European Fixed Income Strategy
J.P. Morgan Securities Ltd.
London, November 10, 2006

Euro Fixed Income Momentum Strategy

- **Momentum-based strategies provide attractive risk-adjusted trading returns in European fixed income.**
- **Our unfunded momentum strategy on 10-yr Bund futures gives an information ratio of 1.52 with annualised return of 6.3% since the start of EMU.**
- **Our out-of-sample results are also positive, with an information ratio well above 2.0 in 2006.**
- **A sensitivity analysis of the strategy to key parameters suggests the strategy is robust.**
- **The strategy shows that momentum works with a multi-week horizon. We do not find evidence of evidence of higher frequency momentum.**
- **The strategy is uncorrelated with the underlying market performance, suggesting a diversifying source of alpha.**
- **The strategy offers good downside protection: it offers high returns in trending markets, but the performance is flat in range trading markets.**
- **We discuss some of the academic studies reporting evidence of momentum in financial markets. We believe some of the findings in behavioural finance suggest market momentum may be a persistent process.**

INVESTMENT STRATEGIES: NO. 27

Introduction

In this paper we discuss JPMorgan's proprietary fixed income momentum trading strategy, applied to the Euro area bond market. The strategy employs a trend following strategy, based entirely on historical market prices and volatility. Our research suggests that employing a tactical trading strategy based on our strategy's momentum signal generates returns with an information ratio significantly higher than that of a simple buy-and-hold strategy on the European bond market.

In our view, the fundamental factors determining bond yields – savings gluts, leverage ratios, demographics, disinflation from emerging markets and inflation from commodity prices – are long term processes which are still evolving in significant ways. We expect these changing forces to continue driving bond yields, making many static equilibrium-models redundant. For this reason we believe investment strategies in the fixed income markets should be highly pragmatic, avoiding over-reliance on macro valuation metrics. With this perspective, when developing algorithmic trading strategies for the bond markets, we favour momentum trend-following methods over macro valuation-based models.

The certifying analyst is indicated by an [AC]. See page 14 for analyst certification and important legal and regulatory disclosures.

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By construction, trend-following strategies tend to cut losing trades relatively quickly. By contrast macro value based strategies will tend to advise increasing the size of a trade as the market moves away from the model's measure of fair value. In our view, this makes momentum based algorithms more robust than macro valuation algorithms to paradigm shifts in markets.

There is a substantial body of empirical academic research supporting the evidence of trending behaviour in financial markets. These studies have in turn led to the development of a new field of behavioural finance aiming to explain the presence of market momentum. One of the most common explanations for trending behaviour is that markets do not respond instantaneously to new information – rather it takes time for information to permeate the markets, leading to only gradual price adjustments. We find these explanations compelling, though we suspect it is not the speed at which information travels but rather that investors wait for market price action to confirm their interpretation of the data before acting – herding behaviour in other words.

Of course trend-following strategies are not without their own risks. Most obviously, if markets trade in narrow ranges for substantial periods, the model may repeatedly reverse positions leading to trading losses. This problem cannot be entirely eliminated; however, in our strategy we aim to mitigate this risk with trading rules designed to control trading frequency. Another risk associated with momentum strategies arises from sudden discontinuous market jumps. In practice these moves can lead to significant slippage between the price at which a trade is recommended and that at which it is executed. Again we aim to mitigate this risk by forcing the strategy to close positions in periods of unusually high market momentum.

In choosing any investment strategy, quantitative or otherwise, the data mining problem is ever present. In quantitative strategies the main risk is that a strategy is overly tailored towards historical data, and may not prove robust in the future. This problem can never be eliminated. However steps can be taken to minimize these risks. In particular the model should be parsimonious – the risk of over fitting the data set rises with the number of free parameters in the model. The model should be calibrated and tested on separate data sets, and the model should be checked to ensure it is robust to small changes in its parameter values.

Strategy description

The core principle of the strategy is to identify, as early as possible, a pattern of market returns inconsistent with randomly moving prices. This is done by comparing a weighted average of recent market returns with a measure of recent return volatility. Measuring the market movements against market volatility helps ensure the momentum we are observing is not merely the result of unusually volatile markets. A momentum signal is derived from the ratio of directional and volatility measures.

