Essays on High Frequency and Behavioral Finance

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Abstract

This dissertation presents studies on various aspects of intraday high frequency dynamics of financial markets, as well as analysis of certain phenomena in behavioral finance. The scope of the research includes currency market as well as US equity market. I proposed a volatility estimator using wavelets, which: 1) is easily scalable to various time periods and various frequencies of data; 2) is flexible such that the researcher can set a threshold for volatility depending on his/her needs; 3) is statistically more efficient than other traditional volatility estimators; and 4) captures the underlying dynamics of the data set in as much detail as other volatility estimators. I used this estimator in 3 contexts:

First, I applied it to second by second foreign exchange executed trade data of 2003-2007. I quantified the currency market reaction after the release of 18 major US economic releases on Japanese yen, British pound and euro. I also modeled the induced volatility, and volatility of volatility subsequent to economic releases. These findings have potential applications in electronic market making and algorithmic trading in currency markets.

Secondly, I used the estimator in US equity market and using change point analysis quantified how individuals and institutions behaved during the financial crisis of 2008-2009. In order to perform the analysis, I required data on individual investors' equity holding at daily frequency, and as such data did not exist, I constructed and used an indicator which can be used as a proxy for an individual's holdings at a daily frequency. Moreover I demonstrated disposition effect in the individual investor community as a whole by analyzing their market portfolio holding and comparing their absolute and risk adjusted returns with simulated portfolios.

Lastly, I returned to the currency market to analyze the behavior of individual investors. I used a number of proprietary data sets of individual and institutional investors' currency holdings, including minute by minute data on individuals' positions during year 2007. I demonstrated feedback trading and excessive trading phenomena within individual investor community. I also quantified the likelihood of occurrence of frequent trades by individual investors during the intraday trading session. As individuals' share of trades in financial markets is significant and growing,

our findings of the aforementioned behavioral phenomena may help researchers and practitioners better understand the dynamics of these markets.

This doctoral thesis was supervised by Prof. Dr. S. T. Rachev at the Department for Statistics, Econometrics and Mathematical Finance.

Chapter 1

Introduction to dissertation

This dissertation presents studies on various aspects of intraday high frequency dynamics of financial markets, as well as analysis of certain phenomena in behavioral finance. The scope of the research includes currency market as well as US equity market.

In Chapter 2, we provide the general literature review and necessary background for the subsequent chapters. We cover important issues in dealing with high frequency data, explain the most important characteristics of intraday dynamics of markets and provide an introduction to wavelets. We build upon general background offered in Chapter 2 in subsequent chapters.

In Chapter 3, we use second by second foreign exchange data of 2003-2007, which has not been analyzed before. The currency market is by far the largest financial market in the world, and the economic releases have a significant effect on the intraday dynamics of this market. Given the recent advancements in processing power, availability of tick data and facilities to execute electronically in the market in a fraction of a second, there has been increasing interest in intraday dynamics of all financial markets. Intraday currency market strategies present a fast growing investment opportunity for global financial institutions. Every year, a larger proportion of global currency is traded on electronic platforms where investment banks and others act as market makers. The algorithms which assist banks in market making (e.g. determining the bid and ask spread at each moment) need to dynamically adjust to the changing market during the day. Our analysis of volatility in Chapter 3 will contribute to calibrating such market making models. Moreover our results have practical applications in automated trading models, which seek to capture the very short term intraday movements of the market and generate profit. We demonstrate and quantify the foreign exchange market's reaction to economic releases. In doing so, we also propose a novel approach to estimating volatility based on wavelets which we used in Chapters 3, 4 and 5.

Our contributions in Chapter 3 include:

- Quantifying the currency market reaction after the release of 18 major US economic releases on Japanese yen, British pound and euro. We determined how each currency reacts to each economic release, and determined the importance of releases for the currency market.
- Conducting a survey of major currency asset managers and chief traders in major banks and comparing the results of the poll with our findings
- Quantifying the induced volatility, and volatility of volatility subsequent to economic releases. These findings have potential applications in electronic market making and algorithmic trading in currency markets.
- Further analysis of intraday dynamics of most liquid currency (EUR/USD) after the most important economic release (nonfarm payrolls)
- Proposing a volatility estimator using wavelets, which: 1) is easily scalable to various time periods and various frequencies of data; 2) is flexible such that the researcher can set a threshold for volatility depending on his/her needs; 3) is significantly more efficient than range volatility estimator (range estimator is itself the most efficient estimator of volatility compared to other traditional volatility estimation methods); and 4) captures the underlying dynamics of the data set in as much detail as other volatility estimators.

In Chapter 4, we first described and later quantified how individuals and institutions behaved during the financial crisis of 2008-2009. Individual investors hold a substantial portion of US equity, and understanding the behavior and investment decision making of individuals is therefore highly important in asset pricing and in understanding the dynamics of the equity market. In order to perform the analysis, we required data on individual investors' equity holding at daily frequency, and as such data did not exist, we constructed an indicator which can be used as a proxy for an individual's holdings at a daily frequency. We used this indicator's data in our analysis.

Disposition effect states that individuals keep their losing positions for too long (i.e. they are averse to recognizing loss in their portfolio, hence they hold assets which have been generating losses for too long in the hopes that the market will eventually turn in their favor) and sell their winning positions too early.[1] In this chapter, we tested individual investor community for disposition effect.

Our contributions in Chapter 4 include:

- Constructing and proposing an indicator of individual investors' equity holdings, which: 1) excludes institutional investors and only includes the direct holdings of individuals; 2) has a very high correlation with the equity market and therefore can be reliably used as a proxy of the portion of equity held by individuals; 3) is constructed using publicly available data, therefore it can be replicated by other researchers; and 4) has daily frequency, therefore allowing researchers an abundance of data for analysis (all other publicly available data on individual investors have thus far had monthly frequency).
- Proposing a reliable indicator of equity holdings of institutional investors using publicly available data.
- Using parametric and non parametric methods in analyzing the behavior of individual investors, distinguishing various phases of individuals' investments using change point analysis, and determining the most important drivers for individuals' decision making during each phase using decision tree approach.
- Demonstrating disposition effect in the individual investor community by analyzing their market portfolio holding and comparing their absolute and risk adjusted returns with simulated portfolios, and showing that disposition effect can be observed at 95% confidence. Up to now, disposition effect has only been analyzed using the portfolios of a select group of investors using proprietary data of their trade. Our approach is different in that we demonstrate the disposition effect for the first time not on a group of separate individuals, but on the entire individual investor community as a whole.
- Constructing a highly successful contrarian trading model based on our findings in Chapter 4, and using our individual investors' holdings indicator as an input signal for the model. The success of our model indicates potential applications for our analysis in financial markets.

[1] In this dissertation, we use position (as it is commonly used in the financial industry) as a synonym for an investor's holdings. In other words, the assets held in an investor's portfolio constitute his or her position.

In Chapter 5, we returned back to the currency market to analyze the behavior of individual investors. We used a number of proprietary data sets of individual and institutional investors' currency holdings, including minute by minute data on individuals' positions during year 2007. None of these data have been analyzed before.

In behavioral finance, feedback trading is defined as an instance when investors' trading is in direct reaction and influenced by immediate dynamics of the market. As opposed to micro structure theory of finance, which seeks to explain the change in asset prices based on changes in investors' positions, feedback trading occurs when the changes in investors' holdings is a direct result of changes in asset prices. Feedback trading has been documented in equity market. Another phenomenon discussed in behavioral finance is excessive trading. Studies in the equity market have shown that individuals trade more often than is prudent or required to maintain their portfolios, and this frequent trading diminishes the returns on their portfolios. Excessive trading has been documented in markets other than the currency market.

Our contributions in Chapter 5 include:

- Using parametric and non-parametric approaches and determining the drivers influencing the investment decisions of individuals and institutions.
- Demonstrating feedback trading phenomenon in the individual investor community in the currency market and across the entire individual investor community.
- Demonstrating excessive trading phenomenon in the individual investor community in the currency market. We showed that, similar to the prior results in the equity market, individuals' market portfolio performance suffered due to excessive trading.
- Demonstrating that intraday periods of frequent trading by individuals coincide with the periods of high intraday volatility in the currency market, regardless of the market conditions. The higher the intraday volatility of the currency market, the more likely it is for individual investors to increase their frequency of trades.

In Chapter 6, we present our main findings and conclusions.

Chapter 2

General background and literature review

In this chapter, we review the background literature on high frequency finance, micro structure theory and wavelets. We will build upon these topics in the next chapters.

2.1 General background and literature review

In this section we have reviewed the literature on high frequency finance and financial markets intraday dynamics. Particular emphasis is placed on the research on intraday currency market. The currency market is undergoing radical changes. The advent and expansion of electronic trading is rapidly changing the investment landscape. While the volume transacted has grown rapidly, a large portion of the growth is due to an increase in electronic trading, which accounts for more than half of all global currency trade (see Bloomberg ™ (2007)). More sophisticated execution strategies have facilitated trading and reduced the market impact of the trades. This combined with availability of tick data has provoked unprecedented interest in exploring intraday market dynamics and micro structure.

Apart from the above, there has been growing interest on the part of economists in microstructure for another reason. Forecasting foreign exchange rates remains a particularly challenging task. In light of the difficulty of forecasting exchange rates using traditional economic theory, some economists have searched elsewhere for useful forecasting tools. Study of market micro structure in FX has been mainly such an alternative theory which has attempted in part to explain the so called paradoxes in FX (e.g. lack of success in macro based forecasting, forward rate bias, etc.). Meese and Rogoff (1983) have demonstrated a fact known by many practitioners for a long time, namely the inability of economic theory to forecast exchange rates. Recent work includes De Grauwe and Grimaldi (2006) who present an alternative behavioral framework for forecasting rates and explaining the FX market. Using high frequency data, Lyons and others have demonstrated some predictive power in analyzing the micro structure and flow. Throughout this dissertation, order flow (or simply flow) is defined as signed transaction volume measured between the dealer and buyer or seller. A positive sign indicates a buying pressure as seen by the dealer. As electronic platforms allow various participants to make market, the same definition and related notions may be expanded to incorporate these market makers.

Flow data are widely used by market participants in forecasting short term rates and in market making. According to Rosenberg (2003), 62% of all market participants surveyed believed there that flow information is useful in market forecasts for up to a few days. There is an ongoing debate over whether the flow data convey information contemporaneously or if there is forecasting value in them. The microstructure approach allows a better understanding of the flow and its potential forecasting power. Micro structure forms the basis for explaining the intraday market behavior and is the link between empirical study (the subject of this thesis) and econometric explanation of the markets.

Without getting into details, we will outline some key notions of micro structure approach to currency markets to lead the way into an empirical study of market. But first it is important to note a few fundamental differences between equity and FX micro structure:

- As opposed to currencies, public equity shares are traded in financial exchanges (we are ignoring the private placement of shares, which corresponds to a very small portion of equity markets). The volumes of trades are therefore known. The volume of each trade in the currency market is only known to the parties involved, custodians and electronic exchanges (if applicable). Other market participants do not know the amounts traded in each instance.
- In equity markets, the floating amount of each share (i.e. the total aggregate tradable share) is known. In FX, the total amount of tradable currency is not known and the volume traded at each price has to be approximated.

The following are among the main characteristics of microstructure approach (see Lyons (2001) for details):

1. Micro structure approach acknowledges that there is non public material information which influence market dynamics. This information is gained through dealer's order flow and market interaction. For this reason, dealers typically quote a large client base as one the most important advantages that a market participant may have.
2. Market participants are not homogeneous and engage in currency markets with completely different goals. Microstructure approach emphasizes that various market participants influence the market differently. For instance, market dynamics would be very different if $100 million is transacted by many

retail investors than if it were to be transacted by a few hedge fund investors within the same time period. Some participant's orders possess a higher information content and influence markets more than others. Market participants influence the markets by conveying information through their transactions. The more informed traders, according to this approach, try to adjust their trading patterns so that they will convey the least information to the markets. For instance, Harris and Hasbrouck (1996) show that informed traders rather use market orders than limit orders, as the latter conveys more information about the trader's intentions and may serve as a clue to his/her trading plan, position, etc.[2] In order to avoid conveying such information to the market, many electronic platforms allow the participants to trade anonymously and conceal their trading pattern by breaking the trades into smaller parts, varying the time of execution, etc. Payne(2003) uses vector autoregressive analysis to estimate the cost of asymmetric trading, namely trading with a more informed counterpart. The degree of information is measured by the duration of the price impact, as more informed traders are assumed to influence the market in a longer lasting fashion. Bjonnes and Rime (2000a) explores the information content of the interdealer trades with and without the use of brokers and found that direct trades typically have more influence on the market. Bjonnes and Rime (2000b) argues that the customer trades are the most important source of information for the traders. The paper substantiates this latter claim by referring to an ability to charge customers a wider spread than other dealers and transparency of the interdealer market. Both of these claims seem less convincing at present, since spreads have been reduced on all FX transactions and markets have become more transparent and accessible to almost all customers through electronic platforms. Moreover our private conversations with a number of market makers at major banks also reveal that with the exception of a small group of clients (namely hedge fund and leveraged players), they deem the customer trades to provide less insight into market sentiment on average than the interdealer market. Furthermore as market making is becoming less profitable (due to shrinking spreads and the availability of multitude of alternative electronic means of execution), proprietary trading including price taking have become more significant and therefore interdealer market

[2] Aggregate amount of bought minus sold of a currency as viewed from the stand point of the market maker.

information has become ever more important. At any rate, the notion of customer vs. dealer trades are becoming more obscure as more and more “customers” are now also market makers on various platforms.

3. The microstructure approach also contends that institutions influence the markets differently.
4. Though microstructure study typically deals with intraday high frequency transactions, there seems to be a longer lasting effect. This is partly investigated in long memory analysis of the intraday effects (e.g. see Sun et al (2006a)).
5. Spread is partly reflective of the information content of the flow. Though the flow is not the only determinant of the spread, a market maker will set the spread partly based on who the perceived market participants are at the time.
6. Lyons (2001) and Payne (2003) test and prove the hypothesis that the information content of the flow is less if more trades are happening per unit of time, i.e. the higher the frequency of the trades, the lower the informational value of each trade.
7. The market maker’s inventory is a crucial factor influencing her market interaction at each moment. The aggregate of inventories across all market makers and its change over the course of the day reflects the intraday flow.
8. Information arriving in the market is not immediately absorbed in the market. Instead it is conveyed to the market via market participants’ reaction to the information. In case of the market makers, this includes the market makers’ adjusting the spread and levels which in aggregation will communicate the information to other participants (including other market makers). Breedon and Vitale (2004) analyzes EUR/USD 5 minute data of 6 months and demonstrates that the order flow effect on exchange rates is due to change in liquidity and not any information content. While acknowledging the effect of order flow on price formation, Vitale(2004) argues that after surveying the microstructure literature, it is not clear how much of the effect of the order flow could be associated with information or liquidity. Payne and Love (2006) review the effect of macro new announcement on price level using inter dealer minute data and conclude that a) as much as 30% of the price movement after the announcement of economic release can be statistically explained by flow and b) the economic release effects are absorbed and prices adjust within 2 minutes after an announcement.

2.2 Main intraday characteristic of currency markets

The following are the most important characteristics of the currency market. Some of these characteristics apply to equity and other markets as well.

1. Homogeneity of data

Tick data are inhomogeneous, i.e. the time interval between the occurrences of consecutive data is not constant. This feature makes the analysis more complicated and various methods have been suggested in order to deal with this issue. Dacorogna(2001) and Hautsch(2004) provide detailed description of some of these methods. Given the non homogeneity of the intraday data, new approaches have been studied by researchers. For instance using duration has particular advantages over traditional price action analysis discussed above, as the former could be well adopted to data which arrive at irregular intervals. Duration is defined as the waiting time between 2 successive points in the process. A process may be explained through a duration representation or by using a counting representation (the later emphasizing the number of points in a given interval).

Using the notations of Hautsch (2004), intensity process is defined as follows:

Let N(t) be a point process on [0,∞) that is adapted to F and is a positive process with sample paths that are left continuous and have right handed limits. The process

$$\lambda(t;_{t}) := \lim_{\Delta \to o} \frac{1}{\Delta} E[(N(t+\Delta) - N(t) \mid F_t]$$

$$\lambda(t;F_t) > 0, \forall t,$$

is called F_t-intensity process of the counting process $N(t)$. Closely related hazard function describes a similar concept, but it is used in cross sectional data. In contrast an intensity function is used in analyzing the duration in continuous time point processes. In contrast to duration based analysis, data count models aggregate the points in equal intervals. Though simple to use, this style of analysis ignores the information content attributable to the arrival time of the marks.

The following factors come into play when considering duration based or intensity based models:

- Multivariate vs. single variable drivers
- Ease of censoring the undesirable periods out of the analysis. In our study, this would be removing partial daily data, weekends, holidays, etc.
- Ease of dealing with time varying covariates

Duration based models include the following types (see Hautsch (2004)):

Trade duration:

Trade duration is the time between consecutive trades. Trade duration has been largely associated with the existence of information in the market, the argument being that an informed trader would wish to act on the information as quickly as possible. Hence shorter durations (reflecting high volumes being transacted in short time intervals) may be attributable to the traders' information.

Price duration:

In generating this process, one discards some consecutive prices according to the following:

$$|p_{i+1} - p_i| \leq dp$$

where *dp* is an arbitrary number representing the cumulative absolute price change and p_i is the price. Hence the only data kept for analysis is those data which has a first difference greater than a certain threshold. Data corresponding to smaller changes is discarded.

Directional change duration

This refers to the time that it takes for the market to change its direction of movement (e.g. from ascending to descending).

Volume duration:

This refers to the net flow (i.e. the difference between total amount sold and total amount bought measured in based currency) as seen on the market makers book, and is the subject of micro structure study such as in Lyons. Hautsch(2004) proposes a number of hypothesis based on the above notions:

1. Large volumes decrease subsequent trade durations(i.e. cause more rapid change in prices)
2. Bid ask spread is positively correlated with subsequent trade durations.

3. Trade durations are auto correlated(i.e. large trades which cause large moves and smaller duration are followed by other large trades and similarly for small trades).
4. Absolute price changes are negatively correlated with subsequent trade durations.

Hautsch(2004) analyzes stocks using tick data of a few months. He concludes that:

1. Trade durations show the lowest auto correlations, but once a regime is established (e.g. a period is reached with short duration) that regime persists for a significant time before changing to another regime (e.g. back to long duration).
2. Price and volume durations on the contrary exhibit weak persistence but stronger correlation.
3. Volume durations show the highest first order autocorrelation, consistent with other studies on dynamics of volatility clustering.

Hujer(2003) proposes another alteration of Autoregressive Conditional Duration (ACD) model, namely Discrete Mixture ACD which may provide advantages in modeling certain agent's participation pattern in the market. However she does not clarify the advantages of this model in estimation of market dynamics such as volatility or better suitability for regime switching behavior.

2. Heavy tails

Heavy tails are well known phenomena in financial markets. The following from Mandelbrot(2004)p. 234 is revealing. He indicates that from 1986 to 2003, the US dollar lost about 60% against Japanese Yen. But half of the loss came from only 10 days out of 4695 days. Similarly in the 1980s, about 40% of the S&P 500 return was attributable to only 10 trading days. High frequency data in various asset classes demonstrate heavy tails. The assumption of Gaussian distribution in financial time series may be an acceptable postulation in certain cases of financial modeling, but it is highly suspect in high frequency (e.g. less than hourly frequencies) or even at intraday frequencies. For FX data series, a comprehensive study may be found at Dacorogna et al. (2001) and for the equity market, Sun et al. (2006a) demonstrates the existence of heavy tails in intra day data. Ghashghaie et al (1996) analyzes the 10 minute USD/DEM data and reports that the probability density functions of returns are not time invariant and tend to be closer to Gaussian distribution as the time difference of the returns increases as seen in Figure 2.1.

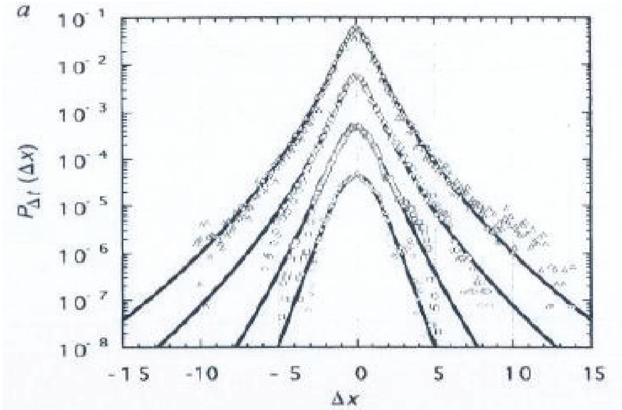


Figure 2.1. Time is noted as Δx in the graph, hence the further away from the center 0 that we move, the more closer the distribution is to Gaussian.

Multiple other studies confirm the non Gaussian distribution of returns in equity and currency markets. For instance, Figure 2.2 below from Voit(2003) depicts the extreme values occurring in returns in equity market. Very similar graphs explain currency market dynamics.

J. Voit / Physica A 321 (2003) 286–299 291

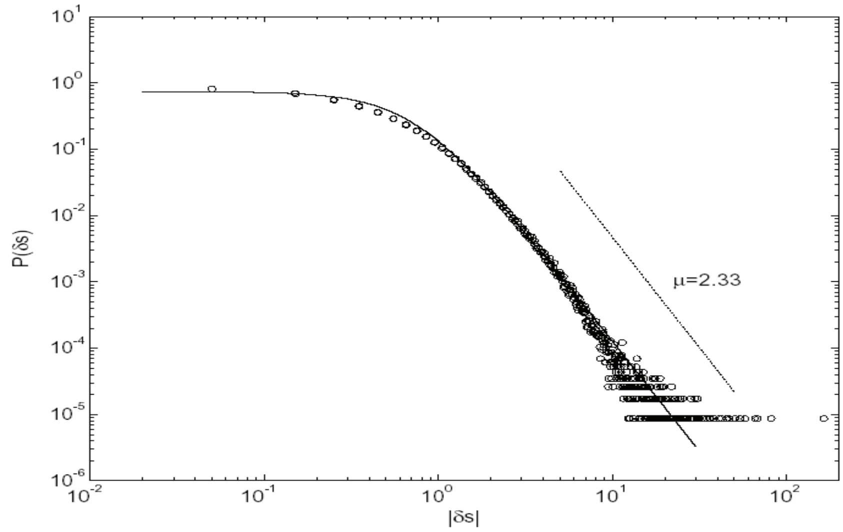


Fig. 4. Probability density function of 15-s DAX returns (dots). The straight dotted line indicates a power law with its exponent derived from extreme value theory (see text). The solid line is a fit to a Student-*t* distribution, again with its exponent determined independently by extreme value theory. (From Ref. [21].)

Figure 2.2

Assuming that there exist power laws to explain the behavior of the markets, intraday observations may be useful in explaining longer term heavy tails.[3] Such power laws have been proposed and studied in detail by Sornette D. and V. Pisarenko(2004) and Stanley et al (2007) among others.

3. Seasonality

Intraday seasonality of FX market has been studied extensively. Hong and Wang(2000) report a typical U shaped pattern in intraday market activity in each time zone, measured by volume traded and number of trades per unit of time. Though currencies may be traded on a 24 hour basis, the peak of the trading in major markets happen at the early hours of the morning, followed by diminished activity towards the middle of the daily trading session. Final hours of the trading day again witness an increase in trading activity. Other studies, such as Bollerslev et al (1993) show an increase in trading activity in the overlapping time period between London and New York markets. Recent studies by the Royal Bank of Scotland and Citigroup confirm these results. Citigroup (2007)used EBS™ and Reuters 3000™ tick data of 2003-2007 and concluded that though markets with well defined open and close times (e.g. Equity market) may demonstrate a U shape intraday pattern, the FX market evidence shows highest volume of trades occur between 13:00 and 16:00 London time when the London and New York markets overlap.

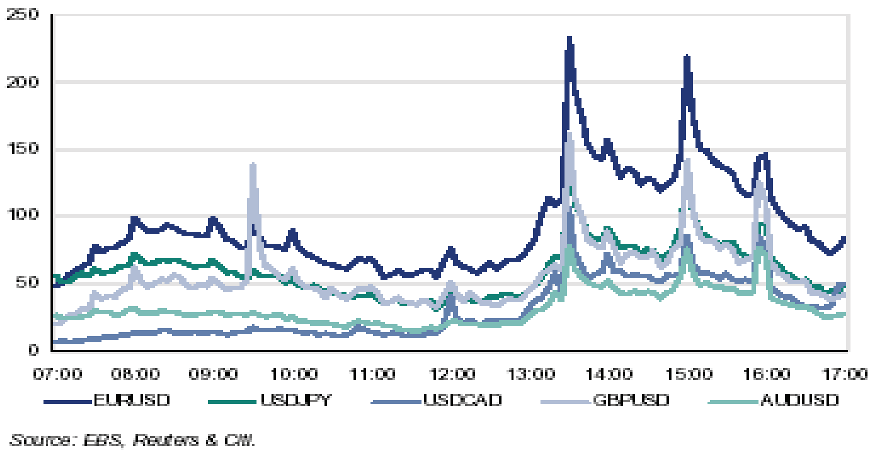


Figure 2.3

[3] Power law: function $f(x)$ abides by power law if $f(x) = ax^k + b$ where *k, a* and *b* are constants.

In the Figure 2.3 above from Citigroup(2007), the spikes in the London market volume coincide with economic releases and data releases, recurring market fixes (egg 13:15 ECB fix), New York currency options market expiration and the last major spike at 16:00 corresponding to WM/Reuters closing spot fix. BIS data confirms Citigroup's findings in the above. Similar studies have been done in the industry on the intraday volatility (see Kasikov and Gladwin(2007)). Figure 2.4 below from *FX Liquidity Update* (Aug. 2006) shows an average of the total number of trades done in each hour. Analysis was done on tick data from Aug. 05-Aug. 06.

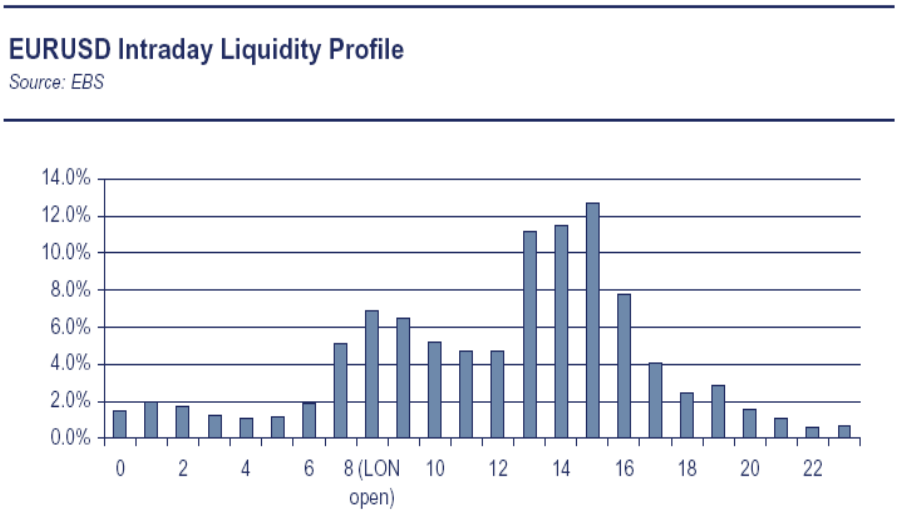
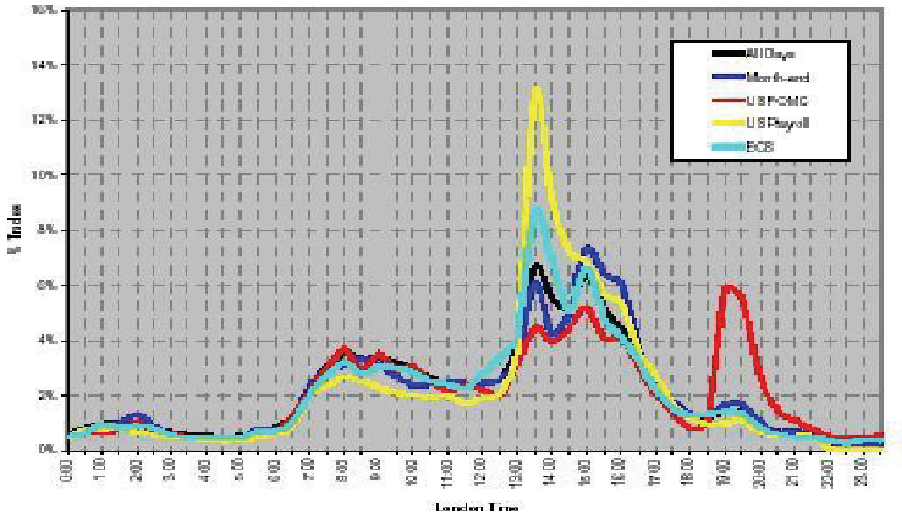


Figure 2.4

Similar intraday pattern can be observed in other major currency crosses[4] as well. Kim(2007) verifies the same intraday liquidity patterns, as well as identifying the average impact of the most important economic announcements. The vertical axis in Figure 2.5 represents the percentage of the trades done during the day.

[4] Cross or currency cross is a currency pair, e.g. USD/JPY



Source: EBS and Bank of America estimates

Figure 2.5

Using the EBS tick data including the volume, Chaboud et al(2007) report distinctive seasonalities in trading volume during a 24 hour period. The first peak in the volume corresponds to 8:30 am NYC time, when most economic numbers are announced. The peak at 11:30 corresponds to WM Company fixing of the rates which is a daily number commonly used by asset managers as a reference. Understanding the intraday seasonality and patterns are of crucial importance in high frequency intraday finance. One needs to normalize for such effects in studying volatility and its relationship with volume, in finding proxies for volume, in constructing trading models.

We will discuss the importance of economic announcements and their consequences for the market in the next chapter. However it is worth noting at this stage that as the economic announcements are typically made with a predetermined schedule, they themselves induce particular seasonality and patterns which may be quantified and exploited in trading.

Various methods have been employed to explain seasonalities within the intraday data series. Gençay et al.(2001) successfully demonstrates the application of a multi scaling wavelet approach which filters out the intraday seasonalities of the 5 minute FX data series. In that study, no data is eliminated from the study and the result clearly reveals the long memory effects of the data. To the degree that patterns such as those described above do exist in intraday markets, various approaches have been used in academia and industry to exploit them. Dempster (2001) uses currency tick data to illustrate the possibility of constructing an automated trading model using technical analysis. Though such a study expands our understanding of micro dynamics of the market, neural models seem to be unwieldy for profitable trading at present, due to complexity of calibrating a multitude of factors in the model. Neural net applications of high frequency may nevertheless have unexplored potential, as is suggested by Alexander (2001) p. 395-407. In currency market, seasonalities also exist in longer time horizons, such as in weekly data (see Eggleston and Farnsworth (2005)).

4. Scaling

Voit(2005)185-188 shows that scaling in returns of USD/DEM using intraday data seem to fit another pdf, namely one derived from Fokker-Planck equation. Other possible pdfs for FX rates returns, according to Breymann et al (2000) may be cascade models studied in fluid dynamics. The scaling seems to vary for different data frequencies. Voit(2005) and others report that volatility does not scale symmetrically, such that coarse volatility (i.e. one based on longer time horizon) predicts the fine volatility better than the reverse.

Mantegna (2004) shows that there are 2 classes of stable stochastic processes, namely Lorentzian and Gaussian. They have the following as their characteristic function assuming symmetric distribution with mean μ=0:

$$\varphi(q) = e^{-\gamma|q|^{\alpha}}$$

α =1 corresponds to Lorentzian and α =2 corresponds to Gaussian distributions.

In such processes, the probability distribution function for large values of the independent variable x (i.e. asymptotic behavior) can be shown to be:

$$P(|x|) \sim |x|^{-(1+\alpha)}$$

In other words, pdf of $|x|$ abides by a power law for large values of x. Gencay and Xu(2003) use 10 minute DEM-USD data to analyze self similarity and scaling. They conclude that power law does describe the occurrence of fat tails most accurately, and demonstrate some indications of multi-fractal behavior as well.

5. Autocorrelation

Autocorrelation of the tick level data has been studied extensively. This includes studies of various estimations of volatility, return, higher order moments, sign of returns, etc. Below we review some of the main findings:

Bollerslev et al(1993) report finding negative first order autocorrelation in both bid and ask time series sampled at 5 minute intervals. During very short time periods (<1 minute) a negative correlation of return may be observed due to bid-ask bounce. While admitting that the returns process does not show autocorrelation, Cont (2006) indicates that absolute returns show positive autocorrelation in various asset classes and is stable across many time horizons. Cont et al(1997) further contends that though various powers of absolute return $|r|^{\alpha}$ demonstrate autocorrelation, this autocorrelation seem to be mostly evident if α = 1. Evans (2002) analyzes interdealer flow and defines common knowledge economic release as one which has impact on the price but does not change the flow. Non common knowledge influences both price and amount of transaction flow. Based on this, it measures the amount of price change attributable to each type of economic release. Though some of this analysis is based on the assumption of lack of transparency in the market (which is becoming increasingly inaccurate with the spread of electronic trading), Evans(2002) nevertheless reports certain stylized facts in the 5 minute DEM/USD over a 4 month period:

- Price changes show statistically significant negative serial correlation
- Flow shows positive autocorrelation and persistence.

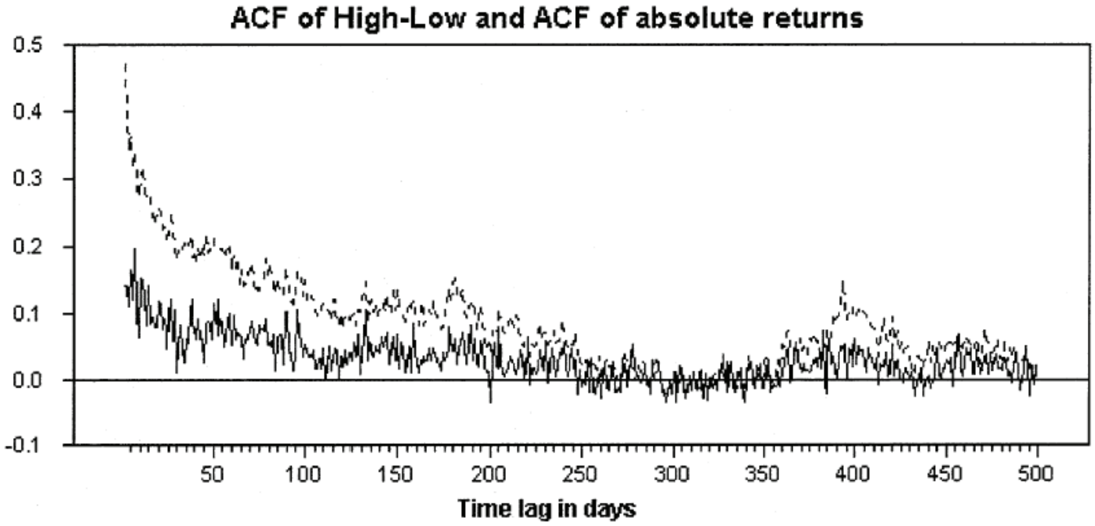


Figure 2.6

The Figure 2.6 from Fiess et al(2002) illustrates the decay of the ACF of absolute return (solid line) vs. that of price range for the daily GBP/USD data of 1989-1996. As the ACF is significantly higher in lower lags, it can be concluded that it constitutes a better forecasting tool for short time intervals. The range (high minus low of the period) ACF also exhibits a slower decay. Fiess et al(2002) imposes various lags and forwards to the data and measure the autocorrelation function. Thus it is shown that the information flow is asynchronous and the order of the data is statistically significant (i.e. there is forward looking information content embedded in the data which provides for a forecasting method).

Tanaka (2003)b analyzes 5 years of quotes in major currency crosses, and estimates the likelihood of bid following bid, ask following ask and the combinations of the aforementioned with varying lags. This led to estimating the conditional probability of down and up returns.

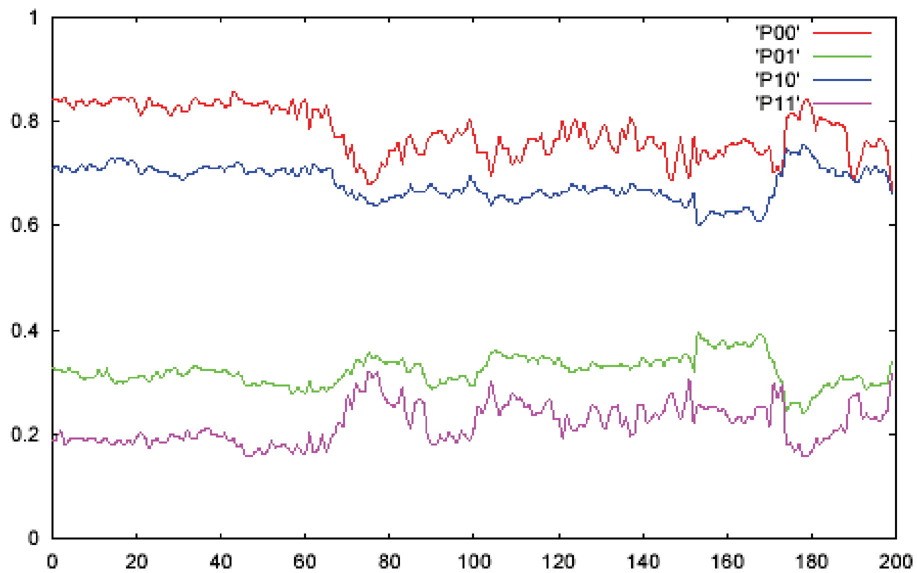


Figure 2.7

In Figure 2.7, y axis is the conditional probability and x axis is time in minutes. Figure 2.7 from Tanaka(2003)a illustrates the conditional probability of up moves (denoted by 1) following down moves(denoted by 0), etc for a 2 tick lag. For instance, red line shows the probability of a down move followed by another down move during a 200 minute window. Similar results and stability exist for 3 ticks, but is not discernable for lags>3. Voit (2005) reports qualitatively similar auto correlation for currency, bond and equity indices. Other studies fail to verify such correlation in returns, though auto correlation in various volatility estimations (including $|\delta S(t)|$) is reported by various researchers.

6. Long memory

Kirman et al(2002) examines daily and intraday FX rates and reports presence of long memory effect. A stationary process with long memory is defined as:

$$\rho(k) \sim L(k)k^{2d-1} \quad \text{as } k \to \infty$$

$\rho(k)$ is the autocorrelation function of the process and *k* is the independent variable. $d \in (0,1/2)$

$L(k)$ is a slowly varying function (as opposed to an exponential or other fast decaying function)with the following characteristic:

$L(\lambda k)/L(k) \to 1$ as $k \to \infty$, $\lambda > 0$

Hence the autocorrelation stays present long after the initial shock or change to the system. Kirman(2002) concludes that as *d* (namely the measure of decay of ACF) is empirically estimated to be the same for various currency pairs, the long memory effect is the same for all crosses. Kirman (2002) quotes Olsen group and others as having performed similar analysis on 30 minute data and having achieved the same results. Finally Kirman(2002) provides a micro economic model to explain the fundamentals behind the long memory and concludes that long memory effect may in fact serve to explain bubbles in the market through participant's "herding" behavior. Lo(1991) and others have observed that while long memory effects seem to exist in equity and FX markets, their existence depends largely on definition of long memory and variations to the above definition for instance may lead to rejecting the existence of such effects.

7. Market discontinuities and Jumps

Though currency market has periods of low and high liquidity, it is possible to trade currencies 24 hours a day. This is due to the fact that Tokyo, London and New York trade in different time zones and they also overlap secondary trading centers such as Sydney, Frankfurt, etc. As such there is no intraday jump in the pure sense of the word, as opposed to equity markets which may experience a jump from the close of the market on one day to the market opening on the subsequent day.

8. Fractal behavior

Researchers have investigated the hypothesis that markets do follow a fractal pattern in intervals less than a day. Alexander (2001) 401-405 and Peters (1994) 133-142 report the existence of chaos effects in intraday equity markets, but the effects are small enough that they may be due to measurement errors, calibrating the models, etc. De Grauwe et al(2006) studied currency markets and reports lack of convincing evidence of fractal behavior. A number of researchers including Voit(2005) have adopted the following as the definition of a multifractal stochastic process $\delta S_\tau(t)$:

$$E(|\delta S_\tau(t)|^n) = c(n)\tau^{H_n}$$

If the Hurst number H_n > ½, the time series exhibits persistence and more jagged motion, while H_n < ½ indicates anti persistence and a somewhat smoother path. By setting up simulations of cascading multifractal processes, Lux (2001) reports that DAX and USD/DEM minute data's pdf may possibly be modeled by a multifractal process.

Peters (1991) reports H_n = 0.6 and therefore persistent behavior for a number of currencies daily returns, but it does not include analysis on intraday data. Han (2007) uses 30 minute currency data and fits Poisson distribution to jumps. It claims that such jumps induce long memory effects in the data series. Chaotic behavior is relevant to understanding a possible path for the future of this research, as the market dynamics at the time of the economic releases may possibly be modeled using chaotic dynamics.

9. Stickiness

In the intraday markets, certain levels can potentially attract more attention from traders than others. Closes or opens of the previous day(s), high and low of the previous day, other historical support or resistance are all candidates for becoming attractive or "sticky" (i.e. markets do not simply pass through these levels as they would with other levels). Sticky numbers are typically characterized by increased market activity (higher trade volume, sometimes more volatility), prices bouncing back and/or lingering around those levels, etc. Another class of sticky numbers are round numbers. Sometimes there are actual restrictions on the placing and execution of the order, such as quoting a stock price in 1/8 in the past and decimal units used in quoting current equity prices. But even among available prices, investors do not choose all numbers equally. Round numbers and number ending in 5 or 0 typically are quoted more often and more trades are executed on or close to these numbers. By analyzing USD/JPY during 1990 to 2003, James(2004) page 78 notes that 20% of the hourly closes end in 0 (i.e. least significant digit is 0) and another 20% end in 5, with all other numbers having a share between 5-10%. This pattern may be observed in other currency pairs as well.

As limit orders are typically put on or close to such sticky numbers, they also contribute and add to the stickiness of these levels. Moreover option strikes set at such numbers can lead to abrupt and relatively disproportionate market moves. Sticky numbers are relevant to this thesis, as one may postulate (and future research should test) the behavior of the markets if the release time happens at a time when prices are close to sticky numbers. Without a release or other shocks, one can assume a tendency of the prices to come to equilibrium at the sticky numbers. It is to be seen how this dynamics holds in the presence of a shock, for instance an economic release.

10. Spread dynamics

There has been a number of academic and professional research publications which have addressed the bid/ask spread and its relationship to liquidity, volatility and volume of trade. Typically a market maker's spread depends on the inventory (net holding of the "items" for sale such as currency, commodity…) and perceived risk and reward profile. Wider spread is to compensate for higher risk in the market. As such, it stands to reason that the market maker would increase her spread during volatile (hence uncertain) times. On the other hand, in times of low liquidity, a market maker may not be able to offload the risk by reducing his position through trading with other parties. Hence periods of low liquidity as also considered risky for the market maker and the market maker will increase her bid ask spread in order to be compensated for taking this risk. Kim et al.(2007) note that in FX market, the spread increases at time of low liquidity and contracts during the daily peaks of liquidity(cf. graphs on seasonality above).

2.3 Volatility Estimation

During the remaining chapters of this thesis, we have used a novel approach to using wavelets in volatility estimation. While noting some of the relevant literature, we here introduce various volatility measures. Volatility estimation in high frequency finance is crucial to understanding the dynamics of the markets, and even many academics and practitioners who have been interested in longer term market dynamics have still analyzed intraday data in the hopes of gaining a better estimation of the longer term volatility.

We start by reviewing various approaches to volatility estimation.

Rolling sample volatility estimation

Most commonly used estimation of volatility is performed by finding the standard deviation of the returns over a particular time period.

$$Volatility = St.Dev(\log(\frac{S_{t+1}}{S_t})) \qquad t = 1, 2 \ldots n$$

A variation of the above comprise of breaking down the measurement period into smaller intervals, as in rolling sample estimation. In this method, the volatility is measured by calculating the standard deviation of the returns over a number of periods and the time window is moved forward on one period at a time. For instance, a 12 month volatility estimation is performed using the latest 12 months and each month the 13 month is added, while the beginning month is dropped. One of the benefits of this method is that it assumes a particular structure on the changing volatility parameters (see Canopius (2003)). Of crucial importance in this method is the length of the rolling estimation window. Too long a period and one would not capture the interim changes in the volatility, too short a period and the estimation would be overshadowed by the interim noise.

ARCH models

ARCH (autoregressive conditional heteroscedasticity) process of *n*th order in its general form refers to a process which abides by the following equation:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \sigma_{t-1}^2 + \ldots + \alpha_n \sigma_{t-n}^2 + \varepsilon$$

In essence, variance at time *t* is assumed to depend on the previous variances. Researchers have investigated ARCH effects in FX for a variety of reasons. In the earlier studies, some researchers attempted to explain the so called forward rate bias by finding the appropriate risk premia through ARCH modeling. A natural extension of such notion is that conditional covariances may be a better predictor of the risk premium. To this end, multivariate ARCH studies were performed as noted in Sarno and Taylor (2002). Until a few years ago, due to unavailability of intraday data, studies of FX volatility was done on daily or lower frequencies. Diebold (1988 and 1989) report statistically significant ARCH characteristics in such data. Since Engle's ground breaking work in formulating ARCH effects, there has been numerous attempts in applying ARCH variations to currency markets. Alexander (1995) analyzes various currency pairs for ARCH effect and reports its existence in some currency pairs, but absence of such effects in other pairs. She also concludes that daily data are too noisy to detect any ARCH effect. Jones (2003) uses 5 minute data series in FX and performs simulations to evaluate the ARCH class models success in explaining the market dynamics. He concludes that these models do not perform well in intraday frequencies. This is illustrated in low R^2. He also demonstrates that addition of another term in GARCH (1,1), first suggested by Martens (2001), will add to its forecasting ability of realized daily variance:

$$\sigma_t^2 = \gamma + \alpha \,.\, \varepsilon_{t-1}^2 + \beta \,.\, \sigma_{t-1}^2 + \kappa \,.\, I_{t-1}$$

Here I_{t-1} is the sum of square of the returns calculated at 30 minute periods. Though Martens (2001) seeks methods of improving volatility estimation for daily returns, suggested methods modifying GARCH (1,1) to include intraday returns or incorporating high-low of the day may be applicable for shorter periods of time (namely intraday time units).

Realized (quadratic) volatility estimation

Realized volatility (sometimes referred to as realized quadratic volatility or RQV) breaks down the period into sub intervals and sums the squared returns of the subintervals. This is easy to calculate and observable in the market. As opposed to rolling sample estimation where there is always a common period between the adjacent windows, in realized volatility estimation each period is distinct and there are no overlaps. If the number of intervals in the study period tends to infinity, the estimation method will effectively integrate the volatility over the period and the result is known as notional volatility. Andersen et al (2003) illustrates that RQV compares favorably to GARCH and other conventional methods in forecasting volatility and suggest building 30 minute time units for analysis from tick data to overcome micro effects.

Absolute return volatility estimation

In this method, the volatility is defined as follows:

$$volatility = \left| \frac{P_{t+1} - P_t}{P_t} \right|$$ where P_t is price at time *t.*

Forsberg and Ghysels(2007) observes that for intraday data, absolute return estimation shows more persistence than squared return, particularly the case in the presence of jump process. In addition to immunity to jump, the article recites better sampling error behavior and population predictability features as advantages of absolute return method. This is supported by in and out of sample study of equity markets.

Cumulative absolute return volatility estimation

Fiess(2002) also compares the ability of range(high minus low of the period) vs. intraday cumulative absolute return and GARCH(1,1) in forecasting daily volatility and concludes that range estimation performs the best. Moreover the study suggests the use of high low and close prices to explore Granger causality in the intraday rates.

Garman Klass estimation

This method incorporates high, low and close to close measures, and may at times be used instead of range estimation.

$$\sigma = \sqrt{\frac{Z}{n} \sum \left[\tfrac{1}{2} \left(\ln \frac{H_i}{L_i} \right)^2 - (2 \ln 2 - 1) \left(\ln \frac{C_i}{O_i} \right)^2 \right]}$$

Where

σ= volatility

Z = number of closing prices in the estimation period

n = number of historical prices used for volatility estimation

O_i = opening price

H_i = high price of period

L_i = low price of period

C_i = closing price

We think that this measure can potentially have a variety of applications for high frequency finance, as it ignores overnight (market close to market opening of subsequent day) and does not include the effects of drift in the underlying. Both of the above can be useful particularly in equity markets. As currency market is functional round the clock, there is no “overnight” jump and therefore simpler range volatility may be used.

Exponentially weighted moving average (EWMA) estimation

Moving averages are among the most common filters used by practitioners, and has been studied by academics as well. Yilmaz(2007b) offers a comparison between rolling window volatility estimation (the most commonly used method in industry) and GARCH, range, realized quadratic variation (RQV) and exponentially weighted moving average (EWMA).

Range volatility estimation

Using price range (namely high of the period minus low of the period) in market analysis is quite common among practitioners and academics have analyzed it for decades.

