Market-Time Data TM

Improving Technical Analysis and Technical Trading

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ABSTRACT

The purpose of this paper is to demonstrate that by changing the underlying data used in technical analysis and technical trading systems the performance of these techniques can be greatly improved. We present two techniques – one for real-time data (intraday) and one for standard daily (end-of-day) data. For high frequency data we present a dynamic sampling technique that can generate a time series that ranges from 5 minutes to many hours in our time scale, Market Time. We present empirical evidence that this modified series is superior for technical analysis and trading. This is based on correlation studies, directional forecasts, and profitability of trading rules for FX rates. In the daily data realm a different technique is used then for intraday data, but it is based on the same first principles. Using the FxDx currency index as a test vehicle, the new daily data series is evaluated and shows increased performance and reduced drawdown. The average increase in performance is greater than 1% per year over the FxDx benchmark. Finally, two other trend following systems are presented that also show performance increase when using Market Time Data.

Keywords: Technical analysis, high frequency data, trading rules, foreign exchange trading.

1 Introduction

In recent years there has been an explosion of research in high frequency data methods by both academics and industry professionals alike. This has been driven by four factors: the increase in computing power, reduction is data storage costs, availability to academic researchers of some data sets, and the constant need to find an edge in the market. This paper adds to this growing body of research from the practitioner's point of view. Our goals are four fold:

1. To introduce the concept of Market Time Data. This is a data series produced by dynamic sampling techniques based on market activity for high frequency or tick data.
2. Evaluate the usefulness of this transformed data series versus physical time and other forms of activity adjusted sampling techniques. To our knowledge this is the first study that compares seasonally adjusted time series to non adjusted time series using trading rules.
3. Extend the concepts of activity adjusted sampling to daily data.
4. Evaluate the usefulness of this activity adjusted daily data versus standard end-of-day data.

The paper is presented in two major sections. The first main section, Section 2, presents work performed with real-time or high frequency data. In Subsection 2.1 we discuss the data used in our work with foreign exchange rates. Subsection 2.2 presents the concept of Market Time Data™, which is our activity adjusted time series. Next, Subsection 2.3, we evaluate our data series versus the standard data series by performing a correlation study. Following this study we perform another study in Subsection 2.4 which looks at direction forecasting using the new series. After examining these two statistical properties, Subsection 2.5 presents an economic evaluation of the Market Time Data against standard data. Finally in Subsection 2.6, we compare our method of activity based sampling to one proposed by Schnidrig and Würtz (1995).

In the second major section, Section 3, we extend the concept of Market Time to daily data. Subsection 3.1 presents the transformation performed to the daily data to create Daily Market Time Data™. Next in Subsection 3.2 we evaluate the economic usefulness of our data series by means of the FxDx currency index. Finally in Subsection 3.3 we also demonstrate the economic usefulness of DMTD via two other trend following trading systems.

2 High Frequency Market-Time Data

2.1 Data

The database of currency quotes used by *High Frequency Finance* in its modeling work consists of numerous sources including future exchanges, banks, brokers, and composite pages provided by data vendors such as Reuters, Telerate, and ADP. The work presented in this paper is all performed using only composite page data. For this data each entry consists of a date, time stamp, bid and ask price. The time stamp is only to the nearest minute but the order of the quotes is correct within a minute. Prices are quoted prices and not trading prices.

Before any analysis was performed on the data, filters were used to remove any spurious or suspect data. The filters used in our work fall into two categories. The first category is zero lag filters. For these filters we can immediately determine if a bid, ask, or the quote pair are valid or not. An example of this would be a decimal place checker. It is quite obvious that a bid or ask in the DEM/USD rate of 16.51 is incorrect due to improper key entry of the decimal point. We have a complete battery of filters like this that operate on the data without lag. Some are rate dependent while others are general and use the same parameters for all rates. The second category of filters introduce a small lag into the price series since we must look ahead a few ticks in order to determine if the price was an outlier or not. The delay introduced by this filter is taken into account two different ways. First we change the time stamp of the quote to the filter decision time not the actual quote time. Second when evaluating and trading system we base the execution price at the current price as indicated by the raw quote stream. Since our lag-based filters are specifically designed to have low delay the price difference between these two is quite small – usually within the bid/ask spread. But there are cases in fast moving or volatile markets this accurate modeling is demanded.

