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Estimation of Beta in a Simple Functional Capital Asset Pricing Model for High Frequency US Stock Data

Yan Zhang
Utah State University

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Estimation of beta in a simple functional capital asset pricing model for high frequency US stock data

Yan Zhang

May 8, 2011

Abstract

This project applies the methods of functional data analysis (FDA) to intra-daily returns of US corporations. It focuses on an extension of the Capital Asset Pricing Model (CAPM) to such returns. The CAPM is essentially a linear regression with the slope coefficient β . Returns of an asset are regressed on index return. We compare the estimates of β obtained for the daily and intra-daily returns. The variability of these estimates is assessed by two bootstrap methods. All computations are performed using statistical software R. Customized functions are developed to process the raw data, estimate the parameters and assess their variability.

The results turn out to be: First, the estimates of β obtained for the intra-daily returns have bigger absolute values than those for the daily returns; secondly, to assess the variability of the estimates of β obtained for the intra-daily returns, residual bootstrap method is more reliable than pairwise bootstrap method; thirdly, the estimates of β obtained for the intra-daily returns are much higher in absolute values in 2004 than those in any other years.

Acknowledgement

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Yan Zhang

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1 Motivation and Introduction

1.1 Functional Data Analysis

In statistics, generally speaking, what we are doing is to analyze given data and try to extract information from them. One of the most important aspects of data is what sort of structure they have. In most cases, we treat data as single numbers. However, when the sample of observations has the form: $X_1(t), X_2(t), \dots, X_N(t)$, where the argument t is almost continuous, it is difficult to apply statistical inference to them since they are “strings of data”, or functions, rather than just single points. If we just pick up one point out of each of these “strings” of data to represent the whole data and try to extract information from it, we will definitively lose the properties of the data as a whole since the values for neighboring arguments t are not always similar. So, if we can perform statistical inferences directly for these “strings” of data, we would probably get more accurate and informative results than using traditional methods.

Functional data analysis (FDA) is especially designed to deal with these “strings” of data: $X_1(t), X_2(t), \dots, X_N(t)$, where the index t is usually either a time or location in an interval. The advantage of FDA is quite obvious: when a sample of observations are functional objects over some consecutive points t , it is natural to convert these structured data into continuous functional objects and apply further mathematical and quantitative analysis to them based on the mathematical branch of functional analysis.

FDA, which is becoming more and more popular recently, finds a wide range of applications: high frequency climatic and geophysical data, internet traffic and stock prices, etc. In this research, we will apply FDA to the analysis of the price at every minute of every single US SP100 stock. Though the data is discrete and of large amount, by applying FDA we can transform these data into functions, and apply further inference to these functional objects.

1.2 Elements of Hilbert Space Formalism

In this section, we will briefly introduce some basic notations used in FDA, and which we will apply in our research. Since our research focuses on practical aspects, we will not introduce much mathematical background here. For more details, see Chapter 2 of Horváth and Kokoszka (2011).

The Hilbert Space L^2

Our research is based on calculations of functional objects in the Hilbert space L^2 . As we know, a Hilbert space is an abstract vector space possessing the structure of an inner product that allows length and angle to be measured. An L^2 is a separable Hilbert space

of square integrable functions with the inner product:

$$\langle x, y \rangle = \int x(t)y(t)dt,$$

in which, both $x(t)$ and $y(t)$ are measurable real-valued functions satisfying the conditions $\int x^2(t)dt < \infty$ and $\int y^2(t)dt < \infty$. The functions are typically rescaled, so that they are defined on the interval $[0, 1]$. The integrals then extend from 0 to 1.

The inner product generates the usual norm via

$$\|x\|^2 = \langle x, x \rangle = \int x^2(t)dt.$$

Random elements in L^2

A random curve $X = \{X(t), t \in [0, 1]\}$ is considered as a random element of L^2 .

We say that a random element X is integrable, if

$$E\|X\| = E\left[\int X(t)^2 d(t)\right]^{1/2} < \infty.$$

We say that a random element X is square integrable, if

$$E\|X\|^2 = E \int X(t)^2 d(t) < \infty.$$

If a random element X is integrable, its mean is defined by $\mu(t) = E[X(t)]$ for almost all $t \in [0, 1]$. If it is square integrable, the covariance and variance functions are also defined.

For ease of reference, we summarize the population parameters for functional data as follows:

Mean function:

$$\mu(t) = E[X(t)]$$

Covariance function:

$$c(t, s) = E[(X(t) - \mu(t))(X(s) - \mu(s))]$$

Variance function:

$$Var(t) = E[X(t) - \mu(t)]^2.$$

1.3 High Frequency Return Data

In our research, the raw data are from the database “Financial Price Data from RC research”, which is a product of 6 CDROMS from Price Data Instructions (for more information, please check the website: <http://www.price-data.com>). In this dataset, there are the values of S&P 100 index at every minute from 1997 to 2007. The S&P 100, or S&P 100 Index, is a stock market index of US stocks maintained by Standard & Poor’s. In fact, S&P 100 is a subset of the S&P 500, and it includes 100 leading U.S. stocks with exchange-listed options. In the dataset, there are 100 different stocks in S&P 100 with their price at every minutes through the year 1999 to 2007. As a preliminary step, we start our research with one of these 100 stocks: F (Ford Motor Corporation).

In finance, rate of return (ROR), also known as return on investment (ROI), rate of profit or sometimes just return, is the ratio of money gained or lost (whether realized or unrealized) on an investment relative to the amount of money invested. The amount of money gained or lost may be referred to as interest, profit/loss, gain/loss, or net income/loss. The money invested may be referred to as the asset, capital, principal, or the cost basis of the investment. Return is usually expressed as a percentage.

Because the data we have are recorded at every minute for 11 consecutive years, we say that we are dealing with high frequency data. In our research, we will calculate two types of returns from these high frequency prices with respect to 100 different stocks: the daily and the intra-daily returns.

1.4 Classical Capital Asset Pricing Model (CAPM)

Perhaps the best known application of linear regression to financial data is the celebrated Capital Asset Pricing Model (CAPM), see e.g. Chapter 5 of Campbell *et al.* (1997).

In finance, the capital asset pricing model (CAPM) is used to determine a theoretically appropriate required rate of return of an asset, if that asset is to be added to an already well-diversified portfolio, given that asset’s non-diversifiable risk. The model takes into account the asset’s sensitivity to non-diversifiable risk (also known as systematic risk or market risk), often represented by the quantity beta (β) in the financial industry, as well as the expected return of the market and the expected return of a theoretical risk-free asset.

In its simplest form, the CAPM is defined by

$$(1.1) \quad r_n = \alpha + \beta r_n^{(I)} + \varepsilon_n,$$

where α is a constant value, ε_n is a random noise which follows a normal distribution, r_n is the daily return, in percent, over a unit of time on a specific asset, e.g. a stock of a corporation, $r_n^{(I)}$ is the analogously defined return on a relevant market index, and P_n is the price the stock at the day n .

1.5 Daily Returns and Intra-daily Returns

As we mentioned in former subsection that we will apply CAPM to our research, one question that comes out is what difference will FDA brings out compared to the traditional methods. Traditionally, when researchers try to apply CAPM model, the return they implement in the model is called “Daily Return”, a return simply calculated by the closing price of the stock and the index. The daily return is defined by following definition.

DEFINITION 1.1 Suppose $P_n, n = 1, \dots, N$, is the closing price (the price of the last minute during a business day) of a financial asses at day n (N is the total number of days). We call the functions

$$r_n = 100[\ln P_n - \ln P_{n-1}], \quad n = 1, \dots, N,$$

the *daily returns*.

One may notice that, for the daily returns, information about the stock’s micro-behaviors during the whole day is neglected because we just apply the closing price of the day in daily returns. We would really like to work with intra-daily price data, which are known to have properties quite different than those of daily or monthly closing prices, see e.g. Chapter 5 of Tsay (2005); Guillaume *et al.* (1997) and Andersen and Bollerslev (1997a, 1997b). For these data, $P_n(t_j)$ is the price on day n at tick t_j (time of trade); we do not discuss issues related to the bid-ask spread, which are not relevant to what follows. For such data, it is not appropriate to define returns by looking at price movements between the ticks because that would lead to very noisy trajectories for which the methods d based on the FPC’s are not appropriate (Johnstone and Lu (2009) explain why principal components cannot be meaningfully estimated for noisy data). Instead, we adopt the following definition.

DEFINITION 1.2 Suppose $P_n(t_j), n = 1, \dots, N, j = 1, \dots, m$, is the price of a financial asses at time t_j on day n . We call the functions

$$r_n(t_j) = 100[\ln P_n(t_j) - \ln P_n(t_1)], \quad j = 2, \dots, m, \quad n = 1, \dots, N,$$

the *intra-daily cumulative returns*.

Figure 1.1 shows intra-daily cumulative returns on 10 consecutive days for the Standard & Poor's 100 index and the Exxon Mobil corporation.

Usually, what will people do to process statistical inferences to the intra-daily returns is to apply dummy variables with respect to different time intervals. However, in our research, we will try a new method to apply intra-daily returns, that is through FDA. So without breaking up the intra-daily return of one day into pieces, we will transform the whole days' intra-daily returns of every minute into a functional object and apply further statistical inferences to the functional object.

We propose an extension of the CAPM to such intra-daily return by postulating that

$$(1.2) \quad r_n(t) = \alpha + \beta r_n^{(I)}(t) + \varepsilon_n(t), \quad t \in [0, 1],$$

where the interval $[0, 1]$ is the rescaled trading period (in our examples, 9:30 to 16:00 EST).

1.6 Estimates of β for Daily Returns and Intra-daily Returns

The main purpose of our research is to calculate the estimates of the β of the CAPM model through both daily and intra-daily returns and try to find out some difference between these two methods. So, what we may concern is how to calculate the estimate of the β 's.

For daily returns, it is not difficult to calculate the beta by solving normal equation. Since the daily returns $r_n^{(I)}$ and r_n are scalars, the beta is estimated by the formula:

$$(1.3) \quad \hat{\beta} = (1/n \sum_{i=1}^N x_i^2)^{-1} (1/n \sum_{i=1}^N x_i y_i),$$

in which, we denote $x_i = r_i^{(I)}$ and $y_i = r_i$.

However, for intra-daily returns, the above formula is not applicable. Since we have already converted the "strings" of returns into functional objects, we can apply further calculations and deductions based on functional data analysis to find out $\hat{\beta}$ for the daily returns $r_n(t)$ and the intra-daily returns $r_n^{(I)}(t)$.

Now, let's derive the formula to calculate $\hat{\beta}$ for functional objects of intra-daily returns:

Denote $Y_n = r_n, X_n = r_n^{(I)}$. Then the model takes the form

$$Y_n = \alpha + \beta X_n + \varepsilon_n, \quad n = 1, \dots, N,$$

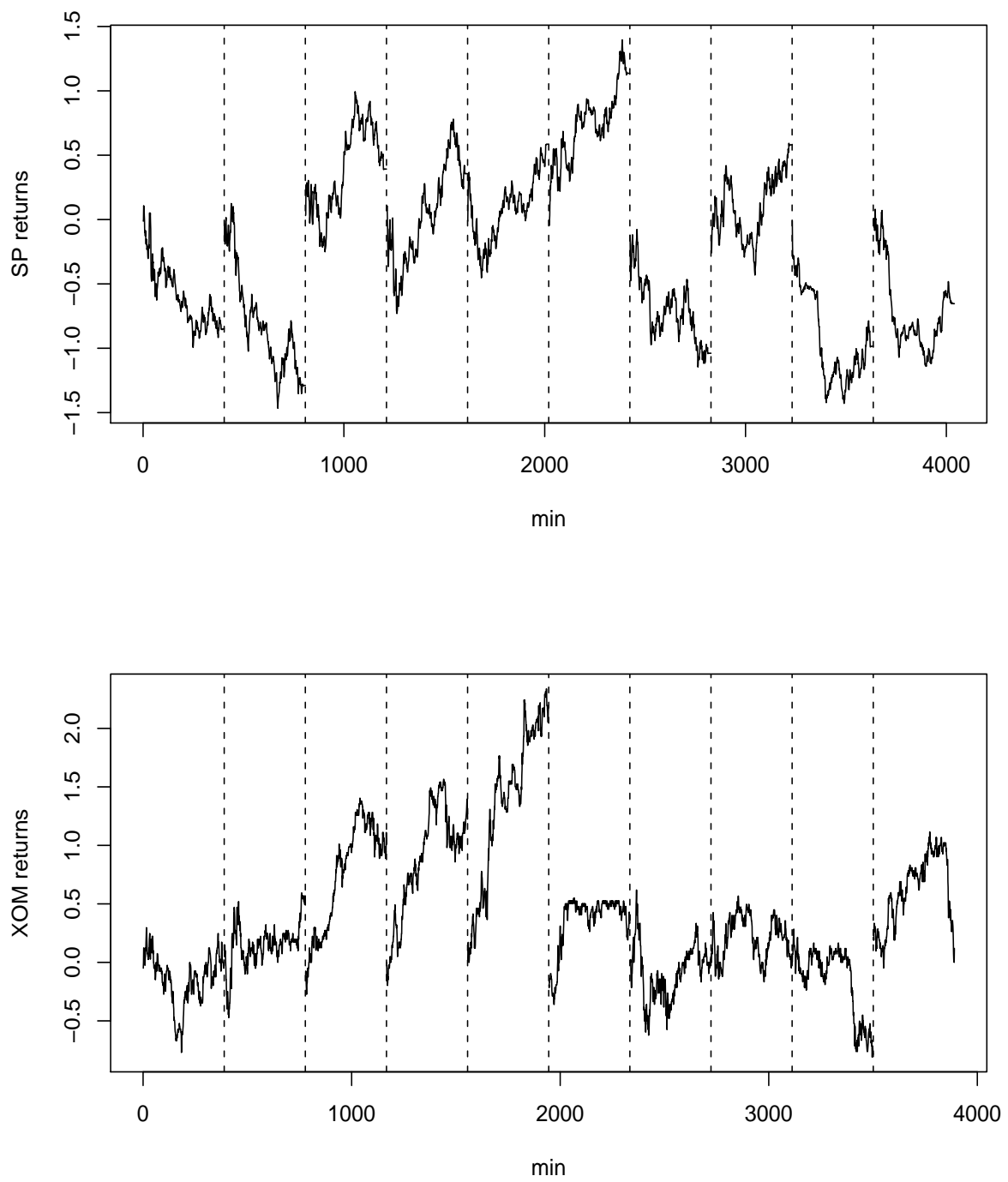


FIGURE 1.1 Intra-daily cumulative returns on 10 consecutive days for the Standard & Poor's 100 index (SP) and the Exxon-Mobil corporation (XOM).

We assume that the functional series Y_n and X_n are stationary. In particular the distribution of (X_n, Y_n) does not depend on n .

We define the optimal β as the value which minimizes the expected integrated square error

$$\begin{aligned} E \|Y_n - \beta X_n - \alpha\|^2 &= E \int [Y_n(t) - \beta X_n(t) - \alpha]^2 dt \\ &= E \|Y_n\|^2 + \beta^2 E \|X_n\|^2 + \alpha^2 - 2\beta E \langle Y_n, X_n \rangle - 2\alpha E \langle Y_n, 1 \rangle + 2\alpha\beta E \langle X_n, 1 \rangle. \end{aligned}$$

Differentiating with respect to α and β separately and let them equal to 0, we obtain:

$$\frac{\partial E \|Y_n - \beta X_n - \alpha\|^2}{\partial \alpha} = 2\alpha - E \langle Y_n, 1 \rangle + 2\beta E \langle X_n, 1 \rangle = 0$$

and

$$\frac{\partial E \|Y_n - \beta X_n - \alpha\|^2}{\partial \beta} = 2\beta E \|X_n\|^2 - 2E \langle Y_n, X_n \rangle + 2\alpha E \langle X_n, 1 \rangle = 0$$

We can solve α through the first equation above:

$$\alpha = E \langle Y_n, 1 \rangle - \beta E \langle X_n, 1 \rangle.$$

Then, we plug α into the second equation and obtain:

$$2\beta E \|X_n\|^2 - 2E \langle Y_n, X_n \rangle + 2(E \langle Y_n, 1 \rangle - \beta E \langle X_n, 1 \rangle) E \langle X_n, 1 \rangle = 0.$$

i.e.,

$$2\beta E \|X_n\|^2 - 2E \langle Y_n, X_n \rangle + 2E \langle Y_n, 1 \rangle E \langle X_n, 1 \rangle - 2\beta E \langle X_n, 1 \rangle E \langle X_n, 1 \rangle = 0.$$

i.e.,

$$\beta [E \|X_n\|^2 - (E \langle X_n, 1 \rangle)^2] = E \langle Y_n, X_n \rangle - E \langle X_n, 1 \rangle E \langle Y_n, 1 \rangle.$$

So, we can solve β from it:

$$\beta = \frac{E \langle Y_n, X_n \rangle - E \langle X_n, 1 \rangle E \langle Y_n, 1 \rangle}{E \|X_n\|^2 - (E \langle X_n, 1 \rangle)^2}.$$

This leads to a method of moments estimator for β :

$$\hat{\beta} = \frac{\frac{1}{N} \sum_{n=1}^N \langle Y_n, X_n \rangle - \frac{1}{N^2} \left(\sum_{n=1}^N \langle Y_n, 1 \rangle \right) \left(\sum_{n=1}^N \langle X_n, 1 \rangle \right)}{\frac{1}{N} \sum_{n=1}^N E \|X_n\|^2 - \frac{1}{N^2} \left(\sum_{n=1}^N \langle X_n, 1 \rangle \right)^2} = \frac{N \sum_{n=1}^N \langle Y_n, X_n \rangle - \left(\sum_{n=1}^N \langle Y_n, 1 \rangle \right) \left(\sum_{n=1}^N \langle X_n, 1 \rangle \right)}{N \sum_{n=1}^N E \|X_n\|^2 - \left(\sum_{n=1}^N \langle X_n, 1 \rangle \right)^2}$$

In sum, the formula of estimating beta for functional objects of intra-daily returns is given by:

$$(1.4) \quad \hat{\beta} = \frac{N \sum_{n=1}^N \langle Y_n, X_n \rangle - \left(\sum_{n=1}^N \langle Y_n, 1 \rangle \right) \left(\sum_{n=1}^N \langle X_n, 1 \rangle \right)}{N \sum_{n=1}^N E \|X_n\|^2 - \left(\sum_{n=1}^N \langle X_n, 1 \rangle \right)^2}$$

1.7 Objectives of Project

The objective of this project is to estimate the parameter β in model (1.2) for about 100 US stocks and several indices using high frequency data in one minute resolution. In addition, we will estimate β in model (1.1) for daily returns. The results will be organized by year, by sector, by index. We want to see if the estimates of β in model (1.2) and model (1.1) are similar, if there are any interesting patterns for years and sectors, how their variability changes from year to year and sector to sector, and how the variance estimates depend on the particular bootstrap method used.

So, in Section 2, we will introduce how to calculate the estimates of β of the CAPM for both daily and intra-daily returns. We will also introduce how to assess the variability of the estimates of β 's from both daily and intra-daily returns through both residual and pairwise bootstrap methods. In section 3, we will apply our method in section 2 to all the 100 US SP 100 stocks and check if there is any patterns we can find from a more general perspective, like whether the estimates of β behave differently across different sectors of the stock market. In section 4, we will introduce the conclusion and some possible directions of future work. Appendix A.1 to A.5 will illustrate the R and C code used for this project. Appendix A.6 will show all the tables containing comparison between the estimates of β and comparison of variability of estimates of β between two type of bootstrap method for both daily and intra-daily returns of each stock of US SP 100.

All work was done in R Development Core Team (2008), using R package FDA Ramsay *et al.* (2010) and XTABLE Dahl (2009).

2 Estimation of Beta in the Functional Framework

2.1 Raw Data Description and Processing

Given that a functional datum for the replication of n arrives as a set of discrete measured values, x_{n1}, \dots, x_{ni} , the first task is to convert these values to a function F_n with $F_n(t)$ computable for any desired continuous argument value t .

To start our research, the first step is to arrange our data into the form $F_n(t)$, where $F_n(t)$ represents the functional data form of a stock's price in day n with time t . Since we are going to use the data from 2002 to 2007 for each single stock due to the fact that some of the stocks have missing values for early years or certain days, n will be 2251 (2251 total business days from 2002 to 2007) and t will be 390 (total minutes within each business day).

However, the raw data from the dataset need to be transformed so that they can be processed by R. The raw data have following structures:

Date	Time	Start	High	Low	End
04/09/1997	09:34	13.3022	13.3022	13.3022	13.3022
04/09/1997	09:35	13.3022	13.3022	13.3022	13.3022
04/09/1997	09:36	13.3022	13.3022	13.3022	13.3022
.
.
.
04/10/1997	12:04	13.7163	13.7163	13.7163	13.7163
04/10/1997	12:05	13.7163	13.7163	13.7163	13.7163
04/10/1997	12:06	13.7163	13.7163	13.7163	13.7163
.
.
.
04/02/2007	15:57	8.09	8.09	8.08	8.09
04/02/2007	15:58	8.09	8.09	8.08	8.09
04/02/2007	15:59	8.08	8.09	8.08	8.09

There are 6 columns of the raw data: the first column is the Date including 2251 business days: from April 9th 1997 to April 2nd 2007 (we will separate these data into different 10 years). The remaining 4 columns correspond to the starting trading value, closing trading value, highest trading value and lowest trading value of one minute during one day. What

we do first is to take the average of the highest and lowest value at a particular minute, and then use this value to represent the price of the stock at this minute.

After that process, we will get the dataset table like:

Date	Time	Price
04/09/1997	09:34	13.3022
04/09/1997	09:35	13.3022
04/09/1997	09:36	13.3022
.	.	.
.	.	.
.	.	.
04/10/1997	12:04	13.7163
04/10/1997	12:05	13.7163
04/10/1997	12:06	13.7163
.	.	.
.	.	.
.	.	.
04/02/2007	15:57	8.085
04/02/2007	15:58	8.085
04/02/2007	15:59	8.085

Now, here comes the problem: all the data are arranged in a column with time order (390 minutes * 2251 days), but what we want is a matrix with rows corresponding to days, and columns corresponding to minutes. Besides, we observed that in this data set the days in a year differ from each other, for example, in the stock F, there are 185 business days for 1997, 251 days for 1998 and 61 days for 2005. So we cannot easily break this line of data simply by using some constant number (like a constant days of a year).

To solve this problem, we wrote a function in R, so that we can read the first column of the data (date) and put the days value into a row corresponding to certain columns as different time in a day as below:

	09:34	09:35	15:58	15:59
04/09/1997	13.3022	13.3022	NA	NA
.....
04/10/1997	13.6645	13.6645	13.5093	13.5093
.....
04/02/2007	7.8999	7.9200	8.085	8.085

We can either write some program in C++ to arrange the data, or we can use a R command to achieve this, the command is:

“reshape”

By using this code, we can reshape our data from vector into a matrix (rows representing date, and columns representing specific time of a business day). The code to arrange our data is like below:

```
data.F = read.table("F.txt")
colnames(data.F) = c("date","time","price")
wide.F = reshape(data.F, idvar="date",timevar="time",direction="wide")
```

Here, we defined the reshaped dataset as “wide.F”. In the parameter “idvar” we should input the variable in our rows and in the parameter “timevar” we should input the variable in our matrix’s columns.

So, after reshaping, the dataframe “wide.F” will appear like this in R:

```
      date price.09:34 price.09:35 price.09:36 price.09:37 price.09:38
1  04/09/1997  13.30220  13.30220  13.30220  13.30220  13.30220
356 04/10/1997  13.63865  13.69040  13.71630  13.71630  13.76805
709 04/11/1997  13.35400         NA         NA  13.37985  13.37985
1048 04/14/1997         NA  13.40570  13.40570  13.40570  13.45750
1364 04/15/1997  13.66450  13.63865  13.66450         NA  13.66450
1712 04/16/1997         NA         NA  14.02690  14.00100  13.97510
2085 04/17/1997  14.36330  14.36330  14.38920  14.38920  14.38920
2450 04/18/1997  14.18210  14.15625  14.18210  14.20800  14.18210
2783 04/21/1997         NA  14.23390  14.23390  14.28565  14.28565
3146 04/22/1997  14.33740  14.33740  14.28570  14.28570  14.28570
3481 04/23/1997  14.44090  14.38920  14.41505  14.38920  14.38920
```

Now we can see that columns from the 3rd column to the 392th column of this data matrix represent 390 minutes of a trading day. You may notice that the first column of this matrix actually shows how many data we have for a specific trading day. For example, in 04/09/1997, there are 355 numbers, however, in 04/10/1997, there are 353 numbers. The differences among these different trading day is due to the missing values.

At the same time, this program puts the dates in the second column in our date matrix, so we drop the first column of matrix, and let the row name equal to it:

```
F = wide.F[,-1]
rownames(F) = wide.F[,1]
```

Now, we have the dataset "F" as the stock "F" in the form of $F_n(x)$:

	price.09:34	price.09:35	price.09:36	price.09:37	price.09:38
04/09/1997	13.30220	13.30220	13.30220	13.30220	13.30220
04/10/1997	13.63865	13.69040	13.71630	13.71630	13.76805
04/11/1997	13.35400	NA	NA	13.37985	13.37985
04/14/1997	NA	13.40570	13.40570	13.40570	13.45750
04/15/1997	13.66450	13.63865	13.66450	NA	13.66450
04/16/1997	NA	NA	14.02690	14.00100	13.97510
04/17/1997	14.36330	14.36330	14.38920	14.38920	14.38920
04/18/1997	14.18210	14.15625	14.18210	14.20800	14.18210
04/21/1997	NA	14.23390	14.23390	14.28565	14.28565
04/22/1997	14.33740	14.33740	14.28570	14.28570	14.28570
04/23/1997	14.44090	14.38920	14.41505	14.38920	14.38920

What is more convenient is that, by reshaping the vector into the matrix, R automatically shows the missing value in our original dataset and labels it as "NA", which helps us substantially in the further steps of the study: it maintains the whole structure of data without losing important information while we we can still fix the missing values later.

The problem with NA values is that they will make R report errors when it comes to building functional objects through these data, so what we will do is to replace all these "NA" with a linear interpolation. The corresponding code is given in Appendix A.1

In the R function for linear interpolation we mentioned above, there are 3 parts: filling the first missing value (if they exist), filling the last missing values (if they exist), and

filling the elements in the middle (if they exist).

So, when we plug the data frame “F” into this function, it gives us the new “F”:

	price.09:30	price.09:31	price.09:32	price.09:33	price.09:34
04/09/1997	13.3022	13.3022	13.3022	13.30220	13.30220
04/10/1997	13.6645	13.6645	13.6645	13.66450	13.63865
04/11/1997	13.3540	13.3540	13.3540	13.35400	13.35400
04/14/1997	13.4057	13.4057	13.4057	13.40570	13.40570
04/15/1997	13.6128	13.6128	13.6128	13.63865	13.66450
04/16/1997	14.0269	14.0269	14.0269	14.02690	14.02690
04/17/1997	14.3892	14.3892	14.3633	14.38920	14.36330
04/18/1997	14.1821	14.1821	14.1821	14.15625	14.18210
04/21/1997	14.2339	14.2339	14.2339	14.23390	14.23390
04/22/1997	14.3374	14.3374	14.3374	14.33740	14.33740
04/23/1997	14.4409	14.4409	14.4409	14.41505	14.44090

2.2 Construction of the Returns as Functional Objects in R

Since we have all the data input in $F_n(x)$ form, now what we need to do is to transform them into the functional data returns. First of all, we take the natural log value of our data:

```
log.F = log(F.data)
```

Next, we will construct two types of returns in R. To begin with, let’s find out how to find the intra-daily return. In R, we write a simple loop procedure to build the numerical daily return like below:

```
log.1.F.a = mat.or.vec(dim(log.1.F)[1]-1,1)
for (i in 1:length(log.1.F.a))
{
log.1.F.a[i] = (log.1.F[i+1,dim(log.1.F)[2]])-
(log.1.F[i,dim(log.1.F)[2]])
}
```

```

}
Rn.1.F = data.frame( 100*(log.1.F.a))

```

What we did in this part of the code was to simply make the daily functional returns through loops which make the log price value of stock “F” of the minute of day “n” minus the log value of of stock “F” of the last minute of day “n-1”, namely the former day.

