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Beta Estimation on Different Trading Periods

Candidate: **Alessandra Insana**

Supervisor: **Prof. Edoardo Otranto**
Co-supervisor: **Prof. Walter Distaso**

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Contents

Introduction

The purpose of this thesis is to investigate on beta estimation considering different trading periods. Starting from a literature review, given in the first chapter, we explain the meaning of beta and the different methodologies used for its estimation. We find that there is poor literature evidence on the differences between daily, intraday and overnight betas, so we decide to focus on this topic.

In order to understand if beta estimation on different trading periods matter, in the first chapter, we divide the total daily return in intraday and overnight return and evaluate daily, intraday and overnight betas using two different models. Starting by the classical Capital Asset Pricing Model (CAPM), and assuming a constant systematic risk, i.e. a constant beta over time, we estimate our three betas. Subsequently, we consider a nonparametric method for time-varying conditional betas, proposed by Ang and Kristensen (2012) and Li and Yang (2011). By using this model we compute time-varying betas in conditional factor models which are conditional on the realized betas. For both these models we estimate daily, intraday and overnight betas considering US stocks traded on the NYSE, AMEX, and NASDAQ markets. Furthermore, we try to understand if there is some relation between the beta parameter and the stock size. Taking into account the differences in pattern between the daily intraday and overnight betas, found in the second chapter, we decide to investigate if it is possible to take advantage of the different behaviors in a trading strategy based on the beta estimation. In particular, we consider the statistical arbitrage strategy, proposed by Frazzini and Pedersen (2014), Betting Against Beta (BAB) and we adapt it constructing three different portfolios ranked and organized by daily, intraday and overnight betas.

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Chapter 1

Systematic risk and beta estimation

Introduction

When we talk about investments we have to talk about risk. Every individual investment is exposed to two types of risk: unsystematic risk and systematic risk. Unsystematic risk, said also residual risk or diversifiable risk, represents the risk related to one security or to a group of specific securities, it is indeed associated to microeconomics factors. This kind of risk can be mitigated through diversification, investing on securities belonging to different sectors. Systematic risk depends on the uncertainty related to the market. Macroeconomic factors, like inflation, change in interest rate, recession and wars, can be considered as sources of systematic risk. This kind of risk cannot be diversified, it can be mitigated by a good asset allocation strategy, and so investing on different financial products (i.e. bonds and stocks). When markets are perfect and frictionless, and we have a well diversified portfolio, the only relevant risk is systematic risk (Elton et al., 2009), that can be evaluated by beta, 'β'.
Beta can be considered as a measure of the systematic risk, it represents the stock's sensitivity of returns with respect to the changes in the market. A beta less than one implies that the investment will be less volatile than the market. A beta greater than one indicates that the investment's price will be more volatile than the market. This suggests that a risk-averse investor will choose to invest on a stock with a low beta. A not risk-averse investor will consider a stock with a beta greater than one. Of course higher risk implies higher profit.
Beta is an unknown coefficient, unobservable to investors. Various evaluation strategies have been proposed in order to obtain a more precise estimator as proxy for its true value. The simplest way is to consider the CAPM and evaluate beta by a classical OLS method, assuming a constant beta on the whole period. This assumption has been criticized because it implies a constant systematic risk over

time, and this is not realistic because systematic risk represents the uncertainty inherent to the market. In order to overcome this problem, and evaluate time-varying beta, several different econometric methods have been proposed. The most popular approaches consider non parametric techniques, different versions of the GARCH model and Kalman filtering procedure.

In the first sections we give a literature review on beta estimation. We present the limits of the CAPM and the different econometric methodologies used for constant and time-varying betas evaluation. Finally we talk about beta estimation through the use of high frequency data, and on different trading periods.

1.1 The Capital Asset Pricing Model

When we talk about beta, the first model that we have to consider is the Capital Asset Pricing Model (CAPM), developed by Sharpe (1964), Lintner (1965) and Mossin (1966), where beta represents the slope from regressing the asset returns on market returns. The expected return of a security, $E(r)$, expressed by the classical CAPM is given by:

$$E(r) = r_f + \beta[E(r_M) - r_f] \,, \tag{1.1}$$

where r_f is the return of a risk free investment and r_M is the return from the market portfolio. If we denote with $R = r - r_f$ and $R_M = r_M - r_f$ the excess return on the security and on the market portfolio, we can write the model as:

$$E(R) = \beta E(R_M) \,. \tag{1.2}$$

Another parameter, which is often used in combination with beta, is the alpha or Jensen index (Jensen, 1968) and it is related with volatility or risk. It can be used to determine how much the realized return of the security differs from the theoretical return determined by the CAPM. Mathematically speaking it is given by:

$$\alpha = E(r) - r_f - \beta[E(r_M) - r_f] \,. \tag{1.3}$$

It provides a relationship between risk and return (technically called 'security market line' SML). Its value describes the performance of an investment in relation with its benchmark. In an efficient market we expect that this value is equal to zero. Having negative values for alpha means that we have a security's under-performance, on the other hand having a positive alpha means that our security outperform its benchmark index.

The CAPM gives a way to measure the relationship between expected return and risk. It is one of the most used models for the portfolio performance analysis. As in all mathematical models also in the CAPM there are some implicit assumptions, as reported in Hull (2012):

1. “Investors care only about the expected return and the standard deviation of return of their portfolio”;
2. “The returns from investments are correlated with each other only because of their correlation with the market portfolio”;
3. “Investors focus on returns over just one period and the length of this period is the same for all investors”;
4. “Investors can borrow and lend at the same risk-free rate”;
5. Tax does not influence investment decisions;
6. “All investors make the same estimates of expected returns, standard deviations of returns, and correlations between returns”.

To test the validity of the CAPM, many empirical studies have been conducted, considering time-series and cross-sectional regressions. First studies support the CAPM (Fama et al., 1969; Blume, 1970), but subsequently, some empirical researches put some questions on the explanatory power of market betas for explaining the cross-section of expected returns (Basu, 1977, 1983; Roll, 1977; Banz, 1981; Stattman, 1980; Rosenberg et al., 1985; Bhandari, 1988; Fama and French, 1992). It is important to mention that verify the accuracy of CAPM could be difficult, because if the value used as proxy for the market is inefficient, the resulting beta estimates are less accurate (Roll, 1977; Ross, 1977; Roll and Ross, 1994). The poor empirical results obtained, probably due to the very restrictive and unrealistic assumptions of the CAPM, brought to a long review debate, in which many authors tried to develop and extend some of the crucial problems, in order to give a more realistic model (for reviews of the CAPM literature see Campbell (2000); Fama and French (2004); Jagannathan et al. (2010a,b); Subrahmanyam (2010); Goyal (2012)).

The most discussed assumptions are the first one, for which investors look only at the first two moments of return distribution, and the third one, in which the model assumes a constant risk over time. The first hypothesis implies that returns are normally distributed, but this is not true for many assets that have skewness and excess kurtosis. This is supported by empirical results, in which it has been shown that the corresponding third and fourth moment (skewness and kurtosis) of asset distribution are very different from those of the normal distribution (Kraus and Litzenberger, 1976; Harvey and Siddique, 2000; Hwang and Satchell, 1999; Fang and Lai, 1997).

Probably one of the most criticized assumptions of the CAPM, is related to consider the risk associated with an asset constant over time. Indeed, in reality, investment horizon consists of many periods, and many studies showed empirical evidence for time-varying risk premia of financial assets (Shiller et al., 1984; Lettau and Ludvigson, 2001b). To overcome this problem there are two ways. The first one considers a multiple source of systematic risk, by intertemporal models developed by Merton (1973) and then extended by the three-factor model of Fama and French (1993) and multifactor models.

For example Fama and French (1993), in order to explain the expected returns of an investment, introduce in the CAPM other sources of systematic risk related to size and book to market through the following three factor model:

$$E(r) - r_f = +\beta_M [E(r_M) - r_f] + \beta_S E(SMB) + \beta_h E(HML) \,, \tag{1.4}$$

where SMB (Small Minus Big) is the difference between the returns on portfolios of small and large stocks, HML (High Minus Low) is the difference between portfolios of high and low book to market value stocks.

The second methodology, used to add time-varying systematic risk factors, implies the evaluation of conditional time-varying models (Jagannathan and Wang, 1996; Lettau and Ludvigson, 2001a). Considering conditional variances and covariances (Bodurtha and Mark, 1991), conditional factor models and conditional CAPM are a good way to include the time-varying systematic risk factors. From literature it seems that the use of a conditional version of the CAPM could better explain the systematic risk (Jagannathan and Wang, 1996; Lettau and Ludvigson, 2001a).

By the conditional CAPM, we have the following relationship:

$$E\left[r_{i,t} - r_{f,t} | \mathscr{F}_{t-1}\right] = E\left[\beta_{i,t} | \mathscr{F}_{t-1}\right] E\left[r_{M,t} - r_{f,t} | \mathscr{F}_{t-1}\right] \,, \tag{1.5}$$

here all the parameters are estimated at time t, they are conditional to $\mathscr{F}_{t-1}$, that represents the information set at time $t-1$. This equation can be written as:

$$E\left[R_{i,t+1} | \mathscr{F}_t\right] = E\left[\beta_{i,t+1} | \mathscr{F}_t\right] E\left[R_{M,t+1} | \mathscr{F}_t\right] \,, \tag{1.6}$$

where the conditional beta can be evaluated as:

$$E\left[\beta_{i,t+1} | \mathscr{F}_t\right] = \frac{\operatorname{cov}\left[R_{i,t+1}, R_{M,t+1} | \mathscr{F}_t\right]}{\operatorname{var}\left[R_{M,t+1} | \mathscr{F}_t\right]} \,.$$

1.2 Constant beta estimation

The most adopted approach for beta estimation, assumes the systematic risk as constant, and evaluates it by an ordinary least squares (OLS) method. Considering a bivariate time series $(R_i, R_{Mi})_{i=1}^n$ of excess returns of a security and excess market returns, the empirical formulation of the CAPM (1.1) can be written as:

$$R_i = \alpha + \beta R_{Mi} + \varepsilon_i \qquad \varepsilon_i \sim (0, \sigma^2) \,, \tag{1.7}$$

where α is expected to be zero, ε_i are the error terms i.i.d, and the systematic risk beta, is the estimated slope of the linear regression of R_i on R_{Mi}. It can be evaluated considering the sample covariance between the excess returns of a security and excess market returns divided by the sample variance of the excess market returns:

$$\hat{\beta} = \frac{\text{cov}(R_i, R_{Mi})}{\text{var}(R_{Mi})} \,. \tag{1.8}$$

If the covariance with the return of the market is zero we will have beta equal to zero, so a risk free asset, otherwise, if the covariance is equal to the market variance, we will have beta equal to one.

An equivalent beta formula is given by:

$$\hat{\beta} = \rho \frac{\sigma}{\sigma_M} \,,$$

where σ and σ_M are the standard deviation of the security returns and of the market returns, ρ represents their correlation.

Evaluating beta by a simple OLS method is not efficient, because the market is complex and volatile. For example, OLS is not suitable for estimating beta coefficient in the cases of normal distribution, tail or other distributions, that cannot be explained successfully by the model. Furthermore the existence of outlier or extreme data can create a problem of efficiency for the OLS regression model (Jiang, 2011; Shalit and Yitzhaki, 2002; Martin and Simin, 2003; Tofallis, 2008). To eliminate standard parametric model inefficiency, robust regression techniques have been developed (Genton and Ronchetti, 2008; Alp and Bilir, 2015). For example Sharpe (1971) considers the least absolute deviations (or the L1-estimator) for beta estimation. Chan and Lakonishok (1992) use quantile regression, linear combinations of regression quantiles, and trimmed regression quantiles. Martin and Simin (2003) propose to evaluate beta by means of redescending M-estimators.

The across time instability given by OLS standard beta estimation, can be overcome considering different strategies. For Blume (1970) and Levy (1971), it is possible increase precision of beta, grouping stocks into portfolios and compute the beta, for each portfolio, in time series regression. Other authors (Baesel, 1974; Altman et al., 1974; Blume, 1975; Roenfeldt et al., 1978) assert that a more stable evaluation can be given considering a longer estimate period. Furthermore, has been proposed the use of autoregressive adjustment methods (Blume, 1975; Vasicek, 1973). The Blume (1975) autoregressive adjustment method, try to capture the tendency of the standard betas to converge towards the value of unity over time. Considering how much the historical betas are different from their average value, Blume regresses betas from one historical period on beta from a prior period and then uses this regression to adjust betas for the forecast period. Instead, Vasicek (1973) develops a Bayesian estimation technique, considering the accuracy of the historical betas. In particular, he modifies the past betas in relation to the average beta, taking into account the value of the beta sampling error. When this error is higher, there could be an higher difference from the average beta. To betas with a larger sampling error will be assigned a lower weight. Respect to the standard evaluation, these two adjustment techniques led to a more accurate forecast for beta (Klemkosky and Martin, 1975; Luoma et al., 1996; Murray, 1995; Hawawini et al., 1985; Sarker, 2013). As shown by Cloete et al. (2002) the use of robust estimators with the Vasicek's technique, generates a new class of estimators that perform better respect to the traditional.