Volatility = High of period – Low of period

Range based volatility is one in which a function of the period range as volatility estimate. This measure of volatility has some important characteristics:

- Compared to close to close estimate, high low range captures the price dynamics better throughout the period. Close to close may be misleading as a measure of volatility, as the close of one period may be very close to the close of the previous period, despite the fact that prices may have gyrated radically throughout the period.
- Low and high indicate the turning points in the market and as such constitute potential supports and resistance respectively. Support and resistance possess stickiness which affects the micro dynamics of the markets.

- As high and low are sticky levels (and become stickier as more market participants pay attention to them) typically large volume is traded on and around those levels. Therefore the market activity may be more informative around high and lows (i.e. flow containing more information) than other times during the period.
- While log absolute return and log squared returns are not normal (particularly in high frequency intraday time frame) log of range has approx. normal distribution (see Alizadeh et al (2003)).
- Due to discrete sampling, there is a bias introduced in this estimation. This is particularly true when compared with realized quadratic variation (RQV) for instance. The latter divides the time period into smaller intervals and sums up the squared returns of the intervals. Using high frequency data, Yilmaz (2007a) shows less bias and higher efficiency if a clean price process can be assumed (i.e. if price prices is assumed normal and microstructure noise can be ignored).

  Christensen et al (2006) survey a few propositions to overcome the aforementioned bias. They also address the problem of finding an optimum division of data into sub intervals to minimize asymptotic conditional variance.
- Range volatility estimation is a more statistically efficient estimation than close to close return based estimation (see for instance Parkinson (1980)).

Yilmaz (2007c) compares the range estimation method with various GARCH methods in forecasting accuracy on out of sample data using the following two evaluation criteria:

Root mean square error

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\sigma_t^2 - \hat{\sigma}_t^2)^2}$$

T is the number of data points in the sample.

Mincer-Zarnowitz regression

$$\sigma_t^2 = \alpha + \beta\hat{\sigma}_t^2 + \varepsilon_t$$

Here the historical volatility is regressed on the forecast. If $\beta \neq 1$, then the volatility forecast is inefficient and if $\alpha \neq 0$ the forecast is biased. Duque and Paxson(1997) suggest using efficiency of the estimator for comparing estimation methods:

Efficiency of the estimator = $\dfrac{\text{Variance of the benchmark}}{\text{Variance of the estimator}}$

We used the above definition of efficiency to compare our proposed volatility estimator with range estimator in Chapter 3.

A few key themes in volatility studies are discussed below, taking into account that the topics do overlap in practice:

Noise effects in intraday volatility estimation

Bandi , Russel and Zhu(2006) investigates using 5 and 15 minute equity data in order to estimate daily volatility. The authors' goal is to use the volatility estimate in a covariance matrix which is used in portfolio construction. In order to minimize the effect of intraday day noise in the volatility estimation, authors propose a method for "selecting" data points. To evaluate their selection process with 5 or 15 minute sampling, they analyzed the economics performance (i.e. gain/loss) of constructing portfolios (rebalancing portfolios based on mean variance optimization) according to both methods.

Intraday seasonalities effect on volatility estimation

Existence of intraday seasonalities, as discussed in the previous chapter, complicates the task of volatility estimation. Wang et al (2007) suggests dividing volatility by average volatility of the whole period to allow for seasonality.

Volatility clustering

Voit (2003) analyzes the 15 second data for 1999 and 2000 on DAX. Defining the auto correlation as:

$$Corr(\tau) = E(\delta S(t)\delta S(t+\tau))$$

where $\delta S(t)$ is the return on the underlying for period t . Figure 2.8 below from Voit(2003) depicts the correlation versus a 3σ band.

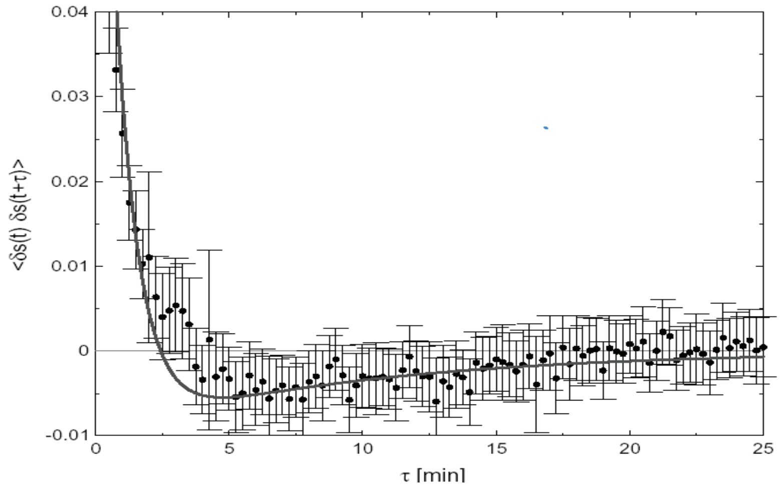


Figure 2.8

We observe that the autocorrelation exists within short time intervals but decreases rapidly as we increase the return time interval and eventually settles at zero.

Berger et al.(2006) analyzes the executed second by second FX data (including traded volume) to characterize the long memory in volatility. It argues that the variation in volatility is a function of information (represented by order flow) and sensitivity of the market to the information. We will examine the clustering tendency of volatility around news releases later in this dissertation.

Volatility spillover

Volatility spillovers (spreading of the volatility from one financial asset to the other) have been studied most extensively in equity markets. Milunovich (2006) illustrates how allowing for spillovers may improve the equity portfolio construction. In FX, Engle has performed some pioneering and very influential work on the subject. Engle, Ito and Lin (1990) use hourly data to explore volatility clusters. They test the hypothesis that increase in volatility in one currency pair leads to increase in volatility in the following time intervals ("heat wave") vs. the hypothesis that increase in volatility in one currency pair spills over into other pairs ("meteor shower"). They allow for intraday seasonalities and analyze the effect of major economic releases impacts using ARCH models. They conclude that volatility does in fact spill over into other currencies. Apergis (2001) uses daily data and claims that GARCH measured volatility spills over from FX markets to equity, but not the reverse.

Volatility scaling

Batten and Ellis (2001) studies daily return of 4 major currencies during 1985-98. It reports that scaling with a power law with k= 0.5 (square root of time) underestimates the risk for all 4 pairs as measured by the options market implied volatilities. It explains that time series which demonstrate non linear dependence scale by their Hurst exponent. Moreover it notes that a Gaussian series should scale with a Hurst exponent H= 0.5.

Scaling with the square root of time therefore fits as a specific case of the above. However as the frequency of the measurement increases (i.e. as smaller time intervals between observations is used to project the volatility farther and farther out), the leptokurtic feature of the distribution becomes more prominent.

The long memory effect, and dependence of conditional variance are noted as possible explanations for the fact that time series scale faster than $\sqrt{T}$. This faster scaling was observed in all currencies, but was not evident with GBP. It also quotes Muller (1990) as having found the intraday price changes to scale with H =0.59.

Diebold et al (1998) demonstrates that scaling with H=0.5 only holds under identical and independent distribution (i.i.d.) conditions. Even assuming conditional mean independence in return of daily data, conditional variance independence certainly does not hold in such frequencies. By using a GARCH(1,1) model and comparing the results, the magnitude of errors is estimated. The paper suggests that different models are needed for different time horizons. Christoffersen and Diebold (1997) shows that the predictable volatility dynamics in many asset returns diminish rapidly with time horizon, indicating that scaling can be misleading. This paper also concede that even if volatility is estimated successfully, scaling with $\sqrt{t}$ may result in overestimating the volatility in conditional volatility. This may be significant in constructing intraday trading algorithms. Vuorenmaa (2005) notes that in order for the square root of time scaling law to apply, the data series should be identically and independently distributed. Therefore square root scaling clearly is inappropriate for use in the nonstationary tick data time series which exhibits among other things auto regressive patterns in second moment (see also Hamilton (1994)).

Volatility, liquidity, spreads and frequency of trades

The relation between volatility, liquidity, bid/ask spread and frequency of trade is of crucial interest to high frequency trading and therefore has garnered notable interest among academia and practitioners. The relationship between volatility, expectation of future volatility (i.e. market sentiment) and liquidity has been modeled for equity market at Deuskar (2006). The argument goes that at times when investors expect the volatility to rise, they are less willing to invest in the market and rather invest in low risk low volatility low return assets. This leads to lower liquidity in more volatile assets. Gopikrishnan et al (2000) analyzes the tick data on 1000 stocks for 2 years, and concludes that the number of trades is in fact the driver for not only the number of shares traded, but also the absolute value of price change. Gillemot et al (2005) reviews years of equity market tick data to investigate the causes of volatility cluster and heavy tails. It demonstrates that even though transaction frequency and volume are positively correlated with volatility, they are not the main drivers of volatility in their data set. By scrambling the data and using measures of transaction other than clock time, they conclude that contemporaneous relationship with the size of price change seems to be the main driver of volatility. It is also noted that other data sets of equally large size do not readily demonstrate the above. Dominquez and Panthaki (2006) analyzes 10 months of 20 minute data in various currency crosses to determine the effects of the announced vs. unexpected economic releases. It reports a positive autocorrelation in returns in 20 minute time, but not at longer time horizons. Moreover it recognizes a contemporaneous association between order flow, price change, order flow volatility and transaction frequency after market economic releases. It reports a causal effect between fundamental and non fundamental economic release and intraday return and volatility.

Clifton and Plumb (2007) measured the liquidity (as measured by average number of trades, also known as turnover) and volatility of EUR/USD during a few months in 2007 and reported a high correlation as seen in Figure 2.9:

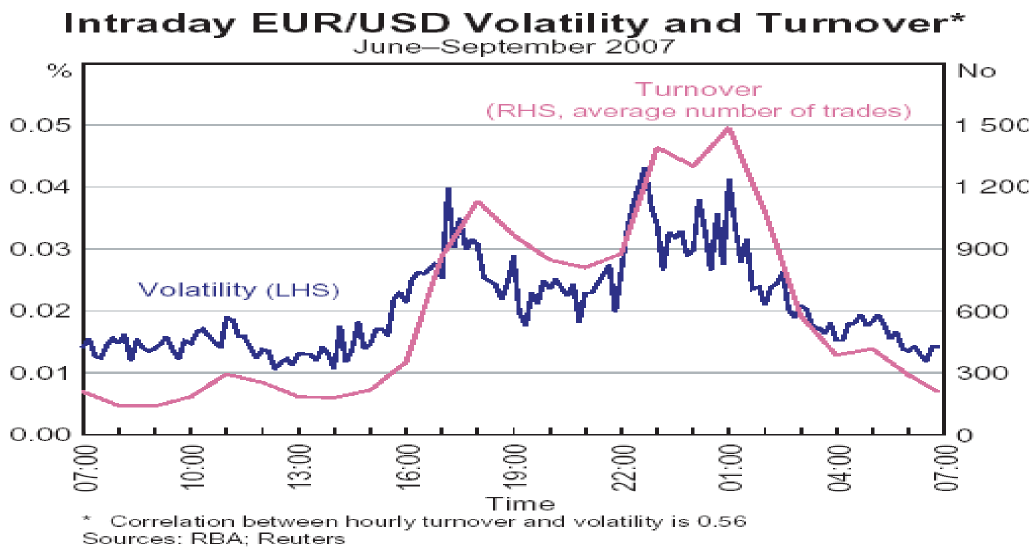


Figure 2.9

This coincidence of volatility and volume can be seen with very similar intraday pattern with other major currencies as well.

2.4 Wavelets and their application in our research

Though wavelets have been utilized in finance for some time, in this dissertation we will demonstrate a new application for wavelets in volatility analysis. We will use wavelets in analysis of intraday currency market dynamics and evaluating the effects of economic releases, and later apply our wavelet volatility estimator to equity market.

A wavelet is a filter which is constructed by applying a mathematical transform function (called the wavelet function) to a data series (or signal). The wavelet transform is similar to the Fourier transform with one important difference: although Fourier transforms the data into frequency space, wavelet transforms allow manipulation of the data in both time space and frequency space. A wavelet is characterized by its scale, and changing the scale allows for changing the resolution in frequency space (thereby capturing the frequency effects) or time space (thereby capturing the local time effects). Thus, wavelets may be adapted to best suit the signal. Various wavelet transfer functions have been developed each representing a different class of wavelets suitable for filtering different data; among these classes are Daubechies, Morlet, Haar, Symlets, and Coiflets.

A wavelet as a function should meet the following two criteria of admissibility and unit energy.
Admissibility requirement states that:

$$\int_0^\infty \frac{|\Psi(f)|}{f} df < \infty$$

Where $\Psi(f)$ is the Fourier transform and f is the frequency.

We define energy of a signal as:

$$\int_{-\infty}^{\infty} x^2(t)dt$$

The second requirement for wavelets is that the energy should equal 1.

A square-integrable function $x(t)$ is one for which we have:

$$\int_{-\infty}^{\infty} x^2(t)dt < \infty$$

A wavelet transform allows any square-integrable function to be decomposed (also called analyzed) into an approximation (i.e. main function) and detail(i.e. noise). A reconstruction of the approximation and addition of detail will yield the original signal. Hence using wavelets we construct a simpler signal while ensuring that the original characteristics of the function are kept.

Wavelets lend themselves very nicely to the short term volatility study. Study of short term volatility by its very nature concerns local phenomena. Wavelets allow one to separate the local variation (i.e. noise if one has a longer term horizon) from the major directional move of the currency. In the jargon of wavelets, the former is captured in details, whereas the latter is depicted in the approximation.

Gençay et al (2002) quote the following among the applications of filters:

1. Analyzing the time series with seasonalities
   The existence of seasonalities in time series may mask the underlying dynamics of the time series. Filtering enables us to separate the seasonality effects as has been done in academic studies of economic cycles.
2. Analyzing the effects of noise
   Intraday observations of currency market includes a noise process as mentioned in chapter one. A successful trading model separates the noise from the underlying movement, yet recognizes the part of the underlying dynamics which contributes to the trading signal.

3. Analyzing non stationary characteristics of time series
   In many time series, including intraday FX markets, the variance of the process is not stationary. Change in variance could be identified using filters.

A description of the process of applying wavelets, de-noising data, and construction may be found in Gençay et al. (2002), Keinert (2004, pp. 89-97), Gençay and Whitcher (2005), and Crowley (2007), among others. Crowley (2007) surveys how wavelet methods have been used in the economics and finance literature. Capobianco(1997) applies wavelets to daily Nikkei index to explore the volatility of the returns. It concludes that GARCH effects are less prominent in the shrunken dataset and that de-noised volatility (as measured by squared returns) can estimate the latent volatility better than the original data set. Capobianco(1999) reports success in determining intraday periodicity in returns when applying wavelets to 1 minute Nikkei index data. It fails to show further utility in forecasting volatility while using wavelets. Fan and Wang (2006) use wavelets to distinguish the effect of increase in volatility due to jumps versus the realized intraday volatility of 2 FX time series. Setting thresholds of 10% and 20% of total volatility, they conclude that in minute data in EUR/USD and JPY/USD, for the 7 months in 2004, there were 20-40% of the days where jump volatility exceeded the thresholds. These included some days when the effect of jump variation was greater than estimated integrated volatility. Wang (1995) reports satisfactory results in identifying jumps in simulated and real data. Using the universal threshold of Donoho and Johnstone (1994), Wang (1995) reports satisfactory results in identifying jumps in simulated and real data using wavelets.

Chapter 3

Effects of economic releases on intraday dynamics of currency market

3.1 Introduction

With the availability of high-frequency trading data, market participants are increasingly interested in understanding the intraday effects of economic announcements. Typically to explain the volatility around releases, studies have used a microstructure approach and commonly used ARCH family models. In comparison to the prevailing research, our contribution to the study of volatility induced by economic announcements is as follows: First, typically intraday research has been limited to quoted data over a period of some months and often for only a single currency. In contrast, our dataset is the second-by-second *actual executed trade data* over four years in pound sterling, Japanese yen, and the euro. These three currencies traded against the US dollar account for more than 80% of annual global currency trade. The data file for each currency comprises 70-80 million ticks. Each tick corresponds to one second and consists of time stamp, bid, ask and an indication of whether a trade was executed at bid or ask price. Second, unlike other studies investigating the volatility following economic announcements which use standard deviation as a volatility estimator, we use the range as a volatility estimator because previous research has shown the range to be more efficient than other estimators. Moreover, we found that range lends itself conveniently to intraday study. Third, rather than using traditional econometric tools, we use wavelets to analyze volatility around economic releases. Moreover, our use of wavelets is different from traditional wavelet applications in the sense that we use the “noise” (which is typically discarded in wavelets analysis) as our main focus, and discard the underlying “trend” in the data. Fourth, we compare the results of our analysis with the results of a poll that we conducted of major market participants. Finally, we propose a new volatility estimator using our wavelet approach and demonstrate that this estimator is on average 39 times more efficient than the range estimator and yet it does capture the dynamics of the market as reliably as the range estimator.

After providing a short review of the literature in Section 3.2, we describe our dataset and its construction in Section 3.3. In Section 3.4, we use analyze the data and determine the effects of various economic releases. We conducted a poll of both head traders in major currency management firms and chief economists in major investment banks. We asked them how they thought the economic releases affect the foreign exchange market. We then compared the regression results with the results of our poll to see how the expectations of traders and economists regarding the foreign exchange market fit the actual market dynamics. Based on our regression analysis findings, we selected four representative economic releases for studying volatility. We used the range to estimate the volatility and demonstrate a novel approach in wavelets to quantify the volatility characteristics prior to and after the representative releases, and compare the results for each currency and each individual release. We then modeled the volatility clusters and volatility of volatility. In Section 3.5, we conclude with a summary of our findings.

3.2 Review of literature on the effects of economic releases

There have been several studies that have assessed the effects of economic releases on various financial markets. Reviewing minute-by-minute price data from 1991 to 1995 for the U.S. Treasury market, Balduzzi et al. (2001) report an increase in volatility and bid-ask spread after an economic release, but a reversion to the pre-release levels within 5 to 15 minutes after the release. Also examining the U.S. Treasury market, Kuttner (2001) investigated the effects of Federal Reserve announcements and government interventions. He found that scheduled announcements have minimal effect on the Treasury market, while surprise announcements significantly impact the market.

Dominguez and Panthanki (2006 and 2007) observe that government intervention and the news of imminent government intervention (even if the intervention did not occur) had a statistically significant effect on intraday 20-minute lagged prices of the GBP/USD and JPY/USD exchange rates but not the EUR/USD exchange rate. Hasbrouck (1998) and other studies by the same author look at micro structure in the equity market and estimate volatility around various events. He observed that the market reaction varied significantly based on the type of news and announcements. Edison (1997), utilizing daily foreign exchange rates to analyze the effect of various news from 1980 to 1995, reports that, in general, nonfarm payroll, industrial production, retail sales, and unemployment have a greater effect on the exchange rates than the Consumer Price Index and the Producer Price Index. According to Edison (1997), there seems to be cointegration between the forecast and the release data for nonfarm payroll which, although small, is statistically significant. Other major news did not demonstrate cointegration. Analyzing 5-minute data of the EUR/USD exchange rate for a few months in 2001, Bauwens et al. (2005) find volatility is induced by major economic releases; however, they did not include the most important economic release for the foreign exchange market (namely, nonfarm payroll) in their analysis.

As gauged by their affect on major currencies, several studies have shown that U.S. economic announcements are by far the most important in the world. Minor currencies (i.e., emerging market currencies as well as those of smaller economies such as New Zealand) are shown in some studies (see, for example, Kearns and Manners (2005)) to be influenced as much by their local news and announcements. James and Kasikov (2008), Kearns and Manners (2005), and Kuttner (2001) studied the effects of economic releases in foreign exchange markets and other asset classes. James and Kasikov (2008) conclude that U.S. data seem to affect major markets more consistently than other markets, while Japanese, European, and Swiss releases seem to matter least. Kasikov and Gladwin (2007) attempt to estimate market behavior given an upside surprise (i.e., an economic release which beats the market's expectation) and downside surprise (i.e., an announcement which falls short of the market's consensus), and claim slightly different coefficients in the linear regression for each set of surprise data.

3.3 Data description

The dataset we used in this study consists of second-by-second tick data as it reported on two interbank electronic platforms, Reuters 3000 Xtra™ and Electronic Brokerage Systems ™ (EBS). These two platforms are by far the most liquid electronic platforms globally where traders can execute transactions in currency markets 24 hours a day. The two platforms are mostly accessed by market makers, but recently some investment banks allow their clients to gain access to these platforms using the banks as an intermediary. The electronic platforms do not provide the volume traded, but the trader who is executing on the electronic platform is able to see if a particular limit order that she entered earlier was filled and by whom. In other words, though the volume at each row is not known to us, the trader who executed at a price at that particular time would see the total amount of currency offered at bid and ask level, in addition to the identity of the counterpart if and when the trade is executed. This provides additional information for the bank market makers, not readily available to other market participants.

The tick data comprise the best quotes (i.e., highest bid and lowest offer, also known as “top of the book” and tightest bid/ask spread), time stamp (including hour, minute, and second), and an indication as to whether a trade was executed and at which side (i.e., if the trade was at the bid price or at the ask price). The dataset include all data from January 1, 2004 to December 31, 2007 in EUR, GBP, and JPY.

It is important to note that the dataset consists of actual prices on which trades were executed, not quoted data. Quoted data suffer from many inaccuracies, among them the fact that market makers may decide to quote a price momentarily and retrieve the quote without full intention of trading at that price. Because the volume associated with a quoted data is unknown in most cases in the foreign exchange market, quoted data may at times significantly reduce the accuracy of the analysis. By restricting our dataset to actual executed trades, our study does not suffer from the inaccuracies associated with quoted data.

As a final note, the quality of data is of paramount importance in high frequency analysis, and its significance increases significantly when one deals with frequencies below one minute. At those frequencies, the quality of data becomes disproportionately reliant upon the following:

- Momentary physical interruptions in data communications
  This may lead to erroneous quotes at the time of the disruption, and typically appear as unusually large jumps in the price.
- Cycling and randomizing effect of data providers (e.g. data from the largest electronic currency trading platform, Electronic Broking Services EBS). Data providers relay the data globally via a number of servers. Depending on the location of the server, the data may appear on one computer screen a fraction of a second later than it does appear on another computer in another part of the globe. In order to deter traders to buy in one locality and immediately sell in another one (as this would constantly penalize the market makers with higher execution latency), some data providers including the largest 2 electronic platforms change the price ever so slightly from one server to another, and they do so in a random fashion.
- Physical limitations resulting in longer required time for delivery. Vicinity to the main servers causes the user to receive the data a fraction of a second earlier than another user who is physically located further from the data.

Data preparation is a major part of any high frequency research, and literature suggests various methods. Dacorogna et al (2001) adopts (and suggests among other methods) a dynamic filter which adapts itself to the data and using an expectable volatility, allocates an amount of "trustworthiness" to the data, thus removing the less reliable data.

We used the following criteria in cleaning the data:

1. If there were no executed trades for a particular day, the data corresponding to that day were removed from the data series. This was the case with files with partial data corresponding to some weekends and some public holidays.

2. In order to remove the outliers generated by erroneous data, a percentage limit was used. If any bid or ask was larger than that percentage of the previous bid or ask, that record was assumed erroneous and removed. Various limits were used to generate data to ensure that no proper data point is inadvertently omitted. A tick was generated using interpolation from the preceding and succeeding ticks, and substituted in place of the outlier.

3. If for a single tick, bid or ask or both were missing, the past and previous ticks were interpolated and substituted in their place. If the adjacent ticks were also missing the bid or ask, an error was generated and that tick was omitted. Only a handful of the latter cases existed in our data.

4. Though there is informational value in the tick data with frequency that is less than one second, such data will have very little practical value to intraday trading unless the trading system is equipped with the means of sub-second execution across various electronic platforms. The success of such a trading system largely depends upon the speed of execution, low latency, high-speed access to trading centers, and so on. Such issues change the nature of the trading operation to a pure engineering project where the goal is to arbitrage across various electronic platforms in micro seconds. Because this approach to the markets is not the subject of this paper, we ensured a maximum of one tick per second. If there was more than one tick per second, the average of bids and asks were calculated and used for that particular second.

5. If there was a second in our time series with no corresponding tick data, we generated a tick for that second by interpolating the preceding and

succeeding ticks and substituting the result for the missing tick. Therefore, if there were multiple seconds with no corresponding data, the bids and asks thus generated would be reflective of how close or far those seconds have been from the existing adjacent records. In this way, a smoothed data series was generated.

6. We use mid price for the analysis. As an example, Figure 3.1 below shows the bid ask spread on a volatile day in the market. Blue line in Figure 3.1 is bid price and green line represents ask price. Unless one is studying this spread itself, it seems that bid or ask are substitutable. Using mid also circumvents the problem that at certain instances of jump, the market makers may decide to increase the spread much more than usual in order to benefit from the momentary dynamics of the market. These jumps will bring inaccuracies into the analysis which would be best avoided, hence the use of mid price (i.e. bid price plus ask price).

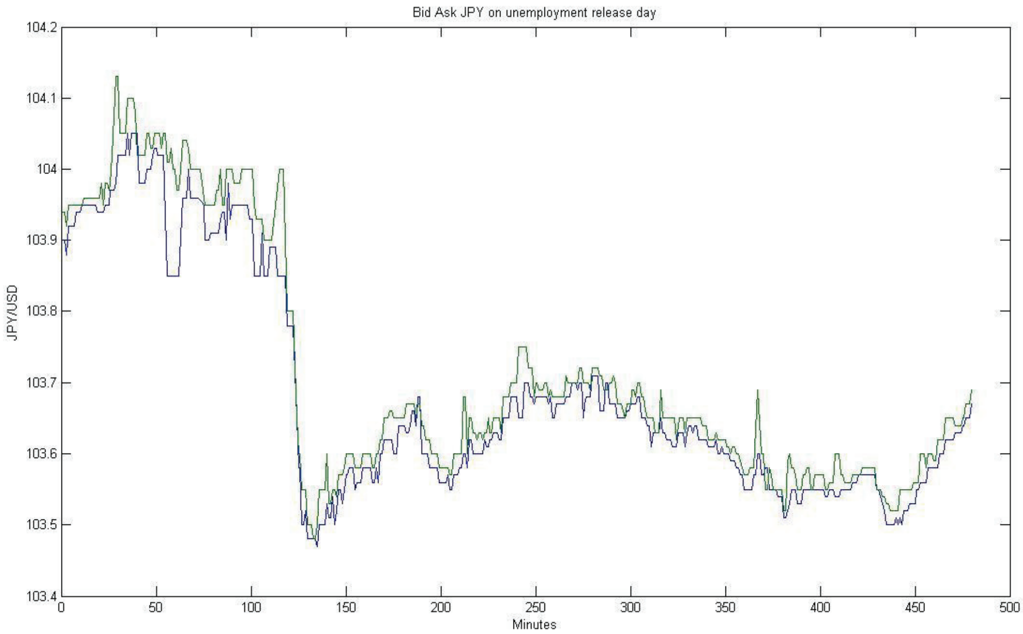


Figure 3.1

Once data was prepared, it was loaded into Matlab™ which is also the software principally used to perform the analysis. Given that there is approximately one tick per second in the data, the data series consisted of approximately 70-80 million rows of data (7 columns per row) for each of the 3 currencies analyzed. Our codes allow us to clean the data, select any time interval and perform variety of classifications, grouping and analysis on the data. As the data set includes 70-80 million rows of data per currency similar to the sample above, the coding and cleaning of the data took some months, as we were told to be the case with other researchers dealing with tick data (see Gillemot et al (2005) for cleaning and data preparation of equity market tick data, and as orally discussed with authors).

3.4 Analysis of effects of economic releases

Various studies have shown that the US economic announcements are by far the most important in the world as measured by their affect on major currencies. Minor currencies (i.e. emerging market currencies as well as those of smaller economies such as Australia and New Zealand) are shown by some (see Kearns and Manners (2005)) to be influenced as much by their local news and announcements. We therefore concentrated on U.S. releases for our study.

3.4.1. Regression analysis

James and Kasikov(2008), Kearns and Manners(2005) and Kuttner (2001) have studied the effects of the economic release on price levels in FX and other asset classes. We verify and expand on their results and later we focus on the effects of the economic releases on the dynamics of the volatility prior and after major data releases. Kuttner (2001) uses an ordinary least squares (OLS) linear regression to measure the effect of the economic releases on exchange rates. We adopt this method because it is simple and reliable. The existence of a sufficient number of data points (12 data points per annum for a period of four years) provides an acceptable confidence level and it can be adapted to apply to various time intervals prior to and after the release.

We apply the methodology used by Kuttner (2001) to our data in order to select a representative group of economic announcements for further analysis. In doing so, we also repeated and verified the results of James and Kasikov (2007). In this part of our analysis, we analyzed the EUR/USD exchange rate because it is the most liquid currency pair globally, accounting for more than a quarter of all global currency trade.

The following regression of the log of the foreign exchange rate (denoted by *fx*) on the surprise amount (measured as explained later by $release_{i,t} - consensus_{i,t}$) was estimated using the OLS methodology:

$$fx_{i,t+k} - fx_{i,t-1} = \alpha + \beta(release_{i,t} - consensus_{i,t}) + \varepsilon_t$$

We choose to use minute data in order to avoid excessive noise. We started the data at one minute prior to the release (t – 1) because there is occasionally a delay in the release (sometimes up to 30 seconds). The one minute time interval allows us to pick the closest clean data to the release as possible.

Initially we defined the surprise as any announcement which deviated from the median forecast by one standard deviation. We used Bloomberg L.P. as our source for actual and forecasts of the announcement data. Though this may be the correct approach for calibrating the dynamic response based on market sentiment or similar studies, it reduces the number of data points. (For instance, based on Bloomberg™ historical data, during the period 1998-2007, there were 122 nonfarm payroll releases but only 36 of them were more than one standard deviation away from the mean for this period.). The Table 3.1 below shows this for nonfarm payroll:

	St. deviation of data	Total data points	Surprise>1 St. dev.
1998-2007	95	122	36
2003-2007	87	60	15

Table 3.1

Hence we opted to include all data and define surprise as simply the difference between release and median of forecasts. If one were to use mean of forecasts as consensus, it seems to make small difference with major releases, as there is more consensus among forecasters. The median was picked in order to remove the effect of the outliers. Table 3.2 below shows the major US releases and their time of release. We used these releases in our study.

Before we discuss the regression results, it is important to note a few issues about the releases which may influence the results of such study. First one should note the choice of data to include in the analysis. Another issue in such a study is the choice of forecast data. Economist in investment banks and other institutions contribute their forecasts to various news and data agencies and industry estimate is calculated using these contributions. However the forecasters change their forecasts over time, and they then may or may not provide the data agencies with the new numbers. Moreover as time goes by and one approaches the time of release, more information becomes available and hence more economists forecast their numbers as we get closer to the release time, in order to use the latest data available. The “market forecast” therefore changes over time and its own dynamics can be subject for future research. We opted to only use the latest market forecast, which corresponds to the forecast immediately prior to the release. Finally the quality of the economic releases across various regions is not the same. James and Kasikov(2008) notes that the rate of absorption of the economic release differ across various regions; US traders seem to react fastest to the economic release, but the jump due to the economic release decays rapidly as well. Northern European markets tend to react slower to the same economic release. The authors distinguish between positive and negative surprises (as measured by Bloomberg™ survey vs. the published data), but do not address the question of how dispersion among economists’ forecasts prior to the release affects the dynamics of the markets after the data release. James and Kasikov(2008) concludes that US data seem to affect major markets more consistently than others, while Japanese, European and Swiss releases seem to matter least. Combination of the above leads to limited understanding of the market dynamics around economic releases. James and Kasikov (2008) attempts to estimate market behavior given upside and downside surprises, and claims slightly different coefficients in the linear regression for each set of surprise data. Furthermore what is known among researchers as “release discipline” affects the market dynamics. Some economic releases are not published in an orderly fashion, are leaked to the marker prior to the official release, are not on time, etc. For instance, European data frequently lack the “release discipline” which implies that:

- Data leaks into the markets prior to the official release.
- Data are not released consistently at the same time of the day, rather the release time may differ by a few minutes.
- Releases are postponed or completely omitted on public holidays and some other occasions.

Table below shows the most important US economic releases and the time of each release:

Major US economic releases	Release time (GMT)
University of Michigan Consumer Confidence	15:00
Institute of Supply Management (ISM) Index : Manufacturing	15:00
Institute of Supply Management (ISM) Index : Non- Manufacturing	15:00
Philadelphia Fed report	15:00
New Home Sales	15:00
Conference Board Consumer Confidence	15:00
Chicago Purchasing Managers Index	15:00
Treasury International Capital System (TIC) Flow of Funds	14:00
Industrial Production	14:15
Durable Goods Orders	13:30
GDP, QoQ Annualized	13:30
Core CPI	13:30
Trade Balance	13:30
Empire Manufacturing Index	13:30
Housing Starts	13:30
Unemployment Rate	13:30
Change in Non-farm payrolls	13:30
Retail Sales Less Autos	13:30

Table 3.2

Separately, we polled the chief global economists of the following major banks: HSBC, Credit Suisse, Citigroup, Deutsche Bank, Barclays, UBS, Goldman Sachs, and Bank of America/Merrill Lynch. As a group, these banks account for more than 80% of all currency traded globally. We asked these economists to indicate (1) how important they think an economic release is for the currency market and (2) if the releases typically affects all three currencies (GBP, JPY, and EUR) equally or if a release matters more for one currency than the other two.

In addition, we asked the same two questions of the head traders of the following asset management firms: Millennium Asset Management, State Street Global Advisors, Pareto Partners, Alliance Bernstein, Wellington Asset Management, BlackRock Financial Management, Pacific Investment Management Company (PIMCO), and Rogge Asset Management. Collectively, these asset management firms account for the majority of the currency managed globally in various portfolios. While the sample size is small, it does represent the most important institutional economists and traders in the currency markets. The forecasts of the economists queried in our study are widely used by market participants; the traders in our sample of asset management firms trade the largest amounts of currencies executed every day. We expected the traders' responses to be based on shorter term effects, including intraday observations of the markets, while the economist's viewpoints to be based on economic fundamentals and long-term drivers of currency values. The results of our poll are reported in Tables 3.3 and 3.4. The most and least important releases in both tables seem to be very similar (note the shaded top and bottom rows in the tables). Furthermore, both traders and economists unanimously agreed that the change in nonfarm payroll is the single most important economic release for currency markets. By comparing the poll respondents' expectations of the effects of the economic releases (as reported in Tables 3.3 and 3.4) with the regression results (as reported in Table 3.5), we note that, for the most part, the two match.

Economist respondents	very important	moderately important	not important	affects all 3 currencies equally	affects one currency more than other 2
Change in non-farm payrolls	100%	0%	0%	75%	25%
ISM Manufacturing	75%	25%	0%	63%	38%
Unemployment rate	75%	13%	13%	75%	13%
Retail sales less autos	75%	25%	0%	75%	25%
GDP, QoQ annualised	50%	38%	13%	75%	13%
ISM Non-manufacturing	25%	50%	13%	50%	38%
Philadelphia Fed	25%	38%	38%	50%	25%
Durable Goods Orders	25%	63%	13%	63%	38%
Core CPI	25%	38%	38%	63%	25%
Housing Starts	25%	38%	50%	50%	25%
Univ. Michigan consumer confidence	13%	75%	13%	63%	38%
New Home Sales	13%	50%	38%	50%	38%
Industrial Production	13%	63%	25%	63%	25%
Trade Balance	13%	50%	38%	50%	25%
CB Consumer Confidence	0%	63%	38%	50%	38%
Chicago PMI	0%	38%	63%	38%	38%
TIC portfolio flows	0%	50%	50%	63%	13%
Empire Manufacturing	0%	38%	63%	38%	38%

Table 3.3. Poll results of chief/global economists in eight largest global investment banks. Respondents were asked whether they believed that an economic release is important for foreign exchange market, and if the economic release affects EUR/USD, JPY/USD, and GBP/USD equally

Trader respondents	very important	moderately important	not important	affects all 3 currencies equally	affects one currrency more than the other 2
Change in non-farm payrolls	100%	0%	0%	75%	25%
ISM Manufacturing	75%	25%	0%	63%	38%
ISM Non-manufacturing	63%	38%	0%	88%	13%
Retail sales less autos	63%	25%	13%	63%	38%
Unemployment rate	50%	50%	0%	75%	25%
GDP, QoQ annualised	38%	63%	0%	75%	25%
Trade Balance	38%	75%	0%	50%	50%
Univ. Michigan consumer confidence	25%	50%	25%	75%	13%
New Home Sales	13%	88%	0%	88%	25%
Chicago PMI	13%	63%	25%	75%	13%
Industrial Production	13%	88%	0%	75%	25%
Durable Goods Orders	13%	63%	25%	63%	38%
Core CPI	13%	38%	0%	75%	25%
Empire Manufacturing	13%	38%	50%	63%	25%
Philadelphia Fed	0%	75%	25%	75%	13%
CB Consumer Confidence	0%	63%	38%	75%	13%
TIC portfolio flows	0%	63%	38%	63%	38%
Housing Starts	0%	100%	0%	75%	25%

Table 3.4. Poll results of chief/head traders in the eight largest global currency management firms. Respondents were asked whether they believe that an economic

release is important for foreign exchange market, and if the economic release affects EUR/$, JPY/$ and GBP/$ equally.

Regarding the responses above, we noticed that the most and least important releases in both tables seem to be very similar (see the colored rows. Table 3.5 summarizes the price move and the *t* statistic of our regressions one hour after the release based on our regressions:

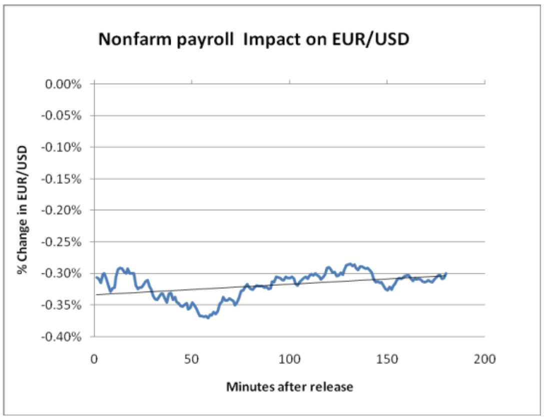
Economic Release	% change in EUR/USD one hour after release	t Statistic one hour after release
Change in Non-farm Payrolls	-0.3	-6
Institute of Supply Management Index: Manufacturing	-0.2	-5.4
Trade Balance	-0.15	-4.7
Unemployment Rate	-0.13	-0.9
Treasury International Capital System(TIC) Flow of Funds	-0.1	-1.8
Empire Manufacturing Index	-0.1	-2
Retail Sales Less Autos	-0.9	-2.8
GDP Quarterly Growth	-0.8	-4.5
Conference Board Consumer Confidence	-0.06	-2
Industrial Production	-0.04	0
Durable Goods Orders	-0.04	-1
Chicago Purchasing Manager Index(PMI)	-0.04	-2
Philadelphia Fed Business Outlook Survey	-0.04	-4
Housing Starts	-0.03	0
Institute of Supply Management Index: Non-Manufacturing	-0.03	-1
Core CPI	-0.02	-1.8
New Home Sales	-0.01	-0.2
Univ. of Michigan Consumer Confidence	0	0

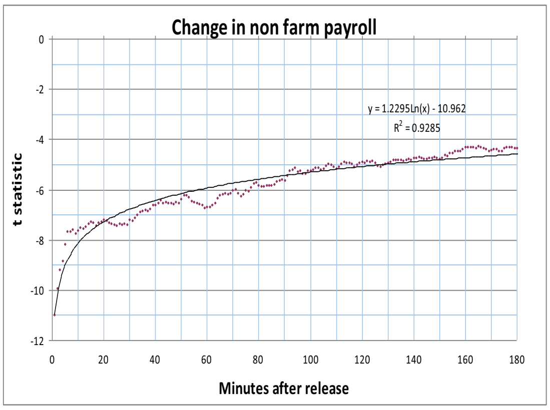
Table 3.5 Regression results of the equation

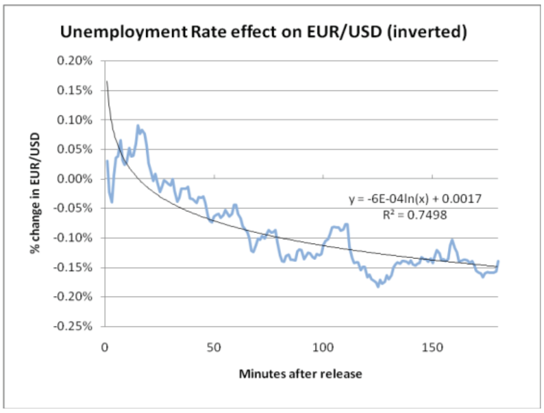
$$fx_{i,t+k} - fx_{i,t-1} = \alpha + \beta(release_{i,t} - consensus_{i,t}) + \varepsilon_t .$$

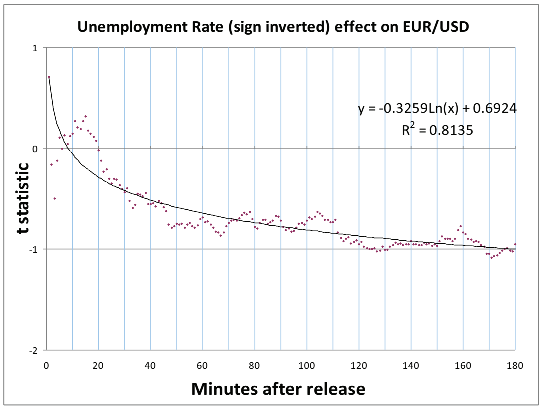
The left-hand side of equation is the difference in log of exchange rates one hour after the release and log of exchange rate one minute prior to the release. The reported *t* statistic is for *β.*

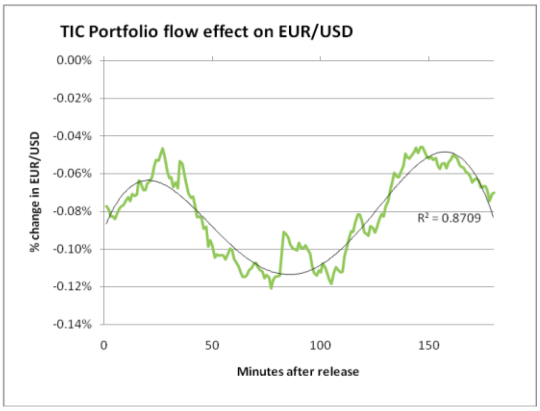
Figure 3.2 shows the changes in EUR/USD and the t statistic of β in the regression equation. The regression is done from 1 minute prior to the release to 180 minutes after the release.

