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Two centuries of trend following

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We establish the existence of anomalous excess returns based on trend-following strategies across four asset classes (commodities, currencies, stock indexes and bonds) and over very long time scales. We use for our studies both futures time series that have existed since 1960 and spot time series that allow us to go back to 1800 on commodities and indexes. The overall t-statistic of the excess returns is approximately equal to five since 1960 and approximately equal to ten since 1800, after accounting for the overall upward drift of these markets. The effect is very stable, across both time and asset classes. It makes the existence of trends one of the most statistically significant anomalies in financial markets. When analyzing the trend-following signal further, we find a clear saturation effect for large signals, suggesting that fundamentalist traders do not attempt to resist "weak trends", but step in when their own signal becomes strong enough. Finally, we study the performance of trend following in the recent period. We find no sign of a statistical degradation of long trends, whereas shorter trends have significantly withered.

This work is the result of many years of research at Capital Fund Management (CFM). Many colleagues must be thanked for their insights, in particular P. Aliferis, N. Bercot, A. Berd, D. Challet, L. Dao, B. Durin, P. Horvai, L. Laloux, A. Landier, A. Matacz, D. Thesmar, T. Tu and M. Wyart.

1 INTRODUCTION

Are markets efficient, in the sense that all public information is included in current prices? If this were so, price changes would be totally unpredictable in the sense that no systematic excess return based on public information could be achievable. After decades of euphoria in economics departments,[1] serious doubts were raised by behavioral economists, who established a long series of pricing "anomalies" (Schwert 2003). The most famous of these anomalies (and arguably the most difficult to sweep under the rug) is the so-called excess volatility puzzle, unveiled by Shiller and others (Leroy and Porter 1981; Shiller 1981). Strangely (or wisely?) the 2013 Nobel committee decided not to take sides, and declared that markets are indeed efficient (as claimed by laureate Eugene Fama), but that the theory actually makes "little sense" (as argued by Robert Shiller, who shared the same prize!).[2] (See also de Bondt and Thaler (1985), Black (1986) and Summers (1986) for insightful papers on this debate.)

In the list of long-known anomalies, the existence of trends plays a special role. First, because trending is the exact opposite of the mechanisms that should ensure that markets are efficient, ie, reversion forces that drive prices back to the purported fundamental value. Second, because persistent returns validate a dramatically simple strategy, "trend following", which amounts to buying when the price goes up, and selling when it goes down. Simple as it may be (Covel 2009), this strategy is at the heart of the activity of commodity trading advisors (CTAs; Bartas and Kosowski 2012), an industry that now manages (as of 2013 Q4) no less than US$325 billion, representing around 16% of the total assets of the hedge fund industry, and accounting for several percent of the daily activity of futures markets (Mundt 2014).[3] These numbers are by no means small, and make it hard for efficient market enthusiasts to dismiss this anomaly as economically irrelevant.[4] The strategy is furthermore deployed over a wide range of instruments (indexes, bonds, commodities, currencies, etc) with positive reported performance over long periods, suggesting that the anomaly is to a large extent universal, across both epochs and asset classes.[5] This reveals an extremely

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[1] "There is no other proposition in economics which has more solid empirical evidence supporting it than the efficient market hypothesis", as M. Jensen famously wrote in 1978.

[2] Together with a third scientist, Lars Hansen, who had not directly taken part in the debate.

[3] Futures markets allow traders to go short as easily as going long. Therefore, both up-trends and down-trends can be exploited equally.

[4] Jensen (1978) actually stressed the importance of trading profitability in assessing market efficiency. In particular, if anomalous return behavior is not definitive enough for an efficient trader to make money trading on it, then it is not economically significant.

[5] Note that the excess return of trends cannot be classified as a risk premium either (see Lempérière *et al* 2014; Narasimhan and Titman 2011). On the contrary, trend following is correlated with "long-vol" strategies.

persistent, universal bias in the behavior of investors who appear to hold "extrapolative expectations", as argued in many papers coming from different strands of the academic literature (see, for example, Bouchaud and Cont 1998; DeLong *et al* 1990; Greenwood and Shleifer 2014; Hirshleifer and Yu 2012; Hommes *et al* 2008; Hong and Stein 1999; Kent *et al* 1998; Kirman 1991, 1993; Smith *et al* 1988 and the references therein).

Many academic studies have already investigated this trend anomaly on a wide range of assets, and have convincingly established its statistical significance in the last few decades (Clare *et al* 2012; Szakmary *et al* 2010). Recently, this time horizon has been extended to 100 years by Hurst *et al* (2012), and the effect still exists unabated. The aim of the present paper is to extend the time horizon even further, to 200 years, as far in the past as we have been able to go in terms of data. We find that the amplitude of the effect has been remarkably steady over two centuries. This also allows us to assess the recent weakening of the effect (as testified by the relatively poor performance of CTAs over the last five years). We show that the very recent past is fully compatible with a statistical fluctuation. Although we cannot exclude that this recent period is a precursor of the "end of trends", we argue theoretically that this is an unlikely scenario. We give several mechanisms that could explain the existence and persistence of these trends throughout history.

Note that trends exist not only for market factors such as indexes, bonds and currencies, but also cross-sectionally in stock markets. The so-called momentum anomaly consists in buying the past winners and selling the past losers in a market-neutral way, again with a high statistical significance across many decades and different geographical zones (see Barroso and Santa-Clara 2013; Kent and Moskowitz 2013; Narasimhan and Titman 1993; see also Narasimhan and Titman (2011) and Geczy and Samonov (2013) for recent reviews). Although interesting in its own right (and vindicating the hypothesis that trend following is universal (Asness *et al* 2013)), we will not study this particular aspect of trend following in the present paper.