1.3 Time-varying beta estimation

Market risk premia changes over time, consequently stock betas will vary over time, implying a change in the stock's price (Bollerslev et al., 1988; Lettau and Ludvigson, 2001b). The betas used within the CAPM are calculated on a set period-by-period basis, ignoring its continuous evolution. Assuming a constant beta the CAPM does not describe the cross-section of average returns on equities and the market, considered to explain dynamics in volatility (Bos and Newbold, 1984; Collins et al., 1987; Brooks et al., 1992; Choudhry, 2002, 2005; Adrian and Franzoni, 2009).

In order to estimate time-varying betas it is possible adopt more sophisticate strategies. The most used methods make assumptions about the dynamics of betas (parametric and non-parametric approaches, considering rolling regression, Kalman filters) or make assumptions about the conditional covariance matrix of returns (GARCH models).

Applying a parametric approach, we can model beta as a function of state variable (Shanken, 1990) or firm characteristics (Jagannathan and Wang, 1996; Lettau and Ludvigson, 2001a). Shanken (1990) assumes a linear relation between beta and some state variables, and estimates the parameters of this function in a conditional CAPM time-series regression. Jagannathan and Wang (1996) and Lettau and Ludvigson (2001a) represent the variation of the conditional distribution of returns as a function of lagged state variables. They model the covariance between the market returns and portfolio returns defining affine functions of these variables. With this approach beta can be estimated by a multi-factor model, in which the additional factors are given by the relations between the market return and the state variables. There is also a non parametric version of this methodology (Ferreira et al., 2011).

Kalman filters give a direct estimate of time varying betas. Betas are calculated from an initial set of priors, producing a series of conditional betas, assuming standard stochastic processes such as random walk, autoregressive, mean reverting and switching models (Black et al., 1992; Wells, 1994; Faff et al., 2000; Brooks et al., 2002; Hillier, 2002; Gao and Yao, 2004; Ebner and Neumann, 2005; Mergner and Bulla, 2008).

The GARCH models use the conditional variance information to construct the conditional beta series. Generally, for time-conditional moments models is considered an autoregressive moving average relation. The first who introduced the Autoregressive Conditional Heteroscedasticity (ARCH) model was Engle (1982). Subsequently, in order to parametrize the conditional mean and the conditional covariance of financial time series, Bollerslev (1986) introduces the Generalized ARCH (GARCH). The Multivariate-GARCH (M-GARCH) model, first proposed by Bollerslev (1990), evaluates the beta time-series indirectly, considering the estimates of the time-varying conditional covariance of security and market returns and the time-varying conditional variance of market returns. The GARCH approach for time-varying beta has been considered in various studies (Bollerslev et al., 1988; Engel and Rodrigues, 1989; Braun et al., 1995; Giannopoulos, 1995; McClain et al., 1996; Bodurtha and Mark, 1991; Brooks et al., 1998; Lie et al., 2000; Brooks et al., 2002; Li, 2003; Mergner and Bulla, 2008; Darolles et al., 2018). Instead of the multivariate-GARCH models it is possible consider a new class of multivariate models called Dynamic Conditional Correlation (DCC) models proposed by Engle (2002). As said by the author these estimators “have the flexibility of univariate GARCH but not the complexity of conventional multivariate GARCH”. In recent papers Engle (2016) and Bali et al. (2016) consider this model for beta estimation.

The last methodology for the estimation of time-varying betas assumes that betas vary smoothly over time. Starting from the Fama and MacBeth (1973) work, it is possible to consider a rolling window ordinary least square estimation. Considering this approach we do not have a parametrization problem, but we have to select the window length. Within the family of rolling least squares estimators, we can include the nonparametric time-varying betas estimator (Robinson, 1989) and nonparametric time-varying conditional betas (Esteban and Orbe-Mandaluniz, 2010; Li and Yang, 2011; Ang and Kristensen, 2012).

Many different papers evaluate the various approaches for time-varying betas, discussed above. The most compared are the GARCH-based estimators and the Kalman filter approaches. By the results obtained it seems that the last methodology performs better in terms of forecasting ability (Faff et al., 2000; Mergner and Bulla, 2008; Adrian and Franzoni, 2009; Choudhry and Wu, 2008; Nieto et al., 2014; Bali et al., 2016).

1.4 High-frequency data and trading period on beta estimation

During the last few years there has been an explosion in the amount of financial high frequency data. This led to the improvement and the development of new techniques and models for the evaluation of financial parameters, both in time-series than in cross-sectional dimensions.
Using higher frequency data, on simple autoregressive time series models, allows a more accurate beta estimation and forecasting (Barndorff-Nielsen and Shephard, 2004; Andersen et al., 2005, 2006). Furthermore, systematic risk estimation with daily-frequency data, can give a good relationship between betas and the cross-section of expected stock returns. For example Bali et al. (2016), considering dynamic conditional beta at daily frequency, find that results are efficient in explaining the cross-section of daily stock returns, confuting the previous empirical tests for which the CAPM fails to describe the cross-section of stock returns (Fama and French, 1992).

The use of high-frequency data allows also the development of new estimators. Starting from techniques used for realized volatility (Foster and Nelson, 1994; Andersen and Bollerslev, 1998), it is possible forecast and model a new estimator for beta, the 'realized betas' (Barndorff-Nielsen and Shephard, 2004; Andersen et al., 2005, 2006; Patton and Verardo, 2012). These new beta estimates are time-varying and are defined as the ratio between the realized covariance of stock and market and the realized market variance. They can be considered as a non-parametric estimator of underlying beta.

One of the most relevant aspects, when we talk about high frequency data, is the sampling frequency. Indeed, using low-frequency data, could determine imprecise and noisy estimates for beta (Andersen et al., 2006), but conducting the analysis to a very high frequency induces distortion on estimate, because intraday returns are corrupted by the market microstructure noise, due to the market friction. In order to overcome these problems, it is possible consider different approaches like adjustments by including filtering (Ebens et al., 1999; Andersen et al., 2001; Bandi and Russell, 2005), subsampling (Andersen et al., 2011), correction for overnight price changes (Hansen and Lunde, 2004), considering kernel estimators (Hansen and Lunde, 2004; Barndorff-Nielsen et al., 2011).

Most of the papers, using high-frequency data, do not take into account the non trading effect in their estimation, indeed they employ just intraday values. For example, Ryu (2011) finds that the realized beta, computed using only the intraday returns, provides a good estimation of underlying beta that could outperform the constant beta.

Some empirical studies put on evidence that the use of intraday returns can improve the forecast accuracy of models based on daily returns (Taylor and Xu, 1997; Koopman et al., 2005; Pong et al., 2004; Liu and Maheu, 2009; Fuertes and Olmo, 2013). Although, ignoring completely the overnight period, considering only the intraday returns, could be an error, because of course non-trading periods influence the following trading hours. The computation of financial measures, including the overnight return, could change significantly, from those that exclude that values.

Different authors, analyzing intraday and overnight price returns, show a difference in return patterns (Tsai et al., 2012; Branch and Ma, 2012, 2006; Cooper et al., 2008; Berkman et al., 2009; Wang et al., 2009). Many of them find that daytime returns and overnight returns tend to be anti-correlated. For example, Tsai et al. (2012) investigate on the correlation between the three components on the Taiwan stock market, and compare their results with others markets as the New York Stock Exchange (NYSE) and the National Association of Securities Dealers Automated Quotation (NASDAQ). They find a negative cross correlation between the sign of daytime returns and the sign of overnight returns. Also Branch and Ma (2006) and Wang et al. (2009) show that daytime returns and overnight returns are significantly negatively correlated. In particular, Wang et al. (2009) studying the statistical distribution and correlation between total return, overnight return, and daytime return, on 2215 stocks in New York Stock Exchange, find an higher mean value for daytime returns respect to overnight. In opposition, Gallo (2001), shows that daytime returns and overnight returns are not significantly negatively correlated, furthermore, Kelly and Clark (2011) and Cooper et al. (2008) suggest that stock returns are higher overnight than intraday.

Analyzing the momentum returns Bogousslavsky (2016) and also Polk et al. (2018), find that it increases overnight. Indeed their empirical studies show that intraday, momentum returns do not exhibit any clear pattern except at the end of the day, when returns tend to be negative. This is probably related to overnight liquidity risk.

Obviously, periodic market closures impact also on stock price volatility. Volatility of returns during trading periods is found to be higher, than those during non trading periods (French and Roll, 1986; Lockwood and Linn, 1990; Güner and Önder, 2002). Also Linton and Wu (2017), in a recent paper, analyzing second moments, and so volatility, they find that intraday is higher than overnight. Although between 2009 to 2012 they note higher values for overnight volatility, due probably to the European sovereign debt crisis. Furthermore, the ratio between overnight and intraday volatility is increasing over part of the last 20 years.

Many approaches have been considered in realized volatility literature, most of them ignore completely the non trading effect and scale upward the value obtained, in this way the evaluation includes an entire 24-hour day (Koopman et al., 2005; Martens, 2002). Hansen and Lunde (2005) derive optimal weights for the overnight return and the sum of intraday returns. Other authors (Bollerslev et al., 2009; Pooter et al., 2008; Martens, 2002; Blair et al., 2010) estimate the overnight return subtracting the day's close value from the next day's open, and add this squared return as one of the factors in the sum of intraday returns. Andersen et al. (2011) model the overnight returns as discontinuous movements.

Few authors put their attention on beta estimation considering different trading periods. Liu (2003) evaluates the relationship between a security's systematic risk, considering high-frequency data for overnight and intraday returns. He computes the security beta as a weighted average of its intraday beta and overnight beta, the weight is the variance ratio between the intraday market index return and the overnight market index return. Considering different trading periods for beta estimation, Todorov and Bollerslev (2010) suggest a pricing framework in which they evaluate three separate market betas: a continuous beta for the 'smooth' intraday co-movements with the market, and two 'rough' betas associated with intraday price discontinuities, or jumps, during the trading hours, and the overnight close-to-open return. They found that the average of the two rough betas is higher than the continuous beta.

Chapter 2

Daily, intraday and overnight betas

Introduction

As we have seen in the first chapter, there are many papers about the financial meaning of beta and the different methodologies used for its estimation, on the other hand few studies investigate on the value of intraday and overnight betas.

Since we want to understand whether evaluating systematic risk, i.e. beta, on different trading periods could lead to different results and if there are some differences in patterns between the daily, intraday and overnight betas, we divide the total daily return into intraday and overnight return. In order to do that, in this chapter, we focus our attention on two models, the first one uses constant beta and the other one allows time-varying beta.
The first evaluation is obtained starting from the classical CAPM applying a simple OLS method. As we said in the first chapter this is not the best choice for beta estimation because this model assumes a constant systematic risk over time and furthermore because there are obvious inefficiency problems using a standard parametric model.
For the time-varying betas we consider the conditional CAPM, and we solve it using a non parametric method through a standard weighted regression in which the kernel is around time. This procedure for conditional betas has been proposed by Robinson (1989) and then by Ang and Kristensen (2012) and Li and Yang (2011).

We choice this approach because it can be quite simple and flexible from a computational point of view, these are fundamental features considering the variety of comparisons that we want to do and the big amount of data. Of course the choice of the kernel and the bandwidth represents a crucial point for efficient results. In particular, in order to obtain more accurate values, we decide to use a Gaussian kernel and three different bandwidths for our estimations. As first bandwidth we consider the simple Silverman's rule (Silverman, 1986), then we adopt

the optimal bandwidth evaluated by Ang and Kristensen (2012) and finally we derive an optimal bandwidth adapting the Ruppert et al. (1995)'s rule of thumb.
Daily, intraday and overnight betas are estimated considering US stocks values traded on the NYSE, AMEX, and NASDAQ markets. The data have been taken from the Center for Research in Security Prices (CRSP). As benchmark for the market index we first consider the same daily value for all the trading periods, subsequently we use our intraday and overnight weighted index. In order to understand if there is some relationship between beta and the size, we evaluate our betas stock by stock but also grouping them into ten portfolios sorted month by month by market capitalization.
In the first sections of this chapter we present the conditional CAPM and the methodology used for beta evaluation, focusing on the kernel and bandwidth selection. In the last section we explain our procedure and show our results.

2.1 Local least square kernel regression

We evaluate our time-varying beta starting by the conditional CAPM, where the excess returns of a generic stock, at discrete time points $t = 1, \cdots, n$, respect to the excess market returns, are given by:

$$R_t = \alpha_t + \beta_t R_{Mt} + \omega_t z_t \ , \tag{2.1}$$

α_t and β_t are the conditional alphas and betas, z_t is the error term and ω_t is the conditional variance of errors.
Considering the filtration $\mathscr{F}_t = \mathscr{F}(R_j, R_{Mj}, \alpha_j, \beta_j \ : \ j \leq t)$ the error term have to satisfies

$$\mathrm{E}\left[z_t \middle| \mathscr{F}_t\right] = 0, \qquad \mathrm{E}\left[z_t z_t' \middle| \mathscr{F}_t\right] = 1 \ , \tag{2.2}$$

these assumptions can be viewed as a generalization of the classical OLS conditions, they state that errors and factor are orthogonal.
Under the orthogonality condition (2.2), there is a conditional relation between parameter and observation, Ang and Kristensen (2012), define the realization of alphas and betas that generated data as:

$$[\alpha_t, \beta_t]' = \Lambda_t^{-1} \mathrm{E}\left[X_t R_t' | \mathscr{F}_t\right] \ ,$$

where $X_t = (1, R_{Mt})'$ and $\Lambda_t = \mathrm{E}\left[X_t X_t' | \mathscr{F}_t\right]$ is the conditional second moment of the regressors.