Now we are ready to construct the functional intra-daily return in R:

```

log.F = log(F.data)
log.F.a = mat.or.vec(dim(log.F)[1],dim(log.F)[2])
for (j in 1:dim(log.F)[2])
{
log.F.a[,j] = log.F[,j]-log.F[,1]
}

```

```

Rn.2.F = log.F.2.a[,2:390]

```

What we did in this part of the code was to simply make the daily functional returns through loops which make “log.F.2[,j]”, the log price value of stock “F” of minute “j” of every day minus “log.F.2[,1]”, the log value of of stock “F” of minute “1” (the first minute of a business day) of the same day.

Besides, after we calculate the return for stock F, we use the R code to write them to the document we use as default, so next time when we try to reload it, all we need to do is to use the command:

```

write(as.matrix(Rn.2.F), "Rn.2.F.txt", ncolumns=dim(Rn.2.F)[2])

```

In the same manner we can build functional return for SP100 as the predictor variable for later functional regression.

Due to the different definitions, the daily and the intra-daily returns are constructed as objects of different dimensions. For the daily returns, there are 2250 values in a 2250×1 dimension vector. The first row of our data matrix will not give us a return, since they are the starting row, so we have to calculate returns from the second row by starting using the last entry of the first row. On the other hand, for intra-daily return, its dimension is

2251×389, since the first column (representing the starting time of a day) is used up in this algorithm, leaving only 389 columns, namely from the second minute of a day to the last minute of a day.

Make functional objects by using B-spline basis for the returns.

So far, we have constructed two types of return: the daily return r_n and the intra-daily return $r_n(t_j)$ and $r_n^{(I)}$ from the stock price of F and S&P 100 separately. We will investigate the linear dependence between them in the next subsection. One thing that should be emphasized is that the daily return is just numerical value while the intra-daily return is a string of points, which need to be smoothed to be available for processing in the framework of functional data analysis. Here, a functional observation $\{r_n(t_j), 1 \leq t_j \leq 389\}$ is known to have a functional form $R_n(t)$. That means that we assume the existence of a function $R_n(t)$ giving rise to the observed data and the discrete points of $\{r_n(t_j)\}$ are also belong to a continuous function $R_n(t)$.

In functional data analysis, after we convert original data into the sequential form of functional data, $F_n(t)$ (or $R_n(t)$ for this section), what we usually apply to these functional data $F_n(t)$ is to smooth them by using linear combinations of basis functions as our main method to represent these functions. Smoothing, the conversion from discrete functional data into functions, is necessary to link adjacent data values in our functional data to some extent. If smoothing is not applied, few things can be gained by treating these data as functional rather than just multivariate.

So, to smooth the functional returns we need to construct functional objects through B-spline basis. A basis function system is “ a set of known functions ϕ_i which are mathematically independent from each other and have the property that we can approximately fit any function by taking a weighted sum or linear combinations of a sufficiently large number K of these functions” (See Chapter 3 of Ramsay and Silverman (2005)). Basis expansions represent a function $F_n(t)$ by a linear expansion

$$F_n(t) = \sum_{i=1}^K c_i \phi_i(t)$$

in terms of K known basis functions ϕ_i , c_i is the coefficient of basis function ϕ_i , and $c_i \in \mathbf{R}$.

Spline functions are the most common choice to smooth approximately non-periodic functions. Among many spline systems, the B-spline system developed by de Boor (2001) is the most popular, and the code to apply this method is available in many statistical

programming languages, such as R. One of the advantages of B-spline bases is that this method has a faster speed to compute, which, considering the size of our data set, is really helpful to our research.

Using the price of the stock Ford Motors and SP 100 in 1997, we will use the following code below to construct functional objects through B-spline bases in R:

```
library(fda)

minutetime = seq(from = 1, to = 389, by =1 )
minutebasis = create.bspline.basis(rangeval = c(0,389),nbasis = 49)
fd.2 = data2fd(c(rep(1,389)),minutetime,basisobj = minutebasis)
fd.F.2.1997 = data2fd(t(Rn.2.F.1997),minutetime,basisobj = minutebasis)
fd.sp.2.1997 = data2fd(t(Rn.2.sp.1997),minutetime,basisobj = minutebasis)
```

2.3 Estimating Beta for Functional Returns

Now, since we have formulas (1.3) and (1.4) to calculate $\hat{\beta}$ for daily and intra-daily return separately, what we need to do is to implement these mathematical formula to program code in R.

Given the daily return we get from Section 1.6, to estimate $\hat{\beta}$ for daily return by solving normal equations, we apply Formula 1.3:

$$\hat{\beta} = (1/N \sum_{i=1}^N x_i^2)^{-1} (1/N \sum_{i=1}^N x_i y_i),$$

and program this formula in R given in Appendix A.2, which is a function in R to calculate the $\hat{\beta}$ for daily return.

For the intra-daily return, since we have already wrote the R code for functional objects of intra-daily returns, what we should do now is to apply Formula 1.2:

$$\hat{\beta} = \frac{N \sum_{n=1}^N \langle Y_n, X_n \rangle - \left(\sum_{n=1}^N \langle Y_n, 1 \rangle \right) \left(\sum_{n=1}^N \langle X_n, 1 \rangle \right)}{N \sum_{n=1}^N E \|X_n\|^2 - \left(\sum_{n=1}^N \langle X_n, 1 \rangle \right)^2}$$

and code this estimate into R. (see Appendix A.3).

Below is the result of estimation of beta of stock F from 1997 to 2007 for daily and intra-daily returns separately:

Table 1: Two types of beta for Stock F from 1997 to 2007

Year	Daily Return	Intra-daily Returns
1997	0.67	0.70
1998	1.19	5.01
1999	0.94	2.54
2000	0.53	0.62
2001	0.79	-0.59
2002	1.07	7.73
2003	1.24	0.02
2004	1.39	-23.41
2005	1.36	-5.37
2006	1.14	-5.58
2007	1.12	3.65

From Table 1, we can see that pairwised $\hat{\beta}$ for daily returns and for intra-daily returns are very different except in the years 1997 and 2000. In most of the cases, $\hat{\beta}$'s for functional returns are larger than $\hat{\beta}$'s for daily returns. In 2004, the $\hat{\beta}$ for intra-daily return is -23.41, showing extremely large negative relationship between the stock F and the S&P 100 Index. This means that most of the time on a trading day, the trend of the rising and falling of the price of stock F is almost opposite to the trend of S&P 100 Index. The $\hat{\beta}$ for daily return is 1.39 in 2004, however, it seems that the price of stock F follows the trend of S&P 100 Index approximately. This illustrates the difference between the two types of returns. For the daily return, $\hat{\beta}$ is calculated only from the last price of a trading day without the continuous behavior of the stock for every minute of the day and ignoring the stock prices' fluctuation throughout the trading process. It will make sense that, in a wider perspective, every stock approximately follows the pooled S&P 100 Index in the long run, given that the information within a day is omitted. However, the intra-daily returns are obviously more informative, since we can extract more practical messages of the stocks' micro-behavior, than daily returns which can only offer more general information, i.e., the macro-behaviors, which would not help much to some people such as traders and brokers.

To illustrate this point, the Figure 2.1 shows the discrepancy between the trend of price of stock Ford Motor and the trend of S&P 100 Index in the first 10 trading days in 1997. In this graph, we can see that even though the trend for the stock Ford Motor and S&P

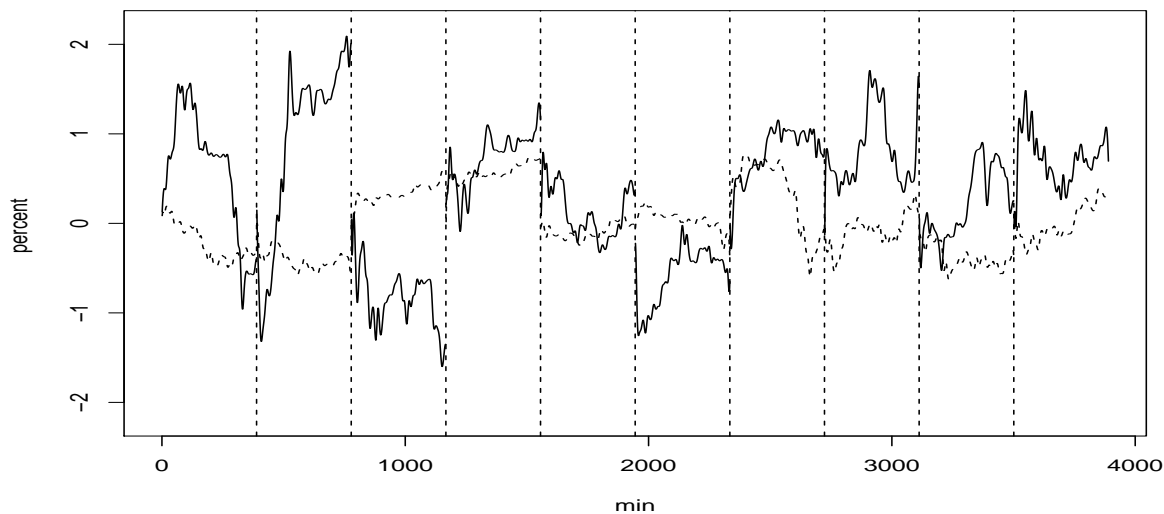


FIGURE 2.1 Intra-daily cumulative returns on first 10 consecutive days for the Ford Motor Corporation (F) (solid lines) and S&P 100 Index (dotted lines) in 2007.

100 Index are sometimes similar, but we also see that during some days, the two trends are totally different from each other. That is probably why $\hat{\beta}$'s from intra-daily returns are larger and more variable than $\hat{\beta}$'s from daily returns.

2.4 Accessing Variability of Beta through Residual and Pairwise Bootstrap Methods

After we calculated the estimates of β using formulas (1.3) and (1.4), representing daily returns and intra-daily returns separately, what we are concerned with now is how to evaluate the variability of these estimates of β .

One of the most common method in statistics to assess the variability of estimates is bootstrapping, which is a computer-based method for assigning measures of accuracy to sample estimates. The idea of bootstrap is to make inference about population quantity, β , for which we have already calculated the data-based estimate, $\hat{\beta}$. What we are interested in is to obtain information on the distribution of the sample estimates without making additional assumptions. What we can do is to resample with replacement from the data to get a great number of bootstrap samples. The observations are drawn from the original sample, with some appearing once, some twice, and so on. For each of these new samples,

we recalculate the estimate $\hat{\beta}$, and we denote these bootstrap estimates as $\hat{\beta}^*$'s. These $\hat{\beta}^*$'s contain information that can be used to apply inferences to the sample distribution, and we assume that $\hat{\beta}^*$ to $\hat{\beta}$ is like $\hat{\beta}$ to β .

In regression, there are two ways to resample with replacement from the data to get a bootstrap sample: to “resample residuals” or to “resample cases”. We use these two types of bootstrap: the residual bootstrap and the pairwise bootstrap. We will apply these methods in the framework of functional data analysis. We note that these methods have not been used for functional data yet, so one application will shed some light on their performance in this context.

Residual Bootstrap

The idea of Residual Bootstrap is as follows: we resample the residuals from the regression, and add the resampled residuals back to the models and recalculate the β 's. To illustrate this process, let us review the functional regression model we applied in previous sections:

$$Y_i = \alpha + \beta X_i + \varepsilon_i, \quad i = 1, \dots, N.$$

where, ε_i , Y_i and X_i are supposed to be functional objects, and N is the total number of observations.

We calculated the estimate of β : $\hat{\beta}$, which leads to the following equation:

$$\hat{Y}_i = \hat{\alpha} + \hat{\beta} X_i, \quad i = 1, \dots, N.$$

Next, we will plug back $\hat{\beta}$ to the model and calculate the estimated error $\hat{\varepsilon}_i$, which is functional object, too. This is the formula to calculate $\hat{\varepsilon}_i$:

$$\hat{\varepsilon}_i = Y_i - \hat{\beta} X_i - \hat{\alpha}, \quad i = 1, \dots, N.$$

To construct a bootstrap sample and randomly draw the residuals in R, we use the following code, in which we use the stock F for both daily and intra-daily returns in 1997 as an example:

- For daily returns:

```

alfa1.F.1997 = mean(Rn.1.F.1997-(beta1.F.1997[1,1])*(Rn.1.sp.1997))
e1.F.1997 = Rn.1.F.1997-(beta1.F.1997[1,1])*(Rn.1.sp.1997)-alfa1.F.1997

```

- For intra-daily returns:

```

alfa2.F.1997 = mean(Rn.2.F.1997-(beta2.F.1997[1,1])*(Rn.2.sp.1997))
e2.F.1997 = Rn.2.F.1997-(beta2.F.1997[1,1])*(Rn.2.sp.1997)-alfa2.F.1997

```

Then, we randomly reorder these estimated errors residuals while we denote them by $\hat{\varepsilon}_i'$. We add these $\hat{\varepsilon}_i'$'s back to $\hat{\beta}X_i$'s and get new response variables, Y_i' 's.

$$Y_i' = \hat{\alpha} + \hat{\beta}X_i + \varepsilon_i, \quad i = 1, \dots, N.'$$

Here, $\{\varepsilon_i'\}$ is the randomly drawn sample from $\hat{\varepsilon}_i$'s.

Finally, from the new pairs of predictor variables (X_i 's) and response variables (Y_i' 's), we calculate the estimator of the regression coefficient between them, $\hat{\beta}^*$.

$$Y_i' = \alpha + \hat{\beta}^*X_i, \quad i = 1, \dots, N.$$

Usually, if we apply confidence interval to assess the variability of the estimates of β , we will need at least 1000 bootstrap sample to make it meaningful. However, based on our condition, we can not afford that much time and resources. So in our research, we will draw 50 different bootstrap samples, namely, we will draw samples of ε_i' 's for 50 different times. Based on these 50 bootstrap sample, we will apply standard deviations to assess the variability of the estimates of β . So we will have a bootstrap sample with sample size equal to 50.

The above process is implemented in R as follows:

- For daily returns:

```

len.1.1997 = length(Rn.1.F.1997)[1]
bs.beta1.F.1997 = mat.or.vec(1,50)

```

```

for (i in 1:50)

```



```

{
sample.e1.F.1997 = e1.F.1997[sample(1:length(e1.F.1997))]
bs.1.F.1997 = (beta1.F.1997[1,1])*(Rn.1.sp.1997)+sample.e1.F.1997
bs.beta1.F.1997[i] = beta1(Rn.1.sp.1997,bs.1.F.1997,len.1.1997)
}

```

Table 2 lists 50 $\hat{\beta}^*$'s from 50 different residual bootstrap samples for daily returns:

Table 2: 50 $\hat{\beta}^*$'s from 50 different residual bootstrap samples for daily returns for stock F in 1997.

1.23	1.20	1.16	1.17	1.22	1.24	1.13	1.17	1.11	1.23
1.23	1.08	1.09	1.30	1.13	1.24	1.25	1.17	1.28	1.39
1.19	1.19	1.15	1.08	1.28	1.28	1.25	1.21	1.18	1.27
1.14	1.11	1.25	1.17	1.21	1.19	1.18	1.33	1.15	1.15
1.07	1.24	1.10	1.11	1.23	1.22	1.38	1.13	1.12	1.28

- For intra-daily returns:

```

minutetime = seq(from = 1, to = 389, by =1 )
minutebasis = create.bspline.basis(rangeval = c(0,389),nbasis = 49)
fd.2 = data2fd(c(rep(1,389)),minutetime,basisobj = minutebasis)
fd.sp.2.1997 = data2fd(t(Rn.2.sp.1997),minutetime,basisobj = minutebasis)
len.1997 = dim(Rn.2.F.1997)[1]
bs.beta2.F.1997 = mat.or.vec(1,50)

for (i in 1:50)
{
sample.e2.F.1997 = e2.F.1997[sample(1:dim(e2.F.1997)[1]),]
bs.2.F.1997 = (beta2.F.1997[1,1])*(Rn.2.sp.1997)+sample.e2.F.1997
fd.bs.2.F.1997 = data2fd(t(bs.2.F.1997),minutetime,basisobj = minutebasis)
bs.beta2.F.1997[i] = beta2(fd.sp.2.1997,fd.bs.2.F.1997,len.1997)
}

```

Table 3 lists 50 $\hat{\beta}^*$'s from 50 different residual bootstrap samples for intra-daily returns:

Table 3: 50 $\hat{\beta}^*$'s from 50 different residual bootstrap samples for intra-daily returns for stock F in 1997.

-0.51	-0.21	0.14	-0.41	-0.52	-0.68	-0.61	-1.25	-0.40	-0.22
-0.36	-0.13	-0.70	0.13	-0.88	-0.86	-0.42	-0.32	0.11	-0.08
-0.41	-0.42	-0.48	-0.14	-0.43	-0.67	-0.56	-0.18	0.02	0.08
-0.48	-0.60	-0.84	-0.84	-0.81	-0.30	-0.92	-0.29	-0.32	-0.93
-0.39	-0.27	-0.69	-0.62	-0.53	-0.83	-0.55	-0.32	-0.12	-1.34

Pairwise Bootstrap

The pairwise bootstrap, or bootstrap by pairs, proposed by Freedman (1981), means to resample directly from the original data: that is, to resample the response–predictor pairs.

Like the residual bootstrap, pairwise bootstrap begins with the typical regression model regardless whether the variables in the model are functional objects or numerical variables. Recall that the data are assumed to satisfy the relation:

$$Y_i = \alpha + \beta X_i + \varepsilon_i, \quad i = 1, \dots, N.$$

As noted by Flachaire (1999): resampling (Y_i, X_i) is equivalent to resampling $(X_i; \varepsilon_i)$ and then generating the dependent variable with the bootstrap DGP (data generating process):

$$Y_i^* = \alpha + \beta X_i^* + \varepsilon_i^*, \quad i = 1, \dots, N.$$

where Y_i^* and X_i^* are jointly resampled independently and with replacement in Y_i and X_i .

To apply the pairwise bootstrap method, all we need to do is to resample the pairs $\{Y_i, X_i\}$ 50 times, and estimate β from these resampled variables and record the estimators as $\hat{\beta}^*$'s. The estimators are calculated as the LSE's in the formula:

$$\hat{Y}_i^* = \hat{\alpha} + \hat{\beta}^* X_i^*, \quad i = 1, \dots, N.$$

For daily returns, it is quite simple to calculate the $\hat{\beta}^*$'s in R. Taking the stock F in 1997, as an example, the corresponding code is:

```

pair.bs.beta1.F.1997 = mat.or.vec(1,50)

for (i in 1:50)
{

sample.F.1997 = sample(1:length(Rn.1.sp.1997),replace=T)
pair.bs.Rn.1.F.1997 = Rn.1.F.1997[sample.F.1997]
pair.bs.Rn.1.sp.1997 = Rn.1.sp.1997[sample.F.1997]
pair.bs.beta1.F.1997[i] = beta1(pair.bs.Rn.1.sp.1997,pair.bs.Rn.1.F.1997,len.1.1997)
}

write(as.vector(pair.bs.beta1.F.1997),"pair.bs.beta1.F.1997.txt",ncolumns=50)

```

Table 4 lists 50 $\hat{\beta}^*$'s from 50 different pairwise bootstrap samples for daily returns:

Table 4: 50 $\hat{\beta}^*$'s from 50 different pairwise bootstrap samples for daily returns.

1.27	1.19	1.19	1.24	1.35	1.21	1.23	1.14	1.14	1.11
1.20	1.20	1.16	1.18	1.14	1.21	1.26	1.18	1.10	1.17
1.18	1.28	1.21	1.15	1.08	1.27	1.21	1.06	1.22	1.34
1.07	1.16	1.20	1.15	1.20	1.15	1.10	1.20	1.23	1.47
1.02	1.17	1.30	0.98	1.01	1.10	1.05	1.17	1.15	1.23

For intra-daily returns, however, since both predictors and response variables are both functional objects, the R code is more complicated. See Appendix A.4.

Table 5 lists 50 $\hat{\beta}^*$'s from 50 different pairwise bootstrap samples for the intra-daily returns:

Table 5: 50 $\hat{\beta}^*$'s from 50 different pairwise bootstrap samples for the intra-daily returns.

0.96	0.05	2.43	4.83	3.72	11.66	4.89	3.94	0.55	2.54
1.00	1.83	-67.15	3.01	-15.30	0.12	0.98	1.77	1.76	12.29
2.05	1.08	2.80	2.21	-0.10	1.72	-7.06	1.08	-3.89	2.27
1.05	7.62	1.53	3.69	3.33	0.47	1.43	4.82	2.29	1.64
-250.82	5.68	4.36	1.56	3.40	-12.54	2.40	2.61	5.51	2.06

Bootstrap standard deviation of the estimates of β

As mentioned in a former subsection, there are several methods to assess the variability of the least square estimates of β 's through both residual and pairwise bootstrap samples. Because we cannot afford to take 1000 bootstrap samples to apply the confidential intervals, we decide to use the standard deviation from a bootstrap sample of size 50 to assess the variability of the estimates of β .

Table 6: Standard deviations for the least square estimates of β 's for two types of returns resulting from two types of bootstrap samples for Ford Motor in 1997.

	residual	pairwise
daily	0.118	0.128
intra-daily	0.021	11.694

From Table 6, we can see that the standard deviation of daily returns remains around 0.12 for both residual and pairwise bootstrap methods. On the other hand, for the intra-daily returns, the residual bootstrap method has a much smaller standard deviation than the pairwise method. The residual bootstrap method gives a standard deviation of about 0.02, which is much smaller than for the daily returns. On the other hand, the pairwise method gives a much bigger standard deviation, 11.694. The reason why the standard deviation of the pairwise method is so large is because there are two extreme outliers in the sample of estimates of β 's (see Table 5) from the pairwise bootstrap method: -250.82 and -67.15, while other estimated β 's are within an absolute value of about 10. We also checked all the other 99 stocks, (see Appendix A.6), and it turns out that all of their standard deviations from the pairwise bootstrap samples are much higher than for the residual bootstrap method. This is probably because when we shuffle the Y's and X's in pairs, there is a small chance that some pairs of X and Y will show a significantly different pattern between them and will eventually give a huge number of β as regression coefficient. Based on this assumption and our calculations, we conclude that, to access the variability of the estimates of beta for intra-daily returns, the residual bootstrap method is a more precise way than the pairwise bootstrap method. As for traditional daily returns, both bootstrap methods behave almost identically. It must be emphasized that the above discussion is a bit speculative, and a systematic study of the behavior of bootstrap methods in the setting of functional regression is needed. We leave it as a topic for further research.

3 Application to 100 US Stocks from SP 100

3.1 Application to 100 Stocks from SP 100

In this section, we apply our research to all 100 stocks forming the S&P 100 index and check whether there is some pattern among these data. The research provided 100 tables, corresponding to 100 stocks, which are given in Appendix A.6. For a single stock, there are 7 columns in each table: year, Beta Daily ($\hat{\beta}$ for the daily returns), Beta Intra ($\hat{\beta}$ for the functional intra-daily returns), R.B.S Daily (standard deviation for the residual bootstrap sample for the daily returns), R.B.S Intra (standard deviation for the residual bootstrap sample for the functional intra-daily returns), P.B.S Daily (standard deviation for the pairwise bootstrap sample for the daily returns) and P.B.S Intra (standard deviation for the pairwise bootstrap sample for the intra-daily returns).

3.2 Patterns of Estimates of β for 100 Stocks from SP 100

From the results of above subsection, we discerned several patterns:

1. About 70 percent of the estimates of beta for intra-daily returns in 2004 are much larger in scale than any other years. In fact, they are so large that we can almost treat them as outliers. We have checked the functional returns in 2004 for both individual stocks and S&P 100 index in comparison with other years. We can find no specific reason for such a huge discrepancy. One hypothesis for this phenomenon is that the ratio between the single stock and SP100 index in 2004 are highest among these 11 years. Let us take the stock Ford Motor in the year 2001 and 2004 as an example . We find out that the span for the intra-daily returns in 2001 for stock F and S&P 100 index are both in the interval $(-6, 6)$, while the span for the stock F in 2001 is $(-4, 6)$ while span for the S&P 100 index in 2004 is merely $(-1.5, 1.5)$. The other hypothesis is that because the positive variability of the intra-daily returns for stock F in 2004 is much larger than the negative part, namely the span of the returns is not symmetric around the X-axis while in the other years the span is almost symmetric. I think more work need to be applied to investigate what is going on with the year 2004.
2. The estimates of beta from functional returns differ for the different sectors of S&P 100. To illustrate the difference among these sectors, we plot the average estimates of beta for different sectors (by using different colors) from year 1997 to 2007. Despite the huge outliers in 2004, the betas' spans differ just a little bit for each year: in 1997, all the sectors behave quite the same; in 1998, betas from every sector show negative values, and the average beta from the sector Bank has the most deviant

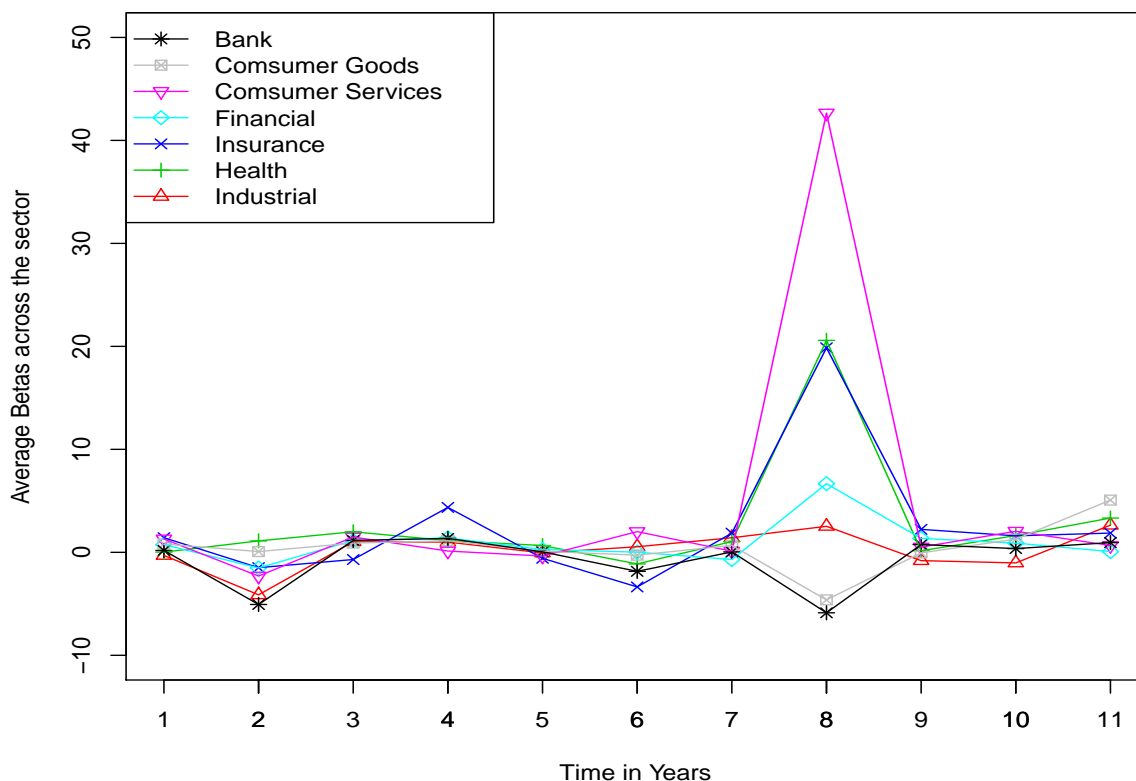


FIGURE 3.1 Average value of β of different sectors of S&P 100 Index from 1997 to 2007.

value; in the years 1999 to 2006, excluding 1997, the betas from all the sectors remain a constant pattern while the sector Insurance has an obviously larger scale than the other sectors; in 2007, it seems that the average betas from all the sectors show a positive value, with the sector Consumer Goods having the largest value.

