Market Time Data™
Improving Technical Analysis and Technical Trading

Marc E. Levitt

High Frequency Finance Inc.
1083 Robbia Drive
Sunnyvale, CA 94087

marcl@highfrequency.com
www.highfrequency.com

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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 (intraday) data 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 show performance increases when using Daily 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 in data storage costs, availability to academic researchers of some data sets, and the constant need to find an edge in the market. The current literature in high frequency data methods can be broken down into four main areas. First is looking at the actual statistical properties of the data or the stylized facts regarding the data. These studies examine the volatility, bid/ask spread, volumes, correlations etc. of tick data or subsamples of tick data, e.g. 10-minute bars. Examples of this type of study include Guilluame et. al. for the spot FX market (1994), Buckle et. al. for the LIFFE futures contracts (1995), and Lequeux (1997) for the Simex Nikkei 225 futures. The second type of work performed in the field is to take the information from the stylized fact studies and create a deseasonalized time series based on the observed data. Work in this area goes back to Mandelbrot and Taylor (1967), Clark (1973), more recently Dacorogna et. al. (1993), and Schnidrig & Würtz (1995). The third type of work regards development of volatility forecasting methods. Most of this work has focused on GARCH type models fitted to the deseasonalized time series. Examples here include Schnidrig & Würtz (1995), and Chang (1997). Finally, the last area of investigation has been the development and testing of trading rules. This has been done on both the raw data and deseasonalized data series. Examples of this type of work using raw data series are Acar & Lequeux (1995), LeBaron (1993), and Chang (1997). For the deseasonalized data example work includes Pictet et. al. (1992), Levitt (1996), and Schnidrig et. al. (1997). A related work to trading model development is that of Acar & Lequeux (1996) for the DAX future contract, where they investigate volume weighted pricing methods via trading rule profitability.

This paper adds to the growing body of research from the practitioner's point of view in two areas – the development of an alternative time scale and the evaluation of the time scale with trading rules and other statistical tests. Our goals are four-fold:

1. To introduce the concept of Market Time Data™ (MTD). 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 parts. The first part, 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. Subsection 2.6 looks at the economic importance of support and resistance levels in Market Time compared to physical time. Finally in Subsection 2.7, we compare our method of activity based sampling to one proposed by Schnidrig & Würtz (1995).

In the second part, 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™ (DMTD). 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, Dow Jones Markets, and ADP/GTIS. The work presented in this paper was all performed using only composite page data. For this data each entry consists of a date, time stamp in GMT, bid and ask price. Prices are quoted prices and not trading prices. An example of the raw database is given in Figure 1.

```
01/04/1993  08:52:01  1.6305  1.6315
01/04/1993  08:52:12  1.6306  1.6311
01/04/1993  08:52:26  1.6303  1.6308
01/04/1993  08:52:37  1.6300  1.6310
01/04/1993  08:52:53  1.6309  1.6314
01/04/1993  08:53:05  1.6300  1.6310
01/04/1993  08:53:06  1.6295  1.6305
01/04/1993  08:53:18  1.6298  1.6303
```

Figure 1: Example of the raw tick database used by High Frequency Finance. The instrument is the DEM/USD spot rate.

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 type filter 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 incoming data without lag. Some are instrument dependent while others are general and use the same parameters for all instruments. 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 a 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. 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 and trade 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 or business time scale. This is not an ideal situation since it has been shown from the intra-day and intra-week analysis, performed by others (Olsen & Associates Müller 1990) and High Frequency Finance (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 the 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 Market Time 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 & 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[1]. 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 et al. 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 available from 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 one hour in Market Time. These new bars are then published back over the Triarch network for further analysis and use in any Triarch compatible program. Figure 2 shows a sample screen shot of the program running with canned playback data on a Triarch network.

A DDE interface is available to access the data for users who prefer this type of interface, e.g. Excel™ users. This open interface through Triarch and DDE allows end users to develop their own technical trading systems and quantitative methods utilizing the full power of Market Time Data, without relying on prepackaged black or gray box trading systems.