The outline of the paper is as follows. In Section 2, we define the trend-following indicator used for this study and test its statistical significance on available futures data. We start with futures since they are the preferred instruments of trend followers in finance. Also, their prices are unambiguously defined by transparent market trades, and not the result of a proprietary computation. In Section 3, we carefully examine, for each asset class, how the available time series can be extended as far in the past as possible. In Section 4 we then present our results over two centuries, and show how exceptionally stable long trends have been. We examine more deeply the linearity of the signal, and find that the trend predictability saturates for large values of the signal, which is needed for the long-term stability of markets. And finally, in Section 5, we discuss the significance of the recent performance of the trend in light of this long-term simulation.

2 TREND FOLLOWING ON FUTURES SINCE 1960

2.1 Measuring trends

We choose to define our trend indicator in a way similar to simulating a constant risk trading strategy (without costs). More precisely, we first define the reference price level at time t, $\langle p \rangle_{n,t}$, as an exponential moving average of past prices (excluding $p(t)$ itself) with a decay rate equal to n months. Long simulations can often only be performed on monthly data, so we use monthly closes. The signal $s_n(t)$ at the beginning of month t is constructed as

$$s_n(t) = \frac{p(t-1) - \langle p \rangle_{n,t-1}}{\sigma_n(t-1)}, \tag{2.1}$$

where the volatility σ_n is equal to the exponential moving average of the absolute monthly price changes, with a decay rate equal to n months. The average strength of the trend is then measured as the statistical significance of fictitious profits and losses (P&Ls) of a risk managed strategy that buys or sells (depending on the sign of s_n) a quantity $\pm\sigma_n^{-1}$ of the underlying contract α:[6]

$$Q_n^{\alpha}(t) = \sum_{t'<t} \operatorname{sgn}[s_n(t')] \frac{p(t'+1) - p(t')}{\sigma_n(t'-1)}. \tag{2.2}$$

In the rest of the paper, we will focus on the choice $n = 5$ months, although the dependence on n will be discussed. Of course, different implementations can be proposed. However, the general conclusions are extremely robust against changes to the statistical test or to the implemented strategy (see, for example, Bartas and Kosowski 2012; Clare *et al* 2012; Szakmary *et al* 2010).

In the following, we will define the Sharpe ratio of the P&L as its average return divided by its volatility, both annualized. Since the P&L does not include interest earned on the capital, and futures are self-financed instruments, we do not need to subtract the risk-free rate to compute the Sharpe ratio. The t-statistic of the P&L (ie, the fact that the average return is significantly different from zero) is therefore given by the Sharpe ratio times $\sqrt{N}$, where N is the number of years over which the strategy is active. We will also define the drift μ of a time series as the average daily return of the corresponding instrument, which would be the P&L of the long-only strategy if financing costs were to be neglected.

2.2 The pool of assets

Since we wish to prove that trend following is a universal effect not restricted to any one asset, we would like to test this signal on as large a pool as possible. This is also

[6] We call this a fictitious P&L since no attempt is made to model any realistic implementation costs of the strategy.

important in practice, since diversification plays an important role in the performance of CTAs. However, since the purpose of this paper is to backtest the trend on a very large history, we voluntarily limit ourselves to the contracts for which a long data set is available. This naturally makes the inclusion of emerging markets more difficult. Therefore, for indexes, bonds and currencies, we only consider the following seven countries: Australia, Canada, Germany, Japan, Switzerland, the United Kingdom and the United States. We believe the results of this section would only be improved by the choice of a wider pool.

We also need to select a pool of commodities. In order to have a well-balanced pool, we chose the following seven representative contracts: crude oil, Henry Hub natural gas, corn, wheat, sugar, live cattle and copper.

In summary, we have a pool made up of seven commodity contracts, seven ten-year bond contracts, seven stock index contracts and six currency contracts. All the data used in the current paper comes from Global Financial Data (GFD).[7]

2.3 The results

Our history of futures starts in 1960, mostly with commodities. As we can see from Figure 1 on the next page, the aggregated performance $\sum_{\alpha} Q_n^{\alpha}(t)$ looks well-distributed in time, with an overall t-statistic of 5.9, which is highly significant. The Sharpe ratio and t-statistic are only weakly dependent on n (see Table 2 on page 47).

However, we might argue that this comes from the trivial fact that there is an overall drift μ in most of these time series (for example, the stock market tends to go up over time). It is therefore desirable to remove this "long" bias, by focusing on the residual of the trend-following P&L when the β with the long-only strategy has been factored in. In fact, the correction is found to be rather small, since the trend-following P&L and the long-only strategy are only $+15\%$ correlated. Still, this correction slightly decreases the overall t-statistic of the trend-following performance, to 5.0.

In order to assess the significance of the above result, we break it down into different sectors and decades. As shown in Table 2 on page 47 and Table 3 on page 47, the t-statistic of the trend-following strategy is above 2.1 for all sectors and all decades, and above 1.6 when debiased from the drift μ. Therefore, the performance shown in Figure 1 on the next page is well-distributed across all sectors and periods, which strongly supports the claim that the existence of trends in financial markets is indeed universal. One issue, though, is that our history of futures only goes back fifty years or so, and the first ten years of those fifty is only made up of commodities. In order to test the stability and universality of the effect, it is desirable to extend the time series to go back further in the past, in order to span many economic cycles and different

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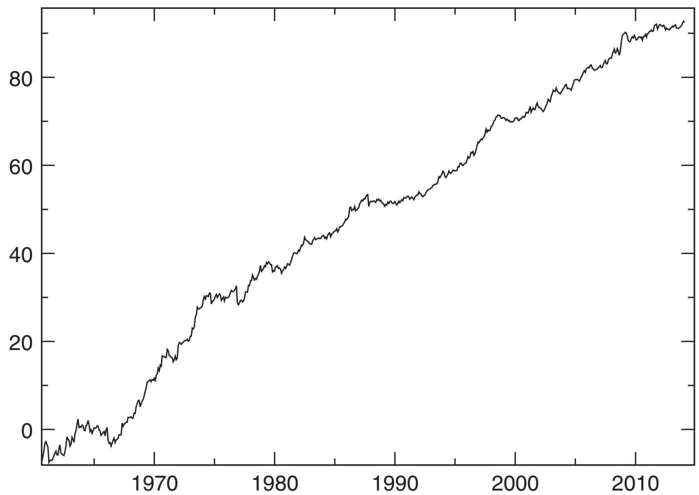
[7] See www.globalfinancialdata.com.