As other authors have done (Robinson, 1989; Li and Yang, 2011; Ang and Kristensen, 2012; Esteban and Orbe-Mandaluniz, 2010), in order to estimate the model (2.1) we assume that the sequences of α_t and β_t, vary smoothly over time and lie on unknown functions of the time index:

$$\alpha_t = \alpha(t/n) \in C^2[0,1] \quad \text{and} \quad \beta_t = \beta(t/n) \in C^2[0,1] \, .$$

This assumption makes α_t and β_t dependent on the sample size n. We map each observation labelled by $t = 1,2,\cdots,n$, into an interval between 0 and 1 through the transformation t/n. We do not impose a functional form but we use local information to estimate the two quantities, for this reason the method can be viewed as a non-parametric method.

Given the observations of excess returns and excess market returns at $t = 1,2,\cdots,n$, it is possible to derive an estimate of the functions $\alpha(\tau)$ and $\beta(\tau)$, for a generic asset, at any normalized time point $\tau \in (0,1)$. This is done using a local least square kernel regression:

$$\left[\hat{\alpha}(\tau),\hat{\beta}(\tau)\right]' = \underset{(\alpha,\beta)}{\arg\min} \sum_{t=1}^{n} K_h\left(t/n-\tau\right)\left(R_t - \alpha(t/n) - \beta(t/n)R_{Mt}\right)^2 \, , \tag{2.3}$$

where,

$$K_h(z) \equiv \frac{1}{h} K\left(\frac{z}{h}\right) \, ,$$

$K(\cdot)$ is a kernel function and h the bandwidth.

Solving the equation (2.3) we can obtain the optimal estimators running, for each asset, a series of kernel-weighted ordinary least square (OLS) regressions

$$\left[\hat{\alpha}(\tau),\hat{\beta}(\tau)\right]' = \left[\sum_{t=1}^{n} K_h\left(t/n-\tau\right) X_t X_t'\right]^{-1} \left[\sum_{t=1}^{n} K_h\left(t/n-\tau\right) X_t R_t\right] \, . \tag{2.4}$$

The use of a kernel function gives the possibility to estimate conditional alphas and betas at any time, using all the data efficiently. Obviously, the most relevant aspect of the implementation of this method is the selection of the kernel shape and the bandwidth h.

2.2 Kernel

Using a kernel function we assign different weights to the observations. These weights depend on how close the observations are to the point τ. The most frequently used kernel functions are the uniform function

$$K(\tau) = \begin{cases} \frac{1}{2}, & \text{for} \, |\tau| \leq 1 \\ 0, & \text{for} \, |\tau| > 1 \end{cases}$$

and the Epanechnikov kernel function

$$K(\tau) = \begin{cases} \frac{3}{4}(1-\tau^2), & \text{for} |\tau| \leq 1 \\ 0, & \text{for} |\tau| > 1 \end{cases}$$

In the first case, all the observations have the same weights. In the second one, the observations closer to the estimation point τ have an higher weight compared to those farther from it. This implies that weights decline with the increase of the time lag. Although many authors like Li and Yang (2011), Andersen et al. (2006) and Lewellen and Nagel (2006) use one-sided and uniform kernel, following Ang and Kristensen (2012), we consider for our estimates, a Gaussian density

$$K(\tau) = \frac{1}{\sqrt{2\pi}} exp\left(-\frac{\tau^2}{2}\right).$$

The main problem that can occur using a two-sided symmetric kernel is an excess of bias at the beginning and at the end of the sample. There are many techniques that could be used to avoid this problem, such as locally linear kernel estimator or boundary kernels. The simplest methodology, used also by Ang and Kristensen (2012), is to delete the first and the last year of the conditional betas estimated. In particular in our estimation we evaluate our beta on all the time period and delete the results related to the first and last year. For this reason for the single stocks analysis we consider only that with more than three years of observations.

2.3 Bandwidth

As pointed by many authors, the bandwidth selection is perhaps the most crucial choice for this method. A small h tends to correspond a small bias in betas and alphas, at the same time a large h involves a small variance in the estimates, for these reasons we need estimate it optimally. The most popular techniques for the bandwidth selection are the cross-validation method (Rudemo, 1982; Bowman, 1984; Robinson, 1989) and the plug-in method (Sheather and Jones, 1991; Ruppert et al., 1995). The first one is completely data driven, on the other hand the second requires to choose some unknown parameters, in order to estimate the optimal window size. We decide to implement our procedure considering three different bandwidths: the Silverman's rule (Silverman, 1986) for a data driven bandwidth and two plug-in methods considering the Ang and Kristensen (2012) methodology and a the modified Ruppert's rule of thumb (Ruppert et al., 1995).

Applying the Silverman's rule (Silverman, 1986) we evaluate the bandwidth for each stock as:

$$h_S = 1.06 \min\left(\text{std dev}(t), \text{interquartile range}(t)/1.34\right) n^{-1/5}.$$

Clearly this first choice is the simplest one from a computational point of view, it depends just on the number of observations that we are considering. Conversely, it is not optimal since it considers just the time vector, ignoring other data.

The other two optimal global bandwidths can be obtained minimizing the conditional Integrated Mean Square Error (MISE), given by:

$$\int_0^1 \left[bias\left(\hat{\beta}(\tau)\right)\right]^2 + var\left(\hat{\beta}(\tau)\right) d\tau \, .$$

Bias and variance of our beta are:

$$bias\left(\hat{\beta}_t\right) = \frac{1}{2}\mu_2 \beta_t^{(2)} h^2 \, , \qquad\qquad var\left(\hat{\beta}_t\right) = \nu_0 \left[n h \Lambda_{FF\,t}\right]^{-1} \sigma_t^2 \, ,$$

where:
$\mu_2 = \int u^2 K(t)dt = 1$ and $\nu_0 = \int K(t)^2 dt = 1/2\sqrt{\pi} = 0.2821$ for a Gaussian kernel. $\Lambda_{FFt} = \Lambda_{FF}(t/n)$ is the conditional variance of our factor and $\sigma_t^2 = \sigma^2(t/n)$ is the conditional variance of residuals. $\beta_t^{(2)} = \beta(t/n)^{(2)}$ where $\beta(\cdot)^{(2)}$ denotes the second order derivative of $\beta(t/n)$.
The optimal bandwidth can be written as:

$$h_{opt} = \left[\frac{\nu_0 \int_0^1 \Lambda_{FF}(\tau)^{-1}\sigma^2(\tau)d\tau}{n\int_0^1 \beta(\tau)^{(2)^2} d\tau}\right]^{1/5} \, . \tag{2.5}$$

In order to apply this formula we have to derive the conditional variance of the factor and the conditional variance of residuals which depend on unknown parameters. First we evaluate them adapting the Ruppert's rule of thumb procedure (Ruppert et al., 1995) and then we use the Ang and Kristensen (2012) bandwidth selection.

2.3.1 Ruppert rule of thumb

Ruppert et al. (1995) in their paper give some methodologies for bandwidth selection in local least square regression. We emphasize that we need to adjust their method to our case since in our work the kernel is around time and this means that we are dealing with a different model. In particular, we modify the rule of thumb procedure, in which, assuming conditional variance and conditional variance of residual as constants, they estimate the unknown parameters used in the bandwidth formula by a blocked quartic fit. They divide data into blocks and for each block they evaluate the parameters. The optimal block, used in the formula, is chosen by the Mallows's C_p (Mallows, 1973).

Considering $\Lambda_{FFt} = \text{var}(R_M)$ and $\sigma_t^2 = \sigma^2$ as constants and denoting $B = \int_0^1 \beta_\tau^{(2)^2} d\tau$, equation (2.5) can be written as:

$$h = \left[\frac{\nu_0 \, \sigma^2}{n \, \text{var}(R_M) \, B} \right]^{1/5}$$

where σ^2 and B are unknowns, so we need to estimate them by the following procedure.

1. Considering our n observations we divide them in χ_j blocks for $j = 1, \cdots, N$, where the maximum number is given by:

$$N_{max} = \max\{\min(\lfloor n/20 \rfloor, N^*), 1\} \tag{2.6}$$

   we select $N^* = 5$, like in the Ruppert's paper.

2. We assume $\beta_t = b_0 + b_1(t/n) + b_2(t/n)^2 + b_3(t/n)^3 + b_4(t/n)^4$, a polynomial of order 4, and we estimate these coefficients applying a parametric least square method for each block j by the following equation:

$$R_t = \alpha + \left(b_0 + b_1(t/n) + b_2(t/n)^2 + b_3(t/n)^3 + b_4(t/n)^4\right) R_{Mt} + \varepsilon_t \tag{2.7}$$

   $t = \lfloor (j-1)n/N \rfloor + 1, \cdots, \lfloor jn/N \rfloor$ and $j = 1, \cdots, N$.

   For each block j we obtain:

$$\hat{\beta}_{Q_{jt}} = \hat{b}_{0j} + \hat{b}_{1j}(t/n) + \hat{b}_{2j}(t/n)^2 + \hat{b}_{3j}(t/n)^3 + \hat{b}_{4j}(t/n)^4 \; . \tag{2.8}$$

3. Once we get $\hat{\beta}$ we can estimate $\hat{B}^Q$ as

$$\hat{B}^Q(N) = \frac{1}{n} \sum_{t=1}^{n} \sum_{j=1}^{N} \left[\left(\hat{\beta}_{Q_j}(t/n) \right)^{(2)} \right]^2 \mathbb{1}_{\{t \in \chi_j\}} \; , \tag{2.9}$$

   or equivalently

$$\hat{B}^Q(N) = \frac{1}{n} \sum_{t=(j-1)n/N+1}^{jn/N} \sum_{j=1}^{N} \left(2\hat{b}_{2j} + 6\hat{b}_{3j}(t/n) + 12\hat{b}_{4j}(t/n)^2\right)^2 \; . \tag{2.10}$$

4. We evaluate also $\hat{\sigma}_Q^2$ by

$$\hat{\sigma}_Q^2(N) = \frac{1}{(n-5N)} \sum_{i=1}^{n} \sum_{j=1}^{N} \left[R_t - \hat{\alpha} - \hat{\beta}_{Q_j}(t/n) R_{Mt} \right]^2 \mathbb{1}_{\{t \in \chi_j\}} \; , \tag{2.11}$$

it can be written as

$$\hat{\sigma}_Q^2(N) = \frac{1}{(n-5N)} \sum_{t=(j-1)n/N+1}^{jn/N} \sum_{j=1}^{N} \Bigg[R_i - \hat{\alpha} + \tag{2.12}$$

$$- \left(\hat{b}_{0j} + \hat{b}_{1j}(t/n) + \hat{b}_{2j}(t/n)^2 + \hat{b}_{3j}(t/n)^3 + \hat{b}_{4j}(t/n)^4\right) R_{Mt} \Bigg]^2 . \tag{2.13}$$

5. In order to derive the optimal block $\hat{N}$, following Mallows (1973), from the set $\{1, 2, \cdots, N_{max}\}$, we consider the one that minimizes

$$C_p(N) = \frac{RSS(N)(n-5N_{max})}{RSS(N_{max})} - (n-10N) , \tag{2.14}$$

where $RSS(N) = \sum_{t \in N} (R_t - \hat{\alpha} - \hat{\beta}(t/n) R_{Mt})^2$ is the residual sum of squares of a blocked quartic N-block-OLS.

6. Considering the previous estimates, we can now compute the modified Ruppert rule-of-thumb bandwidth $\hat{h}_R$ as

$$\hat{h}_R = \left[\frac{\nu_0 \, \hat{\sigma}_Q^2(\hat{N})}{n \, \mathrm{var}(R_M) \, \hat{B}^Q(\hat{N})} \right]^{1/5} . \tag{2.15}$$

2.3.2 Ang and Kristensen

Ang and Kristensen (2012) use for their conditional beta estimation a global plug-in bandwidth. They start from the methodology presented by Ruppert et al. (1995), but they take into account also the time-varying correlation between beta and the factor. Their procedure for the bandwidth selection involves two steps. In the first step they evaluate a preliminary bandwidth, considering for the unknown parameters of equation (2.5) parametric estimates. In the second step they use this first bandwidth for conditional beta, conditional variance and conditional standard errors computation that will be used in the bandwidth formula (2.5). We show below in detail their procedure.