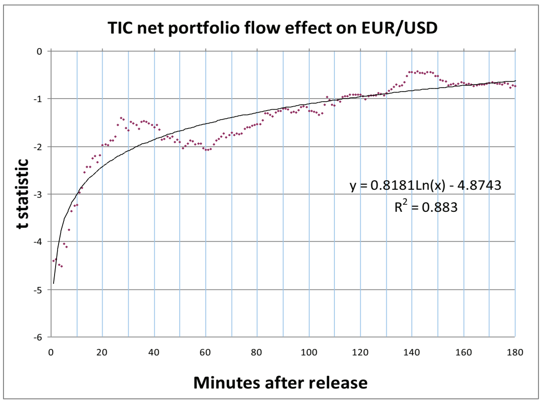

Nonfarm payroll Impact on EUR/USD
% Change in EUR/USD
Minutes after release

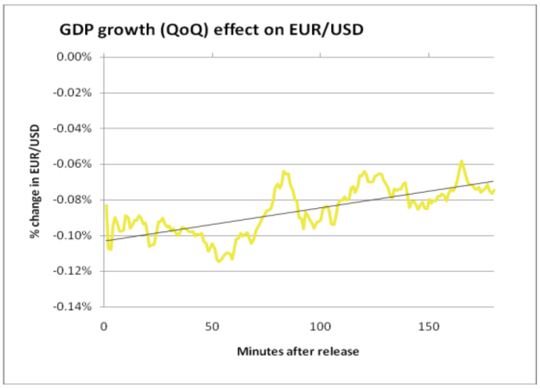

Change in non farm payroll
t statistic
y = 1.2295Ln(x) - 10.962
R^2 = 0.9285
Minutes after release

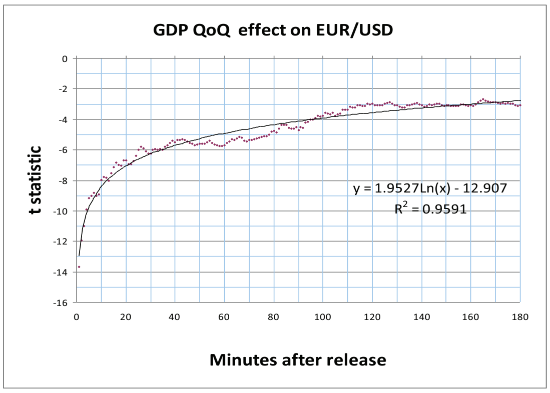

Unemployment Rate effect on EUR/USD (inverted)
% change in EUR/USD
y = -6E-04ln(x) + 0.0017
R² = 0.7498
Minutes after release

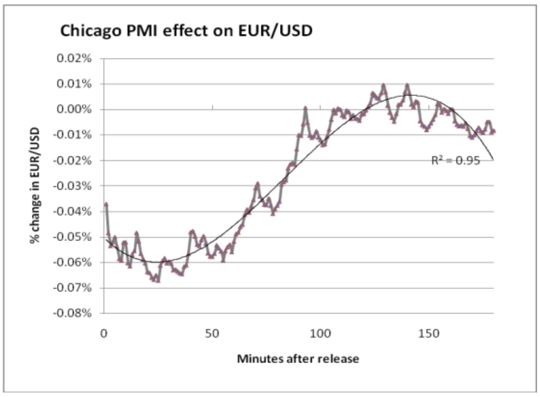

Unemployment Rate (sign inverted) effect on EUR/USD
t statistic
y = -0.3259Ln(x) + 0.6924
R^2 = 0.8135
Minutes after release

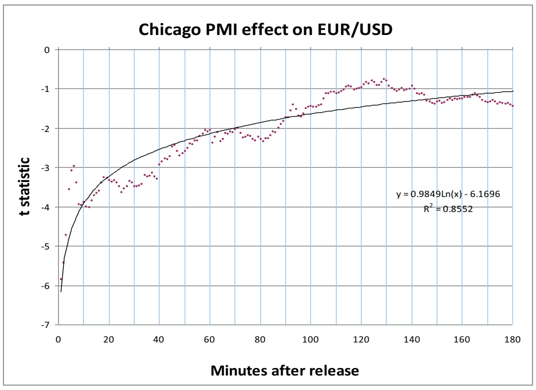

TIC Portfolio flow effect on EUR/USD
% change in EUR/USD
R² = 0.8709
Minutes after release

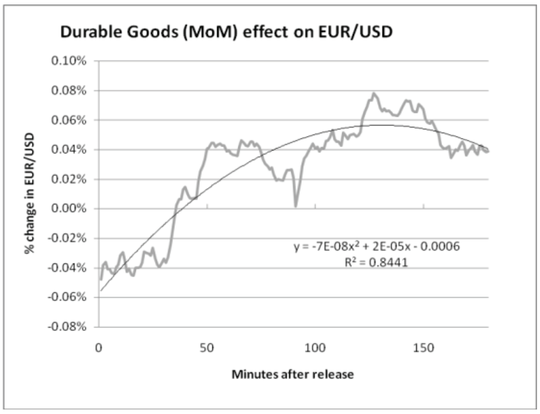

TIC net portfolio flow effect on EUR/USD
t statistic
y = 0.8181Ln(x) - 4.8743
R^2 = 0.883
Minutes after release

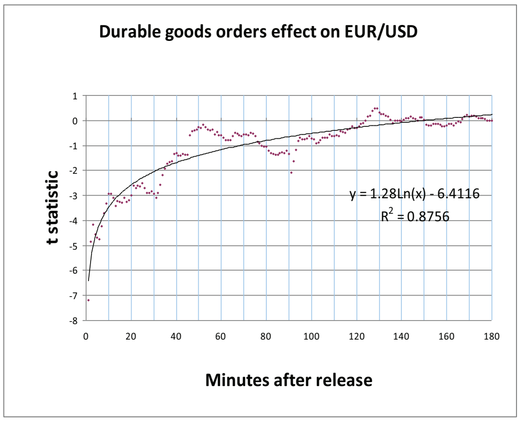

GDP growth (QoQ) effect on EUR/USD
% change in EUR/USD
Minutes after release

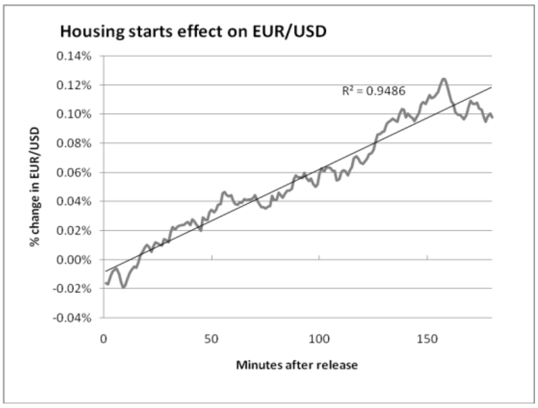

GDP QoQ effect on EUR/USD
t statistic
y = 1.9527Ln(x) - 12.907
R^2 = 0.9591
Minutes after release

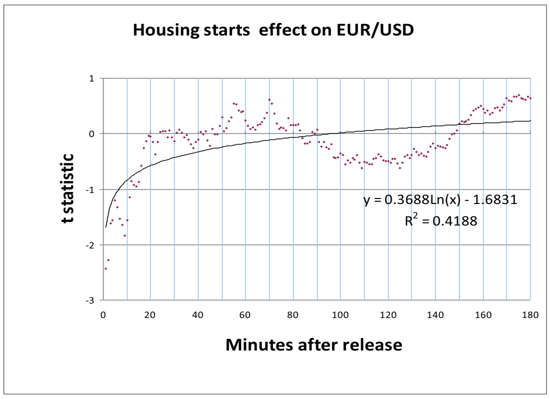

Chicago PMI effect on EUR/USD
% change in EUR/USD
R² = 0.95
Minutes after release

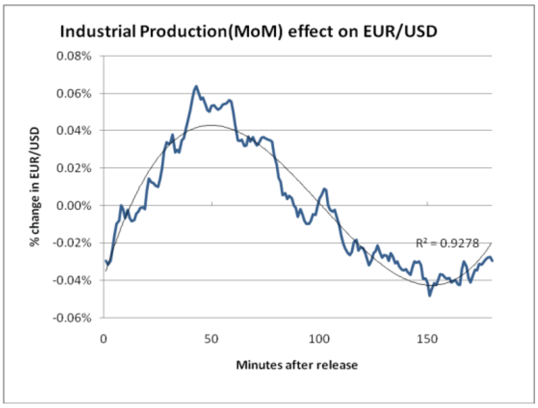

Chicago PMI effect on EUR/USD
t statistic
y = 0.9849Ln(x) - 6.1696
R² = 0.8552
Minutes after release

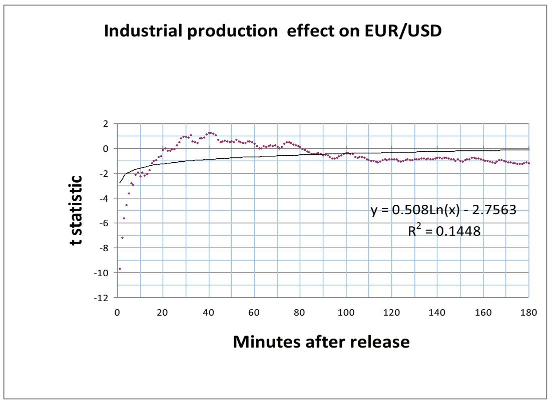

Durable Goods (MoM) effect on EUR/USD
% change in EUR/USD
y = -7E-08x² + 2E-05x - 0.0006
R² = 0.8441
Minutes after release

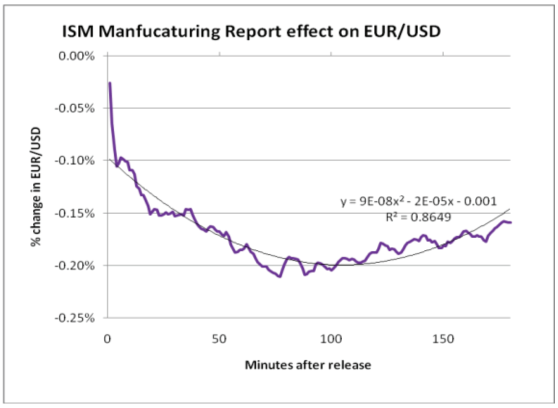

Durable goods orders effect on EUR/USD
t statistic
y = 1.28Ln(x) - 6.4116
R² = 0.8756
Minutes after release

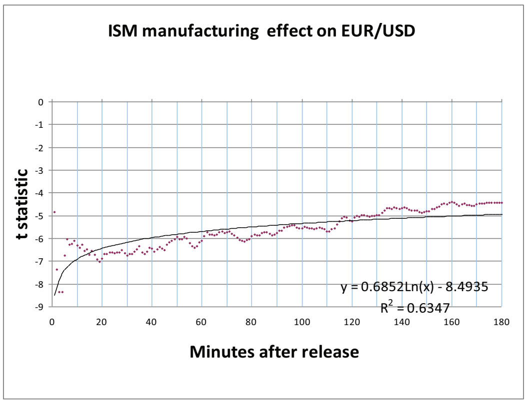

Housing starts effect on EUR/USD
% change in EUR/USD
R² = 0.9486
Minutes after release

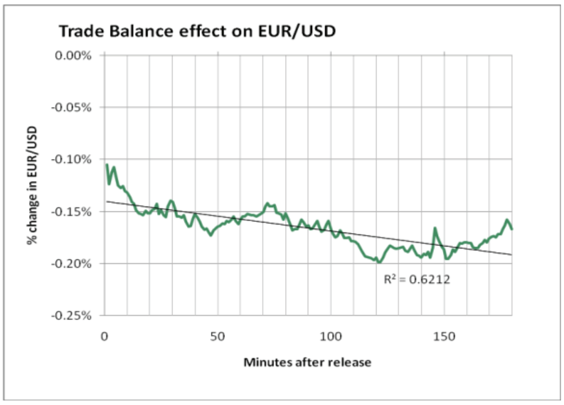

Housing starts effect on EUR/USD
t statistic
y = 0.3688Ln(x) - 1.6831
R² = 0.4188
Minutes after release

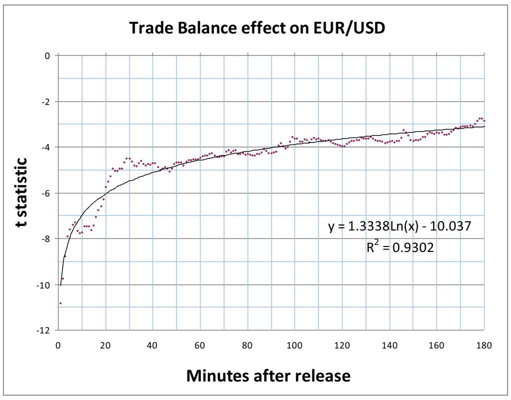

Industrial Production(MoM) effect on EUR/USD
% change in EUR/USD
Minutes after release
R² = 0.9278

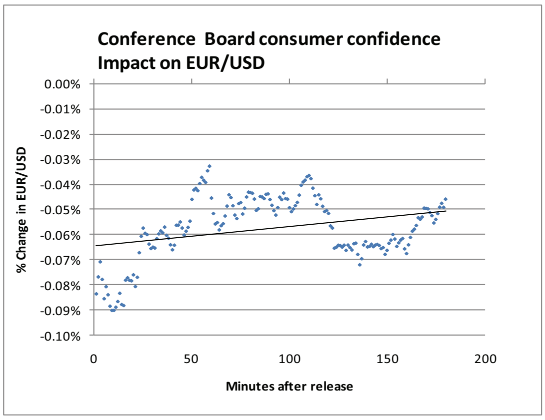

Industrial production effect on EUR/USD
t statistic
Minutes after release
y = 0.508Ln(x) - 2.7563
R² = 0.1448

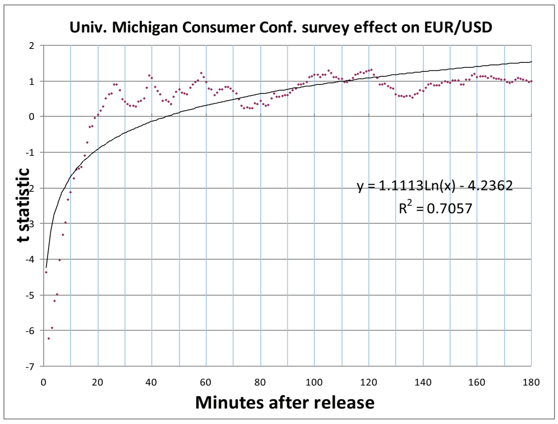

ISM Manfucating Report effect on EUR/USD
% change in EUR/USD
Minutes after release
y = 9E-08x² - 2E-05x - 0.001
R² = 0.8649

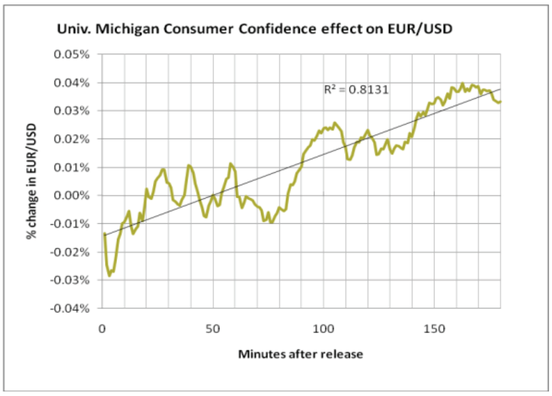

ISM manufacturing effect on EUR/USD
t statistic
Minutes after release
y = 0.6852Ln(x) - 8.4935
R² = 0.6347

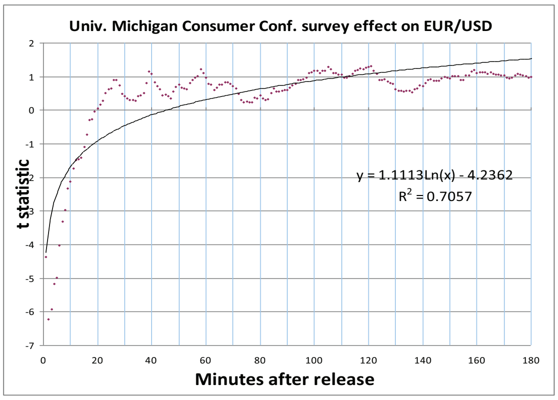

Trade Balance effect on EUR/USD
% change in EUR/USD
Minutes after release
R² = 0.6212

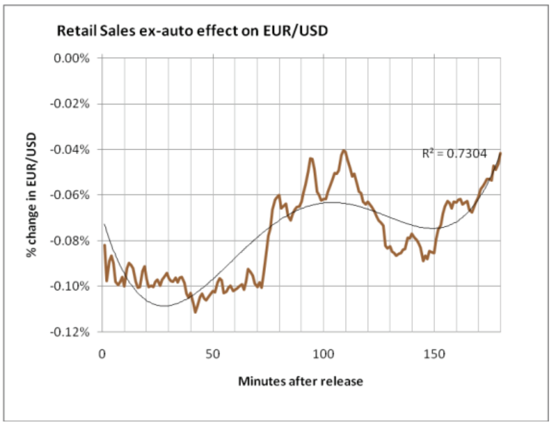

Trade Balance effect on EUR/USD
t statistic
Minutes after release
y = 1.3338Ln(x) - 10.037
R² = 0.9302

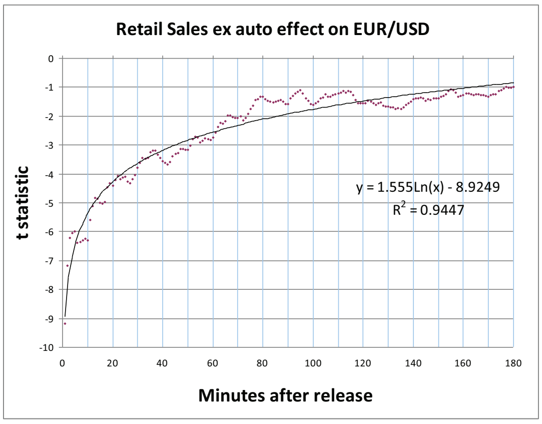

Conference Board consumer confidence
Impact on EUR/USD
% Change in EUR/USD
Minutes after release

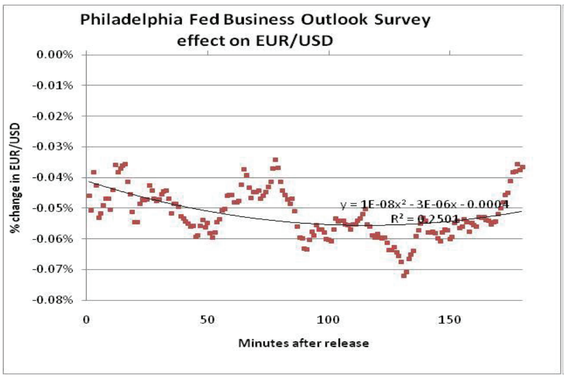

Univ. Michigan Consumer Conf. survey effect on EUR/USD
t statistic
y = 1.1113Ln(x) - 4.2362
R2 = 0.7057
Minutes after release

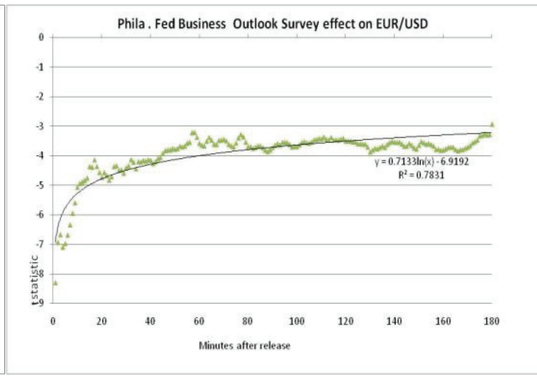

Univ. Michigan Consumer Confidence effect on EUR/USD
% change in EUR/USD
R² = 0.8131
Minutes after release

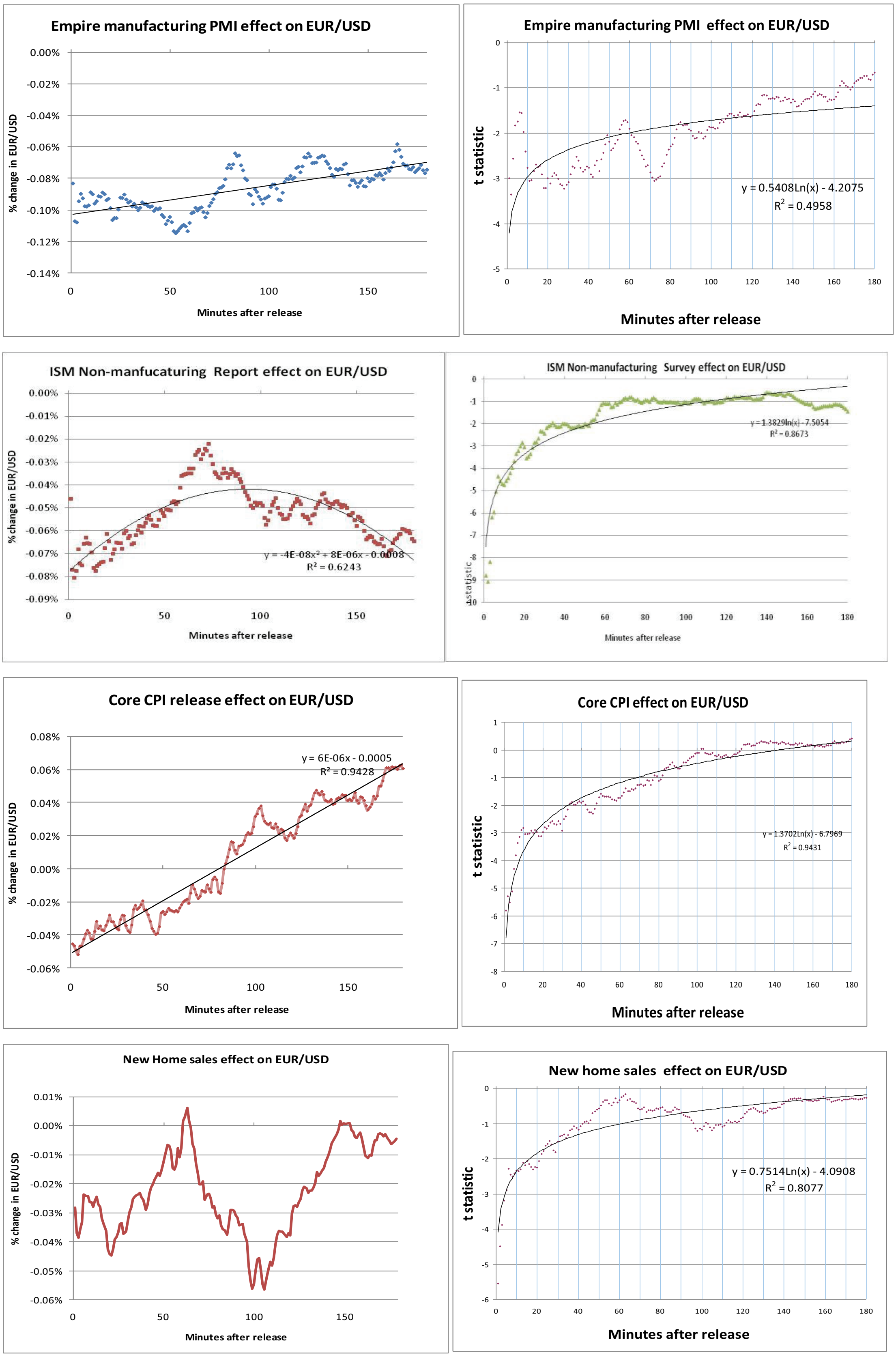

Univ. Michigan Consumer Conf. survey effect on EUR/USD
t statistic
y = 1.1113Ln(x) - 4.2362
R2 = 0.7057
Minutes after release


Retail Sales ex-auto effect on EUR/USD
% change in EUR/USD
R² = 0.7304
Minutes after release


Retail Sales ex auto effect on EUR/USD
t statistic
y = 1.555Ln(x) - 8.9249
R2 = 0.9447
Minutes after release


Philadelphia Fed Business Outlook Survey
effect on EUR/USD
% change in EUR/USD
y = 1E-08x² - 3E-06x - 0.0004
R² = 0.2501
Minutes after release


Phila . Fed Business Outlook Survey effect on EUR/USD
t statistic
y = 0.7133ln(x) - 6.9192
R² = 0.7831
Minutes after release



Empire manufacturing PMI effect on EUR/USD
% change in EUR/USD
Minutes after release
Empire manufacturing PMI effect on EUR/USD
t statistic
y = 0.5408Ln(x) - 4.2075
R² = 0.4958
Minutes after release
ISM Non-manfucaturing Report effect on EUR/USD
% change in EUR/USD
y = -4E-08x² + 8E-06x - 0.0008
R² = 0.6243
Minutes after release
ISM Non-manfucaturing Survey effect on EUR/USD
y = 1.3829ln(x) - 7.5054
R² = 0.8673
Minutes after release
Core CPI release effect on EUR/USD
% change in EUR/USD
y = 6E-06x - 0.0005
R² = 0.9428
Minutes after release
Core CPI effect on EUR/USD
t statistic
y = 1.3702Ln(x) - 6.7969
R² = 0.9431
Minutes after release
New Home sales effect on EUR/USD
% change in EUR/USD
Minutes after release
New home sales effect on EUR/USD
t statistic
y = 0.7514Ln(x) - 4.0908
R² = 0.8077
Minutes after release

Figure 3.2

Figures 3.3 and 3.4 illustrates the data from the above graphs in the first hour and three hours after the release.

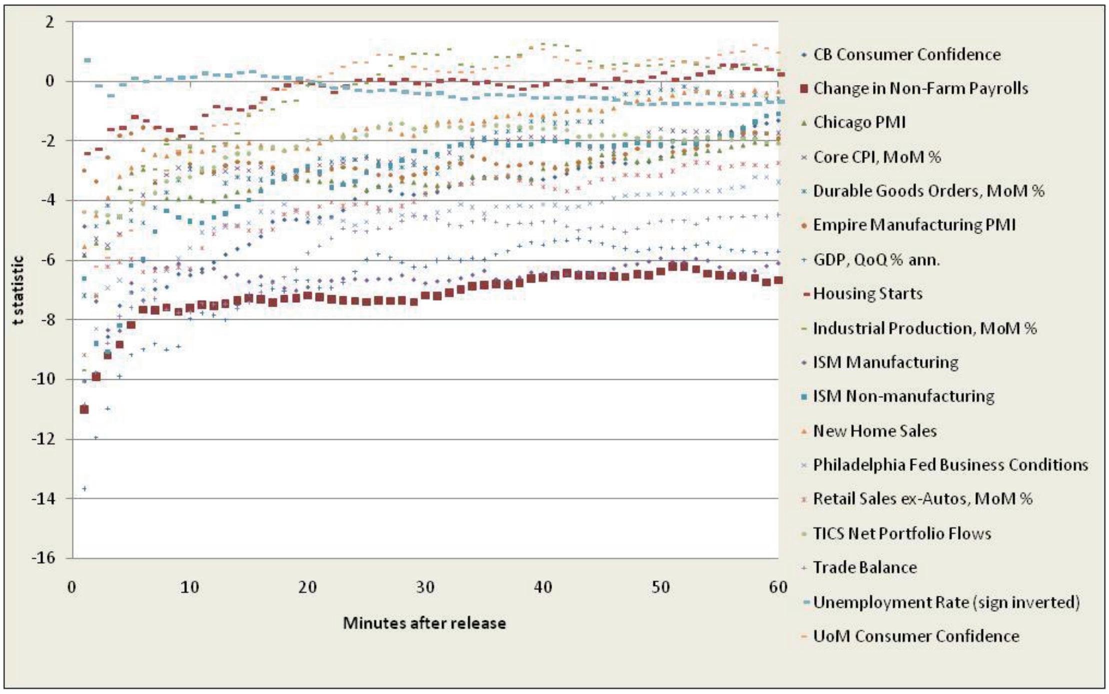


Figure 3.3

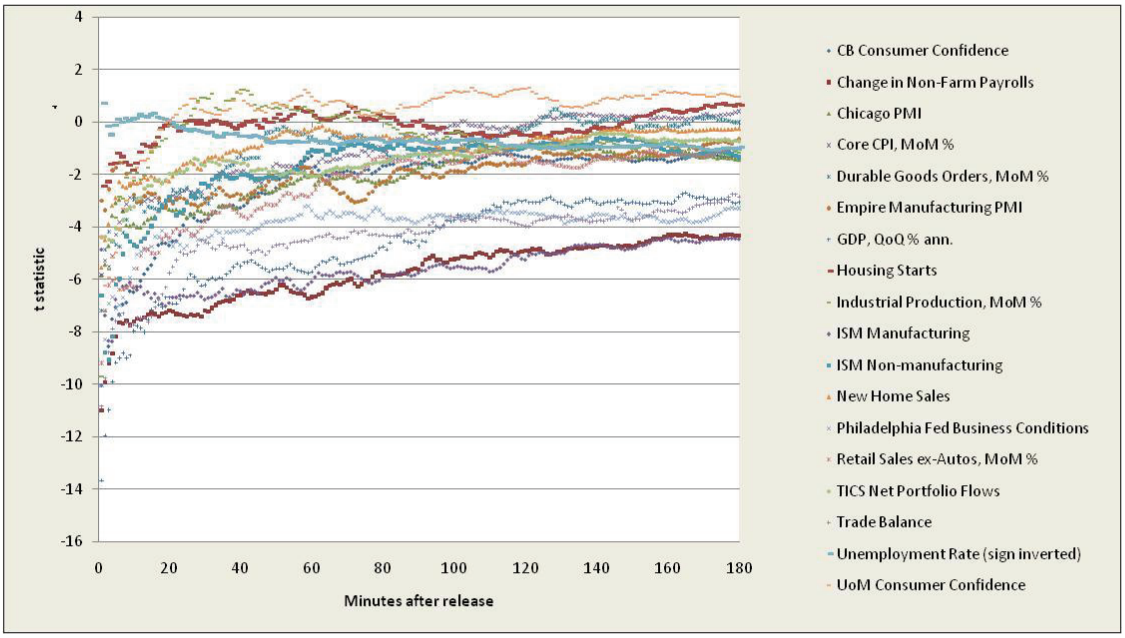


Figure 3.4

Based on Figures 3.3 and 3.4 above and the regression results, we think of the release to be important if it shows the highest impact on the price level , impact stays fairly constant in the minutes after the release all the way to 180 minutes and if the t statistic is comparatively large. With these in mind, we observe the following in the regression graphs:

- The more important releases result in larger jumps in the price level.
- The more important the economic release, the more likely that the t value of the regression would be larger. Therefore the statistical significance of the release is higher for more important releases.
- More important economic releases not only cause a large jump, but the price stays at the new levels longer than the lesser economic release. In contrast, the effect of the release dissipates rapidly and price moves to levels prior to the release in less important releases (see new home sales graphs as an example).
- The t value decreases exponentially after the release, and this is more visible in the case of more important economic release (e.g. see nonfarm payroll graphs with less important announcements such as TIC portfolio flow graphs).
- The exponential decay in the t statistics is sharper in the case of more important news. This effect may probably be explained by the fact that market participants pay attention to the important releases, absorb the news rapidly and thereafter the effect of the news is reduced.

As with our survey respondents, the regression graphs seem to support some of their opinions but not all of them. With these criteria in mind, nonfarm is the most important news in the market- various studies by investment banks and central banks (e.g. Clifton and Plumb(2007) of Australian central bank) confirm this result- and Philadelphia Fed survey is among the least important. Our respondents' views match our findings in these cases. However, both economists and traders contended that ISM non manufacturing survey is among the top 5 releases, but based on price impact and t statistic our regression results do not support this.

Market participants involved in currency market all agree that various themes become important for currency market during some period of time, and then those themes lose their significance after a while. As an example, informal conversation with traders and currency investors indicates that TIC flows data were among the most important release that market participants watched carefully in 1990s, but that is not the case in the period of our study, nor is TIC flow data mentioned by the respondents as an important release. The survey results may be to some degree a reflection of respondents' most recent observations, hence incorporating a bias in their views.

Reaction to the news and market economic releases differ based on general market sentiment. It is a fact well known by practitioners and academics alike that in bear markets, investors tend to discard good news (upside surprises) and overweight negative news. In a buoyant bull market, all is rosy and investors tend to down play negative news. Hence evaluating the effect of the economic release should invariably take the market sentiment into account. Due to the limited history of tick data (typically 4-5 years), there is not enough data points to even cover one complete business cycle and enough cycles of market sentiment. Hence the data typically suffers from a selection bias.

Specifically in the case of the data set used in this thesis, the period of 2002 to mid 2007 has coincided with a bull market across almost all asset classes. Therefore gauging the reaction of investors to the economic release ought to include that general underlying market sentiment.

Another very important factor in interpreting the dynamics of the markets at new releases is positioning. Large long or short positions taken by investors result in large aggregate positions across the market which may become sizable. Such large cumulative positions may lead to rapid unwinding at the time of the news release, thus increasing the magnitude of price change as well as affecting the ensuing volatility. Estimating the market positions reliably at the time of economic releases is impossible, therefore one has to allow for this severe limitation in interpreting the market response.

3.4.2 Market behavior after nonfarm payroll announcement

As the most important data release for currency markets, we proceeded to further analyze the dynamics of the markets around nonfarm payroll.

The nonfarm payroll data surprise is here defined as the release being one standard deviation away from the consensus. No differentiation is made to whether there is an upside or downside surprise. James and Kasikov(2008) review the dispersion of economists' forecasts in the days leading to the nonfarm payroll release. The dispersion for nonfarm release and other releases does seem to indicate some herding behavior among analyst , but this behavior seems to become less significant given other effects such as individual characteristics of data releases.

The following equation indicates OLS regression of the log of FX rates on surprise amount.

$$fx_{i,t+k} - fx_{i,t-1} = \alpha + \beta(release_{i,t} - consensus_{i,t}) + \varepsilon_t$$

The t-1 is chosen because there is occasionally a delay in the release(sometimes up to 30 seconds). The one minute time interval allows us to pick the closest clean data to the release as possible.

Table 3.6 below shows the statistics of the OLS regression EUR/USD (from t-1 to minutes after release). The t statistic is that of β.

Minutes after release	t-statistic	R-squared
5	8.1	0.92
10	7.5	0.92
30	5.5	0.9
60	5.4	0.88
120	4.1	0.78
180	3.9	0.75
240	3.7	0.75
300	3.6	0.72

Table 3.6

As seen in Table 3.6, the effect of the release continues to be statistically significant even after 5 hours. If we were to include data points which do not constitute a surprise, we expect to find lower t scores across all time intervals and perhaps sharper decline in the t statistic at longer intervals.

We calculated the consistency of analysts' ability in forecasting the nonfarm over time. This was done by finding the variation of consensus vs. the actual number (depicted as a rolling standard deviation) over the period of 1999-2007 using Bloomberg™ data. In Figure 3.5, each point represents the standard deviation of the surprise (i.e. the difference between the actual and the consensus) over the previous 12 months.

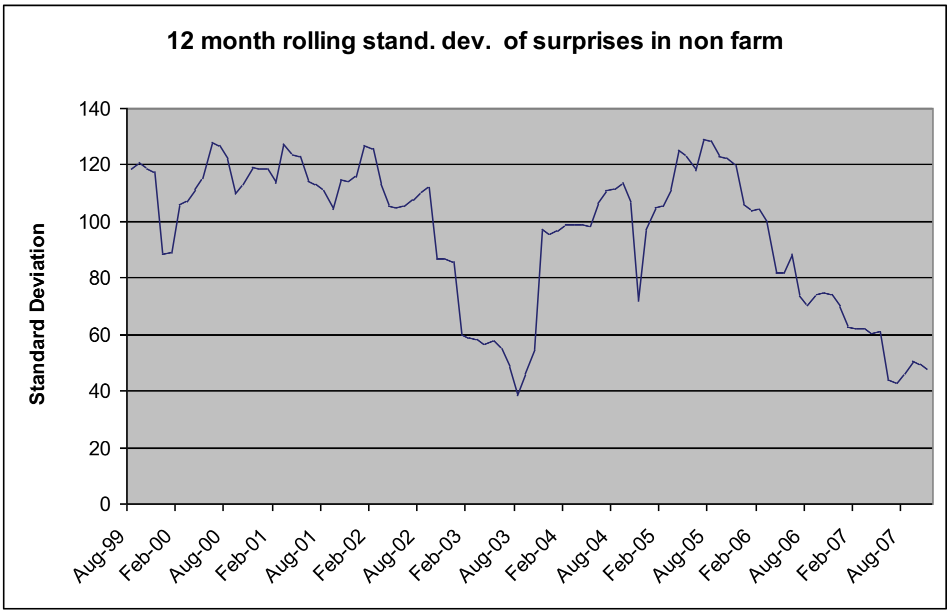


Figure 3.5

The graph illustrates that the economists' accuracy in forecasts seems to change over time. This makes it harder to draw conclusions on the market behavior and its link to the market forecasts. Nonfarm payroll, being the quintessentially important release, shows significant variation in its dynamics over time, despite maintaining its rank as the most important release. All of the above add to the complexity of understanding the market dynamics around major announcements. The difficulty may be even more in case of lesser releases.

In the Figures 3.6 and 3.7, we have calculated the distribution of consensus forecasts over the years 98-07 using Bloomberg™ historical data. It seems that analysts have a bias in underestimating the change in nonfarm payroll, as the data is skewed to the left. There has been a bull market for parts of this period (98-00), bear market for parts (00-03) and bull market for the remainder (03-07) as measured by S&P and other major equity indices. Possibly the downside bias in the forecasts could be explained by the analysts tendency to adjust their forecasts to the majority and try to stay "within the pack". Hence in a bull market, they have tended to underestimate the strength of the economy and caused upside surprises.

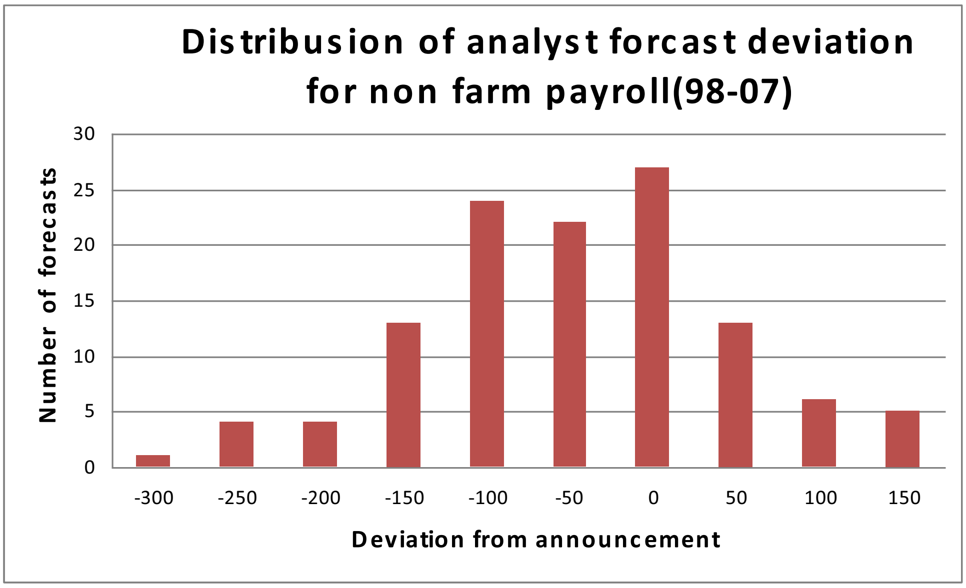


Figure 3.6

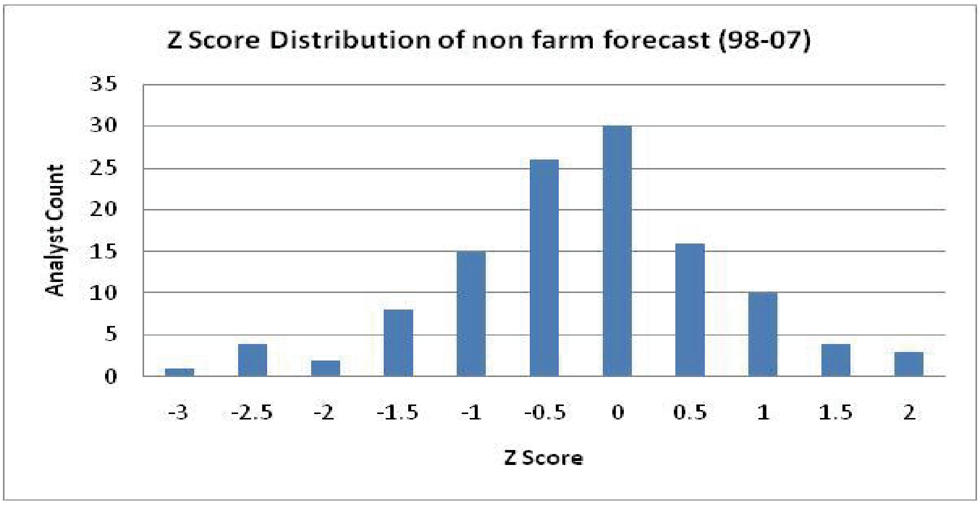


Figure 3.7

James and Kasikov(2007) investigates the change in the analyst consensus in the days prior to nonfarm payroll release. Natividade(2008) also analyzes the effects of the dispersion of forecasts and concludes that the less the dispersion, the higher the price impact will be in case of a surprise (i.e. +1 standard deviation away from the consensus). This is intuitive, as the most market participants will be "on the same side" of the trade, having previously assumed a particular outcome for the announcement. This may also indicate that most participants pay more attention to the consensus rather than any particular economic forecaster. If this wasn't the case and each participant had their favorite economist in whom she trusted, then dispersion of forecasts may lead to different response and perhaps higher market impact The dispersion of the analysts forecasts differ as one approaches the release date, but according to our study, there does not seem to be a persuasive pattern of converging forecasts despite the arrival of new information as one approaches the release.

3.4.3 Analysis of volatility subsequent to the economic releases

For our volatility study, we selected four of the previously analyzed major economic releases. Based on the results reported in Table 3.5, we selected four economic releases based on the following two criteria: (1) the magnitude of the price change due to the release compared to other releases (as depicted by percentage price movement in Table 3.5) and (2) the statistical significance of the price change due to the release one hour after the release (as illustrated by the *t* statistic of β one hour after the release as reported in Table 3.5).

Nonfarm payroll is shown in our regression study to be the most important release. All of our poll respondents believed that nonfarm payroll is the most important economic release as well. Unemployment is also considered important by our respondents and shown to be influential in our regression analysis. Retail sales is a somewhat less important release, although it ranked fairly highly in our poll, and yet of lesser influence according to our regression results. Finally, we selected an economic release which is considered much less important in the foreign exchange market based on our poll results and seems to have little comparative intraday influence on exchange rates based on our regression results, namely the University of Michigan Consumer Confidence Survey.

For each of the above four releases, we selected six hours of tick data from three hours prior to the release to three hours after the release for JPY, EUR and GBP. To the aforementioned 12 data series, we applied various classes of wavelets and selected the appropriate wavelet based on the following: The selected wavelet should reduce the number of data points as much as possible (parsimony of the data after wavelet application), while preserving the main characteristics of the data. Moreover, the synthesized wavelet function should reflect the dynamics of the economic release.[5] One class of wavelets, Daubechies wavelets, met the above

[5] Wavelets simplify the analysis by reducing the number of data points. Once the analysis is performed on the reduced dataset in frequency space, the data are reconstructed (synthesized) back into time space in order to interpret the results.

criteria better than all other wavelets. In particular, the asymmetrical form of this class of wavelets conveniently lends itself to the jump induced by the economic release, as the volatility dynamics are different after the release compared to prior to the release. Moreover, exact reconstruction of the time series from the detail data series is feasible, enabling us to interpret the results in time space.

We considered using the continuous rather than discrete wavelet. Discrete analysis was preferred because it (1) saved space in coding (by avoiding overfitting and excessive modeling), (2) allowed exact reconstruction, and (3) the high resolution of tick data already provided enough information so that the redundancy of continuous analysis was not needed. We applied the Daubechies wavelet at fifth level to the six-hour dataset.[6] We did this for the four economic releases that we selected previously. Once the analysis was completed, we transferred the detail data back into time space in order to reconcile the results with the time of release. We modified the codes of Misiti et al. (2003) for direct reconstruction of the wavelet coefficients.

Traditionally, wavelets have been used in filtering out the noise from data. When wavelets are applied to time series data, the data are transformed into two data series in frequency space as follows: (1) an approximation or trend data series which captures the main underlying characteristic of the original time series and (2) a detail data series which represents the noise or local fluctuations of the original time series. Once the noise is removed, analysis is performed on the approximation series and results are then transformed back into time space. We took a different approach from the traditional one just described. Instead of the approximation data series, we concentrated on the detail series because it captures the volatility characteristics of the time series data. In other words, as our goal was to explore the volatility, we were not interested in the major currency directional move. Whether the currency was appreciating or depreciating was irrelevant to this analysis, rather it is the local short term noise which determines the short term volatility and is the subject of interest.

[6] The Daubechies class of wavelets comprise Daubechies wavelets with different scales (also known as levels). Increasing the scale increases the resolution, hence providing a filter which detects finer (more minute) details. We applied the wavelet at fifth level as it allows us to capture the details required for our volatility study, while at the same time making an accurate reconstruction of the original signal computationally feasible. Daubechies wavelets are derived from a compactly supported function with maximum number of vanishing moments. There is no closed form representation for Daubechies wavelets, but the extremal phase values are tabulated in various literature (e.g. see Daubechies (1988)) and used iteratively by commercial software to generate the wavelet.

This meant that we were interested in the details rather than the approximation. This use of wavelets is novel, as researchers so far have used wavelets to remove the noise so that they would be able to discern the underlying directional movement, as with economic cycles(see Gençay et al(2002) for examples).

We propose the following new volatility estimator using wavelets. In the detail series, for each minute, we selected the second within that minute that has the highest absolute value and used that as the volatility estimator for that minute. This is similar to using the range volatility estimator. However, in contrast to the range estimator which captures the difference between the high and low in time series data, our wavelet estimator is applied to the detail data series (the detail data series by its very definition reflects the volatility of the original time series data).

We measured the variance of the range volatility estimator and compared it to the variance of our wavelet estimator to see which estimator is more efficient. We defined the efficiency ratio as:

Efficiency ratio = variance of range estimator/variance of wavelet estimator

Table 3.7 summarizes our findings.

Efficiency ratios (variance of range estimator/variance of wavelet estimator)

	JPY	EUR	GBP
Nonfarm Payroll	43.1	49.7	36.5
Retail Sales	31.5	44.8	29.3
Unemployment	43.3	55.4	28.3
Univ. Michigan survey	30.4	40.8	36.0

Table 3.7 Comparison of efficiency of wavelet volatility estimator and range volatility estimator. Range volatility estimator is the range of the exchange rate for each minute. Wavelet volatility estimator is based on the detail data series obtained by applying 5th Daubechies wavelet to the exchange rate time series.

Across all three currencies and four releases, our wavelet estimator is on average 39 times more efficient than the range estimator, the latter itself being a more efficient estimator than other volatility estimators. Moreover, we were interested to see how our wavelet estimator compares with the range estimator in capturing the dynamics of the market. To that end, we estimated the following OLS regression:

$$y = \alpha + \beta x$$

where x is the range estimation volatility series and y is the wavelet estimation volatility series.

The results of the regression are reported in Table 3.8.

JPY Statistics	Minute by minute data regression results					Ten minute moving average regression results				
	OLS R-squared	OLS mean residuals	OLS MSE	OLS t-statisic	OLS t-statisic	OLS MA R-squared	OLS MA mean residuals	OLS MA MSE	OLS MA t-statistic	OLS MA t-statistic
Nonfarm Payroll	8.1%	-5.6E-13	9.7E-11	12.1	5.4	59.5%	-1.3E-13	1.4E-11	14.2	23.7
Retail Sales	3.3%	-8.2E-13	5.4E-11	12.9	3.1	42.3%	-5.6E-13	8.1E-12	11.9	16.5
Unemployment	8.2%	-6.8E-13	1.1E-10	11.9	5.5	60.1%	-1.5E-13	1.6E-11	13.9	23.8
Univ. Michigan survey	6.1%	-3.3E-10	2.4E-05	12.2	4.5	55.3%	-1.4E-10	3.5E-06	8.7	22.0

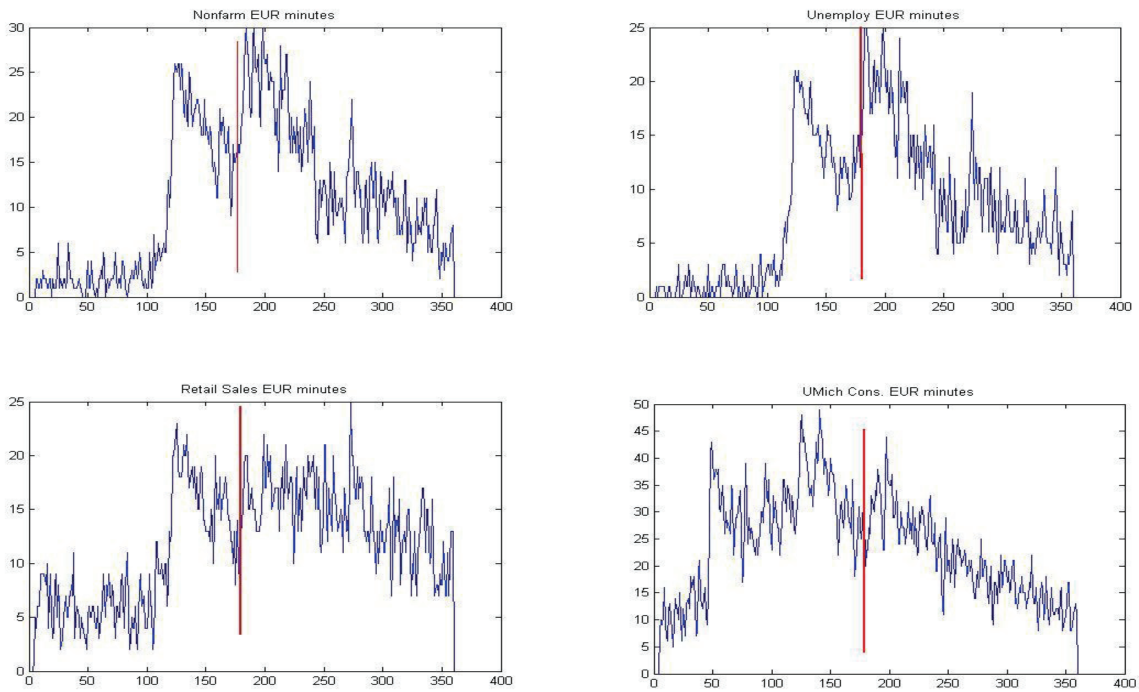
EUR Statistics	Minute by minute data regression results					Ten minute moving average regression results				
	OLS R-squared	OLS mean residuals	OLS MSE	OLS t-statisic	OLS t-statisic	OLS MA R-squared	OLS MA mean residuals	OLS MA MSE	OLS MA t-statistic	OLS MA t-statistic
Nonfarm Payroll	11.6%	-2.6E-12	-2.6E-12	8.8	6.7	69.7%	6.9E-13	1.1E-09	6.1	29.8
Retail Sales	7.6%	-2.7E-12	2.1E-09	10.9	5.2	61.3%	2.1E-13	3.2E-10	6.5	24.8
Unemployment	9.4%	-6.1E-13	7.6E-11	11.9	5.9	66.7%	-2.1E-13	8.7E-12	17.3	27.5
Univ. Michigan survey	5.1%	-4.4E-13	4.1E-11	14.0	4.1	48.2%	-2.4E-13	5.8E-12	16.7	18.8

GBP Statistics	Minute by minute data regression results					Ten minute moving average regression results				
	OLS R-squared	OLS mean residuals	OLS MSE	OLS t-statisic	OLS t-statisic	OLS MA R-squared	OLS MA mean residuals	OLS MA MSE	OLS MA t-statistic	OLS MA t-statistic
Nonfarm Payroll	8.3%	-5.5E-13	1.4E-10	10.1	5.4	62.0%	-1.4E-13	2.2E-11	9.5	25.3
Retail Sales	3.9%	-5.1E-12	4.1E-09	12.2	3.3	47.1%	-2.4E-12	6.4E-10	8.5	18.5
Unemployment	5.4%	-6.1E-12	7.4E-09	11.7	4.1	52.7%	-3.2E-12	1.1E-09	8.2	20.7
Univ. Michigan survey	9.4%	-6.1E-12	1.2E-08	9.7	5.9	66.0%	-1.1E-12	1.8E-09	6.4	27.6

Table 3.8. Regressions results of range volatility estimator and wavelet volatility estimator. Note that over a moving 10-minute period and after smoothing the data, there is a good fit between the range and wavelet estimations of volatility.

In this table, we regressed the minute-by-minute volatility series as measured by range estimator on the minute-by-minute volatility series measured by our wavelet estimator. In estimating range and wavelet volatility, we used second-by-second data to reach a volatility number for each minute. We then smoothed the datasets by calculating 10 minute moving averages of range and wavelet estimation series and ran the regression again on the smoothed data. The results of the regression on the smoothed data were highly satisfactory because the estimated regression statistics all point to a good fit. Hence, our wavelet estimator clearly captures the dynamics which are captured by range estimation, but at the same time being more efficient than the range estimator

Using the second-by-second tick data, we calculated the minute return. We then defined a *volatile minute* as one in which the highest (lowest) tick was above (below) one standard deviation of the mean volatility in that minute throughout the dataset. We defined *volatility clusters* if two or more volatile minutes were adjacent to each other. Figure 3.8 shows the time up to 360 minutes on the horizontal axis and the number of volatility clusters in any minute on the vertical axis. The economic release occurs on minute 180, depicted in the graphs by a red vertical line. As an illustration, in the nonfarm EUR figure, at minute 120 we read 25 on the vertical axis. This means that throughout the dataset, there were 25 instances of volatility cluster occurring at minute 120.