3. Generally speaking, for all the stocks from the S&P 100, the span of values of beta from intra-daily returns are much larger than those from the daily returns. As discussed in former section, it may be due to the fact that the intra-daily returns contain more information about micro-behaviors between a stock and the S&P 100 index, the discrepancy between which will give a larger value of beta than for daily returns.

4 Conclusions and Future Work

Generally speaking, our results show that:

1. The estimates of β from the intra-daily returns are generally higher in absolute values than those from daily returns.
2. The estimates of β from the intra-daily returns in 2004 are much larger in absolute values than in other years, and more work is required to investigate what leads to this phenomenon.
3. The estimates of β from the intra-daily returns are more variable than those of the daily returns. The variability obtained from residual bootstrap is quite small while the variability obtained by the pairwise bootstrap is larger. Compared with the pairwise bootstrap method, the residual bootstrap method is more reliable. All we can assume is that when we shuffle the pairs $\{X_i, Y_i\}$ for the pairwise bootstrap sample, there will be some chance to generate some extreme pair of $\{X_i, Y_i\}$ with a huge $\hat{\beta}$ value. By this we mean, since the conclusion is basically speculative, more systematical investigations are needed for the bootstrap method for functional regression.
4. It seems there is no obvious pattern of dependence in sector or year. This may infer that the connections between the index and single stock have no differences across different sectors and time. Given that we suppose the intra-daily returns contain more information about micro-behaviors of the stock market, the stability of the behaviors of the estimates of beta is a sign that people's trading behaviors are not easily affected by different sectors or time.

For further application, we can check individual stocks' operating behaviors and compare those with the estimates of β 's we've got. We can try to analyze whether our results coincide with the micro-behavior of specific stock and whether there is better method to interpret the results.

Additionally, there are several things we can do to improve this research. One of them is to apply Machine Learning and Statistical Learning method into regressions based on functional data analysis. Machine Learning, known as a scientific discipline concerned with the design and development of algorithms that allow computers to evolve behaviors based on empirical data, is strong in calculation of regression and classification. It would be exciting to see if we can apply Machine Learning methods into functional data analysis.

Actually, some methods, Classification Trees for example, are quite applicable so far. In Classification Trees, the algorithm is called “Gini” criterion. Likewise, in Functional Data Analysis, we can set up certain scales of norm in Hilbert space as the criterion of “Gini”, and try to apply regression trees to functional data objects. The advantage of Statistical Learning method applied in functional data analysis should be exploit in the future. We hope it can save calculation time and bring more accuracy than simple algorithms. Hopefully it will also provide more opportunities to apply functional data analysis. We will definitively perform further research in this topic.

The other interesting direction is to apply a different formation of CAPM, the Fama-French 3-Factor Model (See Fama and French (1993)). The model is:

$$R_{i,t} = \alpha + \beta_1 MKTR_t + \beta_2 SMB_t + \beta_3 HML_t$$

in which $R_{i,t}$ is the portfolio’s rate of return, $MKTR_t$ is the return of the whole stock market, SMB_t stands for “small (market capitalization) minus big”, and HML_t stands for “high (book-to-market ratio) minus low”. Actually, to apply this model to our data, for SMB_t , we can use small stock portfolio minus big stock portfolio with each of them containing 5 or 10 stocks. Likewise, for HML_t , we can use the returns from high B/M values minus the returns from low B/M values, where the B/m, a measure of book-to-market ratio, is calculated by the ratio between the book value of Equity and the Market Capital. We can apply our functional returns into this model and see what result will we find.

The other improvement we can make is to apply an extension of CAPM to our functional returns by postulating the formula (See Gabrys *et al.* (2010)):

$$r_n(t) = \alpha(t) + \int \beta(t, s) r_n^{(I)}(s) d(s) + \varepsilon_n(t)$$

If the $\beta(t, s)$ is a Hilbert-Schmidt kernel, then

$$\beta(t, s) = \sum_{i=1, j=1}^{\infty} \beta_{i,j} \nu_i(t) \nu_j(s),$$

where ν_i forms a basis in $L^2([0, 1])$ and the products $\nu_i(t) \nu_j(s)$ forms a basis in $L^2([0, 1] \times [0, 1])$.

By applying this more complex model, we would see what the difference would be and which model fits the data better.

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A C and R Code used in the project

A.1 Linear Interpolation Function

This section presents R code developed to implement the interpolation method discussed in Section 2.1.

```
l_interpolation = function(df){

lx = length(df[,1])
ly = length(df[,1])

for (i in 1:ly){
  #filling first missing elements
  if( is.na(df[i,1])){
    l = 1;
    while (is.na(df[i,l])){
      l = l+1;
      if (l == lx){break;}
    }
    while (l>1){
      df[i,l-1] = c(df[i,l]);
      l = l-1;
    }
  }
  #filling last missing elements
  if( is.na(df[i,lx])){
    l = lx;
    while (is.na(df[i,l])){
      l = l-1;
      if (l == lx){break;}
    }
    while (l<lx){
      df[i,l+1] = c(df[i,l]);
      l = l+1;
    }
  }
  #filling elements in the middle
  l = 1;
  while(l = lx){
    if(is.na(df[i,l])){
      k = 1;
      while(is.na(df[i,l])){l = l+1;}
      m = l-1;
      d = c(df[i,m+1]-df[i,k-1])/(m-k+2);
      for(t in k:m){df[i,t] = df[i,t-1]+d}
      l = m;
    }
    l = l+1;
  }
}
}
```

```
return(df)
}
```

A.2 R Code for Estimate of Beta for Daily Returns

This section presents R code developed to calculate the estimate of β for the daily returns in Section 2.3.

```
beta1=function(X,Y,leng)
{
  up    = mat.or.vec (leng,1)
  down  = mat.or.vec (leng,1)

  for (i in 1:leng)
  {
    up[i] = (X[i]-mean(X))*(Y[i]-mean(Y))
  }

  for (i in 1:leng)
  {
    down[i] = (X[i]-mean(X))^2
  }
  total.up    = sum(up)
  total.down  = sum(down)
  total      = total.up / total.down
  return(total)
}
len.1.1997 = length(Rn.1.F.1997)[1]
beta1.F.1997 = beta1(Rn.1.sp.1997,Rn.1.F.1997,len.1.1997)
```

A.3 R Code for Estimation of Beta for Intra-daily Returns

This section presents R code developed to calculate the estimate of β for the intra-daily returns in Section 2.3.

```
beta2=function(X,Y,leng)
{
  upleft    = mat.or.vec (leng,1)
  upright1  = mat.or.vec (leng,1)
  upright2  = mat.or.vec (leng,1)
  downleft  = mat.or.vec (leng,1)
  downright = mat.or.vec (leng,1)

  for (i in 1:leng)
  {
    upleft[i] = inprod(Y[i,],X[i,])
  }
}
```

```

for (i in 1:leng)
{
    upright1 [i] = inprod(Y[i,],fd.2)
}

for (i in 1:leng)
{
    upright2 [i] = inprod(X[i,],fd.2)
}

upright = sum(upright1)*sum(upright2)

for (i in 1:leng)
{
    downright [i] = inprod(X[i,],fd.2)
}
for (i in 1:leng)
{
    downleft [i] = inprod(X[i,],X[i,])
}
total.up    = 1/leng*(sum(upleft))-1/(leng^2)*upright
total.down  = 1/leng*(sum(downleft))-1/(leng^2)*((sum(downright))^2)
total      = total.up / total.down
return(total)
}
len.1997 = dim(Rn.2.F.1997) [1]
beta2.F.1997 = beta2(fd.sp.2.1997,fd.F.2.1997,len.1997)

```

In which, function “beta2” is designed to calculate $\hat{\beta}$ from (1.4). And by the command “inprod” from R package “fda”, we can calculate the inner product between any pair of functional objects.

A.4 R Functions for Calculating Pairwise Bootstrap Samples of Intra-daily Returns for Stock F 1997

This section presents R code developed to implement the pairwise bootstrap sample for the estimates of β with a sample size equal to 50 in Section 2.4.

```

pair.bs.beta2.F.1997=mat.or.vec(1,50)

for (i in 1:50)
{
    sample.F.1997=sample(1:dim(Rn.2.sp.1997) [1],replace=T)

    pair.bs.fd.F.2.1997=data2fd(t(Rn.2.F.1997[sample.F.1997,]),
    minutetime,basisobj = minutebasis)

    pair.bs.fd.sp.for.F.2.1997=data2fd(t(Rn.2.sp.1997[sample.F.1997,]),
    minutetime,basisobj = minutebasis)

```

```

pair.bs.beta2.F.1997[i]= beta2(pair.bs.fd.sp.for.F.2.1997,
pair.bs.fd.F.2.1997,len.1997)

}
write(as.vector(pair.bs.beta2.F.1997),"pair.bs.beta2.F.1997.txt",ncolumns=50)

```

A.5 R Code for Stock F

In this section, we attached the whole piece of code to process the data of a single stock (Stock Ford Motor in this case) from the raw data stage to the last part of the data processing.

```

#####
#input raw data into the right form    #
#####

data.F = read.table("F_1.txt",sep=",")
colnames(data.F)
mean.value.F = apply(data.F[,5:6],1,mean)
data.new.F = cbind(data.F[,1:2],mean.value.F)
colnames(data.new.F) = c("date","time","price")
wide.F = reshape(data.new.F, idvar = "date",timevar="time",direction="wide")
F = wide.F[,-1]
rownames(F) = wide.F[,1]

#order the columns
F.sorted = F[,order(colnames(F))]
F.data = l_inteprolation(F.sorted)
dim(F.sorted)

write(t(as.matrix(F.data)),"F.data.txt",ncolumns=dim(F.data)[2])
write(as.vector(rownames(F.data)),"F.data.rownames.txt",ncolumns=dim(F.data)[1])
write(as.vector(colnames(F.data)),"F.data.colnames.txt",ncolumns=dim(F.data)[2])

Rn.2.sp = read.table("Rn.2.sp.txt")
rownames(Rn.2.sp) = t(t(read.table("Rn.2.sp.rownames.txt")))
colnames(Rn.2.sp) = t(t(read.table("Rn.2.sp.colnames.txt")))
Rn.1.sp = data.frame(t(read.table("Rn.1.sp.txt")))
rownames(Rn.1.sp) = rownames(Rn.2.sp)[-1]
Rn.2.sp = Rn.2.sp[7:2517,]

F.data.t = F.data[rownames(Rn.2.sp),]
rownames(F.data.t) = rownames(Rn.2.sp)

```

```

#F.data = data.frame(read.table("F.data.txt"))
#rownames(F.data) = t(t(as.vector(read.table("F.data.rownames.txt"))))
#colnames(F.data) = t(t(as.vector(read.table("F.data.colnames.txt"))))

mean.F=(sum(F.data.t,na.rm=T)/sum(F.data.t!=0,na.rm=T))

for( i in 1:dim(F.data.t)[2])
{
F.data.t[is.na(F.data.t[,i]),i] = mean.F
}
for( i in 1:dim(F.data.t)[2])
{
F.data.t[i,is.na(F.data.t[i,])] = mean.F
}

F.data = mat.or.vec(dim(F.data.t)[1],dim(F.data.t)[2])
F.data = F.data.t

#####
# the daily return #
#####

log.1.F = log(F.data)
log.1.F.a = mat.or.vec(dim(log.1.F)[1]-1,1)
for( i in 1:length(log.1.F.a))
{
log.1.F.a[i]= (log.1.F[i+1,dim(log.1.F)[2]])-(log.1.F[i,dim(log.1.F)[2]])
}
Rn.1.F = data.frame( 100*(log.1.F.a))
rownames(Rn.1.F)=rownames(F.data[-1,])

Rn.1.sp = data.frame(Rn.1.sp[c(rownames(Rn.1.F)),])
rownames(Rn.1.sp) = rownames(Rn.1.F)

Rn.1.sp.1997 = Rn.1.sp [1:185,]
Rn.1.sp.1998 = Rn.1.sp [186:437,]
Rn.1.sp.1999 = Rn.1.sp [438:689,]
Rn.1.sp.2000 = Rn.1.sp [690:941,]
Rn.1.sp.2001 = Rn.1.sp [942:1190,]
Rn.1.sp.2002 = Rn.1.sp [1191:1441,]
Rn.1.sp.2003 = Rn.1.sp [1442:1693,]
Rn.1.sp.2004 = Rn.1.sp [1694:1946,]

```

```
Rn.1.sp.2005 = Rn.1.sp [1947:2197,]
Rn.1.sp.2006 = Rn.1.sp [2198:2448,]
Rn.1.sp.2007 = Rn.1.sp [2449:2250,]
```

```
Rn.1.F.1997 = Rn.1.F [1:185,]
Rn.1.F.1998 = Rn.1.F [186:437,]
Rn.1.F.1999 = Rn.1.F [438:689,]
Rn.1.F.2000 = Rn.1.F [690:941,]
Rn.1.F.2001 = Rn.1.F [942:1190,]
Rn.1.F.2002 = Rn.1.F [1191:1441,]
Rn.1.F.2003 = Rn.1.F [1442:1693,]
Rn.1.F.2004 = Rn.1.F [1694:1946,]
Rn.1.F.2005 = Rn.1.F [1947:2197,]
Rn.1.F.2006 = Rn.1.F [2198:2448,]
Rn.1.F.2007 = Rn.1.F [2449:2250,]
```

```
#####
#the intra-daily return:      #
#####
```

```
F.data[,1]
```

```
log.F = log(F.data)
log.F.a = mat.or.vec(dim(log.F)[1],dim(log.F)[2])
for (j in 1:dim(log.F)[2])
{
log.F.a[,j] = log.F[,j]-log.F[,1]
}
```

```
#for (i in 1:dim(log.F)[2])
#{
#for (j in 1:dim(log.F)[1])
#{
#log.F.a[j,i] = log.F[j,i]- log.F[j,1]
#}
#}
Rn.2.F = 100*(log.F.a[,2:dim(log.F.a)[2]])
```

```
rownames(Rn.2.F) = rownames(F.data)
colnames(Rn.2.F) = colnames(F.data[, -1])
```

```
write(t(as.matrix(Rn.2.F)), "Rn.2.F.txt", ncolumns = dim(Rn.2.F)[2])
write(as.vector(rownames(Rn.2.F)), "Rn.2.F.rownames.txt", ncolumns = dim(Rn.2.F)[1])
write(as.vector(colnames(Rn.2.F)), "Rn.2.F.colnames.txt", ncolumns = dim(Rn.2.F)[2])
```

```
#Rn.2.F = Rn.2.F[c(rownames(Rn.2.sp)),]
```

```
#for( i in 1:dim(Rn.2.sp)[2])  
#{  
#Rn.2.F[is.na(Rn.2.F[,i]),i]=0  
#}
```

```
Rn.2.sp.1997 = Rn.2.sp [1:186,]  
Rn.2.sp.1998 = Rn.2.sp [187:438,]  
Rn.2.sp.1999 = Rn.2.sp [439:690,]  
Rn.2.sp.2000 = Rn.2.sp [691:942,]  
Rn.2.sp.2001 = Rn.2.sp [943:1191,]  
Rn.2.sp.2002 = Rn.2.sp [1192:1442,]  
Rn.2.sp.2003 = Rn.2.sp [1443:1694,]  
Rn.2.sp.2004 = Rn.2.sp [1695:1947,]  
Rn.2.sp.2005 = Rn.2.sp [1948:2198,]  
Rn.2.sp.2006 = Rn.2.sp [2199:2449,]  
Rn.2.sp.2007 = Rn.2.sp [2450:2251,]
```

```
Rn.2.F.1997 = Rn.2.F [1:186,]  
Rn.2.F.1998 = Rn.2.F [187:438,]  
Rn.2.F.1999 = Rn.2.F [439:690,]  
Rn.2.F.2000 = Rn.2.F [691:942,]  
Rn.2.F.2001 = Rn.2.F [943:1191,]  
Rn.2.F.2002 = Rn.2.F [1192:1442,]  
Rn.2.F.2003 = Rn.2.F [1443:1694,]  
Rn.2.F.2004 = Rn.2.F [1695:1947,]  
Rn.2.F.2005 = Rn.2.F [1948:2198,]  
Rn.2.F.2006 = Rn.2.F [2199:2449,]  
Rn.2.F.2007 = Rn.2.F [2450:2251,]
```

```
#####  
#the estimation beta of daily return: #  
#####
```

```
len.1.1997 = length(Rn.1.F.1997)[1]  
len.1.1998 = length(Rn.1.F.1998)[1]  
len.1.1999 = length(Rn.1.F.1999)[1]  
len.1.2000 = length(Rn.1.F.2000)[1]  
len.1.2001 = length(Rn.1.F.2001)[1]  
len.1.2002 = length(Rn.1.F.2002)[1]  
len.1.2003 = length(Rn.1.F.2003)[1]  
len.1.2004 = length(Rn.1.F.2004)[1]  
len.1.2005 = length(Rn.1.F.2005)[1]
```



```

len.1.2006 = length(Rn.1.F.2006)[1]
len.1.2007 = length(Rn.1.F.2007)[1]

beta1.F.1997 = beta1(Rn.1.sp.1997,Rn.1.F.1997,len.1.1997)
beta1.F.1998 = beta1(Rn.1.sp.1998,Rn.1.F.1998,len.1.1998)
beta1.F.1999 = beta1(Rn.1.sp.1999,Rn.1.F.1999,len.1.1999)
beta1.F.2000 = beta1(Rn.1.sp.2000,Rn.1.F.2000,len.1.2000)
beta1.F.2001 = beta1(Rn.1.sp.2001,Rn.1.F.2001,len.1.2001)
beta1.F.2002 = beta1(Rn.1.sp.2002,Rn.1.F.2002,len.1.2002)
beta1.F.2003 = beta1(Rn.1.sp.2003,Rn.1.F.2003,len.1.2003)
beta1.F.2004 = beta1(Rn.1.sp.2004,Rn.1.F.2004,len.1.2004)
beta1.F.2005 = beta1(Rn.1.sp.2005,Rn.1.F.2005,len.1.2005)
beta1.F.2006 = beta1(Rn.1.sp.2006,Rn.1.F.2006,len.1.2006)
beta1.F.2007 = beta1(Rn.1.sp.2007,Rn.1.F.2007,len.1.2007)

write(beta1.F.1997,"beta1.F.1997.txt")
write(beta1.F.1998,"beta1.F.1998.txt")
write(beta1.F.1999,"beta1.F.1999.txt")
write(beta1.F.2000,"beta1.F.2000.txt")
write(beta1.F.2001,"beta1.F.2001.txt")
write(beta1.F.2002,"beta1.F.2002.txt")
write(beta1.F.2003,"beta1.F.2003.txt")
write(beta1.F.2004,"beta1.F.2004.txt")
write(beta1.F.2005,"beta1.F.2005.txt")
write(beta1.F.2006,"beta1.F.2006.txt")
write(beta1.F.2007,"beta1.F.2007.txt")

#####
#the estimation of beta intra-daily return:                                     #
#####

#Rn.2.F = read.table("Rn.2.F.txt")
#rownames(Rn.2.F) = t(t(read.table("Rn.2.F.rownames.txt")))
#colnames(Rn.2.F) = t(t(read.table("Rn.2.F.colnames.txt")))

library(fda)

minutetime = seq(from = 1, to = 389, by = 1 )
minutebasis = create.bspline.basis(rangeval = c(0,389),nbasis = 49)
fd.2 = data2fd(c(rep(1,389)),minutetime,basisobj = minutebasis)

fd.F.2.1997=data2fd(t(Rn.2.F.1997),minutetime,basisobj = minutebasis)
fd.F.2.1998=data2fd(t(Rn.2.F.1998),minutetime,basisobj = minutebasis)
fd.F.2.1999=data2fd(t(Rn.2.F.1999),minutetime,basisobj = minutebasis)
fd.F.2.2000=data2fd(t(Rn.2.F.2000),minutetime,basisobj = minutebasis)
fd.F.2.2001=data2fd(t(Rn.2.F.2001),minutetime,basisobj = minutebasis)
fd.F.2.2002=data2fd(t(Rn.2.F.2002),minutetime,basisobj = minutebasis)
fd.F.2.2003=data2fd(t(Rn.2.F.2003),minutetime,basisobj = minutebasis)

```

```

fd.F.2.2004=data2fd(t(Rn.2.F.2004),minutetime,basisobj = minutebasis)
fd.F.2.2005=data2fd(t(Rn.2.F.2005),minutetime,basisobj = minutebasis)
fd.F.2.2006=data2fd(t(Rn.2.F.2006),minutetime,basisobj = minutebasis)
fd.F.2.2007=data2fd(t(Rn.2.F.2007),minutetime,basisobj = minutebasis)

fd.sp.2.1997=data2fd(t(Rn.2.sp.1997),minutetime,basisobj = minutebasis)
fd.sp.2.1998=data2fd(t(Rn.2.sp.1998),minutetime,basisobj = minutebasis)
fd.sp.2.1999=data2fd(t(Rn.2.sp.1999),minutetime,basisobj = minutebasis)
fd.sp.2.2000=data2fd(t(Rn.2.sp.2000),minutetime,basisobj = minutebasis)
fd.sp.2.2001=data2fd(t(Rn.2.sp.2001),minutetime,basisobj = minutebasis)
fd.sp.2.2002=data2fd(t(Rn.2.sp.2002),minutetime,basisobj = minutebasis)
fd.sp.2.2003=data2fd(t(Rn.2.sp.2003),minutetime,basisobj = minutebasis)
fd.sp.2.2004=data2fd(t(Rn.2.sp.2004),minutetime,basisobj = minutebasis)
fd.sp.2.2005=data2fd(t(Rn.2.sp.2005),minutetime,basisobj = minutebasis)
fd.sp.2.2006=data2fd(t(Rn.2.sp.2006),minutetime,basisobj = minutebasis)
fd.sp.2.2007=data2fd(t(Rn.2.sp.2007),minutetime,basisobj = minutebasis)

len.1997 = dim(Rn.2.F.1997) [1]
len.1998 = dim(Rn.2.F.1998) [1]
len.1999 = dim(Rn.2.F.1999) [1]
len.2000 = dim(Rn.2.F.2000) [1]
len.2001 = dim(Rn.2.F.2001) [1]
len.2002 = dim(Rn.2.F.2002) [1]
len.2003 = dim(Rn.2.F.2003) [1]
len.2004 = dim(Rn.2.F.2004) [1]
len.2005 = dim(Rn.2.F.2005) [1]
len.2006 = dim(Rn.2.F.2006) [1]
len.2007 = dim(Rn.2.F.2007) [1]

beta2.F.1997 = beta2(fd.sp.2.1997,fd.F.2.1997,len.1997)
beta2.F.1998 = beta2(fd.sp.2.1998,fd.F.2.1998,len.1998)
beta2.F.1999 = beta2(fd.sp.2.1999,fd.F.2.1999,len.1999)
beta2.F.2000 = beta2(fd.sp.2.2000,fd.F.2.2000,len.2000)
beta2.F.2001 = beta2(fd.sp.2.2001,fd.F.2.2001,len.2001)
beta2.F.2002 = beta2(fd.sp.2.2002,fd.F.2.2002,len.2002)
beta2.F.2003 = beta2(fd.sp.2.2003,fd.F.2.2003,len.2003)
beta2.F.2004 = beta2(fd.sp.2.2004,fd.F.2.2004,len.2004)
beta2.F.2005 = beta2(fd.sp.2.2005,fd.F.2.2005,len.2005)
beta2.F.2006 = beta2(fd.sp.2.2006,fd.F.2.2006,len.2006)
beta2.F.2007 = beta2(fd.sp.2.2007,fd.F.2.2007,len.2007)

write(beta2.F.1997,"beta2.F.1997.txt")
write(beta2.F.1998,"beta2.F.1998.txt")
write(beta2.F.1999,"beta2.F.1999.txt")
write(beta2.F.2000,"beta2.F.2000.txt")
write(beta2.F.2001,"beta2.F.2001.txt")
write(beta2.F.2002,"beta2.F.2002.txt")
write(beta2.F.2003,"beta2.F.2003.txt")
write(beta2.F.2004,"beta2.F.2004.txt")
write(beta2.F.2005,"beta2.F.2005.txt")

```

```

write(beta2.F.2006,"beta2.F.2006.txt")
write(beta2.F.2007,"beta2.F.2007.txt")

# draw a picture for Piotr Jan 11th:
plot.ts(c(Rn.2.F[1:10,]),xlab = "time in minutes",ylab="return in percents")
abline(v = 0,lty = 2)
abline(v = 389,lty = 2)
abline(v = 389*2,lty = 2)
abline(v = 389*3,lty = 2)
abline(v = 389*4,lty = 2)
abline(v = 389*5,lty = 2)
abline(v = 389*6,lty = 2)
abline(v = 389*7,lty = 2)
abline(v = 389*8,lty = 2)
abline(v = 389*9,lty = 2)
abline(v = 389*10,lty = 2)

#####
# stepwise bootstrap beta for Rn.1: #
#####
beta1.F.1997 = read.table("beta1.F.1997.txt")
beta1.F.1998 = read.table("beta1.F.1998.txt")
beta1.F.1999 = read.table("beta1.F.1999.txt")
beta1.F.2000 = read.table("beta1.F.2000.txt")
beta1.F.2001 = read.table("beta1.F.2001.txt")
beta1.F.2002 = read.table("beta1.F.2002.txt")
beta1.F.2003 = read.table("beta1.F.2003.txt")
beta1.F.2004 = read.table("beta1.F.2004.txt")
beta1.F.2005 = read.table("beta1.F.2005.txt")
beta1.F.2006 = read.table("beta1.F.2006.txt")
beta1.F.2007 = read.table("beta1.F.2007.txt")

e1.F.1997 = Rn.1.F.1997-(beta1.F.1997[1,1])*(Rn.1.sp.1997)
e1.F.1998 = Rn.1.F.1998-(beta1.F.1998[1,1])*(Rn.1.sp.1998)
e1.F.1999 = Rn.1.F.1999-(beta1.F.1999[1,1])*(Rn.1.sp.1999)
e1.F.2000 = Rn.1.F.2000-(beta1.F.2000[1,1])*(Rn.1.sp.2000)
e1.F.2001 = Rn.1.F.2001-(beta1.F.2001[1,1])*(Rn.1.sp.2001)
e1.F.2002 = Rn.1.F.2002-(beta1.F.2002[1,1])*(Rn.1.sp.2002)
e1.F.2003 = Rn.1.F.2003-(beta1.F.2003[1,1])*(Rn.1.sp.2003)
e1.F.2004 = Rn.1.F.2004-(beta1.F.2004[1,1])*(Rn.1.sp.2004)
e1.F.2005 = Rn.1.F.2005-(beta1.F.2005[1,1])*(Rn.1.sp.2005)
e1.F.2006 = Rn.1.F.2006-(beta1.F.2006[1,1])*(Rn.1.sp.2006)
e1.F.2007 = Rn.1.F.2007-(beta1.F.2007[1,1])*(Rn.1.sp.2007)

len.1.1997 = length(Rn.1.F.1997)[1]
len.1.1998 = length(Rn.1.F.1998)[1]
len.1.1999 = length(Rn.1.F.1999)[1]
len.1.2000 = length(Rn.1.F.2000)[1]
len.1.2001 = length(Rn.1.F.2001)[1]

```

```

len.1.2002 = length(Rn.1.F.2002)[1]
len.1.2003 = length(Rn.1.F.2003)[1]
len.1.2004 = length(Rn.1.F.2004)[1]
len.1.2005 = length(Rn.1.F.2005)[1]
len.1.2006 = length(Rn.1.F.2006)[1]
len.1.2007 = length(Rn.1.F.2007)[1]

