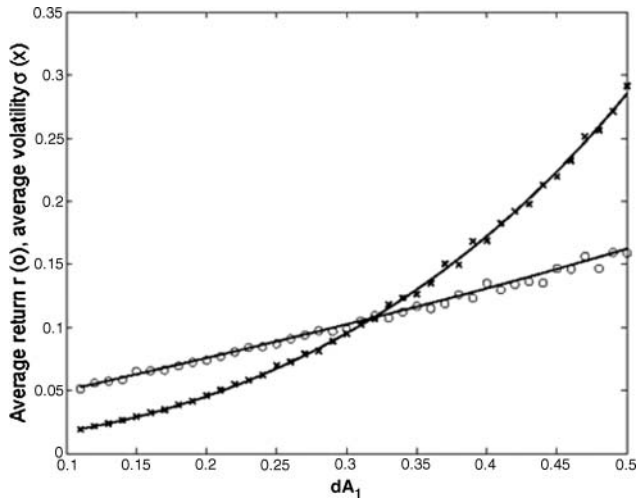


FIGURE 2 Averaged return R_{av} (circles) and volatility (crosses) versus dA_1 . The data points were obtained in steady state by the algorithm (9) using a memory $m = 5$ to estimate A_i from which in turn the classification was made according to Figure 1. The random price time series (with the randomness stemming from the sign of dA_i) were generated with fixed values ($A_1 = A_2 = 1$, $dA_2 = 0.11$). Solid lines represent analytical results (11), (12).

the last m price values. As seen after a transient the averaged return reaches the steady state expression (9) as it should.

The points in Figure 2 represent the steady state results obtained by the algorithm for the averaged return R_{av} and volatility Σ versus dA_1 . As seen, the simulation results of the algorithm agree with the expressions (9) and (10) represented by solid lines.

The algorithm was then applied to real market data. However, as noted in Gil [2007], a general problem arises because of long-term drifts in anchor of the price, A_i , which is never truly “quasi-static”. I.e. A_i is time dependent and for sufficient strong drifts the return of the algorithm was then shown to vanish. To circumvent this obstacle, the algorithm was modified so as always to be market neutral, independent of any drift the portfolio of the N assets might perform. Figure 3 shows the market neutral algorithm applied to real market data of the Dow Jones Industrial Average, as well as the CAC40 stock index. First half of the time period for the DJIA was used in sample to determine the best choice among three values of the parameter $m = 5, 10, 15$ days. Only three possible values corresponding to one, two or three weeks were probed in sample. Since this article look into any possible impact coming from human anchoring, using only daily or weekly data seems a priori justified, since the higher the frequency of the trading (say seconds/minutes) the more computer dominated becomes the trading.

To look for arbitrage possibilities, weekly data were used to avoid the impact of transaction costs by trading too often. Another reason only to have looked at weekly data was because market participants, by actively following the price, create a subjective reference (anchor) and memory of when an asset is “cheap” or “expensive.” Several studies on the

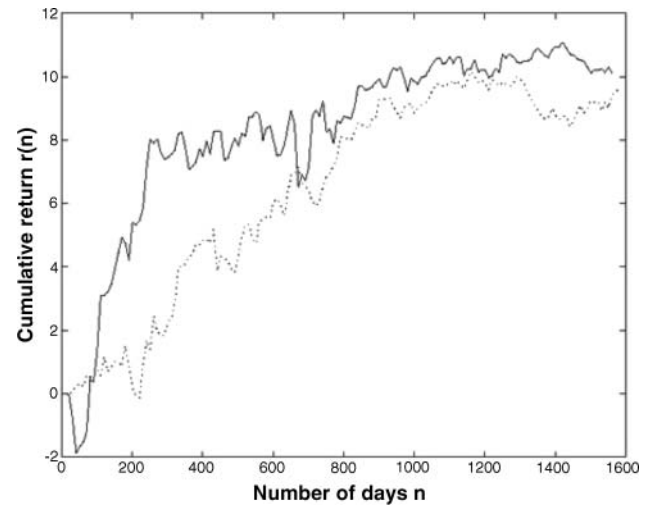


FIGURE 3 Cumulative return of the market neutral algorithm applied to daily price data of the Dow Jones stock index (dotted line), as well as the CAC40 stock index (solid line) over the period March 1, 2000–February 5, 2006. First half of the time period for the Dow Jones Industrial Average was used in sample to determine the best choice among three values of the parameter $m = 5, 10, 15$ days. Second half of the time period for the Dow as well as full period of the CAC40 index was done out of sample with $m = 10$. As a measure of the performance of the algorithm, the Sharpe ratio was found to be 2.0 and 2.94 for the Dow, respectively, CAC40 price time series. A trading cost of 0.1% was included for each transaction.