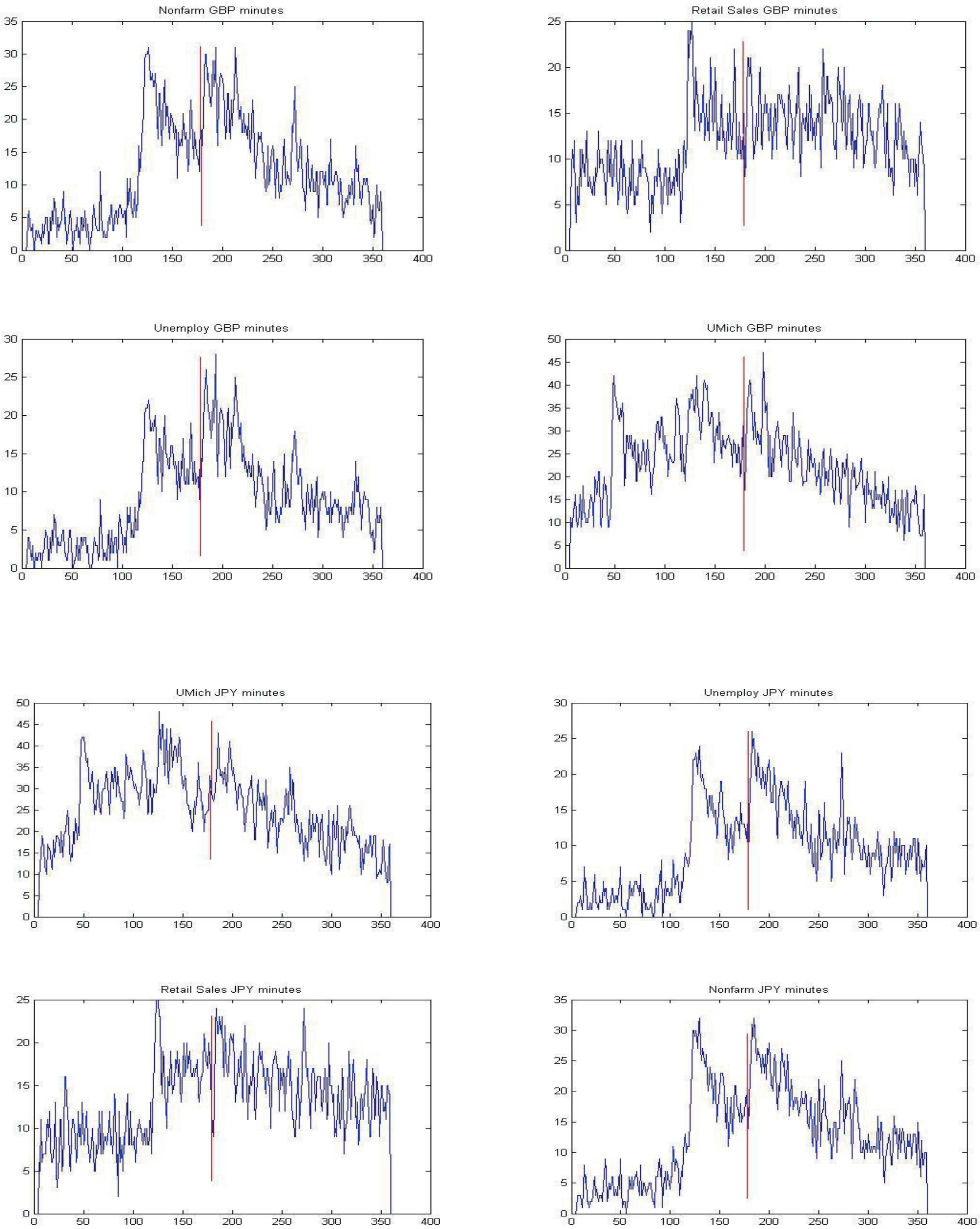


Figure 3.8 . Volatility clusters for EUR/USD, JPY/USD and GBP/USD (vertical axis is the number of minutes with volatility cluster; horizontal axis is the time in minutes starting three hours prior to release to three hours after the release. The release is at minute 180.

Table 3.9 below shows the decay rates of volatility clusters:

	EUR	GBP	JPY
Nonfarm Payroll	0.049	0.035	0.028
Retail Sales	0.045	0.034	0.025
Unemployment	0.021	0.018	0.013
Univ. Michigan survey	0.016	0.026	0.026

Table 3.9. Decay rate of volatility clusters. A volatile minute is a minute where the volatility is at least one standard deviation higher than the mean volatility for that minute in the exchange rate time series. Volatility cluster is defined when two volatile minutes are adjacent to each other. Decay rate is α in the following differential equation:

$$dN/dt = -\alpha N$$

where N is the number of volatility clusters at time t.

Note that the likelihood of volatility clusters decrease at a slightly faster rate in case of more important releases with the exception of the University of Michigan survey.

The number of volatility clusters increase as we approach the release. The first peak in the volatility cluster (which occurs between 100 and 150 minute interval in the graphs) correspond to an intraday market seasonality due to the timing of open and close of the markets. Ignoring that increased activity for the moment, we observe that volatility cluster starts at its lowest level for a period starting 3 hours prior to the release. The volatility clusters jump to their local high at or immediately after the release, and declines sharply afterwards. We note the following in the results depicted in Figure 3.8 and Table 3.9:

- The more important the release, the less the level of the volatility clusters early on for all currencies. This may be due to the fact that as traders are aware of the impending important economic announcement, they may feel that taking a position may put them in an unfavorable situation and rather wait for the announcement to engage in heavy trading.
- The more important the economic release, the higher the jump at the release time. This is reflective of the heightened trading activity subsequent to the release. An important release will affect the traders' positions more, hence some will rush to rectify their position in light of the release data, while others

try to use the release to engage in trading for profit. All of the aforementioned may lead to a volatile period.

- More important economic releases seem to lead to a faster decline in volatility in the 3 hours following the release than the lesser economic data. This is intuitive, as a more important release is one which is expected and its effects analyzed prior to the release. Therefore once released, the traders react rapidly to the released number and the information content in the release is rapidly absorbed. Such scrutiny does not typically exist for a lesser release, hence traders reaction is slower and volatility clusters may continue for a bit longer.

As with our survey respondents, the regression results seem to support some of their opinions but not all of them. Nonfarm payroll is the most important news for the foreign exchange market — various studies by investment banks and central banks (e.g., Clifton and Plumb, 2007) confirm this result — and the Philadelphia Fed survey is among the least important. Our respondents views' match our findings in these cases. However, although both economists and traders contended that the ISM Non-Manufacturing survey is among the top five releases, our regression results do not support this view.

Participants in the currency market all agree that various themes become important for that market during some period of time, and those themes lose their significance after a while. Hence the survey results may to some degree be a reflection of what the respondents deem to be important *at the time of the poll*.

We demonstrated that nonfarm payroll and unemployment are the most important of the four releases selected, followed by retail sales and then the University of Michigan survey. On the days that market participants are expecting an important economic release, in the absence of other volatility-inducing events, on average, they become less active in the market. This leads to the low volatility cluster phase at the starting minutes of the three-hour period prior to the release. After the release, volatility cluster decays faster in the case of the more important economic release. This is also intuitive, as market participants pay attention to important economic releases, and hence absorb the economic release rapidly. In the case of a less important economic release, the jump in volatility is less and, because fewer market participants pay attention to it, the volatility clustering behavior does not change materially subsequent to the release.

We performed a Wald-Wolfowitz runs test (simply "runs test" hereafter) to evaluate the hypothesis as to whether the sequence of volatility clusters is randomly distributed. (Note that the number of data points differs from one release to the other.) On the vast majority of release days, the hypothesis that volatility clusters occur randomly is rejected with 95% statistical significance. The ratio of the minutes after the release to minutes before the release in which the random distribution of volatility clusters can be rejected is reported in Table 3.10.

	EUR	GBP	JPY
Nonfarm payroll	1.22	1.18	0.99
Unemployment	1.26	1.25	1.13
Retail Sales	1.22	1	1.03
Univ. of Michigan survey	0.99	1.01	1.01

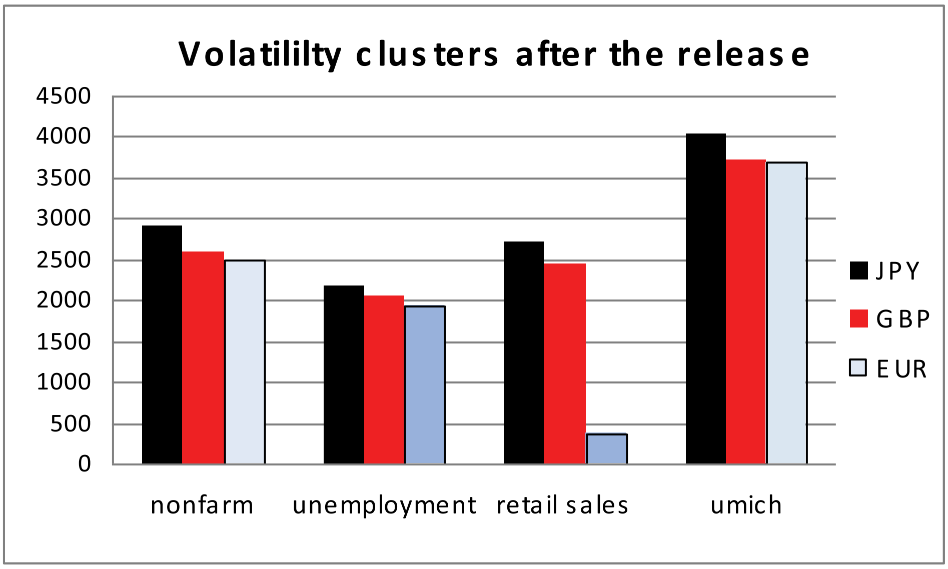
Table 3.10. Results of Wald Wolfowitz Runs Test. The numbers are the ratio of instances when the volatility clusters are non random prior to the release to instances when volatility clusters are nonrandom subsequent to the release. Note that the likelihood of nonrandom distribution of volatility clusters increases in almost all cases after the release.

In Table 3.10 we also observe that:

- For all releases and all currencies, there are more than or equal instances of rejecting the hypothesis after the release than prior to the release. In other words, the release tends to increase the likelihood of non-random clustering of volatile minutes.
- The more important the economic release, the more likely it is that the post release clusters are non-random.
- The more important the economic release, the higher the ratio of post to prior non-random days. In other words, the more important economic releases are more likely to introduce a non-random volatility inducing effect into the market.
- The non-random likelihood of distribution is most noticeable in the euro followed by the British pound and Japanese yen.

In Figure 3.9 we compare the volatility clusters for the four selected releases. From the figure we can draw the following two conclusions. First, the number of volatility clusters increases after all releases, but it increases significantly more for more important releases (nonfarm and unemployment) followed by retails sales, and finally the least important economic release (the University of Michigan survey). Hence the more important the economic release, the more likely it is for the market to become volatile after the release and for volatility to cluster subsequent to the release. Second, except in the case of the University of Michigan survey, the Japanese yen has the highest tendency to show volatility clustering, followed by the British pound and then the euro. Because the University of Michigan survey is the least important of the releases analyzed, the Japanese yen’s volatility behavior may be the result of traders’ preference for using this currency as a means of short intraday trading.

Our empirical results thus far suggest that the majority of the economists and traders polled in our survey were incorrect in contending that the effect of the release is the same for all three major currency exchange rates. Figure 3.9 clearly shows that Japanese yen seems to be affected more and demonstrates a higher likelihood of volatility clustering than the euro and the British pound. Further research into the possible explanations of this phenomenon is suggested.



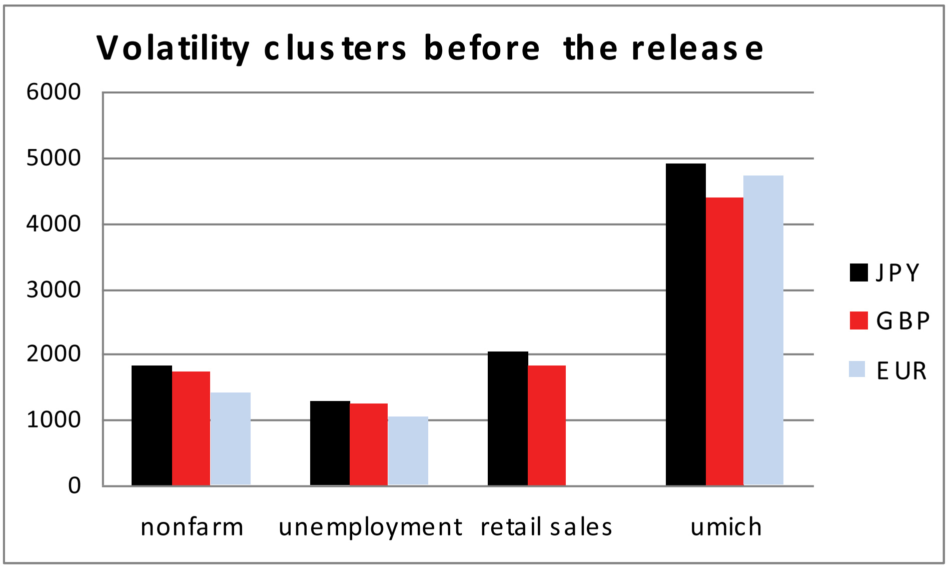


Figure 3.9: Volatility clustering before and after four representative releases. Vertical axis is the number of minutes (three hours prior to release, and three hours after the release) with volatility clusters in four years of data. The releases are nonfarm payroll, unemployment, retail sales and University of Michigan Consumer Confidence survey.

We can draw the following conclusions:

- The number of volatility clusters increased after all releases, but it increase significantly more for more important releases (nonfarm and unemployment) followed by retails sales and finally the least important economic release, U Michigan survey. Hence the more important the economic release, the more likely it is for the market to become volatile after the release and for volatility to cluster subsequent to the release.
- Except in the case of U Michigan, JPY has the highest tendency to show volatility cluster followed by GBP and finally EUR. As University of Michigan survey is the least important of the releases analyzed, the JPY volatility behavior may be the results of traders preference for using JPY as a means of short intraday trading. Perhaps EUR is used by corporations and other investors which have less interest in intraday short term profit taking, but this observation merits further investigation.

Figure 3.10 compares the volatility cluster results between currencies and between the four releases. Except for the least important release, the number of cluster minutes increases after the release.

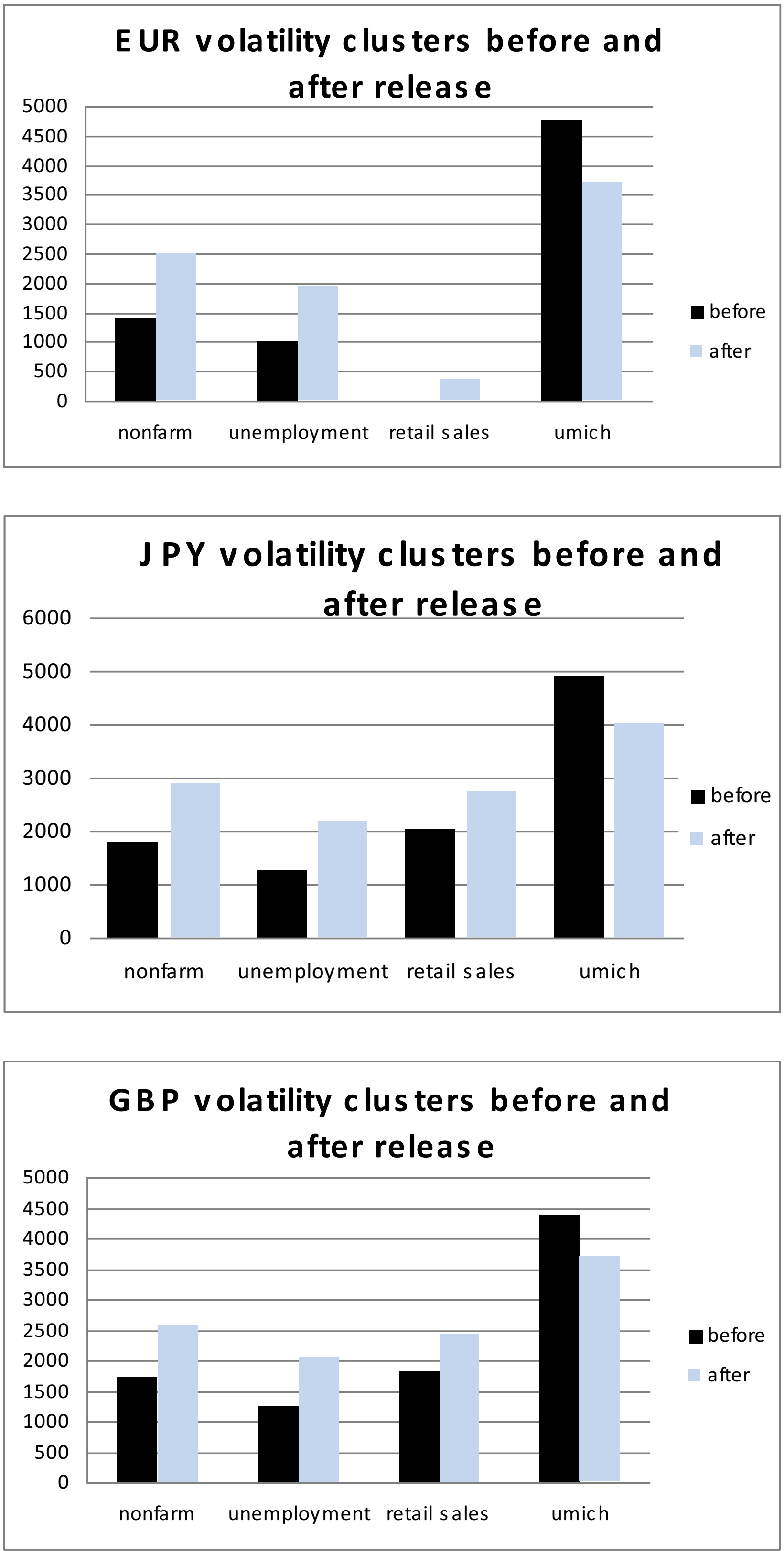


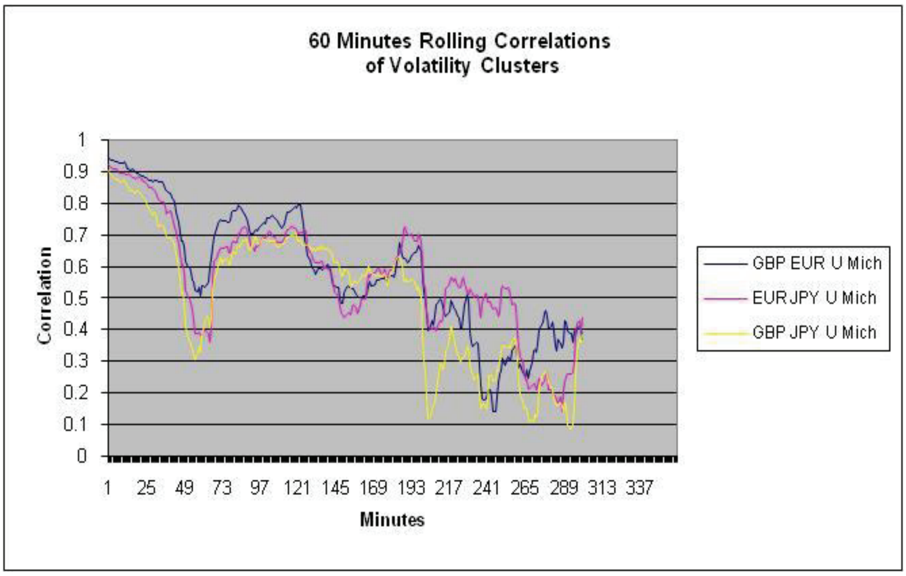
Figure 3.10. Volatility clustering comparison between three major currencies. Vertical axis is the number of minutes with volatility clusters in four years of data (three hours prior to three hours after the release). The releases are nonfarm payroll, unemployment, retail sales and University of Michigan Consumer Confidence survey.

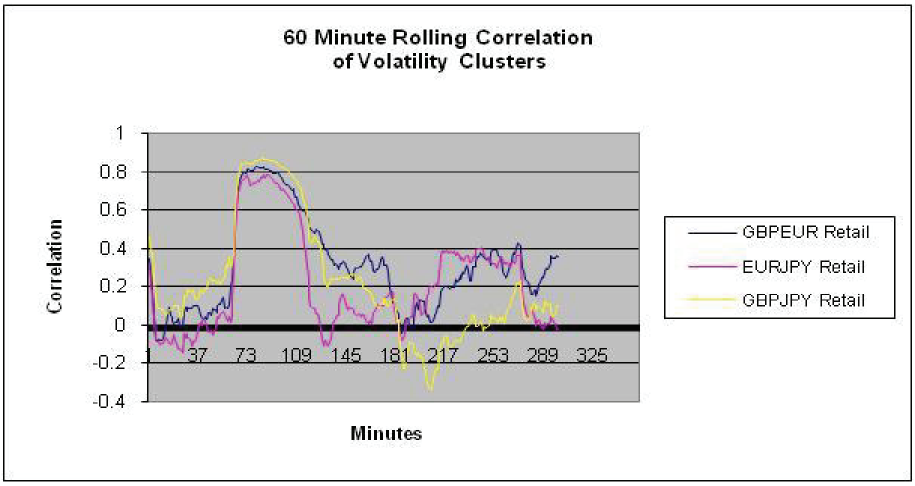
One may observe from the graphs that nonfarm seems to have the highest likelihood of increasing post release volatility cluster among the important releases. Moreover our analysis shows that the probability of volatility clustering in case of major economic releases is higher post release compared to prior to the release with 95% confidence.

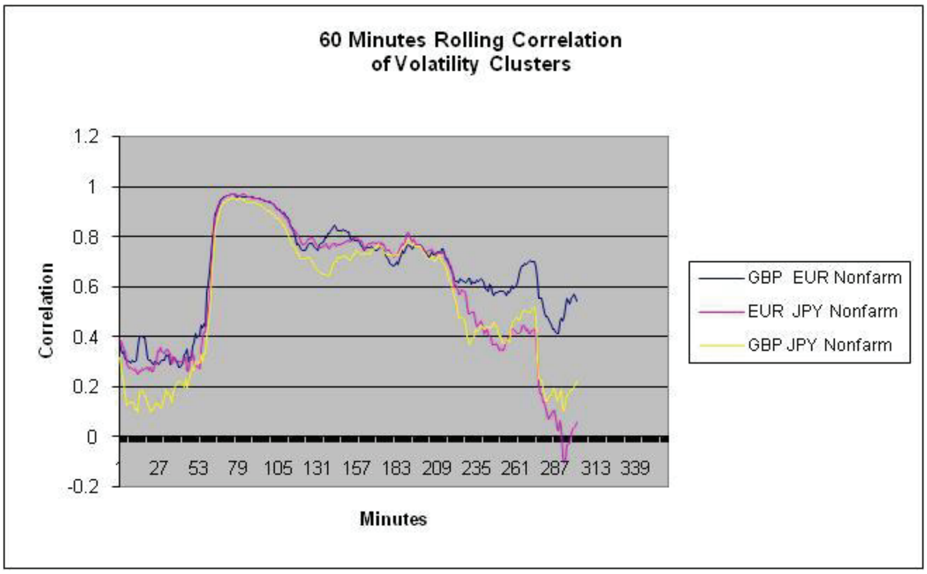
The anomaly observed for the University of Michigan Consumer Confidence Survey is worth commenting upon. Based on the results for both the runs test and volatility cluster analysis, it seems that this least important release is not significant in changing the likelihood of volatility clustering. One possible explanation may be that on the days that market participants are expecting important announcements, the market is cautious prior to the release. Volatile behavior may not continue as market participants may take the opposite side of a trade, or not participate at all. Subsequent to the release, market participants absorb the information in the economic release, witness the initial surge in activity in the immediate vicinity of the release, and may be forced to reduce or increase their positions based on the release. This would lead to higher trade volume and, if some of these trades which are initiated by various market participants coincide or are executed with little time in between, may increase volatility clustering.

Having analyzed the volatility clustering of individual currencies, it would be interesting to see if there are co movements (and possible spill over) of volatilities. The graphs in Figure 3.11 were generated by finding the correlation of volatility clusters between each 2 currencies. The correlation is calculated using a 60 minute moving window, i.e. each correlation data point uses the 60 minutes preceding that minute. The data release occurs at the 120 minute mark on x axis on these graphs.

As an example in the graph of University of Michigan release immediately below, the blue line corresponds to the 60 minute rolling window correlation of GBP/USD and EUR/USD.


60 Minutes Rolling Correlations
of Volatility Clusters
Correlation
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
1 25 49 73 97 121 145 169 193 217 241 265 289 313 337
Minutes
GBP EUR U Mich
EUR JPY U Mich
GBP JPY U Mich


60 Minute Rolling Correlation
of Volatility Clusters
Correlation
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
1 37 73 109 145 181 217 253 289 325
Minutes
GBPEUR Retail
EURJPY Retail
GBPJPY Retail


60 Minutes Rolling Correlation
of Volatility Clusters
Correlation
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
1 27 53 79 105 131 157 183 209 235 261 287 313 339
Minutes
GBP EUR Nonfarm
EUR JPY Nonfarm
GBP JPY Nonfarm

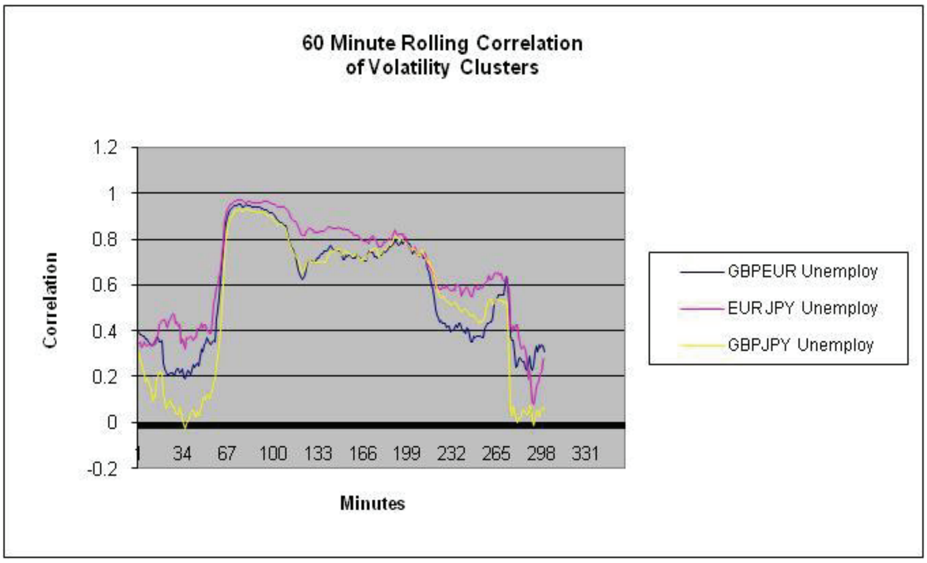


Figure 3.11

In the Figure 3.11 above, we observe that in the case of the 2 more important releases, the correlations prior to release increase most and approach 1, while the 2 lesser releases exhibit a lower correlation. This indicates that traders utilize all currencies to express their views on the release. In other words, traders are really expressing their views on US dollar and will use the most liquid currencies (EUR, GBP and JPY) to trade based on those views. Moreover, the increase in the correlation in the minutes leading to the release is more visible in case of the more important news, and the increase happens at a very rapid pace followed by a plateau. Lastly we observe that the shape of the volatility curves for all 3 pairs are very similar for each release.

We may conclude that prior to the release, the behavior of the market is mostly driven by dollar side of the currency pair rather than by the other currency. All dollar crosses (i.e. EUR/USD, GBP/USD, JPY/USD) exhibit very similar volatility dynamics prior to the release as the correlation of the volatility clusters increases and decreases similarly across the crosses. The likelihood of the volatility clusters rises in all 3 crosses and the correlation increase towards 1. After the release, the correlation falls, albeit more gradually in case of the more important releases. In the case of the least important news (Univ. of Michigan survey), the correlation shows little relation to the release itself and shows a significantly different dynamics prior and after the release compared with the important releases.

3.4.4 Analyzing the volatility of volatility

We used second-by-second data to analyze the volatility of volatility. Here we used the following definition of volatility:

$$volatility = abs(\ln \frac{P_t}{P_{t-1}})$$

where P_t represents the exchange rate at time *t.*

We constructed volatility series to which we applied various wavelets. We selected the 5th Daubechies wavelet at 5th level based on criteria discussed earlier and applied it to the volatility data series. In other words, we applied the wavelets once to generate the volatility data series and applied it a second time to generate the data set for volatility of volatility. The 5th level wavelet gave a clear visual picture, retained a high degree of energy (above 90%) and reduced the number of coefficients significantly so that the signal behavior could be captured with least number of coefficients.

We defined a volatility cluster as any two or more seconds where the jump in volatility is above one standard deviation of the mean for the corresponding minute throughout the dataset. We then counted the volatility clusters for each minute (from three hours prior to three hours after the release) of each day and aggregated the results.

After performing the analysis, we reconstructed the original signal so that the data points in detail will correspond to the time space as the original data. The Matlab™ codes used were the same as the ones in the volatility analysis in the previous section of this chapter. Once the DB(5,5) was applied and the number of data points were reduced, the data comprised of 21,600 points and the economic release occurred on the 11052 tick.

To illustrate our method, in Figure 3.12 below, we have counted (for each second) the volatility of volatility clusters in the detail signal for one day of data, and generated a line for each cluster. The red line corresponds to the time when non nonfarm payroll number was released to the market. The denser part of the spectrum corresponds to periods with higher density of volatility clusters. One can visually verify that those periods increase significantly subsequent to the release.

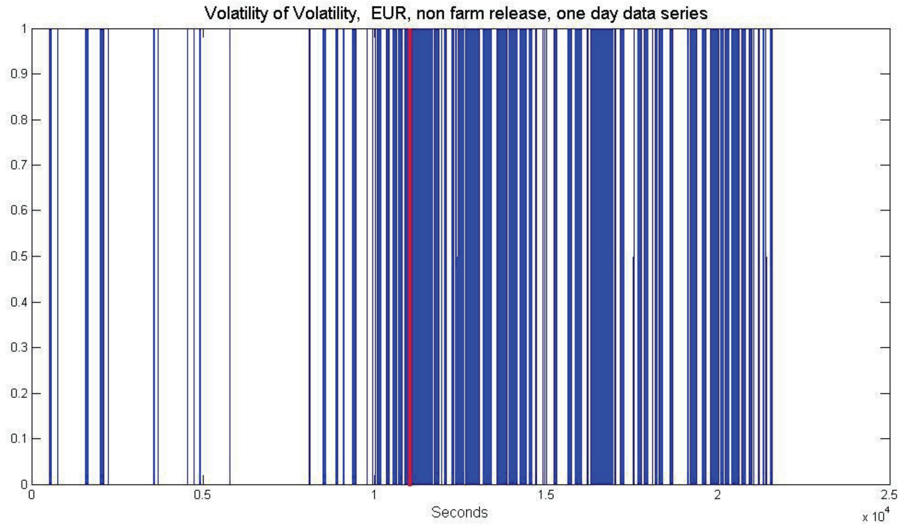
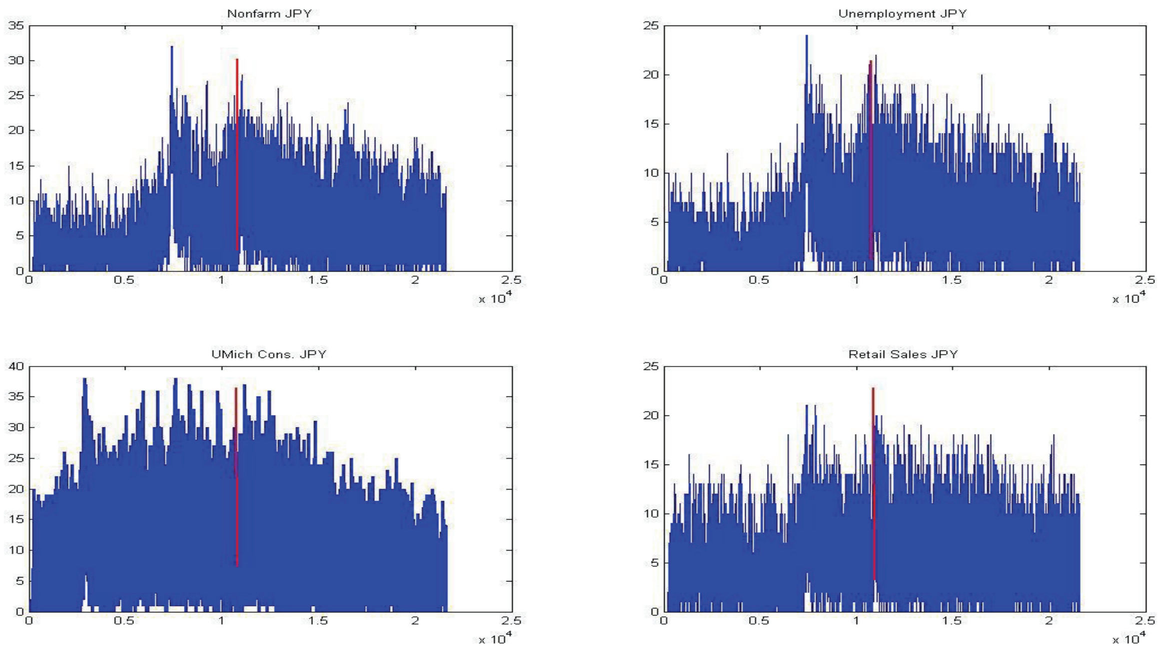


Figure 3.12

This visual representation is indeed similar to the visualization used in signal processing known as scalograms, which would have visually represented the high frequency regions (corresponding to high volatility) and low frequency. An example of scalograms approach could be seen on page 96 of Ogden (1997).

In the Figure 3.13, the data count as above have been repeated, but for all days of the 4 years of data. So for each second of the period (announcement time -3 hour, announcement time +3 hour), we have counted the volatility clusters. The red line depicts the actual second when the announcement was made.



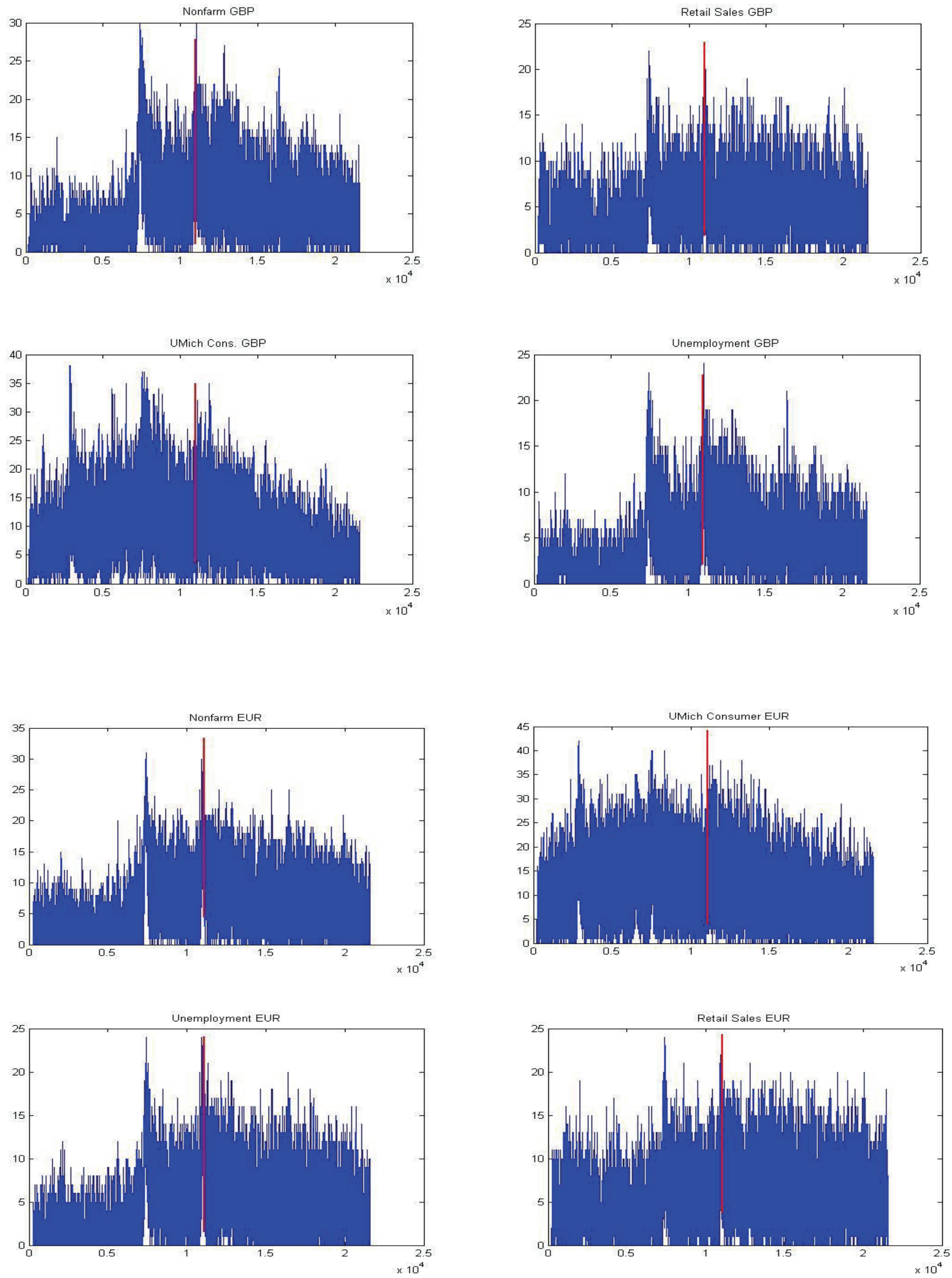

Nonfarm GBP
Retail Sales GBP
UMich Cons. GBP
Unemployment GBP
Nonfarm EUR
UMich Consumer EUR
Unemployment EUR
Retail Sales EUR
0 0.5 1 1.5 2 2.5
x 10^4

Figure 3.13

Table 3.11 shows the decay rate of volatility of volatility clusters. In order to model the behavior of the volatility of volatility, we smoothed the second-by-second data by applying moving averages. We tried various models and exponential decay seem to fit the data best.

	EUR	GBP	JPY
Nonfarm payroll	0.015	0.028	0.027
Unemployment	0.021	0.021	0.02
Retail Sales	0.012	0.018	0.011
Univ. of Michigan survey	0.013	0.021	0.023

Table 3.11. Decay rate of volatility of volatility clusters. A volatile minute is a minute where the volatility is at least one standard deviation higher than the mean volatility for that minute in the exchange rate time series. Volatility cluster is defined when two volatile minutes are adjacent to each other. Decay rate is α in the following differential equation:

$$dN/dt = -\alpha N$$

where N is the number of volatility of volatility clusters at time t. The higher up in the table the release is, the more important the release as measured by its effect on currency market. Note that generally the likelihood of occurrence of volatility of volatility clusters decreases at a slightly faster rate in case of more important releases.

We observe the following about volatility of volatility: (1) it is lower prior to the more important releases, (2) the jump is higher from the pre-release to post-release levels for more important announcements, and (3) it decreases after the release, with occasional peaks still observable.

Applying the exponential decay model to the 5 minute moving average of volatility of volatility of the data after the release (namely repeating the procedure described above for all currencies and 4 releases), we compared the results as seen in the following graphs:

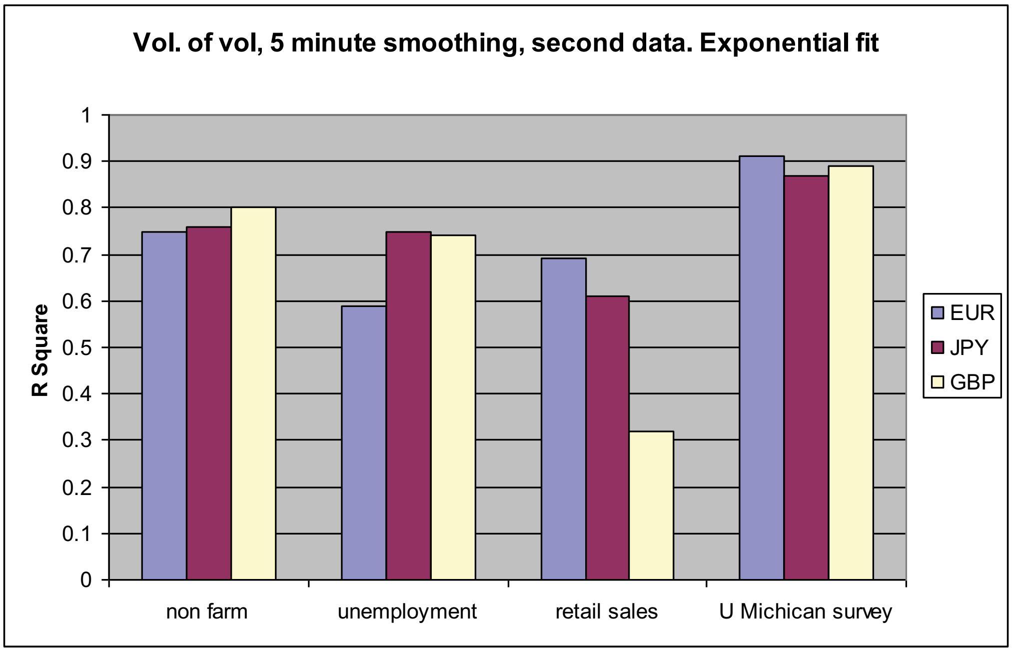


Figure 3.14

In Figure 3.14, we are comparing the goodness of fit of exponential model for all 4 releases and 3 currencies. We observe that with the possible exception of retail sales, all other economic releases show a very good fit with exponential decay. Comparing this with the results of the volatility clustering phenomenon discussed earlier, we were expecting the best fit to come from the more important announcements (nonfarm and unemployment). However the results show surprisingly good statistics for University of Michigan survey. Therefore the volatility of volatility decays exponentially after the release, but the very good fit for the least important release may be an artifact of the data and we cannot explain it.

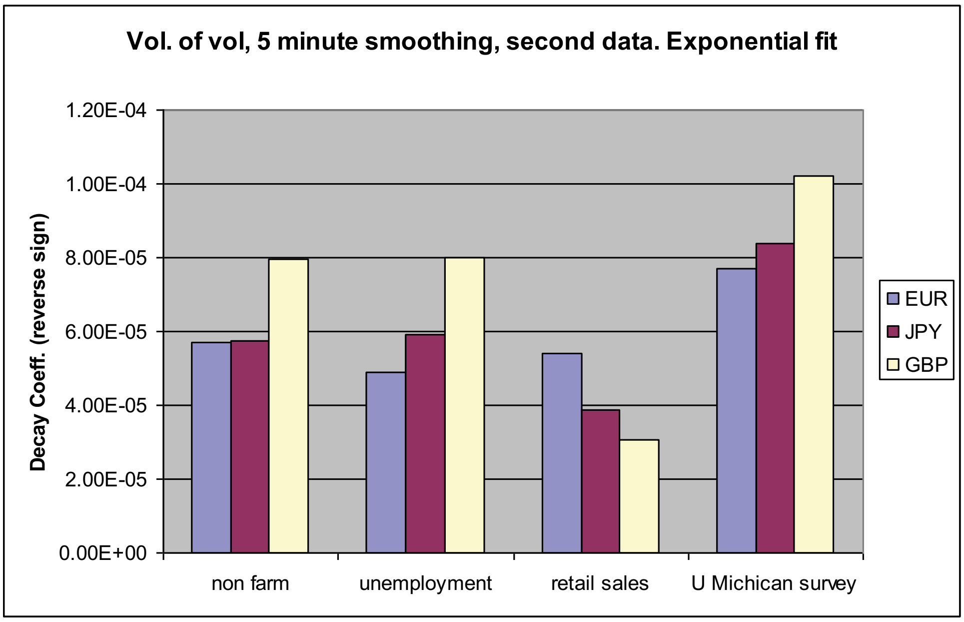


Figure 3.15

The graph above attempts to compare the rate of exponential decay in volatility of volatility after the releases is somewhat more interesting. Concentrating on the 3 releases which had a high R Square from the previous graph, we observe that:

- Volatility of volatility decays fastest with GBP, followed by JPY and EUR.
- Volatility of volatility decays at about the same rate for the 2 most important economic releases.
- The volatility of volatility due to release of the least important of the announcements seem to decay faster than the more important releases. This may be explained by noting that the more important news are reviewed by many market participants and digested rapidly. Therefore if the news causes volatility, this effect is still observable in the market some time after the release. In contrast, if a nonmaterial announcement increases the volatility, this effect dies away rapidly. Hence a low volatility day reverts to being low volatility and the same with highly volatile day.

3.5 Conclusions

We propose a new volatility estimator based on wavelet analysis and demonstrate that this wavelet estimator is 39 times more efficient than the commonly used measure of volatility, the range estimator. Moreover, a regression on the results of range volatility estimation and our wavelet volatility estimation indicates that there is a very good fit, suggesting that our proposed estimation method successfully captures the dynamics of the market as accurately as a range estimator. Empirically we find that for the three major currencies we investigated and for the four representative economic releases we analyzed, the volatility clusters occur prior and post release. However the likelihood of occurrence of clusters increases significantly after the release compared to prior to the release, and the likelihood decreases exponentially following the release. The likelihood of clustering of volatility of volatility also decreases exponentially after the release. This may be explained by the fact that traders watch the market carefully in anticipation of an important release, rapidly absorb the information in the release, and then act upon it quickly. This urgency to react to the release does not exist in the case of less important releases, hence the slower decay and lesser concentration of volatility clusters.

We further demonstrated that the volatility clusters occur more frequently for the Japanese yen, followed by the pound sterling and euro. We also show that the arrival of volatility clusters is not random, and the nonrandomness increases significantly after the release. However, the rate of decay is not the same with all four releases, and the most important releases decay faster than less the important ones.

Chapter 4

Behavioral finance analysis of individual and institutional investors during the financial crisis of 2008-2009

4.1 Introduction

Understanding the behavior and decision making of individual investors is very important in understanding the dynamics of the equity markets. According to Gallup polls, as of 2011, 54% of American households own equity directly or indirectly through pension plans, mutual funds, etc. (see www.Gallup.com). In 2009, individuals directly held $196 Billion of stocks, compared to $308 equity investment indirectly through mutual funds and other investment companies (see Investment Company Institute (2010)). Therefore approximately 2/3 of all US equity held by US households was held directly by individuals who purchased those shares, and equity held by households may well increase as global markets appreciate and when the after effects of global crisis are resolved. This is indeed a very large portion of global equity and understanding the behavior of the individual investors is therefore important in understanding global equity market dynamics as well as asset pricing.

To analyze the behavior of individual investors, we picked the years 2008 and 2009. These years were among the most volatile periods in the history of financial markets and offer the opportunity to observe the behavior of individual investors during distressed markets.

To analyze this behavior, we need reliable data on individual investors' equity holdings at sufficiently high frequency. Behavioral finance researchers have historically used data during a particular period from specific sources (e.g. investment records of a particular brokerage house for a certain time period). However, such data are not readily available to the public, thereby limiting research opportunities to researchers who are fortunate enough to obtain non-public data. Moreover as the data is limited to a particular time, it is not replicable for other time intervals. Consequently, there is a need for replicable and publicly accessible data that can represent individual and institutional investors' investment positions at daily frequency. Daily frequency not only allows researchers to analyze the short-term nuances of the decision-making process, but also an abundance of data will allow for more rigorous analysis. Because a daily indicator of the equity holdings of individual investors is not available, we construct such an indicator which is replicable from publicly accessible data.

In Section 4.2, we describe the data used in our analysis. In Section 4.3, we describe the behavior of institutional and individual investors, and subsequently present our parametric and non parametric analysis to explain the behavior of individuals. We test the disposition effect in Section 4.4 and present a practical application for our findings by constructing a profitable trading model in Section 4.5. We conclude in Section 4.6.

4.2 Selection of data series

We start by reviewing the available investor holding databases and then describe our methodology for constructing our proposed indicator.

4.2.1 Review of available data sources

There are very few publicly available data which might be suitable for use as indicators of equity holdings for individual investors. The Federal Reserve's Z1 quarterly holdings database breaks down the holdings of U.S. securities into various sectors, including what is labeled as "household sector." However the household sector includes not only holdings of retail investors, but also "domestic hedge funds." As such, it fails to provide a pure and reliable indicator of individual investor holdings.

Lipper Fundflows Insight Report™, a weekly publication by Lipper Thompson Reuters™, includes the moving average of the flow of capital into various mutual funds during the preceding four weeks. Because the published data are smoothed by averaging and data are only published every month, this source lacks the frequency and detail to empirically analyze the behavior of individual investors, although it is useful for determining the long-term flow of capital.

We also analyzed the data published by the American Association of Individual Investors (AAII) which is the largest nonprofit organization of individual investors. The AAII Investor Sentiment Survey measures the percentage of individual investors who are bullish, bearish, and neutral on the stock market for the next six months.

A measure of the trading activity of institutional investors is their block trading. Exchanges define a block trade as any trade in more than 10,000 and up to (but not including) one million shares. Such trades are recorded with the exchanges at the close of each trading day and the sizes of these trades are by definition out of reach for the vast majority of individual investors. We used the daily aggregate of all block trades in companies comprising the S&P 500 as our measure of the change in institutional investors' holdings.[7] The information on institutional investors block trades is publicly available from Bloomberg Professional™.

4.2.2 Construction of our proposed individual investors' holdings indicator

In order to study the impact of volatility on decision-making behavior, we needed a dataset with sufficiently high frequency which would show the short-term changes in individual investors' holdings. Since there are no indicators of individual investors' holdings and investment positions at any frequency higher than the monthly we constructed our own daily indicator using publicly available data. We used the Bloomberg Professional™ database of approximately 1,200 exchange-traded funds (ETF)s, and separated 440 ETFs with net asset value of less than $100 million. We use this category of ETFs as a proxy for individual investors' holdings. Among the small ETFs in our proposed indicator (i.e. net assets less than $100 million), we further separated 340 equity ETFs, with the remaining small ETFs being in fixed income and other asset classes. We then aggregated the positions in these 340 small capitalization equity ETFs on a daily basis to come up with a single daily number which we propose as a proxy for the U.S. individual investors' equity holdings. The growth in an ETF net asset holding may be due to flow of money into ETFs or due to an increase in the value of the ETF. In order to isolate the effect of the flow of money, we divided the daily change in flow by the average value of the U.S. equity market (as represented by the S&P 500 Index) during that day, and used this daily number as our indicator for the daily change in individual investors' holdings. We repeated the same normalization for monthly data of our indicator. There is survivorship bias in the dataset because it includes ETFs which may have been eliminated due to lack of investor interest or other reasons. But as long as the net assets of these ETFs are within our range (which is the case with all ETFs at the time

[7] There exist a very small category of stocks, known as penny stocks, which have very low value and some individuals may be able to trade a block of them, but the number of such stocks and their aggregate market capitalization is so small that we ignore their effect in our analysis.

of their introduction into the market), we believe that those who are investing in these ETFs are individuals as opposed to institutions. The turnover in the ETF market is small, with monthly drop or addition to the equity ETF universe being about 1-2 over the period of our study. Such small turnover and very small assets of the new or dying ETFs reduces the error resulting from survivorship bias to a negligible level.