FIGURE 1 Fictitious P&L, as given by (2.2), of a five-month trend-following strategy on a diversified pool of futures.



t-statistic = 5.9 (corresponding to a Sharpe ratio = 0.8). Debiased t-statistic = 5.0.

TABLE 1 Sharpe ratio and t-statistic of the trend (T) and t-statistic of the debiased trend (T^*) for different time horizons n (in months), since 1960.

Time-scale n (months)	SR (T)	t-statistic (T)	t-statistic (T^*)
2	0.8	5.9	5.5
3	0.83	6.1	5.5
5	0.78	5.7	5.0
7	0.8	5.9	5.0
10	0.76	5.6	5.1
15	0.65	4.8	4.5
20	0.57	4.2	3.3

macroenvironments. This is the goal of the next section, which provides a convincing confirmation of the results based on futures.

3 EXTENDING THE TIME SERIES: A CASE-BY-CASE APPROACH

We now try to find proxies for the futures time series that are reasonably correlated with the actual futures prices on the recent period but allow us to go back in the

TABLE 2 Sharpe ratio and t-statistic of the trend (T) for $n = 5$, of the debiased trend (T^*) and of the drift component μ of the different sectors, and the starting date for each sector.

Sector	SR (T)	t-statistic (T)	t-statistic (T^*)	SR (μ)	t-statistic (μ)	Start date
Currencies	0.57	3.6	3.4	0.05	0.32	May 1973
Commodities	0.8	5.9	5.0	0.33	2.45	Jan 1960
Bonds	0.49	2.8	1.6	0.58	3.3	May 1982
Indexes	0.41	2.3	2.1	0.4	2.3	Jan 1982

TABLE 3 Sharpe ratio and t-statistic of the trend (T) for $n = 5$, of the debiased trend (T^*) and of the drift component μ for each decade.

Period	SR (T)	t-statistic (T)	t-statistic (T^*)	SR (μ)	t-statistic (μ)
1960–1970	0.66	2.1	1.8	0.17	0.5
1970–1980	1.15	3.64	2.5	0.78	2.5
1980–1990	1.05	3.3	2.85	−0.03	−0.1
1990–2000	1.12	3.5	3.03	0.79	2.5
>2000	0.75	2.8	1.9	0.68	2.15

past a lot further. Natural candidates are spot prices on currencies, stock indexes and commodities, and government rates for bonds. We shall examine each sector independently. Before doing so, however, we should mention other important restrictions on the use of the historical data. First, we expect trends to develop only on freely traded instruments, where price evolution is not distorted by state interventions. Also, we require a certain amount of liquidity, in order to have meaningful prices. These two conditions, free-floating and liquid assets, will actually limit us when we look back in the distant past.

3.1 Currencies

The futures time series goes back to 1973. In the previous period (1944–71), the monetary system operated under the rules set out in the Bretton Woods agreements. According to these international treaties, the exchange rates were pegged to the US dollar (within a 1% margin), which remained the only currency that was convertible into gold at a fixed rate. Therefore, no trend can be expected on these time series, where prices are limited to a small band around a reference value.

Prior to this, the dominant system was the Gold Standard. In this regime, the international value of a currency was determined by a fixed relationship with gold. Gold in turn was used to settle international accounts. In this regime we also cannot expect trends to develop, since the value of the currency is essentially fixed by its conversion rate with gold. In the 1930s, many countries dropped out of this system, massively devaluing in a desperate attempt to manage the consequences of the Great Depression (the "beggar thy neighbor" policy). This also led to massively managed currencies, with little hope of finding any genuine trending behavior.

All in all, therefore, it seems unlikely that we can find a free-floating substitute for our futures time series on foreign exchange prior to 1973.

3.2 Government rates

Government debt (and default!) has been around for centuries (Reinhart and Rogoff 2009), but in order to observe a trend on interest rates we need a liquid secondary market, on which the debt can be exchanged at all times. This is a highly nontrivial feature for this market. Indeed, throughout most of the available history, government debt has been used mostly as a way to finance extraordinary liabilities, such as wars. In other periods of history, debt levels gradually reduced, as the principals were repaid, or washed away by growth (as debt levels are quoted relative to GDP).

As a typical example, we can see in Figure 2 on the facing page that the US debt, inherited from the War of Independence, fell to practically zero in 1835–6, during the Jackson presidency. There is another spike in 1860–65, during the American Civil War, which then gets gradually washed away by growth. We have to wait until World War I to see a significant increase in debt, which then persists until today. Apart from Australia, whose debt has grown at a roughly constant rate, and Japan, whose turning point is around 1905, during the Russo-Japanese War, the situation in all other countries is similar to that of the United States. From this point onward, the debt has never been repaid in its totality in any of the countries we consider in this study, and has mostly been rolled over from one bond issuance to the next.

Another more subtle point can explain the emergence of a stable debt market: at the beginning of the twentieth century, the monetary policy (in its most straightforward sense: the power to print money) was separated from the executive instances and attributed to central banks, supposedly independent of the political power (see Figure 4 on the facing page). This move increased the confidence in the national debt of these countries, and helped boost subsequent debt levels.

All of this leads us to the conclusion that the bond market before 1918 was not developed enough to be considered as "freely traded and liquid". Therefore, we start our interest rate time series in 1918. We should note as well that we exclude from the

FIGURE 2 Global debt of the US government (a) in billions of US dollars and (b) as a fraction of GDP.