The essence of this approach is similar in spirit to statistical process control methods employed by manufacturing industries. These techniques are used to detect real-time errors in manufacturing processes, seeking to identify when parameters are no longer following a pattern consistent with normally distributed errors. Translated into financial markets, we seek to spot similar events: when bond returns are no longer random and uncorrelated the market may be drifting. That said, the distribution of returns in financial markets is neither normal nor consistent over time, making the process of defining an abnormal pattern of returns more difficult. A degree of empirical calibration is therefore required.

The virtues of exponential moving averages

With most momentum-based strategies, a fixed time window is specified over which momentum is measured – monthly or quarterly price changes or monthly moving average changes are typical momentum signals. These fixed window measures suffer the drawback of base effects: even in stagnant markets spurious signals can be generated as the passage of time causes old data to leave the sample window. In our strategy this problem is mitigated by employing an exponentially weighted moving average (also known as exponential moving average) of returns. This gives increasing weights to the most recent, and we believe most relevant, data. Using the exponential average, the parameter of the time window width is replaced with the decay rate of the moving average, lambda, this being one of the key parameters of the strategy.

The higher the lambda, the higher the weight attached to the most recent observation. In mathematical terms, given a series, x_t, x_{t-1}, ..., the exponential moving average $\bar{x}_t$ is:

$$\bar{x}_t = \lambda \sum_{i=0} (1-\lambda)^i x_{t-i}$$

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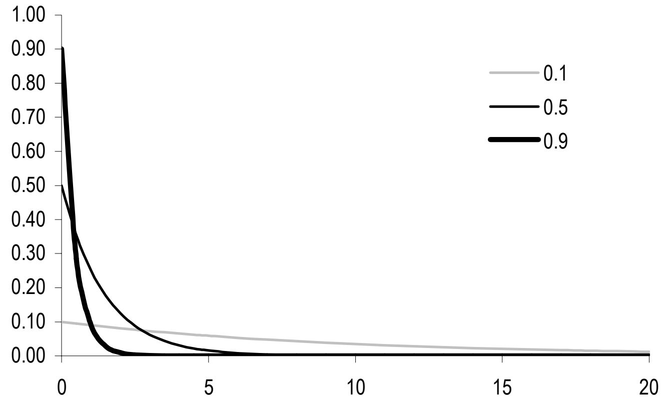
Chart 1: Relative weight of past observations in exponential moving average by lambda

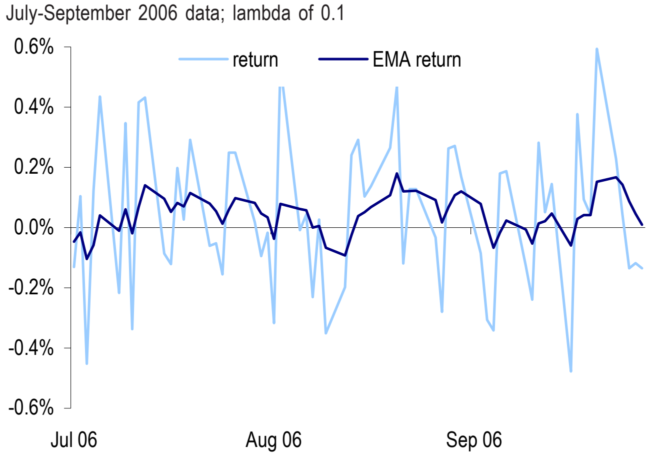
Days from last observation on x-axis



Source: JPMorgan

Chart 2: Example: 10-yr Bund futures daily return and exponential moving average

July-September 2006 data; lambda of 0.1



Source: JPMorgan

Table 1: Relative weight of past observations by lambda

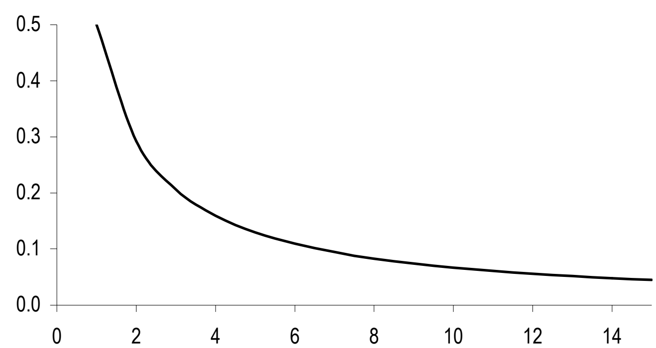
0 indicates the most recent observation; grey area indicates observations that make up 50% of weight