1. From equation (2.5) we can consider $\Lambda_{FFt} = \mathrm{var}(R_M)$ and $\sigma_t^2 = \sigma^2$ as constants and write $B = \int_0^1 \beta_\tau^{(2)^2} d\tau$, so h can be written as:

$$h = \left[\frac{\nu_0 \, \sigma^2}{n \, \mathrm{var}(R_M) \, B} \right]^{1/5}$$

In order to estimate σ^2 and B, we consider, for $t = 1, \cdots, n$

$$\beta_t = b_0 + b_1(t/n) + b_2(t/n)^2 + b_3(t/n)^3 + b_4(t/n)^4 + b_5(t/n)^5 + b_6(t/n)^6$$

a polynomial of order 6, and evaluate the coefficients applying parametric least square on this equation:

$$R_t = \alpha + \beta_t R_{Mt} + \varepsilon_t \qquad t = 1, \cdots, n \tag{2.16}$$

obtaining

$$\hat{\beta}_t = \hat{b}_0 + \hat{b}_1(t/n) + \hat{b}_2(t/n)^2 + \hat{b}_3(t/n)^3 + \hat{b}_4(t/n)^4 + \hat{b}_5(t/n)^5 + \hat{b}_6(t/n)^6 \, . \tag{2.17}$$

We evaluate $\hat{B}$ as

$$\hat{B} = \frac{1}{n} \sum_{t=1}^{n} \left[\hat{\beta}_t^{(2)} \right]^2 \, , \tag{2.18}$$

where $\hat{\beta}_t^{(2)}$ represents the second derivative given by:

$$\hat{\beta}_t^{(2)} = 2\hat{b}_2 + 6\hat{b}_3(t/n) + 12\hat{b}_4(t/n)^2 + 20\hat{b}_5(t/n)^3 + 30\hat{b}_6(t/n)^4 \, . \tag{2.19}$$

We compute $\hat{\sigma}^2$ as

$$\hat{\sigma}^2 = \frac{1}{n} \sum_{t=1}^{n} \left[R_t - \hat{\alpha} - \hat{\beta}(t/n) R_{Mt} \right]^2 \, . \tag{2.20}$$

Considering the previous estimates, we now can evaluate the first step bandwidth h_1 as:

$$h_1 = \left[\frac{\nu_0 \, \hat{\sigma}^2}{\mathrm{var}(R_M) \, \hat{B} \, n} \right]^{1/5} \, . \tag{2.21}$$

2. Once obtained h_1 we estimate the variance components and $\hat{\beta}(\tau)$.

$$\hat{\Lambda}_{FF}(\tau) = \frac{\sum_{t=1}^{n} K_{h_1}(t/n - \tau) \left[R_{Mt} - \hat{\mu}_F(t/n) \right]^2}{\sum_{t=1}^{n} K_{h_1}(t/n - \tau)}$$

where

$$\hat{\mu}(\tau) = \frac{\sum_{t=1}^{n} K_{h_1}(t/n - \tau) R_{Mt}}{\sum_{t=1}^{n} K_{h_1}(t/n - \tau)}$$

is an approximation of the conditional mean.
The conditional variance of residual, $\sigma^2(\tau)$, can be computed as:

$$\hat{\sigma}^2(\tau) = \frac{\sum_{t=1}^{n} K_{h_1}(t/n - \tau) \hat{\varepsilon}_t^2}{\sum_{t=1}^{n} K_{h_1}(t/n - \tau)}$$

where $\hat{\varepsilon}_t = \hat{\varepsilon}(t/n) = R_t - \hat{\alpha}(t/n) - \hat{\beta}(t/n)R_{Mt}$.
The numerator of equation (2.5) can be written as:

$$\hat{V} = \nu_0 \frac{1}{n} \sum_{t=1}^{n} \hat{\Lambda}_{FF}^{-1}(t/n)\hat{\sigma}^2(t/n)$$

The denominator of (2.5) is given by:

$$\hat{B} = \frac{1}{n} \sum_{t=1}^{n} \left[\hat{\beta}(t/n)^{(2)}\right]^2 ,$$

where $\hat{\beta}(\tau)^{(2)}$ is the second derivative, with respect to τ, of the kernel estimator:

$$\hat{\beta}(\tau) = \frac{\sum_{t=1}^{n} \bar{K}_{h_1} \sum_{t=1}^{n} \bar{K}_{h_1} R_{Mt} R_t - \sum_{t=1}^{n} \bar{K}_{h_1} R_{Mt} \sum_{t=1}^{n} \bar{K}_{h_1} R_t}{\sum_{t=1}^{n} \bar{K}_{h_1} \sum_{t=1}^{n} \bar{K}_{h_1} R_{Mt}^2 - [\sum_{t=1}^{n} \bar{K}_{h_1} R_{Mt}]^2} .$$

where $\bar{K}_{h_1} = K_{h_1}(t/n - \tau)$.
Considering the previous estimates we can evaluate the bandwidth as

$$\hat{h}_{AK} = \left[\frac{\hat{V}}{n\hat{B}}\right]^{1/5} . \tag{2.22}$$

2.4 Data and Estimation

In our empirical analysis we evaluate US stock betas, traded on the NYSE, AMEX, and NASDAQ markets. We compute daily, intraday and overnight betas by an unconditional and a conditional CAPM. As benchmark for the market, we first use, for all the trading periods, the same daily excess market return, provided by French's data library [1]. After that we assign a market index for daily intraday and overnight period. The conditional betas are computed considering the three different bandwidths exposed in the previous paragraph. We conduct our analysis evaluating betas stocks by stocks and then, for a more complete analysis, we aggregate them in ten portfolios sorted by market capitalization.

The data are taken from the Center for Research in Security Prices (CRSP)[2]. The original data set covers the period from December 31, 1925 to December 30, 2016. Since daily open prices are not available between July 1962 and June 1992, we decided to consider just the series from June 15, 1992 to December 30, 2016.

[1] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[2] http://www.crsp.com/

We have 15125 stocks to analyze, as shown in Figure 2.1, the stocks belong to different industry areas and are divided according to the Standard Industrial Classification (SIC) code associated to each stock. The most significant percentage of stocks, 35%, belong to transportation, communications, electric, gas and sanitary service sectors, the 21% belong to retail trade and 20% to finance, insurance and real estate sectors. In the case of the stock by stock analysis we exclude from the data set all the stocks with less of three years of observations, i.e. with less of 765 business days, obtaining 10849 stocks to analyze. We delete these stocks because, as we said previously, the estimator for time-varying beta could give biased results on the tails and for this reason we need to delete the first and last year estimate betas from the analysis.

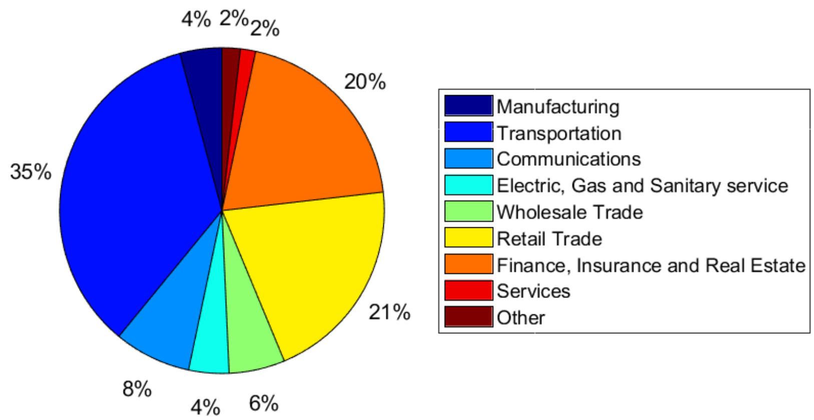


Figure 2.1: Percentage of CRSP stock, from June 16, 1992 to December 30, 2016 divided by the Standard Industrial Classification (SIC) code.

In order to evaluate the daily, intraday and overnight returns, we adjust open and closing price for dividends and splits, by the cumulative adjustment factor, provided by the CRSP data set (CFACPR). The total return or daily return (close-to-close) are calculated on the close price of the previous trading day and the close price of the subsequent trading day:

$$r_t^d = \frac{p_t^{close}}{p_{t-1}^{close}} - 1 \, .$$

It can be decomposed, in daytime or intraday (open-to-close) and overnight (close-to-open) return:

$$r_t^{id} = \frac{p_t^{close}}{p_t^{open}} - 1 \, , \qquad r_t^{ov} = \frac{p_t^{open}}{p_{t-1}^{close}} - 1 \, .$$

The intraday returns are calculated over the trading hours, from current day opening to closing. The overnight returns are computed considering the variation of the price from the previous trading day closure to current trading day opening. Following Bogousslavsky (2016), for the excess returns computation we subtract the daily risk-free rate, representing the daily treasury bill returns and obtained from Kenneth French's database, from our daily and overnight returns. This must be done because intraday returns transactions are settled at the end of the day thus the risk-free rate should not be earned (Heston et al., 2010).

In order to compare the results and before we compute any beta we adjust our dataset so as to keep for each stock only those days in which we have daily, intraday and overnight returns.

Market Index Correlation				
	MR^{FF}	MR^{d}	MR^{id}	MR^{ov}
MR^{FF}	1			
MR^{d}	0.9997	1		
MR^{id}	0.8515	0.8517	1	
MR^{ov}	0.5468	0.5470	0.0274	1

Table 2.1: Correlations between the Fama and French daily market return (MR^{FF}) with our daily (MR^{d}), intraday (MR^{id}) and overnight (MR^{ov}) weighted market index.

Market Index				
	MR^{FF}	MR^{d}	MR^{id}	MR^{ov}
Mean	0.0004	0.0004	0.0002	0.0002
Std. dev.	0.0114	0.0115	0.0096	0.0060
Variance	0.0001	0.0001	0.0001	0.0000
Skewness	-0.1339	-0.1303	-0.1513	-0.6397
Kurtosis	11.1109	11.1048	11.2023	16.8949

Table 2.2: Some statistics of daily Fama and French's market index (MR^{FF}) and the daily (MR^{d}), intraday (MR^{id}) and overnight (MR^{ov}) weighted market index computed. Index series are from June 16, 1992 to December 30, 2016.

For the purpose of having a more precise comparison, we decide to evaluate betas considering also an intraday and overnight market benchmark. We think that by a dimensionality point of view, it could be more correct to have a market value for each trading period. Unfortunately, we do not have the value of the open price of the market, in addition we are considering stocks belonging to three different markets. Therefore, in order to have a daily, intraday and overnight market index we construct a weighted index for each trading period, considering all the stocks in the series, from June 16, 1992 to December 30, 2016. Our market index is given by the following formulas:

$$MR_t^{d} = \frac{\sum_i w_{i,t}\, r_{i,t}^{d}}{\sum_i w_{i,t}}, \qquad MR_t^{id} = \frac{\sum_i w_{i,t}\, r_{i,t}^{id}}{\sum_i w_{i,t}}, \qquad MR_t^{ov} = \frac{\sum_i w_{i,t}\, r_{i,t}^{ov}}{\sum_i w_{i,t}},$$

$w_{i,t} = p_{i,t-1}^{close}\, s_{i,t-1}$ are the weights for each stock i at time t given by the market capitalization. We take the values of the number of shares outstanding, s, from CRSP database and adjust them considering a cumulative adjustment factor (CFACSHR). We also evaluated the weights for intraday period, considering open price and number of shares outstanding at the time t, but since we did not find relevant differences, we decide to consider the same weight for each trading period.

We find that the Fama and French index correlates very highly with our daily and intraday indices, also intraday and overnight market indices seem to be correlated (Table 2.1). The mean and standard deviation of our daily index is similar to Fama and French (Table 2.2). All the four series have a negative skew, this means that the left tail is longer and the mass of the distribution is concentrated on the right. This behaviour is more evident for overnight market index. Furthermore the series exhibit a positive excess kurtosis, and so a leptokurtic distribution. These results are also shown in the histograms of Figure 2.7 in Appendix A.

Portfolios

Portfolio	Number of monthly stocks	Market capitalization (billion USD)	Mean R^d	Mean R^{id}	Mean R^{ov}	Std. dev. R^d	Std. dev. R^{id}	Std. dev. R^{ov}
1	551	0.06	-0.0624	0.2615	-0.0082	0.1600	0.1261	0.0909
2	521	0.13	-0.0005	0.1429	0.0036	0.1391	0.1127	0.0705
3	503	0.24	0.0503	0.0967	0.0390	0.1596	0.1331	0.0730
4	493	0.41	0.0721	0.0542	0.0704	0.2006	0.1711	0.0860
5	485	0.64	0.0856	0.0449	0.0756	0.2249	0.1954	0.0943
6	481	1.14	0.0997	0.0575	0.0643	0.2236	0.1936	0.0954
7	479	1.92	0.0961	0.0685	0.0413	0.2183	0.1891	0.0938
8	477	3.45	0.0913	0.0701	0.0288	0.2126	0.1834	0.0927
9	476	10.3	0.0823	0.0492	0.0373	0.1966	0.1668	0.0905
10	476	61.7	0.0622	0.0343	0.0296	0.1809	0.1520	0.0966

Table 2.3: Monthly average of the number of stock and market capitalization of each portfolio. Annualized mean and standard deviation of the daily intraday and overnight excess returns of our portfolios, are computed multiplying for 252 and $\sqrt{252}$, respectively.