persistence of human memory have reported that sleep and posttraining wakefulness before sleep play important roles in the offline processing and consolidation of memory (Peignexu et al. [2006]). It therefore makes sense to think that conscious as well as unconscious mental processes influence the judgment of people who specialize in active trading on a day-to-day basis. The out-of-sample profit from the market neutral trading algorithm (with transaction costs taking into account) on the CAC40 index as well as the second period performance on the DJIA give evidence that anchoring does indeed play a dominant role on the weekly price fixing of the Dow and CAC40 stock markets and reconfirms the claim in Gil [2007] where especially the policy imposed by the European Monetary System was shown to lead to arbitrage possibilities. The results also give yet another illustration on the difficulty proving market efficiency by only considering lower order correlations in past price time series.

CONCLUSION

A trading algorithm inspired by biological motors and introduced by L. Gil is suggested as a testing ground for anchoring in financial markets. An exact solution of the algorithm was found for arbitrary price distributions and the algorithm was extended to cover the case of a market neutral portfolio. The exposure of arbitrage possibilities by the market neutral algorithm reveals additional evidence that anchoring is indeed involved in the decision making of market participants.

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APPENDIX: QUANTITATIVE DESCRIPTION OF THE TRADING ALGORITHM

Assume an agent at every time step t uses a fixed amount of his wealth to hold a long position in one out of N assets. For simplicity $N = 2$ will be used in the following, but the arguments can be extended to arbitrary N . Assume furthermore that the probability distribution functions (pdfs) of

the *price* of the two assets, $P_1(A_1)$, $P_2(A_2)$, are stationary distributions. Instead of the usual assumption of a random walk of the returns, short time anchoring of prices at quasi static price levels is imposed. No specific shape is assumed and the assets can be correlated or not, but any correlation is irrelevant for the following arguments. As noted in Gil [2007], the assumption of short-term "stationarity" of prices can arise because of price reversal dynamics caused by, for example, monetary policies. As will be argued and tested in the following, short-term "stationarity" in prices can also be created due to short-term human memory as to when an asset is "cheap" or "expensive." Consider any given instantaneous fluctuation of the prices (A_1, A_2) around their quasi static price levels ($\bar{A}_1, \bar{A}_2$). Classifying the $2^{**}N$ different cases according whether $A_i < \bar{A}_i$ or $A_i > \bar{A}_i$, one has for $N = 2$ the four different configurations xi:

x_1	x_2	x_3	x_4
$A_1 -$	$A_1 -$		
$\uparrow dA_1$	$\uparrow dA_1$		
$\bar{A}_1 -$	$\bar{A}_1 -$	$\bar{A}_1 -$	$\bar{A}_1 -$
		$\uparrow dA_1$	$\uparrow dA_1$
		$A_1 -$	$A_1 -$
	$A_2 -$		$A_2 -$
	$\uparrow dA_2$		$\uparrow dA_2$
$\bar{A}_2 -$	$\bar{A}_2 -$	$\bar{A}_2 -$	$\bar{A}_2 -$
$\uparrow dA_2$		$\uparrow dA_2$	
$A_2 -$		$A_2 -$	

In steady state the probability flux into a given configuration x_i equals the probability flux out of that configuration:

$$\sum_j P(x_j)P(x_j \rightarrow x_i) = \sum_j P(x_i)P(x_i \rightarrow x_j) \quad (1)$$

The averaged return per time unit in the steady state, R_{av} , is then given by:

$$R_{av} = \sum_{i=1}^4 \sum_{j=1}^4 P(x_i)P(x_i \rightarrow x_j)\tau_{av}(x_i \rightarrow x_j) \quad (2)$$

with $\tau_{av}(x_i \rightarrow x_j)$ the averaged return gained/lost in the transition $x_i \rightarrow x_j$. For each configuration x_i , one is assumed to hold a long position of either asset 1 or asset 2. Let $s = I$ be a state variable indicating that one is long one position of asset i . Then:

$$\tau_{av}(x_j \rightarrow x_k | s = k) = \int dA_k \int dA'_k \ln \left(\frac{A'_k}{A_k} \right) \times P(A'_k | x_i)P(A_k | x_j) \quad (3)$$

where $P(s = i | x_j)$ denotes the probability holding asset I given the knowledge to be in configuration x_j . $\tau_{av}(x_i \rightarrow x_j | s = k)$ denotes the averaged return in steady state holding asset k with a transition from configuration x_i to x_j and is given by:

$$R_{av} = \sum_{i=1}^4 \sum_{j=1}^4 \sum_{s=1}^2 P(x_i)P(x_i \rightarrow x_j)P(s | x_i) \int dA_k \int dA_l \times \ln \left(\frac{A_l}{A_k} \right) P(A_l | x_i)P(A_k | x_j) \quad (4)$$