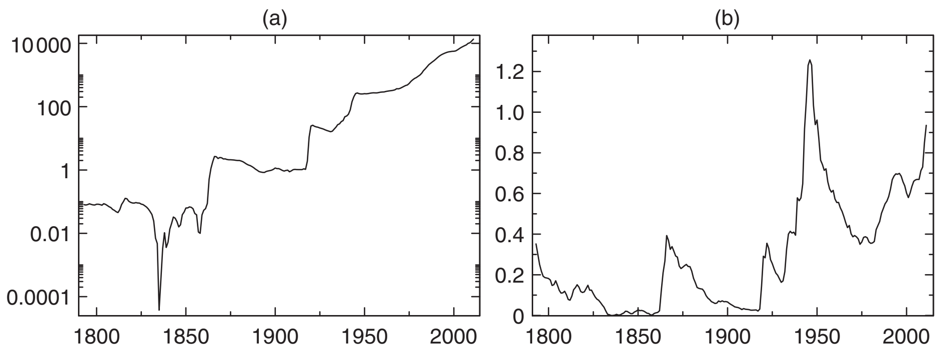


TABLE 4 Starting date of the central bank's monopoly on the issuance of notes.

Country	Start
United States	1913
Australia	1911
Canada	1935
Germany	1914
Switzerland	1907
Japan	1904
United Kingdom	1844

The Bank of England does not have this monopoly in Scotland and Ireland, but regulates the commercial banks that share this privilege.

time series World War II and the immediate post-war period in Japan and Germany, where the economy was heavily managed, therefore leading to price distortions.

3.3 Indexes and commodities

For these sectors, the situation is more straightforward. Stocks and commodities were actively priced throughout the nineteenth century, so it is relatively easy to get clean, well-defined prices. As we can see from Table 5 on the next page and Table 6 on the next page, we can characterize trend-following strategies for over two centuries on some of these time series. Apart from some episodes that we excluded, such as World War II in Germany and Japan, where the stock market was closed, or the period through which the price of crude oil was fixed (in the second half of the twentieth

TABLE 5 Starting date of the spot index monthly time series for each country.

Country	Start
United States	1791
Australia	1875
Canada	1914
Germany	1870
Switzerland	1914
Japan	1914
United Kingdom	1693

TABLE 6 Starting date of the spot price for each commodity.

Commodity	Start
Crude oil	1859
Natural gas	1986
Corn	1858
Wheat	1841
Sugar	1784
Live cattle	1858
Copper	1800

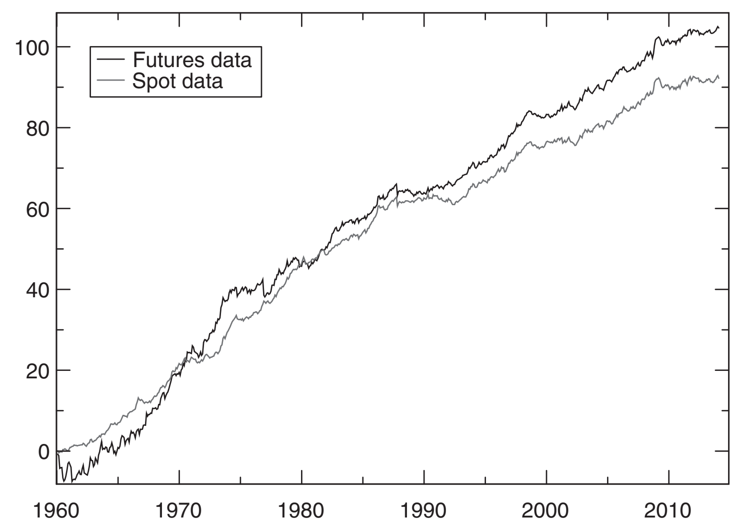
century), the time series are of reasonably good quality, ie, prices are actually moving (no gaps) and there are no major outliers.

3.4 Validating the proxies

We now want to check that the time series selected above, essentially based on spot data on ten-year government bonds, indexes and commodities, yield results that are very similar to those we obtained with futures. This will validate our proxies and allow us to extend, in the following section, our simulations to the pre-1960 period.

In Figure 3 on the facing page we show a comparison of the trend applied to futures prices and to spot prices in the period of overlapping coverage between the two data sets. From 1982 onward we have futures in all four sectors and the correlation is measured to be 91%, which we consider to be acceptably high. We show the correlations per sector calculated since 1960 in Table 7 on the facing page and observe that the correlation remains high for indexes and bonds but is lower for commodities, with a correlation of 65%. We know that the difference between the spot and futures prices is the so called "cost of carry", which is absent for the spot data, this additional

FIGURE 3 Trend on spot and on futures prices.



The overall agreement since the late 1960s (when the number of traded futures contracts becomes significant) is very good, although the average slope on spots is slightly smaller, as expected.

TABLE 7 Correlation between spot and futures trend-following strategies.

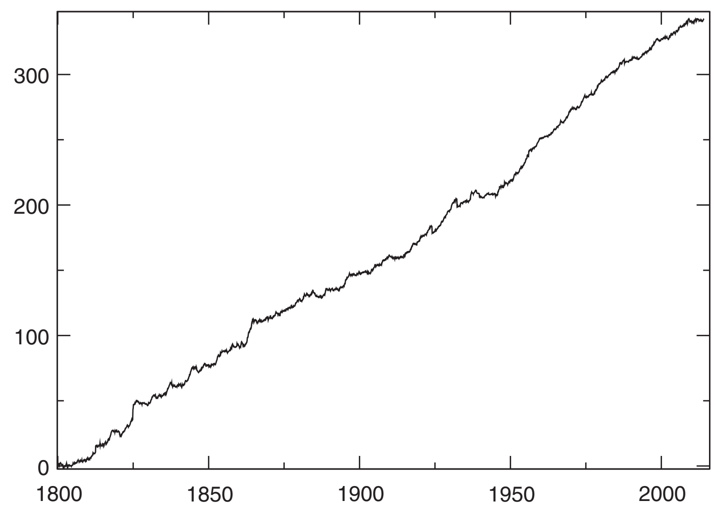
Sector	Spot–future correlation
Commodities	0.65
Bonds	0.91
Indexes	0.92

Even though the “cost of carry” plays an important role for commodities, the trends are still highly correlated.

term being especially significant and volatile for commodities. We find, however, that the level of correlation is sufficiently high to render the results meaningful. In any case the addition of the cost of carry can only improve the performance of the trend on futures and any conclusion regarding trends on spot data will be further confirmed by the use of futures data.