For a more complete and simple analysis we aggregate our stocks in portfolios. As we said in the first chapter, this could allows a more precise beta estimation (Blume, 1970; Levy, 1971). In order to do this, on the last day of the month, we evaluate the market capitalization for each stock traded and then we sort our stocks in ascending order and divide them in ten portfolios. Portfolio 1 contains stocks with lower market capitalization, each month on average a total of 60 milliards USD. Instead, portfolio 10 has stocks with higher market capitalization, each month on average 61 billions USD. The series are from July 1, 1992 to December 30, 2016 and so in each portfolio we have 6170 trading days. As we show in Table 2.3 in each decile we have on average 500 stocks traded each month. Furthermore evaluating the daily, intraday and overnight returns, in excess of the risk free rate (annualized, i.e. multiplied by 252), we find that almost all portfolios have a greater daily excess return and a lower overnight return. Also evaluating the annualized standard deviation, multiplying for $\sqrt{252}$, we note an higher volatility for daily returns. Looking at the table and at the cumulative returns represented in Figure 2.9 Appendix A, we note an higher value for intraday return in the first and second portfolio.

We start analyzing the values of the constant betas, for all the single stocks, obtained applying the simple OLS model. We observe that, considering the daily Fama and French market index for all the trading periods, on 10 849 stocks, 9 586 have an intraday beta greater than overnight, so, only 1 263 have the opposite relationship. If instead we compute betas with a daily intraday and overnight market index we obtain 6 122 stocks with an intraday beta greater than overnight and so 4 727 with an overnight larger than intraday. This means that to consider or not an equal market index, for all the trading periods, changes significantly the value of intraday and overnight betas. The main statistics, computed considering the values obtained by each stock, are in Table 2.4. With a variable market index, our three betas have the same means, although the distribution is different (Figure 2.8 Appendix A), furthermore we have a greater variation for overnight betas.

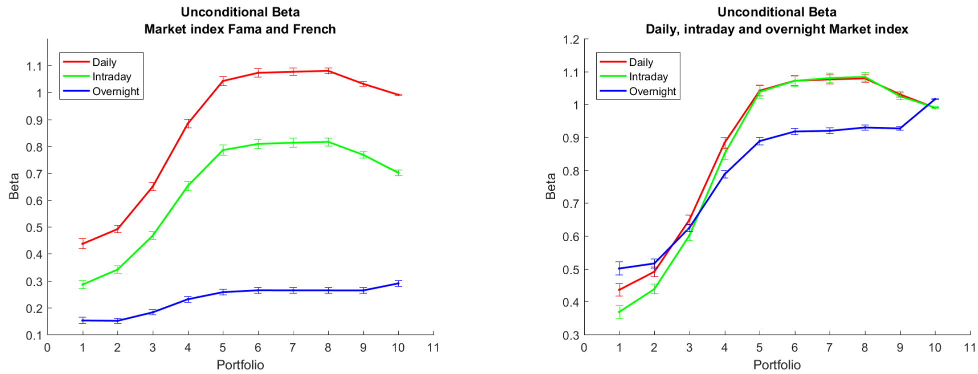
	Market Index Fama and French			**Daily intraday and overnight Market Index**		
	β^d	β^{id}	β^{ov}	β^d	β^{id}	β^{ov}
Mean	0.7663	0.5654	0.2013	0.7659	0.7301	0.7217
Std. dev.	0.4663	0.3742	0.1745	0.4655	0.5028	0.4673

Table 2.4: Mean and standard deviation of the betas across all the stocks. Betas are computed, for each stock, by OLS considering first Fama and French market index and then daily, intraday and overnight market index.

Aggregating our stocks in ten portfolios by market capitalization, we note that the values of betas on all periods are increasing by size (Table 2.5). Furthermore, as in the case of the single stocks, we have higher values for intraday and overnight betas, if we consider the specific trading market benchmark. Using a weighted index the values of daily and intraday betas are very similar, instead the overnight values remain lower. These results are better shown by Figure 2.2, in which we add the 95% confidence interval by the error bars. Looking at these results and to the value of standard error for alphas and betas (Table 2.6) we can say that our estimate is sufficiently precise. Although, as we have seen in the first chapter, to assume a constant beta is not the best choice, because systematic risk varies with time.

Unconditional Beta												
	Market Index Fama and French						Daily intraday and overnight Market Index					
	α^{d}	α^{id}	α^{ov}	β^{d}	β^{id}	β^{ov}	α^{d}	α^{id}	α^{ov}	β^{d}	β^{id}	β^{ov}
1	-0.0004	0.0009	-0.0001	0.4371	0.2853	0.1520	-0.0004	0.0010	-0.0001	0.4358	0.3685	0.5007
2	-0.0002	0.0005	-0.0000	0.4920	0.3415	0.1507	-0.0001	0.0005	-0.0000	0.4909	0.4381	0.5161
3	-0.0000	0.0002	0.0001	0.6500	0.4674	0.1823	0.0000	0.0003	0.0001	0.6490	0.6016	0.6249
4	-0.0000	-0.0000	0.0002	0.8840	0.6525	0.2309	0.0001	0.0001	0.0002	0.8831	0.8495	0.7871
5	-0.0000	-0.0001	0.0002	1.0427	0.7857	0.2573	0.0001	0.0000	0.0002	1.0418	1.0382	0.8884
6	0.0000	-0.0000	0.0002	1.0730	0.8086	0.2642	0.0001	0.0001	0.0001	1.0720	1.0718	0.9175
7	0.0000	0.0000	0.0001	1.0770	0.8131	0.2639	0.0001	0.0001	0.0001	1.0760	1.0802	0.9196
8	0.0000	0.0000	0.0000	1.0804	0.8164	0.2638	0.0001	0.0001	0.0000	1.0793	1.0839	0.9297
9	-0.0000	-0.0001	0.0001	1.0319	0.7679	0.2637	0.0001	0.0000	0.0000	1.0305	1.0246	0.9269
10	-0.0001	-0.0001	0.0000	0.9912	0.7009	0.2898	-0.0000	-0.0000	-0.0000	0.9895	0.9903	1.0162

Table 2.5: Unconditional alpha and beta on 10 Portfolios. Portfolios are divided and sorted considering the market capitalization at the end of each month. Alphas and betas are evaluated in each portfolio considering the same daily Fama and French market index and also with a daily intraday and overnight market index.



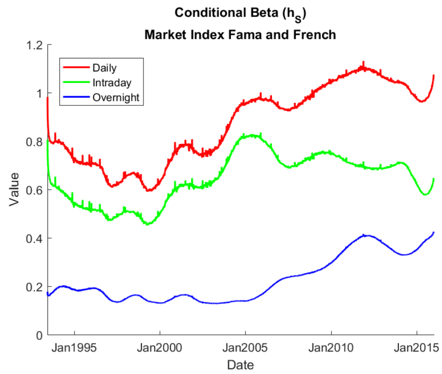
(a) (b)

Figure 2.2: Unconditional beta values on the 10 portfolios. Betas are evaluated considering the Fama and French market index (a) and a daily intraday and overnight market index (b). We plot also the 95% confidence interval by the error bars.

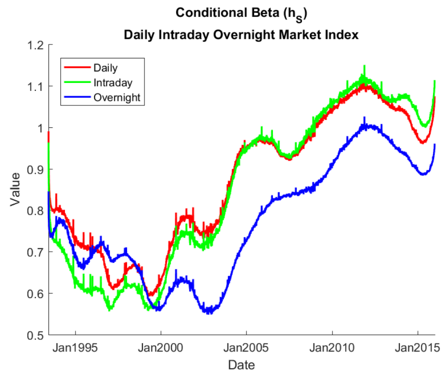
Standard error unconditional Beta												
	Market Index Fama and French						Daily intraday and overnight Market Index					
	SE α^{d}	SE α^{id}	SE α^{ov}	SE β^{d}	SE β^{id}	SE β^{ov}	SE α^{d}	SE α^{id}	SE α^{ov}	SE β^{d}	SE β^{id}	SE β^{ov}
1	9.81E-05	6.45E-05	3.48E-05	9.73E-03	8.05E-03	6.07E-03	9.79E-05	7.53E-05	5.96E-05	9.72E-03	9.40E-03	1.04E-02
2	6.54E-05	4.69E-05	2.02E-05	7.47E-03	6.59E-03	4.55E-03	6.53E-05	5.38E-05	3.02E-05	7.45E-03	7.56E-03	6.81E-03
3	7.56E-05	6.02E-05	2.10E-05	7.52E-03	7.18E-03	4.56E-03	7.55E-05	6.73E-05	2.63E-05	7.50E-03	8.02E-03	5.72E-03
4	1.06E-04	9.31E-05	2.85E-05	8.42E-03	8.64E-03	5.26E-03	1.06E-04	1.00E-04	3.10E-05	8.39E-03	9.29E-03	5.71E-03
5	1.20E-04	1.15E-04	3.42E-05	8.49E-03	9.35E-03	5.74E-03	1.20E-04	1.17E-04	3.38E-05	8.45E-03	9.52E-03	5.68E-03
6	1.08E-04	1.08E-04	3.47E-05	7.66E-03	8.83E-03	5.77E-03	1.07E-04	1.05E-04	3.14E-05	7.62E-03	8.61E-03	5.22E-03
7	9.30E-05	9.85E-05	3.34E-05	6.76E-03	8.27E-03	5.65E-03	9.24E-05	9.17E-05	2.74E-05	6.72E-03	7.70E-03	4.63E-03
8	7.65E-05	8.74E-05	3.25E-05	5.71E-03	7.56E-03	5.56E-03	7.60E-05	7.61E-05	2.24E-05	5.67E-03	6.58E-03	3.83E-03
9	5.13E-0 5	6.72E-05	3.06E-05	4.14E-03	6.39E-03	5.37E-03	5.09E-05	5.04E-05	1.61E-05	4.11E-03	4.79E-03	2.83E-03
10	1.28E-05	5.57E-05	3.45E-05	1.12E-03	5.81E-03	5.67E-03	1.24E-05	1.20E-05	4.38E-06	1.09E-03	1.26E-03	7.20E-04

Table 2.6: Standard error for the unconditional beta estimate on the 10 Portfolios. Portfolios are divided and sorted considering the market capitalization at the end of each month. Alpha and beta are evaluate in each portfolio considering the same daily Fama and French market index and also with a daily intraday and overnight market index.

We begin now to analyze the results obtained applying, stock by stock, the conditional CAPM. As for the constant beta analysis we consider the same daily Fama and French market index and our daily, intraday and overnight weighted index. Furthermore, as we said, we use three different bandwidths: Silverman (1986), a modified Ruppert et al. (1995) and Ang and Kristensen (2012). Looking at Figure 2.3, in which we represent the daily, intraday and overnight mean of beta across the stocks in the period, it is obvious the time-varying nature of betas and their difference behaviors. In particular we observe that daily, intraday and overnight betas, obtained by considering a daily intraday and overnight market index, are very similar until the 2000, then overnight is always lower respect the daily and intraday that have very similar values in all the following time period. Furthermore, we can notice that all three beta values are increasing from November 2004.



(a)



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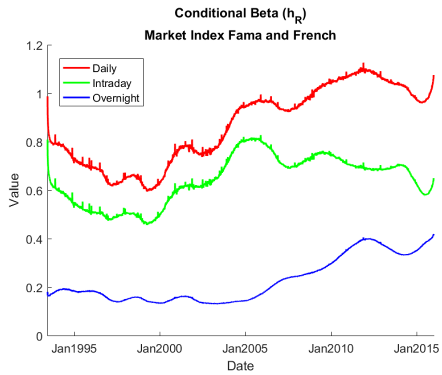

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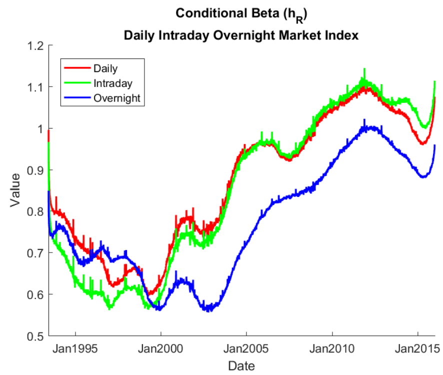

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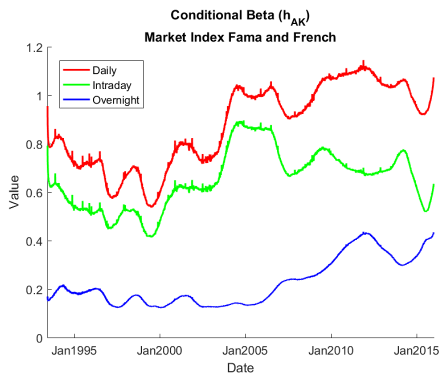

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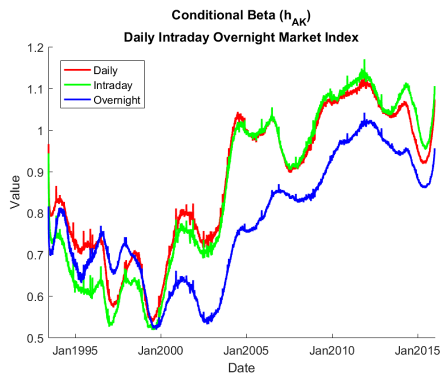


(f)

Figure 2.3: Mean of conditional betas day by day. We evaluate conditional betas stock by stock and plot the mean of betas for each day. Beta evaluation are given considering the Silverman (h_S), the modified Ruppert (h_R) and the Ang and Kristensen (h_{AK}) bandwidths. On the left betas computed considering the Fama and French daily market index; on the right betas computed with weighted market index for each trading period.