It is well known that the FX market shows strong seasonal effects caused by the hour of the day and day of the week , for example see Müller (1990). This can be seen in both the volatility and the quote activity in the series. This seasonality can and does effect the ability to predict the market and must be accounted for in any prediction or trading scheme. This is the purpose of the Market Time transformation described next.

2.2 Market Time Data

Traditional and commonly used forecasting models and many technical analysis indicators assume equally spaced data on a physical time scale. But as been shown from the intra-day and intra-week analysis, performed by others (Olsen & Associates Müller 1990) and us (Levitt 1997), there are certain times of day or the week that are more important than others. This leads to three distinct time scales:

- Physical time where a minute is a minute 24 hours a day seven days a week.
- Business time where a minute is a minute during normal business hours and days. This is the time scale most people are use to dealing with for time series analysis with equally spaced data.
- Market Time where a minute depends on what the market or instrument is doing. For purposes of clarity in Market Time scale a minute is just the minimal measure of time.

Market Time lets the actual traded instrument determine what a minute is. This allows the time scale, measured in physical time, to expand and contract based on market activity. A forecasting model or technical indicator will update itself more when activity is high and less when it is low. This expansion and contraction allows techniques to adapt to the market by adapting the *data* fed into them. Making linear methods in Market Time actually nonlinear in physical time since the mapping form physical time to MarketTime is nonlinear. This idea in not new, and has been proposed by numerous authors going back to Mandelbrot and Taylor in 1967 and more recently has been used by Dacorogna *et. al.* (1993) and Ghysels and Jasiak (1995).

To map from physical time to Market Time we enlarge the active periods and shorten the less active periods. Volatility and other proprietary measures based on price are used as the definition of activity for this transformation. Tick or quote volumes are not included in the activity measure since they are heavily data source dependent. The mapping works on a one week, 168 hour, cycle where 168 hours in Market Time is equivalent to 168 hours in physical time. Mapping between the two times is done via interpolating a local neighborhood fit of the cumulative activity. The mapping is continually updated and is not a static lookup table. This makes Market Time unique since it takes into account long term average seasonalities like Olsen's Theta time and Schnidrig's Operational time (1995), but also adapts to current activity which may be a transient lasting hours, days, weeks, or months.

The concepts presented above have been implemented in a program sold by High Frequency Finance called the Market Time Data Server™ (MTDS). This is a Microsoft Windows NT application that currently operates in a Triarch™ environment. The program takes quotes off the Triarch datafeed performs its calculations and produces new bars in the range of 5 minutes to many hours in Market Time. These new bars are then published back over the Triarch network for further analysis and use in any Triarch compatible program. Also, a DDE interface is available to the data for users who prefer this type of interface, e.g. Excel users. This open interface allows end users to develop their own technical trading systems and quantitative methods but still utilize the full power of Market Time data (MT-data) without relying on black or gray box trading systems. In the next sections we empirically demonstrate the power or Market Time data compared to other data.

2.3 Correlation Study

This section presents the results of the correlation study based on a technical indicator event. An event occurs when a condition is met on a technical indicator. For example, when the price crosses from below to above a moving average. We then calculate the correlation of this positive change with the price N-bars later, where N ranges from 1 to 20. The results for the USD/DEM rate using a one-hour sample in both physical and Market Time is presented in Table 1. The table gives the level of statistical significance versus the random walk hypothesis. While standard physical time bars are never significant at 10% or better level there is a whole range, from 2 through about 10, bars where the results are significant for Market Time data.