We therefore feel justified in using the spot data to build statistics over a long history. We believe that the performance will be close to (and in any case, no worse than) that on real futures, in particular because average financing costs are small, as illustrated by Figure 3.

FIGURE 4 Aggregate performance of the trend on all sectors.



t-statistic = 10.5. Debiased t-statistic = 9.8. Sharpe ratio = 0.72.

TABLE 8 Sharpe ratio and t-statistic of the trend (T), of the debiased trend (T^*) and of the drift component μ of the different sectors, with the starting date for each sector.

Sector	SR (T)	t-statistic (T)	t-statistic (T^*)	SR (μ)	t-statistic (μ)	Start date
Currencies	0.47	2.9	2.9	0.1	0.63	1973
Commodities	0.28	4.1	3.1	0.3	4.5	1800
Bonds	0.4	3.9	2.7	−0.1	−1	1918
Indexes	0.7	10.2	6.3	0.4	5.7	1800

4 TREND OVER TWO CENTURIES

4.1 Results of the full simulation

The performance of the trend-following strategy defined by (2.2) over the entire time period (two centuries) is shown in Figure 4. It is visually clear that the performance is highly significant. This is confirmed by the value of the t-statistic, which is found to be above 10, and 9.8 when debiased from the long-only contribution, ie, the t-statistic of "excess" returns. For comparison, the t-statistic of the drift μ of the same time series is 4.6. As documented in Table 8, the performance is furthermore significant on each individual sector, with a t-statistic of 2.9 or higher, and 2.7 or higher when the long

TABLE 9 Sharpe ratio and t-statistic of the trend and of the drift μ over periods of fifty years.

Period	SR (T)	t-statistic (T)	SR (μ)	t-statistic (μ)
1800–1850	0.6	4.2	0.06	0.4
1850–1900	0.57	3.7	0.43	3.0
1900–1950	0.81	5.7	0.34	2.4
After 1950	0.99	7.9	0.41	2.9

bias is removed. Note that the debiased t-statistic of the trend is in fact higher than the t-statistic of the long-only strategy, with the exception of commodities, where it is slightly worse (3.1 versus 4.5).

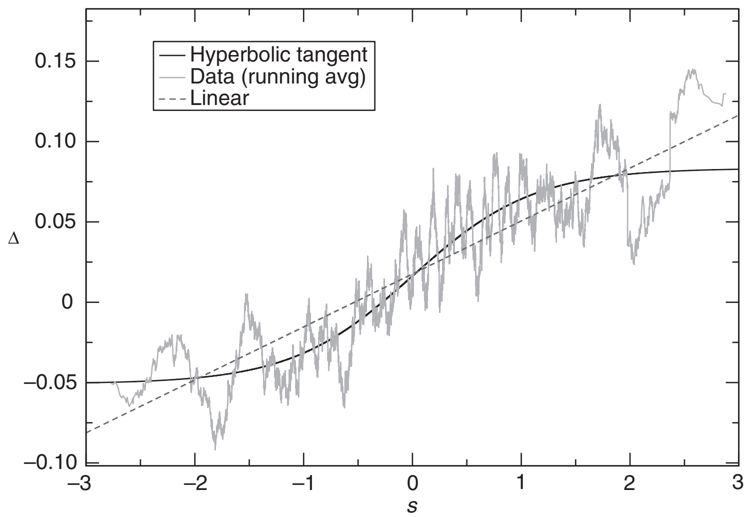
The performance is also remarkably constant over two centuries: this is obvious from Figure 4 on the facing page, and we report the t-statistic for different periods in Table 9. The overall performance is in fact positive over every decade in the sample (see Figure 7 on page 55). The increase in performance in the second half of the simulation probably comes from the fact that we have more and more products as time goes on (indeed, government yields and currencies both start well into the twentieth century).

4.2 A closer look at the signal

It is interesting to delve deeper into the predictability of the trend-following signal $s_n(t)$, defined in (2.1). Instead of computing the P&L given by (2.2), we can instead look at the scatter plot of $\Delta(t) = p(t+1) - p(t)$ as a function of $s_n(t)$. This gives a noisy blob of points with, to the naked eye, very little structure. However, a regression line through the points leads to a statistically significant slope, ie, $\Delta(t) = a + bs_n(t) + \xi(t)$, where $a = 0.018 \pm 0.003$, $b = 0.038 \pm 0.002$ and ξ is a noise term. The fact that $a > 0$ is equivalent to saying that the long-only strategy is, on average, profitable, whereas $b > 0$ indicates the presence of trends. However, it is not *a priori* obvious that we should expect a linear relation between Δ and s_n. Trying a cubic regression gives a very small coefficient for the s_n^2 term and a clearly negative coefficient for the s_n^3 term, indicating that strong signals tend to flatten, as suggested by a running average of the signal shown in Figure 5 on the next page. However, the strong mean reversion that such a negative cubic contribution would predict for large values of s_n is suspicious. We have therefore instead tried to model a nonlinear saturation through a hyperbolic tangent (Figure 5 on the next page):

$$\Delta(t) = a + bs^* \tanh\left(\frac{s_n(t)}{s^*}\right) + \xi(t), \tag{4.1}$$

FIGURE 5 Fit of the scatter plot of $\Delta(t) = p(t+1) - p(t)$ as a function of $s_n(t)$, for $n = 5$ months, and for futures data only.



We do not show the 240 000 points on which the fits are performed, but rather show a running average over 5000 consecutive points along the x-axis. We also show the results of a linear and hyperbolic tangent fit. Note the positive intercept $a \approx 0.02$, which indicates the overall positive long-only bias. The best fit to the data is provided by the hyperbolic tangent, which suggests a saturation of the signal for large values.