In the next few sections we empirically demonstrate the power of Market Time Data compared to other data. All tests presented in this paper are carried out on the DEM/USD spot rate covering the 9-month period from 1/4/93 through 9/30/93[2,3].

[1] This is true even for exchange traded instruments. An example would be the new rules regarding ECNs and NASDAQ stocks, quote volume doubled due to a regulatory rule.
[2] This time period was chosen to be compatible between our database and the widely used HFDF93 data set available from Olsen & Associates. This study does not use Olsen & Associates data.
[3] While the results presented here only cover 9 months, they are representative of results High Frequency Finance has over longer periods using our full data base with numerous FX rates.

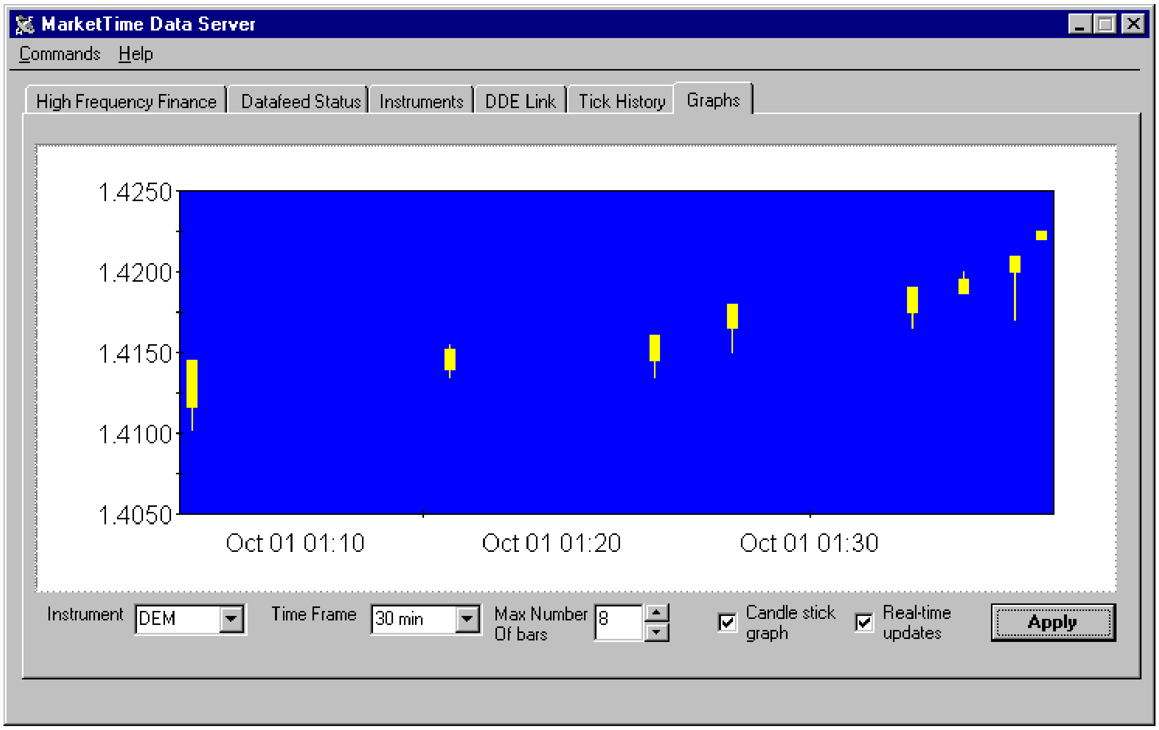

Figure 2: Market Time Data Server™ in action. This screen shot shows the Graphs tab which allows a user to visualize the dynamics of the Market Time Data. With the DEM/USD market moving 100 pips in ~45 minutes the server has produced 8 30 min. Market Time bars. These bars would allow your technical indicators to be more sensitive to this type of large movement.