Our rational for this categorization of ETFs is that their small market means that institutional investors would find it costly to continuously report on ownership of such funds (as majority share holders are required by federal securities law to report their positions). Moreover, small market capitalization means that in almost all of these securities, the shares cannot be borrowed (hence investors cannot short the security) or lent (hence investors cannot generate additional revenue by lending shares overnight or lending shares to those who wish to short the security). This limitation makes ETFs less attractive to institutional investors. Most importantly, the limited daily liquidity means that large investors would be impacting the price every time they seek to trade sizes that are typically large. These liquidity constraints make it practically impossible for institutional money managers to trade such comparatively very illiquid securities.[8] To illustrate the liquidity constraint, we compare some statistics of our proposed indicator with those of the US equity market.

The following table presents some statistics on the size of commonly used US equity indices according to Bloomberg Professional™ and Reuters™.

	Number of stocks in the index	Highest market capitalization	Lowest market capitalization	Weighted average market capitalization	Median market capitalization
Russell 3000	3000	$ 283,061,000,000	$112,000,000	$62,620,000,000	$ 813,000,000
Russell 2000	2012	$ 2,274,000,000	$112,000,000	$ 987,000,000	$ 448,000,000

Table 4.1

As an asset class, ETFs on average trade 8% of their assets every day, with 80% of ETFs trading volume being under 5% of their assets (See NYSE ARCA). However

[8] Various episodes of abrupt market moves and significant losses have been recorded due to lack of sufficient liquidity. For example, Lo and Khandani (2008) document the hedge funds' loss of August 2007 and demonstrated the role of insufficient liquidity.

20 ETFs account for 80% of the daily trading volume of all ETFs. Those 20 ETFs would be the ones commonly owned by institutions. However as seen in Table 4.2 below, our indicator consists of ETFs with much smaller trading volumes.

	Total market capitalization ($ million)	Total number of shares traded daily
Russell 3000	15,580,000	1,250,000,000
Russell 2000	1,470,000	230,334,000
Individual Investor index	14,532	17,192,000

Table 4.2

In wider US equity market, Russell 3000 index encompasses 98% of all US stocks. Russell 2000 index consists the 2000 companies within Russell 3000 index with the smallest market capitalization. These 2000 companies account for approximately only 8% of total US equity market. However the average market capitalization of the ETFs in our indicator is 0.0014 of the average market capitalization of Russell 2000 stocks. So our proposed index market liquidity is less than 1% of the smallest 8% of all US public equity. Liquidity and available trading volume is therefore prohibitive of institutional asset managers to invest in the ETFs that constitute individual investors indicator. Finally, there are other venues available to institutional investors to express their market views instead of employing such illiquid ETFs. Such venues include futures and options markets which provide flexibility and abundance of liquidity. Even using algorithmic trading and splitting the trade into very small pieces, it would be very unlikely that an institutional investor with reasonable knowledge of the market would choose these securities given the alternative venues. In contrast, individual investors rarely invest in futures and options markets due to lack of sophistication in these markets and high capital requirements. Instead, individual investors would gravitate towards using ETFs.

Despite the small size of the ETFs in our indicator and lack of liquidity for institutions, the ETFs in our indicator cover all sectors of the market and the indicator is therefore a well diversified portfolio. In fact the correlation of daily returns of our proposed indicator (i.e. a portfolio consisting of small ETFs in our indicator with equal weights) with daily returns of S&P 500 is 0.89. The figure below shows the performance of our indicator over a longer period.

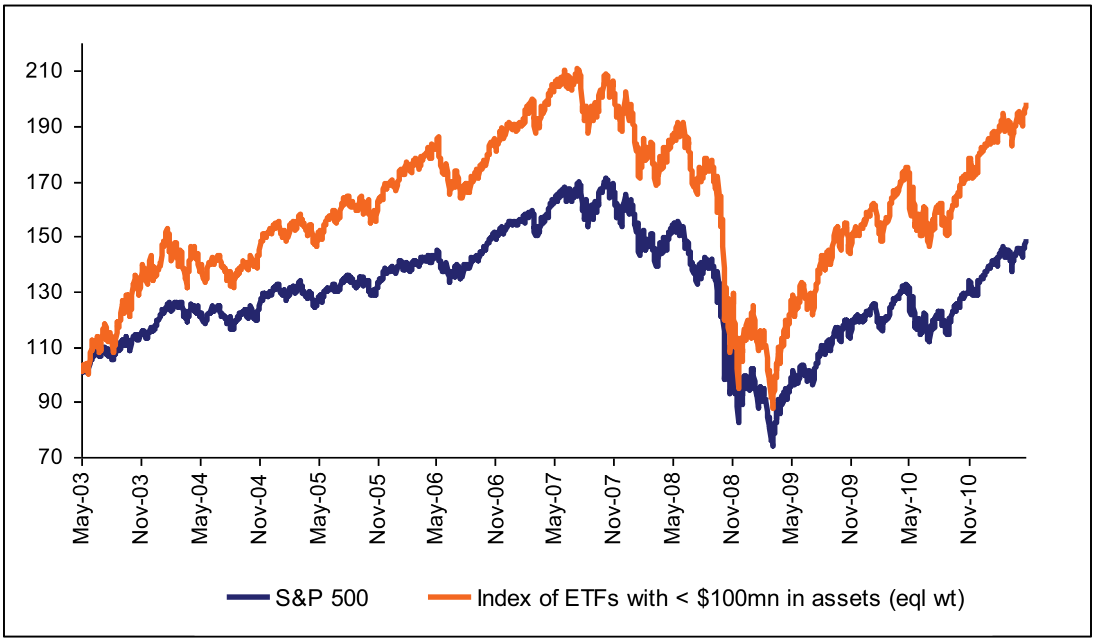


Figure 4.1.

Further more, the indicator ETFs are not included in Russell or Standard and Poor or other commonly used equity indices. This is beneficial for construction of our index because despite the fact that we have constructed an index which can be used as proxy for equity market, the constituents of the index are not included in the traditional equity market indices therefore these constituents will not influence the calculation of the traditional equity indices (in other words, we will not be “double counting” the effects of the investors as measured in our proposed indicator when analyzing the traditional equity market indices).

To summarize, we have constructed an indicator for individual investors holding which is 1) exclusive of any other investor groups and for all practical purposes prohibitive for investments by any group of investors other than individuals 2) has high correlation with equity markets which allows the researchers to use it as a proxy for wider equity market investment 3) the liquidity of it can be measured daily and 4) is constructed using publicly available data so that it is replicable by other researchers.

4.3. Analyzing individual investor’s decision making

We now use our proposed indicator to analyze the behavior of individual investors during our study period. For this analysis, we utilize a parametric and a non parametric approach. The parametric study based on multivariable regressions showed unsatisfactory results. Due to the fact that we are dealing with a very volatile period, there are frequent jumps in the data and the data is for the most part not stable which makes this type of analysis less fruitful. Next we used robust regressions which give more weight to data points closer to the regression line, and less weight to the data points further away. In this way the robust regression reduces the effects of outliers. The results obtained in this way were statistically significant, however removing the outliers and smoothening the data does in fact reduce the potency of the results as those outliers were in fact an integral part of the market dynamics during the crisis period. Hence we concluded that there was limited utility for parametric approach and proceeded to employ a non parametric method. As a comparison, we also ran the regressions on institutional investors' data.

We start by describing what occurred in the US equity market and the institutional and individual investors' reaction to the market. This would serve as a background for our subsequent quantitative evaluation.

4.3.1 Description of behavior of individual and institutional investors

Figure 4.2 shows that in the first quarter of 2008, investors moved their assets largely out of equity mutual funds and as equity market (represented by S&P 500) stabilized over the next quarter, some capital found its way back into equities. During the sell off which occurred in the remainder of 2008, investors sold out of equity markets with 9 consecutive weeks of net cash outflow. When the equity markets fell again during the January and February of 2009, individual investors rushed to sell out of equity markets again. Once the market started its rally in March 2009, individual investors kept selling for the next 10 week, exactly at the time which would have been most profitable to buy equities. Individual investors for the most part did not participate in the major rally in the second part of 2009.

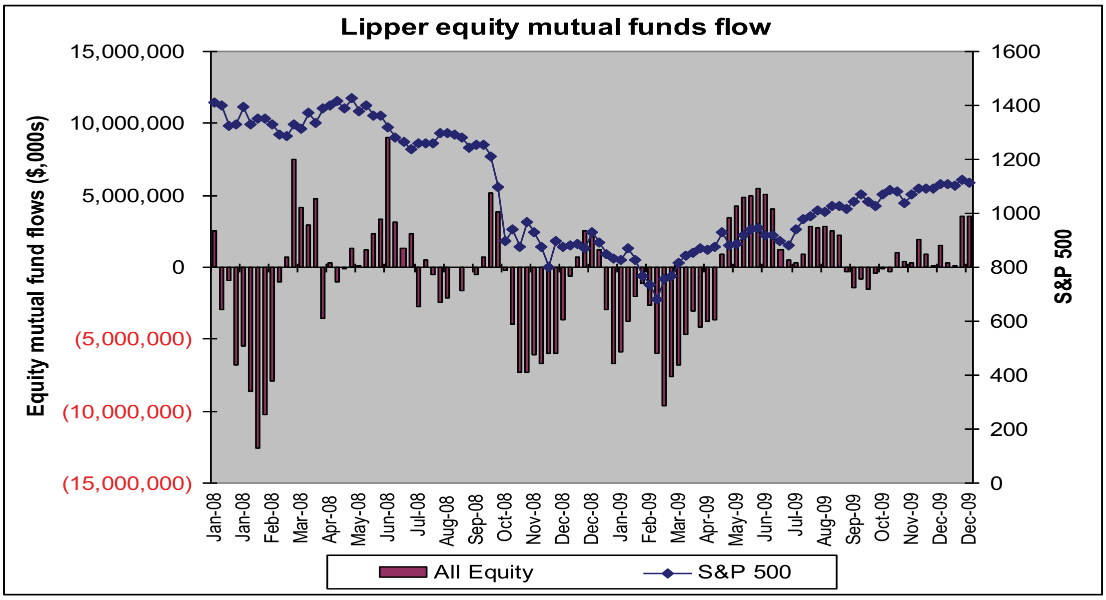


Figure 4.2. Monthly flow of money into US equity mutual funds shows that after some erratic flow in the early months of 2008, investors sold out of these funds in 4th quarter of 2008 and continued taking money out at the bottom of the market. When the market rallied starting June 2009, very little capital came back into the equity mutual funds.

Figure 4.3 which depicts the individual investors' market sentiment may help us partly explain the behavior of individual investors during 2008-2009.

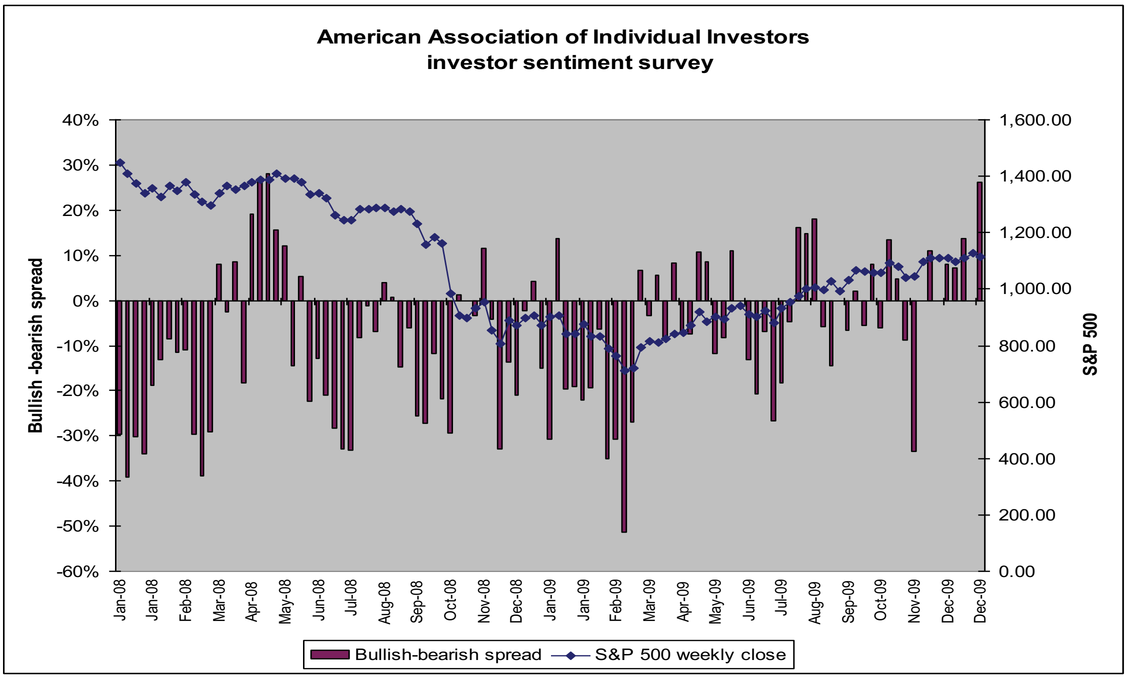


Figure 4.3. Investment sentiment as measured by the AAII sentiment survey hits its trough at a time coinciding with the bottom of the equity market. During the

subsequent rally, the sentiment changed from bullish to bearish from one week to the next but never gained the historical bullish levels for more than 3 weeks. The bearish sentiment during this period is often at historical highs compared with the rest of the history of this data set.

Having gained a broad understanding on how individuals invested during our study period, we now utilize our proposed ETF indicator for more detailed analysis. The growth in an ETF net asset holding may be due to flow of money into ETF or due to increase in the value of the ETF. In order to isolate the effect of the flow of money, we divided the monthly change in flow by the average value of the US equity market (represented by S&P 500) during that month. This normalized result is shown in Figure 4.4. We observe a sharp allocation of assets out of equity ETFs by individual investors during the first quarter of 2008. That was followed by a move back into equities as the equity markets rallied slightly. Hence individual investors first sold after the fall in the markets and then chased the market as it was going back up. Starting in September 2008, as housing market crisis was intensifying (Lehman Brothers investment bank bankruptcy filing and acquisition of largest US brokerage house Merrill Lynch were among the news in mid September), individual investors sold equities. This sell off continued in October, but stabilized in November 2008. Individuals then increased their small equity ETF holdings in January, demonstrating a reactive behavior. They reduced their positions slightly during a 10% drop in equity market in February. At the very bottom of the market, they sold their holdings sharply to a local minimum in March. Starting in March, equity market rallied and the year ended 70% higher than the March trough. By then, it seems like the individual investors got disenchanted by the equity market and the flow into small equity ETFs practically stayed at zero. This is in accordance with the flow of funds discussed earlier. Throughout this period, we notice that individual investors have been reactive to the market rather than being engaged proactively with the market.

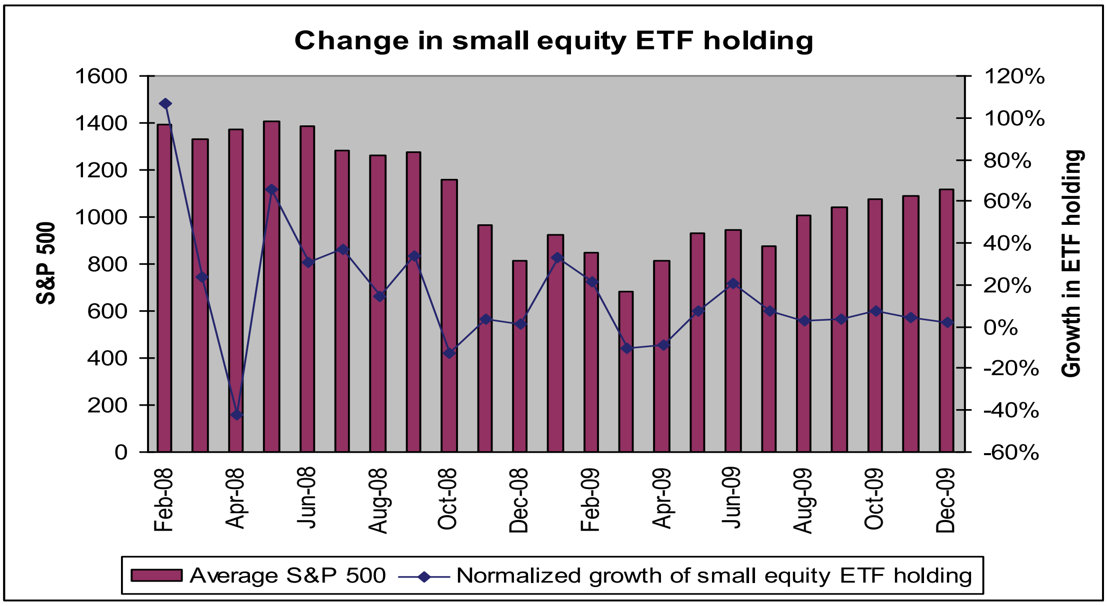


Figure 4.4. Normalized small ETF holding data is constructed by dividing the change in the assets in those ETFs by the mean of S&P 500 for each month.

Figure 4.5 compares the flow of capital into equity mutual funds (indirect ownership of equity) and flow of capital as measured by our proposed small ETF indicator (direct ownership of equity). Small ETF indicator seem to pick up the major trends just as the mutual fund flow indicator, yet allows us to access and analyze the data at a daily frequency and provides us with more data points for statistical analysis. As Lipper Thompson Reuters weekly mutual fund flow is the four week moving average of the flow of the preceding 4 weeks, we compared this flow with a four week moving average of our small ETF flow indicator.

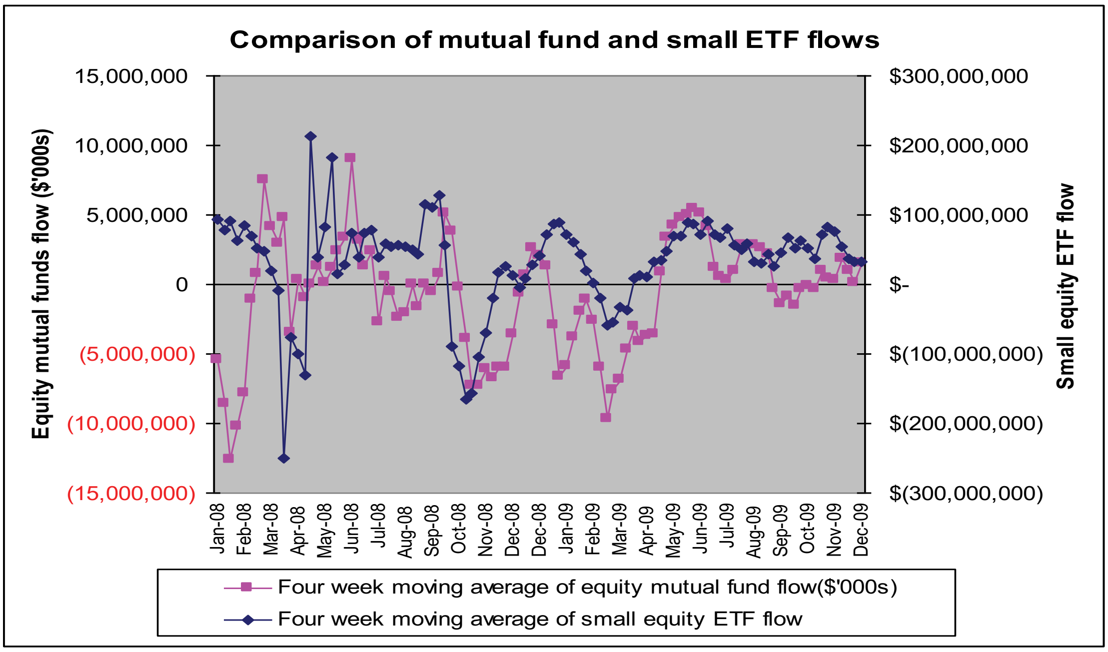


Figure 4.5. Mutual fund equity flow and our individual investor equity holding indicator are cointegrated. Small ETF investors are a smaller (and possibly a more active subset) of individual investors than mutual fund investors yet the graphs show high correlation at the extreme market moves such as those occurring on September and October 08 and June 09.

As both of these 2 data sets correspond to the individual investor, we expect the 2 data sets to be fundamentally related. We performed Augmented Dickey-Fuller test for cointegration on the difference of the 2 data series with the results shown in Table 4.3. We could reject the null hypothesis of a stochastic trend at 95% confidence, hence verifying the cointegration between the two data series.

Results of Augmented Dickey-Fuller test for cointegration between small equity ETF flow and equity mutual fund flow			
H	P value	Test Statistic	Critical value
1.00	0.001	-4.37	-1.94

Table 4.3. Small equity ETF daily flow (our proposed individual investor holding indicator) is cointegrated with the monthly equity mutual fund flow.

Returning to institutional investors, in Figure 4.6 we observe that in the second half of 2008, the net short interest across all S&P 500 stocks increased, reached its peak in July and stayed at that elevated level until October 2008. This is in contrast to individual investors who shifted their position in reaction to the market, as if they were looking back at recent performance as a guide for their decision making. The institutional investors holding the short position were proactive and increased their short positions prior to the sell off in equity market. At the onset of the market rally in March 2009, institutional investors again increased their short position proactively, but reduced their short position in July 2009 back to the levels seen prior to 2008. Thus these institutional investors demonstrated proactive positioning of their investments based on their forecast for the markets.

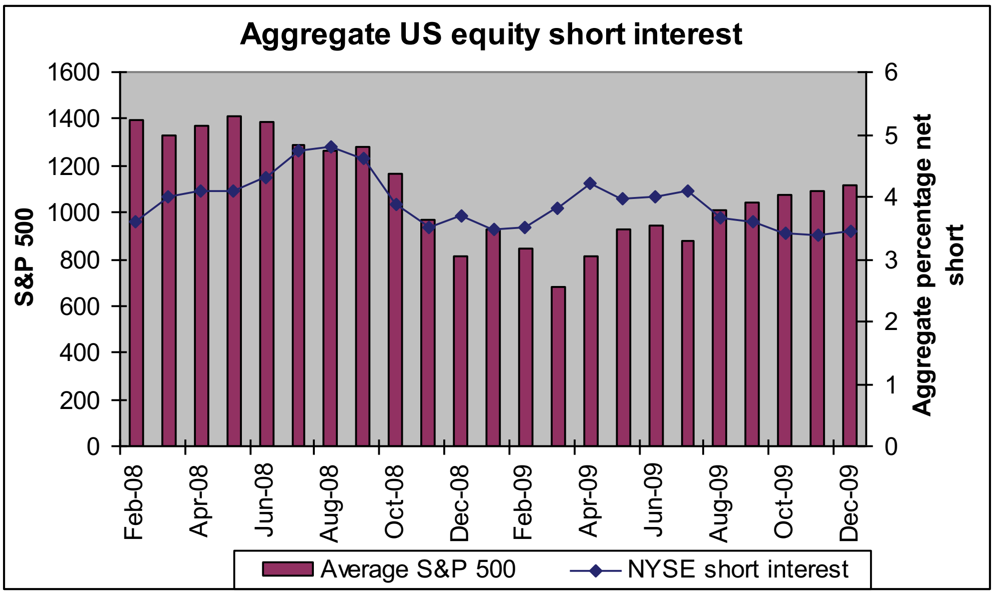


Figure 4.6. Institutional investors seem to have predicted the major collapse of 4th quarter 2008 as indicated by increase in short interest prior to the equity market collapse.

Figure 4.7 depicts the aggregate of all block trades in S&P 500 stocks in the form of capital flow [9]. We note that as market was declining during the latter part of 2008 and up until the onset of rally in March 2009, the flow of institutional money into S&P 500 in the form of block trades increased marginally. However as opposed to individual investors who for the most part did not return to equity markets and missed

9 S&P 500 capital flows are the sum of the capital flows of the constituent stocks. Capital flows are only calculated when the price of the security changes. The value of capital flow is set to zero at the start of the trading day. When a trade is performed, its price is compared to the price of the previous trade (the first trade of the day is compared to the previous day's close). If the prices differ, the capital associated with the trade (price times number of shares) is added to or subtracted from the capital flow. Additions (inflows, buys) are done on upticks; subtractions (outflows, sells) are done on downticks.

the 2009 rally(see Figure 4.4), institutional investors increased their positions radically and this increased pace continued (and contributed to) the historical rally.

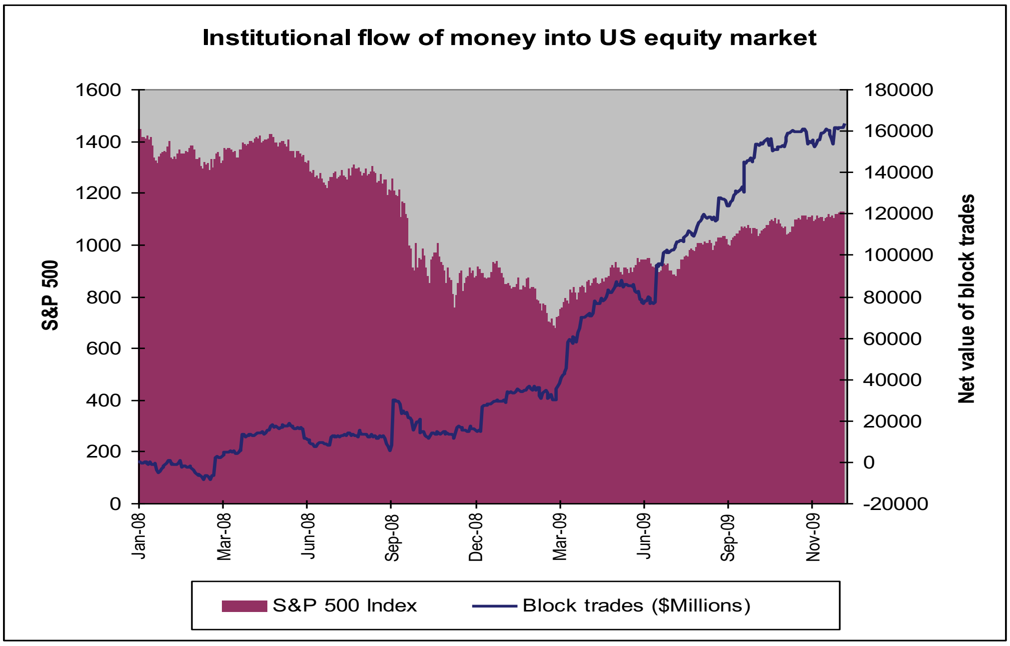


Figure 4.7. Institutional investors notably increased their positions as the market rallied in 2009 as indicated by increasing volume of block trades.

4.3.2 Parametric study of the institutional and individual investors' decision making

We now utilize our proposed indicator to analyze the behavior of individual investors. We use the changes in our proposed indicator as a proxy for the changes in all U.S. individual investors' equity holdings.

We adopted the wavelet volatility estimator proposed by in chapter 3 and applied it to the S&P 500 daily return time series. When wavelets are applied to time series data, the data are transformed into two data series in frequency space as follows: (1) an approximation or trend data series which captures the main underlying characteristic of the original time series and (2) a detail data series which represents the noise or local fluctuations of the original time series. Once the noise is removed, analysis is performed on the approximation series and results are then transformed back into time space. Instead of the approximation data series, we concentrated on the detail series as the latter captures the characteristics of the volatility in the time series data. We applied various classes of wavelets and selected the appropriate wavelet based on the following: The selected wavelet should reduce the number of data points as much as possible (parsimony of the data after wavelet application), while preserving the main characteristics of the data. Moreover, the synthesized wavelet function should reflect the dynamics of the original time series. One class of wavelets, Daubechies wavelets, meets the above criteria better than all other wavelet classes. We applied the fifth Daubechies wavelet at first level to the S&P 500 return series.[10] The figure below shows the wavelet volatility estimation of the S&P 500 index.

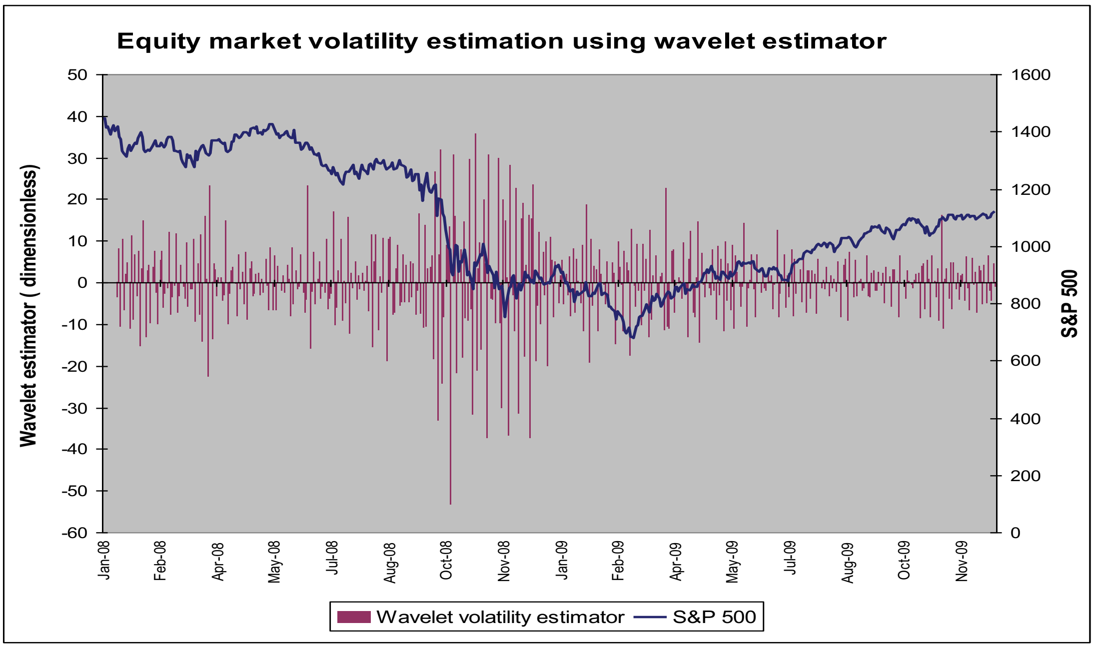


Figure 4.8. Vertical lines are graphical representation of volatility, and the longer the lines, the more volatile the day.

We define a volatile day as one where the volatility of that day is more than one standard deviation away from the mean volatility in 2008 and 2009. To test the hypothesis that the sequence of volatile days is randomly distributed, we performed a runs test (also known as Wald Wolfowitz test). We rejected the random distribution of the volatile days with 95% confidence. This result is in accordance with the tendency of volatile periods to follow other volatile periods, also known as volatility clustering. There is a high concentration of block trades in months of January in our data, which is partly due to asset managers positioning their portfolio for the new year and offsetting some of the trades that they have done in the previous year due to tax and other reasons (this latter phenomenon is known in financial industry as “year end window dressing”). This phenomenon is a seasonality in equity market

10 As discussed in the previous chapter, the Daubechies class of wavelets comprise Daubechies wavelets with different scales. Increasing the scale increases the resolution, hence providing a filter which detects finer (more minute) details.

and we reduced this seasonality effect in our regressions by removing 15 largest block trades of January from our data series. We replaced the removed data points by an interpolation of the block trade amounts of preceding and succeeding days. We ran multiple linear regressions on daily changes of S&P 500, individual investor indicator daily changes, and daily change in volatility. The regression results were poor.

Next we ran robust regressions with bisquare weights to estimate the following regression coefficients: [11]

Individual Investors:

$$\Delta ETF = 0.87 + 7.0\Delta SPX - 1.1WL$$

Adj. R^2 = 0.96; RMSE = 1.94

t value of constant term =9.82	p value of t= 0.00
t value of ΔSPX term =2.12	p value of t=0.035
t value of WL term= -2.44	p value of t = 0.015

Institutional Investors:

$$\Delta Block = 0.002 - 0.23\Delta SPX - 0.03WL$$

Adj. R^2 = 0.93; RMSE = 0.96

t value of constant term = 0.73	p value of t = 0.46
t value of ΔSPX term =-2.67	p value of t=0.01
t value of WL term= -1.64	p value of t = 0.10

where:

ΔETF = daily return of small equity ETF flow (i.e., individual investor flow indicator);

11 Bisquare weights method minimizes the weighted sum of squares, such that the weight given to each data point depends on how far the point is from the fitted line. Points which are closest to the fitted line get the highest weights, and weights become smaller the farther the points are from the fitted line. Robust regression estimation is done using iteratively reweighted least square error method.

$\Delta Block$ = daily return of S&P 500 block trades (i.e., institutional investor's flow indicator);

ΔSPX = daily return of S&P 500 with one day lag; and

WL = 10-day moving average of wavelet volatility estimation of S&P 500.

Although in other regressions we found that the daily wavelet volatility was a poor factor in explaining the behavior of individual investors, a 10-day moving average of volatility is a statistically significant factor. Hence while a volatile day may not be an important factor for individual investors, the cumulative effect of volatility over a few days as indeed been important to them. The change in individual investors' holdings was also notably influenced by changes in the equity market return. This may be viewed as individuals reacting to the market (or "chasing the market" as it is known in the financial industry) rather than adjusting their investments based on their forecast of future market return.

Moreover, we partitioned the volatility and trades into separate groups: if on any day volatility was above one standard deviation from the mean volatility of the two years, we categorize that as a high volatility day. If the equity market rallied on that day, we note it as upside volatility and if the equity market fell on that day, it is noted as a downside volatile day. In the same way, if on any particular day there was a change in the ETF indicator flow the magnitude of which was above one standard deviation of the mean flow of the two years, we treat it as a large trade day. If on that day the equity market was up, we categorize that day as a large buy day and if equity market was down, it would be categorized as a large sell day. We repeated the above procedure with the aggregate of S&P500 block trades (institutional investors' indicator). Because we are now concentrating on a subcategory of data with high volatility and high trading activity, the number of data points in our data set is significantly reduced, and the reduction in number of data points makes it impractical to set up robust statistical tests on the datasets. Nonetheless comparison of the results are revealing (see Table below):

Upside volatility clusters	53
Downside volatility clusters	56
Large block buys	27
Large block sells	27
Large ETF buys	16
Large ETF sells	20

Table 4.4. Comparison of individual and institutional investors' large trades. Individual investors were more likely to sell following a few volatile days than institutional investors.

Out of 20 sizable ETF sell offs on down market days, 17 happened within one to two weeks of occurrence of a volatility cluster. Hence, a few days of large sell off in the equity market seem to increase the likelihood of individual investors selling. More specifically, downside volatility seemed to have increased the probability of sells, while upside volatility did not increase the probability of buys. Though it is possible that this is just a spurious effect, we find it to be suggestive for further research once more data becomes available.

4.3.3 Non parametric analysis of individual investor behavior

The years 2008 and 2009 started with a period when news of a potential financial crisis were beginning to appear and this was followed by the onset of the crisis (for a timeline of events of the financial crisis of 2008-2009, see Appendix 2). That period was followed by a period of sharp decline in the markets during the crisis, and finally a period of recovery during the latter part of 2009. Figure 4.9 below shows the daily closing price of S&P 500 during 2008-2009 with the 3 periods mentioned above corresponding to approximate periods of January 2008 to August 2008, August 2008 to March 2009 and the recovery period of March 2009 to end of 2009.

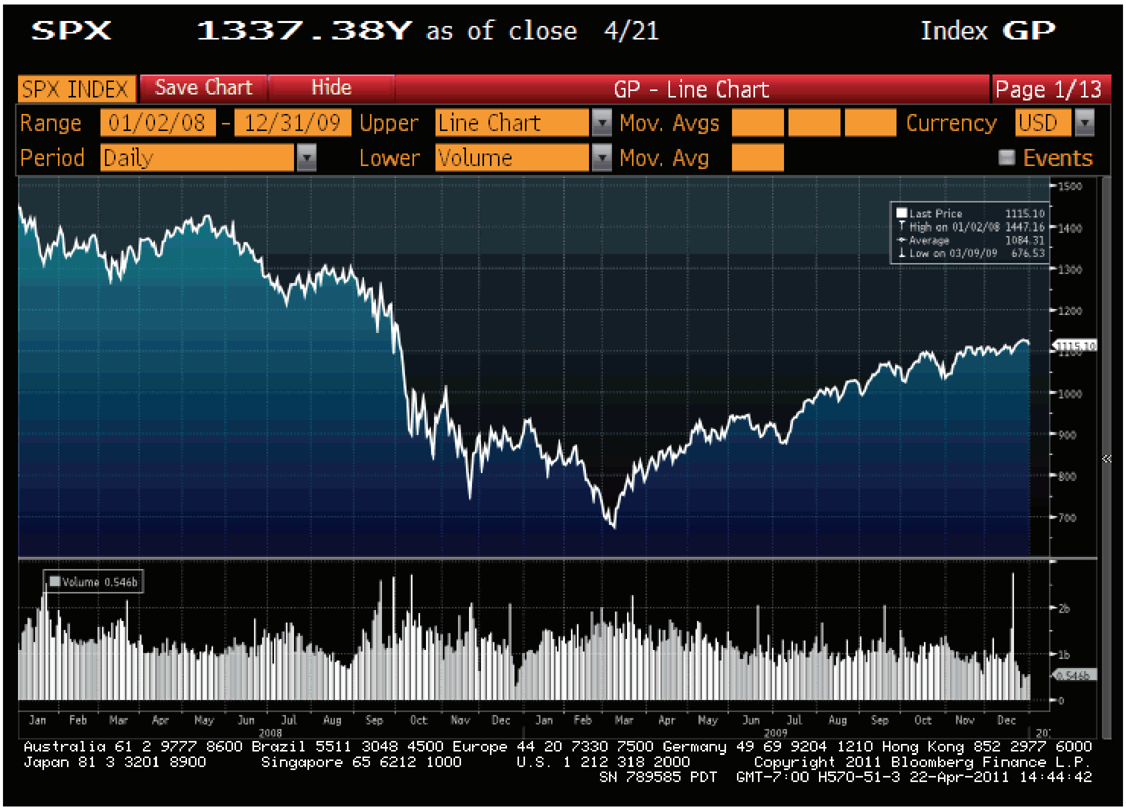


Figure 4.9. The top part shows the daily close of S&P 500 index, and lower part the total volume of share in the index traded on each day.

We applied the change point methods to the individual investor data to determine if there were any shifts in the behavior of the investors, similar to the shifts in the equity market described above. Analyzing change points in data series have seen wide applications in various disciplines. In general, the problem could be thought as determining 2 or more segments in a particular data series such that the means and variances of those segments are different, in other words we are seeking to find out at which points do the mean or variance of the data change distinctively. Brodsky and Darkhovsky(2010) describe the mathematical foundations of change point[12] problems and provide the background for determining the change point in mean of a series.

Chen and Gupta(1997) define testing the variance change points as follows: Suppose we have a series of independent random variables each with the parameters (μ_1, σ_1), (μ_2, σ_2), …

$$H_0 : \sigma_1^2 = \sigma_2^2 = \sigma_3^2 = \ldots = \sigma_n^2$$

[12] In some literature, change points are referred to as break points. In this dissertation, we use the two terms interchangeably.

Where σ_n is unknown

Versus

$H_1 : \sigma_1^2 = \sigma_2^2 = ... = \sigma_n^2 \neq \sigma_k^2 \neq \sigma_{k+1}^2 \neq ...$

Where

The number of change points k and the position of the change points are unknown.

They propose a method which has been widely used by other researchers as well, one which is based on Schwarz information criterion (SIC) (see Schwarz (1978)).

SIC is defined as:

$-2\log L(\theta) + p\log n$

Where:

$L(\theta)$ is the maximum likelihood function,

p is the number of free parameters in the model, and

n is the sample size.

The problem is then reduced to complying with the minimum information criterion.

Chen and Gupta (1997) suggest not rejecting H_0 if:

$SIC(n) \leq \min_k SIC(k)$ and

rejecting H_0 if:

$SIC(n) > SIC(k)$

for some k and estimating the position of change point j such that:

$SIC(k_j) = \min_{1 \leq k < n} SIC(k)$

Where $SIC(n)$ is the SIC under null hypothesis and

$SIC(k)$ is the SIC under H_1 for $k = 1,...,n-1$.

In our analysis, we use the methodology described by Lavielle (1999) which is based on the Schwarz Information Criterion described above. Lavielle (1999) methodology has the advantage that it is applicable to both normally and non-normally distributed data and results are obtained by a non parametric method. Despite being convenient to use, the method proposed by Lavielle (1999) has the potential short coming that it is only applicable a posteriori, i.e. when the data set is complete at the time of analysis. If one were to use change points to construct a trading model in financial markets for instance, one would need to detect the change points as the new data is being generated and therefore this method will not be useful. However in our study, we are merely analyzing the ex post financial data and hence we find this method suitable for our analysis. Lavielle (1999) defines a penalizing function such that increasing the number of segments (i.e. increasing the number of change points) will penalize the model. This is done in order to minimize the number of change points using which the dynamics of the model could be defined. We think this approach is particularly suitable since during our period of study, markets underwent significant gyrations and rapid movements. If one was to increase the number of change points, one would be able to come up with many segments during which the market dynamics changed, however we wish to concentrate on the major changes in the dynamics of market and investor behavior and not to be carried away by local gyrations and discontinuities. We therefore endeavor to find the minimum number of change points (i.e. minimum number of quantitative shifts in the data) which would satisfactorily explain the behavior of the investors.

In order to examine the existence of different states of investor behavior, we applied the wavelet volatility estimation method and generated the volatility data set. Specifically we applied Daubechies first wavelet at first level to the individual investor holdings indicator, discarded the approximation and kept the detail signal as the volatility in the investor holding indicator. Then we applied Lavielle (1999) method to determine if there have been distinct points were the variance in the above volatility series changed. The result is shown in the figure below, where Y axis shows the comparative estimation of variance:

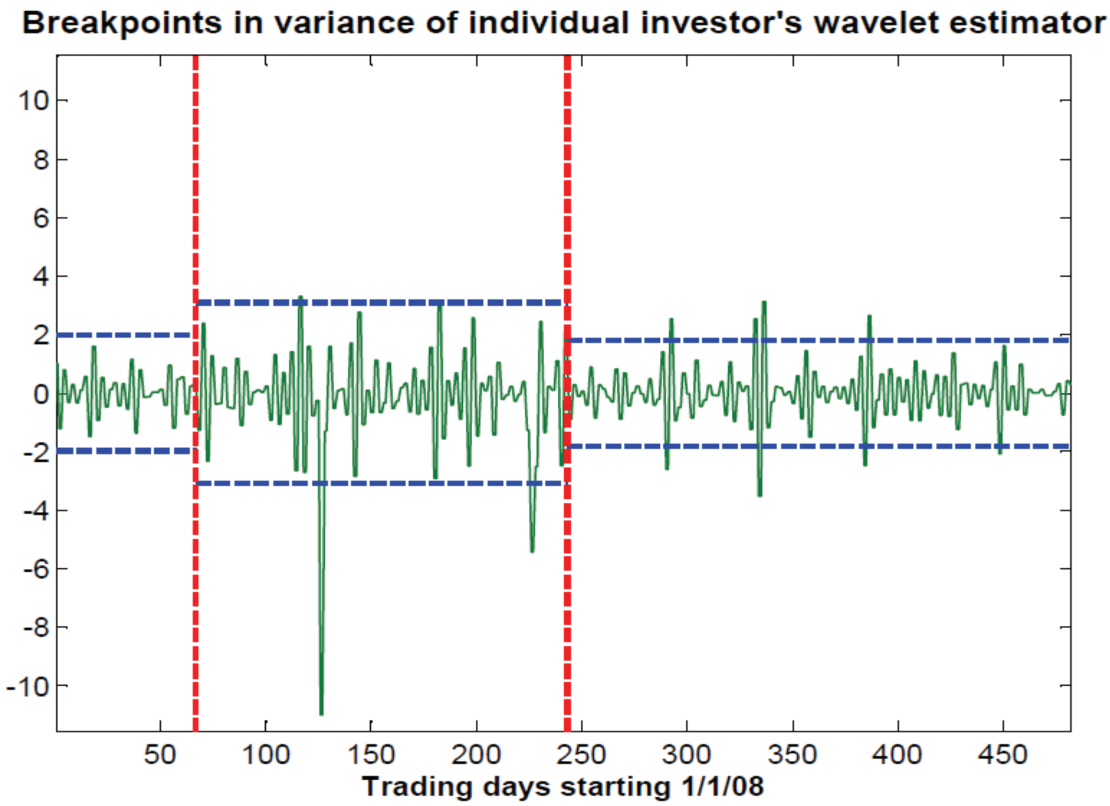


Figure 4.10. Change points generated using penalizing function based on Schwarz Information Criterion. Each red line corresponds to one change point.

A seen in the figure above, our analysis signifies 3 distinct phases for the volatility of the individual investors' holding indicator. Variance of the volatility signal stayed constant in the first phase up to 67th data point (i.e. first red dashed vertical line), increased in the second phase up to data point 243 (i.e. second vertical dashed line) and then decreased for the remainder of the data series in phase 3.

In the figure below, we have shown the Russell 3000 index performance during 2008-2009 period. The 2 red square markers on the graph correspond to the days when change points in the variance of individual investor volatility series occurred (i.e. the red squares in Figure 4.11 correspond to the red dotted lines in Figure 4.10).

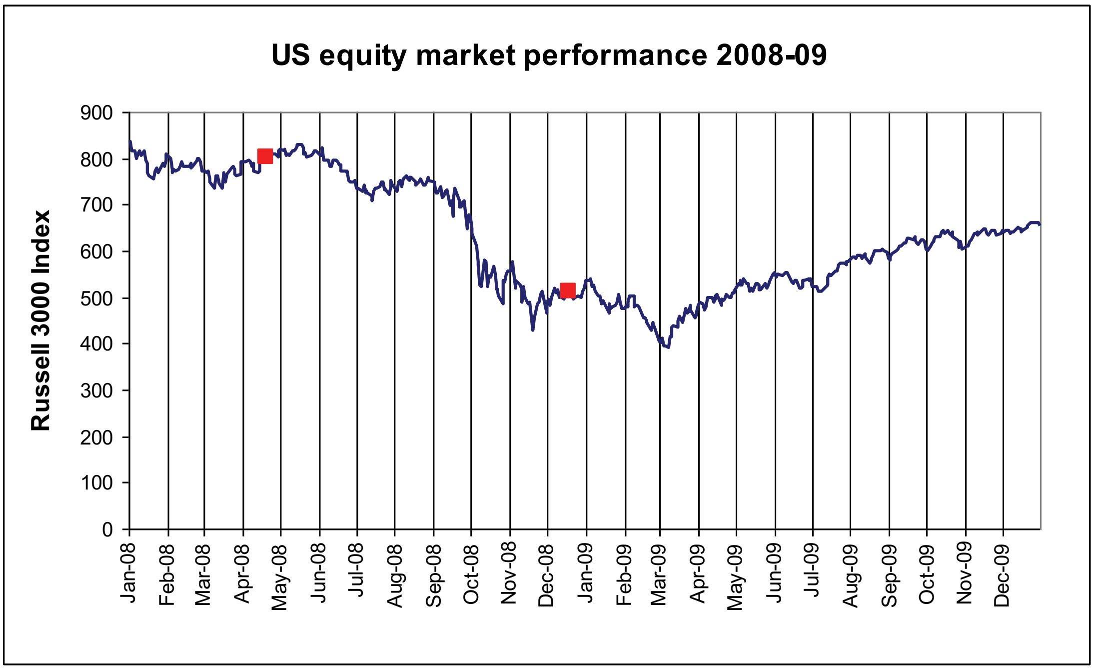


Figure 4.11. Red dots correspond to the times when according to the change point non parametric analysis the variance of the capital flow of individual investors changed significantly.

Thus the investor behavior derived from our change point analysis exhibits an intuitive relation to the equity market. In the first phase, volatility of the changes in individuals' positions is low. This phase corresponds to the relatively steady equity market early in 2008. As the news of financial crisis start to enter the markets, individual investors' behavior becomes more erratic, the change in their holdings (as demonstrated by the volatility of their holdings) exhibits a higher variance. This high variance period approximately corresponds to the sharpest decline in the market and ends in December 2008. Given the small appreciation in equity market in November and December 2008, investors may have thought that the worst of the crisis was behind them and hence the erratic and rapid changing in their holdings (leading to the higher variance in phase 2) subsided. In the third phase, the variance in the volatility of the investors' holding changes is less than phase 2. This last phase for the most part includes the market's steady appreciation starting in March 2009 until the end of 2009. Hence although in determining the change points, we did not refer to the market conditions at all and let the mathematical algorithm select the change points, the results are intuitive because they roughly correspond to the underlying changes in the equity market.

Hence the change point analysis applied to the wavelet volatility estimator successfully captures the major changes in the volatility of investors' holdings, and furthermore, these changes roughly occur at the same time as the major shifts in the equity market. Why the change points in investor behavior does not exactly match the changes in the equity market is of course an interesting question and one which deserves more future research, however here we showed the validity of applying the change point method, reached intuitive results (i.e. investors behavior was influenced by the market dynamics) and showed that our proposed indicator indeed offers a tool for investigating the behavior of individuals even during the most volatile times in financial market history.