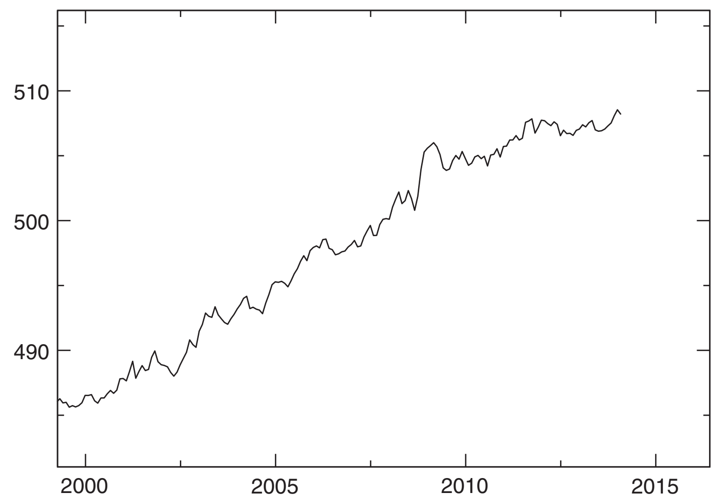
which recovers the linear regime when $|s_n| \ll s^*$ but saturates for $|s_n| > s^*$. This nonlinear fit is found to be better than the cubic fit as well as the linear fit, as it prefers a finite value $s^* \approx 0.89$ and now $b \approx 0.075$ (a linear fit is recovered in the limit $s^* \to \infty$). Interestingly, the values of a, b and s^* hardly change when n increases from 2.5 months to 10 months.

4.3 A closer look at the recent performance

The plateau in the performance of the trend over the last few years (see Figure 6 on the facing page) has received a lot of attention from CTA managers and investors. Among other explanations, the overcrowdedness of the strategy has frequently been evoked to explain this relatively poor performance. We now want to reconsider these conclusions in the context of the long-term simulation.

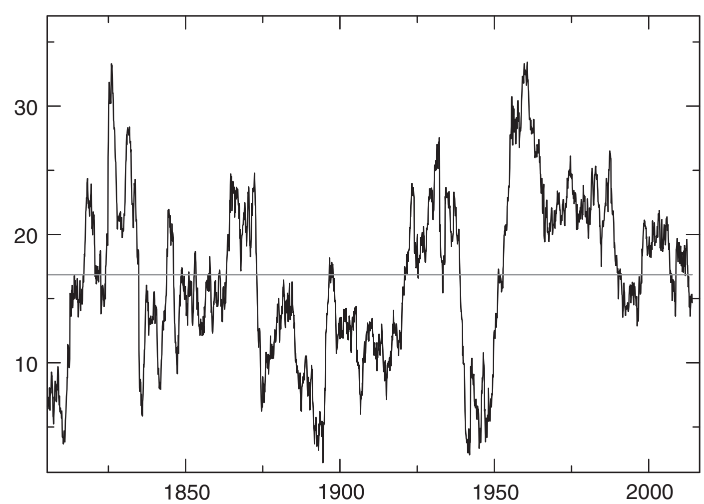
First, it should not come as a surprise that a strategy with a historical Sharpe ratio below 0.8 shows relatively long drawdowns. In fact, the typical duration of a drawdown is given by $1/S^2$ (in years) for a strategy of Sharpe ratio S. This means that, for a Sharpe of 0.7, typical drawdowns last two years, while drawdowns of four

FIGURE 6 Recent performance of the trend.



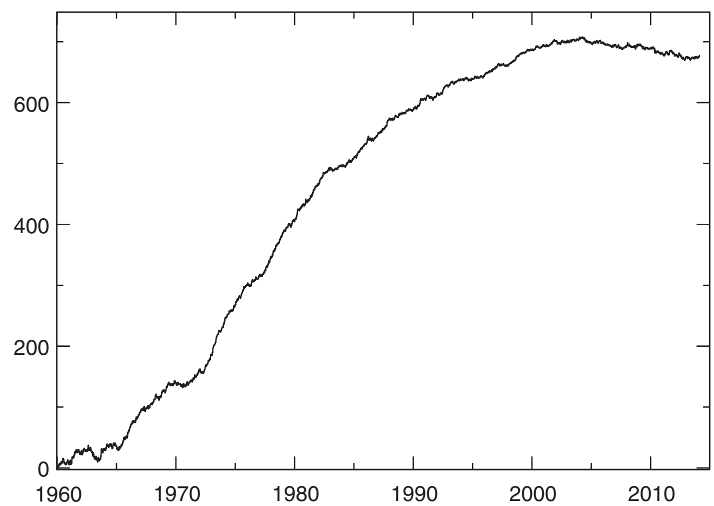
Since 2011, the strategy is virtually flat.

FIGURE 7 Ten-year cumulated performance of the trend (arbitrary units).



The horizontal line is the historical average.

FIGURE 8 Performance of a three-day trend on futures contracts since 1970.



The effect seems to have completely disappeared since 2003 (or has maybe even inverted).

years are not exceptional (see Bouchaud and Potters (2003) and Seager *et al* (2014) for more on this topic).

To see how significant the recent performance is, we have plotted in Figure 7 on the preceding page the average P&L between time $t - 10\text{Y}$ and time t. We find that, though we are currently slightly below the historical average, this is by no means an exceptional situation. A much worse performance was in fact observed in the 1940s. Figure 7 on the preceding page also reveals that the ten-year performance of trend following has, as noted above, never been negative in two centuries, which is again a strong indication that trend following is ingrained in the evolution of prices.

The above conclusion is however only valid for long-term trends, with a horizon of several months. Much shorter trends (say, over three days) have significantly decayed since 1990 (see Figure 8). This is perfectly in line with a recent study by the Winton group (Duke *et al* 2013). We will now propose a tentative interpretation of these observations.