2.4 Directional Results

To further measure the predictive ability of MT-data a second study was performed that only looked at the direction of the event and the direction of the market 1 to 20 bars in the future. This evaluation allows one to compare market time verses physical time for the given predictor. The results are in Table 2. The given predictor works best with market time data, giving the user anywhere from a 5% to 14% edge. Thus technical traders or traders that use technical indictors as input to the decision making process will have more accurate information with Market Time version of their favorite indicators. It is interesting to note that this predictor, a moving average, does not have accuracy above 50%. Since most technical traders are well aware that their systems will have less then 50% winning trades, i.e. correct direction, they rely on the fact that the average winning trade will be greater then the average loosing trade giving them an overall profitable system. While MT-data performing better then physical data in both the correlation study and the directional study points to the superior nature we still wanted to close the case by performing a study of the profits of a technical trading system.

2.5 Trading System Results

As mentioned previously, many technical trading systems have less then 50% winning trades but rely on the fact that the winning trades more then make up for the more numerous loosing trades. To this end we tested MT-data and physical time data using a stop-and-reverse trading system based on simple moving averages. The system is not professionally tradable in it's current form, but is used for illustration purposes to test if the advantages of MT-data in the correlation and direction prediction study translated into bottom line profits. The results for the simple trading system are presented in Table 3. Both return and maximum peak-to-valley drawdown are presented. Market time significantly outperforms the standard physical time series in both measures. The market time series produces a profit with minimal drawdown while the system using physical time data looses money and suffers a drawdown twice as large. While this test is somewhat idealized, since only half the transaction costs are accounted for, in both systems the number of trades were approximately equal overall and on the long and short side. Thus, any biases in this study are equal and do not effect the underlying comparison of the two data series.

2.6 Comparison to other Adjusted Time Scales

In recent years other time scales have been proposed by numerous researchers to remove seasonailities and rescale data to improve analysis. This section compares Market Time Data to another seasonally adjusted series, Operational time data. We build three simple moving average trading systems and apply it to three series over a 9-month period from 1/4/93 through 9/30/93 for the USD/DEM rate[1]. The three series are

1. Hourly Operational time data
2. Hourly Market Time data
3. Hourly physical time data

Results for the return and maximum peak-to-valley drawdown are in Table 4. For System 1, the shortest-term system, MT-data is the only one with a positive return. Even with this positive return it does have a high maximum drawdown. This is due to the fact that the equity curve about mid way through the sample is

[1] This time frame was chosen to be compatable between our database and the widely available HFDF93 data set available from Olsen & Associates. This study does not use Olsen data.

at +11% and then proceeds to head down eking out a 1.2% profit for the period. The other two data series equity curves start their losses early and keep their losses for the entire period. While it could have been quite painful for an investor getting in at the peak of the MT-data series, it was comforting to see this large drawdown was due to a large profit that got away. This shows that the technical indicator combined with MT-data was able to pick up on some profitable structures in the data, while the other two combinations were not able to discern any profit opportunities. With better techniques in risk management and capital allocation, hopefully a skilled system developer and trader will hold onto those gains. Bottom line, there were better structures for profitability in the MT-data based equity curves.

For the second trading system, which is medium term, MT-data comes into its full force. Returning the only positive gain with the least drawdown. In system 3, which is long term, MT-data gives no advantage over physical data due to the time frames used. This is to be expected since some of the microstructure and other effects modeled by Market Time are averaged out when longer time frames are used.

3 Daily Market-Time Data

While the primary intent of developing Market Time Data and its supporting infrastructure was to support intraday analysis and trading techniques, in talking with customers it became apparent that daily data still plays a very important role in proprietary trading operations. To this end we have extended the basic concepts of high frequency Market Time Data to the daily time frame. While it is possible to use our current method of high frequency MT-data generation and create 24-hour bars, this did not fit the criterion set forth by many traders. Traders wanted a single bar per day no matter the “activity” that would always be produced at the same time(s). This could be an open-to-open daily bar or the very common close-to-close daily bar, where the close is defined by the local trading hours for a cash market or the corresponding futures market.