The overall poor results for the regressions earlier in the chapter may be indicative of the fact that the driving factors for investor behavior change over time. However now that we determined the main phases of individual investors behavior, we proceed to determine the main drivers of their behavior in each phase.

We selected a number of factors which may have influenced the behavior of individual investors and determined the importance of those factors in individuals' decision making. To select the factors, we note that we were dealing with financial crises. There is large body of research which points to the fact that macroeconomic drivers (so called fundamental drivers) affect the market over a long period of time (see for instance Hasbrouck (1998)). In a period of financial crises and rapid and radical market changes, it follows that investors would be more interested in news and market dynamics than longer term macroeconomic factors. Liquidity, solvency and viability of global financial and economic system were at stake at times during our period of study, and hence economic releases would gain much less attention.
As such, we selected our driving factors from those which reflect market dynamics rather than longer term fundamental economic drivers of the equity markets. Moreover because we are dealing with individual investors, we limited the factors to those which are commonly accessible by individuals. Specific market data which are typically used by professionals seem unlikely to influence the behavior of individuals as much, simply because individuals are not aware of them or do not have the expertise to use those data. Lastly given the market crisis environment, headline news attracted most attention rather than in depth analysis of the details of the news.

The factors that we selected in the numerical order are therefore as follows:

Number	Factor	Number	Factor
1	VIX	11	1 day return of Russell 3000 index
2	1 day return of VIX	12	5 day return of Russell 3000 index
3	5 day return of VIX	13	1 day percentage change in traded volume of Russell 3000 index
4	S&P 500	14	Russell 2000 index
5	S&P 500 daily range	15	1 day return of Russell 2000 index
6	1 day return of S&P 500	16	5 day return of Russell 2000 index
7	5 day return of S&P 500	17	Dow Jones industrial average
8	5 day moving average of traded volume in S&P 500	18	1 day return of Dow Jones industrial average
9	S&P 500 daily range	19	5 day return of Dow Jones industrial average
10	Russell 3000 index		

Table 4.5.

The first 3 factors are VIX, daily and weekly change of VIX.[13] VIX is commonly used by professionals and individuals as a measure of market estimation of short term risk. It is commonly quoted and discussed in the media and quoted commonly as “fear index”. As such it stands to reason that individual investors may be paying attention to it, particularly at times of crisis. The next 5 factors have to do with S&P 500 and its daily and weekly return, in addition to daily traded volume. S&P 500 represents the largest share of US equity market and is widely monitored by individuals and institutions. We also included daily range (i.e. highest price of the day minus the lowest price of the day) as a measure of intraday volatility. Range has been commonly used as measure of volatility, as we showed in Chapter 3. Items number 5 and number 9 are identical, and were both included in the analysis to test the validity and robustness of the non parametric tree bagger algorithm. We included them and expected to see identical results for the importance of both items in our non parametric analysis.

[13] VIX measures 30 day expected volatility of S&P 500. It is based on the implied volatility calculated from short dated options.

The next few factors relate to the wide market as represented by Russell 3000 index (as noted before in this chapter, this index accounts for 98% of all US stocks). We also included factors relating to small capitalization index, namely Russell 2000. This index together with Russell 3000 are not as commonly followed by individuals and not as commonly quoted in the media as S&P 500 or Dow Jones industrial average. However small capitalization stocks typically exhibit higher volatility than large capitalization as seen in the table below:

Garman Klass volatility (1/1/2000 to 4/20/2011)		
	Weekly	Daily
S&P 500	16.52	13.97
Russell 2000	20.48	16.9

Table 4.6.

Alternatively it can be said that though there is a high correlation between Russell 2000 and S&P 500, a weekly regression on the returns show a beta =1.14 indicating that a one unit change in S&P 500 corresponds to 1.14 change in Russell 2000 (see figure below). For these reasons, we included Russell 2000 in our analysis as a representative of the more volatile sector of the general equity market.

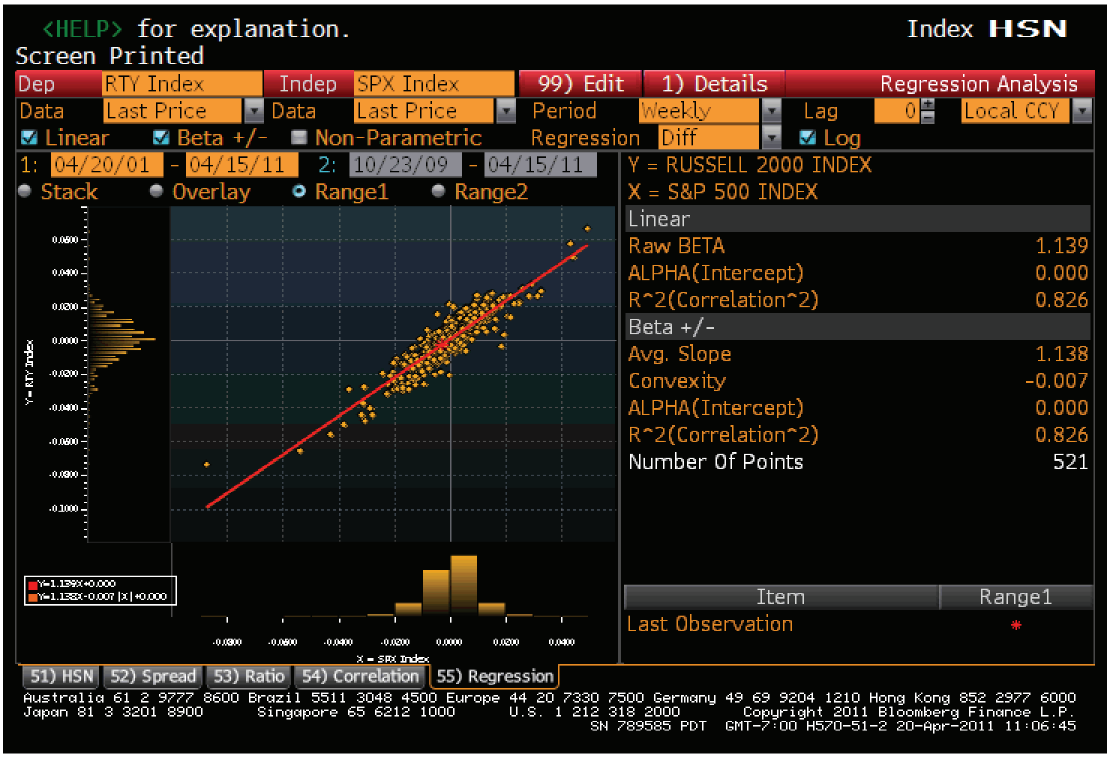


Figure 4.12. Linear regression results of weekly returns of Russell 2000 index and S&P 500 index.

Finally we included Dow Jones industrial average index in our factors. Though this index only comprise 30 stocks and thus has a limited effect on the performance of the larger equity market, it is quoted in the media very widely and hence individual investors pay attention to it.

We used the decision tree non parametric approach for our analysis of driving factors for each phase. We employed bootstrap aggregation (also known as bagging) decision tree method suggested by Breiman (1996). In this method, a number of random drawings (with substitution) are made from the data and regressions are run on those samples. The above process is repeated thousands of times, with each run generating a tree branch. As branches are increased, the results of the regression predictions are compared with actual data to calculate the error terms, and the errors are minimized in the subsequent branches. This method is commonly used in estimating the comparative importance of the factors in nonlinear estimations. In our analysis, the results converged and became stable after a few hundred trials and remained stable afterwards.[14]

The results of the non parametric analysis are shown in the following graphs:

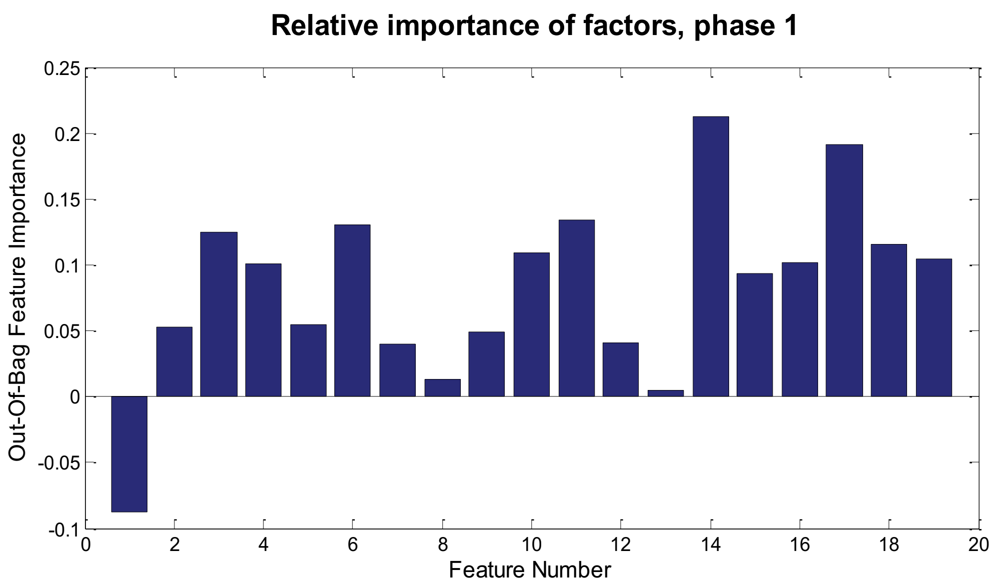


Figure 4.13.

[14] A random sampling of data is used for each branch of the tree and relative importance of factors is measured over the entire ensemble and divided by the standard deviation of the ensemble to come up with a number used for importance ranking.

In phase 1, the 2 most important drivers of the individual investors daily return has been the Russell 2000 index and Dow Jones Industrial average. This was the phase when equity market was comparatively steady and individuals seem to be affected by the levels of the equity indices.

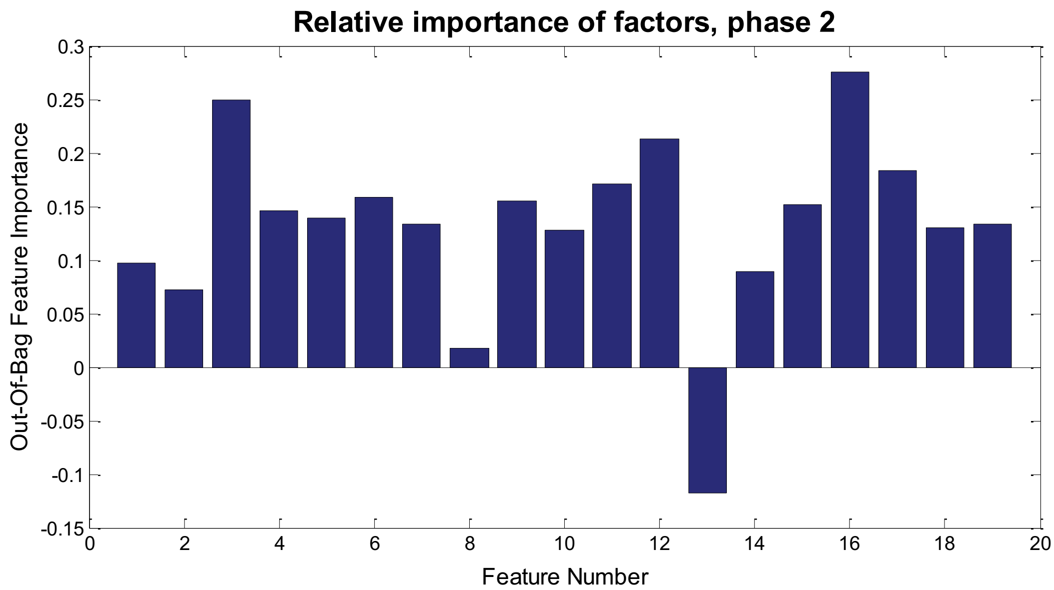


Figure 4.14.

In phase 2, the 3 distinctively important drivers have been the 5 day change in VIX, 5 day change in Russell 3000 index and 5 day change in Russell 2000 index. Five day change corresponds to a weekly change in the underlying asset, and weekly performance is one which is commonly quoted and followed by investors. During the most volatile phase of our study corresponding to the height of financial crisis, weekly returns of wide equity market (i.e. Russell 3000), the more volatile sector of the equity market (namely Russell 2000) and weekly change in volatility(namely VIX) were the most important factors influencing the change in individual investors' indicator. As seen from the figure above, from the 3 most important factors, Russell 2000 weekly return and VIX weekly return seem to be more important than the wide market Russell 3000 weekly return. This is intuitive, as during this particular volatile phase of financial crisis, measures of risk such as VIX should play a particular role in investors' minds. As with Russell 2000, we showed earlier that it is the more volatile sector of the US equity market, which makes it a likely candidate as a driving factor during the more volatile phases.

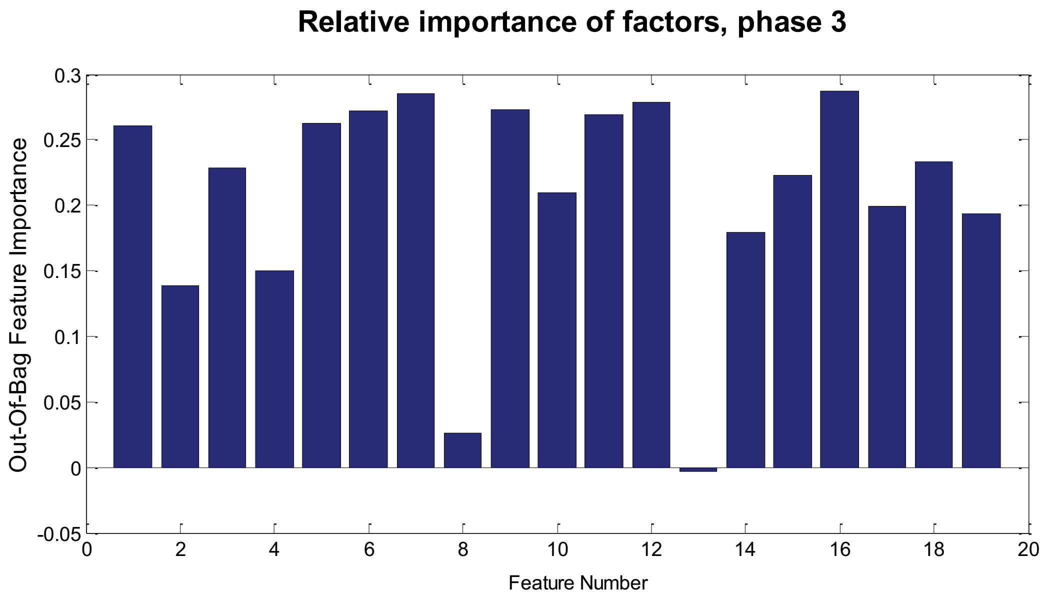


Figure 4.15.

In phase 3, the number of important factors increase and of the 18 factors considered, 7 factors become the most important and those are the VIX index, 1 day and 5 day change in S&P 500 as well as daily range of S&P 500, 1 day and 5 day change in Russell 3000 index and 5 day change in Russell 2000 index. What is more interesting is that in this phase, there is less comparative difference between the most important drivers compared and the rest. In other words, in the comparatively calmer and steady phase 3, investors' behavior was not distinctively influenced by any of the factors that we analyzed.

4.4 Testing the disposition effect in individual investor community

We now proceed to test the existence of disposition effect among individual investors during our period of study. Disposition effect is based on the fact that individual investors keep their loss making positions for too long (i.e. they are reluctant to realize their losses, hence hold on to their positions as market keeps declining) and sell their winning positions too early (i.e. when doubtful about the future performance of their investments, they will sell stocks that have made them money rather than holding the winning stocks and selling the loss making shares). The researchers dealing with disposition effect typically have considered individuals' portfolios and followed the pattern of individual buys and sells of the shares to verify the disposition effect (see for instance Dhar Zhu (2006)). While reviewing various investor emotions and its effects on decision making, Ackert et al.(2003) noted that disposition effect arises as part of regret aversion tendency. Investors who demonstrate disposition effect are avoiding the regret which may come from selling their long positions at a loss. On the other hand they sell their winning positions early in order to avoid regret that they may feel if the market were to decline causing them to miss an opportunity to realize a profit. Ackert and Deaves(2010) explain the regret aspect of disposition effect in more detail. Regret is a negative feeling which is avoided as much as possible by investors, while pride could be thought of as its positive equivalent. However the effects of pride and regret are asymmetrical and studies have shown that people generally are more influenced by strong emotions such as regret than they are motivated by the possibility of positive emotions due to gains (see Kahneman (1979) for one of the first analysis of this phenomenon). Shefrin and Statman(1985) note that fear of experiencing regret is what derives investors to avoid realizing their losses (hence causing them to keep their loss making positions and incur further losses), and the feeling of pride and elation is what contributes to them realizing a profit (hence selling their winners too early and thus depriving themselves from further gains). Finally Summers and Duxbury (2007) note that how investors came to own the shares is also a contributing factor to their decision of selling the shares, such that the more individuals direct involvement in making the decision to acquire the share, the more they demonstrate disposition effect. For instance, those who inherit some equity shares feel less regret and therefore exhibit disposition effect to a lesser degree than those who purchased the shares themselves, because the latter group feels more “responsible” for the decision of owning the shares and hence feel more regret if the decisions ended in a loss.

Our approach is different from the tradition approach to disposition effect, since instead of considering individual buys and sells, we analyze the performance of the individual investors aggregate holdings (as indicated by our individual investor position indicator). In other words, as opposed to the literature which use the data on a group of individuals, we used our individual investor’ holdings indicator to analyze the entire individual investor community. We consider the timing of buys and sells in the aggregate positions of the individual investor community as a group rather than analyzing each investor’s portfolio individually. This approach can only work if one has reliable data of holdings for the whole individual investor community and was not possible until now due to lack of such holdings data. However we now can perform such analysis using our individual investors holding indicator. Kaustia (2010) provides the theoretical case for why it is possible to exhibit disposition effect across a group of investors rather than only individuals within that group. Our approach of testing the disposition effect on individual investor community is thus in accordance with Kaustia (2010).

We calculated the net asset value of the portfolio shares on each day and normalized it by dividing net asset value of each ETF by the closing price of the ETF for that day. This resulted in the net capital flow in and out of each ETF and in aggregate provided us with net capital flow in and out of the index. To evaluate the performance of the individual investor community, we compared the performance of the portfolio of small ETFs (i.e. individual investors' market portfolio) with that of Russell 3000 (as noted before, Russell 3000 accounts for 98% of all US equity market capitalization).

PERFORMANCE SUMMARY				
	Annualized Return	Annualized Std Deviation	Annualized Return-Risk Ratio	Cumulative Return
Total Period				
BMK	-13.3866%	36.0086%	-0.3718	-24.025%
Rule	-17.8848%	34.3817%	-0.5202	-31.3898%
Excess	-4.4982%	49.7656%	-0.0904	-7.3648%

Table 4.7.

In the table above, we have used the following notations:
BMK refers to benchmark of our study, namely Russell 3000 index.
Rule refers to the individual investors' market portfolio.
Excess refers to the excess performance of the benchmark relative to Russell 3000 index (i.e. the difference between benchmark and Russell 3000 index)
Annualized return to risk ratio is what is commonly known as information ratio.

PERFORMANCE DETAILS									
	Average Return when Positive	Average return when Negative	Worst "Single" Negative Performance	Worst "Single" Negative Performance occurred on	Longest Underperformance	Longest Underperformance occurred on	Recovery Period	Longest winning streak	Longest losing streak
Total Period									
BMK	1.3825%	-1.6561%	-9.281%	12/01/2008	498	01/03/2008-11/30/2009	190	6	13
Rule	0.705%	-0.3936%	-26.0903%	07/08/2008	478	01/31/2008-11/30/2009	330	4	13
Excess	1.7956%	-1.7896%	-27.9501%	07/08/2008	260	12/02/2008-11/30/2009	141	8	8

Table 4.8.

In the table above, longest winning streak refers to the longest period of consecutive profitable trades, for instance 6 consecutive profitable trades would generate a winning streak of 6 (similar definition for losing streak).

RISK CHARACTERISTICS						
	Max. Drawdown	Max. Drawdown occurred on	Correlation with BMK	Ratio of Good/ Bad Risk	Down side Risk - 1%	Down side Risk - 5%
Total Period						
BMK	-53.4611%	03/09/2009	1	0.9516	27.4229%	24.5692%
Rule	-41.3228%	08/25/2008	0.0009	1.5076	104.2654%	151.3022%
Excess	-36.6667%	08/22/2008	-0.723	0.9437	50.6001%	99.7409%

Table 4.9.

In the table above, good risk is the standard deviation of positive returns (similar definition for bad risk). In a successful portfolio, one would seek higher ratio of good/bad risk, because volatility to the upside (volatility in return of trades which are profitable) has a different connotation for the portfolios assets and performance compared with volatility of returns of the losing trades.

	Confidence in Skill	Success Ratio
Total Period		
Excess	45.6573%	47.5104%
Rule : Disposition test		

Table 4.10.

In the table above, Confidence in Skill is a measure which allows comparison of various portfolio performances given the noise in the returns and duration of the track record of the portfolio (see Muralidhar (2001)). Success ratio is the number of profit making (winning) trades divided by loss making (losing) trades.

We used multiple performance measures as above rather than simply comparing the cumulative return of individuals with that of the benchmark. We believe that this provides us with a more comprehensive understanding of investors' behavior. To test the disposition effect, we noted the buys in the market portfolio as days when there was flow of money into the portfolio, and sells when there was net capital outflow. We ignored the small daily trades as noise in our study and instead concentrated on large buys and sells. We define a large buy or sell as one whose value was above one standard deviation of the mean trade for the study period. We ignored the bid/ask spread in our analysis meaning that we assumed no spread when individuals traded. This will give us a more conservative estimate on the performance of individuals, because the performance of individual investors market portfolio can only get worse if we included the bid ask spread. But if we can prove our point with assumption of no spread, our case would be even stronger if we were to include spreads.

We calculated the above performance measures for a series of portfolios with the same large buys and sells, but now we moved the date of the sells in the following manner: Disposition effect states that individuals sell their winning positions too early. Therefore in a rising market, we delayed (lagged) the large sell trades by a few days to test whether the performance improves. We lagged the trades by 2, 5, 10 and 15 days and documented the results. Disposition effect also states that in a declining market, individuals sell their holdings too late. To test this part, in a declining market, we moved the large sell trades forward (lead the trades) to test whether this time lead improves the performance. Similar to above, we lead the trades by 2, 5, 10 and 15 days and documented the results.

Tables below summarize the results:

Performance of individual investors' market portfolio in 2008 is below:

PERFORMANCE SUMMARY				
	Annualized Return	Annualized Std Deviation	Annualized Return-Risk Ratio	Cumulative Return
Total Period				
BMK	-37.7014%	41.0679%	-0.918	-37.8143%
Rule	-8.1391%	43.3912%	-0.1876	-8.1689%
Excess	29.5624%	59.7568%	0.4947	29.6454%

PERFORMANCE DETAILS									
	Average Return when Positive	Average return when Negative	Worst "Single" Negative Performance	Worst "Single" Negative Performance occurred on	Longest Underperformance	Longest Underperformance occurred on	Recovery Period	Longest winning streak	Longest losing streak
Total Period									
BMK	1.5151%	-1.8645%	-9.281%	12/01/2008	261	01/03/2008-01/01/2009	30	6	13
Rule	1.0294%	-0.4551%	-26.0903%	07/08/2008	241	01/31/2008-01/01/2009	93	4	13
Excess	2.1151%	-2.0311%	-27.9501%	07/08/2008	152	03/11/2008-10/08/2008	33	8	6

	RISK CHARACTERISTICS			
	Max. Drawdown	Max. Drawdown occurred on	Correlation with BMK	Ratio of Good/ Bad Risk
Total Period				
BMK	-48.8957%	11/20/2008	1	*0.9809*
Rule	-41.3228%	08/25/2008	-0.0004	1.7086
Excess	-36.6667%	08/22/2008	-0.6876	*0.9413*

	Confidence in Skill	Success Ratio
Total Period		
Excess	*68.4105%*	50.7937%

Table 4.11.

Performance of individual investors' market portfolio in 2008 with 2 day lag and lead is below:

PERFORMANCE SUMMARY				
	Annualized Return	Annualized Std Deviation	Annualized Return-Risk Ratio	Cumulative Return
Total Period				
BMK	-37.7014%	41.0679%	-0.918	-37.8143%
Rule	-15.7476%	16.1%	-0.9781	-15.8029%
Excess	21.9538%	37.8175%	0.5805	22.0114%

	RISK CHARACTERISTICS			
	Max. Drawdown	Max. Drawdown occurred on	Correlation with BMK	Ratio of Good/ Bad Risk
Total Period				
BMK	-48.8957%	11/20/2008	1	*0.9809*
Rule	-19.4819%	09/17/2008	0.3899	*0.6006*
Excess	-9.8639%	05/19/2008	-0.92	*0.8676*

PERFORMANCE DETAILS									
	Average Return when Positive	Average return when Negative	Worst "Single" Negative Performance	Worst "Single" Negative Performance occurred on	Longest Underperformance	Longest Underperformance occurred on	Recovery Period	Longest winning streak	Longest losing streak
Total Period									
BMK	1.5151%	-1.8645%	-9.281%	12/01/2008	261	01/03/2008-*01/01/2009*	30	6	4
Rule	0.2444%	-1.2927%	-4.6851%	09/17/2008	261	01/03/2008-*01/01/2009*	76	73	4
Excess	1.0134%	*-1.6503%*	*-11.4747%*	10/13/2008	147	03/12/2008-10/02/2008	98	19	6

	Confidence in Skill	Success Ratio
Total Period		
Excess	77.956%	47.3988%

Table 4.12.

Performance of individual investors' market portfolio in 2008 with 5 day lag and lead is below:

PERFORMANCE SUMMARY				
	Annualized Return	Annualized Std Deviation	Annualized Return-Risk Ratio	Cumulative Return
Total Period				
BMK	-37.7014%	41.0679%	-0.918	-37.8143%
Rule	-5.0547%	17.293%	-0.2923	-5.0736%
Excess	32.6467%	37.2629%	0.8761	32.7407%

PERFORMANCE DETAILS									
	Average Return when Positive	Average return when Negative	Worst "Single" Negative Performance	Worst "Single" Negative Performance occurred on	Longest Underperformance	Longest Underperformance occurred on	Recovery Period	Longest winning streak	Longest losing streak
Total Period									
BMK	1.5151%	-1.8645%	-9.281%	12/01/2008	261	01/03/2008-*01/01/2009*	30	6	4
Rule	0.3353%	-1.1908%	-3.7809%	09/22/2008	261	01/03/2008-*01/01/2009*	122	66	4
Excess	0.9341%	*-1.6515%*	*-11.4747%*	10/13/2008	157	02/07/2008-09/12/2008	71	22	4

RISK CHARACTERISTICS				
	Max. Drawdown	Max. Drawdown occurred on	Correlation with BMK	Ratio of Good / Bad Risk
Total Period				
BMK	-48.8957%	11/20/2008	1	*0.9809*
Rule	-19.0736%	07/15/2008	0.4204	*0.8336*
Excess	-10.0969%	06/05/2008	-0.907	*0.8355*

	Confidence in Skill	Success Ratio
Total Period		
Excess	85.6411%	48.7342%

Table 4.13.

Performance of individual investors' market portfolio in 2008 with 10 day lag and lead is below:

PERFORMANCE SUMMARY				
	Annualized Return	Annualized Std Deviation	Annualized Return-Risk Ratio	Cumulative Return
Total Period				
BMK	-37.7014%	41.0679%	-0.918	-37.8143%
Rule	-14.9795%	17.1429%	-0.8738	-15.0324%
Excess	22.7219%	37.3554%	0.6083	22.7819%

PERFORMANCE DETAILS	Average Return when Positive	Average return when Negative	Worst "Single" Negative Performance	Worst "Single" Negative Performance occurred on	Longest Underperformance	Longest Underperformance occurred on	Recovery Period	Longest winning streak	Longest losing streak
Total Period									
BMK	1.5151%	-1.8645%	-9.281%	12/01/2008	261	01/03/2008-*01/01/2009*	30	6	4
Rule	0.2807%	-1.3259%	-4.3411%	10/02/2008	261	01/03/2008-*01/01/2009*	122	65	4
Excess	0.9415%	*-1.7071%*	*-11.4747%*	10/13/2008	131	03/18/2008-09/16/2008	86	29	4

RISK CHARACTERISTICS	Max. Drawdown	Max. Drawdown occurred on	Correlation with BMK	Ratio of Good/ Bad Risk
Total Period				
BMK	-48.8957%	11/20/2008	1	*0.9809*
Rule	-21.9313%	07/15/2008	0.4155	*0.7383*
Excess	-11.5633%	05/19/2008	-0.9087	*0.8548*

	Confidence in Skill	Success Ratio
Total Period		
Excess	78.7041%	47.1698%

Table 4.14.

Performance of individual investors' market portfolio in 2008 with 15 day lag and lead is below:

PERFORMANCE SUMMARY	Annualized Return	Annualized Std Deviation	Annualized Return-Risk Ratio	Cumulative Return
Total Period				
BMK	-37.7014%	41.0679%	-0.918	-37.8143%
Rule	-18.3987%	18.5012%	-0.9945	-18.4622%
Excess	19.3028%	36.7038%	0.5259	19.3521%

PERFORMANCE DETAILS	Average Return when Positive	Average return when Negative	Worst "Single" Negative Performance	Worst "Single" Negative Performance occurred on	Longest Underperformance	Longest Underperformance occurred on	Recovery Period	Longest winning streak	Longest losing streak
Total Period									
BMK	1.5151%	-1.8645%	-9.281%	12/01/2008	261	01/03/2008-*01/01/2009*	30	6	4
Rule	0.2435%	-1.5891%	-8.5203%	09/29/2008	261	01/03/2008-*01/01/2009*	68	68	4
Excess	1.012%	*-1.5649%*	*-11.4747%*	10/13/2008	63	03/31/2008-06/25/2008	27	32	6

RISK CHARACTERISTICS	Max. Drawdown	Max. Drawdown occurred on	Correlation with BMK	Ratio of Good/ Bad Risk
Total Period				
BMK	-48.8957%	11/20/2008	1	*0.9809*
Rule	-18.4622%	09/29/2008	0.4486	*0.4701*
Excess	-9.1601%	05/19/2008	-0.8928	*0.8518*

	Confidence in Skill	Success Ratio
Total Period		
Excess	76.1268%	48.6486%

Table 4.15.

Performance of individual investors' market portfolio in 2009 below:

PERFORMANCE SUMMARY	Annualized Return	Annualized Std Deviation	Annualized Return-Risk Ratio	Cumulative Return
Total Period				
BMK	22.1744%	29.3644%	0.7551	22.1744%
Rule	-23.0602%	20.518%	-1.1239	-23.0602%
Excess	-45.2346%	35.3527%	-1.2795	-45.2346%

PERFORMANCE DETAILS	Average Return when Positive	Average return when Negative	Worst "Single" Negative Performance	Worst "Single" Negative Performance occurred on	Longest Underperformance	Longest Underperformance occurred on	Recovery Period	Longest winning streak	Longest losing streak
Total Period									
BMK	1.2509%	-1.395%	-5.5043%	01/20/2009	87	01/07/2009-05/07/2009	43	6	10
Rule	0.3902%	-0.3253%	-15.8866%	10/07/2009	235	01/06/2009-11/30/2009	23	4	10
Excess	1.3747%	-1.5463%	-16.1309%	10/07/2009	190	03/10/2009-11/30/2009	10	7	8

RISK CHARACTERISTICS	Max. Drawdown	Max. Drawdown occurred on	Correlation with BMK	Ratio of Good/ Bad Risk
Total Period				
BMK	-27.8206%	03/09/2009	1	0.974
Rule	-25.6677%	10/28/2009	0.0278	0.7345
Excess	-55.5217%	11/16/2009	-0.8145	0.7491

	Confidence in Skill	Success Ratio
Total Period		
Excess	12.3064%	44.1048%

Table 4.16.

Performance of individual investors' market portfolio in 2009 with 2 day lag and lead is below:

PERFORMANCE SUMMARY	Annualized Return	Annualized Std Deviation	Annualized Return-Risk Ratio	Cumulative Return
Total Period				
BMK	22.1744%	29.3644%	0.7551	22.1744%
Rule	9.2668%	19.0097%	0.4875	9.2668%
Excess	-12.9076%	22.4101%	-0.576	-12.9076%

PERFORMANCE DETAILS	Average Return when Positive	Average return when Negative	Worst "Single" Negative Performance	Worst "Single" Negative Performance occurred on	Longest Underperformance	Longest Underperformance occurred on	Recovery Period	Longest winning streak	Longest losing streak
Total Period									
BMK	1.2509%	-1.395%	-5.5043%	01/20/2009	87	01/07/2009-05/07/2009	43	6	4
Rule	0.4556%	-1.3164%	-5.5043%	01/20/2009	146	01/07/2009-07/29/2009	136	75	4
Excess	0.3732%	*-1.8414%*	*-7.1308%*	03/23/2009	190	03/10/2009-*11/30/2009*	9	97	4

RISK CHARACTERISTICS	Max. Drawdown	Max. Drawdown occurred on	Correlation with BMK	Ratio of Good/ Bad Risk
Total Period				
BMK	-27.8206%	03/09/2009	1	*0.974*
Rule	-13.9038%	01/20/2009	0.6462	*0.6182*
Excess	-27.7614%	11/17/2009	-0.7622	*0.5796*

	Confidence in Skill	Success Ratio
Total Period		
Excess	*32.9115%*	52.0833%

Table 4.17.

Performance of individual investors' market portfolio in 2009 with 5 day lag and lead is below:

PERFORMANCE SUMMARY	Annualized Return	Annualized Std Deviation	Annualized Return-Risk Ratio	Cumulative Return
Total Period				
BMK	22.1744%	29.3644%	0.7551	22.1744%
Rule	3.3514%	19.2367%	0.1742	3.3514%
Excess	*-18.823%*	22.2058%	-0.8477	*-18.823%*

PERFORMANCE DETAILS	Average Return when Positive	Average return when Negative	Worst "Single" Negative Performance	Worst "Single" Negative Performance occurred on	Longest Underperformance	Longest Underperformance occurred on	Recovery Period	Longest winning streak	Longest losing streak
Total Period									
BMK	1.2509%	-1.395%	-5.5043%	01/20/2009	87	01/07/2009-05/07/2009	43	6	4
Rule	0.4377%	-1.3578%	-5.5043%	01/20/2009	176	01/07/2009-09/09/2009	75	70	4
Excess	0.373%	*-1.6914%*	*-7.1308%*	03/23/2009	190	03/10/2009-*11/30/2009*	9	67	4

RISK CHARACTERISTICS	Max. Drawdown	Max. Drawdown occurred on	Correlation with BMK	Ratio of Good/ Bad Risk
Total Period				
BMK	-27.8206%	03/09/2009	1	*0.974*
Rule	-16.9905%	05/27/2009	0.6543	*0.5856*
Excess	-29.9422%	11/17/2009	-0.7555	*0.57*

	Confidence in Skill	Success Ratio
Total Period		
Excess	24.1297%	48.5149%

Table 4.18.

Performance of individual investors' market portfolio in 2009 with 10 day lag and lead is below:

PERFORMANCE SUMMARY	Annualized Return	Annualized Std Deviation	Annualized Return-Risk Ratio	Cumulative Return
Total Period				
BMK	22.1744%	29.3644%	0.7551	22.1744%
Rule	14.07%	16.0395%	0.8772	14.07%
Excess	-8.1044%	24.6229%	-0.3291	-8.1044%

PERFORMANCE DETAILS	Average Return when Positive	Average return when Negative	Worst "Single" Negative Performance	Worst "Single" Negative Performance occurred on	Longest Underperformance	Longest Underperformance occurred on	Recovery Period	Longest winning streak	Longest losing streak
Total Period									
BMK	1.2509%	-1.395%	-5.5043%	01/20/2009	87	01/07/2009-05/07/2009	43	6	4
Rule	0.335%	-1.2142%	-5.5043%	01/20/2009	146	01/07/2009-07/29/2009	136	88	4
Excess	0.5296%	-1.6497%	-7.1308%	03/23/2009	190	03/10/2009-11/30/2009	146	89	4

RISK CHARACTERISTICS	Max. Drawdown	Max. Drawdown occurred on	Correlation with BMK	Ratio of Good/ Bad Risk
Total Period				
BMK	-27.8206%	03/09/2009	1	0.974
Rule	-13.9038%	01/20/2009	0.5449	0.5638
Excess	-24.6218%	05/08/2009	-0.8376	0.7137

	Confidence in Skill	Success Ratio
Total Period		
Excess	42.208%	49.5935%

Table 4.19.

Performance of individual investors' market portfolio in 2009 with 15 day lag and lead is below:

PERFORMANCE SUMMARY	Annualized Return	Annualized Std Deviation	Annualized Return-Risk Ratio	Cumulative Return
Total Period				
BMK	22.1744%	29.3644%	0.7551	22.1744%
Rule	13.1876%	13.3376%	0.9888	13.1876%
Excess	-8.9868%	26.1858%	-0.3432	-8.9868%

PERFORMANCE DETAILS	Average Return when Positive	Average return when Negative	Worst "Single" Negative Performance	Worst "Single" Negative Performance occurred on	Longest Underperformance	Longest Underperformance occurred on	Recovery Period	Longest winning streak	Longest losing streak
Total Period									
BMK	1.2509%	-1.395%	-5.5043%	01/20/2009	87	01/07/2009-05/07/2009	43	6	4
Rule	0.2616%	-1.0938%	-3.4875%	01/14/2009	149	01/07/2009-08/03/2009	18	112	4
Excess	0.6246%	-1.6435%	-7.1308%	03/23/2009	190	03/10/2009-11/30/2009	121	84	4

RISK CHARACTERISTICS	Max. Drawdown	Max. Drawdown occurred on	Correlation with BMK	Ratio of Good/ Bad Risk
Total Period				
BMK	-27.8206%	03/09/2009	1	0.974
Rule	-12.8591%	07/08/2009	0.4525	0.5357
Excess	-26.0056%	06/12/2009	-0.8909	0.7853

	Confidence in Skill	Success Ratio
Total Period		
Excess	41.9759%	49.2754%

Table 4.20.

The figure below summarizes the results for the period of study:

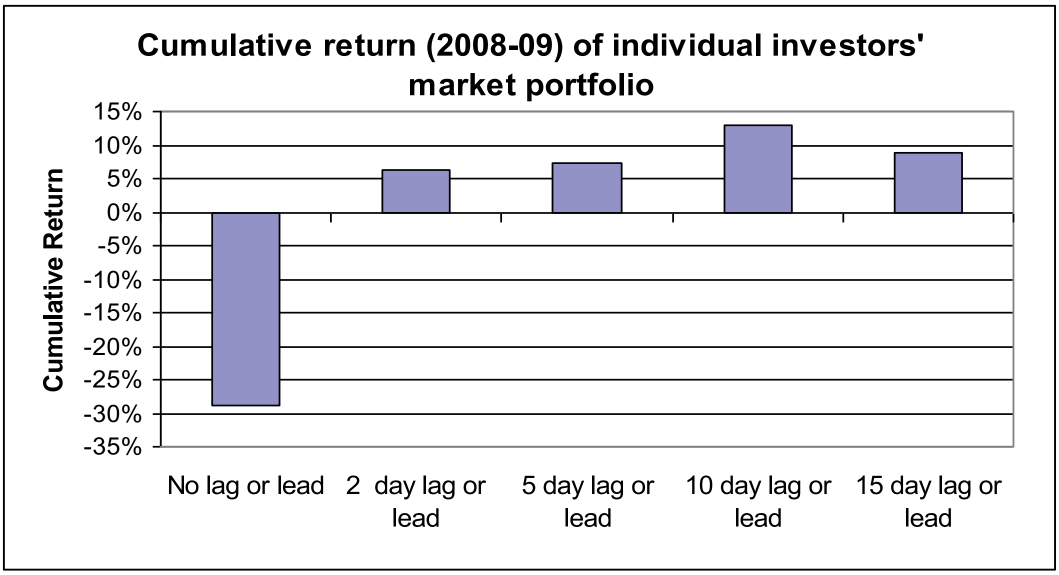


Figure 4.16.

By lagging or leading the time of trades in individual investors' market portfolio, the cumulative return has improved in all cases. The results demonstrate that if the individual investors were to sell their winners later than they did, and close their losing positions earlier than they did, they in fact would have increased their profits significantly. Hence individual investors as a group did demonstrate disposition effect during our period of study. This is in accordance with the literature on disposition effect (see for instance Frazzini (2006)).

Moreover, we calculated the information ratio[15] of the market portfolio with and without lead and lags. As a commonly used measure of a portfolio's performance, information ratio signifies the risk adjusted performance of the investors. We believe that a discussion of disposition effect should not only include the influence of disposition effect on portfolio returns, but also the risk adjusted performance. As seen in the graph below, the information ratio improved for all cases of lead and lag compared to the original return of the portfolio (the latter is noted in Figure 4.17 as "no lag or lead").

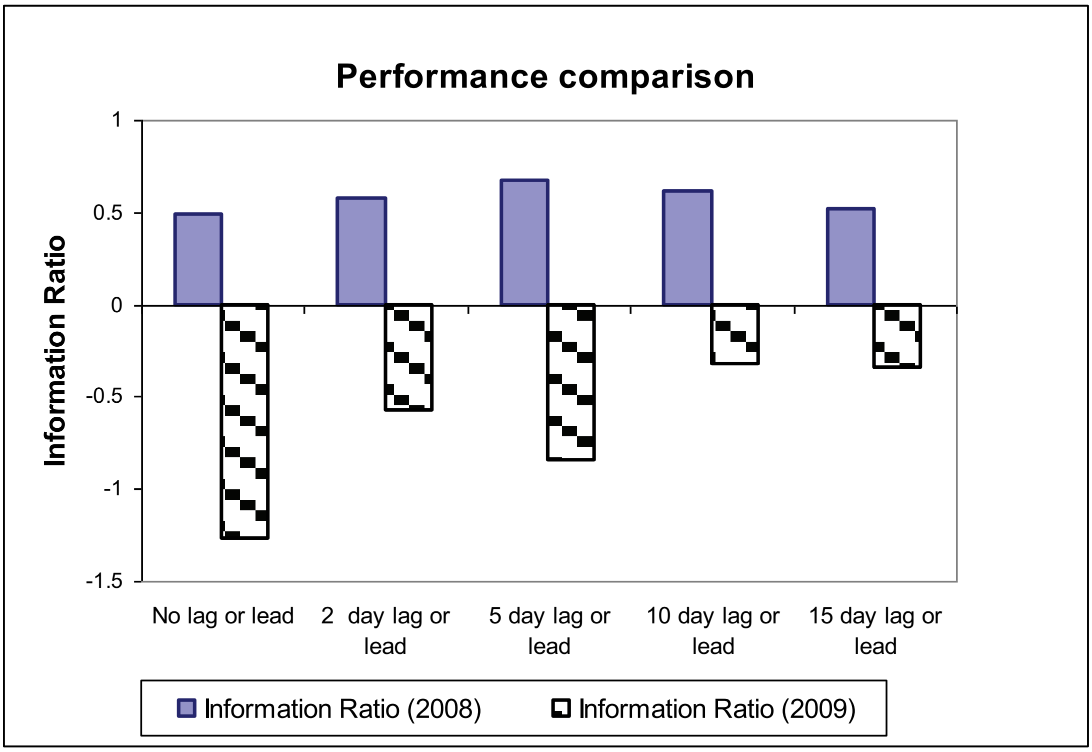


Figure 4.17.

[15] Information ratio is the ratio of annualized excess return divided by annualized standard deviation of the excess return.

Information ratio in both years of our study seem to improve most with a 5 day lead or lag. The pattern of improving information ratio up to 5 days lag or lead and then gradual decrease in that improvement may well be an artifact of this particular data set, but what is more important is the very fact of improvement of the information ratio over the base case performance (i.e. no lag or lead). Given that 5 trading days correspond to a calendar week, perhaps weekly close (i.e. whether the market has appreciated or depreciated over the course of the week) may be important to investors' decision making.

In order to verify the statistical significance of the above results, we ran the following simulations: We selected the large sells as defined above and applied 2, 5, 10 and 15 day lags and leads to them at random, and computed the performance numbers. We then repeated the above procedure 1000,000 times and calculate the mean excess returns in each case. The results in Table 4.21 show the percentage of the simulated portfolios' information ratios which were below the model portfolio seen above:

Performance of simulated portfolios			
2 day lag/lead	5 day lag/lead	10 day lag/lead	15 day lag/lead
98%	96%	96%	92%

Table 4.21.

The above results verify that including lead and lag as we discussed earlier improves the performance of the individual investors' market portfolio, and that the results are not generate by pure luck. The results are statistically significant at 95% confidence in the case of 2, 5 and 10 day lead/lags.

To conclude, by setting up the individual investors' market portfolio and by leading and lagging the trades done by individual investors, and proving that their portfolio would have improved both in cumulative returns and in risk adjusted returns, we showed that individuals holding the market portfolio did sell their winners too soon and kept their loss making positions for too long, in other words they demonstrated disposition effect. What occurred during 2008-2009 is that individual investors have had lower return due to disposition effect. Moreover by setting up simulated portfolios and measuring their performance, we showed that the improvement in the individual investors portfolio due to lead and lag is in fact statistically significant at 95% in 3 out of 4 lead and lag scenarios.

4.5 A financial market application of our findings

In this section, we test if it if possible to profit from what we have demonstrated above by constructing a trading model and measuring its performance in the market. We construct a model based on taking positions to the contrary of individual investors. As the disposition effect existed in individual investor community, a contrarian trading model should have been profitable during our study period. We describe the model specifications below, and later we verify the statistical significance of the model performance results.

We use our individual investors' holdings indicator as our trading signal. We measure the change in the daily holding indicator at the end of each business day. If on any day, the net daily change is an increase in holdings which is above one standard deviation of the mean daily change during the study period, we identify that day as a large buy day. On the very next day, we take the opposite position and short the market one unit. If on any day, the net daily change is a decrease in holdings which is more than one standard deviation from the mean daily change of the study period, we identify that day as a large sell day. On the subsequent day, we go long the market one unit. Hence on the days subsequent to any large change in individual investors' holdings, we take a position opposite to that of individual investors. We execute the trades by trading an S&P 500 ETF issued by State Street Global Advisors with the ticker symbol SPY16. We purchase or sell the SPY at the market rate (bid or ask side depending on the buy or sell signal) at the closing of the trading day. On a daily basis, by definition, SPY will have the same return as the S&P 500 or very close to it. We use the return of S&P 500 as our benchmark, hence the profit and loss of the trading strategy could be verified each day by comparing the S&P 500 index with the value of the S&P index on the day that we entered the trade. We keep the long or short SPY position until the next sell or buy signal is generated. If we are long one unit and a sell signal in generated, we close the position and similarly for the short positions. If we are long and another buy signal is generated, we go long

[16] SPDR™ S&P 500 is a very liquid ETF, with daily trading volume being hundreds of millions of share. It is commonly used to obtain the returns of the S&P 500 without the need to use index derivatives.

another unit until the next sell signal. In closing the positions, we use the first-in first-out rule. If there are any long or short positions left with no offsetting trades, we close all those positions at the close of the last day of our study. We used 0.06% of price as the bid ask spread for our trades, which is slightly above the average spread for SPY for the period of our study. The performance summary results are shown in Table 4.22 below.

Number of buys	20
Number of sells	16
Profitable to loss making trades	9 to 1
Maximum trade profit	25%
Maximum trade drawdown	-5%
Average bid/ask spread	0.06%
SPY cumulative operating expense	0.02%
Net model cumulative profit	127%
S&P 500 cumulative return	-23%
Model cumulative outperformance	148%
Sharpe ratio of model	8.7

Table 4.22. The ratio of profitable to loss making trades indicates that individual investors were wrong in timing of their buys and sells 90% of the time.

The results show that during our study period taking positions opposite to that of the individual investor community would have been highly profitable, outperforming the U.S. equity benchmark return by 148%. In constructing the model, we ignored small trades by individuals as noise in our data. But the model took a contrarian position against all large trades (as defined earlier), and the large trades are those in which the individual investor community had higher conviction (i.e. instances when more people bought or sold, or more capital was traded). Though the model lost money in a few such cases (i.e. individuals were correct in “timing” the market in those cases), the model was highly profitable over the two years of the financial crisis. In other words, in the vast majority of the instances when the individual investor community had high conviction in their buys or sells, the community was wrong in timing those buys and sells.

To measure the statistical significance of our model results, we set up the following simulations: We generated random buys and subsequent sells (or random short sales and subsequent buys) using the same data as our trading model, i.e. entered a trade and closed the trade subsequently at a randomly chosen date (chosen from the remaining days in the study period) at the daily closing level of S&P 500. The number of random trades was equal to that of the trading model. We used the same buy sell spread and calculated the profit or loss for that series of trades, which comprised one simulation. We repeated the process 300,000 times (equivalent to 600,000 years of trading using the same data as equity market in 2008 and 2009) and sorted the end of period results. Based on the above simulations, the contrarian model did better than 95% of the simulated results.

Though the model is highly profitable ex post, it needs modifications if it was to be used in financial markets. We used the mean of daily change in investors' holding in our model which would only be known ex post. In practice, one may use the mean of some past period and adjust it based on new market conditions.