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, such as when the price crosses from below to above a moving average. We then calculate the linear 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[4] of bars where the results are significant for Market Time data.

[4] From 2 through about 10 bars. At all times Market Time is better than physical time although not statistically significant versus the random walk.

Table 1: Correlation of events versus future change in price for Market time and physical USD/DEM series January-93 through September-93. 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%

2.4 Directional Results

To further measure the predictive ability of Market Time 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.

Table 2: Percentage of correct directional movement after an event for DEM/USD Market Time and physical time series.

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

The given predictor works best with market time data, giving the user anywhere from a 5% to 14% edge. Technical traders or traders that use technical indictors as input to the decision making process will have more accurate information with the Market Time Data 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 Market Time Data performing better then physical data in both the correlation study and the directional study points to its superior nature, we wanted to close the case by performing a study of the profitability of a technical trading system.

2.5 Simple 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 make up for the more numerous loosing trades. To this end, we tested Market Time 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 Market Time Data in the correlation and direction prediction study translated into bottom line profits. The results for the simple trading system unleveraged are presented in Table 3.

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

	Market Time Data	Physical Time Data
Return (%)	10.6	-6.5
Max Drawdown (%)	8.3	9.6

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 reasonable drawdown while the system using physical

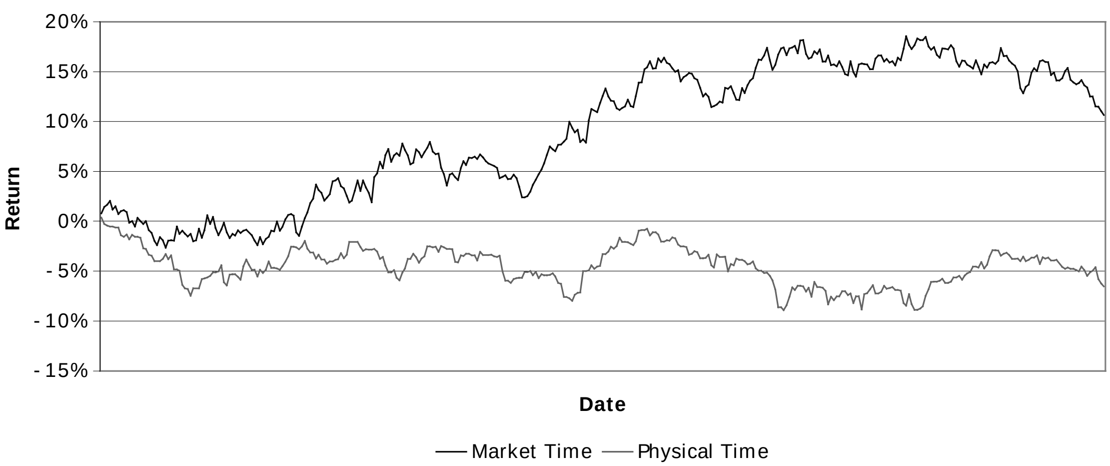

Figure 3: Daily equity curves for the simple trading system in both Market Time and physical time.

time data looses money and suffers a larger drawdown. Figure 3 shows the two equity curves marked to market daily.

The annualized Sharpe ratio for the Market Time system is 0.76. 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 Support and Resistance Results

A popular technical analysis method is to look at support and resistance levels in the market. When either is broken the common wisdom is that the direction of the market has changed and the new trend will carry through. Therefore, when the support level is broken the market will head down and when resistance is broken the market will head up. Recently these rules have been tested in intraday FX markets by Curcio, Goodhart, Guillaume, and Payne (1997) and have not held up well over their sample, either before or after transaction costs. Their study bases support and resistance levels on two different sources – Reuters FXNL screen and taking the range (Max-Min) over a window of past hourly observations. To continue our investigation of Market Time Data we have recently undertaken a study of support and resistance type rules in both Market Time and physical time (Levitt 1998). A brief version of one part of the study is presented here. For this part of the study we use only the Min-Max type channel rule since the FXNL data was not available to us. Four time frames were examined - 50, 100, 150, and 200 bar look backs were used to calculate the support and resistance levels. If the current bar was greater then the maximum of the previous 50 bars then we went long, if the current bar was less then the minimum of the previous 50 bars then we went short the currency pair. The position was held for 10 bars and then closed out. While this study is similar to the well known channel rule (Taylor 1994), the important difference is that we try to mimic the short term nature of spot FX traders by holding the position for only 10 bars, unless the position is reversed by another signal. The results of the study are in Table 4.