lambda	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50
0	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50
1	0.05	0.09	0.13	0.16	0.19	0.21	0.23	0.24	0.25	0.25
2	0.05	0.08	0.11	0.13	0.14	0.15	0.15	0.14	0.14	0.13
3	0.04	0.07	0.09	0.10	0.11	0.10	0.10	0.09	0.07	0.06
4	0.04	0.07	0.08	0.08	0.08	0.07	0.06	0.05	0.04	0.03
5	0.04	0.06	0.07	0.07	0.06	0.05	0.04	0.03	0.02	0.02
6	0.04	0.05	0.06	0.05	0.04	0.04	0.03	0.02	0.01	0.01
7	0.03	0.05	0.05	0.04	0.03	0.02	0.02	0.01	0.01	0.00
8	0.03	0.04	0.04	0.03	0.03	0.02	0.01	0.01	0.00	0.00
9	0.03	0.04	0.03	0.03	0.02	0.01	0.01	0.00	0.00	0.00
10	0.03	0.03	0.03	0.02	0.01	0.01	0.00	0.00	0.00	0.00
11	0.03	0.03	0.03	0.02	0.01	0.01	0.00	0.00	0.00	0.00
12	0.03	0.03	0.02	0.01	0.01	0.00	0.00	0.00	0.00	0.00
13	0.03	0.03	0.02	0.01	0.01	0.00	0.00	0.00	0.00	0.00
14	0.02	0.02	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00
15	0.02	0.02	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00

Source: JPMorgan

Chart 3 : Relationship between lambda and number of trading days required to reach a 50% weight in signal

Lambda on y-axis



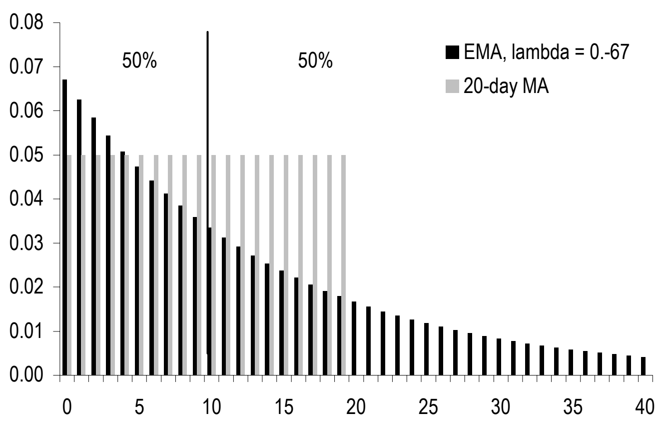
Source: JPMorgan

To make the concept of lambda a bit more intuitive, we can associate each lambda with the number of the most recent observations that sum up to a total weight of 50%. For instance if the lambda is 0.5, the return in the last day of trading has as much importance as all the previous trading information; if the lambda is set to 0.067, the most recent 10 trading days have a total weight of 50%, and so on.

Defining the relationship between the lambda in the exponential moving average and the number of observations required to reach at least a 50% weight helps a comparison with the more intuitive simple moving average. For example, using a lambda of 0.067, the most recent 10 observations have a total weight of 50%. In a simple moving average, 20 days have to be included, both with a 1/20 weight to give a weight of 50% to the most recent 10 observations.

Chart 4 shows that the weight attached to the 40 most recent observations of the two averages are very different. The mapping from one measure to the other is difficult but we think that 50% weight statistic is the best solution to make our results more intuitive. The higher the lambda, the lower the number of days in the simple moving average.

Chart 4 : 0.67 lambda EMA vs 20-day moving average weights
Observations on x-axis, 0 indicates the most recent observation



Source: JPMorgan

Building a momentum signal

Once we have calculated the exponential moving average of returns, we then divide it by a similar exponentially weighted average of historical return volatility. This series is our volatility adjusted momentum indicator.

$$\text{momentum signal} = \frac{\text{exponentially weighted average of returns}}{\text{exponentially weighted return volatility}}$$

From momentum signal to trading strategy

Having defined the momentum signal, the next step is to convert that signal into a trading strategy. The remaining parameters are the levels at which to initiate and cut trades. Being a trend-following strategy, the essence of the trading algorithm is to hold long positions when the signal shows positive momentum and short positions with negative momentum.