```

```

bs.beta1.F.1997 = mat.or.vec(1,50)
bs.beta1.F.1998 = mat.or.vec(1,50)
bs.beta1.F.1999 = mat.or.vec(1,50)
bs.beta1.F.2000 = mat.or.vec(1,50)
bs.beta1.F.2001 = mat.or.vec(1,50)
bs.beta1.F.2002 = mat.or.vec(1,50)
bs.beta1.F.2003 = mat.or.vec(1,50)
bs.beta1.F.2004 = mat.or.vec(1,50)
bs.beta1.F.2005 = mat.or.vec(1,50)
bs.beta1.F.2006 = mat.or.vec(1,50)
bs.beta1.F.2007 = mat.or.vec(1,50)

```

```

for (i in 1:50)
{

```

```

sample.e1.F.1998 = e1.F.1998[sample(1:length(e1.F.1998))]
sample.e1.F.1999 = e1.F.1999[sample(1:length(e1.F.1999))]
sample.e1.F.2000 = e1.F.2000[sample(1:length(e1.F.2000))]
sample.e1.F.2001 = e1.F.2001[sample(1:length(e1.F.2001))]
sample.e1.F.1997 = e1.F.1997[sample(1:length(e1.F.1997))]
sample.e1.F.2002 = e1.F.2002[sample(1:length(e1.F.2002))]
sample.e1.F.2003 = e1.F.2003[sample(1:length(e1.F.2003))]
sample.e1.F.2004 = e1.F.2004[sample(1:length(e1.F.2004))]
sample.e1.F.2005 = e1.F.2005[sample(1:length(e1.F.2005))]
sample.e1.F.2006 = e1.F.2006[sample(1:length(e1.F.2006))]
sample.e1.F.2007 = e1.F.2007[sample(1:length(e1.F.2007))]

```

```

bs.1.F.1998 = (beta1.F.1998[1,1])*(Rn.1.sp.1998)+sample.e1.F.1998
bs.1.F.1999 = (beta1.F.1999[1,1])*(Rn.1.sp.1999)+sample.e1.F.1999
bs.1.F.2000 = (beta1.F.2000[1,1])*(Rn.1.sp.2000)+sample.e1.F.2000
bs.1.F.2001 = (beta1.F.2001[1,1])*(Rn.1.sp.2001)+sample.e1.F.2001
bs.1.F.1997 = (beta1.F.1997[1,1])*(Rn.1.sp.1997)+sample.e1.F.1997
bs.1.F.2002 = (beta1.F.2002[1,1])*(Rn.1.sp.2002)+sample.e1.F.2002
bs.1.F.2003 = (beta1.F.2003[1,1])*(Rn.1.sp.2003)+sample.e1.F.2003
bs.1.F.2004 = (beta1.F.2004[1,1])*(Rn.1.sp.2004)+sample.e1.F.2004
bs.1.F.2005 = (beta1.F.2005[1,1])*(Rn.1.sp.2005)+sample.e1.F.2005
bs.1.F.2006 = (beta1.F.2006[1,1])*(Rn.1.sp.2006)+sample.e1.F.2006
bs.1.F.2007 = (beta1.F.2007[1,1])*(Rn.1.sp.2007)+sample.e1.F.2007

```

```

bs.beta1.F.1998[i] = beta1(Rn.1.sp.1998,bs.1.F.1998,len.1.1998)
bs.beta1.F.1999[i] = beta1(Rn.1.sp.1999,bs.1.F.1999,len.1.1999)
bs.beta1.F.2000[i] = beta1(Rn.1.sp.2000,bs.1.F.2000,len.1.2000)

```

```

bs.beta1.F.2001[i] = beta1(Rn.1.sp.2001,bs.1.F.2001,len.1.2001)
bs.beta1.F.1997[i] = beta1(Rn.1.sp.1997,bs.1.F.1997,len.1.1997)
bs.beta1.F.2002[i] = beta1(Rn.1.sp.2002,bs.1.F.2002,len.1.2002)
bs.beta1.F.2003[i] = beta1(Rn.1.sp.2003,bs.1.F.2003,len.1.2003)
bs.beta1.F.2004[i] = beta1(Rn.1.sp.2004,bs.1.F.2004,len.1.2004)
bs.beta1.F.2005[i] = beta1(Rn.1.sp.2005,bs.1.F.2005,len.1.2005)
bs.beta1.F.2006[i] = beta1(Rn.1.sp.2006,bs.1.F.2006,len.1.2006)
bs.beta1.F.2007[i] = beta1(Rn.1.sp.2007,bs.1.F.2007,len.1.2007)
}

write(as.vector(bs.beta1.F.1998),"bs.beta1.F.1998.txt",ncolumns=50)
write(as.vector(bs.beta1.F.1999),"bs.beta1.F.1999.txt",ncolumns=50)
write(as.vector(bs.beta1.F.2000),"bs.beta1.F.2000.txt",ncolumns=50)
write(as.vector(bs.beta1.F.2001),"bs.beta1.F.2001.txt",ncolumns=50)
write(as.vector(bs.beta1.F.1997),"bs.beta1.F.1997.txt",ncolumns=50)
write(as.vector(bs.beta1.F.2002),"bs.beta1.F.2002.txt",ncolumns=50)
write(as.vector(bs.beta1.F.2003),"bs.beta1.F.2003.txt",ncolumns=50)
write(as.vector(bs.beta1.F.2004),"bs.beta1.F.2004.txt",ncolumns=50)
write(as.vector(bs.beta1.F.2005),"bs.beta1.F.2005.txt",ncolumns=50)
write(as.vector(bs.beta1.F.2006),"bs.beta1.F.2006.txt",ncolumns=50)
write(as.vector(bs.beta1.F.2007),"bs.beta1.F.2007.txt",ncolumns=50)

res.bs.beta1.F.1998 = bs.beta1.F.1998
res.bs.beta1.F.1999 = bs.beta1.F.1999
res.bs.beta1.F.2000 = bs.beta1.F.2000
res.bs.beta1.F.2001 = bs.beta1.F.2001
res.bs.beta1.F.1997 = bs.beta1.F.1997
res.bs.beta1.F.2002 = bs.beta1.F.2002
res.bs.beta1.F.2003 = bs.beta1.F.2003
res.bs.beta1.F.2004 = bs.beta1.F.2004
res.bs.beta1.F.2005 = bs.beta1.F.2005
res.bs.beta1.F.2006 = bs.beta1.F.2006
res.bs.beta1.F.2007 = bs.beta1.F.2007

#####
# stepwise bootstrap beta for Rn.2: #
#####

beta2.F.1997 = read.table("beta2.F.1997.txt")
beta2.F.1998 = read.table("beta2.F.1998.txt")
beta2.F.1999 = read.table("beta2.F.1999.txt")
beta2.F.2000 = read.table("beta2.F.2000.txt")
beta2.F.2001 = read.table("beta2.F.2001.txt")
beta2.F.2002 = read.table("beta2.F.2002.txt")
beta2.F.2003 = read.table("beta2.F.2003.txt")
beta2.F.2004 = read.table("beta2.F.2004.txt")
beta2.F.2005 = read.table("beta2.F.2005.txt")
beta2.F.2006 = read.table("beta2.F.2006.txt")

```

```
beta2.F.2007 = read.table("beta2.F.2007.txt")
```

```
alfa.F.1997 = mean(Rn.2.F.1997-(beta2.F.1997[1,1])*(Rn.2.sp.1997))
alfa.F.1998 = mean(Rn.2.F.1998-(beta2.F.1998[1,1])*(Rn.2.sp.1998))
alfa.F.1999 = mean(Rn.2.F.1999-(beta2.F.1999[1,1])*(Rn.2.sp.1999))
alfa.F.2000 = mean(Rn.2.F.2000-(beta2.F.2000[1,1])*(Rn.2.sp.2000))
alfa.F.2001 = mean(Rn.2.F.2001-(beta2.F.2001[1,1])*(Rn.2.sp.2001))
alfa.F.2002 = mean(Rn.2.F.2002-(beta2.F.2002[1,1])*(Rn.2.sp.2002))
alfa.F.2003 = mean(Rn.2.F.2003-(beta2.F.2003[1,1])*(Rn.2.sp.2003))
alfa.F.2004 = mean(Rn.2.F.2004-(beta2.F.2004[1,1])*(Rn.2.sp.2004))
alfa.F.2005 = mean(Rn.2.F.2005-(beta2.F.2005[1,1])*(Rn.2.sp.2005))
alfa.F.2006 = mean(Rn.2.F.2006-(beta2.F.2006[1,1])*(Rn.2.sp.2006))
alfa.F.2007 = mean(Rn.2.F.2007-(beta2.F.2007[1,1])*(Rn.2.sp.2007))
```

```
e2.F.1997 = Rn.2.F.1997-(beta2.F.1997[1,1])*(Rn.2.sp.1997)-alfa.F.1997
e2.F.1998 = Rn.2.F.1998-(beta2.F.1998[1,1])*(Rn.2.sp.1998)-alfa.F.1998
e2.F.1999 = Rn.2.F.1999-(beta2.F.1999[1,1])*(Rn.2.sp.1999)-alfa.F.1999
e2.F.2000 = Rn.2.F.2000-(beta2.F.2000[1,1])*(Rn.2.sp.2000)-alfa.F.2000
e2.F.2001 = Rn.2.F.2001-(beta2.F.2001[1,1])*(Rn.2.sp.2001)-alfa.F.2001
e2.F.2002 = Rn.2.F.2002-(beta2.F.2002[1,1])*(Rn.2.sp.2002)-alfa.F.2002
e2.F.2003 = Rn.2.F.2003-(beta2.F.2003[1,1])*(Rn.2.sp.2003)-alfa.F.2003
e2.F.2004 = Rn.2.F.2004-(beta2.F.2004[1,1])*(Rn.2.sp.2004)-alfa.F.2004
e2.F.2005 = Rn.2.F.2005-(beta2.F.2005[1,1])*(Rn.2.sp.2005)-alfa.F.2005
e2.F.2006 = Rn.2.F.2006-(beta2.F.2006[1,1])*(Rn.2.sp.2006)-alfa.F.2006
e2.F.2007 = Rn.2.F.2007-(beta2.F.2007[1,1])*(Rn.2.sp.2007)-alfa.F.2007
```

```
minutetime=seq(from = 1, to = 389, by =1 )
minutebasis=create.bspline.basis(rangeval = c(0,389),nbasis = 49)
fd.2 =data2fd(c(rep(1,389)),minutetime,basisobj = minutebasis)
```

```
fd.sp.2.1997 = data2fd(t(Rn.2.sp.1997),minutetime,basisobj = minutebasis)
fd.sp.2.1998 = data2fd(t(Rn.2.sp.1998),minutetime,basisobj = minutebasis)
fd.sp.2.1999 = data2fd(t(Rn.2.sp.1999),minutetime,basisobj = minutebasis)
fd.sp.2.2000 = data2fd(t(Rn.2.sp.2000),minutetime,basisobj = minutebasis)
fd.sp.2.2001 = data2fd(t(Rn.2.sp.2001),minutetime,basisobj = minutebasis)
fd.sp.2.2002 = data2fd(t(Rn.2.sp.2002),minutetime,basisobj = minutebasis)
fd.sp.2.2003 = data2fd(t(Rn.2.sp.2003),minutetime,basisobj = minutebasis)
fd.sp.2.2004 = data2fd(t(Rn.2.sp.2004),minutetime,basisobj = minutebasis)
fd.sp.2.2005 = data2fd(t(Rn.2.sp.2005),minutetime,basisobj = minutebasis)
fd.sp.2.2006 = data2fd(t(Rn.2.sp.2006),minutetime,basisobj = minutebasis)
fd.sp.2.2007 = data2fd(t(Rn.2.sp.2007),minutetime,basisobj = minutebasis)
```

```
len.1997 = dim(Rn.2.F.1997) [1]
len.1998 = dim(Rn.2.F.1998) [1]
len.1999 = dim(Rn.2.F.1999) [1]
len.2000 = dim(Rn.2.F.2000) [1]
```

```

len.2001 = dim(Rn.2.F.2001)[1]
len.2002 = dim(Rn.2.F.2002)[1]
len.2003 = dim(Rn.2.F.2003)[1]
len.2004 = dim(Rn.2.F.2004)[1]
len.2005 = dim(Rn.2.F.2005)[1]
len.2006 = dim(Rn.2.F.2006)[1]
len.2007 = dim(Rn.2.F.2007)[1]

```

```

bs.beta2.F.1997 = mat.or.vec(1,50)
bs.beta2.F.1998 = mat.or.vec(1,50)
bs.beta2.F.1999 = mat.or.vec(1,50)
bs.beta2.F.2000 = mat.or.vec(1,50)
bs.beta2.F.2001 = mat.or.vec(1,50)
bs.beta2.F.2002 = mat.or.vec(1,50)
bs.beta2.F.2003 = mat.or.vec(1,50)
bs.beta2.F.2004 = mat.or.vec(1,50)
bs.beta2.F.2005 = mat.or.vec(1,50)
bs.beta2.F.2006 = mat.or.vec(1,50)
bs.beta2.F.2007 = mat.or.vec(1,50)

```

```

for (i in 1:50)
{
sample.e2.F.1998 = e2.F.1998[sample(1:dim(e2.F.1998)[1]),]
sample.e2.F.1999 = e2.F.1999[sample(1:dim(e2.F.1999)[1]),]
sample.e2.F.2000 = e2.F.2000[sample(1:dim(e2.F.2000)[1]),]
sample.e2.F.2001 = e2.F.2001[sample(1:dim(e2.F.2001)[1]),]
sample.e2.F.1997 = e2.F.1997[sample(1:dim(e2.F.1997)[1]),]
sample.e2.F.2002 = e2.F.2002[sample(1:dim(e2.F.2002)[1]),]
sample.e2.F.2003 = e2.F.2003[sample(1:dim(e2.F.2003)[1]),]
sample.e2.F.2004 = e2.F.2004[sample(1:dim(e2.F.2004)[1]),]
sample.e2.F.2005 = e2.F.2005[sample(1:dim(e2.F.2005)[1]),]
sample.e2.F.2006 = e2.F.2006[sample(1:dim(e2.F.2006)[1]),]
sample.e2.F.2007 = e2.F.2007[sample(1:dim(e2.F.2007)[1]),]

```

```

bs.2.F.1998 = (beta2.F.1998[1,1])*(Rn.2.sp.1998)+sample.e2.F.1998
bs.2.F.1999 = (beta2.F.1999[1,1])*(Rn.2.sp.1999)+sample.e2.F.1999
bs.2.F.2000 = (beta2.F.2000[1,1])*(Rn.2.sp.2000)+sample.e2.F.2000
bs.2.F.2001 = (beta2.F.2001[1,1])*(Rn.2.sp.2001)+sample.e2.F.2001
bs.2.F.1997 = (beta2.F.1997[1,1])*(Rn.2.sp.1997)+sample.e2.F.1997
bs.2.F.2002 = (beta2.F.2002[1,1])*(Rn.2.sp.2002)+sample.e2.F.2002
bs.2.F.2003 = (beta2.F.2003[1,1])*(Rn.2.sp.2003)+sample.e2.F.2003
bs.2.F.2004 = (beta2.F.2004[1,1])*(Rn.2.sp.2004)+sample.e2.F.2004
bs.2.F.2005 = (beta2.F.2005[1,1])*(Rn.2.sp.2005)+sample.e2.F.2005
bs.2.F.2006 = (beta2.F.2006[1,1])*(Rn.2.sp.2006)+sample.e2.F.2006
bs.2.F.2007 = (beta2.F.2007[1,1])*(Rn.2.sp.2007)+sample.e2.F.2007

```

```

fd.bs.2.F.1998 = data2fd(t(bs.2.F.1998),minutetime,basisobj = minutebasis)

```

```

fd.bs.2.F.1999 = data2fd(t(bs.2.F.1999),minutetime,basisobj = minutebasis)
fd.bs.2.F.2000 = data2fd(t(bs.2.F.2000),minutetime,basisobj = minutebasis)
fd.bs.2.F.2001 = data2fd(t(bs.2.F.2001),minutetime,basisobj = minutebasis)
fd.bs.2.F.1997 = data2fd(t(bs.2.F.1997),minutetime,basisobj = minutebasis)
fd.bs.2.F.2002 = data2fd(t(bs.2.F.2002),minutetime,basisobj = minutebasis)
fd.bs.2.F.2003 = data2fd(t(bs.2.F.2003),minutetime,basisobj = minutebasis)
fd.bs.2.F.2004 = data2fd(t(bs.2.F.2004),minutetime,basisobj = minutebasis)
fd.bs.2.F.2005 = data2fd(t(bs.2.F.2005),minutetime,basisobj = minutebasis)
fd.bs.2.F.2006 = data2fd(t(bs.2.F.2006),minutetime,basisobj = minutebasis)
fd.bs.2.F.2007 = data2fd(t(bs.2.F.2007),minutetime,basisobj = minutebasis)

```

```

bs.beta2.F.1998[i] = beta2(fd.sp.2.1998,fd.bs.2.F.1998,len.1998)
bs.beta2.F.1999[i] = beta2(fd.sp.2.1999,fd.bs.2.F.1999,len.1999)
bs.beta2.F.2000[i] = beta2(fd.sp.2.2000,fd.bs.2.F.2000,len.2000)
bs.beta2.F.2001[i] = beta2(fd.sp.2.2001,fd.bs.2.F.2001,len.2001)
bs.beta2.F.1997[i] = beta2(fd.sp.2.1997,fd.bs.2.F.1997,len.1997)
bs.beta2.F.2002[i] = beta2(fd.sp.2.2002,fd.bs.2.F.2002,len.2002)
bs.beta2.F.2003[i] = beta2(fd.sp.2.2003,fd.bs.2.F.2003,len.2003)
bs.beta2.F.2004[i] = beta2(fd.sp.2.2004,fd.bs.2.F.2004,len.2004)
bs.beta2.F.2005[i] = beta2(fd.sp.2.2005,fd.bs.2.F.2005,len.2005)
bs.beta2.F.2006[i] = beta2(fd.sp.2.2006,fd.bs.2.F.2006,len.2006)
bs.beta2.F.2007[i] = beta2(fd.sp.2.2007,fd.bs.2.F.2007,len.2007)
}

```

```

write(as.vector(bs.beta2.F.1998),"bs.beta2.F.1998.txt",ncolumns = 50)
write(as.vector(bs.beta2.F.1999),"bs.beta2.F.1999.txt",ncolumns = 50)
write(as.vector(bs.beta2.F.2000),"bs.beta2.F.2000.txt",ncolumns = 50)
write(as.vector(bs.beta2.F.2001),"bs.beta2.F.2001.txt",ncolumns = 50)
write(as.vector(bs.beta2.F.1997),"bs.beta2.F.1997.txt",ncolumns = 50)
write(as.vector(bs.beta2.F.2002),"bs.beta2.F.2002.txt",ncolumns = 50)
write(as.vector(bs.beta2.F.2003),"bs.beta2.F.2003.txt",ncolumns = 50)
write(as.vector(bs.beta2.F.2004),"bs.beta2.F.2004.txt",ncolumns = 50)
write(as.vector(bs.beta2.F.2005),"bs.beta2.F.2005.txt",ncolumns = 50)
write(as.vector(bs.beta2.F.2006),"bs.beta2.F.2006.txt",ncolumns = 50)
write(as.vector(bs.beta2.F.2007),"bs.beta2.F.2007.txt",ncolumns = 50)

```

```

res.bs.beta2.F.1998 = bs.beta2.F.1998
res.bs.beta2.F.1999 = bs.beta2.F.1999
res.bs.beta2.F.2000 = bs.beta2.F.2000
res.bs.beta2.F.2001 = bs.beta2.F.2001
res.bs.beta2.F.1997 = bs.beta2.F.1997
res.bs.beta2.F.2002 = bs.beta2.F.2002
res.bs.beta2.F.2003 = bs.beta2.F.2003
res.bs.beta2.F.2004 = bs.beta2.F.2004
res.bs.beta2.F.2005 = bs.beta2.F.2005
res.bs.beta2.F.2006 = bs.beta2.F.2006
res.bs.beta2.F.2007 = bs.beta2.F.2007

```



```
#####  
# Pairwise bootstrap for Rn.1 #  
#####
```

```
pair.bs.beta1.F.1997 = mat.or.vec(1,50)  
pair.bs.beta1.F.1998 = mat.or.vec(1,50)  
pair.bs.beta1.F.1999 = mat.or.vec(1,50)  
pair.bs.beta1.F.2000 = mat.or.vec(1,50)  
pair.bs.beta1.F.2001 = mat.or.vec(1,50)  
pair.bs.beta1.F.2002 = mat.or.vec(1,50)  
pair.bs.beta1.F.2003 = mat.or.vec(1,50)  
pair.bs.beta1.F.2004 = mat.or.vec(1,50)  
pair.bs.beta1.F.2005 = mat.or.vec(1,50)  
pair.bs.beta1.F.2006 = mat.or.vec(1,50)  
pair.bs.beta1.F.2007 = mat.or.vec(1,50)
```

```
for (i in 1:50)  
{  
sample.F.1997 = sample(1:length(Rn.1.sp.1997),replace = T)  
sample.F.1998 = sample(1:length(Rn.1.sp.1998),replace = T)  
sample.F.1999 = sample(1:length(Rn.1.sp.1999),replace = T)  
sample.F.2000 = sample(1:length(Rn.1.sp.2000),replace = T)  
sample.F.2001 = sample(1:length(Rn.1.sp.2001),replace = T)  
sample.F.2002 = sample(1:length(Rn.1.sp.2002),replace = T)  
sample.F.2003 = sample(1:length(Rn.1.sp.2003),replace = T)  
sample.F.2004 = sample(1:length(Rn.1.sp.2004),replace = T)  
sample.F.2005 = sample(1:length(Rn.1.sp.2005),replace = T)  
sample.F.2006 = sample(1:length(Rn.1.sp.2006),replace = T)  
sample.F.2007 = sample(1:length(Rn.1.sp.2007),replace = T)
```

```
pair.bs.Rn.1.F.1997 = Rn.1.F.1997[sample.F.1997]  
pair.bs.Rn.1.F.1998 = Rn.1.F.1998[sample.F.1998]  
pair.bs.Rn.1.F.1999 = Rn.1.F.1999[sample.F.1999]  
pair.bs.Rn.1.F.2000 = Rn.1.F.2000[sample.F.2000]  
pair.bs.Rn.1.F.2001 = Rn.1.F.2001[sample.F.2001]  
pair.bs.Rn.1.F.2002 = Rn.1.F.2002[sample.F.2002]  
pair.bs.Rn.1.F.2003 = Rn.1.F.2003[sample.F.2003]  
pair.bs.Rn.1.F.2004 = Rn.1.F.2004[sample.F.2004]  
pair.bs.Rn.1.F.2005 = Rn.1.F.2005[sample.F.2005]  
pair.bs.Rn.1.F.2006 = Rn.1.F.2006[sample.F.2006]  
pair.bs.Rn.1.F.2007 = Rn.1.F.2007[sample.F.2007]
```

```
pair.bs.Rn.1.sp.1997 = Rn.1.sp.1997[sample.F.1997]  
pair.bs.Rn.1.sp.1998 = Rn.1.sp.1998[sample.F.1998]  
pair.bs.Rn.1.sp.1999 = Rn.1.sp.1999[sample.F.1999]
```

```

pair.bs.Rn.1.sp.2000 = Rn.1.sp.2000[sample.F.2000]
pair.bs.Rn.1.sp.2001 = Rn.1.sp.2001[sample.F.2001]
pair.bs.Rn.1.sp.2002 = Rn.1.sp.2002[sample.F.2002]
pair.bs.Rn.1.sp.2003 = Rn.1.sp.2003[sample.F.2003]
pair.bs.Rn.1.sp.2004 = Rn.1.sp.2004[sample.F.2004]
pair.bs.Rn.1.sp.2005 = Rn.1.sp.2005[sample.F.2005]
pair.bs.Rn.1.sp.2006 = Rn.1.sp.2006[sample.F.2006]
pair.bs.Rn.1.sp.2007 = Rn.1.sp.2007[sample.F.2007]

```

```

pair.bs.beta1.F.1997[i] = beta1(pair.bs.Rn.1.sp.1997,
pair.bs.Rn.1.F.1997,len.1.1997)
pair.bs.beta1.F.1998[i] = beta1(pair.bs.Rn.1.sp.1998,
pair.bs.Rn.1.F.1998,len.1.1998)
pair.bs.beta1.F.1999[i] = beta1(pair.bs.Rn.1.sp.1999,
pair.bs.Rn.1.F.1999,len.1.1999)
pair.bs.beta1.F.2000[i] = beta1(pair.bs.Rn.1.sp.2000,
pair.bs.Rn.1.F.2000,len.1.2000)
pair.bs.beta1.F.2001[i] = beta1(pair.bs.Rn.1.sp.2001,
pair.bs.Rn.1.F.2001,len.1.2001)
pair.bs.beta1.F.2002[i] = beta1(pair.bs.Rn.1.sp.2002,
pair.bs.Rn.1.F.2002,len.1.2002)
pair.bs.beta1.F.2003[i] = beta1(pair.bs.Rn.1.sp.2003,
pair.bs.Rn.1.F.2003,len.1.2003)
pair.bs.beta1.F.2004[i] = beta1(pair.bs.Rn.1.sp.2004,
pair.bs.Rn.1.F.2004,len.1.2004)
pair.bs.beta1.F.2005[i] = beta1(pair.bs.Rn.1.sp.2005,
pair.bs.Rn.1.F.2005,len.1.2005)
pair.bs.beta1.F.2006[i] = beta1(pair.bs.Rn.1.sp.2006,
pair.bs.Rn.1.F.2006,len.1.2006)
pair.bs.beta1.F.2007[i] = beta1(pair.bs.Rn.1.sp.2007,
pair.bs.Rn.1.F.2007,len.1.2007)
}

```

```

write(as.vector(pair.bs.beta1.F.1997),"pair.bs.beta1.F.1997.txt",ncolumns = 50)
write(as.vector(pair.bs.beta1.F.1998),"pair.bs.beta1.F.1998.txt",ncolumns = 50)
write(as.vector(pair.bs.beta1.F.1999),"pair.bs.beta1.F.1999.txt",ncolumns = 50)
write(as.vector(pair.bs.beta1.F.2000),"pair.bs.beta1.F.2000.txt",ncolumns = 50)
write(as.vector(pair.bs.beta1.F.2001),"pair.bs.beta1.F.2001.txt",ncolumns = 50)
write(as.vector(pair.bs.beta1.F.2002),"pair.bs.beta1.F.2002.txt",ncolumns = 50)
write(as.vector(pair.bs.beta1.F.2003),"pair.bs.beta1.F.2003.txt",ncolumns = 50)
write(as.vector(pair.bs.beta1.F.2004),"pair.bs.beta1.F.2004.txt",ncolumns = 50)
write(as.vector(pair.bs.beta1.F.2005),"pair.bs.beta1.F.2005.txt",ncolumns = 50)
write(as.vector(pair.bs.beta1.F.2006),"pair.bs.beta1.F.2006.txt",ncolumns = 50)
write(as.vector(pair.bs.beta1.F.2007),"pair.bs.beta1.F.2007.txt",ncolumns = 50)

```

```

#####
# Pairwise bootstrap for Rn.2 #
#####

```

```

pair.bs.beta2.F.1997 = mat.or.vec(1,50)
pair.bs.beta2.F.1998 = mat.or.vec(1,50)
pair.bs.beta2.F.1999 = mat.or.vec(1,50)
pair.bs.beta2.F.2000 = mat.or.vec(1,50)
pair.bs.beta2.F.2001 = mat.or.vec(1,50)
pair.bs.beta2.F.2002 = mat.or.vec(1,50)
pair.bs.beta2.F.2003 = mat.or.vec(1,50)
pair.bs.beta2.F.2004 = mat.or.vec(1,50)
pair.bs.beta2.F.2005 = mat.or.vec(1,50)
pair.bs.beta2.F.2006 = mat.or.vec(1,50)
pair.bs.beta2.F.2007 = mat.or.vec(1,50)

```

```

for (i in 1:50)