3.1 Rescaling

In order to carry forth the principles of market time we must expand time of large activity and contract periods of little activity on average. This is the same process many high frequency modelers use when computing the seasonality adjustments. First long term average activities are computed based on a time frame, e.g. hourly for a week, and then the time scale adjusted. The same technique is used in modeling daily market time data. A scaling factor is used to adjust the current market return and then a synthetic series is built up for analysis by standard technical methods.

The scaling factor is defined as follows

$$\kappa(t_i) = \frac{\alpha_s(t_i)}{\alpha_l(t_i)}$$

Where $\alpha_x(t_i)$ is a measure of activity for a long tern (*x*=*l*) and short term (*x*=*s*) time frames.

The activity measure can take on many forms depending on the market under consideration. In markets where the primary trading vehicle is futures the activity function uses both price and volume based measures. For markets that are primarily OTC only price based measures of activity are used since no accurate volume numbers are available. In Figure 1 the daily values for the USD/DEM are plotted on the same scale. While the two series are correlated there are noticeable differences.

3.2 FxDx with DMT-Data

To evaluate the usefulness of daily market time data for technical traders the FxDx currency index was chosen as the initial test vehicle, Lequeux and Acar (1996). This index consists of trading three different moving averages equally weighted over seven currency pairs, which are weighted by their trading volume as determined by Reuters 2000 dealing statistics. This index has been shown to closely correlate with trend following technical currency traders and two major benchmarks of currency funds, the Ferrell FX and TASS indexes. The experiment consisted of computing two versions of the FxDx index:

1. FxDx – this just uses standard closing price data of the spot FX market. This is defined as 3PM Eastern Standard Time for this study. A leverage factor of 3 was used in computing returns.
2. FxDx++ - this uses the same weightings and moving averages as FxDx but performs the moving average calculation using Daily Market Time Data (DMTD). A leverage factor of 3 was used in computing returns.

The returns for the two trading systems are presented in Figure 2. FxDx++ outperforms FxDx by 1.2% per year on average.

When comparing FxDx++ to FxDx we note the following statistics

1. The difference between FxDx++ and FxDx was positive in 60% of the months over the 10 year period
2. FxDx++ outperformed FxDx in 7 out of the 10 calendar years
3. The T-statistic for the monthly and daily difference in returns between FxDx++ and FxDx is significant at the 10% level.
4. FxDx++ rolling 12 month return was negative for only one month when FxDx was positive (0.15% gain vs. 3% loss) while FxDx++ was positive for 2 months when FxDx was negative (3.61% vs. –1.89% and 3.56% vs. –1.28%).
5. The maximum drawdown measured over the 10 years on monthly data is less for FxDx++ by 2%, i.e. 19% vs. 21%.
6. The maximum drawdown measured daily was less for FxDx++.

For the investment manager Daily Market Time Data offers the ability to increase performance and management fees by just changing the input data to their current systems. Using the example above if an CTA started with $100MM under management in 1986 using both systems and the standard 2%/20% fee structure, the amount of extra management and performance fees earned assuming that all net profits are reinvested in the program is $8.2MM to the FxDx++ manager over the 10 years. If every year the initial balance is reset to $100MM then the extra earnings drops to $2.4MM over the 10 years due to the loss of compounded returns. The investors would have earned an extra $30MM net of fees extra in the compounding case and an extra $12MM without compounding.

3.3 Other Trend Following Systems with DMTD

To further test the economic value of DMTD two other trend following systems were evaluated using both data series. The first system is the well-known channel breakout method and the second is a volatility breakout system. When trading just the two major cross rates (DEM/USD and JPY/USD) with a leverage factor of three and a single breakout length, DMDT outperforms daily data by 121% over the ten years. Using DMDT produces an annual compound return of 15% versus the 10% for the standard data. A similar result was seen for the volatility breakout system.