Table 4: Results for the support and resistance study. The currency is bought or sold based on a breakout of the channel. Positions are held 10 bars and then closed out.

Length of Channel	Market Time		Physical Time	
	Return %	MaxDD %	Return %	MaxDD %
50	6.4	4.5	1.3	8.2
100	7.4	3.4	-0.5	8.8
150	3.4	3.7	2.3	6.6
200	1.5	4.4	0.2	5.4

In all four time frames Market Time Data out performs physical time data in both return and in minimizing drawdown. This can easily be determined by computing the ratio of return to maximum drawdown, which is a commonly used measure in evaluating trading systems. The worst value in Market Time, 0.34 for 200 bars, is almost equal to the best ratio for physical bars, 0.35 for 150 bars.

2.7 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 (Schnidrig 1995). We build three simple moving average trading systems and apply it to the three series over our standard testing period. The three series are:

1. Hourly Operational (or Theta) 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 5.

Table 5: Returns and maximum drawdown for three trading systems.

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

For the short-term system, Market Time Data is the only one with a positive return. Even with this positive return, it does have a very high maximum drawdown. This is due to the fact that the equity curve about mid way through the sample is 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 Market Time Data series, it was comforting[5] to see this large drawdown was due to a large profit that got away. This shows that the technical indicator combined with Market Time 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 Market Time Data based equity curves.

[5] This is not exactly the best word since no drawdown, large or small, is comforting to traders!

With the medium term system the advantages of Market Time Data comes into full force. Returning the only positive gain with the least drawdown. For the long term system Market Time Data gives no advantage over physical data due to the indicator 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 with simple moving averages.

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 trading operations, especially 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 Market Time 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 the 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 is 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 term (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 4 the daily values for the USD/DEM are plotted on the same scale for 1990. While the two series are correlated there are noticeable differences.

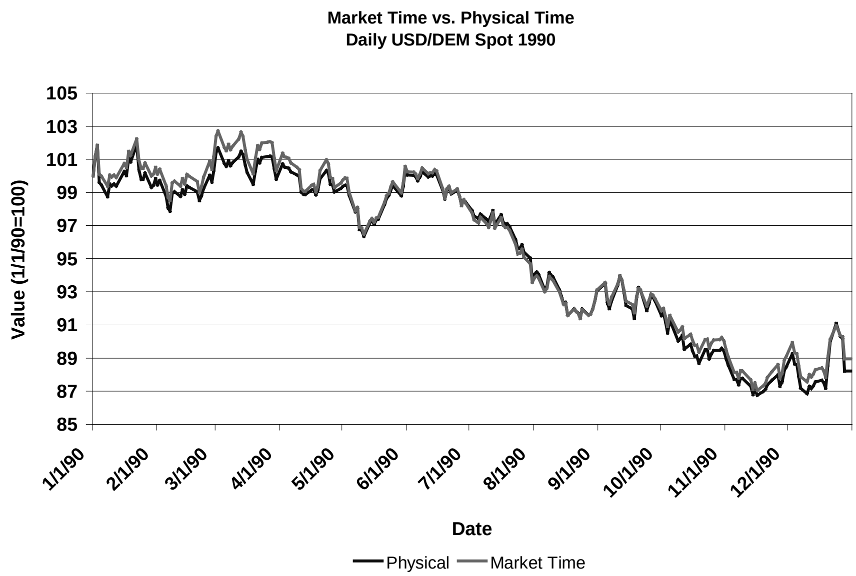

Figure 4: Daily Market Time Data (DMTD) series and standard daily series for USD/DEM spot rate 1/1/90 to 12/31/90 with 1/1/90=100.