```

```

{
sample.F.1997 = sample(1:dim(Rn.2.sp.1997)[1],replace = T)
sample.F.1998 = sample(1:dim(Rn.2.sp.1998)[1],replace = T)
sample.F.1999 = sample(1:dim(Rn.2.sp.1999)[1],replace = T)
sample.F.2000 = sample(1:dim(Rn.2.sp.2000)[1],replace = T)
sample.F.2001 = sample(1:dim(Rn.2.sp.2001)[1],replace = T)
sample.F.2002 = sample(1:dim(Rn.2.sp.2002)[1],replace = T)
sample.F.2003 = sample(1:dim(Rn.2.sp.2003)[1],replace = T)
sample.F.2004 = sample(1:dim(Rn.2.sp.2004)[1],replace = T)
sample.F.2005 = sample(1:dim(Rn.2.sp.2005)[1],replace = T)
sample.F.2006 = sample(1:dim(Rn.2.sp.2006)[1],replace = T)
sample.F.2007 = sample(1:dim(Rn.2.sp.2007)[1],replace = T)

```

```

pair.bs.fd.F.2.1997=data2fd(t(Rn.2.F.1997[sample.F.1997,]),
minutetime,basisobj = minutebasis)
pair.bs.fd.F.2.1998=data2fd(t(Rn.2.F.1998[sample.F.1998,]),
minutetime,basisobj = minutebasis)
pair.bs.fd.F.2.1999=data2fd(t(Rn.2.F.1999[sample.F.1999,]),
minutetime,basisobj = minutebasis)
pair.bs.fd.F.2.2000=data2fd(t(Rn.2.F.2000[sample.F.2000,]),
minutetime,basisobj = minutebasis)
pair.bs.fd.F.2.2001=data2fd(t(Rn.2.F.2001[sample.F.2001,]),
minutetime,basisobj = minutebasis)
pair.bs.fd.F.2.2002=data2fd(t(Rn.2.F.2002[sample.F.2002,]),
minutetime,basisobj = minutebasis)
pair.bs.fd.F.2.2003=data2fd(t(Rn.2.F.2003[sample.F.2003,]),
minutetime,basisobj = minutebasis)
pair.bs.fd.F.2.2004=data2fd(t(Rn.2.F.2004[sample.F.2004,]),
minutetime,basisobj = minutebasis)
pair.bs.fd.F.2.2005=data2fd(t(Rn.2.F.2005[sample.F.2005,]),
minutetime,basisobj = minutebasis)
pair.bs.fd.F.2.2006=data2fd(t(Rn.2.F.2006[sample.F.2006,]),
minutetime,basisobj = minutebasis)
pair.bs.fd.F.2.2007=data2fd(t(Rn.2.F.2007[sample.F.2007,]),
minutetime,basisobj = minutebasis)

```

```

pair.bs.fd.sp.for.F.2.1997=data2fd(t(Rn.2.sp.1997[sample.F.1997,]),
minutetime,basisobj = minutebasis)
pair.bs.fd.sp.for.F.2.1998=data2fd(t(Rn.2.sp.1998[sample.F.1998,]),
minutetime,basisobj = minutebasis)
pair.bs.fd.sp.for.F.2.1999=data2fd(t(Rn.2.sp.1999[sample.F.1999,]),
minutetime,basisobj = minutebasis)
pair.bs.fd.sp.for.F.2.2000=data2fd(t(Rn.2.sp.2000[sample.F.2000,]),
minutetime,basisobj = minutebasis)
pair.bs.fd.sp.for.F.2.2001=data2fd(t(Rn.2.sp.2001[sample.F.2001,]),
minutetime,basisobj = minutebasis)
pair.bs.fd.sp.for.F.2.2002=data2fd(t(Rn.2.sp.2002[sample.F.2002,]),
minutetime,basisobj = minutebasis)
pair.bs.fd.sp.for.F.2.2003=data2fd(t(Rn.2.sp.2003[sample.F.2003,]),
minutetime,basisobj = minutebasis)
pair.bs.fd.sp.for.F.2.2004=data2fd(t(Rn.2.sp.2004[sample.F.2004,]),
minutetime,basisobj = minutebasis)
pair.bs.fd.sp.for.F.2.2005=data2fd(t(Rn.2.sp.2005[sample.F.2005,]),
minutetime,basisobj = minutebasis)
pair.bs.fd.sp.for.F.2.2006=data2fd(t(Rn.2.sp.2006[sample.F.2006,]),
minutetime,basisobj = minutebasis)
pair.bs.fd.sp.for.F.2.2007=data2fd(t(Rn.2.sp.2007[sample.F.2007,]),
minutetime,basisobj = minutebasis)

```

```

pair.bs.beta2.F.1997[i] = beta2(pair.bs.fd.sp.for.F.2.1997,
pair.bs.fd.F.2.1997,len.1997)
pair.bs.beta2.F.1998[i] = beta2(pair.bs.fd.sp.for.F.2.1998,
pair.bs.fd.F.2.1998,len.1998)
pair.bs.beta2.F.1999[i] = beta2(pair.bs.fd.sp.for.F.2.1999,
pair.bs.fd.F.2.1999,len.1999)
pair.bs.beta2.F.2000[i] = beta2(pair.bs.fd.sp.for.F.2.2000,
pair.bs.fd.F.2.2000,len.2000)
pair.bs.beta2.F.2001[i] = beta2(pair.bs.fd.sp.for.F.2.2001,
pair.bs.fd.F.2.2001,len.2001)
pair.bs.beta2.F.2002[i] = beta2(pair.bs.fd.sp.for.F.2.2002,
pair.bs.fd.F.2.2002,len.2002)
pair.bs.beta2.F.2003[i] = beta2(pair.bs.fd.sp.for.F.2.2003,
pair.bs.fd.F.2.2003,len.2003)
pair.bs.beta2.F.2004[i] = beta2(pair.bs.fd.sp.for.F.2.2004,
pair.bs.fd.F.2.2004,len.2004)
pair.bs.beta2.F.2005[i] = beta2(pair.bs.fd.sp.for.F.2.2005,
pair.bs.fd.F.2.2005,len.2005)
pair.bs.beta2.F.2006[i] = beta2(pair.bs.fd.sp.for.F.2.2006,
pair.bs.fd.F.2.2006,len.2006)
pair.bs.beta2.F.2007[i] = beta2(pair.bs.fd.sp.for.F.2.2007,
pair.bs.fd.F.2.2007,len.2007)
}

```

```

write(as.vector(pair.bs.beta2.F.1997),"pair.bs.beta2.F.1997.txt",ncolumns=50)

```

```

write(as.vector(pair.bs.beta2.F.1998),"pair.bs.beta2.F.1998.txt",ncolumns=50)
write(as.vector(pair.bs.beta2.F.1999),"pair.bs.beta2.F.1999.txt",ncolumns=50)
write(as.vector(pair.bs.beta2.F.2000),"pair.bs.beta2.F.2000.txt",ncolumns=50)
write(as.vector(pair.bs.beta2.F.2001),"pair.bs.beta2.F.2001.txt",ncolumns=50)
write(as.vector(pair.bs.beta2.F.2002),"pair.bs.beta2.F.2002.txt",ncolumns=50)
write(as.vector(pair.bs.beta2.F.2003),"pair.bs.beta2.F.2003.txt",ncolumns=50)
write(as.vector(pair.bs.beta2.F.2004),"pair.bs.beta2.F.2004.txt",ncolumns=50)
write(as.vector(pair.bs.beta2.F.2005),"pair.bs.beta2.F.2005.txt",ncolumns=50)
write(as.vector(pair.bs.beta2.F.2006),"pair.bs.beta2.F.2006.txt",ncolumns=50)
write(as.vector(pair.bs.beta2.F.2007),"pair.bs.beta2.F.2007.txt",ncolumns=50)

```

```

#####
#   stand deviation of beta of bootstrap sample of F                               #
#####

```

```

std = function(x)
{
  xbar = sum(x)/length(x)
  return(sqrt(sum((x-xbar)^2)/(length(x)-1)))
}

```

```

std.res.bs.beta1.F.1997 = std(res.bs.beta1.F.1997)
std.res.bs.beta1.F.1998 = std(res.bs.beta1.F.1998)
std.res.bs.beta1.F.1999 = std(res.bs.beta1.F.1999)
std.res.bs.beta1.F.2000 = std(res.bs.beta1.F.2000)
std.res.bs.beta1.F.2001 = std(res.bs.beta1.F.2001)
std.res.bs.beta1.F.2002 = std(res.bs.beta1.F.2002)
std.res.bs.beta1.F.2003 = std(res.bs.beta1.F.2003)
std.res.bs.beta1.F.2004 = std(res.bs.beta1.F.2004)
std.res.bs.beta1.F.2005 = std(res.bs.beta1.F.2005)
std.res.bs.beta1.F.2006 = std(res.bs.beta1.F.2006)
std.res.bs.beta1.F.2007 = std(res.bs.beta1.F.2007)

```

```

std.pair.bs.beta1.F.1997 = std(pair.bs.beta1.F.1997)
std.pair.bs.beta1.F.1998 = std(pair.bs.beta1.F.1998)
std.pair.bs.beta1.F.1999 = std(pair.bs.beta1.F.1999)
std.pair.bs.beta1.F.2000 = std(pair.bs.beta1.F.2000)
std.pair.bs.beta1.F.2001 = std(pair.bs.beta1.F.2001)
std.pair.bs.beta1.F.2002 = std(pair.bs.beta1.F.2002)
std.pair.bs.beta1.F.2003 = std(pair.bs.beta1.F.2003)
std.pair.bs.beta1.F.2004 = std(pair.bs.beta1.F.2004)
std.pair.bs.beta1.F.2005 = std(pair.bs.beta1.F.2005)
std.pair.bs.beta1.F.2006 = std(pair.bs.beta1.F.2006)
std.pair.bs.beta1.F.2007 = std(pair.bs.beta1.F.2007)

```

```

std.res.bs.beta2.F.1997 = std(res.bs.beta2.F.1997)
std.res.bs.beta2.F.1998 = std(res.bs.beta2.F.1998)
std.res.bs.beta2.F.1999 = std(res.bs.beta2.F.1999)
std.res.bs.beta2.F.2000 = std(res.bs.beta2.F.2000)
std.res.bs.beta2.F.2001 = std(res.bs.beta2.F.2001)
std.res.bs.beta2.F.2002 = std(res.bs.beta2.F.2002)

```

```
std.res.bs.beta2.F.2003 = std(res.bs.beta2.F.2003)
std.res.bs.beta2.F.2004 = std(res.bs.beta2.F.2004)
std.res.bs.beta2.F.2005 = std(res.bs.beta2.F.2005)
std.res.bs.beta2.F.2006 = std(res.bs.beta2.F.2006)
std.res.bs.beta2.F.2007 = std(res.bs.beta2.F.2007)
```

```
std.pair.bs.beta2.F.1997 = std(pair.bs.beta2.F.1997)
std.pair.bs.beta2.F.1998 = std(pair.bs.beta2.F.1998)
std.pair.bs.beta2.F.1999 = std(pair.bs.beta2.F.1999)
std.pair.bs.beta2.F.2000 = std(pair.bs.beta2.F.2000)
std.pair.bs.beta2.F.2001 = std(pair.bs.beta2.F.2001)
std.pair.bs.beta2.F.2002 = std(pair.bs.beta2.F.2002)
std.pair.bs.beta2.F.2003 = std(pair.bs.beta2.F.2003)
std.pair.bs.beta2.F.2004 = std(pair.bs.beta2.F.2004)
std.pair.bs.beta2.F.2005 = std(pair.bs.beta2.F.2005)
std.pair.bs.beta2.F.2006 = std(pair.bs.beta2.F.2006)
std.pair.bs.beta2.F.2007 = std(pair.bs.beta2.F.2007)
```

```
write(as.vector(std.res.bs.beta1.F.1997), "std.res.bs.beta1.F.1997.txt")
write(as.vector(std.res.bs.beta1.F.1998), "std.res.bs.beta1.F.1998.txt")
write(as.vector(std.res.bs.beta1.F.1999), "std.res.bs.beta1.F.1999.txt")
write(as.vector(std.res.bs.beta1.F.2000), "std.res.bs.beta1.F.2000.txt")
write(as.vector(std.res.bs.beta1.F.2001), "std.res.bs.beta1.F.2001.txt")
write(as.vector(std.res.bs.beta1.F.2002), "std.res.bs.beta1.F.2002.txt")
write(as.vector(std.res.bs.beta1.F.2003), "std.res.bs.beta1.F.2003.txt")
write(as.vector(std.res.bs.beta1.F.2004), "std.res.bs.beta1.F.2004.txt")
write(as.vector(std.res.bs.beta1.F.2005), "std.res.bs.beta1.F.2005.txt")
write(as.vector(std.res.bs.beta1.F.2006), "std.res.bs.beta1.F.2006.txt")
write(as.vector(std.res.bs.beta1.F.2007), "std.res.bs.beta1.F.2007.txt")
```

```
write(as.vector(std.pair.bs.beta1.F.1997), "std.pair.bs.beta1.F.1997.txt")
write(as.vector(std.pair.bs.beta1.F.1998), "std.pair.bs.beta1.F.1998.txt")
write(as.vector(std.pair.bs.beta1.F.1999), "std.pair.bs.beta1.F.1999.txt")
write(as.vector(std.pair.bs.beta1.F.2000), "std.pair.bs.beta1.F.2000.txt")
write(as.vector(std.pair.bs.beta1.F.2001), "std.pair.bs.beta1.F.2001.txt")
write(as.vector(std.pair.bs.beta1.F.2002), "std.pair.bs.beta1.F.2002.txt")
write(as.vector(std.pair.bs.beta1.F.2003), "std.pair.bs.beta1.F.2003.txt")
write(as.vector(std.pair.bs.beta1.F.2004), "std.pair.bs.beta1.F.2004.txt")
write(as.vector(std.pair.bs.beta1.F.2005), "std.pair.bs.beta1.F.2005.txt")
write(as.vector(std.pair.bs.beta1.F.2006), "std.pair.bs.beta1.F.2006.txt")
write(as.vector(std.pair.bs.beta1.F.2007), "std.pair.bs.beta1.F.2007.txt")
```

```
write(as.vector(std.res.bs.beta2.F.1997), "std.res.bs.beta2.F.1997.txt")
write(as.vector(std.res.bs.beta2.F.1998), "std.res.bs.beta2.F.1998.txt")
write(as.vector(std.res.bs.beta2.F.1999), "std.res.bs.beta2.F.1999.txt")
write(as.vector(std.res.bs.beta2.F.2000), "std.res.bs.beta2.F.2000.txt")
write(as.vector(std.res.bs.beta2.F.2001), "std.res.bs.beta2.F.2001.txt")
```

```
write(as.vector(std.res.bs.beta2.F.2002),"std.res.bs.beta2.F.2002.txt")
write(as.vector(std.res.bs.beta2.F.2003),"std.res.bs.beta2.F.2003.txt")
write(as.vector(std.res.bs.beta2.F.2004),"std.res.bs.beta2.F.2004.txt")
write(as.vector(std.res.bs.beta2.F.2005),"std.res.bs.beta2.F.2005.txt")
write(as.vector(std.res.bs.beta2.F.2006),"std.res.bs.beta2.F.2006.txt")
write(as.vector(std.res.bs.beta2.F.2007),"std.res.bs.beta2.F.2007.txt")
```

```
write(as.vector(std.pair.bs.beta2.F.1997),"std.pair.bs.beta2.F.1997.txt")
write(as.vector(std.pair.bs.beta2.F.1998),"std.pair.bs.beta2.F.1998.txt")
write(as.vector(std.pair.bs.beta2.F.1999),"std.pair.bs.beta2.F.1999.txt")
write(as.vector(std.pair.bs.beta2.F.2000),"std.pair.bs.beta2.F.2000.txt")
write(as.vector(std.pair.bs.beta2.F.2001),"std.pair.bs.beta2.F.2001.txt")
write(as.vector(std.pair.bs.beta2.F.2002),"std.pair.bs.beta2.F.2002.txt")
write(as.vector(std.pair.bs.beta2.F.2003),"std.pair.bs.beta2.F.2003.txt")
write(as.vector(std.pair.bs.beta2.F.2004),"std.pair.bs.beta2.F.2004.txt")
write(as.vector(std.pair.bs.beta2.F.2005),"std.pair.bs.beta2.F.2005.txt")
write(as.vector(std.pair.bs.beta2.F.2006),"std.pair.bs.beta2.F.2006.txt")
write(as.vector(std.pair.bs.beta2.F.2007),"std.pair.bs.beta2.F.2007.txt")
```

A.6 Tables for 100 Stock from SP 100 and Different Sectors

This section presents all the tables for 100 stock from SP 100. Table 7–102 show estimates of β for both daily and intra-daily returns as well as the standard deviation for both residual and pairwise bootstrap methods for each stock of SP 100. Besides, Table 103–114 show the comparison tables for different sectors of SP 100 for the estimates of β for two types of returns. For more details, please check Section 3.1.

Table 7: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock AA(ALCOA INC). The 7 columns in this table separately represent for: Year, Beta Daily ($\hat{\beta}$ for the daily returns), Beta Intra ($\hat{\beta}$ for the functional intra-daily returns), R.B.S Daily (standard deviation for the residual bootstrap sample for the daily returns), R.B.S Intra (standard deviation for the residual bootstrap sample for the functional intra-daily returns), P.B.S Daily (standard deviation for the pairwise bootstrap sample for the daily returns) and P.B.S Intra (standard deviation for the pairwise bootstrap sample for the intra-daily returns).

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.82	0.67	0.08	0.02	0.11	2.08
1998	0.83	-5.20	0.09	0.48	0.10	10.39
1999	0.28	-2.41	0.15	0.20	0.14	15.07
2000	0.54	0.08	0.13	0.16	0.17	6.17
2001	1.08	1.95	0.09	0.03	0.09	30.29
2002	1.12	2.20	0.06	0.08	0.07	5.20
2003	1.32	2.84	0.09	0.16	0.11	45.35
2004	1.51	-48.91	0.15	30.35	0.16	25.90
2005	1.23	-3.90	0.13	0.13	0.11	96.86
2006	1.29	-0.98	0.15	0.05	0.17	42.90
2007	1.24	5.04	0.17	0.58	0.22	558.60

Table 8: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock ABT(ABBOTT LABORATORIES). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.93	1.65	0.07	0.03	0.06	7.42
1998	0.86	5.80	0.07	0.41	0.06	11.27
1999	1.01	1.25	0.10	0.11	0.11	7.13
2000	0.21	0.92	0.10	0.11	0.13	16.75
2001	0.25	-0.43	0.09	0.02	0.09	23.47
2002	0.71	0.77	0.09	0.08	0.07	3.53
2003	0.84	1.93	0.08	0.12	0.06	26.13
2004	0.71	32.94	0.09	20.88	0.13	66.22
2005	0.62	0.83	0.12	0.04	0.13	9.41
2006	0.82	2.37	0.10	0.04	0.09	6.78
2007	0.53	10.19	0.22	1.41	0.13	25.45

Table 9: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock AEP(AMER ELECTRIC POW CO). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.40	0.21	0.05	0.01	0.05	0.80
1998	0.20	-1.17	0.05	0.14	0.05	5.72
1999	0.29	1.00	0.06	0.10	0.06	16.26
2000	0.09	1.12	0.09	0.11	0.10	26.73
2001	0.13	1.89	0.06	0.04	0.08	4.51
2002	0.94	3.91	0.13	0.24	0.14	22.10
2003	0.82	1.70	0.08	0.12	0.08	8.64
2004	0.63	18.73	0.09	12.58	0.08	5.39
2005	0.84	0.28	0.08	0.04	0.11	3.92
2006	0.68	0.43	0.09	0.02	0.06	1.15
2007	0.84	6.21	0.14	0.90	0.13	48.67

Table 10: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock AES(AES CP INC). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.51	0.87	0.13	0.03	0.18	5.01
1998	0.91	-13.95	0.18	0.93	0.19	14.32
1999	0.40	-0.31	0.15	0.16	0.12	50.57
2000	0.67	0.57	0.17	0.16	0.13	20.54
2001	0.56	5.49	0.21	0.10	0.14	22.02
2002	1.88	18.95	0.30	0.90	0.41	177.83
2003	1.17	-3.30	0.20	0.42	0.22	390.15
2004	1.08	25.85	0.17	14.48	0.22	6.58
2005	1.21	3.70	0.14	0.11	0.16	11.32
2006	0.66	1.05	0.15	0.03	0.15	2.23
2007	1.30	8.94	0.26	1.18	0.18	41.51

Table 11: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock AIG(AMER INTL GROUP INC). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	1.02	0.06	0.06	0.01	0.10	3.58
1998	1.30	-6.19	0.08	0.49	0.09	7.87
1999	1.07	1.75	0.11	0.13	0.10	11.02
2000	0.73	0.73	0.08	0.10	0.11	6.26
2001	0.61	2.34	0.07	0.04	0.09	14.26
2002	1.16	1.72	0.06	0.07	0.08	546.73
2003	1.39	2.13	0.06	0.11	0.07	10.56
2004	1.20	-2.06	0.11	2.07	0.14	6.23
2005	1.12	0.97	0.12	0.05	0.13	21.79
2006	0.94	-1.10	0.07	0.03	0.08	8.94
2007	0.65	-2.66	0.12	0.50	0.18	13.35

Table 12: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock ALL(ALLSTATE CP). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	1.01	1.42	0.09	0.02	0.09	4.13
1998	0.92	-1.49	0.09	0.16	0.11	10.81
1999	0.84	-0.70	0.13	0.16	0.11	51.70
2000	0.86	4.36	0.13	0.32	0.17	26.28
2001	0.40	-0.58	0.08	0.02	0.08	6.71
2002	0.53	-3.36	0.04	0.21	0.04	13.26
2003	0.66	1.86	0.06	0.13	0.07	107.78
2004	0.79	19.86	0.07	11.88	0.07	2.87
2005	0.83	2.23	0.10	0.06	0.09	6.31
2006	0.76	1.60	0.10	0.02	0.08	1.86
2007	0.59	1.87	0.14	0.22	0.20	4.09

Table 13: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock AMGN(AMGEN). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.17	-1.27	0.65	0.03	0.54	10.24
1998	0.88	6.24	0.11	0.46	0.12	51.41
1999	1.24	2.77	0.16	0.22	0.14	24.59
2000	1.27	-0.50	0.17	0.19	0.15	16.16
2001	1.02	-0.26	0.13	0.03	0.13	3.26
2002	0.98	-2.39	0.10	0.21	0.12	12.00
2003	0.87	-0.27	0.07	0.09	0.07	3.66
2004	1.16	51.15	0.11	38.79	0.11	22.82
2005	1.14	6.30	0.11	0.14	0.14	11.55
2006	0.80	-0.55	0.10	0.03	0.11	60.26
2007	0.63	-0.19	0.27	0.24	0.18	6.61

Table 14: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock AVP(AVON PRODUCTS INC). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.95	1.09	0.11	0.03	0.15	10.02
1998	0.90	0.50	0.12	0.14	0.13	10.16
1999	0.48	0.10	0.21	0.14	0.24	10.98
2000	0.23	-0.45	0.18	0.18	0.19	26.06
2001	0.16	0.27	0.08	0.02	0.06	2.13
2002	0.42	-1.35	0.06	0.10	0.05	13.61
2003	0.45	-0.60	0.06	0.11	0.05	5.87
2004	0.72	-25.08	0.48	19.31	0.15	19.18
2005	1.12	-1.95	0.19	0.10	0.23	6.31
2006	0.62	0.61	0.15	0.03	0.14	21.26
2007	0.98	11.00	0.28	1.51	0.21	92.80

Table 15: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock ATI(ALLEGHENY TECH NEW). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.00	0.00	0.00	0.00	0.00	0.00
1998	0.00	0.00	0.00	0.00	0.00	0.00
1999	0.00	0.12	0.04	0.04	0.03	2.26
2000	0.50	1.54	0.12	0.17	0.19	9.87
2001	0.86	1.45	0.08	0.03	0.11	2.66
2002	0.91	9.14	0.08	0.51	0.12	27.84
2003	1.85	5.58	0.19	0.43	0.18	23.96
2004	3.14	-37.80	0.83	21.72	0.39	32.37
2005	2.28	-2.75	0.28	0.17	0.26	88.77
2006	2.79	2.84	0.29	0.07	0.36	24.78
2007	2.36	9.79	0.31	1.37	0.24	37.07

Table 16: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock AXP(AMER EXPRESS INC). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	1.09	1.59	0.09	0.03	0.07	9.53
1998	1.54	-3.79	0.10	0.34	0.10	24.79
1999	1.35	0.73	0.10	0.10	0.10	9.72
2000	1.11	1.54	0.09	0.14	0.09	11.70
2001	1.42	0.80	0.10	0.03	0.12	2.29
2002	1.31	-3.28	0.05	0.23	0.06	28.34
2003	1.23	-0.61	0.06	0.13	0.05	4.31
2004	0.85	26.75	0.05	14.81	0.07	31.29
2005	1.15	0.82	0.12	0.04	0.11	3.20
2006	1.12	1.47	0.07	0.02	0.09	6.64
2007	1.28	-4.03	0.14	0.64	0.24	17.63

Table 17: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock BA(BOEING CO). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	1.03	-3.74	0.11	0.07	0.13	25.52
1998	0.98	-4.24	0.13	0.42	0.11	6.30
1999	0.43	-0.89	0.12	0.15	0.09	14.74
2000	0.45	3.70	0.08	0.26	0.13	22.29
2001	0.99	0.78	0.09	0.02	0.21	6.46
2002	0.83	1.57	0.08	0.11	0.08	6.99
2003	1.00	-1.09	0.08	0.20	0.10	6.19
2004	1.07	32.81	0.10	20.33	0.11	99.25
2005	0.98	2.57	0.13	0.07	0.14	6.91
2006	1.20	-0.94	0.12	0.04	0.12	2.77
2007	0.80	2.79	0.19	0.37	0.13	9.66

Table 18: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock BAC(BK OF AMERICA CP). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	1.54	1.79	0.10	0.03	0.09	3.96
1998	1.52	0.51	0.12	0.12	0.13	15.88
1999	1.29	2.09	0.09	0.13	0.10	7.98
2000	1.02	1.11	0.11	0.13	0.12	9.54
2001	0.93	-1.85	0.07	0.04	0.08	7.25
2002	0.89	-6.45	0.05	0.38	0.06	13.48
2003	0.75	-2.34	0.05	0.19	0.04	243.49
2004	0.79	-37.01	0.42	19.38	0.07	18.65
2005	0.91	0.79	0.06	0.03	0.07	3.67
2006	0.94	2.46	0.06	0.03	0.08	21.68
2007	1.20	0.79	0.09	0.19	0.12	10.96

Table 19: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock BAX(BAXTER INTL INC). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	1.25	-1.46	0.08	0.04	0.10	20.15
1998	0.64	-1.47	0.09	0.19	0.09	6.03
1999	0.69	0.48	0.08	0.10	0.09	29.30
2000	0.25	1.98	0.08	0.16	0.12	346.31
2001	0.13	1.24	0.08	0.03	0.08	3.76
2002	0.70	4.32	0.10	0.27	0.13	28.35
2003	0.62	0.98	0.15	0.13	0.31	11.23
2004	0.80	39.42	0.08	21.72	0.12	54.28
2005	0.87	1.64	0.09	0.05	0.13	5.08
2006	0.68	2.21	0.12	0.04	0.12	7.14
2007	0.53	6.33	0.17	0.72	0.16	21.09

Table 20: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock BDK(BLACK DECKER CP). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.78	0.05	0.09	0.02	0.09	8.69
1998	0.99	0.34	0.10	0.12	0.11	42.41
1999	0.26	1.34	0.12	0.14	0.13	19.42
2000	0.81	-0.16	0.14	0.16	0.17	18.19
2001	0.86	0.69	0.08	0.02	0.09	1.71
2002	0.79	-0.18	0.08	0.08	0.09	27.58
2003	0.93	2.59	0.08	0.15	0.07	8.42
2004	1.06	13.27	0.11	6.40	0.09	7.86
2005	1.14	-5.91	0.14	0.16	0.14	10.43
2006	0.56	0.49	0.30	0.03	0.62	8.01
2007	1.09	3.39	0.16	0.37	0.15	9.59