4 Summary

This abstract has present the work performed by High Frequency Finance in both high frequency (or real-time) modeling and daily modeling of FX rates. In the high frequency area we present our dynamic sampling technique which produces an alternative time series, Market Time Data, to physical time based data. We demonstrate that by using this new data series in technical trading indicators and rules the performance of these techniques can be greatly improved. This improvement is attainable to both model traders or to traders that use technical analysis as part of the decision making process.

In the daily data realm we extend the principal of Market Time Data under the constraints imposed by many end-of-day data users. Using three different trading techniques we demonstrate that Market Time Data can improve the bottom line performance by increasing returns and reducing drawdown.

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Tables

Table 1: Correlation of events versus future change in price for Market time and physical USD/DEM series June-93 through June-95. The level of significance is presented in the table versus a random walk.

	Market Time Data	Physical Time Data
1 Bar	42%	72%
2 Bars	11%	70%
5 Bars	5%	25%
10 Bars	16%	40%

Table 2: Percentage of correct directional movement after and event for Market time and physical USD/DEM series June-93 through June-95.

	Market Time Data	Physical Time Data
1 Bar	50%	36%
2 Bars	47%	39%
5 Bars	46%	41%
10 Bars	49%	42%

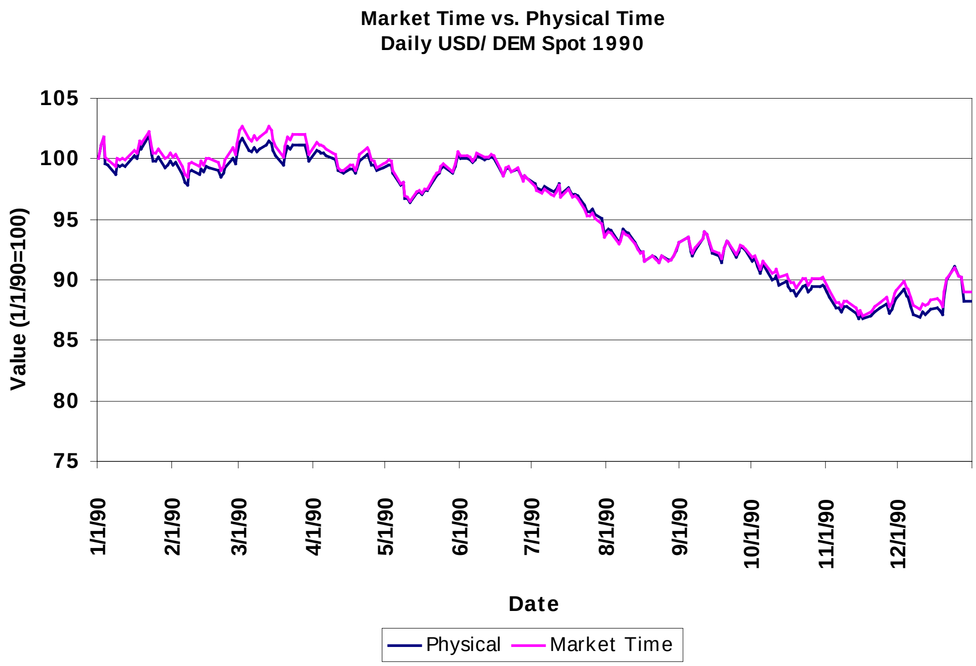
Table 3: Trading results for simple technical trading for Market time and physical USD/DEM series June-93 through June-95.

	Market Time Data	Physical Time Data
Return	10.6%	-6.5%
Max Darwdown	4.0%	8.0%

Table 4: Returns and maximum drawdown for three trading systems. The systems' speed decreases moving from system 1 to system 3, i.e. system 1 is the shortest time frame trading system.