Strategy calibration

Sample, trading signal and timing

We use daily data between January 1999 (start of EMU) and December 2005 on the 10-year Bund future contract, assuming a roll on the fifth day of the delivery month. Expanding the sample to include the pre-EMU period gives very similar numbers in terms of parameters and results. The trading rule is then tested out of sample using 2006 data.

The strategy generates a buy/hold/sell signal at the close of each business day. The size of the trade is fixed, and not proportional to the strength of the signal. If the signal generates a trade recommendation, we enter the trade at the close of business level of the following working day.

Key parameters

In order to identify an optimal level for lambda in the exponential moving average, we start with a simple specification of the trading strategy: we buy the futures contract when the momentum signal is positive and we sell it when the signal is negative. This specification does not require any parametric choice of a trigger level for entering or exiting a trade.

Even for this very simple trading rule we found encouraging results with positive information ratios for different levels of the parameter lambda. The peak in the information ratio is in correspondence of a lambda of 0.1, equivalent to 7 most recent observations needed to reach a total weight of 50%. Therefore, according to our mapping the best evidence of momentum in associated to a simple moving average of around 13 days. We find no evidence of short term (a few days) momentum in the bond market nor of medium-long term momentum, present in other asset classes. Effectively, **a profitable momentum strategy in Bunds exploits the information provided by price movements over the past 2-3 weeks, rather than 2-3 days or 2-3 months**. See Appendix 1 for further analysis and Appendix 2 for a summary of the literature on momentum trading.

Having defined the lambda parameter in the exponential moving average, we then analyse a number of different trading algorithms. We find that removing weak signals around 0 does not improve the quality of the strategy. However, the strategy is improved if extreme signals are excluded. Intuitively, an upper threshold helps avoid overbought and oversold market conditions.

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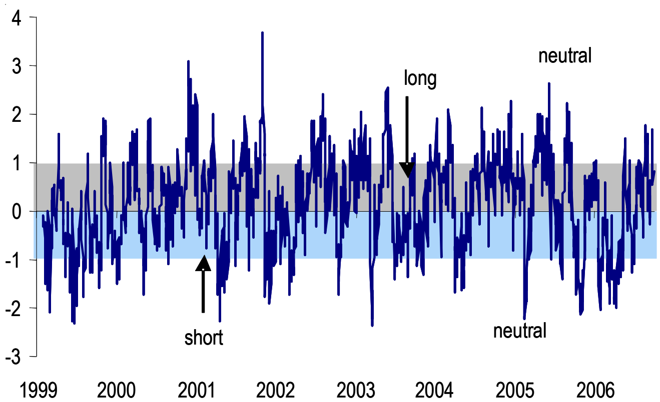
Chart 5 shows the normalised momentum signal and the trading recommendation. If the momentum signal is between 0 and 1, the recommendation is to be long the futures contract. Vice versa, if the momentum signal is negative, but higher than -1, the recommendation is to short the market.

Chart 5: Our momentum strategy: long when signal is between 0 and 1, short between -1 and 0

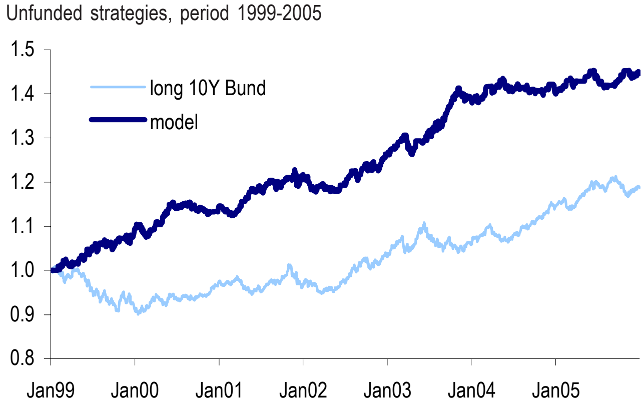


Source: JPMorgan

Summary results

Over our test period (Jan99-Dec05) our trading strategy showed an information ratio of 1.23, with annualised returns of 5.3% and annualised volatility of 4.3%. By contrast a simple buy and hold strategy on the Bund futures contract would have generated a Sharpe ratio of 0.45 with an annualised return of 2.3%. The two results assume unfunded investors. Chart 6 shows the daily performance of our strategy vs a long strategy in 10Y Bund futures.