Using the first two bandwidths we obtain very similar results and there could be a little undershooting in our estimate, so the Ang and Kristensen bandwidth seems to be the better choice. Similar results are evident also analyzing single stocks, in which sometimes we have an overlapping between the Silverman and modified Ruppert bandwidths (Figure 2.10 Appendix A), and looking at the mean of the bandwidths, across all stocks (Table 2.7). The values of these two bandwidths are similar and larger respect than of Ang and Kristensen.

	Bandwidth												
		Market Index Fama and French						**Daily intraday and overnight Market Index**					
	h_S	h_R^d	h_R^{id}	h_R^{ov}	h_{AK}^d	h_{AK}^{id}	h_{AK}^{ov}	h_R^d	h_R^{id}	h_R^{ov}	h_{AK}^d	h_{AK}^{id}	h_{AK}^{ov}
mean	0.0664	0.0782	0.0797	0.0860	0.0471	0.0479	0.0537	0.0782	0.0792	0.0792	0.0470	0.0475	0.0481
std. dev.	0.0083	0.0277	0.0279	0.0294	0.0203	0.0202	0.0224	0.0279	0.0276	0.0290	0.0202	0.0200	0.0204

Table 2.7: Mean and standard deviation across the bandwidth of all the stocks. We consider three bandwidths: the constant bandwidth of Silverman (1986) (h_s) equal for all the trading periods; the modified Ruppert et al. (1995) bandwidth (h_R) and that of Ang and Kristensen (2012)(h_{AK}). The last two are different for each portfolio and each trading period, furthermore we evaluate them also with the Fama and French market index and daily, intraday and overnight market index.

	Conditional Beta Market Index Fama and French								
	h_S			h_R			h_{AK}		
	β^d	β^{id}	β^{ov}	β^d	β^{id}	β^{ov}	β^d	β^{id}	β^{ov}
media	0.7876	0.5824	0.2059	0.7861	0.5811	0.2053	0.7906	0.5861	0.2052
std. dev	0.2931	0.2506	0.1491	0.2753	0.2331	0.1320	0.3602	0.3120	0.1804
	Conditional Beta Daily Intraday and Overnight Market Index								
	h_S			h_R			h_{AK}		
	β^d	β^{id}	β^{ov}	β^d	β^{id}	β^{ov}	β^d	β^{id}	β^{ov}
media	0.7876	0.7499	0.7322	0.7860	0.7486	0.7316	0.7904	0.7525	0.7324
std. dev	0.2927	0.3105	0.3484	0.2750	0.2914	0.3220	0.3598	0.3814	0.4357

Table 2.8: Mean of conditional beta across the stocks. Time-varying betas are evaluated stock by stock considering the same daily Fama and French market index and daily intraday and overnight market index.

On average our three time-varying betas have similar values to the unconditional betas (Table 2.8), but different distributions (Figure 2.12 2.11 2.11 Appendix A). Also in this case, we find higher values if we consider a daily, intraday and overnight weighted index as proxy for the market, specially for overnight betas. Furthermore, with this approach, we obtain an higher correlation between intraday and overnight betas independently by the bandwidth choice (Table 2.9).

Correlation Conditional Beta
Market Index Fama and French

	h_S			h_R			h_{AK}		
	β^d	β^{id}	β^{ov}	β^d	β^{id}	β^{ov}	β^d	β^{id}	β^{ov}
β^d	1			1			1		
β^{id}	0.8062	1		0.7895	1		0.7966	1	
β^{ov}	0.4915	0.0513	1	0.4762	0.0691	1	0.4678	0.0270	1

Correlation Conditional Beta
Daily Intraday and Overnight Market Index

	h_S			h_R			h_{AK}		
	β^d	β^{id}	β^{ov}	β^d	β^{id}	β^{ov}	β^d	β^{id}	β^{ov}
β^d	1			1			1		
β^{id}	0.7790	1		0.7650	1		0.7621	1	
β^{ov}	0.5066	0.3897	1	0.4976	0.3896	1	0.4719	0.3550	1

Table 2.9: Correlation of conditional beta across the stocks. We evaluate time-varying betas stock by stock considering the same daily Fama and French market index and daily intraday and overnight market index. Then for each stock we compute the correlation between the three betas, obtained the values for all the stocks we consider the mean across all.

Aggregating our stocks in ten portfolios, sorted by size, and observing the three different bandwidth values, we find that, as for the single stocks case, the bandwidths of Ang and Kristensen (2012) are smaller implying more variability in the betas, instead the Silverman (1986) and the modified Ruppert et al. (1995) bandwidths are very similar (Table 2.10). Considering the same market index or a daily, intraday and overnight give us similar results. As before, the best choice for the bandwidth is the Ang and Kristensen (2012) bandwidth because other two give some under smoothing on betas.

For these reasons, for conditional betas on portfolios, we decide to show just results obtained considering the daily, intraday and overnight market index and the Ang and Kristensen (2012) bandwidth, other cases are in Appendix A. Looking at Table 2.11, displaying for each portfolio the means of alphas and betas across all the period, we note that the values are very similar to the OLS estimates. Indeed, also in this case, beta increases by size and for first and last portfolio overnight beta is greater than intraday. The different trends of our three betas can be ob-

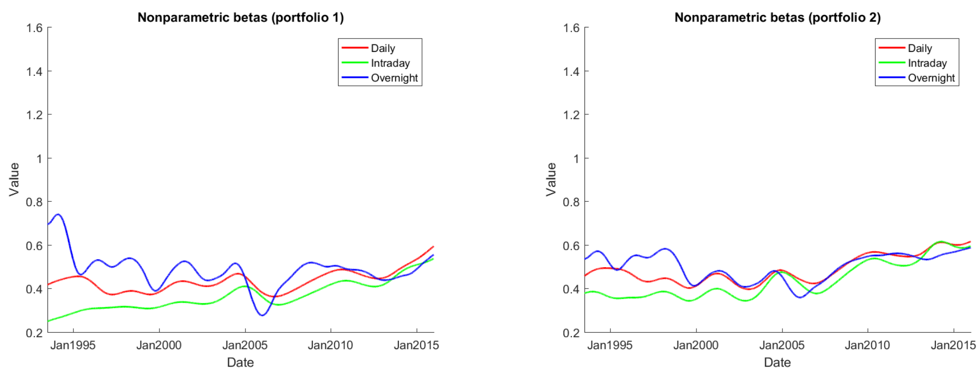
Bandwidth														
		Market Index Fama and French						**Daily intraday and overnight Market Index**						
Portfolio	h_S	h_R^d	h_R^{id}	h_R^{ov}	h_{AK}^d	h_{AK}^{id}	h_{AK}^{ov}	h_R^d	h_R^{id}	h_R^{ov}	h_{AK}^d	h_{AK}^{id}	h_{AK}^{ov}
1	0.0534	0.0715	0.0622	0.1005	0.0368	0.0474	0.0288	0.0711	0.0923	0.0523	0.0369	0.0424	0.0221
2	0.0534	0.0735	0.0637	0.0444	0.0339	0.0378	0.0305	0.0730	0.0853	0.0555	0.0347	0.0342	0.0241
3	0.0534	0.0348	0.0448	0.0386	0.0201	0.0270	0.0254	0.0348	0.0360	0.0292	0.0202	0.0224	0.0176
4	0.0534	0.0342	0.0446	0.0356	0.0206	0.0272	0.0226	0.0341	0.0348	0.0254	0.0206	0.0216	0.0166
5	0.0534	0.0370	0.0365	0.0406	0.0224	0.0208	0.0250	0.0369	0.0389	0.0303	0.0226	0.0226	0.0177
6	0.0534	0.0380	0.0350	0.0400	0.0208	0.0198	0.0246	0.0379	0.0385	0.0289	0.0207	0.0237	0.0176
7	0.0534	0.0367	0.0341	0.0420	0.0198	0.0194	0.0232	0.0366	0.0364	0.0310	0.0196	0.0222	0.0143
8	0.0534	0.0383	0.0355	0.0436	0.0184	0.0211	0.0225	0.0381	0.0379	0.0318	0.0182	0.0198	0.0120
9	0.0534	0.0468	0.0399	0.0438	0.0156	0.0272	0.0218	0.0468	0.0453	0.0308	0.0155	0.0168	0.0099
10	0.0534	0.0520	0.0573	0.0526	0.0151	0.0241	0.0255	0.0509	0.0493	0.0262	0.0155	0.0154	0.0073

Table 2.10: Bandwidth on 10 Portfolios. Portfolios are divided and sorted considering the market capitalization at the end of each month. We consider three bandwidths: the constant bandwidth of Silverman (1986) (h_s) equal for all the portfolios and for all the trading periods; the modified Ruppert et al. (1995) bandwidth (h_R) and that of Ang and Kristensen (2012)(h_{AK}). The last two are different for each portfolio and each trading period, furthermore we evaluate them also with the Fama and French market index and daily, intraday and overnight market index.

served in Figure 2.4 (in Figure 2.19, Figure 2.20, Figure 2.21 in Appendix A, we show same results adding, in dashed lines, the 95% confidence bands), from portfolio 3 to portfolio 8 we have a greater variability, furthermore the daily and intraday betas have similar behaviors while overnight remain lower. In particular looking at these portfolios we note an increasing value for beta between August 2002 and September 2006. Looking to lower cap and higher cap portfolios we can see lower variations between betas, but higher values for portfolio 10, in which all the three betas varying around one.

Conditional Beta (h_{AK}) Daily intraday and overnight Market Index						
	α^d	α^{id}	α^{ov}	β^d	β^{id}	β^{ov}
1	-2.94E-04	9.83E-04	-4.74E-05	0.4344	0.3659	0.4830
2	-1.22E-04	4.68E-04	-1.99E-05	0.4879	0.4375	0.5006
3	-3.49E-05	2.10E-04	8.91E-05	0.6527	0.6223	0.6138
4	5.54E-06	1.33E-05	1.97E-04	0.8602	0.8404	0.7710
5	3.66E-05	-1.76E-05	1.86E-04	1.0152	1.0155	0.8739
6	9.90E-05	3.87E-05	1.44E-04	1.0628	1.0598	0.9048
7	9.12E-05	9.45E-05	4.47E-05	1.0737	1.0732	0.9035
8	8.49E-05	1.13E-04	-2.52E-06	1.0709	1.0735	0.9015
9	6.27E-05	3.19E-05	3.91E-05	1.0136	1.0090	0.8803
10	-6.84E-06	-1.48E-05	-3.73E-06	0.9923	0.9932	1.0272

Table 2.11: Mean of conditional alpha and beta on 10 Portfolios. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying alpha and beta are evaluated in each portfolio considering a daily intraday and overnight market index. Results are from June 30, 1993 to December 31, 2015.



(a) (b)

Figure 2.4: Conditional betas on portfolios 1-2 between June 30, 1993 to December 31, 2015. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying betas are evaluated in each portfolio considering a daily intraday and overnight market index and the Ang and Kristensen bantwidth.