	Theta Time		Market Time		Physical Time	
	Return	**MaxDD**	**Return**	**MaxDD**	**Return**	**MaxDD**
System 1	-6.26%	-7.9%	1.22%	-11.1%	-9.80%	-12.1%
System 2	-8.89%	-10.8%	6.18%	-8.27%	-10.58%	-11.2%
System 3	-9.28%	-13.1%	-6.51%	-11.7%	-6.30%	-10.2%

Figures


Market Time vs. Physical Time
Daily USD/ DEM Spot 1990
105
100
95
90
85
80
75
Value (1/1/90=100)
1/1/90
2/1/90
3/1/90
4/1/90
5/1/90
6/1/90
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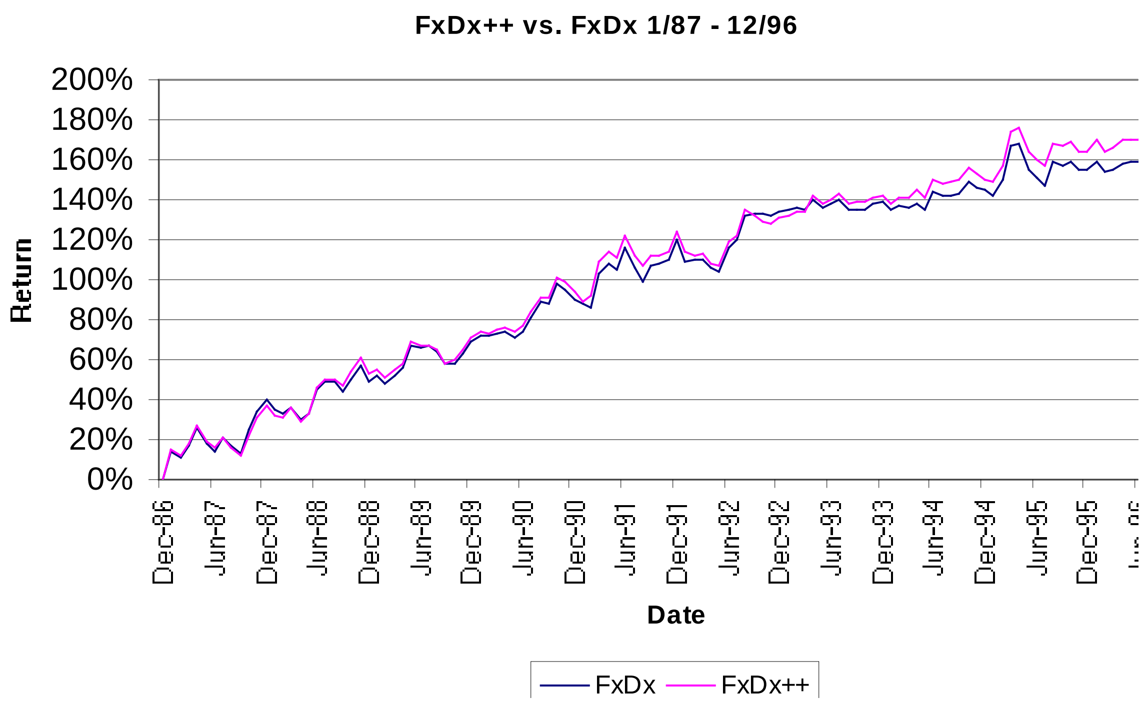
8/1/90
9/1/90
10/1/90
11/1/90
12/1/90
Date
Physical
Market Time