While the model performed well during the period of our study, the best performance was during the most volatile months (49% of all profit was generated during the months of October to December 2008 which were the most volatile months in 2008 and 2009, as seen in Figures 4.18 and 4.19 below.

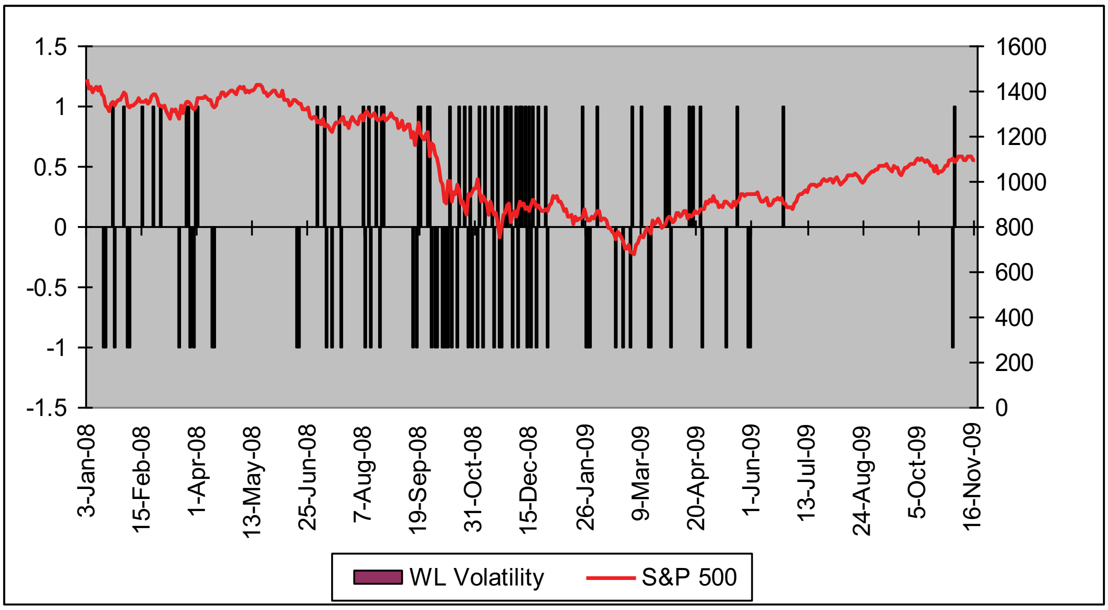


Figure 4.18. Each volatile day is represented by a vertical line, with denser areas representing volatility clusters.

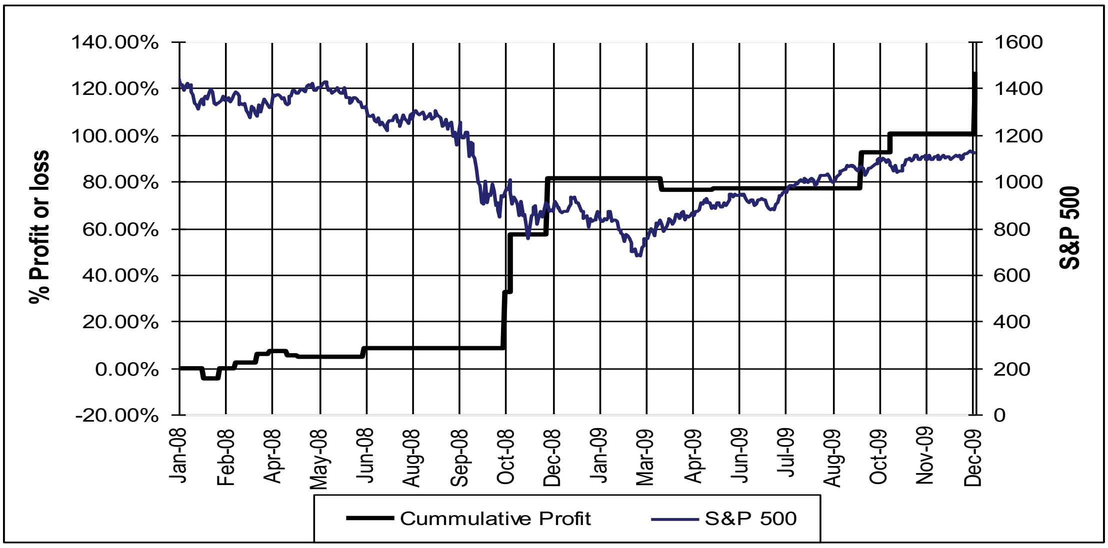


Figure 4.19.

The most profitable period for the contrarian trading model coincides with the period of highest volatility. This is in accordance with our robust regression results and our non parametric analysis; an increase in market turbulence increased the likelihood of individual investors selling their positions. Moreover, this sell off period occurred after a long period of market decline (approximately May 2008 to October 2008), indicating that in accordance with disposition effect, individual investors held on to their losing positions for too long and eventually sold at the lowest points in our study period.

This observation is consistent with our finding earlier about the significance of volatility in explaining the behavior of individual investors, particularly in phase 2 of the study period (see Section 4.3.3). Periods of high volatility perhaps bring out the more instinctive behaviors of individuals (e.g. the so-called fear and greed behaviors) which result in the individuals trading precisely at the wrong times.

4.6 Conclusions

We propose a daily indicator which may be used as a proxy for the individual investor holdings in U.S. equity market using publicly available data. The indicator is exclusive of institutional investors, is well diversified and has high correlation with US equity market such that it may be used as a proxy for individual investors' market portfolio, is constructed using publicly available data and has daily frequency with provides an abundance of data for researchers.

Using our proposed indicator, we first ran various regressions on data using multiple independent variables. We then tried step wise regressions and ensured lack of multicollinearity between the drivers. As the results were not convincing, we proceeded to robust regressions and found the best results were obtained by bi-square robust regression. Upon closer inspection however, we concluded that the due to shifts in the dynamics of the markets during this time period, in order to achieve satisfactory results, the robust regression gives small weights to outliers and increase the weights of the data points which were closer to regression line. This in practice removed the effect of a number of outliers and reduced the effects of significant portion of data. However these outliers were an integral part of the market dynamics during the financial crisis of 2008-2009, and removal of the outliers from the data will inherently influence the integrity of the data set and reduce the robustness of our approach. Therefore we concluded that regressions were of limited utility for such data series and proceeded to use non parametric methods for understanding the dynamics of investors' behavior.

We applied a non parametric approach know as change point analysis to the investors' data set to determine if there were major shifts in investor behavior during our study period. We distinguished three phases of investor behavior and proceeded to use non parametric decision tree methodology to determine the main factors influencing the decision of individual investors in each phase. These 3 phases of individual investors behavior approximately match the performance of the equity market in the following manner: in the early part of 2008 (when there were news of the developing market problems, but the crisis has not started yet), the investors' volatility of investments (as measured by wavelet volatility indicator) showed low variance, hence the volatility estimator is stable and investors' flow of capital in and out of equity market exhibits a steady state.

In the second phase, which corresponds to the peak of financial crisis, the variance of investors' volatility increased. This change in volatility could possibly be explained by sequence of periods in which investors felt optimistic and periods of pessimism, all leading to an uncertain time for the investors. In this phase, investors' change in capital flows was mostly influenced by weekly returns of the more volatile sector of the equity market (namely Russell 2000 index) as well as inherent equity market volatility(namely VIX). Finally in the third phase of our study period which mostly corresponded to the market recovery, the variance of the individual investors' capital flow was once again reduced. Moreover there were no distinctively strong drivers for the investor’s behavior in the third phase. This could be related to the fact that as we showed earlier in the chapter, individual investors did not increase their holdings in equity market after the major fall in the market, thus staying somewhat less active in the third phase and hence not participating the major recovery that followed in the latter part of 2009.

Next we tested the disposition effect among individual investor community and showed that indeed individual investors’ market portfolio exhibited disposition effect and we verified our results by a series of simulations. Our approach is different than traditional literature on disposition effect, because instead of using data on each individual’s buys and sells, we analyzed the entire market portfolio of individual investors. Moreover we not only compared the returns on individual investors portfolio (as it has been done so far in literature) but we also measured and compared the risk adjusted returns (namely by measuring information ratio) and confirmed the disposition effect in both returns and risk adjusted returns.

Finally using our results, we set up a contrarian trading model using the individual investor indicator as a trading signal. We showed that such contrarian portfolio could have been highly profitable during our study period, pointing to further potential applications of our findings in financial markets.

Chapter 5

Analysis of behavioral phenomena and intraday investment dynamics of individual investors in currency market

5.1 Introduction

Historically, the participation of individual investors in currency market has been limited. However this is rapidly changing and individual's investment in foreign exchange market is increasing significantly. Understanding the behavior of individuals in this market is important not only because their role is growing, but also it may help us better understand the dynamics of individual investors in other markets. Moreover, the effect of individuals in certain less liquid currencies and at particular times may be in aggregate significant to the dynamics of those particular currencies. To understand the behavior of individuals, we analyze 2 behavioral phenomena which have been observed and analyzed in other financial markets, namely feedback trading and excessive trading.

Researchers who have analyzed the decision making and trading patterns of individual investors have demonstrated evidence of feedback trading. Feedback trading (which has been investigated in bond and equity markets) states that investors' decisions are mainly based on the immediate changes in the market and changes in the price of securities induce changes in the positions of investors (i.e. induces flow). This is in contrast to the traditional micro structure study of markets which demonstrates that changes in flow induce changes in price of securities. Another behavior observed in individual investors in equity market is excessive trading. This phenomenon refers to the fact that individuals typically trade more often than needed and change their holdings too frequently.

In Section 5.2 we introduce the data that we used in our study. Section 5.3 contains a comparison of the individual and institutional investors' data and sets the background for our analysis in subsequent sections. In Section 5.4, we introduce the feedback trading phenomenon and provide non parametric and parametric analysis of feedback trading in Sections 5.4.1 and 5.4.2. We analyze the intraday data and occurrence of excessive trading in Section 5.5 and analyze the intraday volatility of individual investors' trading in Section 5.6. We conclude in Section 5.7.

5.2 Description of data sets

We analyzed the individual investors' positioning data provided by FXCM Holdings, LLC. FXCM offers the largest global electronic platform where individuals can trade currency. With hundreds of thousands of clients worldwide, the data on the clients positions constitute the largest individual investor (also known as retail client) currency database. Once an individual trades on FXCM, her account shows the net currency bought or sold and until the trade is close, the long and short balance will remain on that account. FXCM aggregates the long and short positions in major currencies each minute across all its retail clients. In aggregating the data, FXCM disregards the size of individual portfolios, giving equal weight to each individual investor. We used minute by minute EUR/USD aggregate position data of individuals from 2 January 2007 to 31 December 2007, to which we would refer as FXCM in this paper. We also used the Reuters quoted minute by minute data in EUR/USD over the same period. We selected EUR/USD [17] as it is by far the most liquid currency pair traded by individuals and institutions, accounting for approximately 40%-50% of all global currency trade. Therefore we believe that the data in this pair would be most representative of individual investors and more reliable then less liquid currency pairs. Moreover year 2007 represents a more "normal" year in financial markets compared to the subsequent years of financial crisis, therefore it allows for study of the individuals behavior in a more steady state. We also used daily data on the following in our study: S&P 500 and VIX as indicators of market and risk sentiment, implied 1 month at the money volatility in EUR/USD as quoted in over the counter market as a measure of idiosyncratic risk , and CVIX which is a proprietary measure of general risk level in currency market published by Deutsche Bank.

In cases when we needed a daily number for FXCM, we used the median of the day. However when we analyzed volatility, we used minute by minute data and reduced the number of data points through wavelet application to come up with daily volatility estimate.

[17] We may at times use the market convention of referring to EUR/USD simply as EUR in this chapter

To measure the aggregate positions of institutional investors, we used the Deutsche Bank Positioning Index (henceforth noted as DB) daily data for 2007. DB aggregates three different holdings and sentiment measures in currency market:

1. IMM report: the Commitment of Traders (COT) report is released every Friday by the International Money Market (IMM), which is part of the Chicago Mercantile Exchange. It provides a breakdown of each Tuesday's open interest in currency futures (the outstanding number of short/long contracts) on the exchange.
2. CTAs holdings: Commodity Trading Advisor (CTA) data is based on Deutsche Bank's proprietary access to these investors' accounts. CTAs are typically short-term oriented, model based investors. Data on CTAs holdings is updated daily. As Deutsche Bank is among the top 3 global banks with highest volume of currency trades, its share of CTA observed trades is significant and reliable.
3. Risk Reversals: a risk reversal is a currency option position that consists of the purchase of an out-the-money (typically 25 delta) call and the simultaneous sale of an out-the money (typically 25 delta) put, in equal amounts and with the same expiration date. Risk reversals are quoted in terms of the implied volatility spread between the call and put. A positive risk reversal indicates that the market is attaching a higher probability to a large currency appreciation than to a large currency depreciation. Risk reversals data is available from Bloomberg™ financial services.

DB is constructed by splitting each of the three individual time series into two samples (depending on whether they signal long or short positioning, bullish or bearish sentiment), and normalizing them by calculating their percentile rank. This results in a score which is subsequently rebased on a scale of +10 to -10, where the maximum/minimum values are the most extreme long/short (or bearish/bullish) value that indicator has taken in the whole sample period. DB is the average of all scores.

In addition to the above, we used daily data on VIX, daily data of one month at the money implied volatility for EUR/USD and daily CVIX. CVIX is a proprietary number calculated and published by Deutsche Bank. CVIX is the weighted average of 3 month implied volatilities on a basket of currencies, and represents the overall currency market short term volatility.[18]

5.3 Analysis of individual and institutional investor holdings data

Table 5.1 shows the distributional features of the returns of EUR/USD (henceforth noted as EUR), FXCM (holdings of individual investors) and DB(daily holdings of institutional investors). As noted in literature, EUR demonstrates leptokurtosis at daily frequency and this tendency increases as we increase the data frequency to hourly and minute by minute observations (see for instance Alexander (2001) pp 389-405). FXCM and DB also have leptokurtic distribution at daily frequency, but this is more prominent in institutional investors' data. The heavy tails increase substantially in hourly and minute by minute returns of individual investors (see Figure 5.1)

		daily	**hourly**	**minute by minute**
EUR	variance	1.49E-05	7.00E-07	1.40E-08
EUR	skewness	-0.2631	-0.0577	-0.3358
EUR	kurtosis	4.0814	8.7979	65.7988
FXCM	variance	0.0376	0.0012	9.92E-06
FXCM	skewness	0.5437	-0.6326	0.1481
FXCM	kurtosis	3.3693	30.2411	900.6129
DB	variance	5.1865		
DB	skewness	0.7879		
DB	kurtosis	31.6123		

Table 5.1

[18] The underlying basket for CVIX is based on the weights of global currency trades published by Bank of International Settlement and includes EUR/USD, USD/JPY and GBP/USD as well a number of less liquid currencies.

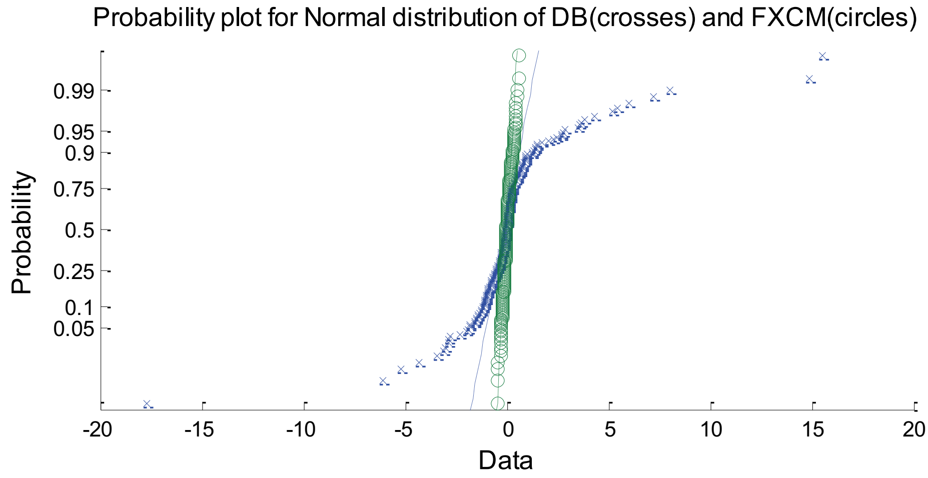


Figure 5.1 Daily returns of DB and FXCM . If DB and FXCM were normally distributed, the green circles and blue crosses would coincide with the solid blue line. The deviations from the solid blue line indicate the heavy tails.

Figures 5.2 and 5.3 show that while there is autocorrelation in both FXCM and DB up to 15 days, the autocorrelation decreases faster in FXCM. In other words, once a trend is set (for instance when the institutional investors become bullish on EUR and their long positions are increasing), that trend continues for some time. However individual investors seem to vary their positions more frequently, resulting in lower autocorrelation after a few days lag. We provide a possible explanation for this phenomenon later in this chapter when we discuss the role of intraday volatility in the decision making of the individuals and institutions.

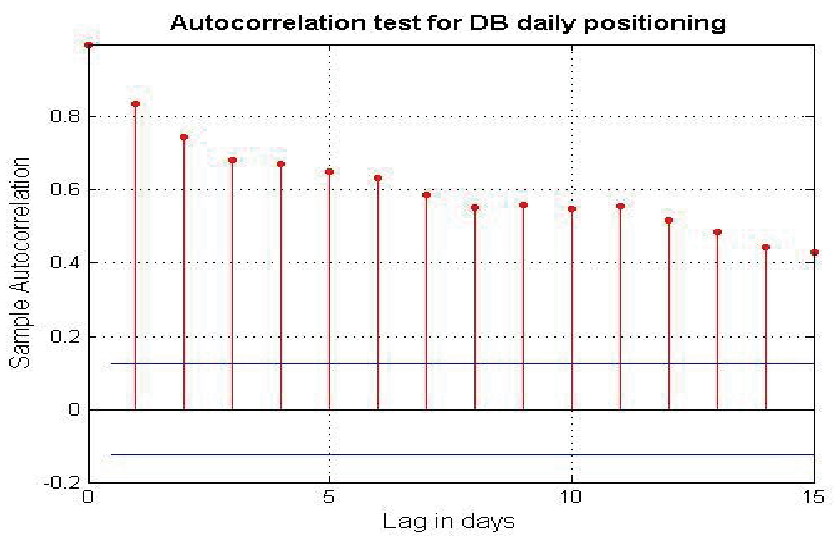


Figure 5.2

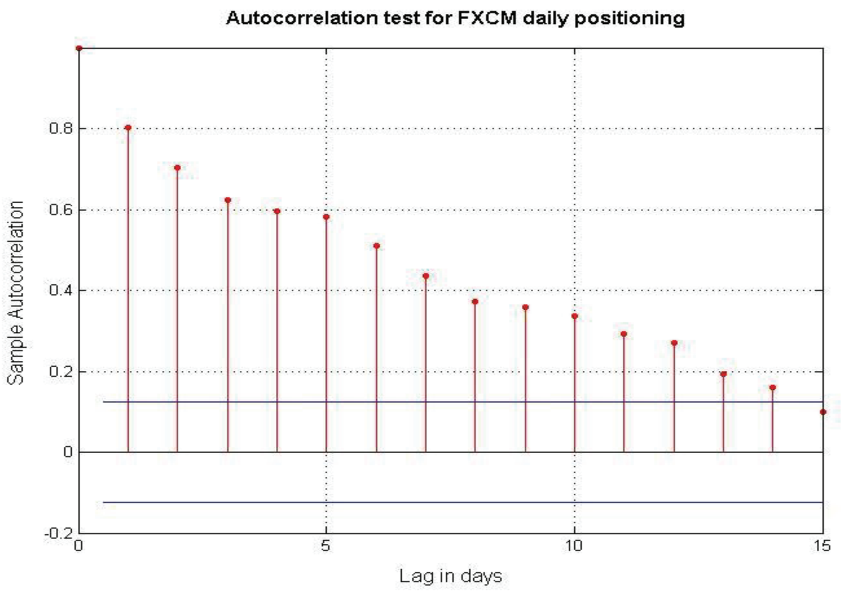


Figure 5.3

We performed the augmented Dickey-Fuller test for unit root on daily return data. The test rejected the existence of unit root in EUR, FXCM and DB daily returns at 95% confidence. This is accord with other literature which has dealt with daily foreign exchange data (see Danielsson and Love(2006) for instance). However we could not reject the unit root at hourly and minute by minute frequency. We also tested the hourly FXCM and EUR for ARCH effect (see Table 5.2). While existence of ARCH effect in EUR is in accord with literature (see Dacorogna et al (2001) 221-226), we demonstrated existence of ARCH effect in intraday data of individual investors' holdings as well.

	ARCH effect test for lags 1,2,3 and 4 hours at 95% confidence							
	EUR hourly returns				**FXCM hourly returns**			
	h =	P =	Stat =	CV =	h =	P =	Stat =	CV =
		1.0e-007 *				1.0e-005 *		
1 hour lag	1	0.0172	36.2636	3.8415	1	0.003	30.7185	3.8415
2 hours lag	1	0.0322	39.1075	5.9915	1	0.0173	31.1445	5.9915
3 hours lag	1	0.1217	39.7277	7.8147	1	0.0651	31.5498	7.8147
4 hours lag	1	0.3528	40.4291	9.4877	1	0.1373	32.7049	9.4877

Table 5.2 H=1 indicates that the null hypothesis that no ARCH effect exist is rejected. CV is the critical value of the chi-square distribution for the corresponding Stat value. P is the p-value of the test statistic.

5.4 Testing feedback trading among individual and institutional investors

Studies of market micro structure have shown that within short time intervals (typically at tick level), the order flow induces price changes in securities. This has been studied in equity market (see Engle and Patton(2004)), in currency market (see Payne (2003)) and in US treasuries market (Cohen and Shin(2003)). However once we increase the study period, there is evidence of contemporaneous price and flow changes. In other words, not only the capital flow results in a change in price (see Nofsinger (1999) for this phenomenon in equity market), but asset price changes cause order flow (see Danielsson and Love(2006)). In behavioral finance, the trading induced by and in reaction to price change is known as feedback trading. Feedback trading is defined by some researchers as a special case of herding behavior (see Nofsinger (1999)). Current literature typically use the flow as seen on a dealing desk (for instance in a market making investment bank) and compare that with the price change. We use the individual investors change in aggregate holdings as the measure of trading activity by individuals and analyze this trading activity for evidence of feedback trading.

In order to test the existence of feedback trading in individual investors, we take the following two approaches: First we use a non parametric method to determine the most important determinant for the individual investors' holdings at daily frequency. Then we use a parametric approach and run a multivariable regression to demonstrate which factors are statistically important to explain the change in individual investors' holdings. We used daily data for analyzing the feedback trading phenomenon, because we needed various inputs into our models and most of the input data only exist at daily frequency.

5.4.1 Nonparametric analysis

In estimating the volatility in our study, we adopted the wavelet volatility estimator proposed in previous chapters and applied it to minute by minute data of FXCM and EUR. We applied various classes of wavelets and selected the appropriate wavelet based on the following: The selected wavelet should reduce the number of data points as much as possible (parsimony of the data after wavelet application), while preserving the main characteristics of the data. Moreover, the synthesized wavelet function should reflect the dynamics of the original time series. One class of wavelets, Daubechies wavelets, meets the above criteria better than all other wavelet classes.

We applied the first Daubechies wavelet at different levels for different parts of our analysis.

We selected a number of factors to include in our analysis. The returns of EUR with various lags are naturally among those factors, but we considered whether we should include the returns of other currencies as a driving factor as well? To answer that question, we note that there is evidence that some currencies' movements are at times correlated with other currencies (e.g. Australian dollar and New Zealand dollar do exhibit such co movements due to economic and other reasons). However EUR/USD is by far the most liquid currency in the world and while the changes in EUR/USD may be influential in changes of other minor currencies (such as Danish Krone whose value is pegged to EUR/USD), it seems very unlikely that other minor currencies may be influential in the changes of EUR/USD. Hence we include the change in EUR as one factor in our analysis but not the changes in other currencies. Institutional investors engage in transactions which are influenced by the volatility of the underlying assets (such as trading options) and such transactions in aggregate may at times influence the trading activity of institutions. Here we include the implied volatility of EUR to test if individuals' behavior may be affected by it as well. We also include Deutsche Bank's CVIX daily index as a representative of general currency market volatility. As measures of general financial market sentiment, we include S&P 500 equity index and VIX. We used the daily change in the aforementioned factors in our analysis.

We employed bootstrap aggregation (also known as bagging) decision tree method suggested by Breiman(1996). In this method, a number of random drawings (with substitution) are made from the data and regressions are run on those samples. The above process is repeated hundreds of times, with each run generating a tree branch. As branches are increased, the results of the regression predictions are compared with actual data to calculate the error terms, and the errors are minimized in the subsequent branches. This method is commonly used in estimating the comparative importance of the factors in nonlinear estimations.

Figure 5.4 shows the results of running the tree bagger routine. The bars depict the relative importance of each factor.[19]

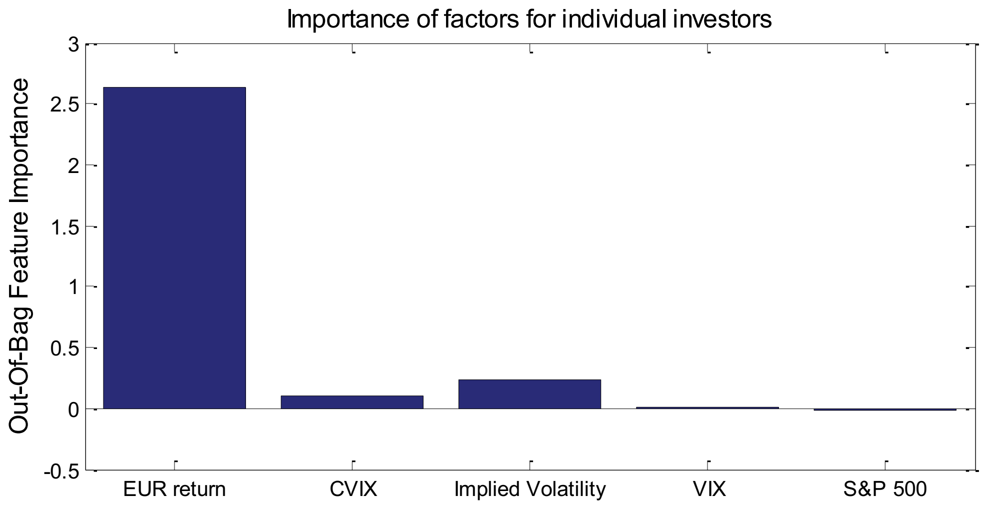


Figure 5.4

Reducing the number of factors did not increase the predictive power of the tree bagger in our analysis. Running the tree bagger 10,000 times indicated a stable relationship in which EUR return is by far the most important factor. Moreover the mean square error of the estimation declined after a few hundred trees and stabilized, ensuring of a robust tree generation process (see Figure 5.5). We ran the same operation on DB data, but the results were not stable and therefore not conclusive.

[19] A random sampling of data is used for each branch of the tree and relative importance of factors is measured over the entire ensemble and divided by the standard deviation of the ensemble to come up with a number used for importance ranking.

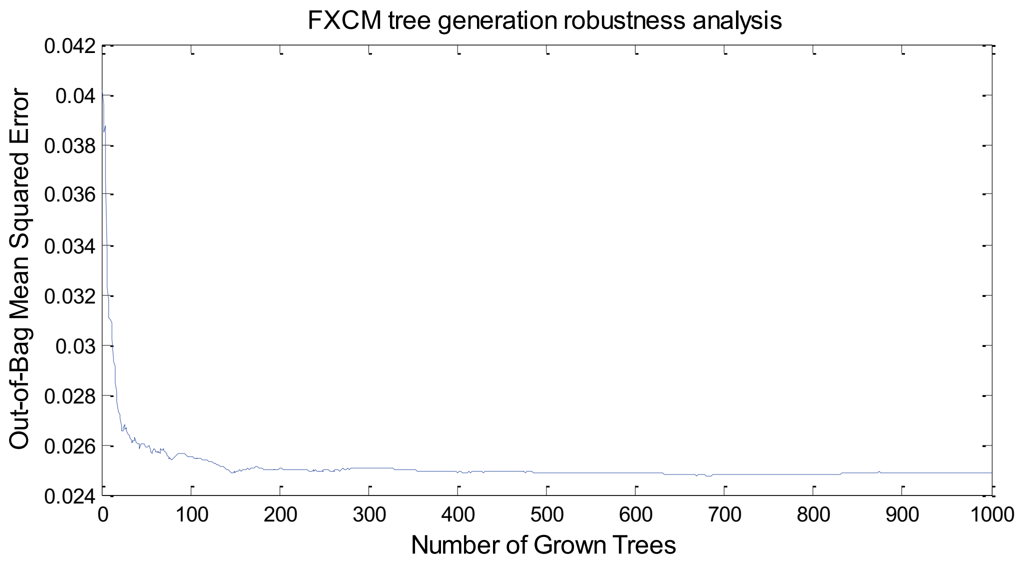


Figure 5.5

Based on the above, we concluded that the most important factor in explaining the changes in individual investors' daily positions is the daily change in EUR, but we did not obtain any conclusive results for institutional investors. In accordance with feedback trading phenomenon, individuals have been changing their positions mostly based on changes in underlying security that they held.

5.4.2 Parametric analysis

Calculating the correlations between various factors daily change also shows highest correlation of changes in FXCM with changes in EUR (see Table 5.3). It is also notable that the same correlation of change between EUR and DB is almost zero. In the table, we also show the correlations for intraday volatility of EUR and FXCM. The intraday volatility is estimated by using the wavelet volatility estimator explained in Sun et al (2011) and introduced in Chapter 3. The correlations are calculated for the daily changes in all cases, except for the estimated intraday wavelet volatilities of FXCM and EUR. In the latter, the actual daily volatility was used.

	EUR	FXCM	DB	SPX	VIX	WL of FXCM	WL of EUR	CVIX	1m ATM Implied Volatility of EUR
EUR	1.00	***0.60***	***0.03***	0.18	(0.13)	0.05	(0.12)	(0.07)	(0.07)
FXCM	0.60	1.00	0.10	0.14	(0.16)	0.05	(0.10)	(0.00)	(0.04)
DB	0.03	0.10	1.00	0.05	(0.07)	0.01	(0.01)	0.09	0.16
SPX	0.18	0.14	0.05	1.00	(0.85)	0.05	(0.08)	0.13	0.07
VIX	(0.13)	(0.16)	(0.07)	(0.85)	1.00	(0.04)	0.01	(0.09)	(0.08)
WL of FXCM	0.05	0.05	0.01	0.05	(0.04)	1.00	0.06	0.01	0.02
WL of EUR	(0.12)	(0.10)	(0.01)	(0.08)	0.01	0.06	1.00	0.03	0.01
CVIX	(0.07)	(0.00)	0.09	0.13	(0.09)	0.01	0.03	1.00	0.75
1m ATM Implied Volatility of EUR	(0.07)	(0.04)	0.16	0.07	(0.08)	0.02	0.01	0.75	1.00

Table 5.3

Having observed the importance EUR return in the decision making of individual investors, we proceeded to quantify the relationship between the above factors.

In Table 5.4, we see the results of multivariable linear regression of daily changes in DB and FXCM data against daily changes in EUR, VIX, S&P 500, CVIX, intraday volatility estimation using wavelet volatility estimator and 1 month at the money implied volatility of EUR.

Dependent variable	Independent variable(s)						R squared	F statistic	p statistic	Estimate of error of variance
DB	EUR						0.001	0.236	0.627	1.423
DB	EUR	VIX					0.005	0.677	0.509	1.423
DB	EUR	VIX	S&P 500				0.006	0.515	0.673	1.427
DB	EUR	VIX	S&P 500	CVIX			0.015	0.954	0.434	1.420
DB	EUR	VIX	S&P 500	CVIX	WL EUR		0.018	0.875	0.498	1.459
DB	EUR	VIX	S&P 500	CVIX	WL EUR	Impl. Vol.	0.036	1.444	0.199	1.439
FXCM	EUR						0.357	143.287	0.000	0.023
FXCM	EUR	VIX					0.365	73.882	0.000	0.023
FXCM	EUR	VIX	S&P 500				0.371	50.226	0.000	0.023
FXCM	EUR	VIX	S&P 500	CVIX			0.372	37.722	0.000	0.023
FXCM	EUR	VIX	S&P 500	CVIX	WL EUR		0.382	29.082	0.000	0.022
FXCM	EUR	VIX	S&P 500	CVIX	WL EUR	Impl. Vol.	0.385	24.430	0.000	0.022

Table 5.4

Significant changes in FXCM may be explained by changes in EUR (i.e. individual investors' decision making was notably influenced by the market and react to it), whereas the daily changes in EUR shows no explanatory effect for changes in DB (i.e. institutional investors decision making cannot be explained by changes in the EUR). Moreover while adding VIX and SPX do improve the regression results, the changes are not significant. We performed Ljung-Box Q-test for on residuals of the regressions of FXCM. In all cases, the residuals are randomly distributed at 95% confidence and no serial correlation was observed. Hence changes in underlying security price induced changes in the individual investors' holdings of the security, demonstrating the existence of feedback trading in this group of investors. Such evidence of feedback trading could not be demonstrated in case of institutional investors.

In order to examine the cumulative effect of volatility for institutional and individual investors, we calculated the correlations of the changes in investors' holdings with moving averages of daily estimated volatility. To estimate the daily volatility of FXCM using the intraday wavelet volatility estimator, we applied the Daubechies 1st wavelet to the minute by minute FXCM data. We repeated the above by applying the wavelet once again to results, hence achieving Daubechies 1st wavelet at 2nd level. We continued the application of the wavelet until 10th level, at which time the number of points in the volatility dataset is reduced to approximately 260 data points (corresponding the number of trading days in a 2007). We "padded" the data by adding zeros to the data set so that we came up with a set of 260 data points. In this way, we are representing the effect of intraday volatility by only enough volatility data to correspond to the daily frequency of other data.[20] An alternative method is to select an intraday minute as representative of the daily volatility (such as median of daily minute by minute volatility). The results of the latter were similar to the above approach.

As seen in Table 5.5, correlation numbers for DB are low and do not follow a pattern, while to the contrary increasing the length of time of the moving average shows a distinctive increase in negative correlation to individuals' holdings. Moreover the correlation of FXCM is negative and stays negative for all periods. This correlation pattern *may* indicate causation; individual investors, influenced by the intraday volatility of EUR, may have tended to reduce their positions if they were long and volatility increased, perhaps expecting a decline in EUR, and increased their positions in EUR if intraday volatility subsided for a few days. This is clearly a reactive behavior in which investors are driven by the immediate dynamics of the

[20] When standard deviation of returns is chosen as measure of volatility, square root of time is used for scaling the results to other time periods. In using wavelet volatility estimator, we can simply reduce the number of wavelet coefficient to scale the results as we have done here.

price, rather than a forecast of EUR price independent of the recent market dynamics. Such behavior in accordance with what is commonly known as “fear and greed” behavior.

	Daily	5 day moving average	10 day moving average	20 day moving average
FXCM	-10.4%	-17.9%	-25.5%	-32.1%
DB	-1.4%	3.4%	-0.6%	5.4%

Table 5.5 .Table shows the correlation of daily changes of FXCM and DB vs. moving averages of intraday volatility. Intraday volatility is measured by wavelet volatility estimator applied to minute to minute data.

We ran the regressions of changes of FXCM against 5 day, 10 day and 20 day moving averages of the daily changes of EUR to see if a pattern similar to the effect of volatility in Table 5.5 could be observed. The results are in Table 5.6.

	R squared	F statistic	p value	Estimate of error variance
1 day return	0.357	143.287	0.000	0.023
5 day MA	0.014	3.643	0.057	0.037
10 day MA	0.006	1.642	0.201	0.037
20 day MA	0.003	0.697	0.404	0.037

Table 5.6 .Regression results of daily changes of individual investors EUR holdings against 1 day return of EUR and 5, 10 and 20 day moving averages of the daily return of EUR.

Cumulative effect of daily changes does not increase the explanatory power of the independent variable and R squared diminishes as we move from one day return to moving averages of multiple day returns. Therefore while individual investors are affected by changes in the currency market, they are mostly influenced by the one day change in EUR and not the cumulative effect of EUR change. In other words, to the extent that the change in individual investors positions can be attributed to the change in underlying currency, such attribution is largely to the most recent dynamics of the currency market and not the cumulative changes of past week or month. This result demonstrates a “speculative” short term trading pattern which involves short term reactions to the market and may be explained by noting that individuals that do trade currency are not the main stream financial market individual investors. Whilst the latter group may be mostly characterized by buy and hold long term investors, the individual currency investors, by virtue of having chosen a non traditional investment vehicle, are likely more actively engaged in the market. This may mean more short term and speculative trading.

5.5 Testing excessive trading among individual investors

In the previous section, we demonstrated that individuals are mostly influenced by one day return of EUR. This implies that individuals traded with sufficient frequency to affect their holdings on a daily basis. The fact that autocorrelation in positions of individuals decays faster than institutions also point to this phenomenon (see Section 5.3.1). Compared to institutions' trading pattern, this may indicate an excessive amount of trading and high turnover of holdings. Institutions changes in holdings could not be explained by immediate changes in EUR, which implies that they did not react as often to the immediate changes in the price. Excessive trading by individuals has been documented in equity markets. Barber and Odean (2000) for instance reviewed the trades of thousands of individual equity market investors and found that on average their performance is worse than the performance of institutions. They attribute this worse performance to the costs associated with excessive trading. Barber et al (2009) further demonstrated that the losses incurred by such trading behavior of individuals are economically substantial. Mangot (2009) shows that there is little economic justification for investors to be trading as often as they typically do.

In order to test the excessive trading behavior in currency market, we set up portfolios using the FXCM data. Approximately 75% of individual investors were short EUR/USD during 2007, which resulted in a loss as EUR/USD appreciated during this period. But for the 25% remaining portion of the individuals who were long EUR/USD, we were interested to see if they could have outperformed their benchmark. In other words, for the investors that owned EUR/USD, we wish to establish if they have performed better than the return on EUR/USD. If an investor were to buy and hold EUR/USD during this period, her return would have been the return of EUR/USD. However individual investors bought and sold EUR during this period in the hopes of gaining more profit. Here we will analyze if this buying and selling improved or diminished their returns.

We measured their performance as follows: Given the change in the holdings of individuals (i.e. individuals buying or selling EUR), and the daily return of EUR/USD, we calculated the cumulative return of their market portfolio. To measure the return of the market portfolio, we calculated the return on investing in 1 EUR/USD. We then adjusted the value of that unit investment according to the changes in holdings (according to the FXCM aggregate holdings data) and return on EUR (see Figure 5.6 for results)

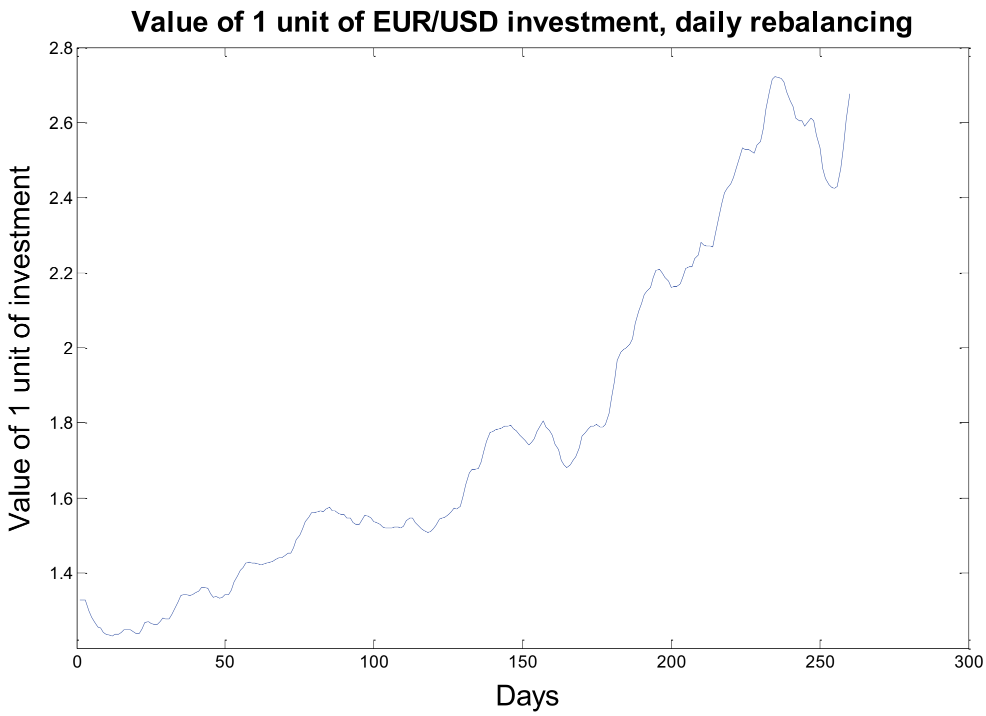


Figure 5.6

We then repeated the above, but instead of changing the holdings every day, we assumed the same aggregate change but with a portfolio which rebalanced with weekly frequency. Hence we only included the weekly returns and weekly changes in holdings, and ignored the changes during the week. In order to account for the events which might have occurred on any particular day of the week resulting in idiosyncratic effect on the returns, we generated 5 portfolios, which rebalanced on Monday of every week, Tuesday of every week, etc (see Figure 5.7)

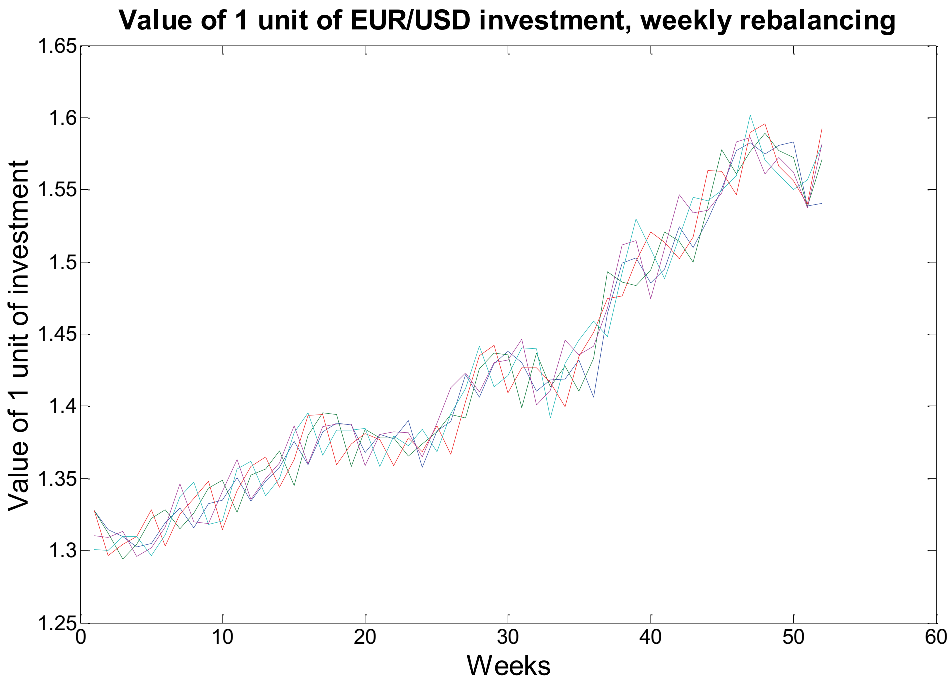


Figure 5.7

Finally we repeated the above with another set of portfolios which rebalanced every month. We had 20 such portfolios, which rebalanced on each trading day of the month (see Figure 5.8)

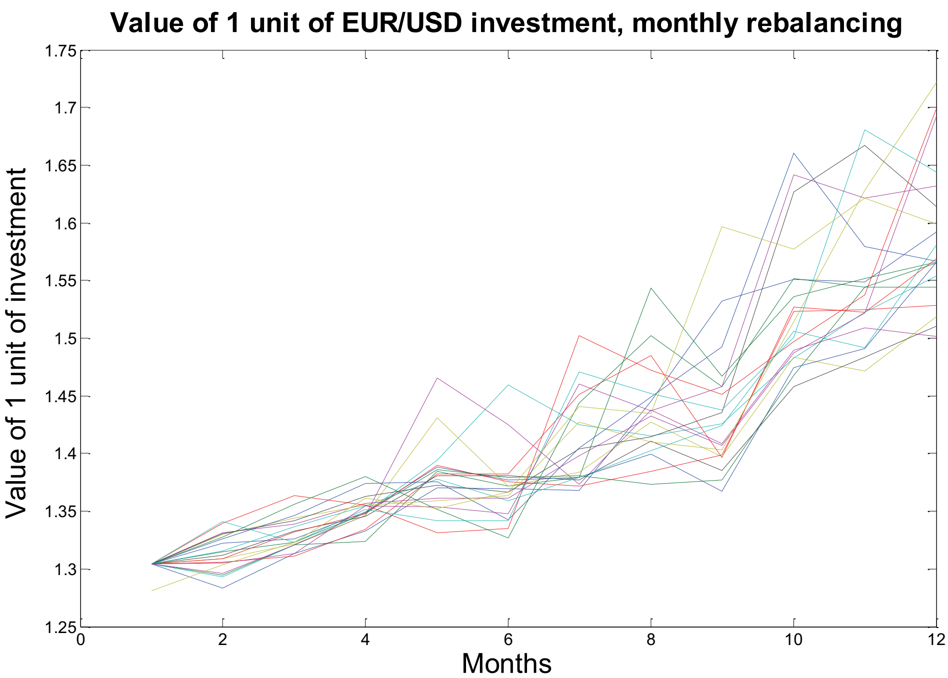


Figure 5.8

Table 5.7 shows the results of the above rebalancing acts. Assuming no bid-ask spread, the individuals who rebalanced their portfolio every day (i.e. owned the individual investors' market portfolio) would have outperformed the return of EUR by a modest amount.

	EUR return	Daily rebalance return	Weekly rebalance return	Monthly rebalance return
	10.84%	11.56%		
Mean Return			18.55%	19.64%
Median Return			19.14%	18.09%
Minimum Return			16.07%	13.10%
Maximum Return			20.00%	29.69%

Table 5.7

However, once we include the market bid ask spread of 0.0004 (average spread for EUR/USD in 2007), we note that the performance of daily rebalanced portfolio diminishes, with the portfolio underperforming the EUR return by approximately 7% (see Table 5.8). This underperformance is more significant in the case of the portfolios with weekly and monthly rebalancing. Not only the mean and median weekly and monthly rebalanced portfolios outperform daily rebalanced portfolio and EUR/USD return, but even the minimum return of our simulated less frequently balanced portfolios would have still performed better than daily rebalance and EUR/USD returns.

	EUR return	Daily rebalance return	Weekly rebalance return	Monthly rebalance return
	10.84%	3.72%		
Mean Return			17.79%	18.89%
Median Return			18.39%	17.34%
Minimum Return			15.31%	12.35%
Maximum Return			19.25%	28.93%

Table 5.8

Therefore excessive trading of individuals which held the market portfolio of individual investors (i.e. portfolio based on FXCM holdings) did in fact generate less profit compared to the individuals which held the market portfolio with the same returns, but rebalanced and traded every week or every month. This confirms the phenomenon of excessive trading similar to what has been reported in literature in equity market.

In weekly and monthly rebalanced portfolios, the difference in performance cannot be explained by the effect of bid ask spread, as the amount of underperformance is clearly much larger than the total bid ask spread on all trades. A possible explanation for the underperformance may be that by reacting to the short term change in EUR in the form of feedback trading, investors have been reducing or increasing their positions radically without waiting for a trend to develop and establish itself in the EUR market. By trading less and rebalancing at weekly or monthly frequencies (i.e. by ignoring the daily noise in the market), investors would have captured the benefit of reacting to a more established and stronger trend, thus generating more profit. In reality however, we saw earlier that individual investors exhibit feedback trading and their behavior was explained most by one day return of EUR, thus they did generate less profit in their portfolio. Therefore similar to equity market, excessive trading has diminished the performance of individual investors in currency market. This is notable since foreign exchange market is by far the largest financial market in the world and thus has very tight bid ask spread. Hence individual investors market portfolio returns suffered because of excessive trading despite the very small bid ask spread (typical bid ask spread in currency market, and in particular in EUR/USD which is the most liquid currency pair, is a fraction of the spread in even the most liquid shares in equity market).

5.6 Intraday volatility analysis

Having established the existence of excessive trading among individual investors, we proceed to analyze this excessive trading in more detail in order to determine when such periods of frequent trading occurred. To that end, we analyzed the intraday dynamics of individual investors by applying the wavelet volatility estimation method to minute by minute data of EUR and FXCM. As opposed to traditional volatility measures which result in a constant value for volatility for a given set of historical data, wavelet volatility estimation allows us to set various thresholds for volatility and analyze the behavior of investors at extremely volatile instances as well as at more moderate volatility. We applied Daubechies first wavelet at first level for this part of the analysis to separate the volatility from the underlying trend.

We ranked the minute by minute wavelet volatility data and defined a volatile minute when the wavelet volatility estimator for that minute was at or above 95%, 80%, 60%, 50% and 40% of the maximum minute by minute volatility for the year 2007. As an example, in Figure 5.9 we have drawn a vertical line for each volatile minute above 95% threshold. Adjacent vertical lines constitute volatility clusters and using the clustering methods, we analyzed how such clustering of volatile minutes occurred in EUR/USD and in individual investor positions.