4.4 Interpretation

The above results show that long-term trends exist across all asset classes and are stable in time. As mentioned in Section 1, trending behavior is also observed in the idiosyncratic component of individual stocks (Barroso and Santa-Clara 2013;

Geczy and Samonov 2013; Kent and Moskowitz 2013; Narasimhan and Titman 1993, 2011). What can explain such universal, persistent behavior of prices? We can find two (possibly complementary) broad families of interpretation in the literature. One explanation assumes that agents underreact to news and only progressively include the available information in prices (Hong and Stein 1999; Kent *et al* 1998). An example of this could be an announced sequence of rate increases by a central bank over several months, which is not immediately reflected in bond prices because market participants tend to only believe in what they see and are slow to change their previous expectations ("conservatism bias"). In general, changes of policy (for governments, central banks or indeed companies) are slow and progressive. If correctly anticipated, prices should immediately reflect the end point of the policy change. Otherwise, prices will progressively follow the announced changes and this inertia leads to trends.

Another distinct mechanism is that market participants' expectations are directly influenced by past trends: positive returns make them optimistic about future prices and vice versa. These "extrapolative expectations" are supported by "learning to predict" experiments in artificial markets (Hommes *et al* 2008; Smith *et al* 1988), which show that linear extrapolation is a strongly anchoring strategy. In a complex world where information is difficult to decipher, trend following – together with herding – is one of the "fast and frugal" heuristics (Gigerenzer and Goldstein 1996) that most people are tempted to use (Bouchaud 2013). Survey data also points strongly in this direction (Greenwood and Shleifer 2014; Menkhoff 2011; Shiller 2000).[8] Studies of agent-based models in fact show that the imbalance between trend following and fundamental pricing is crucial in accounting for some of the stylized facts of financial markets, such as fat tails and volatility clustering (see, for example, Barberis *et al* 2013; Giardina and Bouchaud 2003; Hommes 2006; Lux and Marchesi 2000).[9] Clearly, the perception of trends can lead to positive-feedback trading, which reinforces the existence of trends rather than making them disappear (Bouchaud and Cont 1998; DeLong *et al* 1990; Wyart and Bouchaud 2007).

On this last point, we note that the existence of trends far predates the explosion of assets managed by CTAs. The data shown above suggests that CTAs have neither substantially increased nor substantially reduced the strength of long-term trends in major financial markets. While the degradation in recent performance, although not

[8] Anecdotally, based on a long history of Capital Fund Management (CFM) inflows and outflows, our experience suggests that professional investors have a strong tendency to "chase performance", ie, to invest in CFM's funds after a positive rally and redeem after negative performance.
[9] Within their model, Giardina and Bouchaud (2003) show that, without an element of trend following, markets quickly reach an "efficient" stationary state where nothing much happens.

statistically significant, might be attributed to overcrowding of trending strategies, it is not entirely clear how this would happen in the "extrapolative expectations" scenario, which tends to be self-reinforcing (see, for example, Wyart and Bouchaud (2007) for an explicit model). If, on the other hand, underreaction is the main driver of trends in financial markets, we may indeed see trends disappear as market participants better anticipate long-term policy changes (or indeed policy makers become more easily predictable). Still, the empirical evidence supporting a behavioral trend-following propensity seems to us strong enough to advocate extrapolative expectations over underreactions. It would be interesting to build a detailed behavioral model that explains why the trending signal saturates at high values, as evidenced in Figure 5 on page 54. One plausible interpretation is that, when prices become more obviously out of line, fundamentalist traders start stepping in, and this mitigates the impact of trend followers, who are still lured in by the strong trend (see Bouchaud and Cont (1998), Lux and Marchesi (2000) and Greenwood and Shleifer (2014) for similar stories).

5 CONCLUSIONS

In this study, we established the existence of anomalous excess returns based on trend-following strategies across all asset classes and over very long time scales. We first studied futures, as is customary, then spot data that allows us to go far back in history. We carefully justified our procedure, in particular by comparing the results on spot data in the recent period, which shows a strong correlation with futures, with very similar drifts. The only sector where we found no way to extend the history is for foreign exchange, since the idea of a free-floating currency is a rather recent one.

We found that the trend has been a very persistent feature of all the financial markets we looked at. The overall t-statistic of the excess returns has been around 10 since 1800, after accounting for the long-only bias. Furthermore, the excess returns associated to trends cannot be associated to any sort of risk premium (Lempérière *et al* 2014; Narasimhan and Titman 2011). The effect is very stable, across both time and asset classes. It makes the existence of trends one of the most statistically significant anomalies in financial markets. When analyzing the trend-following signal further, we found a clear saturation effect for large signals, suggesting that fundamentalist traders do not attempt to resist "weak trends", but might step in when their own signal becomes strong enough.

We investigated the statistical significance of the recent mediocre performance of the trend, and found that this was actually in line with a long historical backtest. Therefore, the suggestion that long-term trend following has become overcrowded is not borne out by our analysis and is compatible with our estimate that CTAs only contribute a few percent of market volumes. Still, the understanding of the behavioral causes of trends, and in particular the relative role of "extrapolative expectations" versus “underreaction” or “conservative biases”, would allow us to form an educated opinion on the long-term viability of trend-following strategies. It is actually not obvious how crowdedness would deteriorate trend-following strategies, since more trend following should speed up trends as managers attempt to “front-run” the competition. Figure 8 on page 56, however, adds to the conundrum by showing that faster trends have actually progressively disappeared in recent years, without ever showing an intermediate period where they strengthened. Coming up with a plausible mechanism that explains how these fast trends have disappeared would be highly valuable in understanding the fate of trends in financial markets.

REFERENCES

Asness, C. S., Moskowitz, T. J., and Pedersen, L. H. (2013). Value and momentum everywhere. *Journal of Finance* **58**, 929–895.

Barberis, N., Greenwood, R., Jin, L., and Shleifer, A. (2013). X-CAPM: an extrapolative capital asset pricing model. Working Paper.