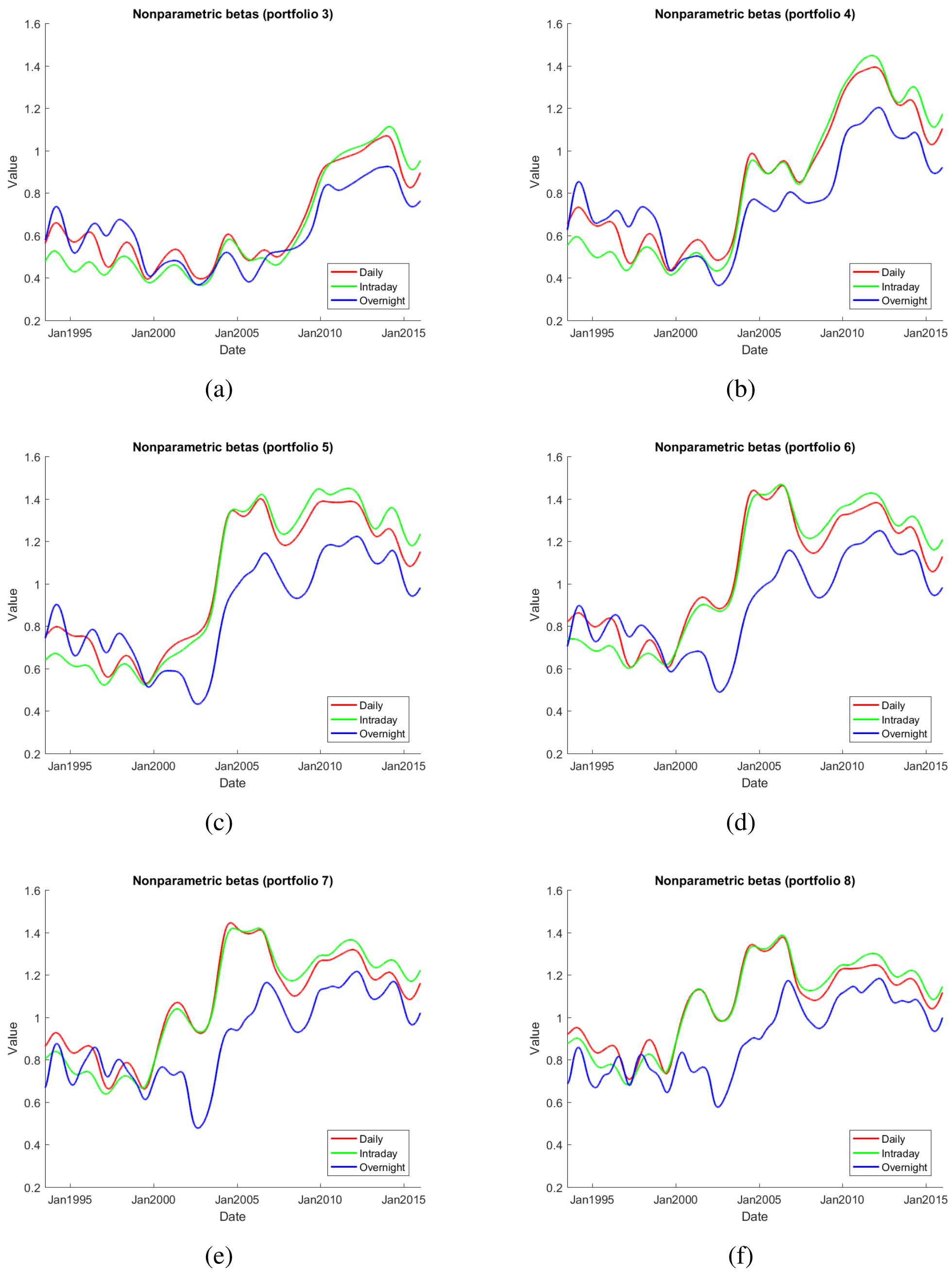
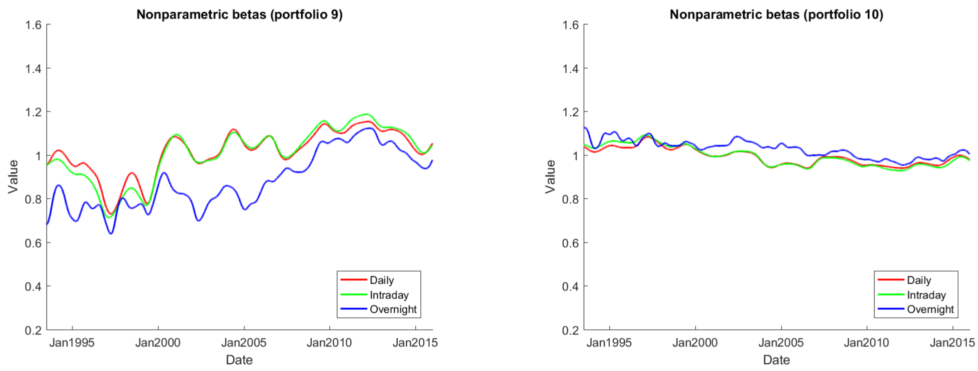


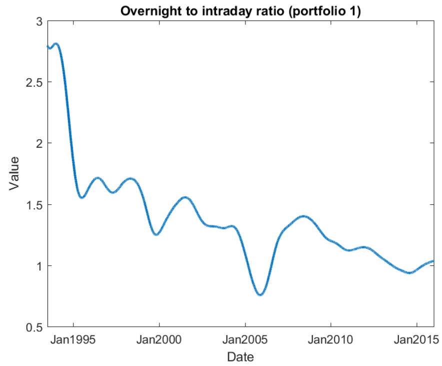
Figure 2.4: Conditional betas on portfolios 3-8 between June 30, 1993 to December 31, 2015. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying betas are evaluated in each portfolio considering a daily intraday and overnight market index and the Ang and Kristensen bantwidth.



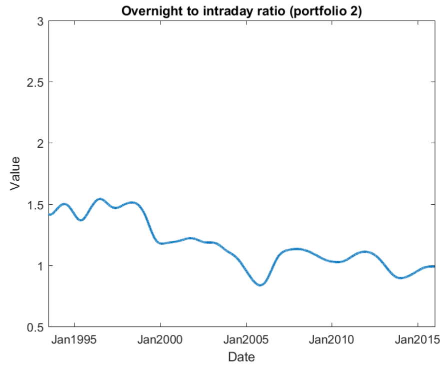
(g) (h)

Figure 2.4: Conditional betas on portfolios 9-10 between June 30, 1993 to December 31, 2015. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying betas are evaluated in each portfolio considering a daily intraday and overnight market index and the Ang and Kristensen bantwidth.

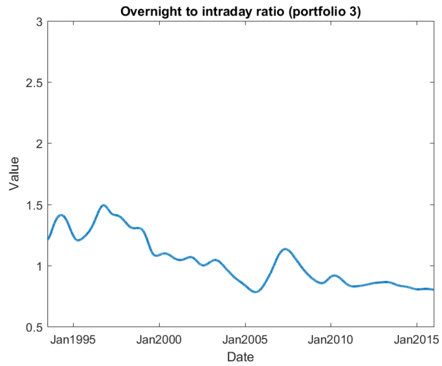
Finally, we decide to analyze the ratio between our overnight and intraday betas over time for each portfolio. Looking at Figure 2.5 we can see that the values are very different over time if we consider little stocks or large stocks it seems that they have an opposite behavior. From the first to the third deciles we have a decreasing ratio between the two periods, overnight betas have different and higher values in relative to the intraday betas. Increasing the size of portfolio the ratio became less variable until portfolio 10, in which the ratio fluctuates near to one for all the time period. If we look at the average over all the ten portfolios, we find that it is decreasing. Looking at volatility as risk measure Linton and Wu (2017) show a different result in their paper. In particular analyzing the ratio of overnight to intraday volatility they find that it is increasing over the last twenty years. Furthermore, considering the volatility over ten market capitalization-based portfolios they find that the ratio is monotonically increasing by the size, so larger stocks have a relative larger increase in overnight volatility respect to intraday volatility. Also in their case small stocks and large stocks have different trends, the ratio is decreasing for small stocks but it is increasing for large stocks, so we find a different behavior for large stocks.



(i)



(j)



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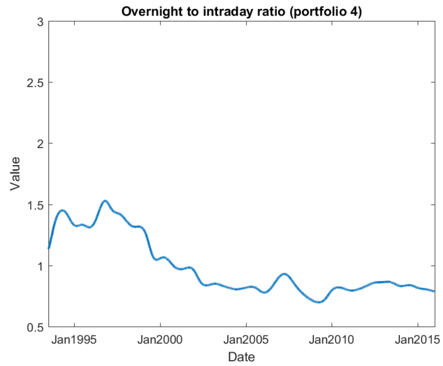

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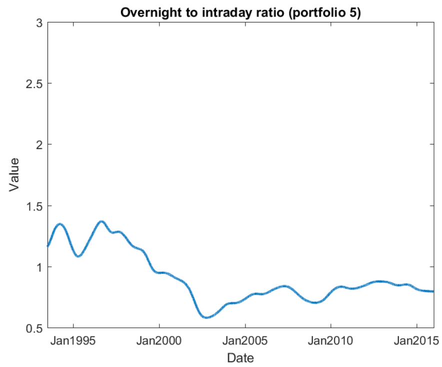

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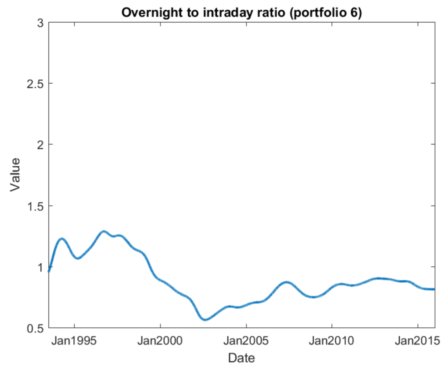


(n)

Figure 2.5: Ratio between overnight and intraday betas of the 1-6 portfolios, between June 30, 1993 to December 31, 2015. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying betas are evaluated in each portfolio considering a daily intraday and overnight market index and the Ang and Kristensen bantwidth.

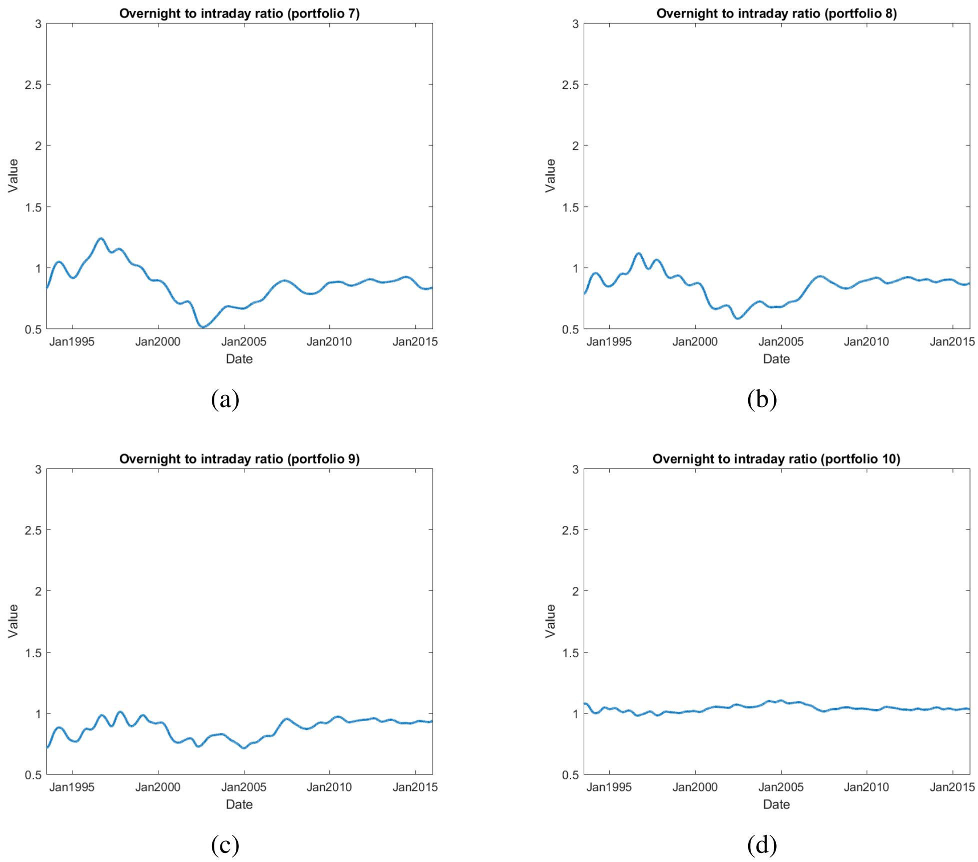


Figure 2.5: Ratio between overnight and intraday betas of the 7-10 portfolios, between June 30, 1993 to December 31, 2015. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying betas are evaluated in each portfolio considering a daily intraday and overnight market index and the Ang and Kristensen bantwidth.

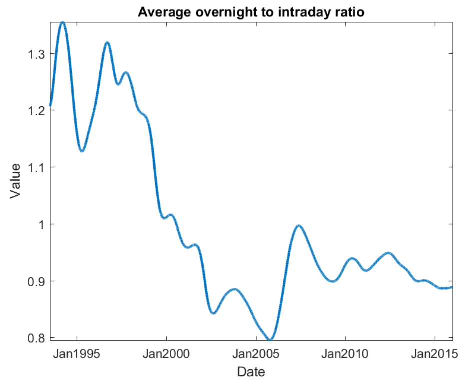
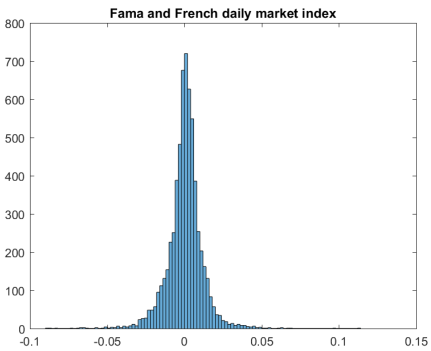


Figure 2.6: Average ratio between overnight and intraday betas on 10 portfolios, between June 30, 1993 to December 31, 2015. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying betas are evaluated in each portfolio considering a daily intraday and overnight market index and the Ang and Kristensen bantwidth.