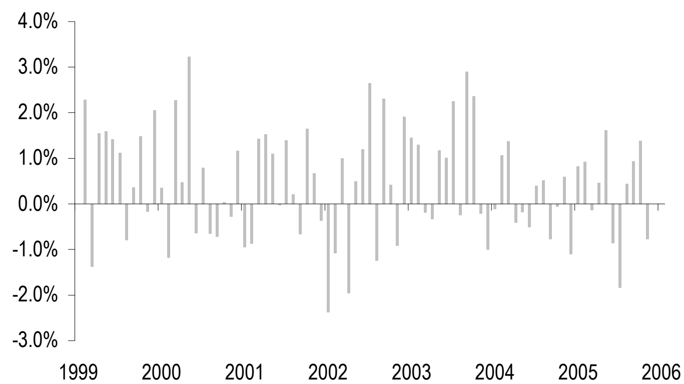
Chart 6: Momentum strategy vs long Bund future: performance
Unfunded strategies, period 1999-2005



Source: JPMorgan

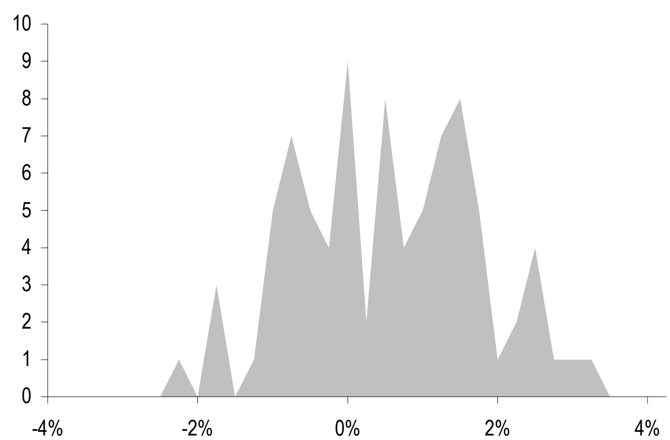
The monthly return profile is shown in Chart 7. **The strategy shows almost no correlation with the underlying market (0.04 for monthly returns)**. As one would expect from a momentum strategy, the strategy performs well in both bullish and bearish months.

Chart 7: Momentum strategy monthly P&L



Source: JPMorgan

Chart 8: Distribution of monthly returns



Source: JPMorgan

As expected from a momentum strategy, **the strategy works well in trending markets. More interestingly, the strategy offers good protection in case of range trading markets.** We divide our sample in two. We define a trending market if the monthly performance of a long 10yr Bund future is higher than 1% in absolute value and a range trading market if the performance of the underlying is less than 1%. The average

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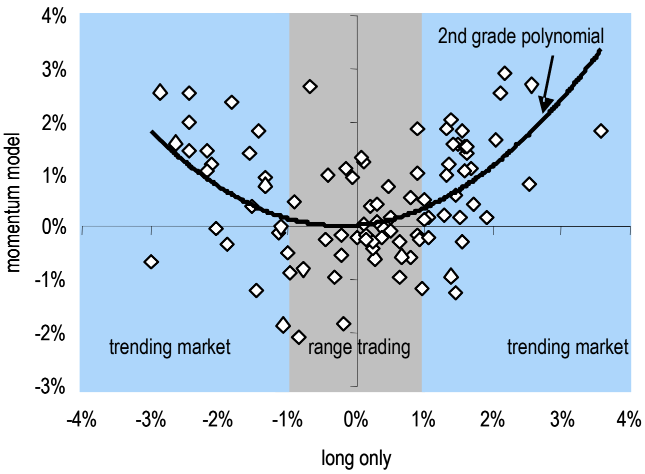
performance of the strategy in trending markets is 0.9%, whereas the performance is zero in range trading markets (see Chart 9).

Chart 9: Monthly strategy returns vs long 10-yr futures returns



Source: JPMorgan

The largest peak to trough loss is -5.7%, between November 27th 2001 and May 27th 2002. The strategy is slightly more successful at picking up bullish signals. The strategy generated 197 buy signals with an average profit of 12.8 ticks and 163 sell signals with an average profit of 8.9 ticks. See Appendix 1 for a sensitivity analysis of the parameters.

Out of sample analysis

The real test for any trading algorithm is the out of sample performance. In 2006, as of the beginning of October, the strategy would have generated an excess return of 6.3% (7.6% annualised) with annualised volatility of 3.4% to give a very high information ratio of 2.3. In the pre-EMU period for which we have data, the information ratio would have been around 1.