3.2 FxDx with Daily Market Time Data

To evaluate the usefulness of Daily Market Time Data™ (DMTD) 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 Index and TASS Index. 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 4PM 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 5. FxDx++ outperforms FxDx by 1.2% per year on average.

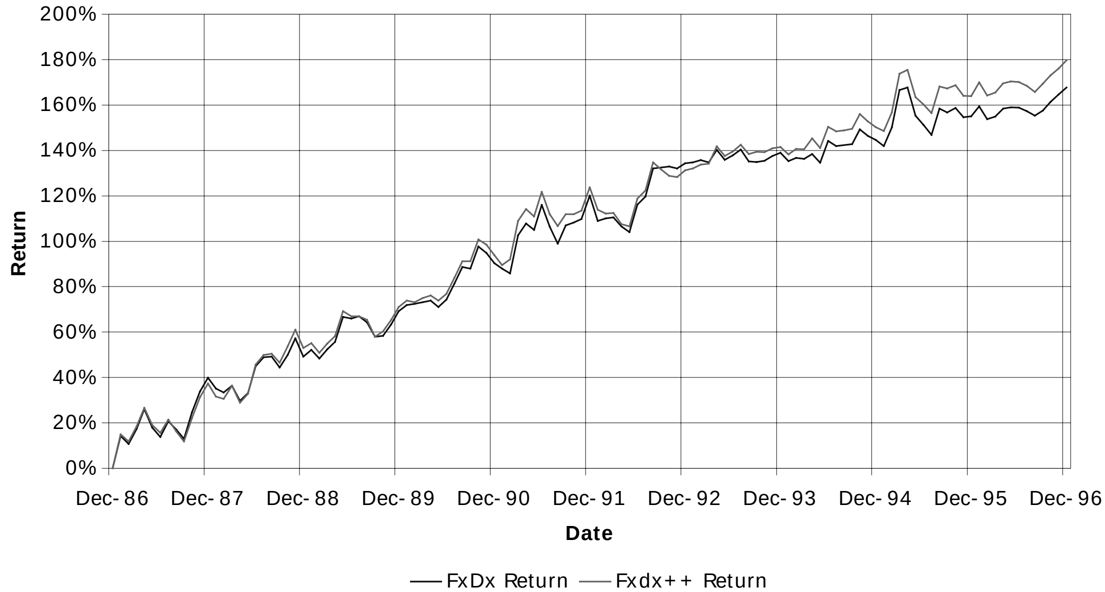

Figure 5: Cumulative return for FxDx and FxDx++ for the years 1987 through 1996.

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%).

Other statistics for the two systems are summarized in Table 6.

Table 6: Return statistics for FxDx and FxDx++ trading systems for Jan. 1987 through Dec. 1996.

Statistic	FxDx	FxDx++
Average annual return %	16.8	18.0
Standard deviation %	19.5	19.7
Sharpe ratio	0.86	0.91
Minimum monthly return %	-12.4	-12.0
Maximum monthly return %	16.8	17.1
Maximum drawdown	21.0	19.0

The rolling 12 month difference in returns between FxDx++ and FxDx is shown in Figure 6. It is interesting to note that FxDx++ did very well in the years 1993 and 1994, which were tough for trend following currency traders.