Barroso, P., and Santa-Clara, P. (2013). Momentum has its moments. Working Paper.

Bartas, A.-N., and Kosowski, R. (2012). Momentum strategies in futures markets and trend-following funds. Paris December Finance Meeting EUROFIDAI-AFFI Paper. URL: http://dx.doi.org/10.2139/ssrn.1968996.

Black, F. (1986). Noise. *Journal of Finance* **41**, 529–543.

Bouchaud, J. P. (2013). Crises and collective socio-economic phenomena: simple models and challenges. *Journal of Statistical Physics* **151**, 567.

Bouchaud, J. P., and Cont, R. (1998). A Langevin approach to stock market fluctuations and crashes. *European Physical Journal* B **6**(4), 543–550.

Bouchaud, J. P., and Potters, M. (2003). *Theory of Financial Risk and Derivative Pricing*. Cambridge University Press.

Clare, A., Seaton, J., Smith, P. N., and Thomas, S. (2012). Trend following, risk parity and momentum in commodity futures. Working Paper. URL: http://dx.doi.org/10.2139/ssrn.2126813.

Covel, M. (2009). *The Complete Turtle Trader*. HarperCollins, New York.

de Bondt, W., and Thaler, R. H. (1985). Does the stock market overreact? *Journal of Finance* **42**, 557–581.

DeLong, J., Bradford, A., Shleifer, A., Summers, L. H., and Waldmann, R. J. (1990). Positive feedback investment strategies and destabilizing rational speculation. *Journal of Finance* **45**, 379–395.

Duke, J., Harding, D., and Land, K. (2013). Historical performance of trend following. Working Paper, December.

Geczy, C., and Samonov, M. (2013). 212 Years of Price Momentum Working Paper. URL: http://ssrn.com/abstract=2292544

Giardina, I., and Bouchaud, J.-P. (2003). Bubbles, crashes and intermittency in agent based market models. *European Physics Journal* B **31**, 421.

Gigerenzer, G., and Goldstein, D. (1996). Reasoning the fast and frugal way: models of bounded rationality. *Psychological Review* **103**, 650.

Greenwood, R., and Shleifer, A. (2014). Expectations of returns and expected returns. *Review of Financial Studies* **27**(3), 714–746.

Hirshleifer, D., and Yu, J. (2012). Asset pricing in production economies with extrapolative expectations. Working Paper.

Hommes, C. H. (2006). Heterogeneous agent models in economics and finance. In *Agent-Based Computational Economics*, Judd, K. L., and Tesfatsion, L. (eds). Handbook of Computational Economics, Vol. 2. North-Holland, Amsterdam.

Hommes, C. H., Sonnemans, J., Tuinstra, J., and van de Velden, H. (2008). Expectations and bubbles in asset pricing experiments. *Journal of Economic Behavior and Organization* **67**, 116–133.

Hong, H., and Stein, J. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance* **54**, 2143–2184.

Hurst, B., Ooi, Y. H., and Pedersen, L. H. (2012). A century of evidence on trend-following investing. AQR Working Paper.

Kent, D., and Moskowitz, T. J. (2013). Momentum crashes. Swiss Finance Institute Research Paper Series 13-61.

Kent, D., Hirshleifer, D., and Subrahmanyam, A. (1998). Investor psychology and security market under- and overreations. *Journal of Finance* **53**, 1839–1885.

Kirman, A. (1991). Ants, rationality and recruitment. *Quarterly Journal of Economics* **108**, 137–156.

Kirman, A. (1993). Epidemics of opinion and speculative bubbles in financial markets. In *Money and Financial Markets*, Taylor, M. P. (ed). MacMillan, London.

Lempérière, Y., *et al* (2014). What is risk premium and how does it differ from alpha strategies? In preparation.

Leroy, S. F., and Porter, R. D. (1981). The present value relation: tests based on implied variance bounds. *Econometrica* **49,** 555.

Lux, T., and Marchesi, M. (2000). Volatility clustering in financial markets: a microsimulation of interacting agents. *International Journal of Theoretical and Applied Finance* **3**, 675–702.

Menkhoff, L. (2011). Are momentum traders different? Implications for the momentum puzzle. *Applied Economics* **43**, 4415–4430.

Mundt, M. (2014). Estimating the capacity of the managed futures industry. *CTA Intelligence* **12**, March 30.

Narasimhan, J., and Titman, S. (1993). Returns to buying winners and selling losers: implications for stock market efficiency. *Journal of Finance* **48**, 65–91.

Narasimhan, J., and Titman, S. (2011). Momentum. Working Paper. URL: http://ssrn.com/abstract=1919226.

Reinhart, C. M., and Rogoff, K. S. (2009). *This Time Is Different: Eight Centuries of Financial Folly*. Princeton University Press.

Schwert, G. W. (2003). Anomalies and market efficiency. In *Handbook of the Economics of Finance*, pp. 939–974, Vol. 1, Part B. Elsevier, Amsterdam.

Seager, P., *et al* (2014). The statistics of drawdowns. In preparation.

Shiller, R. J. (1981). Do stock prices move too much to be justified by subsequent changes in dividends? *American Economic Review* **71**, 421–436.

Shiller, R. J. (2000). Measuring bubble expectations and investor confidence. *Journal of Psychology and Financial Markets* **1**, 49–60.

Smith, V. L., Suchanek, G. L., and Williams, A. W. (1988). Bubbles, crashes and endogenous expectations in experimental spot asset markets. *Econometrica* **56**, 1119–1151.

Summers, L. (1986). Does the stock market rationally reflect fundamental values? *Journal of Finance* **41**, 591.

Szakmary, A. C., Shen, Q., and Sharma, S. C. (2010). Trend-following strategies in commodity futures: a re-examination. *Journal of Banking and Finance* **34**(2), 409–426.

Wyart, M., and Bouchaud, J.-P. (2007). Self-referential behaviour, overreaction and conventions in financial markets. *Journal of Economic Behavior and Organization* **63**, 1.