Table 21: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock BHI(BAKER HUGHES INTL). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.87	-0.76	0.13	0.03	0.13	4.94
1998	1.05	-15.38	0.16	1.26	0.16	132.10
1999	0.41	1.79	0.21	0.18	0.21	18.05
2000	0.21	-0.78	0.15	0.20	0.18	11.99
2001	0.21	3.44	0.12	0.07	0.12	87.04
2002	1.00	0.78	0.08	0.09	0.07	3.27
2003	0.55	0.91	0.10	0.12	0.10	51.97
2004	0.75	27.01	0.15	14.20	0.15	37.95
2005	0.99	0.12	0.13	0.06	0.14	24.59
2006	1.55	-0.42	0.24	0.05	0.23	13.95
2007	0.91	1.65	0.25	0.41	0.26	32.47

Table 22: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock BMY(BRISTOL MYERS SQIBB). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	1.19	1.66	0.09	0.03	0.11	3.97
1998	0.98	-0.96	0.08	0.15	0.10	2.55
1999	1.05	2.65	0.10	0.14	0.09	9.54
2000	0.61	0.89	0.15	0.15	0.16	17.38
2001	0.30	1.49	0.08	0.04	0.13	53.43
2002	0.77	-0.94	0.09	0.10	0.11	4.69
2003	0.97	3.30	0.06	0.18	0.08	241.27
2004	0.93	-28.23	0.10	15.24	0.12	22.49
2005	0.62	-1.69	0.08	0.06	0.11	23.59
2006	1.07	2.12	0.13	0.03	0.13	9.16
2007	1.08	4.76	0.15	0.54	0.13	19.79

Table 23: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock BNI(BURLINGTN N SANTE FE). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.56	0.87	0.06	0.02	0.08	2.88
1998	0.54	-9.90	0.07	0.74	0.10	22.12
1999	0.43	0.44	0.12	0.12	0.11	6.35
2000	0.62	3.55	0.12	0.22	0.09	47.10
2001	0.50	0.18	0.08	0.02	0.08	2.66
2002	0.73	-0.93	0.06	0.10	0.06	5.14
2003	0.79	0.43	0.05	0.07	0.05	28.53
2004	0.94	62.86	0.10	31.42	0.10	96.81
2005	1.44	2.87	0.10	0.07	0.14	3.84
2006	1.75	-2.74	0.18	0.09	0.17	15.93
2007	1.03	8.12	0.21	1.03	0.21	57.84

Table 24: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock BUD(ANHEUSER BUSCH). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.66	0.76	0.07	0.02	0.10	2.25
1998	0.40	1.41	0.06	0.12	0.09	2.43
1999	0.42	0.37	0.10	0.10	0.10	4.79
2000	0.24	1.06	0.10	0.13	0.11	7.88
2001	-0.00	0.28	0.07	0.02	0.12	3.02
2002	0.30	-2.89	0.05	0.19	0.06	7.19
2003	0.51	-1.22	0.05	0.14	0.06	186.26
2004	0.28	10.68	0.06	5.47	0.07	14.36
2005	0.71	0.85	0.09	0.04	0.13	16.88
2006	0.70	0.44	0.08	0.02	0.08	5.79
2007	0.76	1.13	0.12	0.19	0.19	16.01

Table 25: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock C(CI(CITIGROUP INC)). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	1.23	-0.62	0.08	0.03	0.11	5.87
1998	1.73	-8.21	0.13	0.75	0.16	69.82
1999	1.40	1.21	0.11	0.12	0.08	4.11
2000	1.14	1.18	0.08	0.10	0.08	17.23
2001	1.25	0.26	0.06	0.02	0.07	51.37
2002	1.48	0.97	0.05	0.08	0.08	2.15
2003	1.15	0.23	0.05	0.08	0.04	17.72
2004	1.13	-27.60	0.05	15.47	0.06	10.97
2005	0.78	0.24	0.05	0.03	0.09	18.69
2006	1.03	0.34	0.08	0.02	0.10	8.35
2007	1.33	-0.36	0.10	0.25	0.08	17.64

Table 26: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock CAT(CATERPILLAR INC). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.90	0.50	0.09	0.02	0.10	3.80
1998	0.95	-20.22	0.10	1.65	0.12	102.06
1999	0.42	2.32	0.13	0.23	0.14	14.85
2000	0.62	2.44	0.13	0.15	0.12	21.22
2001	0.92	-0.66	0.09	0.03	0.10	142.44
2002	0.91	1.32	0.05	0.07	0.06	4.23
2003	1.05	0.39	0.07	0.08	0.08	12.44
2004	1.27	-21.88	0.13	12.19	0.11	26.93
2005	1.39	-0.22	0.51	0.07	0.14	8.94
2006	1.51	-2.02	0.17	0.05	0.15	33.83
2007	0.95	0.79	0.16	0.22	0.14	26.41

Table 27: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock CBS(CBS CORP CL B). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.00	0.00	0.00	0.00	0.00	0.00
1998	0.00	0.00	0.00	0.00	0.00	0.00
1999	0.00	0.00	0.00	0.00	0.00	0.00
2000	0.00	0.00	0.00	0.00	0.00	0.00
2001	0.00	0.00	0.00	0.00	0.00	0.00
2002	0.00	0.00	0.00	0.00	0.00	0.00
2003	0.00	0.00	0.00	0.00	0.00	0.00
2004	0.00	0.00	0.00	0.00	0.00	0.00
2005	0.00	0.00	0.00	0.00	0.00	0.00
2006	0.73	1.16	0.14	0.04	0.18	8.47
2007	1.12	3.35	0.14	0.32	0.21	10.90

Table 28: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock CCU(CLEAR CHANNEL COM). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.48	0.09	0.12	0.02	0.14	2.04
1998	1.31	-5.58	0.10	0.47	0.12	18.95
1999	0.93	4.37	0.12	0.29	0.11	24.81
2000	0.71	-2.63	0.15	0.24	0.15	55.36
2001	1.26	-2.21	0.10	0.06	0.10	10.27
2002	1.43	5.76	0.11	0.31	0.11	11.88
2003	1.44	2.25	0.10	0.13	0.08	61.01
2004	1.08	-68.97	0.11	35.38	0.14	95.25
2005	0.81	1.45	0.08	0.06	0.09	11.67
2006	0.14	0.86	0.43	0.02	0.42	11.81
2007	0.32	1.97	0.11	0.28	0.11	24.08

Table 29: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock CI(CIGNA CP). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.67	-0.40	0.09	0.02	0.14	5.68
1998	0.70	2.90	0.06	0.20	0.09	3.30
1999	0.53	0.64	0.11	0.11	0.12	8.91
2000	0.36	3.19	0.10	0.22	0.11	45.94
2001	0.44	-0.60	0.12	0.03	0.09	4.38
2002	0.63	-0.19	0.14	0.08	0.14	5.03
2003	0.71	-0.58	0.13	0.15	0.10	200.78
2004	0.83	7.79	0.14	4.09	0.19	9.72
2005	1.03	6.94	0.16	0.16	0.12	70.90
2006	1.04	4.17	0.21	0.06	0.22	49.00
2007	0.77	5.85	0.16	0.79	0.13	23.63

Table 30: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock CL(COLGATE PALMOLIVE). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	1.01	0.56	0.09	0.02	0.09	22.45
1998	1.10	-4.58	0.09	0.41	0.07	12.34
1999	0.63	1.45	0.12	0.10	0.12	16.96
2000	0.46	0.11	0.12	0.14	0.13	9.96
2001	0.32	1.36	0.07	0.03	0.09	5.68
2002	0.41	0.37	0.05	0.05	0.05	1.79
2003	0.48	0.78	0.06	0.07	0.06	12.87
2004	0.54	-20.53	0.11	13.41	0.14	40.40
2005	0.77	-0.65	0.09	0.04	0.07	32.39
2006	0.51	0.66	0.09	0.02	0.09	3.38
2007	0.51	1.75	0.09	0.24	0.08	4.35

Table 31: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock CMCSA(COMCAST CP A). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.44	2.35	0.59	0.03	0.33	6.54
1998	0.89	2.65	0.14	0.22	0.13	17.55
1999	1.72	2.36	0.17	0.19	0.16	18.50
2000	1.02	0.21	0.14	0.15	0.15	8.55
2001	0.55	-1.12	0.07	0.03	0.07	58.95
2002	1.37	2.05	0.10	0.13	0.13	3.46
2003	1.46	-1.92	0.09	0.24	0.11	148.95
2004	0.98	70.74	0.12	37.80	0.12	39.38
2005	0.85	1.72	0.09	0.05	0.09	16.09
2006	1.04	5.98	0.10	0.07	0.10	37.33
2007	1.57	-12.50	1.06	2.86	0.35	90.97

Table 32: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock COF(CAPITAL ONE FINAN-CIA). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.72	1.40	0.16	0.03	0.19	4.23
1998	1.91	-2.28	0.15	0.34	0.17	5.39
1999	1.29	2.65	0.16	0.22	0.19	24.45
2000	1.25	0.89	0.12	0.16	0.13	12.65
2001	1.32	0.65	0.10	0.02	0.11	23.82
2002	1.47	1.19	0.18	0.14	0.20	5.53
2003	1.60	-1.82	0.14	0.27	0.13	21.76
2004	1.22	12.30	0.13	7.16	0.11	42.20
2005	0.83	0.34	0.12	0.05	0.16	17.26
2006	1.14	-2.35	0.15	0.06	0.14	10.13
2007	1.26	-0.22	0.20	0.26	0.19	6.14

Table 33: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock COP(CONOCOPHILLIPS). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.00	0.00	0.00	0.00	0.00	0.00
1998	0.00	0.00	0.00	0.00	0.00	0.00
1999	0.00	0.00	0.00	0.00	0.00	0.00
2000	0.00	0.00	0.00	0.00	0.00	0.00
2001	0.00	0.00	0.00	0.00	0.00	0.00
2002	0.35	2.23	0.07	0.11	0.13	154.09
2003	0.48	0.84	0.06	0.08	0.06	8.00
2004	0.76	17.00	0.12	9.48	0.13	5.22
2005	0.95	-8.87	0.54	0.34	0.40	44.81
2006	1.14	0.75	0.18	0.03	0.18	9.72
2007	1.02	1.36	0.29	0.34	0.23	14.49

Table 34: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock CPB(CAMPBELL SOUP CO). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	1.12	0.81	0.10	0.02	0.10	3.47
1998	0.72	-1.00	0.08	0.16	0.08	3.34
1999	0.49	-0.85	0.10	0.13	0.09	7.30
2000	0.29	2.26	0.10	0.20	0.15	25.61
2001	0.15	0.02	0.05	0.02	0.08	2.37
2002	0.50	1.31	0.04	0.09	0.04	2.65
2003	0.71	2.98	0.05	0.18	0.09	197.03
2004	0.71	-37.77	0.08	19.59	0.08	67.80
2005	0.82	0.12	0.18	0.04	0.16	7.89
2006	0.47	3.12	0.10	0.05	0.12	18.84
2007	0.86	6.46	0.21	0.94	0.14	27.11

Table 35: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock CSC(COMPUTER SCIENCES CP). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.92	0.26	0.11	0.02	0.11	2.50
1998	1.05	-4.60	0.15	0.42	0.14	7.87
1999	0.74	1.90	0.14	0.15	0.13	7.69
2000	0.61	-1.26	0.12	0.20	0.13	18.07
2001	1.03	1.23	0.17	0.05	0.17	13.06
2002	1.16	0.99	0.08	0.09	0.11	498.15
2003	0.82	1.57	0.11	0.18	0.17	21.72
2004	1.19	2.99	0.16	1.67	0.14	5.88
2005	1.00	-3.91	0.20	0.13	0.21	18.31
2006	1.16	2.42	0.14	0.04	0.13	7.54
2007	0.52	1.63	0.14	0.26	0.14	7.68

Table 36: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock CSCO(CISCO SYS INC). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.83	1.81	0.55	0.04	0.54	4.58
1998	1.55	-3.86	0.11	0.32	0.10	8.11
1999	1.59	3.60	0.11	0.19	0.08	25.77
2000	2.13	1.73	0.14	0.15	0.18	7.05
2001	2.40	1.65	0.15	0.04	0.22	4.08
2002	1.55	-3.49	0.11	0.24	0.14	48.42
2003	1.37	-1.25	0.09	0.22	0.08	73.10
2004	1.82	24.06	0.14	13.75	0.16	7.50
2005	1.07	4.73	0.12	0.12	0.12	24.75
2006	1.47	4.92	0.17	0.07	0.17	4.57
2007	1.35	-1.27	0.21	0.44	0.15	43.73

Table 37: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock CVX(CHEVRON CORP). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.00	0.00	0.00	0.00	0.00	0.00
1998	0.00	0.00	0.00	0.00	0.00	0.00
1999	0.00	0.00	0.00	0.00	0.00	0.00
2000	0.00	0.00	0.00	0.00	0.00	0.00
2001	0.17	0.14	0.09	0.01	0.12	1.18
2002	0.70	0.94	0.04	0.04	0.05	8.20
2003	0.59	0.49	0.04	0.07	0.05	14.78
2004	0.67	-52.67	0.42	32.06	0.09	10.38
2005	1.17	-1.43	0.13	0.08	0.12	13.87
2006	0.93	1.26	0.13	0.03	0.11	1.62
2007	1.10	3.14	0.17	0.39	0.13	32.88

Table 38: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock DD(DU PONT E I DE NEM). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	1.02	-0.30	0.10	0.02	0.07	4.98
1998	0.88	-0.37	0.09	0.11	0.12	10.30
1999	0.56	-2.22	0.10	0.17	0.13	35.24
2000	0.35	0.71	0.12	0.13	0.14	21.51
2001	0.82	-0.90	0.07	0.03	0.11	4.89
2002	0.93	-1.33	0.05	0.14	0.06	11.49
2003	0.97	2.25	0.05	0.12	0.07	5.37
2004	0.94	-2.64	0.06	2.69	0.08	2.59
2005	1.16	-0.48	0.11	0.05	0.08	4.52
2006	1.01	1.96	0.12	0.03	0.08	3.68
2007	1.05	6.28	0.14	0.78	0.12	47.64

Table 39: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock DIS(WALT DISNEY-DISNEY C). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.91	0.48	0.06	0.02	0.07	9.46
1998	1.10	-9.70	0.10	0.78	0.11	14.55
1999	0.65	2.17	0.14	0.14	0.12	12.74
2000	0.46	-0.04	0.13	0.12	0.13	12.81
2001	1.21	-0.26	0.10	0.03	0.16	21.94
2002	1.20	0.64	0.08	0.09	0.07	4.04
2003	1.41	1.03	0.08	0.09	0.09	37.85
2004	1.28	19.20	0.14	11.82	0.14	49.33
2005	1.04	1.21	0.10	0.05	0.10	27.44
2006	0.94	5.18	0.09	0.07	0.14	10.44
2007	1.26	4.35	0.12	0.47	0.10	7.58

Table 40: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock EK(EASTMAN KODAK CO). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.46	-3.91	0.13	0.07	0.15	14.05
1998	0.56	-6.78	0.10	0.50	0.08	10.07
1999	0.31	2.95	0.11	0.19	0.11	25.18
2000	0.35	0.71	0.13	0.10	0.11	8.15
2001	0.93	2.89	0.08	0.04	0.11	17.76
2002	0.81	3.85	0.07	0.20	0.06	314.97
2003	1.01	3.17	0.10	0.20	0.09	20.86
2004	0.87	79.38	0.15	46.23	0.15	20.69
2005	0.96	-4.27	0.14	0.14	0.16	25.27
2006	1.49	0.22	0.19	0.04	0.15	13.19
2007	0.67	-1.68	0.19	0.47	0.26	12.38

Table 41: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock EMC(E M C CP). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	1.45	0.04	0.14	0.03	0.16	11.91
1998	1.58	-8.38	0.11	0.75	0.15	30.05
1999	1.55	2.31	0.13	0.16	0.15	13.87
2000	1.79	0.17	0.15	0.18	0.13	28.05
2001	2.76	2.00	0.19	0.06	0.28	4.29
2002	1.66	-3.81	0.17	0.35	0.13	15.28
2003	1.33	-3.20	0.16	0.32	0.16	15.99
2004	1.69	28.46	0.19	21.12	0.19	21.46
2005	1.21	4.32	0.14	0.10	0.16	6.56
2006	1.12	3.92	0.15	0.06	0.14	21.02
2007	0.60	5.33	0.22	0.83	0.16	27.41

Table 42: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock EP(EL PASO CORPORATION). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.00	0.00	0.00	0.00	0.00	0.00
1998	0.00	0.00	0.00	0.00	0.00	0.00
1999	0.00	0.00	0.00	0.00	0.00	0.00
2000	0.00	0.00	0.00	0.00	0.00	0.00
2001	0.18	0.07	0.33	0.00	0.18	0.28
2002	1.73	4.12	0.22	0.29	0.28	70.83
2003	1.65	1.30	0.25	0.25	0.26	20.39
2004	1.11	23.01	0.24	13.25	0.22	40.21
2005	1.14	-0.88	0.16	0.09	0.20	14.23
2006	1.11	-2.09	0.18	0.06	0.23	6.35
2007	0.86	-0.51	0.22	0.36	0.19	11.12

Table 43: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock ETR(ENTERGY CP). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.38	-0.34	0.07	0.02	0.07	5.91
1998	0.08	-1.59	0.08	0.15	0.07	3.05
1999	0.26	-0.76	0.06	0.10	0.07	41.19
2000	0.03	3.11	0.15	0.22	0.15	1320.96
2001	-0.03	0.85	0.09	0.02	0.08	2.23
2002	0.46	1.09	0.07	0.09	0.10	8.11
2003	0.51	0.82	0.05	0.07	0.06	4.28
2004	0.46	37.86	0.09	21.54	0.08	47.84
2005	0.95	1.71	0.11	0.04	0.10	13.16
2006	0.54	1.76	0.08	0.03	0.08	3.63
2007	0.95	8.41	0.15	1.02	0.18	22.35

Table 44: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock EXC(EXELON CORPORATION). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.00	0.00	0.00	0.00	0.00	0.00
1998	0.00	0.00	0.00	0.00	0.00	0.00
1999	0.00	0.00	0.00	0.00	0.00	0.00
2000	-0.14	0.19	0.06	0.06	0.06	5.75
2001	-0.00	0.74	0.08	0.03	0.10	4.61
2002	0.52	-1.21	0.06	0.10	0.09	9.02
2003	0.55	0.10	0.05	0.08	0.05	47.41
2004	0.02	-1.73	0.41	1.65	0.47	5.62
2005	1.13	1.18	0.13	0.05	0.11	12.76
2006	0.67	0.08	0.11	0.03	0.10	1.37
2007	1.02	6.65	0.19	0.88	0.28	20.97

Table 45: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock F(FORD MOTOR CO). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.67	0.70	0.09	0.02	0.09	3.50
1998	1.19	5.01	0.08	0.35	0.10	9.41
1999	0.94	2.54	0.09	0.13	0.08	14.23
2000	0.53	0.62	0.21	0.11	0.12	14.83
2001	0.79	-0.59	0.10	0.03	0.14	75.51
2002	1.07	7.73	0.09	0.38	0.11	18.08
2003	1.24	0.02	0.10	0.15	0.11	89.70
2004	1.39	-23.41	0.11	13.44	0.12	26.03
2005	1.36	-5.37	0.16	0.18	0.22	47.53
2006	1.14	-5.58	0.27	0.09	0.21	43.50
2007	1.12	3.65	0.27	0.44	0.38	13.95

Table 46: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock FDX(FEDEX CORP). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	1.08	-0.21	0.12	0.02	0.13	11.69
1998	0.73	-6.56	0.12	0.51	0.10	54.65
1999	1.00	3.56	0.14	0.26	0.12	73.05
2000	0.80	1.64	0.20	0.15	0.11	22.22
2001	0.72	-2.91	0.08	0.07	0.09	7.66
2002	0.68	-2.81	0.08	0.17	0.11	99.94
2003	0.81	0.92	0.07	0.08	0.06	5.04
2004	1.07	-0.87	0.09	1.13	0.10	3.45
2005	1.28	-1.13	0.14	0.07	0.15	3.95
2006	1.51	-2.94	0.12	0.06	0.13	31.89
2007	0.79	0.36	0.22	0.20	0.23	7.03

Table 47: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock GD(GEN DYNAMICS CP). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.64	0.84	0.07	0.01	0.08	2.05
1998	0.55	-2.52	0.10	0.27	0.15	8.09
1999	0.63	3.75	0.12	0.24	0.13	20.79
2000	0.38	2.51	0.09	0.16	0.09	35.21
2001	0.36	0.75	0.08	0.02	0.13	18.43
2002	0.43	0.33	0.07	0.09	0.08	3.52
2003	0.75	0.66	0.09	0.11	0.09	122.77
2004	0.78	-7.55	0.08	4.57	0.09	5.41
2005	0.81	1.03	0.08	0.04	0.07	36.67
2006	0.15	-5.29	0.48	0.14	0.62	31.29
2007	1.00	4.34	0.18	0.44	0.16	11.72

Table 48: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock GE(GEN ELECTRIC CO). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	1.26	0.51	0.04	0.02	0.09	1.89
1998	1.16	-0.11	0.04	0.11	0.07	20.18
1999	1.11	0.88	0.07	0.07	0.05	4.89
2000	1.04	1.66	0.08	0.09	0.06	6.20
2001	1.45	1.00	0.06	0.02	0.08	78.54
2002	1.31	3.24	0.05	0.14	0.06	8.91
2003	1.11	0.92	0.06	0.08	0.06	52.26
2004	1.12	-3.48	0.06	2.58	0.06	5.51
2005	0.98	0.54	0.06	0.03	0.08	3.28
2006	0.87	0.48	0.06	0.01	0.07	4.33
2007	0.69	-0.09	0.10	0.18	0.15	4.18

Table 49: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock GM(GEN MOTORS). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.81	-0.65	0.06	0.02	0.07	3.56
1998	0.90	-3.70	0.07	0.40	0.08	38.17
1999	0.70	1.08	0.13	0.09	0.15	6.16
2000	0.84	1.82	0.10	0.12	0.10	21.89
2001	0.94	1.67	0.09	0.03	0.11	15.63
2002	1.10	3.59	0.07	0.15	0.08	6.03
2003	1.10	2.33	0.06	0.12	0.09	71.32
2004	1.14	-105.99	0.08	58.14	0.10	56.91
2005	1.43	-8.21	0.32	0.20	0.29	102.82
2006	1.18	-1.71	0.31	0.06	0.21	14.16
2007	1.09	2.43	0.33	0.48	0.26	26.11

Table 50: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock GOOG(GOOGLE). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.00	0.00	0.00	0.00	0.00	0.00
1998	0.00	0.00	0.00	0.00	0.00	0.00
1999	0.00	0.00	0.00	0.00	0.00	0.00
2000	0.00	0.00	0.00	0.00	0.00	0.00
2001	0.00	0.00	0.00	0.00	0.00	0.00
2002	0.00	0.00	0.00	0.00	0.00	0.00
2003	0.00	0.00	0.00	0.00	0.00	0.00
2004	0.33	59.31	0.64	29.47	0.47	18.90
2005	0.79	1.99	0.19	0.07	0.19	10.83
2006	1.52	-2.27	0.22	0.06	0.25	37.29
2007	1.35	0.14	0.23	0.31	0.21	27.00

Table 51: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock HAL(HALLIBURTON CO). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.90	-0.29	0.14	0.04	0.21	2.29
1998	1.16	-19.16	0.15	1.65	0.16	64.92
1999	0.67	0.17	0.18	0.19	0.17	11.15
2000	0.41	-1.65	0.14	0.21	0.14	436.53
2001	0.46	6.98	0.16	0.10	0.13	877.13
2002	1.32	-3.61	0.13	0.31	0.15	6.80
2003	0.58	-0.51	0.09	0.13	0.09	3.67
2004	0.87	41.28	0.16	29.05	0.16	22.36
2005	1.42	0.91	0.18	0.08	0.23	110.22
2006	1.33	-9.81	0.71	0.19	0.36	24.05
2007	0.91	2.76	0.23	0.55	0.22	42.49

Table 52: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock HD(HOME DEPOT INC). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.82	0.35	0.06	0.01	0.07	1.29
1998	1.39	-3.39	0.09	0.38	0.10	47.78
1999	1.18	2.48	0.09	0.15	0.09	9.10
2000	1.20	-0.67	0.17	0.18	0.23	30.95
2001	1.31	0.02	0.11	0.03	0.11	158.56
2002	0.99	4.25	0.08	0.20	0.09	6.91
2003	1.06	1.03	0.08	0.10	0.06	16.62
2004	1.09	34.15	0.09	18.09	0.09	23.09
2005	1.42	-0.13	0.10	0.04	0.11	37.97
2006	1.15	0.22	0.14	0.03	0.11	10.94
2007	0.84	1.23	0.11	0.16	0.13	5.17

Table 53: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock HET(HARRAH'S ENTERTAIN). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.56	-0.57	0.12	0.03	0.14	4.56
1998	0.98	-9.50	0.13	0.81	0.12	79.54
1999	0.65	0.16	0.14	0.15	0.13	6.50
2000	1.51	-0.38	1.42	0.43	1.13	28.58
2001	0.94	-1.45	0.11	0.04	0.15	102.90
2002	0.71	1.20	0.06	0.09	0.08	3.37
2003	1.10	1.52	0.08	0.11	0.11	118.64
2004	1.12	6.64	0.12	3.42	0.13	4.55
2005	1.49	-1.73	0.14	0.09	0.13	58.23
2006	0.90	-0.55	0.18	0.04	0.12	8.51
2007	0.10	1.11	0.06	0.14	0.08	3.23

Table 54: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock HIG(HARTFORD FIN SVC). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.67	0.71	0.06	0.02	0.08	1.82
1998	0.83	2.36	0.18	0.15	0.10	11.02
1999	0.81	0.60	0.11	0.13	0.08	7.32
2000	1.04	0.28	0.10	0.19	0.19	13.09
2001	0.66	-0.55	0.08	0.03	0.09	38.69
2002	0.95	-0.74	0.06	0.10	0.06	6.73
2003	1.26	2.23	0.08	0.16	0.07	129.32
2004	1.12	-19.58	0.09	11.49	0.12	11.55
2005	1.27	2.97	0.09	0.06	0.13	17.48
2006	1.17	0.22	0.12	0.03	0.09	15.75
2007	1.08	6.54	0.10	0.68	0.10	34.82

Table 55: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock HON(HONEYWELL INTL INC). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.77	0.19	0.08	0.01	0.09	2.48
1998	0.95	-2.75	0.08	0.27	0.11	23.94
1999	0.71	0.16	0.13	0.13	0.13	5.71
2000	0.79	-0.69	0.16	0.16	0.16	16.55
2001	1.54	1.29	0.10	0.03	0.14	66.13
2002	1.15	2.10	0.10	0.13	0.10	3.69
2003	1.21	4.53	0.07	0.27	0.07	184.02
2004	1.28	11.09	0.09	5.54	0.09	24.38
2005	1.09	2.16	0.09	0.07	0.11	11.72
2006	1.24	0.36	0.10	0.03	0.10	22.28
2007	0.89	3.03	0.13	0.34	0.11	34.70