We present a summary table for the strategy over the full EMU period January 1999-September 2006.

Table 2: Summary statistics for the momentum strategy

Period: Jan 1999 - Sep 2006

Annualised return	5.5%
Volatility	4.2%
Information ratio	1.31
# trades	402
Average P&L per trade	12.9
Maximum peak to bottom loss	-5.7%
Best month	3.2%
Worst month	-2.4%
Correlation to long only strategy	0.03

Source: JPMorgan

One potential drawback of the momentum strategy is the relatively high frequency of trades as the trade recommendation switches between long and short when the trading signal is around zero. We therefore tested a modified trading rule that prevents from trading for two consecutive days. For instance, if the signal generates a buy recommendation for just one day, the position is kept open for two days.

The results are very positive. Not only is the number of trades drastically reduced (-22%), but the P&L per trade increases by around 50%. As a result, the information ratio rises to 1.52, with an average excess return of 6.3% per year (see Table 3). The out-of-sample performance is maintained: **between January and September 2006, the strategy would have generated an information ratio of 2.9.**

Table 3: Summary statistics for modified momentum strategy

Any position (long, short, neutral) has to be kept for at least two days;
Period: Jan 1999 - Sep 2006

Annualised return	6.3%
Volatility	4.2%
Information ratio	1.52
# trades	313
Average P&L per trade	19.5
Maximum peak to bottom loss	-4.1%
Best month	2.9%
Worst month	-2.1%
Correlation to long only strategy	0.08

Source: JPMorgan

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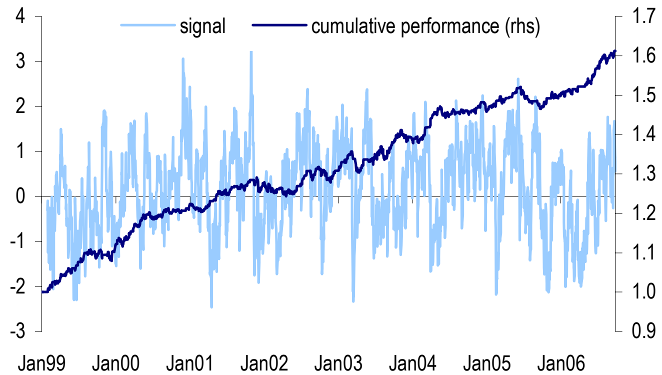
Chart 10: Modified momentum strategy signal and cumulative performance

Any position (long, short, neutral) has to be kept for at least two days;
Period: Jan 1999 - Sep 2006



Source: JPMorgan

Table 4: Modified momentum strategy summary statistics

Any position (long, short, neutral) has to be kept for at least two days;
Period: Jan 1999 - Sep 2006

	2006	2005	2004	2003	2002	2001	2000	1999
Annualised return	9.7%	2.6%	5.0%	6.3%	2.4%	5.1%	9.1%	11.1%
Volatility	3.3%	3.1%	3.5%	5.1%	4.3%	3.9%	4.1%	5.1%
Information ratio	2.90	0.86	1.44	1.23	0.56	1.30	2.20	2.18

Source: JPMorgan

Conclusion

This analysis shows that our momentum strategy on the 10-yr Bund futures would have delivered very good risk-adjusted returns. A profitable momentum strategy exploits the information provided by price movements over the past 2-3 weeks. The out of sample results in 2006 and sensitivity analysis suggest the strategy to is robust. The strategy is almost uncorrelated with the underlying market. The strategy works well in trending markets. More interestingly, the strategy offers good protection in case of range trading markets.

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Appendix 1: Sensitivity analysis

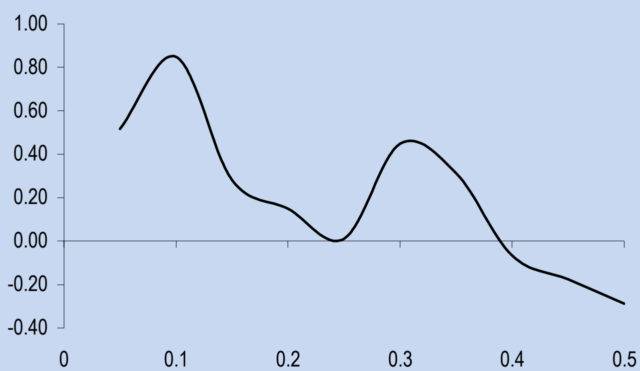
The idea behind our momentum model is very simple and its calibration involves the choices of just two parameters: the lambda in the exponential moving average to calculate the momentum signal and an exit threshold for the trading signal. Below we discuss the sensitivity of our results to the parameters. The sample period is January 1999-December 2005.