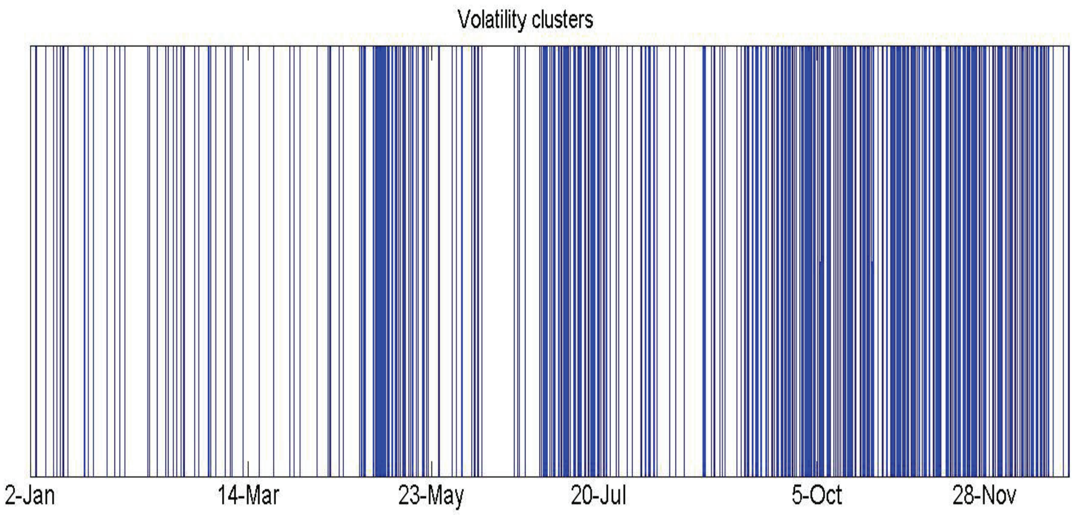


Figure 5.9

For each of the volatility data sets corresponding to the five thresholds, we compared the volatility in FXCM with that of EUR/USD by applying a clustering algorithm to the data points and determining the probability distribution of the occurrence of clusters by kernel smoothening. Clustering methods are used to classify observations according to some common feature without assuming any prior identifiers (see Hoppner et al (1999)). Volatility clustering has been observed in various financial markets (see for instance Alexander (2001)). Here we intended to determine when in the data series did the clusters occurred. Researchers who have analyzed intraday data have explained the occurrence of the clusters by referring to what was happening in the market at the time of those occurrences. We did the same when we related the occurrence of volatility clusters to the time of economic releases in Chapter 3. In this Chapter, we took a different approach and used a purely mathematical model without regard for the underlying causes of the volatility in the market. In this way, we let the algorithm locate the volatility clusters with no priors about the market. We used a hard partitioning method which groups the volatile minutes into clusters such that 1) every volatile minute is included in a cluster 2) there is no overlap between the clusters and 3) there are no empty clusters.

Within each cluster, the algorithm seeks to minimize the sum of the squared distances to the center of that cluster.

Hence for the whole data set we seek to minimize:

$$\sum_{i=1}^{p} \sum_{j \in A_i} (x_k - \mu)^2$$

Where :

μ is the center of a cluster

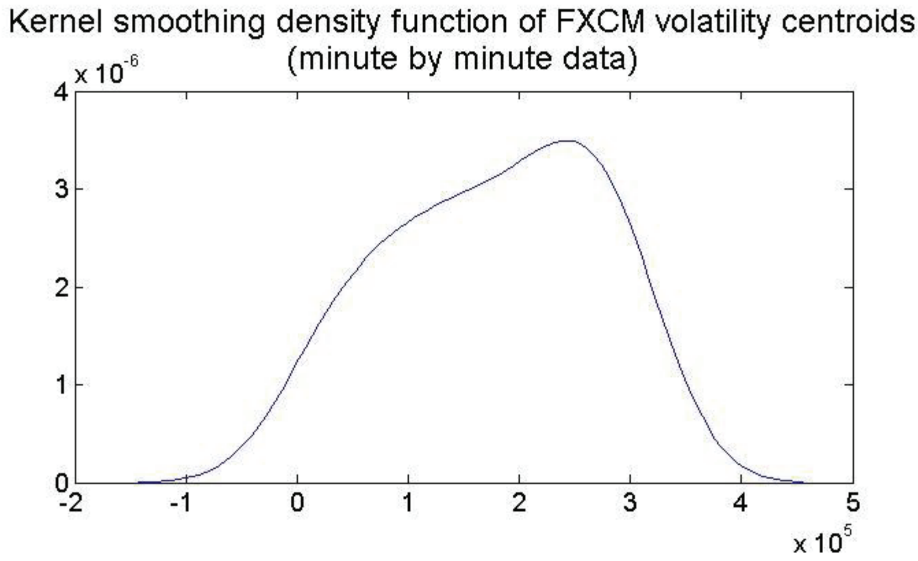
x_k is a point in the *i*-th cluster

A_i is the set containing all data points.

p is the number of clusters in the data set.

The algorithm selects a random point within the data set as the center of a cluster (called centroid hereafter) and through an iterative process, selects the centroids which result in the global minimum for the above sum of squares.

Once the centroids were located, we applied a kernel smoothing function to estimate the distribution probability density for the centroids. We then compared the probability density of the of the volatility clusters centroids of the FXCM and EUR data. As an example, Figure 5.10 shows the volatility cluster centroids when 100 clusters where chosen for each of the EUR and FXCM data. The volatility in this figure is defined as the top 5% most volatile minutes as observed in the wavelet volatility data. We note that there is a close proximity between the two graphs, and similar proximity could also be observed in the QQ plot of Figure 5.11.



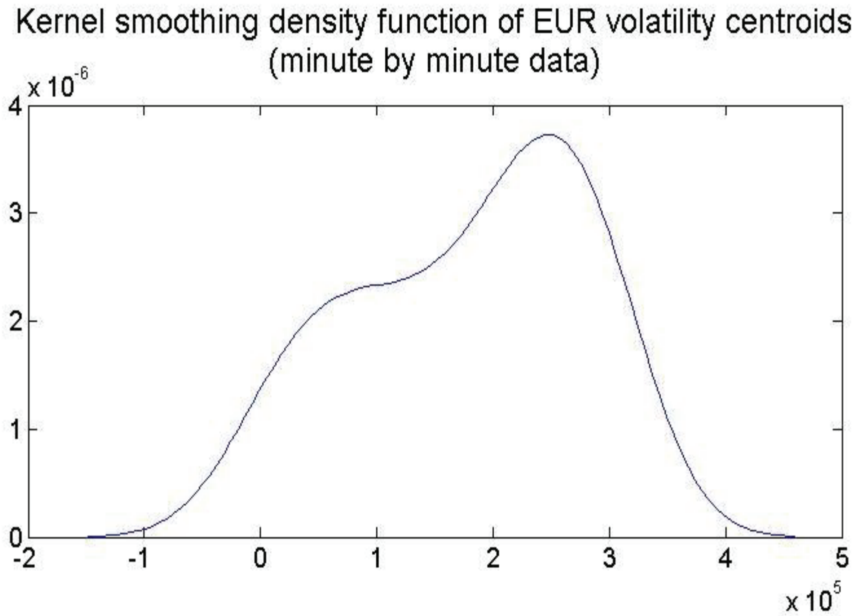


Figure 5.10

The points from 0 to 311118 on x-axis correspond to the minutes in the data series. Y-axis is the density values for each centroid. The estimation is using a normal kernel function.

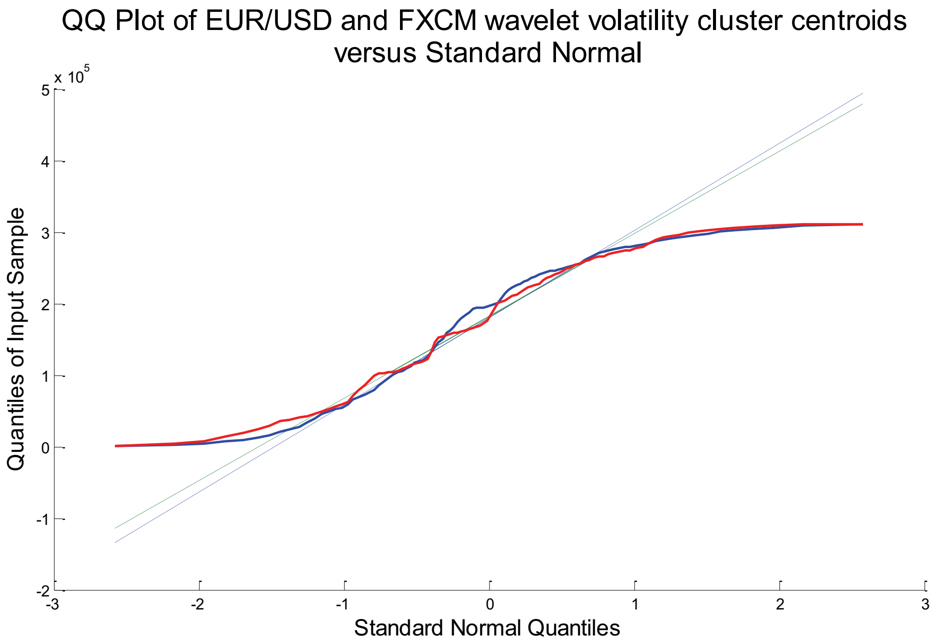


Figure 5.11. The red line corresponds to FXCM and solid blue line depicts EUR/USD.

The distribution of both cluster centroids exhibit excess kurtosis which was confirmed by our Kolmogorov-Smirnov test for normality of data. However the two data series seem to match very closely not only on the middle part which is normally distributed, but also at the extremes when they diverge from standard normal quantiles. When we ran the two sample Kolmogorov-Smirnov test (see Table 5.9), we could not reject the null hypothesis that the two series were drawn from the same distribution at 95% confidence level.

Results of Kolmogorov-Smirnov test applied to EUR/USD and FXCM volatility cluster centroids	
H	0
p	0.8938
k	0.08

Table 5.9 .Null hypothesis is that the 2 data sets have the same continuous distribution. We used 100 cluster centroids for each data set. The statistics k represents the maximum difference between the centroids.

Next we ran a series of regressions between the kernel probability density of EUR and FXCM at various thresholds. As seen in Table 5.10, there is a very close fit between the two data series at higher thresholds, but the R-squared of the regression decreases notably as we set the thresholds at lower volatilities.

Volatility threshold(%)	R squared	F statistic	p value	Estimate of error of variance
95	0.98	826	0.00	0.00
80	0.88	709.93	0.00	0.00
60	0.85	574.29	0.00	0.00
50	0.69	213.80	0.00	0.00
40	0.12	13.67	0.00	0.00

Table 5.10

In the table above, wavelet volatility was estimated for minute by minute data of EUR and FXCM. Volatility thresholds were set as a percentage of the volatility range (i.e. percentage of minute with highest volatility minus minute with lowest volatility). We then find the centers for volatility clusters using hard partitioning clustering algorithm. Next we found the probability of occurrence of these probability centers using kernel smoothening. Finally we ran the regressions between the probability distributions of the volatility cluster centroids for EUR and FXCM at various thresholds.

To determine the statistical significance of the regression results, we ran a series of simulations. We intended to establish if the volatility cluster locations and hence the highly similar kernel distributions of those locations (see Figure 5.10) could have been an artifact of this particular data set. In other words, we wish to establish if the results in Table 5.10 could have been generated by pure luck. We used the wavelet volatility data and set similar thresholds. We then randomly shuffled the position of the volatile minutes for each threshold. Next we ran the clustering algorithm, located the centroids, smoothened the data using normal kernel smoothing and ran similar regressions. By repeating the above 10,000 times, we verified that with the exception of the results corresponding to the last row in Table 5.10 (i.e. results with volatility threshold set to 40%), all regression results in Table 5.10 are significant at 95% confidence.

Given that the wavelet volatility estimator indicates the intraday minute by minute volatility of returns, we conclude that highly volatile periods of EUR are very likely accompanied by volatility in holdings of individual investors. This was most noticeable at extremely volatile intraday periods when volatility was at 95% of the historical high of intraday volatility data and as volatility decreased, the likelihood of coincidence of volatility clusters in EUR and volatility clusters in holdings of individual investors decreased. Moreover our simulations demonstrate our confidence at 95% significance that the coincidence of volatility clusters was not by mere chance.

As we did not relate the volatility of EUR to what the underlying reasons for that volatility might have been (i.e. as we ignored the market conditions including arrival of news, etc.) and demonstrated the coincidence of volatilities by pure mathematical clustering, we indeed demonstrated that the mere increase in intraday volatility increased the likelihood that individuals traded and changed their positions. The higher the volatility in EUR, the more individuals reacted and changed their positions, hence increasing the intraday volatility of the change in their holdings.

5.7 Conclusions

Using minute by minute proprietary data of individual investors' holdings in EUR/USD during 2007 which has not been available to researchers until now and daily data on institutional investor holdings, we investigate the investment dynamics of individuals and institutional investors. We used parametric and non parametric approaches and demonstrate the feedback trading phenomenon in individual investors but did not observe evidence of feedback trading in institutional investors. We show that of the relevant market factors that we analyzed, individual investors were mostly affected by one day return of EUR/USD.

Moreover we tested the excessive trading behavior of individuals which has been documented in equity markets and demonstrate that individual investors did exhibit excessive trading. Furthermore we demonstrated that the reduction in the returns of the individuals occurred despite the very small bid-ask spread in EUR/USD.

Finally we showed that regardless of the market conditions, periods of frequent intraday trading by individuals coincide with periods of high intraday volatility of the EUR/USD, and the likelihood of such coincidence increases as the intraday volatility of EUR/USD increases.

Chapter 6

Conclusions of the dissertation

We started the research by reviewing the literature on high frequency intraday finance. We then narrowed the research to the foreign exchange market and reviewed the stylized facts of that market. Among those intraday characteristics, we emphasized seasonality as it directly influences intraday volatility and volume. We contend that seasonality exists due to the timing of opening and closing of various trading centers around the globe, and the overlap of their time zones. Next we reviewed the literature on volatility in more detail and concluded that range volatility is the most efficient volatility estimator of those commonly used up to now.

In Chapter 3, we used regression analysis to compare the impact of various releases, and verified the results discussed in the literature. At the same time, we conducted a poll of head traders in major asset management firms and chief economists in major investment banks. We asked them to rank the releases based on their effect on the currency market and also indicate if they thought that the releases will affect all 3 currencies equally. We then compared the results of the regression with the results of our poll to see how the traders' and economists' expectations of the market fit the actual market dynamics. We concluded that while their expectation mostly fit the data, there were some discrepancies. Interestingly, the strong majority of respondents believed that the economic releases affect all 3 major currencies (Euro, British Pound and Japanese Yen) equally, but this proved to be inconsistent with our findings.

The most important economic release in our regression, and in poll results, is the nonfarm payrolls release. We replicated the work of other researchers but added the information on dispersion of analysts' forecasts in order to better explain the dynamics of this release. We contend that the quality of forecasts varies over time and there seems to be evidence of herding and conformity among the forecasters.

Based on our regression analysis, and taking into account the poll results, we selected 4 representative economic releases for further investigation. Two of the selected releases are important (i.e. have significant and lasting price impact based on our regression results, and secondarily are considered important by our poll respondents), one is less important and one is of no significance for the intraday dynamics of the markets. We used these 4 representative releases to analyze the volatility dynamics.

We compared the representative releases in their likelihood of generating volatility and volatility clustering. We demonstrated that the likelihood of volatility clusters increased after the releases, and that it increased more in the case of more important releases. Moreover we compared the 3 major currency pairs for this purpose to determine if there are structural differences between the volatility characteristics of various currencies. Japanese yen seems to be the most volatile of the 3 major currencies both immediately prior and after the releases, followed by British pound. We cannot explain this difference at present, but some of the suggested further research may help explain the phenomenon. We found out that volatility cluster likelihood decays exponentially after the release, and the rate of the decay is fastest in the case of more important releases. This may be due to the fact that traders have been watching the market carefully in anticipation of an important release, absorb the release information quickly and act upon it in a short time. This urgency does not exist in case of lesser releases, hence the slower decay and lesser concentration of volatility clusters.

As part of our analysis of intraday volatility, we proposed a wavelet volatility estimator and showed that our proposed estimator is approximately 40 times more efficient than range volatility estimator. We used this wavelet approach to volatility estimation again in Chapters 4 and 5.

We further used the wavelets to explore the volatility of volatility. We demonstrated that it too increased after the release, and the volatility of volatility clustering seem to decay exponentially subsequent to the release. We further demonstrated that the clustering effect between any 2 of the 3 currencies correlates immediately after the release, but the correlation diminishes notably as time passes. We can explain this phenomena by noting that immediately after the release, traders are using all 3 major currencies to trade against US$ without discriminating among them, as the US$ seems to be the currency which is affected most. As time passes, traders start focusing on the specific pairs and their peculiarities, hence the dynamics of the 3 currency pairs differentiate. As each currency pair starts demonstrating its own unique characteristics, the correlations amongst the pairs decline.

As more currencies are traded via electronic platforms, the need for understanding the intraday volatility dynamics increases. Many asset managers and banks are engaged in very high frequency intraday trading. Our results could assist them in constructing trading models, setting profit and loss targets at the onset of economic releases, etc. For instance, many of the current trading models try to capture the volatility of the markets by dynamically trading on bid or ask side during the day. Thus these models will buy or sell partly based on their forecast of the likelihood of being able to reverse the trade at a profit within a few seconds to a few minutes. Our study will directly benefit such trading models as the trading algorithm may be adjusted to the rate of volatility decay after the release. The investor may use our results or use our approach and apply the wavelet method to other currencies and or assets. Moreover our analysis may be used in trading after the release in one currency pair against another currency pair. For instance, knowing that Japanese yen typically exhibits higher volatility clustering than Euro, an algorithm could be designed to trade the volatility in JPY/USD and EUR/USD while using the temporary misalignments in JPY/EUR bid ask spread to generate profit.

Additionally all major investment banks offer electronic trading platforms to their clients and the volume traded electronically is surpassing the traditional currency trades (i.e. by calling the banks and placing the order over the phone). The electronic trading interfaces use algorithms which determine the bid ask spread at each point of time mainly according to liquidity and volatility of that particular currency cross. Our methodology would help such banks calibrate their market making algorithms subsequent to economic releases.

In Chapter 4, we analyzed the individual investors' behavior in the US equity market during the 2008-2009 financial crisis. We did this by constructing an indicator which can be used as a proxy for equity holdings of individual investors, and comparing this indicator with another indicator which is publicly available but was never used in the literature before. We concluded that parametric methods were not the most suitable methods for the task. This was due to the fact that data of the financial crises includes jumps and discontinuities, and removing the outliers will change the nature of the data. Next we used non-parametric methods to determine if there were major changes in investor behavior during this period. We used change point analysis methods which assumed no priors on the distribution characteristics of the data. We concluded that change point analysis lends itself very nicely to our analysis, enabling us to determine 3 distinct phases in investor behavior: During the first part of 2008, investment sentiment is comparatively calmer leading to a lower variance in holdings of individuals. In this phase, individuals changed their positions less often and in smaller quantities compared to the next phase. In phase 2, which coincided approximately with the most volatile period of the financial crises, the variance in individuals' change in positions increased significantly. This meant that individuals were reacting to the radical changes in the market and changing their positions more notably. In the third phase, which roughly coincided with the calmer period after the peak of the financial crises, individuals' variance of trades subsided. Change point analysis used a numeric iterative algorithm to distinguish the various phases of the investors' behavior without any regard to the market conditions. The fact that the change points occur at approximately the same times when major shifts are taking place in the equity market is indeed intuitive and is evidence for the fact that change point analysis is in fact a useful approach for our analysis.

Moreover, we used a variation of decision tree analysis to determine the most important factors influencing the decisions of the individual investors during the 3 phases. In the first phase (which corresponded to a more steady state market), individuals' decisions were mostly influenced by daily returns of the equity market. In the more volatile phase 2, the investors' decisions could be best explained by changes in volatility of the market, rather than the return. The most important factors influencing the decision making of individuals were VIX and the returns of the most volatile sector of the equity market. Hence investors paid attention to and were driven by the volatile state of the market (which captured the headline news and media). In the last phase, which corresponded to a calmer market and appreciation of the equity market during the latter part of 2009, investors were not notably influenced by any individual factor. This lack of clear drivers for individuals' decision making was also evident by the fact that we demonstrated earlier that individuals sold their equity holding during the market crash and they sold most at the worst time when the market was at its lowest levels. After that sell off, individual investors for the most part did not reinvest their assets back into the equity market, and therefore missed the large market appreciation of latter part of 2009.

In Chapter 4, we also concluded that during 2008-2009, the individual investor community exhibited disposition effect. Their performance suffered due to the fact that they sold too early when the market was appreciating and postponed selling their positions when market was declining. We did not use a limited data set on individual investors as has been done before in the literature but used our proposed indicator of individual investor holdings to test disposition effect across all individual investors.

Having concluded that individuals demonstrated disposition effect, and therefore chose the wrong times to sell, we decided to test if a profitable trading model can be constructed that would use individual investor positions as a contrarian indicator. We constructed such a model, and concluded that taking contrarian positions to that of individual investors could have been highly profitable. We believe that our approach can be used in constructing profitable trading models in financial markets. We also showed that the most profitable periods for our contrarian model occurred during the periods of highest market volatility, which points to the fact that perhaps individuals were triggered by increased volatility to trade and react to the market, and this in effect caused further loss for their portfolios.

In Chapter 5, we used intraday data on individual investors' holding in EUR/USD and other high frequency data to quantify the intraday dynamics of investors' behavior. We demonstrated feedback trading in individual investor community. Feedback trading has been documented in other markets, but never before in the currency market. Moreover, typically individual investors' behavior is analyzed using data on individual portfolios, but we concluded that feedback trading could be observed on the individual investor community as a group. We also showed that one day return of EUR/USD has the biggest explanatory value among the factors that influenced individual investors' decision making.

Furthermore we demonstrated excessive trading among individuals. We concluded that similar to what has been documented in the equity market, individual investors in the currency market diminished their returns on their investments because they traded too often in their accounts. We showed that extending the trading period for an individual who held market portfolio could have improved her portfolio performance by a) saving her the bid ask spread and b) allowing a trend to be established in the market and benefiting from that trend.

Having demonstrated excessive trading among individuals, we proceeded to analyze what this excessive trading meant for the daily trading activity of individuals. We concluded that if individuals reacted to immediate market return (i.e. feedback trading) and traded too often (i.e. excessive trading), then we may be able to quantify the effects of these two phenomena on the day to day activity of individuals. We did this in the following manner: We used our wavelet volatility estimator to construct an intraday volatility data series and used a clustering algorithm to mathematically determine the location of clusters among the volatility data points. In this way, we did not relate the volatility clusters to the underlying conditions of the market, and determined the clustering pattern of intraday volatility by using a non-parametric statistical technique. We then determined the distribution of these volatility clusters by a kernel smoothening technique. By repeating this process for the intraday volatility of EUR/USD and intraday volatility of holdings of individual investors, we concluded that the clusters in the 2 data sets indeed coincide.

We further repeated the analysis for various volatility thresholds, and concluded that as intraday volatility increased, so did the likelihood of increasing volatility in individual investors' holdings. By setting up simulated portfolios, we established that this coincidence is statistically significant at 95% confidence. Because we did not use any priors about the market conditions in our study (i.e. we did not assume anything about what was happening at the time in the financial markets), we have established a relationship between an increase in market volatility and an increase in individual investor's trading activity.

This dissertation built upon the literature in understanding the intraday dynamics of the markets. We extended the findings of previous researchers and incorporated behavioral phenomena (namely disposition effect, feedback trading and excessive trading). We quantified the intraday dynamics of the currency market, as well as intraday behavior of individual investors. The common tool that was used throughout the analytical chapters in the dissertation was our proposed wavelet volatility estimator. By applying the wavelet volatility estimator to intraday and daily data in currency and equity data, we demonstrated its efficacy and versatility.

We hope that our findings would prove to be valuable for future researchers and practitioners.

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APPENDIX 1

Suggestions for further research

In Chapter 3, while we analyzed the price and volatility dynamics of major releases, we did not take into account the market conditions on the day of the release. Performing the research while calibrating the results based on various market conditions and specifically market sentiment indicators would provide us with insights into the behavioral aspects of intraday markets.

Moreover we ignored whether the release beat the market expectation (up side surprise) or fell short of it (down side surprise). Further research into the nature of surprises and differentiating the results based on upside or downside surprise will expand our understanding of market dynamics. Another modification would be to include the progression of forecasts leading to the release in the analysis.

As another extension of this research, by changing the order of arriving data in the periods adjacent to the release, one may explore if volatility is a function of magnitude of orders, or if the order of arrival matters for volatility and its clustering. If the order of arrival is important, then changing the order should change the results whereas if magnitude of the orders is the only important factor, then rearranging the order of arrival should not change the results.

Our research in Chapter 3 comprised of analysis of releases on individual currencies. A further step may include analyzing the effects of releases on a group (or a portfolio) of currencies. In this way, the interactions of currencies will provide us with a more detailed picture. Using Kalman filters for this purpose may be particularly fruitful, as its efficacy has been shown in related financial analysis, but not in high frequency finance as of yet (see Doust (2007) and Doust et. al (2007) for an interesting approach using Kalman filters which may be adapted for extension of our research).

Throughout this dissertation, we used a volatility estimation method based on wavelets. In Chapter 5, we showed how changing the level of the wavelet can reduce the number of data points in our volatility series, hence adjusting the volatility data to the desired frequency. For instance, we can use higher levels with more number of data points corresponding to more frequent observations (say daily) and use lower levels with less number of data points for less frequent observations (say weekly or monthly). This shows the flexibility of our proposed volatility estimation method for use with different frequencies. In traditional volatility estimations, one needs to "scale" the volatility using mathematical relationships. For instance, in order to calculate annual volatility (i.e. annualized standard deviation of returns) from monthly volatility, we divide the monthly volatility by square root of time (in this case $\sqrt{12}$). Our volatility estimation method can easily "scale" (i.e. be adjusted for various time periods) by using different wavelet levels. A next step in expanding the use of our volatility estimation method is to compare the scaling of the traditional volatility estimation results with the scaling using our volatility measure.

APPENDIX 2

Timeline of major events affecting the financial markets from 1 January 2008 to 31 December 2009.

January 22, 2008 | Federal Reserve Press Release
In an inter meeting conference call, the FOMC votes to reduce its target for the federal funds rate 75 basis points to 3.5 percent. The Federal Reserve Board votes to reduce the primary credit rate 75 basis points to 4 percent.
January 30, 2008 | Federal Reserve Press Release
The FOMC votes to reduce its target for the federal funds rate 50 basis points to 3 percent. The Federal Reserve Board votes to reduce the primary credit rate 50 basis points to 3.5 percent.
February 17, 2008 | United Kingdom Treasury Department Press Release
Northern Rock is taken into state ownership by the Treasury of the United Kingdom.
March 2008
March 5, 2008 | Carlyle Capital Corporation Press Release
Carlyle Capital Corporation receives a default notice after failing to meet margin calls on its mortgage bond fund.
March 7, 2008 | Federal Reserve Press Release
The Federal Reserve Board announces $50 billion TAF auctions
March 11, 2008 | Federal Reserve Press Release | Additional Information
The Federal Reserve Board announces the creation of the Term Securities Lending Facility (TSLF), which will lend up to $200 billion of Treasury securities for 28-day terms against federal agency debt, federal agency residential mortgage-backed securities (MBS), non-agency AAA/Aaa private label residential MBS, and other securities. The FOMC increases its swap lines with the ECB by $10 billion and the Swiss National Bank by $2 billion and also extends these lines through September 30, 2008.
March 14, 2008 | Federal Reserve Press Release
The Federal Reserve Board approves the financing arrangement announced by JPMorgan Chase and Bear Stearns [see note for March 24]. The Federal Reserve Board also announces they are “monitoring market developments closely and will continue to provide liquidity as necessary to promote the orderly function of the financial system.”

March 18, 2008 | Federal Reserve Press Release
The FOMC votes to reduce its target for the federal funds rate 75 basis points to 2.25 percent. The Federal Reserve Board votes to reduce the primary credit rate 75 basis points to 2.50 percent.
March 24, 2008 | Federal Reserve Bank of New York Press Release
The Federal Reserve Bank of New York announces that it will provide term financing to facilitate JPMorgan Chase & Co.'s acquisition of The Bear Stearns Companies Inc.
April 2008
April 30, 2008 | Federal Reserve Press Release
The FOMC votes to reduce its target for the federal funds rate 25 basis points to 2 percent. The Federal Reserve Board votes to reduce the primary credit rate 25 basis points to 2.25 percent.
June 5, 2008 | Federal Reserve Press Release
The Federal Reserve Board announces approval of the notice of Bank of America to acquire Countrywide Financial Corporation.
July 13, 2008 | Federal Reserve Press Release
The Federal Reserve Board authorizes the Federal Reserve Bank of New York to lend to the Federal National Mortgage Association (Fannie Mae) and the Federal Home Loan Mortgage Corporation (Freddie Mac), should such lending prove necessary.
July 15, 2008 | SEC Press Release
The Securities Exchange Commission (SEC) issues an emergency order temporarily prohibiting naked short selling in the securities of Fannie Mae, Freddie Mac, and primary dealers at commercial and investment banks.
July 30, 2008 | Public Law 110-289
President Bush signs into law the Housing and Economic Recovery Act of 2008 (Public Law 110-289), which, among other provisions, authorizes the Treasury to purchase GSE obligations and reforms the regulatory supervision of the GSEs under a new Federal Housing Finance Agency.
September 7, 2008 | Treasury Department Press Release
The Federal Housing Finance Agency (FHFA) places Fannie Mae and Freddie Mac in government conservatorship..
September 15, 2008 | Bank of America Press Release
Bank of America announces its intent to purchase Merrill Lynch & Co. for $50 billion.
September 15, 2008 | SEC Filing
Lehman Brothers Holdings Incorporated files for Chapter 11 bankruptcy protection.
September 16, 2008 | Federal Reserve Press Release

The Federal Reserve Board authorizes the Federal Reserve Bank of New York to lend up to $85 billion to the American International Group (AIG) under Section 13(3) of the Federal Reserve Act.

September 17, 2008 | Treasury Department Press Release

The U.S. Treasury Department announces a Supplementary Financing Program consisting of a series of Treasury bill issues that will provide cash for use in Federal Reserve initiatives.

September 17, 2008 | SEC Press Release

The SEC announces a temporary emergency ban on short selling in the stocks of all companies in the financial sector.

September 18, 2008 | Federal Reserve Press Release

The FOMC expands existing swap lines by $180 billion and authorizes new swap lines with the Bank of Japan, Bank of England, and Bank of Canada.

September 19, 2008 | Treasury Department Press Release

The U.S. Treasury Department announces a temporary guaranty program that will make available up to $50 billion from the Exchange Stabilization Fund to guarantee investments in participating money market mutual funds.

September 20, 2008 | Treasury Department Press Release | Draft Legislation

The U.S. Treasury Department submits draft legislation to Congress for authority to purchase troubled assets.

September 21, 2008 | Federal Reserve Press Release

The Federal Reserve Board approves applications of investment banking companies Goldman Sachs and Morgan Stanley to become bank holding companies.

September 25, 2008 | Office of Thrift Supervision Press Release

The Office of Thrift Supervision closes Washington Mutual Bank. JPMorgan Chase acquires the banking operations of Washington Mutual in a transaction facilitated by the FDIC.

September 26, 2008 | Federal Reserve Press Release

The FOMC increases existing swap lines with the ECB by $10 billion and the Swiss National Bank by $3 billion.

September 29, 2008 | FDIC Press Release

The FDIC announces that Citigroup will purchase the banking operations of Wachovia Corporation. The FDIC agrees to enter into a loss-sharing arrangement with Citigroup on a $312 billion pool of loans, with Citigroup absorbing the first $42 billion of losses and the FDIC absorbing losses beyond that. In return, Citigroup would grant the FDIC $12 billion in preferred stock and warrants.

September 29, 2008 | Treasury Department Press Release

The U.S. House of Representatives rejects legislation submitted by the Treasury Department requesting authority to purchase troubled assets from financial institutions [see note for September 20].

October 3, 2008 | H.R. 1424 | Public Law 110-343

Congress passes and President Bush signs into law the Emergency Economic Stabilization Act of 2008 (Public Law 110-343), which establishes the $700 billion Troubled Asset Relief Program (TARP).

October 8, 2008 | Federal Reserve Press Release

The FOMC votes to reduce its target for the federal funds rate 50 basis points to 1.50 percent.

October 12, 2008 | Federal Reserve Press Release

The Federal Reserve Board announces its approval of an application by Wells Fargo & Co. to acquire Wachovia Corporation.

October 13, 2008 | Federal Reserve Press Release

The FOMC increases existing swap lines with foreign central banks.

October 14, 2008 | Treasury Department TARP Press Release | Additional Information

U.S. Treasury Department announces the Troubled Asset Relief Program (TARP) that will purchase capital in financial institutions under the authority of the Emergency Economic Stabilization Act of 2008. The U.S. Treasury will make available $250 billion of capital to U.S. financial institutions. This facility will allow banking organizations to apply for a preferred stock investment by the U.S. Treasury. Nine large financial organizations announce their intention to subscribe to the facility in an aggregate amount of $125 billion.

October 29, 2008 | IMF Press Release

The International Monetary Fund (IMF) announces the creation of a short-term liquidity facility for market-access countries.

November 2008

November 10, 2008 | Federal Reserve Press Release

The Federal Reserve Board approves the applications of American Express and American Express Travel Related Services to become bank holding companies.

November 10, 2008 | Federal Reserve Press Release | Treasury Department Press Release

The Federal Reserve Board and the U.S. Treasury Department announce a restructuring of the government's financial support of AIG. The Treasury will purchase $40 billion of AIG preferred shares under the TARP program, a portion of which will be used to reduce the Federal Reserve's loan to AIG from $85 billion to $60 billion.

November 18, 2008 | Senate Hearing

Executives of Ford, General Motors, and Chrysler testify before Congress, requesting access to the TARP for federal loans.

November 23, 2008 | Federal Reserve Press Release | Summary of Terms

The U.S. Treasury Department, Federal Reserve Board, and FDIC jointly announce an agreement with Citigroup to provide a package of guarantees, liquidity access, and capital.

November 25, 2008 | Federal Reserve Press Release

The Federal Reserve Board announces the creation of the Term Asset-Backed Securities Lending Facility (TALF), under which the Federal Reserve Bank of New York will lend up to $200 billion on a non-recourse basis to holders of AAA-rated asset-backed securities and recently originated consumer and small business loans. The U.S. Treasury will provide $20 billion of TARP money for credit protection.

November 25, 2008 | Federal Reserve Press Release

The Federal Reserve Board announces a new program to purchase direct obligations of housing related government-sponsored enterprises (GSEs)—Fannie Mae, Freddie Mac and Federal Home Loan Banks—and MBS backed by the GSEs.

November 26, 2008 | Federal Reserve Press Release

The Federal Reserve Board announces approval of the notice of Bank of America Corporation to acquire Merrill Lynch and Company.

December 2008

December 2, 2008 | Federal Reserve Press Release

The Federal Reserve Board announces that it will extend three liquidity facilities, the Primary Dealer Credit Facility (PDCF), the Asset-Backed Commercial Paper Money Market Fund Liquidity Facility (AMLF), and the Term Securities Lending Facility (TSLF) through April 30, 2009.

December 3, 2008 | SEC Press Release

The SEC approves measures to increase transparency and accountability at credit rating agencies and thereby ensure that firms provide more meaningful ratings and greater disclosure to investors.

December 5, 2008 | Treasury Department CPP Transaction Report

The U.S. Treasury Department purchases a total of $4 billion in preferred stock in 35 U.S. banks under the Capital Purchase Program.

December 10, 2008 | FDIC Press Release

The FDIC reiterates the guarantee of federal deposit insurance in the event of a bank failure.
December 11, 2008 | NBER Press Release
The Business Cycle Dating Committee of the National Bureau of Economic Research announces that a peak in U.S. economic activity occurred in December 2007 and that the economy has since been in a recession.
December 12, 2008 | Treasury Department CPP Transaction Report
The U.S. Treasury Department purchases a total of $6.25 billion in preferred stock in 28 U.S. banks under the Capital Purchase Program.
December 15, 2008 | Federal Reserve Press Release
The Federal Reserve Board announces that it has approved the application of PNC Financial Services to acquire National City Corporation.
December 16, 2008 | Federal Reserve Press Release
The FOMC votes to establish a target range for the effective federal funds rate of 0 to 0.25 percent.
December 19, 2008 | Treasury Department Press Release | General Motors Term Sheet | Chrysler Term Sheet
The U.S. Treasury Department authorizes loans of up to $13.4 billion for General Motors and $4.0 billion for Chrysler from the TARP.
December 31, 2008 | Treasury Department CPP Transaction Report
The U.S. Treasury Department purchases a total of $1.91 billion in preferred stock from seven U.S. banks under the Capital Purchase Program.
January 5, 2009 | Federal Reserve Bank of New York Press Release
The Federal Reserve Bank of New York begins purchasing fixed-rate mortgage-backed securities guaranteed by Fannie Mae, Freddie Mac and Ginnie Mae under a program first announced on November 25, 2008.
January 8, 2009 | Moody's Special Comment on FHLB
Moody's Investor Services issues a report suggesting that the Federal Home Loan Banks are currently facing the potential for significant accounting write-downs on their $76.2 billion.
January 16, 2009 | Federal Reserve Press Release | Term Sheet
The U.S. Treasury Department, Federal Reserve, and FDIC announce a package of guarantees, liquidity access, and capital for Bank of America.
January 16, 2009 | Treasury Department Press Release
The U.S. Treasury Department, Federal Reserve and FDIC finalize terms of their guarantee agreement with Citigroup. (See announcement on November 23, 2008.)
January 16, 2009 | Treasury Department Press Release

The U.S. Treasury Department announces that it will lend $1.5 billion from the TARP to a special purpose entity created by Chrysler Financial to finance the extension of new consumer auto loans.

January 30, 2009 | Federal Reserve Press Release

The Board of Governors announces a policy to avoid preventable foreclosures on certain residential mortgage assets held, controlled or owned by a Federal Reserve Bank. The policy was developed pursuant to section 110 of the Emergency Economic Stabilization Act.

February 10, 2009 | Federal Reserve Press Release

The Federal Reserve Board announces that is prepared to expand the Term Asset-Backed Securities Loan Facility (TALF) to as much as $1 trillion.

February 17, 2009 | American Recovery and Reinvestment Act of 2009

President Obama signs into law the "American Recovery and Reinvestment Act of 2009", which includes a variety of spending measures and tax cuts intended to promote economic recovery.

February 18, 2009 | Executive Summary

President Obama announces The Homeowner Affordability and Stability

February 25, 2009 | Federal Reserve Press Release

The Federal Reserve Board, Federal Deposit Insurance Corporation, Office of the Comptroller of the Currency and Office of Thrift Supervision announce that they will conduct forward-looking economic assessments or "stress tests" of eligible U.S. bank holding companies with assets exceeding $100 billion.

February 26, 2009 | FDIC Quarterly Banking Profile

The FDIC announces that the number of "problem banks" increased from 171 institutions with $116 billion of assets at the end of the third quarter of 2008, to 252 insured institutions with $159 billion in assets at the end of fourth quarter of 2008.

February 26, 2009 | Fannie Mae Press Release

Fannie Mae reports a loss of $25.2 billion in the fourth quarter of 2008, and a full year 2008 loss of $58.7 billion.

February 27, 2009 | Treasury Department Press Release

The U.S. Treasury Department announces its willingness to convert up to $25 billion of Citigroup preferred stock issued under the Capital Purchase Program into common equity.

February 27, 2009 | Treasury Department CPP Transaction Report

The U.S. Treasury Department purchases a total of $394.9 million in preferred stock from 28 U.S. banks under the Capital Purchase Program.

March 2009

March 2, 2009 | AIG Press Release | Federal Reserve Press Release | Treasury Department Press Release

The U.S. Treasury Department and Federal Reserve Board announce a restructuring of the government's assistance to American International Group (AIG).

March 3, 2009 | Federal Reserve Press Release

The U.S. Treasury Department and the Federal Reserve Board announce the launch of the Term Asset-Backed Securities Loan Facility (TALF).

March 4, 2009 | Treasury Department Press Release

The U.S. Treasury Department announces guidelines to enable servicers to begin modifications of eligible mortgages under the Homeowner Affordability and Stability Plan.

March 6, 2009 | Treasury Department CPP Transaction Report

The U.S. Treasury Department purchases a total of $284.7 million in preferred stock from 22 U.S. banks under the Capital Purchase Program.

March 13, 2009 | Treasury Department CPP Transaction Report

The U.S. Treasury Department purchases a total of $1.45 billion in preferred stock from 19 U.S. banks under the Capital Purchase Program.

March 17, 2009 | FDIC Press Release

The Federal Deposit Insurance Corporation (FDIC) decides to extend the debt guarantee portion of the Temporary Liquidity Guarantee Program (TLGP) from June 30, 2009 through October 31, 2009.

March 18, 2009 | Federal Reserve Press Release

The FOMC votes to maintain the target range for the effective federal funds at 0 to 0.25 percent. In addition, the FOMC decides to increase the size of the Federal Reserve's balance sheet by purchasing up to an additional $750 billion of agency mortgage-backed securities, bringing its total purchases of these securities to up to $1.25 trillion this year, and to increase its purchases of agency debt this year by up to $100 billion to a total of up to $200 billion.

March 19, 2009 | Treasury Department Press Release

The U.S. Department of the Treasury announces an Auto Supplier Support Program that will provide up to $5 billion in financing to the automotive industry.

March 19, 2009 | Federal Reserve Bank of New York Press Release

The Federal Reserve Bank of New York releases the initial results of the first round of loan requests for funding from the Term Asset-Backed Securities Loan Facility (TALF). The amount of TALF loans requested at the March 17-19 operation was $4.7 billion.

March 19, 2009 | FDIC Press Release

The FDIC completes the sale of IndyMac Federal Bank to OneWest Bank. OneWest will assume all deposits of IndyMac, and the 33 branches of IndyMac will reopen as branches of OneWest on March 20. As of January 31, 2009, IndyMac had total assets of $23.5 billion and total deposits of $6.4 billion. IndyMac reported fourth quarter 2008 losses of $2.6 billion, and the total estimated loss to the Deposit Insurance Fund of the FDIC is $10.7 billion. The FDIC had been named conservator of IndyMac FSB on July 11, 2008.

March 23, 2009 | Federal Reserve Press Release

The Federal Reserve and the U.S. Treasury issue a joint statement on the appropriate roles of each during the current financial crisis and into the future, and on the steps necessary to ensure financial and monetary stability

March 23, 2009 | Treasury Department Press Release

The U.S. Treasury Department announces details on the Public-Private Investment Program for Legacy Assets.

March 25, 2009 | Treasury Department Press Release | Draft Legislation

The U.S. Treasury Department proposes legislation that would grant the U.S. government authority to put certain financial institutions into conservatorship or receivership to avert systemic risks posed by the potential insolvency of a significant financial firm.

March 26, 2009 | Treasury Department Press Release

The U.S. Treasury Department outlines a framework for comprehensive regulatory reform that focuses on containing systemic risks in the financial system.

March 31, 2009 | Treasury Department Press Release

The U.S. Treasury Department announces an extension of its temporary Money Market Funds Guarantee Program through September 18, 2009. This program will continue to provide coverage to shareholders up to the amount held in participating money market funds as of the close of business on September 19, 2008. The Program currently covers over $3 trillion of combined fund.

April 6, 2009 | Federal Reserve Press Release

The Federal Reserve announces new reciprocal currency agreements (swap lines) with the Bank of England, the European Central Bank, the Bank of Japan and the Swiss National Bank that would enable the provision of foreign currency liquidity by the Federal Reserve to U.S. financial institutions.

May 7, 2009 | Federal Reserve Press Release

The Federal Reserve releases the results of the Supervisory Capital Assessment Program ("stress test") of the 19 largest U.S. bank holding companies.

May 12, 2009 | Freddie Mac Press Release

Freddie Mac reports a first quarter 2009 loss of $9.9 billion, and a net worth deficit of $6.0 billion as of March 31, 2009

May 20, 2009 | FDIC Press Release

President Obama signs the Helping Families Save Their Homes Act of 2009, which temporarily raises FDIC deposit insurance coverage from $100,000 per depositor to $250,000 per depositor.

May 21, 2009 | Standard and Poor's Press Release

Standard and Poor's Ratings Services lowers its outlook on the United Kingdom government debt from stable to negative because of the estimated fiscal cost of supporting the nation's banking system

May 27, 2009 | FDIC Quarterly Banking Profile

The FDIC announces that the number of "problem banks" increased from 252 insured institutions with $159 billion in assets at the end of fourth quarter of 2008, to 305 institutions with $220 billion of assets at the end of the first quarter of 2009.

June 1, 2009 | GM Press Release

As part of a new restructuring agreement with the U.S. Treasury and the governments of Canada and Ontario, General Motors Corporation and three domestic subsidiaries announce that they have filed for relief under Chapter 11 of the U.S. Bankruptcy Code.

June 17, 2009 | U.S. Treasury Department Regulatory Reform Proposal

The U.S. Treasury Department releases a proposal for reforming the financial regulatory system. The proposal calls for the creation of a Financial Services Oversight Council and for new authority for the Federal Reserve to supervise all firms that pose a threat to financial stability, including firms that do not own a bank.

June 19, 2009 | Treasury Department CPP Transaction Report

June 25, 2009 | AIG Press Release

American International Group (AIG) announces that it has entered into an agreement with the Federal Reserve Bank of New York to reduce the debt AIG owes the Federal Reserve Bank of New York by $25 billion

June 30, 2009 | Treasury Department Press Release

The U.S. Treasury proposes a bill to Congress that would create a new Consumer Financial Protection Agency.

July 21, 2009 | Federal Reserve Press Release

Chairman Ben Bernanke presents the second of the Federal Reserve's semi-annual Monetary Policy Report to the Congress. Chairman Bernanke testifies that "the extreme risk aversion of last fall has eased somewhat, and investors are returning to private credit markets."

August 17, 2009 | Federal Reserve Press Release

The Federal Reserve Board and the Treasury Department announce an extension to the Term Asset-Backed Securities Loan Facility (TALF). Eligible loans against newly issued asset-backed securities (ABS) and legacy commercial mortgage-backed securities (CMBS) can now be made through March 31, 2010.

August 25, 2009 | White House Press Release

President Obama nominates Ben S. Bernanke for a second term as Chairman of the Board of Governors of the Federal Reserve System.

August 27, 2009 | FDIC Press Release

The FDIC announces that the number of "problem banks" increased from 305 insured institutions

with $220 billion in assets at the end of first quarter of 2009, to 416 institutions with $299.8 billion of

assets at the end of the second quarter of 2009.

September 14, 2009 | Treasury Department Press Release

The U.S. Treasury releases the report "The Next Phase of Government Financial Stabilization and Rehabilitation Policies." This report focuses on winding down those programs that were once deemed necessary to prevent systemic failure in the financial markets and the broader economy.

September 18, 2009 | Treasury Department Press Release

The U.S. Department of the Treasury announces the expiration of the Guarantee Program for Money Market Funds, which was implemented in the wake of the failure of Lehman Brothers in September 2008.

November 1, 2009 | CIT Bankruptcy Filing

CIT Group, Inc., files for bankruptcy protection under Chapter 11 of the bankruptcy code. The U.S. Government purchased $2.3 billion of CIT preferred stock in December 2008 under the Troubled Asset Relief Program (TARP). The firm's prepackaged bankruptcy is expected to wipe out the equity stakes of CIT's current shareholders, including the U.S. Government.

November 5, 2009 | Fannie Mae Press Release

Fannie Mae reports a net loss of $18.9 billion in the third quarter of 2009, compared with a loss of $14.8 billion in the second quarter of 2009. The loss resulted in a net worth deficit of $15.0 billion as of September 30,2009. The Acting Director of the Federal Housing Finance Agency submitted a request for $15.0 billion from the U.S.

Treasury to cover the deficit. Fannie Mae has lost a total of $111 billion since September, 2008, when the firm was placed under government conservatorship.

November 9, 2009 | Federal Reserve Press Release

The Federal Reserve Board announces that 9 of the 10 bank holding companies that were determined in the Supervisory Capital Assessment Program earlier this year to need to raise capital or improve the quality of their capital now have increased their capital sufficiently to meet or exceed their required capital buffers.

December 9, 2009 | U.S. Treasury Department Press Release

U.S. Treasury Secretary Timothy Geithner sends a letter to Congressional leaders outlining the Administration's exit strategy for the Troubled Asset Relief Program (TARP).

December 14, 2009 | Citigroup Press Release

Citigroup announces that it has reached an agreement with the U.S. Government to repay the remaining $20 billion in TARP trust preferred securities issued to the U.S. Treasury.

December 14, 2009 | Wells Fargo Press Release

Wells Fargo and Company announces that it will redeem the $25 billion of preferred stock issued to the U.S. Treasury under the TARP, upon successful completion of a $10.4 billion common stock offering.