Table 56: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock HNZ(HEINZ H J CO). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.66	1.25	0.07	0.02	0.06	2.75
1998	0.42	-0.99	0.06	0.16	0.09	5.26
1999	0.41	2.72	0.10	0.17	0.08	15.65
2000	-0.01	-0.18	0.09	0.12	0.14	8.80
2001	0.08	0.71	0.06	0.02	0.07	33.24
2002	0.40	0.64	0.05	0.07	0.06	6.39
2003	0.53	1.52	0.04	0.08	0.03	111.83
2004	0.74	-4.18	0.07	2.76	0.06	10.80
2005	0.91	-0.26	0.13	0.03	0.12	15.14
2006	0.47	2.77	0.10	0.04	0.09	15.52
2007	0.66	4.71	0.11	0.55	0.13	22.06

Table 57: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock IBM(INTL BUSINESS MACH). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	1.29	1.95	0.08	0.03	0.10	9.06
1998	0.94	5.74	0.08	0.40	0.06	13.97
1999	1.20	3.31	0.13	0.21	0.12	54.14
2000	1.01	0.94	0.13	0.13	0.11	8.50
2001	1.13	-1.99	0.07	0.05	0.08	8.35
2002	1.13	-0.35	0.07	0.09	0.07	5.59
2003	0.99	-1.39	0.06	0.19	0.05	85.71
2004	0.85	43.35	0.07	27.65	0.07	30.60
2005	0.99	2.44	0.10	0.06	0.14	1536.69
2006	0.92	4.96	0.07	0.06	0.07	12.86
2007	0.72	6.48	0.16	0.80	0.15	28.68

Table 58: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock INTC(INTEL CP). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	1.07	0.72	0.24	0.03	0.29	3.07
1998	1.22	10.97	0.09	0.95	0.08	23.55
1999	1.61	2.01	0.09	0.15	0.10	15.59
2000	1.89	1.70	0.16	0.17	0.17	30.59
2001	1.92	-1.64	0.11	0.05	0.12	8.04
2002	1.66	-1.79	0.10	0.17	0.11	11.46
2003	1.52	-0.67	0.10	0.19	0.10	35.08
2004	1.60	-20.55	0.10	12.10	0.12	8.78
2005	1.26	3.35	0.12	0.07	0.14	43.96
2006	1.66	0.46	0.16	0.02	0.17	3.07
2007	1.13	1.41	0.16	0.24	0.10	16.00

Table 59: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock IP(INTL PAPER). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.80	-2.30	0.11	0.04	0.18	7.16
1998	0.84	-19.05	0.09	1.55	0.08	86.20
1999	0.19	-2.45	0.12	0.21	0.16	14.26
2000	0.62	-2.32	0.15	0.23	0.14	34.31
2001	0.90	0.42	0.06	0.03	0.10	74.34
2002	0.84	-0.72	0.06	0.10	0.06	5.46
2003	0.92	0.47	0.06	0.08	0.05	75.40
2004	1.14	-29.62	0.10	16.39	0.07	15.69
2005	1.17	-4.91	0.11	0.12	0.11	78.58
2006	1.29	-1.71	0.13	0.05	0.11	26.35
2007	1.13	5.07	0.19	0.52	0.17	35.55

Table 60: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock JNJ(JOHNSON AND JOHNS DC). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.96	-1.39	0.08	0.03	0.07	7.04
1998	0.75	-0.47	0.07	0.10	0.07	5.02
1999	0.78	0.99	0.07	0.09	0.08	5.96
2000	0.26	1.09	0.09	0.10	0.09	8.61
2001	0.12	-0.25	0.07	0.02	0.07	1.89
2002	0.72	-2.98	0.06	0.21	0.11	7.85
2003	0.70	0.81	0.06	0.09	0.05	51.38
2004	0.53	66.86	0.08	33.04	0.08	55.22
2005	0.66	0.04	0.09	0.03	0.09	21.07
2006	0.53	0.69	0.07	0.02	0.06	6.68
2007	0.51	-1.15	0.09	0.25	0.07	7.44

Table 61: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock JPM(JP MORGAN CHASE CO). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	1.11	-0.76	0.08	0.02	0.07	4.35
1998	1.28	-11.97	0.12	0.97	0.13	85.40
1999	1.08	1.26	0.09	0.10	0.09	6.89
2000	1.10	3.22	0.11	0.18	0.09	22.84
2001	1.35	0.01	0.08	0.02	0.11	129.42
2002	1.61	-0.25	0.08	0.10	0.11	2.83
2003	1.44	-0.05	0.06	0.10	0.05	159.18
2004	1.12	-6.83	0.05	4.50	0.08	4.88
2005	1.01	2.26	0.05	0.04	0.08	13.65
2006	1.35	3.01	0.07	0.03	0.09	13.23
2007	1.29	3.96	0.11	0.36	0.21	7.88

Table 62: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock KO(COCA COLA CO THE). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	1.14	-0.52	0.06	0.02	0.14	4.76
1998	1.01	-1.42	0.07	0.18	0.09	19.26
1999	0.57	1.05	0.09	0.10	0.08	6.84
2000	0.19	1.56	0.10	0.16	0.13	15.64
2001	0.30	0.07	0.07	0.01	0.08	5.29
2002	0.52	-2.86	0.06	0.16	0.08	5.32
2003	0.60	-0.22	0.07	0.08	0.08	24.60
2004	0.70	24.86	0.08	13.41	0.09	18.93
2005	0.74	-0.84	0.07	0.04	0.07	9.41
2006	0.70	1.79	0.05	0.02	0.05	7.35
2007	0.68	3.52	0.08	0.44	0.13	21.67

Table 63: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock LEH(LEHMAN BROS HLD). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.93	0.22	0.14	0.03	0.17	2.24
1998	1.90	-9.22	0.16	0.74	0.23	15.11
1999	1.81	2.41	0.14	0.16	0.14	4.53
2000	1.81	2.40	0.15	0.17	0.20	43.59
2001	1.73	-0.30	0.10	0.04	0.13	3.99
2002	1.24	1.41	0.06	0.08	0.06	2.26
2003	1.14	-0.08	0.07	0.13	0.07	103.74
2004	1.25	0.14	0.10	1.24	0.12	45.49
2005	1.30	2.88	0.11	0.07	0.12	19.57
2006	1.49	-4.89	0.56	0.16	0.62	46.33
2007	1.99	-3.18	0.18	0.87	0.28	40.64

Table 64: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock LTD(LIMITED BRANDS INC). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.68	0.37	0.09	0.02	0.12	16.03
1998	1.19	2.79	0.11	0.22	0.13	9.26
1999	0.70	-0.77	0.12	0.15	0.11	13.08
2000	0.78	-0.44	0.13	0.19	0.15	10.59
2001	0.96	-1.27	0.10	0.05	0.15	9.11
2002	0.98	1.74	0.09	0.11	0.14	4.05
2003	1.24	4.32	0.09	0.37	0.06	127.08
2004	0.84	-32.59	0.11	22.05	0.11	10.17
2005	1.23	0.44	0.11	0.07	0.11	30.41
2006	1.16	0.35	0.16	0.03	0.11	4.29
2007	1.22	-0.21	0.26	0.52	0.27	10.03

Table 65: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock MCD(MCDONALDS CP). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.68	0.82	0.07	0.02	0.08	2.28
1998	0.87	2.67	0.09	0.20	0.15	13.87
1999	0.65	-0.85	0.09	0.13	0.07	8.97
2000	0.36	-0.04	0.12	0.17	0.10	15.91
2001	0.34	-1.01	0.05	0.03	0.07	99.89
2002	0.50	-2.34	0.06	0.14	0.09	7.53
2003	0.84	0.36	0.12	0.12	0.09	174.41
2004	0.71	82.05	0.09	43.93	0.12	19.21
2005	1.24	3.16	0.10	0.07	0.13	14.08
2006	0.88	1.33	0.11	0.03	0.17	9.01
2007	0.81	4.37	0.13	0.49	0.18	8.99

Table 66: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock MDT(MEDTRONIC INC). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.91	0.32	0.07	0.02	0.09	5.98
1998	1.01	1.45	0.11	0.10	0.09	3.34
1999	0.88	3.35	0.13	0.23	0.12	29.66
2000	0.62	0.68	0.11	0.14	0.12	213.09
2001	0.55	2.00	0.09	0.04	0.10	24.23
2002	0.64	-2.62	0.05	0.19	0.08	7.07
2003	0.68	1.32	0.07	0.09	0.06	8.33
2004	0.67	28.67	0.12	16.60	0.11	12.45
2005	0.53	3.13	0.09	0.08	0.09	10.20
2006	0.47	0.29	0.16	0.03	0.10	5.73
2007	0.62	1.28	0.17	0.26	0.19	10.76

Table 67: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock MEDI(MEDIMMUNE INC). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	-0.05	3.64	1.26	0.07	1.15	59.92
1998	0.93	10.86	0.20	0.77	0.27	8.89
1999	1.35	2.60	0.21	0.31	0.18	17.88
2000	1.53	-2.77	0.23	0.33	0.21	38.74
2001	1.94	-1.01	0.15	0.05	0.17	42.09
2002	1.20	0.74	0.11	0.11	0.14	8.76
2003	0.96	-0.36	0.12	0.19	0.12	23.59
2004	1.05	61.65	0.17	39.23	0.17	60.19
2005	1.00	3.00	0.14	0.09	0.16	23.76
2006	1.33	2.36	0.20	0.04	0.22	4.72
2007	0.79	8.86	0.30	1.24	0.23	27.69

Table 68: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock MER(ML CO CMN STK). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	1.52	0.67	0.09	0.03	0.10	4.32
1998	1.90	-6.62	0.12	0.55	0.10	9.72
1999	1.71	4.04	0.10	0.27	0.11	31.78
2000	1.32	2.71	0.11	0.17	0.10	15.55
2001	1.63	-1.19	0.10	0.04	0.07	15.40
2002	1.31	-0.66	0.06	0.11	0.09	566.48
2003	1.41	-1.57	0.07	0.21	0.05	20.10
2004	1.39	9.46	0.09	5.02	0.07	6.23
2005	1.31	2.18	0.08	0.05	0.07	4.40
2006	1.44	3.05	0.11	0.04	0.12	7.52
2007	1.71	0.80	0.18	0.28	0.30	8.94

Table 69: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock MMM(3M COMPANY). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.63	0.78	0.08	0.02	0.08	1.36
1998	0.72	-8.54	0.07	0.69	0.08	55.62
1999	0.27	-0.74	0.10	0.15	0.11	17.95
2000	0.52	1.99	0.09	0.12	0.11	234.66
2001	0.78	0.01	0.07	0.02	0.09	2.24
2002	0.73	-1.52	0.04	0.14	0.05	6.20
2003	0.78	4.97	0.23	0.49	0.16	29.22
2004	1.02	3.83	0.10	2.28	0.07	4.79
2005	0.95	-1.10	0.10	0.05	0.10	3.45
2006	0.88	-0.64	0.11	0.02	0.11	10.13
2007	0.55	2.40	0.15	0.29	0.16	5.59

Table 70: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock MO(ALTRIA GROUP INC). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	1.00	-1.37	0.13	0.04	0.12	9.14
1998	0.50	-3.79	0.11	0.30	0.08	6.61
1999	0.50	3.54	0.13	0.23	0.16	39.38
2000	0.14	2.57	0.11	0.18	0.15	8.59
2001	0.14	-1.72	0.09	0.04	0.10	20.41
2002	0.31	-0.85	0.08	0.09	0.09	4.97
2003	0.52	-1.45	0.09	0.20	0.12	7.39
2004	0.77	-1.84	0.12	1.58	0.13	17.57
2005	0.92	1.73	0.11	0.06	0.10	8.31
2006	0.60	-0.11	0.11	0.02	0.10	1.02
2007	0.72	4.75	0.69	0.53	0.26	28.42

Table 71: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock MRK(MERCK CO INC). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	1.05	0.37	0.14	0.02	0.08	1.34
1998	0.94	1.53	0.08	0.13	0.07	1.24
1999	0.94	1.60	0.09	0.12	0.08	17.66
2000	0.31	1.85	0.09	0.16	0.14	9.02
2001	0.24	0.32	0.06	0.02	0.09	11.08
2002	0.82	-4.24	0.05	0.26	0.06	10.03
2003	0.90	1.21	0.08	0.11	0.07	10.82
2004	0.77	5.97	0.19	2.91	0.13	120.51
2005	0.83	-2.65	0.13	0.11	0.16	15.58
2006	0.96	4.36	0.11	0.06	0.13	4.66
2007	0.81	2.12	0.16	0.31	0.10	21.52

Table 72: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock MS(MORGAN STANLEY). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.00	0.00	0.00	0.00	0.00	0.00
1998	0.00	0.00	0.00	0.00	0.00	0.00
1999	0.00	0.00	0.00	0.00	0.00	0.00
2000	0.00	0.00	0.00	0.00	0.00	0.00
2001	0.00	0.00	0.00	0.00	0.00	0.00
2002	0.00	0.00	0.00	0.00	0.00	0.00
2003	0.00	0.00	0.00	0.00	0.00	0.00
2004	0.00	0.00	0.00	0.00	0.00	0.00
2005	0.00	0.00	0.00	0.00	0.00	0.00
2006	1.70	1.11	0.14	0.02	0.16	47.10
2007	2.12	2.30	0.15	0.26	0.26	20.91

Table 73: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock MSFT(MICROSOFT CP). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.72	0.74	0.31	0.02	0.46	1.36
1998	1.31	8.38	0.07	0.55	0.07	16.14
1999	1.41	2.51	0.09	0.12	0.08	39.66
2000	1.41	-0.13	0.12	0.14	0.12	33.53
2001	1.35	-3.42	0.07	0.07	0.08	19.76
2002	1.22	-2.96	0.05	0.23	0.09	16.28
2003	1.29	0.94	0.07	0.09	0.05	22.42
2004	0.98	20.48	0.11	12.23	0.07	3.35
2005	0.86	2.59	0.06	0.07	0.09	41.70
2006	1.00	4.36	0.14	0.05	0.12	153.96
2007	1.25	0.10	0.16	0.29	0.15	6.27

Table 74: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock NSC(NORFOLK SO CP). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.98	-0.60	0.06	0.02	0.12	2.65
1998	0.80	-3.43	0.07	0.36	0.10	18.51
1999	0.43	3.29	0.11	0.22	0.12	18.34
2000	0.54	-0.47	0.12	0.12	0.12	13.32
2001	0.77	-1.66	0.10	0.05	0.12	187.71
2002	1.02	1.67	0.07	0.10	0.08	7.40
2003	0.89	1.89	0.06	0.11	0.09	36.42
2004	1.18	35.82	0.11	19.15	0.08	17.85
2005	1.37	1.45	0.14	0.06	0.14	20.18
2006	1.45	-1.53	0.21	0.06	0.20	27.20
2007	1.17	9.30	0.29	0.97	0.33	87.61

Table 75: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock NSM(NATL SEMICONDUCTOR). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	1.17	-2.68	0.19	0.06	0.16	10.03
1998	0.90	-22.34	0.22	1.85	0.21	175.41
1999	1.07	2.03	0.25	0.23	0.19	10.06
2000	1.88	-2.31	0.25	0.28	0.20	56.72
2001	1.84	-3.84	0.14	0.09	0.15	319.76
2002	1.70	5.16	0.11	0.27	0.14	19.05
2003	1.70	-0.61	0.19	0.26	0.13	313.98
2004	1.55	-188.42	0.47	101.62	0.35	49.74
2005	1.79	2.83	0.16	0.11	0.18	8.73
2006	1.94	0.58	0.20	0.05	0.17	6.21
2007	0.79	3.07	0.29	0.41	0.27	24.00

Table 76: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock NXTL. See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.60	-1.39	0.63	0.06	0.54	26.04
1998	1.62	-11.64	0.18	1.20	0.28	25.22
1999	1.44	2.24	0.19	0.26	0.18	10.69
2000	2.10	-2.35	0.22	0.39	0.23	49.72
2001	2.79	2.44	0.18	0.05	0.21	23.34
2002	1.56	0.95	0.25	0.18	0.29	77.57
2003	1.41	1.08	0.14	0.21	0.14	9.12
2004	1.68	-16.72	0.16	12.16	0.14	37.48
2005	0.63	3.09	0.28	0.06	0.17	174.22
2006	0.00	0.00	0.00	0.00	0.00	0.00
2007	0.00	0.00	0.00	0.00	0.00	0.00

Table 77: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock ORCL(ORACLE CORP). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.91	-0.15	0.47	0.03	0.40	5.93
1998	1.20	0.36	0.18	0.20	0.14	10.97
1999	1.67	0.16	0.22	0.26	0.23	15.93
2000	2.09	0.40	0.15	0.19	0.21	41.99
2001	2.31	-1.14	0.14	0.06	0.20	8.68
2002	1.47	-7.41	0.12	0.45	0.11	18.15
2003	1.39	-0.83	0.10	0.18	0.09	30.00
2004	1.42	64.55	0.17	32.69	0.12	55.02
2005	1.06	3.59	0.15	0.09	0.12	33.79
2006	1.15	4.88	0.13	0.08	0.14	59.47
2007	1.22	4.90	0.23	0.79	0.20	23.77

Table 78: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock PEP(PEPSICO INC). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	1.19	3.62	0.12	0.06	0.12	13.49
1998	1.12	3.31	0.13	0.24	0.16	6.05
1999	0.57	-1.52	0.08	0.18	0.11	21.61
2000	0.12	2.32	0.08	0.19	0.08	28.41
2001	0.13	0.95	0.05	0.02	0.10	4.11
2002	0.60	-2.90	0.07	0.21	0.10	7.35
2003	0.65	0.75	0.05	0.09	0.07	22.46
2004	0.64	25.87	0.07	12.67	0.08	27.21
2005	0.65	4.03	0.06	0.08	0.08	22.49
2006	0.42	3.25	0.07	0.05	0.07	32.92
2007	0.72	5.91	0.10	0.83	0.09	38.47

Table 79: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock PFE(PFIZER INC). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	1.23	0.28	0.10	0.02	0.08	1.89
1998	1.02	-3.23	0.08	0.33	0.06	33.07
1999	1.16	2.87	0.10	0.17	0.10	12.73
2000	0.28	2.18	0.12	0.17	0.11	26.58
2001	0.37	1.16	0.07	0.02	0.11	26.74
2002	0.93	-0.94	0.07	0.10	0.08	5.37
2003	0.90	-0.93	0.07	0.14	0.06	184.33
2004	1.10	-32.12	0.11	17.99	0.10	32.90
2005	1.02	-6.37	0.12	0.18	0.18	68.36
2006	1.00	1.56	0.13	0.03	0.13	10.70
2007	0.92	3.28	0.10	0.35	0.10	19.85

Table 80: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock PG(PROCTER GAMBLE CO). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	1.08	1.38	0.06	0.03	0.06	28.25
1998	0.84	2.22	0.07	0.17	0.10	8.28
1999	0.64	-0.55	0.08	0.12	0.09	7.34
2000	0.30	-0.20	0.15	0.12	0.24	14.03
2001	0.18	0.42	0.06	0.02	0.10	2.31
2002	0.40	-1.11	0.05	0.07	0.06	2.11
2003	0.64	0.86	0.25	0.19	0.12	15.83
2004	0.66	34.50	0.07	22.15	0.08	21.38
2005	0.82	4.27	0.08	0.09	0.11	57.97
2006	0.65	4.04	0.08	0.05	0.08	11.03
2007	0.76	4.60	0.08	0.55	0.08	10.27

Table 81: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock RF(REGIONS FINANCIAL CP). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.00	0.00	0.00	0.00	0.00	0.00
1998	0.00	0.00	0.00	0.00	0.00	0.00
1999	0.00	0.00	0.00	0.00	0.00	0.00
2000	0.00	0.00	0.00	0.00	0.00	0.00
2001	0.00	0.00	0.00	0.00	0.00	0.00
2002	0.74	-1.25	0.05	0.10	0.05	5.47
2003	0.74	1.75	0.04	0.10	0.05	92.94
2004	0.81	-0.55	0.13	1.04	0.19	5.82
2005	1.04	-0.73	0.08	0.05	0.14	13.93
2006	0.80	-0.08	0.09	0.02	0.08	13.42
2007	1.14	-2.19	0.13	0.39	0.16	21.81

Table 82: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock ROK(ROCKWELL AUTOMAT INC). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.81	1.32	0.08	0.02	0.11	2.56
1998	0.74	4.90	0.10	0.35	0.17	6.39
1999	0.69	-0.92	0.13	0.14	0.12	7.96
2000	0.61	2.76	0.14	0.13	0.14	26.25
2001	0.67	1.15	0.27	0.03	0.24	35.34
2002	0.95	-2.54	0.05	0.18	0.06	5.60
2003	1.14	0.17	0.09	0.13	0.10	224.42
2004	1.11	46.48	0.12	23.98	0.18	21.63
2005	1.68	1.77	0.23	0.06	0.26	20.82
2006	1.33	4.35	0.17	0.07	0.13	33.63
2007	1.03	3.84	0.15	0.39	0.19	24.07

Table 83: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock RTN(RAYTHEON CO (NEW)). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.00	0.00	0.00	0.00	0.00	0.00
1998	0.00	0.00	0.00	0.00	0.00	0.00
1999	0.00	0.00	0.00	0.00	0.00	0.00
2000	0.00	0.00	0.00	0.00	0.00	0.00
2001	-0.19	0.21	0.12	0.02	0.22	3.34
2002	0.70	0.13	0.08	0.09	0.08	6.70
2003	0.59	1.27	0.07	0.12	0.14	96.45
2004	0.69	22.28	0.10	10.69	0.09	46.21
2005	0.80	0.88	0.08	0.04	0.08	5.10
2006	0.77	2.48	0.09	0.04	0.09	30.31
2007	0.86	4.17	0.16	0.55	0.11	7.60

Table 84: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock SBC. See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.65	0.04	0.08	0.02	0.09	2.69
1998	0.64	-1.08	0.09	0.13	0.10	4.43
1999	0.79	3.40	0.10	0.22	0.13	29.23
2000	0.45	1.06	0.12	0.11	0.13	6.89
2001	0.42	0.43	0.08	0.02	0.10	3.08
2002	1.01	-2.99	0.08	0.21	0.08	241.03
2003	1.16	3.89	0.12	0.23	0.09	17.82
2004	0.91	-8.38	0.09	5.17	0.10	3.43
2005	1.08	-1.02	0.22	0.05	0.37	9.71
2006	0.00	0.00	0.00	0.00	0.00	0.00
2007	0.00	0.00	0.00	0.00	0.00	0.00

Table 85: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock SLB(SCHLUMBERGER LTD). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	1.05	0.17	0.10	0.03	0.18	3.57
1998	1.16	-16.69	0.15	1.59	0.12	29.63
1999	0.51	0.27	0.16	0.13	0.14	5.13
2000	0.22	-1.06	1.60	0.17	1.17	8.38
2001	0.30	2.90	0.10	0.06	0.12	5.59
2002	0.99	-1.24	0.07	0.15	0.08	7.90
2003	0.57	-2.58	0.08	0.28	0.09	84.96
2004	0.73	15.58	0.11	8.32	0.12	4.50
2005	1.12	2.24	0.13	0.07	0.13	4.62
2006	0.92	-6.74	0.44	0.21	0.72	50.78
2007	1.25	4.06	0.27	0.53	0.17	50.73

Table 86: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock SLE(SARA LEE CP). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.66	0.61	0.11	0.02	0.11	29.84
1998	0.55	1.47	0.08	0.13	0.09	3.88
1999	0.52	0.47	0.11	0.11	0.11	7.75
2000	0.29	2.60	0.09	0.21	0.16	25.90
2001	0.13	-0.49	0.05	0.02	0.09	2.43
2002	0.35	-3.71	0.06	0.17	0.06	5.44
2003	0.70	2.10	0.07	0.15	0.08	19.24
2004	0.53	-18.59	0.07	12.15	0.07	28.79
2005	0.47	-1.60	0.12	0.06	0.11	38.42
2006	0.96	2.26	0.11	0.04	0.14	6.82
2007	0.72	4.37	0.12	0.58	0.22	12.14

Table 87: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock SO(SOUTHERN CO). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.39	-0.15	0.07	0.02	0.09	1.24
1998	0.15	3.48	0.06	0.24	0.08	4.86
1999	0.23	-1.32	0.07	0.15	0.09	5.55
2000	0.06	1.26	0.08	0.21	0.11	24.01
2001	-0.01	1.54	0.06	0.04	0.07	4.55
2002	0.41	-0.17	0.07	0.08	0.07	4.46
2003	0.55	1.24	0.05	0.09	0.06	29.90
2004	0.41	8.80	0.08	4.07	0.06	19.03
2005	0.84	0.70	0.07	0.03	0.08	3.71
2006	0.68	0.68	0.06	0.02	0.07	21.48
2007	0.76	4.40	0.07	0.62	0.12	24.62

Table 88: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock TGT(TARGET CP). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.00	0.00	0.00	0.00	0.00	0.00
1998	0.00	0.00	0.00	0.00	0.00	0.00
1999	0.00	0.00	0.00	0.00	0.00	0.00
2000	0.70	0.84	0.13	0.12	0.18	6.63
2001	1.05	-0.39	0.09	0.04	0.12	2.42
2002	1.03	6.85	0.06	0.34	0.09	16.12
2003	0.90	-0.14	0.08	0.12	0.12	22.73
2004	0.81	24.58	0.11	12.09	0.17	16.83
2005	1.21	-2.33	0.14	0.09	0.14	11.20
2006	0.97	-0.86	0.12	0.04	0.13	10.15
2007	1.15	4.48	0.15	0.51	0.16	21.12

Table 89: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock TXN(TEXAS INSTRUMENTS). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	1.49	-0.14	0.16	0.04	0.14	3.35
1998	1.35	2.16	0.12	0.20	0.12	8.00
1999	1.65	1.29	0.11	0.15	0.15	5.04
2000	2.12	-1.19	0.16	0.25	0.20	443.68
2001	1.78	-0.43	0.16	0.05	0.13	20.78
2002	1.66	1.65	0.10	0.12	0.12	6.59
2003	1.53	-3.38	0.12	0.33	0.11	34.58
2004	1.77	-57.94	0.20	34.23	0.15	57.26
2005	1.52	5.30	0.13	0.12	0.16	20.16
2006	1.52	1.41	0.15	0.05	0.13	12.26
2007	0.83	0.32	0.25	0.31	0.22	10.20

Table 90: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock TYC(TYCO INTL LTD). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	1.05	-0.73	0.07	0.03	0.14	5.27
1998	1.17	-4.11	0.07	0.34	0.11	14.33
1999	0.63	4.22	0.19	0.31	0.14	108.39
2000	0.98	0.75	0.11	0.15	0.11	12.00
2001	1.05	2.13	0.06	0.04	0.06	3.40
2002	1.36	1.01	0.25	0.19	0.25	18.22
2003	0.87	-1.19	0.11	0.20	0.18	8.41
2004	1.50	51.79	0.09	27.13	0.07	8.17
2005	0.94	2.12	0.14	0.04	0.13	9.34
2006	0.93	3.34	0.11	0.05	0.10	6.97
2007	1.24	3.97	0.15	0.50	0.14	15.40

Table 91: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock UIS. See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.98	3.37	0.17	0.06	0.33	9.37
1998	1.67	5.30	0.13	0.40	0.21	8.56
1999	0.92	5.44	0.24	0.40	0.20	29.97
2000	1.44	-1.31	0.17	0.23	0.20	10.36
2001	1.24	-1.02	0.11	0.05	0.13	125.35
2002	1.39	-1.77	0.09	0.17	0.16	11.83
2003	1.13	0.53	0.10	0.14	0.08	9.37
2004	1.04	3.76	0.16	2.00	0.12	20.66
2005	0.78	-3.28	1.31	0.14	1.62	161.73
2006	0.01	3.18	0.93	0.07	0.88	90.65
2007	1.03	4.27	0.21	0.55	0.38	130.96