Lambda

The value of lambda in the exponential moving average determines the relative weighting of each of the past observations in the signal.

Chart 11 shows the information ratio of the simplest strategy (buy if momentum signal >0, sell otherwise) for different lamdbas. The information ratio is higher than 0.4 for lambdas lower than 0.15, with a peak at 0.1.

Chart 11: Information ratio of simplest strategy by lambda
Long if momentum signal >0, short otherwise
Period: Jan 1999 - Dec 2005

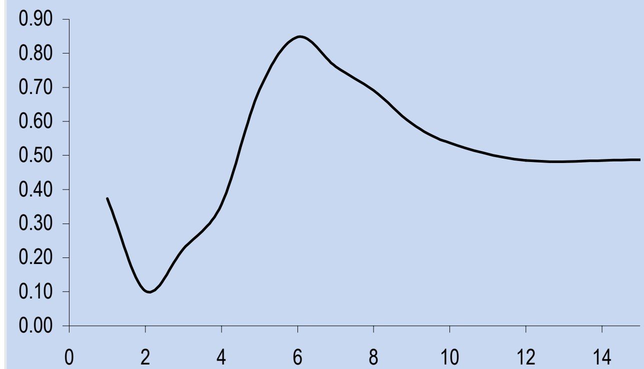


Source: JPMorgan

The data rejects the hypothesis of high frequency momentum, showing low or negative information ratios for lambdas higher than 0.15. As shown in Table 1, lambdas between 0.2 and 0.5 give a weight of 50% or more to 4 or less of the most recent observations. Momentum develops in weeks rather than days.

Chart 12 shows the information ratio by number of observations needed to reach a 50% weighting to better analyse the stability of our results and lower frequency momentum more in detail.

Chart 12: Information ratio of simplest strategy by numbers of trading days required to reach 50% weight in signal
Long if signal >0, short otherwise
Period: Jan 1999 - Dec 2005



Source: JPMorgan

Between 5 and 10 trading days (lambdas between 0.109 and 0.067) the information ratio is higher than 0.6. In other words, the best results are obtained with a distribution of the weighting similar to a 10- to 20-day moving average. The information ratio decreases very slowly as the number of days increases.

Exit threshold

We use a lambda of 0.1 to generate the momentum signal. We can now analyse the implementation of the trading strategy based on the momentum signal. A trading strategy that is long when the normalised momentum signal is between 0 and 1 and short when the signal is between -1 and 0 gives an information ratio of 1.23. This is a sharp improvement on the simplest strategy that does not cut the position in overextended market environments.

Chart 13 shows the information ratio assuming different exit thresholds. On the x-axis the exit threshold is expressed as a percentage of the normalised momentum signal, eg 120% corresponds to a strategy that takes long trading positions between 0 and 1.2 and shorts between -1.2 and 0. The results confirm the stability of our model with information ratios generally higher than 1 for thresholds between 50% and 150% of our chosen level.

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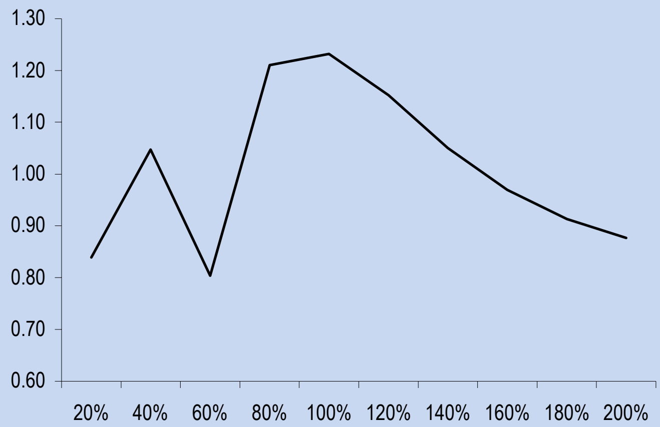
Chart 13: Information ratio of momentum model by exit threshold
Long if signal between x and 0, short between -x and 0
Period: Jan 1999 - Dec 2005