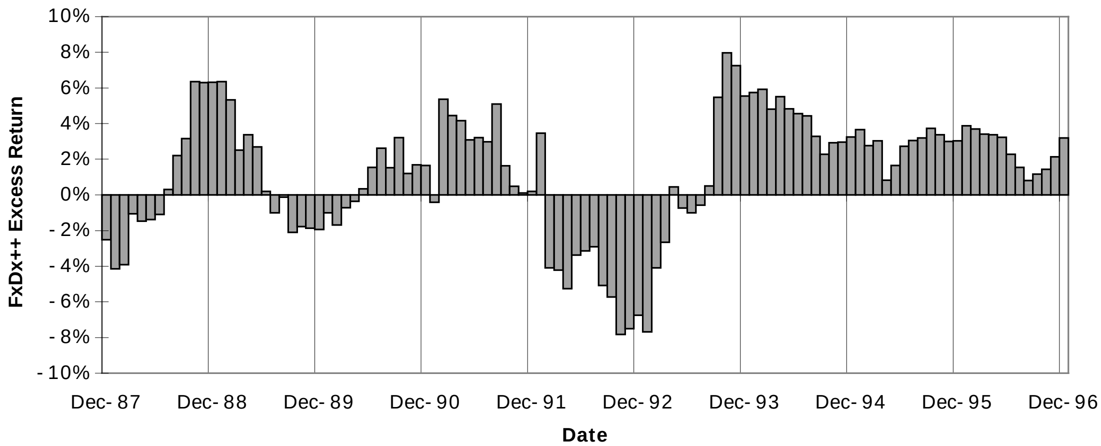

Figure 6: Rolling 12-month return difference between FxDx++ and FxDx. A positive value signifies that FxDx++ is out performing FxDx.

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 FxDx and FxDx++ as example systems, if an CTA started with $100MM under management on 1/1/1987 and had 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 $8.4MM to the FxDx++ program over the 10 years. The investors would have earned an extra $28MM net of fees.

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.

For the volatility based breakout system we combine three trading systems using different time frames, short, medium, and long term, as is commonly done by CTAs and other professional traders. The systems are pure stop-and-reverse and are always in the market.

For this experiment we only trade the four major rates that are available on the IMM. These are the USD/DEM, USD/JPY, USD/CHF, and USD/GBP. The exposure to each currency is equally weighted. The return statistics for both the standard data and DMTD are given in Table 7.

Table 7: Return statistics for volatility breakout system using standard and Daily Market Time Data for Jan. 1987 through Dec. 1996.

Statistic	Standard Data (VB)	DMTD (VB++)
Average annual return %	12.0	14.8
Standard Deviation %	14.5	15.9
Sharpe Ratio	0.83	0.93
Minimum Monthly Return %	-10.4	-8.4
Maximum Monthly Return %	14.0	16.0
Maximum drawdown %	12.6	16.0

The difference in monthly and daily returns for the VB++ system versus the VB system is significant at the 5% level using a T-test. The equity curve for the two systems is presented in Figure 7.

When comparing VB++ to VB we also note the following statistics

1. The difference between VB++ and VB was positive in 75% of the months over the 10 year period.
2. VB++ outperformed VB in 7 out of the 10 calendar years
3. VB++ rolling 12-month return was negative in 4 months when VB was positive (average difference of 4.8%) while VB++ was positive for 8 months when VB was negative (average difference of 4.7%).

The rolling 12-month difference in returns between the two systems is in Figure 8. A money manager using DMTD and starting with $100MM under management would have earned an extra $16MM in fees and the investors would have made an extra $50MM over the ten years.