Table 92: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock UPS(UNITED PARCEL SVC). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.00	0.00	0.00	0.00	0.00	0.00
1998	0.00	0.00	0.00	0.00	0.00	0.00
1999	-0.02	0.32	0.05	0.08	0.03	5.65
2000	0.60	0.03	0.09	0.10	0.09	3.13
2001	0.45	-0.46	0.05	0.02	0.10	1.82
2002	0.36	-0.48	0.04	0.06	0.04	4.23
2003	0.50	0.18	0.04	0.05	0.05	1.80
2004	0.76	-12.83	0.05	9.53	0.05	10.67
2005	1.05	-4.69	0.11	0.13	0.12	17.14
2006	0.92	-1.63	0.13	0.05	0.08	3.43
2007	0.80	-1.98	0.12	0.30	0.12	11.16

Table 93: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock USB(US BANCORP). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.64	0.31	0.08	0.01	0.13	1.18
1998	1.46	-2.93	0.10	0.34	0.19	38.80
1999	1.07	1.26	0.14	0.13	0.12	7.62
2000	0.72	1.06	0.12	0.15	0.13	19.32
2001	0.80	1.36	0.09	0.03	0.11	39.98
2002	0.93	-2.41	0.05	0.16	0.05	10.14
2003	0.98	0.13	0.05	0.09	0.05	70.00
2004	0.87	20.64	0.07	10.86	0.07	13.02
2005	0.95	1.04	0.09	0.04	0.10	34.26
2006	0.59	2.23	0.06	0.03	0.06	12.54
2007	0.73	0.85	0.09	0.16	0.10	11.93

Table 94: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock UTX(UNITED TECH). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.79	-0.61	0.06	0.02	0.12	1.90
1998	1.02	0.42	0.07	0.09	0.07	6.55
1999	0.63	0.58	0.10	0.10	0.10	17.49
2000	0.65	0.22	0.09	0.12	0.13	7.44
2001	1.20	1.57	0.10	0.03	0.28	11.67
2002	1.01	0.91	0.05	0.06	0.07	4.32
2003	0.93	0.33	0.07	0.09	0.07	6.53
2004	0.85	-15.80	0.08	7.90	0.09	17.04
2005	1.07	-9.77	0.50	0.31	0.11	520.37
2006	1.03	-0.70	0.10	0.03	0.10	16.90
2007	0.92	1.22	0.14	0.25	0.12	45.63

Table 95: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock VZ(VERIZON COMMUN). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.00	0.00	0.00	0.00	0.00	0.00
1998	0.00	0.00	0.00	0.00	0.00	0.00
1999	0.00	0.00	0.00	0.00	0.00	0.00
2000	-0.03	0.63	0.11	0.10	0.13	10.15
2001	0.58	-0.02	0.07	0.02	0.10	35.19
2002	1.04	-4.46	0.08	0.29	0.08	11.32
2003	1.06	2.89	0.09	0.16	0.09	186.74
2004	0.80	-19.55	0.08	10.92	0.09	19.23
2005	0.81	-3.08	0.08	0.09	0.08	38.48
2006	1.05	1.05	0.11	0.03	0.08	5.80
2007	1.18	4.89	0.13	0.54	0.12	37.71

Table 96: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock WB(WACHOVIA CP). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.82	1.55	0.25	0.02	0.11	3.10
1998	0.86	-1.15	0.07	0.17	0.07	13.44
1999	0.76	1.68	0.07	0.10	0.09	8.58
2000	0.74	1.76	0.11	0.14	0.14	27.87
2001	0.71	-0.44	0.06	0.03	0.09	3.60
2002	1.00	-2.83	0.06	0.20	0.06	6.90
2003	0.81	0.41	0.05	0.06	0.06	97.99
2004	0.90	21.55	0.06	10.66	0.07	11.06
2005	1.21	-0.89	0.07	0.05	0.07	20.07
2006	0.99	0.97	0.08	0.02	0.08	3.81
2007	1.05	1.28	0.11	0.16	0.07	11.12

Table 97: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock WFC(WELLS FARGO CO NEW). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.88	0.37	0.08	0.02	0.08	1.01
1998	1.05	-7.78	0.10	0.63	0.09	14.70
1999	1.00	1.09	0.12	0.11	0.11	8.68
2000	0.71	1.55	0.09	0.14	0.11	25.56
2001	0.60	0.49	0.06	0.02	0.08	1.84
2002	0.68	-1.70	0.04	0.12	0.05	4.67
2003	0.81	0.53	0.04	0.06	0.05	70.73
2004	0.72	16.11	0.05	8.07	0.05	19.48
2005	0.86	0.92	0.06	0.03	0.06	8.82
2006	1.02	-5.78	0.50	0.20	0.23	67.95
2007	1.15	2.62	0.11	0.26	0.09	3.71

Table 98: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock WMB(WILLIAMS COS). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.56	0.18	0.08	0.02	0.09	25.45
1998	0.79	-6.32	0.10	0.54	0.15	10.39
1999	0.57	1.57	0.13	0.21	0.13	21.30
2000	0.62	-1.35	0.11	0.20	0.10	19.74
2001	0.69	3.76	0.11	0.06	0.12	26.97
2002	2.57	15.35	0.34	0.71	0.60	29.43
2003	1.15	-1.08	0.20	0.34	0.25	35.92
2004	1.06	57.60	0.15	36.50	0.18	84.80
2005	1.48	-1.06	0.17	0.09	0.18	24.47
2006	1.06	-0.39	0.15	0.04	0.15	7.32
2007	1.27	6.57	0.18	0.74	0.12	20.22

Table 99: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock WMT(WAL MART STORES). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.99	3.76	0.08	0.08	0.09	26.37
1998	1.31	-6.08	0.08	0.49	0.06	12.28
1999	1.32	2.75	0.10	0.18	0.09	13.07
2000	0.91	0.44	0.11	0.16	0.13	8.82
2001	0.80	0.60	0.08	0.02	0.08	7.09
2002	0.80	0.61	0.05	0.05	0.06	1.86
2003	0.94	0.29	0.05	0.09	0.05	19.89
2004	0.75	25.21	0.07	15.50	0.07	41.79
2005	0.81	-0.58	0.09	0.05	0.08	46.48
2006	0.95	0.42	0.10	0.02	0.09	2.03
2007	0.89	2.04	0.15	0.22	0.10	7.02

Table 100: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock WY(WEYERHAEUSER CO). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.74	-1.24	0.12	0.03	0.12	3.13
1998	0.65	-1.57	0.10	0.19	0.11	3.67
1999	0.41	-0.93	0.15	0.18	0.12	10.67
2000	0.49	-1.08	0.12	0.17	0.13	26.36
2001	0.77	-0.63	0.07	0.03	0.09	6.43
2002	0.96	0.04	0.07	0.08	0.08	2.55
2003	0.93	2.01	0.06	0.12	0.07	9.44
2004	1.29	-13.11	0.08	7.39	0.12	10.57
2005	1.08	-1.40	0.12	0.06	0.14	9.61
2006	1.19	0.03	0.10	0.04	0.13	5.33
2007	0.66	5.32	0.21	0.74	0.16	32.77

Table 101: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock XOM(EXXON MOBIL CP). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.00	0.00	0.00	0.00	0.00	0.00
1998	0.00	0.00	0.00	0.00	0.00	0.00
1999	-0.03	-0.05	0.05	0.03	0.04	1.03
2000	0.08	1.27	0.09	0.12	0.08	24.65
2001	0.34	0.35	0.06	0.01	0.07	11.27
2002	0.91	0.00	0.04	0.06	0.06	2.21
2003	0.67	0.14	0.06	0.06	0.04	31.64
2004	0.81	64.31	0.07	34.49	0.07	26.93
2005	1.42	1.58	0.11	0.05	0.12	10.37
2006	1.04	3.03	0.12	0.03	0.12	15.44
2007	1.14	2.80	0.14	0.36	0.14	35.37

Table 102: Comparisons of $\hat{\beta}$ between Daily and Intra-daily returns and their variability through residual and pairwise bootstrap methods for stock XRX(XEROX CP). See Table 7 for additional details about the abbreviations.

Year	Beta Daily	Beta Intra	R.B.S Daily	R.B.S Intra	P.B.S Daily	P.B.S Intra
1997	0.87	-0.61	0.10	0.03	0.09	2.95
1998	1.07	1.97	0.09	0.15	0.08	6.10
1999	1.08	5.97	0.20	0.41	0.17	43.04
2000	0.76	-5.98	0.22	0.44	0.18	47.95
2001	0.91	-0.29	0.20	0.05	0.22	23.97
2002	1.06	-3.86	0.13	0.30	0.17	2390.61
2003	1.11	-4.49	0.11	0.40	0.13	28.77
2004	1.21	28.61	0.14	16.61	0.13	8.44
2005	0.98	5.67	0.14	0.16	0.16	22.57
2006	1.03	3.92	0.13	0.05	0.08	15.91
2007	1.08	8.78	0.12	1.11	0.15	29.01

Table 103: Two types of beta for Sector of Bank of SP 100. Here, the 11 columns correspond to the years from 1997 to 2007, “beta1.BAC” represent the estimate of β for daily return and “beta2.BAC” represent the estimate of β for intra-daily returns for Bank of America, etc. All the symbols of the company are given through Table7–102. Details and graphs are given in Sector 3.2.

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
beta1.BAC	1.54	1.52	1.29	1.02	0.93	0.89	0.75	0.79	0.91	0.94	1.20
beta2.BAC	1.79	0.51	2.09	1.11	-1.85	-6.45	-2.34	-37.01	0.79	2.46	0.79
beta1.C	1.23	1.73	1.40	1.14	1.25	1.48	1.15	1.13	0.78	1.03	1.33
beta2.C	-0.62	-8.21	1.21	1.18	0.26	0.97	0.23	-27.60	0.24	0.34	-0.36
beta1.JPM	1.11	1.28	1.08	1.10	1.35	1.61	1.44	1.12	1.01	1.35	1.29
beta2.JPM	-0.76	-11.97	1.26	3.22	0.01	-0.25	-0.05	-6.83	2.26	3.01	3.96
beta1.RF	0.00	0.00	0.00	0.00	0.00	0.74	0.74	0.81	1.04	0.80	1.14
beta2.RF	0.00	0.00	0.00	0.00	0.00	-1.25	1.75	-0.55	-0.73	-0.08	-2.19
beta1.USB	0.64	1.46	1.07	0.72	0.80	0.93	0.98	0.87	0.95	0.59	0.73
beta2.USB	0.31	-2.93	1.26	1.06	1.36	-2.41	0.13	20.64	1.04	2.23	0.85
beta1.WFC	0.88	1.05	1.00	0.71	0.60	0.68	0.81	0.72	0.86	1.02	1.15
beta2.WFC	0.37	-7.78	1.09	1.55	0.49	-1.70	0.53	16.11	0.92	-5.78	2.62

Table 104: Two types of beta for Sector of Basic Material of SP 100. See Table 103 for additional details about the abbreviations.

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
beta1.AA	0.82	0.83	0.28	0.54	1.08	1.12	1.32	1.51	1.23	1.29	1.24
beta2.AA	0.67	-5.20	-2.41	0.08	1.95	2.20	2.84	-48.91	-3.90	-0.98	5.04

Table 105: Two types of beta for Sector of Consumers Goods of SP 100. See Table 103 for additional details about the abbreviations.

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
beta1.AVP	0.95	0.90	0.48	0.23	0.16	0.42	0.45	0.72	1.12	0.62	0.98
beta2.AVP	1.09	0.50	0.10	-0.45	0.27	-1.35	-0.60	-25.08	-1.95	0.61	11.00
beta1.CL	1.01	1.10	0.63	0.46	0.32	0.41	0.48	0.54	0.77	0.51	0.51
beta2.CL	0.56	-4.58	1.45	0.11	1.36	0.37	0.78	-20.53	-0.65	0.66	1.75
beta1.CPB	1.12	0.72	0.49	0.29	0.15	0.50	0.71	0.71	0.82	0.47	0.86
beta2.CPB	0.81	-1.00	-0.85	2.26	0.02	1.31	2.98	-37.77	0.12	3.12	6.46
beta1.F	0.67	1.19	0.94	0.53	0.79	1.07	1.24	1.39	1.36	1.14	1.12
beta2.F	0.70	5.01	2.54	0.62	-0.59	7.73	0.02	-23.41	-5.37	-5.58	3.65
beta1.HNZ	0.66	0.42	0.41	-0.01	0.08	0.40	0.53	0.74	0.91	0.47	0.66
beta2.HNZ	1.25	-0.99	2.72	-0.18	0.71	0.64	1.52	-4.18	-0.26	2.77	4.71
beta1.MO	1.00	0.50	0.50	0.14	0.14	0.31	0.52	0.77	0.92	0.60	0.72
beta2.MO	-1.37	-3.79	3.54	2.57	-1.72	-0.85	-1.45	-1.84	1.73	-0.11	4.75
beta1.KO	1.14	1.01	0.57	0.19	0.30	0.52	0.60	0.70	0.74	0.70	0.68
beta2.KO	-0.52	-1.42	1.05	1.56	0.07	-2.86	-0.22	24.86	-0.84	1.79	3.52
beta1.PEP	1.19	1.12	0.57	0.12	0.13	0.60	0.65	0.64	0.65	0.42	0.72
beta2.PEP	3.62	3.31	-1.52	2.32	0.95	-2.90	0.75	25.87	4.03	3.25	5.91
beta1.PG	1.08	0.84	0.64	0.30	0.18	0.40	0.64	0.66	0.82	0.65	0.76
beta2.PG	1.38	2.22	-0.55	-0.20	0.42	-1.11	0.86	34.50	4.27	4.04	4.60
beta1.SLE	0.66	0.55	0.52	0.29	0.13	0.35	0.70	0.53	0.47	0.96	0.72
beta2.SLE	0.61	1.47	0.47	2.60	-0.49	-3.71	2.10	-18.59	-1.60	2.26	4.37

Table 106: Two types of beta for Sector of Consumers Service of SP 100. See Table 103 for additional details about the abbreviations.

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
beta1.CMCSA	0.44	0.89	1.72	1.02	0.55	1.37	1.46	0.98	0.85	1.04	1.57
beta2.CMCSA	2.35	2.65	2.36	0.21	-1.12	2.05	-1.92	70.74	1.72	5.98	-12.50
beta1.DIS	0.91	1.10	0.65	0.46	1.21	1.20	1.41	1.28	1.04	0.94	1.26
beta2.DIS	0.48	-9.70	2.17	-0.04	-0.26	0.64	1.03	19.20	1.21	5.18	4.35
beta1.HD	0.82	1.39	1.18	1.20	1.31	0.99	1.06	1.09	1.42	1.15	0.84
beta2.HD	0.35	-3.39	2.48	-0.67	0.02	4.25	1.03	34.15	-0.13	0.22	1.23
beta1.MCD	0.68	0.87	0.65	0.36	0.34	0.50	0.84	0.71	1.24	0.88	0.81
beta2.MCD	0.82	2.67	-0.85	-0.04	-1.01	-2.34	0.36	82.05	3.16	1.33	4.37
beta1.TGT	0.00	0.00	0.00	0.70	1.05	1.03	0.90	0.81	1.21	0.97	1.15
beta2.TGT	0.00	0.00	0.00	0.84	-0.39	6.85	-0.14	24.58	-2.33	-0.86	4.48
beta1.WMT	0.99	1.31	1.32	0.91	0.80	0.80	0.94	0.75	0.81	0.95	0.89
beta2.WMT	3.76	-6.08	2.75	0.44	0.60	0.61	0.29	25.21	-0.58	0.42	2.04

Table 107: Two types of beta for Sector of Financial of SP 100. See Table 103 for additional details about the abbreviations.

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
beta1.AXP	1.09	1.54	1.35	1.11	1.42	1.31	1.23	0.85	1.15	1.12	1.28
beta2.AXP	1.59	-3.79	0.73	1.54	0.80	-3.28	-0.61	26.75	0.82	1.47	-4.03
beta1.COF	0.72	1.91	1.29	1.25	1.32	1.47	1.60	1.22	0.83	1.14	1.26
beta2.COF	1.40	-2.28	2.65	0.89	0.65	1.19	-1.82	12.30	0.34	-2.35	-0.22
beta1.GS	0.00	0.00	1.10	1.53	1.46	1.09	1.23	1.25	1.22	1.74	1.98
beta2.GS	0.00	0.00	1.20	3.16	-0.34	2.16	-0.37	-12.39	4.25	3.35	2.23
beta1.MS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.70	2.12
beta2.MS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.11	2.30

Table 108: Two types of beta for Sector of Health Care of SP 100. See Table 103 for additional details about the abbreviations.

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
beta1.ABT	0.93	0.86	1.01	0.21	0.25	0.71	0.84	0.71	0.62	0.82	0.53
beta2.ABT	1.65	5.80	1.25	0.92	-0.43	0.77	1.93	32.94	0.83	2.37	10.19
beta1.BAX	1.25	0.64	0.69	0.25	0.13	0.70	0.62	0.80	0.87	0.68	0.53
beta2.BAX	-1.46	-1.47	0.48	1.98	1.24	4.32	0.98	39.42	1.64	2.21	6.33
beta1.BMY	1.19	0.98	1.05	0.61	0.30	0.77	0.97	0.93	0.62	1.07	1.08
beta2.BMY	1.66	-0.96	2.65	0.89	1.49	-0.94	3.30	-28.23	-1.69	2.12	4.76
beta1.JNJ	0.96	0.75	0.78	0.26	0.12	0.72	0.70	0.53	0.66	0.53	0.51
beta2.JNJ	-1.39	-0.47	0.99	1.09	-0.25	-2.98	0.81	66.86	0.04	0.69	-1.15
beta1.MDT	0.91	1.01	0.88	0.62	0.55	0.64	0.68	0.67	0.53	0.47	0.62
beta2.MDT	0.32	1.45	3.35	0.68	2.00	-2.62	1.32	28.67	3.13	0.29	1.28
beta1.AMGN	0.17	0.88	1.24	1.27	1.02	0.98	0.87	1.16	1.14	0.80	0.63
beta2.AMGN	-1.27	6.24	2.77	-0.50	-0.26	-2.39	-0.27	51.15	6.30	-0.55	-0.19
beta1.MRK	1.05	0.94	0.94	0.31	0.24	0.82	0.90	0.77	0.83	0.96	0.81
beta2.MRK	0.37	1.53	1.60	1.85	0.32	-4.24	1.21	5.97	-2.65	4.36	2.12
beta1.PFE	1.23	1.02	1.16	0.28	0.37	0.93	0.90	1.10	1.02	1.00	0.92
beta2.PFE	0.28	-3.23	2.87	2.18	1.16	-0.94	-0.93	-32.12	-6.37	1.56	3.28

Table 109: Two types of beta for Sector of Industrial of SP 100. See Table 103 for additional details about the abbreviations.

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
beta1.CAT	0.90	0.95	0.42	0.62	0.92	0.91	1.05	1.27	1.39	1.51	0.95
beta2.CAT	0.50	-20.22	2.32	2.44	-0.66	1.32	0.39	-21.88	-0.22	-2.02	0.79
beta1.FDX	1.08	0.73	1.00	0.80	0.72	0.68	0.81	1.07	1.28	1.51	0.79
beta2.FDX	-0.21	-6.56	3.56	1.64	-2.91	-2.81	0.92	-0.87	-1.13	-2.94	0.36
beta1.GD	0.64	0.55	0.63	0.38	0.36	0.43	0.75	0.78	0.81	0.15	1.00
beta2.GD	0.84	-2.52	3.75	2.51	0.75	0.33	0.66	-7.55	1.03	-5.29	4.34
beta1.GE	1.26	1.16	1.11	1.04	1.45	1.31	1.11	1.12	0.98	0.87	0.69
beta2.GE	0.51	-0.11	0.88	1.66	1.00	3.24	0.92	-3.48	0.54	0.48	-0.09
beta1.HON	0.77	0.95	0.71	0.79	1.54	1.15	1.21	1.28	1.09	1.24	0.89
beta2.HON	0.19	-2.75	0.16	-0.69	1.29	2.10	4.53	11.09	2.16	0.36	3.03
beta1.BA	1.03	0.98	0.43	0.45	0.99	0.83	1.00	1.07	0.98	1.20	0.80
beta2.BA	-3.74	-4.24	-0.89	3.70	0.78	1.57	-1.09	32.81	2.57	-0.94	2.79
beta1.MMM	0.63	0.72	0.27	0.52	0.78	0.73	0.78	1.02	0.95	0.88	0.55
beta2.MMM	0.78	-8.54	-0.74	1.99	0.01	-1.52	4.97	3.83	-1.10	-0.64	2.40
beta1.NSC	0.98	0.80	0.43	0.54	0.77	1.02	0.89	1.18	1.37	1.45	1.17
beta2.NSC	-0.60	-3.43	3.29	-0.47	-1.66	1.67	1.89	35.82	1.45	-1.53	9.30
beta1.RTN	0.00	0.00	0.00	0.00	-0.19	0.70	0.59	0.69	0.80	0.77	0.86
beta2.RTN	0.00	0.00	0.00	0.00	0.21	0.13	1.27	22.28	0.88	2.48	4.17
beta1.UPS	0.00	0.00	-0.02	0.60	0.45	0.36	0.50	0.76	1.05	0.92	0.80
beta2.UPS	0.00	0.00	0.32	0.03	-0.46	-0.48	0.18	-12.83	-4.69	-1.63	-1.98
beta1.UTX	0.79	1.02	0.63	0.65	1.20	1.01	0.93	0.85	1.07	1.03	0.92
beta2.UTX	-0.61	0.42	0.58	0.22	1.57	0.91	0.33	-15.80	-9.77	-0.70	1.22
beta1.WY	0.74	0.65	0.41	0.49	0.77	0.96	0.93	1.29	1.08	1.19	0.66
beta2.WY	-1.24	-1.57	-0.93	-1.08	-0.63	0.04	2.01	-13.11	-1.40	0.03	5.32

Table 110: Two types of beta for Sector of Insurance of SP 100. See Table 103 for additional details about the abbreviations.

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
beta1.ALL	1.01	0.92	0.84	0.86	0.40	0.53	0.66	0.79	0.83	0.76	0.59
beta2.ALL	1.42	-1.49	-0.70	4.36	-0.58	-3.36	1.86	19.86	2.23	1.60	1.87

Table 111: Two types of beta for Sector of Oil of SP 100. See Table 103 for additional details about the abbreviations.

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
beta1.BHI	0.87	1.05	0.41	0.21	0.21	1.00	0.55	0.75	0.99	1.55	0.91
beta2.BHI	-0.76	-15.38	1.79	-0.78	3.44	0.78	0.91	27.01	0.12	-0.42	1.65
beta1.COP	0.00	0.00	0.00	0.00	0.00	0.35	0.48	0.76	0.95	1.14	1.02
beta2.COP	0.00	0.00	0.00	0.00	0.00	2.23	0.84	17.00	-8.87	0.75	1.36
beta1.CVX	0.00	0.00	0.00	0.00	0.17	0.70	0.59	0.67	1.17	0.93	1.10
beta2.CVX	0.00	0.00	0.00	0.00	0.14	0.94	0.49	-52.67	-1.43	1.26	3.14
beta1.HAL	0.90	1.16	0.67	0.41	0.46	1.32	0.58	0.87	1.42	1.33	0.91
beta2.HAL	-0.29	-19.16	0.17	-1.65	6.98	-3.61	-0.51	41.28	0.91	-9.81	2.76
beta1.SLB	1.05	1.16	0.51	0.22	0.30	0.99	0.57	0.73	1.12	0.92	1.25
beta2.SLB	0.17	-16.69	0.27	-1.06	2.90	-1.24	-2.58	15.58	2.24	-6.74	4.06
beta1.WMB	0.56	0.79	0.57	0.62	0.69	2.57	1.15	1.06	1.48	1.06	1.27
beta2.WMB	0.18	-6.32	1.57	-1.35	3.76	15.35	-1.08	57.60	-1.06	-0.39	6.57
beta1.XOM	0.00	0.00	-0.03	0.08	0.34	0.91	0.67	0.81	1.42	1.04	1.14
beta2.XOM	0.00	0.00	-0.05	1.27	0.35	0.00	0.14	64.31	1.58	3.03	2.80

Table 112: Two types of beta for Sector of Technology of SP 100. See Table 103 for additional details about the abbreviations.

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
beta1.EMC	1.45	1.58	1.55	1.79	2.76	1.66	1.33	1.69	1.21	1.12	0.60
beta2.EMC	0.04	-8.38	2.31	0.17	2.00	-3.81	-3.20	28.46	4.32	3.92	5.33
beta1.GOOG	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.79	1.52	1.35
beta2.GOOG	0.00	0.00	0.00	0.00	0.00	0.00	0.00	59.31	1.99	-2.27	0.14
beta1.HPQ	1.23	0.98	1.19	1.37	1.59	1.32	1.45	1.49	0.79	1.36	0.92
beta2.HPQ	-0.73	4.95	-0.37	1.01	0.07	-3.80	-1.77	29.76	9.81	8.46	6.92
beta1.IBM	1.29	0.94	1.20	1.01	1.13	1.13	0.99	0.85	0.99	0.92	0.72
beta2.IBM	1.95	5.74	3.31	0.94	-1.99	-0.35	-1.39	43.35	2.44	4.96	6.48
beta1.CSCO	0.83	1.55	1.59	2.13	2.40	1.55	1.37	1.82	1.07	1.47	1.35
beta2.CSCO	1.81	-3.86	3.60	1.73	1.65	-3.49	-1.25	24.06	4.73	4.92	-1.27
beta1.INTC	1.07	1.22	1.61	1.89	1.92	1.66	1.52	1.60	1.26	1.66	1.13
beta2.INTC	0.72	10.97	2.01	1.70	-1.64	-1.79	-0.67	-20.55	3.35	0.46	1.41
beta1.MSFT	0.72	1.31	1.41	1.41	1.35	1.22	1.29	0.98	0.86	1.00	1.25
beta2.MSFT	0.74	8.38	2.51	-0.13	-3.42	-2.96	0.94	20.48	2.59	4.36	0.10
beta1.ORCL	0.91	1.20	1.67	2.09	2.31	1.47	1.39	1.42	1.06	1.15	1.22
beta2.ORCL	-0.15	0.36	0.16	0.40	-1.14	-7.41	-0.83	64.55	3.59	4.88	4.90
beta1.TXN	1.49	1.35	1.65	2.12	1.78	1.66	1.53	1.77	1.52	1.52	0.83
beta2.TXN	-0.14	2.16	1.29	-1.19	-0.43	1.65	-3.38	-57.94	5.30	1.41	0.32
beta1.XRX	0.87	1.07	1.08	0.76	0.91	1.06	1.11	1.21	0.98	1.03	1.08
beta2.XRX	-0.61	1.97	5.97	-5.98	-0.29	-3.86	-4.49	28.61	5.67	3.92	8.78

Table 113: Two types of beta for Sector of Telecommunication of SP 100. See Table 103 for additional details about the abbreviations.

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
beta1.VZ	0.00	0.00	0.00	-0.03	0.58	1.04	1.06	0.80	0.81	1.05	1.18

Table 114: Two types of beta for Sector of Utility of SP 100. See Table 103 for additional details about the abbreviations.

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
beta1.AEP	0.40	0.20	0.29	0.09	0.13	0.94	0.82	0.63	0.84	0.68	0.84
beta2.AEP	0.21	-1.17	1.00	1.12	1.89	3.91	1.70	18.73	0.28	0.43	6.21
beta1.ETR	0.38	0.08	0.26	0.03	-0.03	0.46	0.51	0.46	0.95	0.54	0.95
beta2.ETR	-0.34	-1.59	-0.76	3.11	0.85	1.09	0.82	37.86	1.71	1.76	8.41
beta1.EXC	0.00	0.00	0.00	-0.14	-0.00	0.52	0.55	0.02	1.13	0.67	1.02
beta2.EXC	0.00	0.00	0.00	0.19	0.74	-1.21	0.10	-1.73	1.18	0.08	6.65
beta1.SO	0.39	0.15	0.23	0.06	-0.01	0.41	0.55	0.41	0.84	0.68	0.76
beta2.SO	-0.15	3.48	-1.32	1.26	1.54	-0.17	1.24	8.80	0.70	0.68	4.40