Source: JPMorgan

Appendix 2: Literature on momentum

Empirical evidence of momentum in markets

Numerous academic studies have found empirical evidence of market momentum, though as is common in financial literature the bulk of these studies have concentrated on the equity markets. Initially research focused on momentum in the US equity market: stocks that perform well (poorly) are found likely to continue to outperform (underperform) in the future. Jegadeesh and Titman (1993) find evidence of momentum on a medium term horizon, between 3 and 12 months. In their original paper they show that buying NYSE/AMEX stocks with high returns (top decile) over the previous 3 to 12 months and selling stocks with poor returns (bottom decile) over the same period would have generated an average profit of 1% per month in the period 1965-89.

Their approach had a significant influence on the analysis of momentum strategies. Their work was extended successfully to most foreign equity markets. Rouwenhorst (1998) and Chi et al. (2001) apply a similar methodology to the European and Asian stock markets. However, the evidence presented by Rouwenhorst (1999) and especially Griffin (2003) on emerging markets is less convincing. Bhojraj and Swaminathan (2001) find evidence of momentum between international equity markets: Past six month country stock indices earning the highest returns outperform past six month losers over the next year. Ribeiro (2006) extends the framework to a multi-asset portfolio. The assets included range from the traditional equities and bonds to commodities, hedge funds and real estate indices. Once again, assets that have performed best in the prior six months outperform assets with the worst performance on a medium term horizon. The long-short strategy gives a Sharp ratio close to 1 in the period between 1994 and 2005.

The literature on momentum in fixed income is less abundant. Schneeweis et al. (2006) apply momentum rules to both fixed income and equity futures. The use of highly liquid futures contracts allows increased trading frequency. Also, compared to the papers cited above, evidence of momentum is found at much shorter time horizons. In their specification, the daily trading signal is long (short) if the total return of the futures contract over the prior 15, 27 and 55 days is positive (negative). The trading signals on different futures are aggregated in indices adjusting for the relative risk. The authors report that over the period 1992-2005 and index of fixed income futures based on this strategy would have generated a Sharpe ratio of 0.86 (the Sharpe ratio for the equity index is 0.48).

The analysis and model of Schneeweis et al. is the closest to our model: Futures contracts are used to minimise transaction costs, and trading signals are generated on a daily basis rather than monthly or every six months as in other models. Finally, the signal is on single instruments, generating long or short positions, rather than relative value signals generating switches between past good and bad performers.

Behavioural Finance explains market momentum

Behavioral finance explanations for the presence of market momentum depart from the usual assumption of investor rationality, permitting instead irrational or bounded rational behaviour. Behavioral finance researchers have found experimental evidence indicating the presence of irrational decision making behaviour.

Daniel et al. (1998) aim at developing a psychological theory of security markets to explain well documented anomalies such as short term momentum and long term reversal, event-based return predictability, etc... Their theory is based on investor overconfidence, and variations in confidence due to biased-self attribution. In their words: *"If an investor overestimated his ability to generate information, or to identify the significance of existing data that others neglect, he will underestimate his forecast errors. ... he will tend to be more overconfident about the information he has generated (private signal) but not about public signals. ... We assume that when an investor receives confirming public information, his confidence rises, but disconfirming information causes confidence to fall only modestly, if at all. Thus, if an individual begins with unbiased beliefs about his ability, new public signals on average are viewed as confirming the validity of his private signal. This suggests that public information can trigger further overreaction to a preceding private signal. We show that such continuing overreaction causes momentum in security prices..."*

Barberis et al. (1998) focus on representativeness and conservatism. Representativeness is the tendency to view events as typical or representative of some specific class and to ignore the laws of probability in the process. Conservatism can be defined as slow updating of models in the face of new evidence. In their model, although earnings might follow a random walk, investors "extrapolate" from observed earnings to define two regimes: mean reverting or trending. For instance when a positive surprise is flowed by another positive surprise, investors raise the likelihood that he is in the trending regime.

Market momentum is not necessarily due to investors' irrational behaviour. Hong and Stein (1999) assume bounded investor rationality, but it is the interaction between two types of investors with different characteristics (newswatchers and momentum traders) and slow diffusion of private information that generate momentum: *"Each newswatcher observes some private information, but fails to extract other newswatchers' information from prices. If information diffuses gradually across the population, prices underreact in the short run. The underreaction means that the momentum traders can profit by trend chasing."*

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