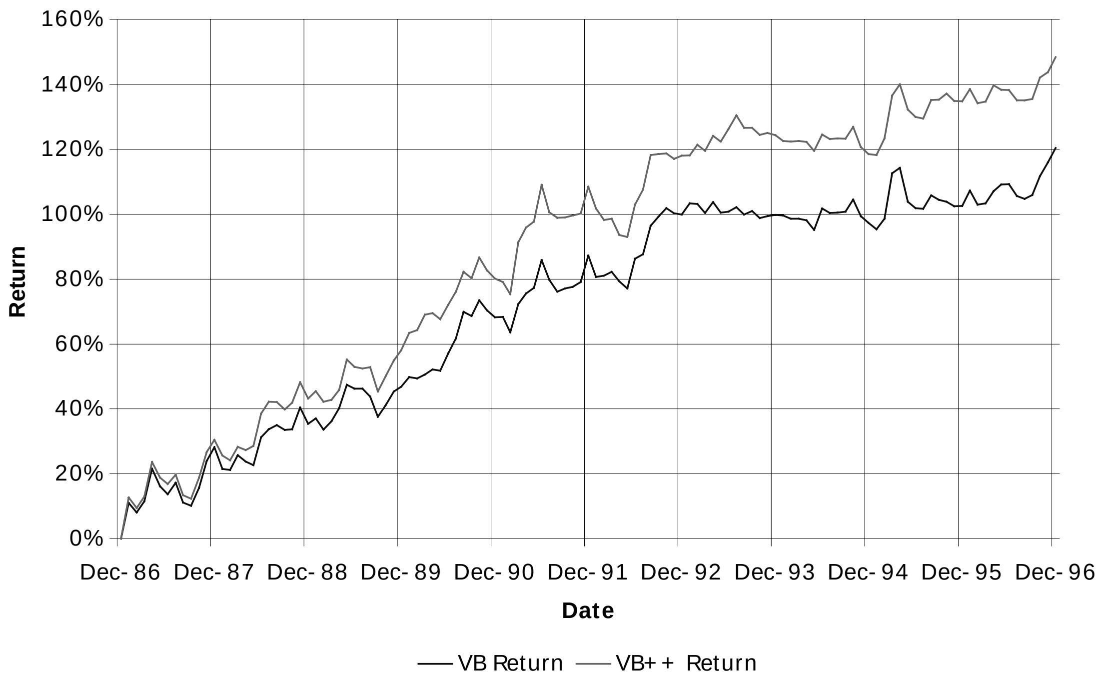

Figure 7: Returns for the two versions of the volatility breakout system.

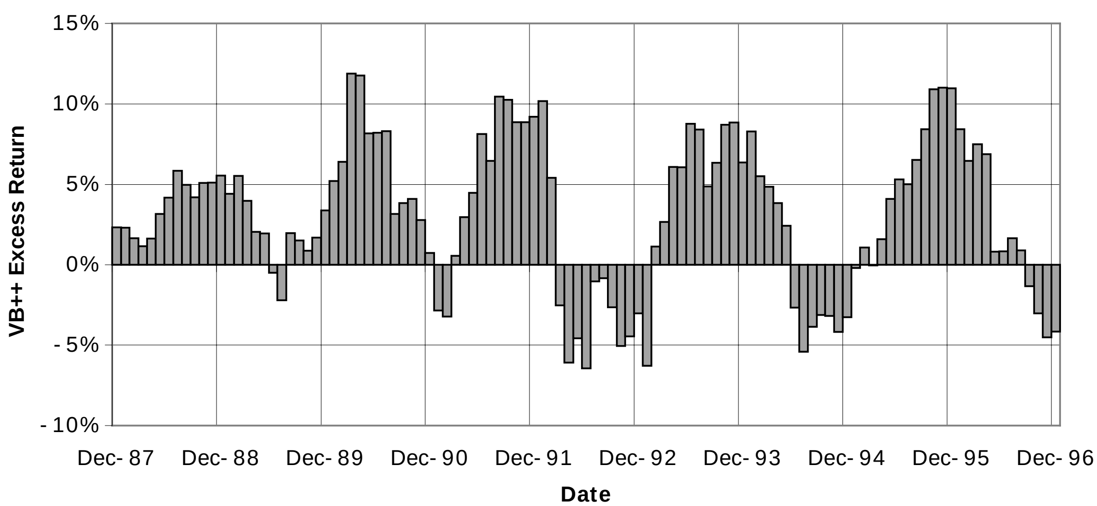

Figure 8: Rolling 12-month difference between VB++ and VB.

4 Summary

This paper has presented 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 drawdowns.

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