FxDx++ vs. FxDx 1/87 - 12/96
200%
180%
160%
140%
120%
100%
80%
60%
40%
20%
0%
Return
Dec-86
Jun-87
Dec-87
Jun-88
Dec-88
Jun-89
Dec-89
Jun-90
Dec-90
Jun-91
Dec-91
Jun-92
Dec-92
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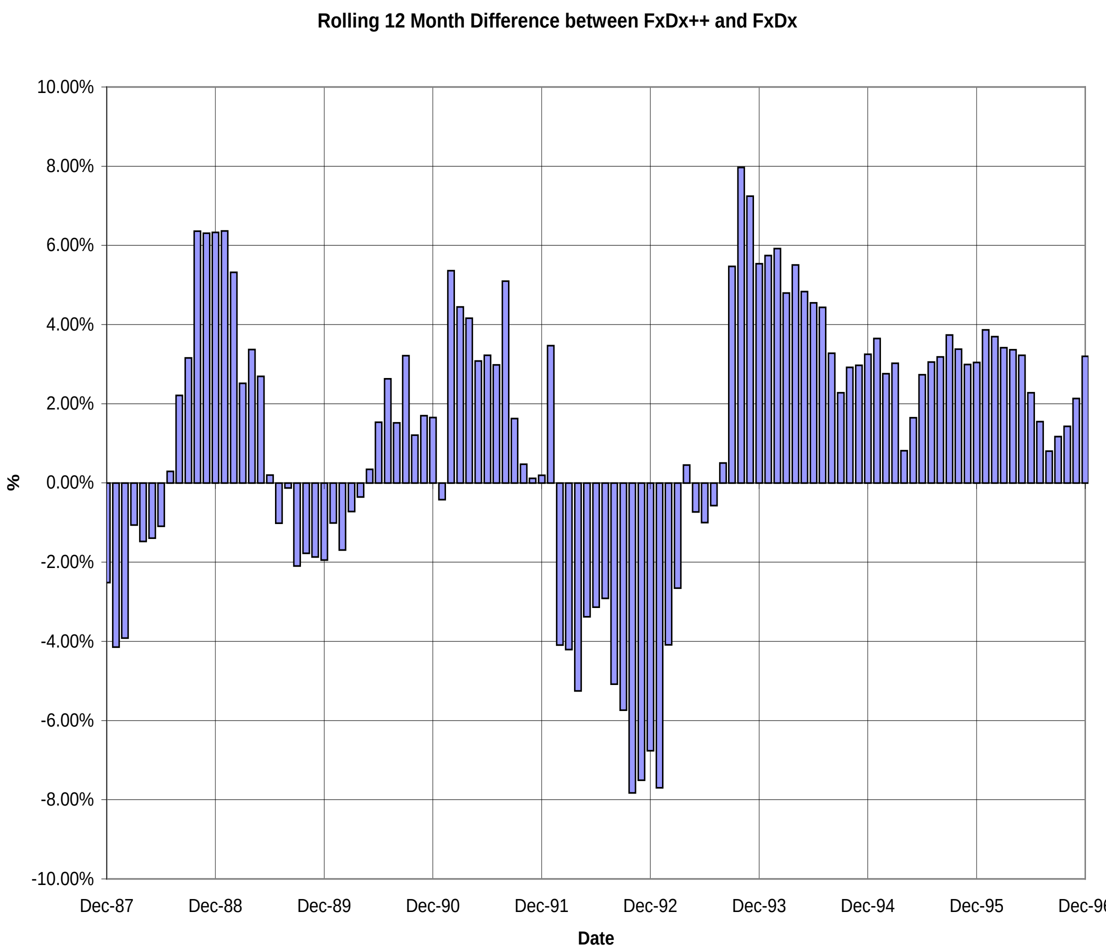
Dec-95
Date
FxDx
FxDx++



Rolling 12 Month Difference between FxDx++ and FxDx
10.00%
8.00%
6.00%
4.00%
2.00%
0.00%
-2.00%
-4.00%
-6.00%
-8.00%
-10.00%
%
Dec-87
Dec-88
Dec-89
Dec-90
Dec-91
Dec-92
Dec-93
Dec-94
Dec-95
Dec-96
Date