$P(A_k | x_i)$ denotes the probability to get the price A_k conditioned on being in configuration x_i . Using (2–4), the general expression for the average return gained by the algorithm takes the form:

$$\sigma^2 = \langle (r - R_{av})^2 \rangle = \sum_{i=1}^4 \sum_{j=1}^4 \sum_{s=1}^2 P(x_i)P(x_i \rightarrow x_j) \times P(s | x_i) \int dA_k \int dA_l \ln \left(\frac{A_l}{A_k} \right)^2 P(A_l | x_i) \times P(A_k | x_j) - R_{av}^2 \quad (5)$$

The corresponding risk measured by the averaged standard deviation of the return is given by:

$$\sigma^2 = \langle (r - R_{av})^2 \rangle = \sum_{i=1}^4 \sum_{j=1}^4 \sum_{s=1}^2 P(x_i)P(x_i \rightarrow x_j)P(s | x_i) \times \int dA_k \int dA_l \ln \left(\frac{A_l}{A_k} \right)^2 P(A_l | x_i)P(A_k | x_j) - R_{av}^2 \quad (6)$$

The “trick” of the algorithm consists in breaking the symmetry by always choosing $P(s | x_i)$ according to the following rules:

$$\begin{aligned} P(s = 1 | x_1) &= 0; P(s = 2 | x_1) = 1; \\ P(s = 1 | x_2) &= P(s = 2 | x_2) = 1/2; \\ P(s = 1 | x_3) &= P(s = 2 | x_3) = 1/2; \\ P(s = 1 | x_4) &= 1; P(s = 2 | x_4) = 0 \end{aligned} \quad (7)$$

That is, if not already long, one always take a long position of asset 2 (1) whenever configuration x_1 (x_4) happens, since the asset is undervalued in this case. Likewise if one is long of asset 1 (2) whenever configuration x_1 (x_4) happens one sell that asset since it is overvalued. To illustrate the algorithm consider the simplest case where $P(A_i)$ take only two values $\bar{A}_i \pm dA_i$ with equal probability 1/2. Inserting:

$$\begin{aligned} P(A_1 | x_1) &= \delta(\bar{A}_1 + dA_1); P(A_1 | x_2) = \delta(\bar{A}_1 + dA_1); \\ P(A_1 | x_3) &= \delta(\bar{A}_1 - dA_1); P(A_1 | x_4) = \delta(\bar{A}_1 - dA_1); \\ P(A_2 | x_1) &= \delta(\bar{A}_2 - dA_2); P(A_2 | x_2) = \delta(\bar{A}_2 + dA_2); \\ P(A_2 | x_3) &= \delta(\bar{A}_2 - dA_2); P(A_2 | x_4) = \delta(\bar{A}_2 + dA_2) \end{aligned} \quad (8)$$

and $P(x_i) = P(x_i \rightarrow x_j) = 1/4$ into (6) one get the average return:

$$R_{av} = 1/8 \left[\ln \left(\frac{\bar{A}_1 + dA_1}{\bar{A}_1 - dA_1} \right) + \ln \left(\frac{\bar{A}_2 + dA_2}{\bar{A}_2 - dA_2} \right) \right] \quad (9)$$

with a variance given by:

$$\begin{aligned} \sigma_{av}^2 &= 15/64 \left[\ln \left(\frac{\bar{A}_1 + dA_1}{\bar{A}_1 - dA_1} \right) \right]^2 + 15/64 \left[\ln \left(\frac{\bar{A}_2 + dA_2}{\bar{A}_2 - dA_2} \right) \right]^2 \\ &\quad - 1/32 \left[\ln \left(\frac{\bar{A}_1 + dA_1}{\bar{A}_1 - dA_1} \frac{\bar{A}_2 + dA_2}{\bar{A}_2 - dA_2} \right) \right] \end{aligned} \quad (10)$$

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