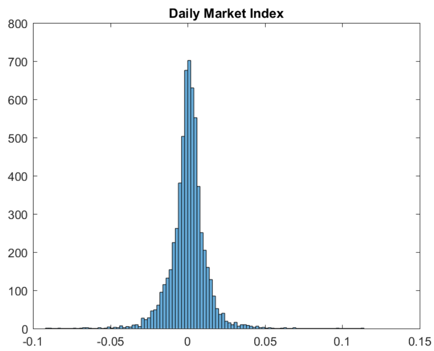
Conclusion

In order to investigate if daily, intraday and overnight betas have different behaviors we divide total daily returns in intraday and overnight and estimate them, stock by stock and in size sorted portfolios, applying two different methods. First we evaluate the betas by a classical CAPM and so using a simple OLS method. In this case we obtain a constant beta related to all period. Of course assuming systematic risk constant by time it is not realistic. Then we evaluate time-varying betas by a conditional CAPM, solved by a kernel weighted OLS, with the kernel around time. As pointed by many authors, the only problem that we have using the last methodology is the correct choice of the bandwidth. Considering three different bandwidths we find always some differences between our three betas, although with the Silverman and modified Ruppert bandwidth we obtain undersmoothing results. As proxy for the market index we decide to consider the same daily market index of Fama and French and then we evaluate a weighted index for each trading period. The use of market index daily intraday and overnight is more coherent with the model dimensionality, and gives more variability and differences in behavior specially for the overnight betas. Looking at results obtained aggregating our stocks into portfolios, by market capitalization, it seems that there is some kind of relationships between stock size and beta. We observe, considering the conditional and the unconditional method, that betas increase by size. Furthermore, the values related to the stocks with lower and higher market capitalization do not exhibit a relevant variation of betas in time series. The ratio between overnight and intraday is decreasing over time, so this means that overnight is always lower respect intraday betas.

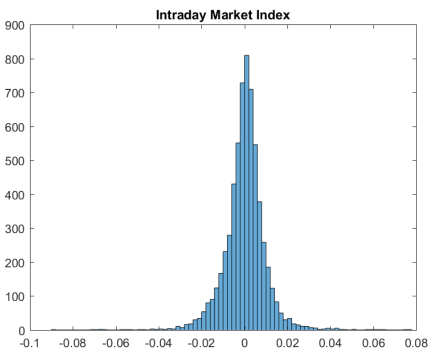
Appendix A



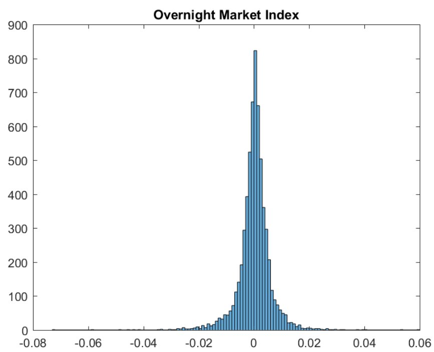
(a)



(b)

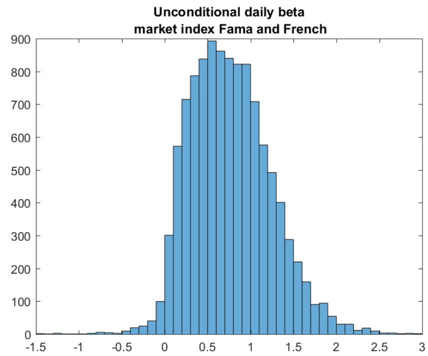


(c)

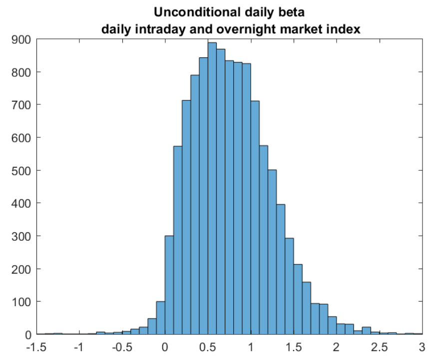


(d)

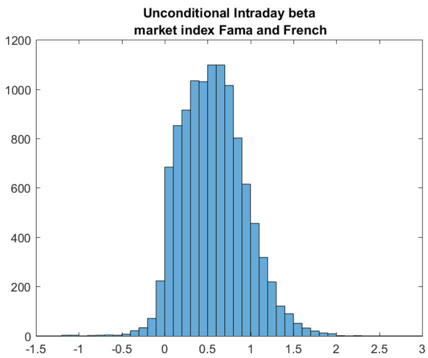
Figure 2.7: Market index distribution: Daily Fama and French daily market index (a), daily weighted market index (b), intraday weighted market index (c) and overnight weighted market index (b).



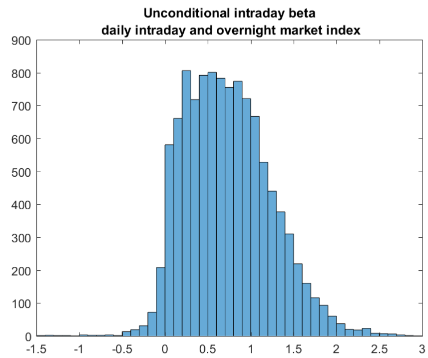
(a)



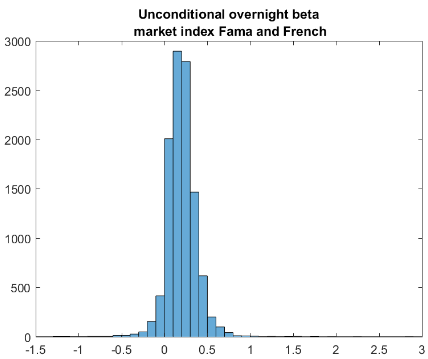
(b)



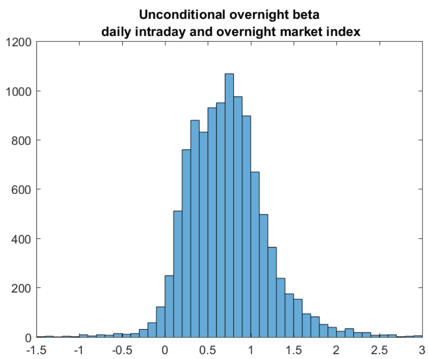
(c)



(d)



(e)



(f)

Figure 2.8: Beta distribution across stocks. On the left daily (a), intraday (c) and overnight (e) betas computed for each stock considering the Fama and French daily market index; on the right daily (b), intraday (d) and overnight (f) computed with weighted market index for each trading period.

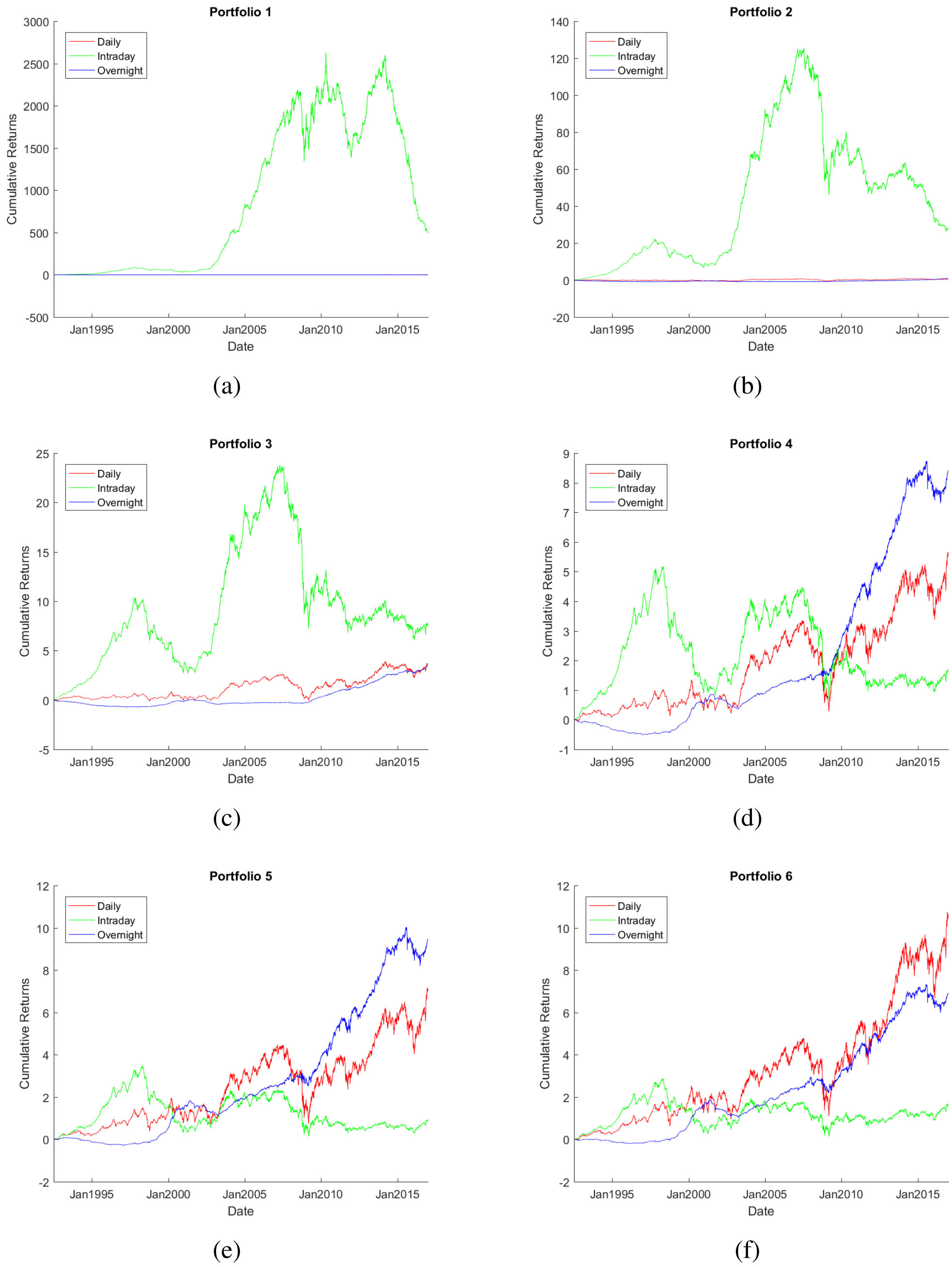


Figure 2.9: Cumulative returns of the 1-6 portfolios. Portfolios are divided and sorted, in ascending order, considering the market capitalization at the end of each month.

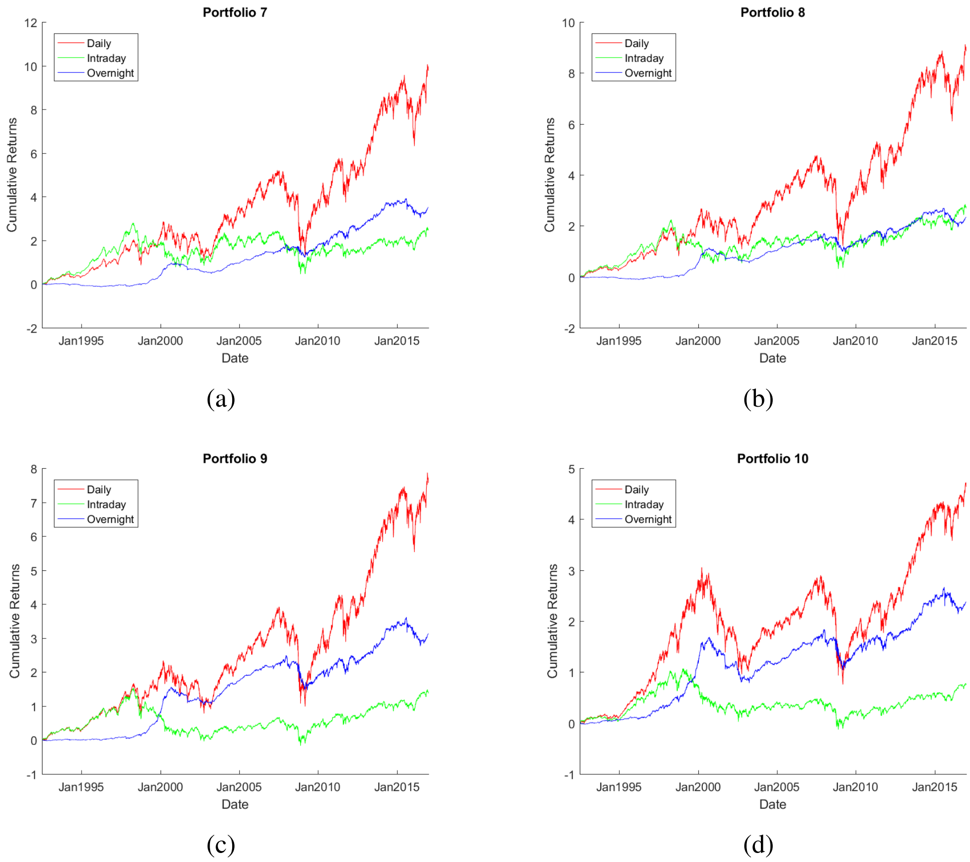


Figure 2.9: Cumulative returns of the 7-10 portfolios. Portfolios are divided and sorted, in ascending order, considering the market capitalization at the end of each month.

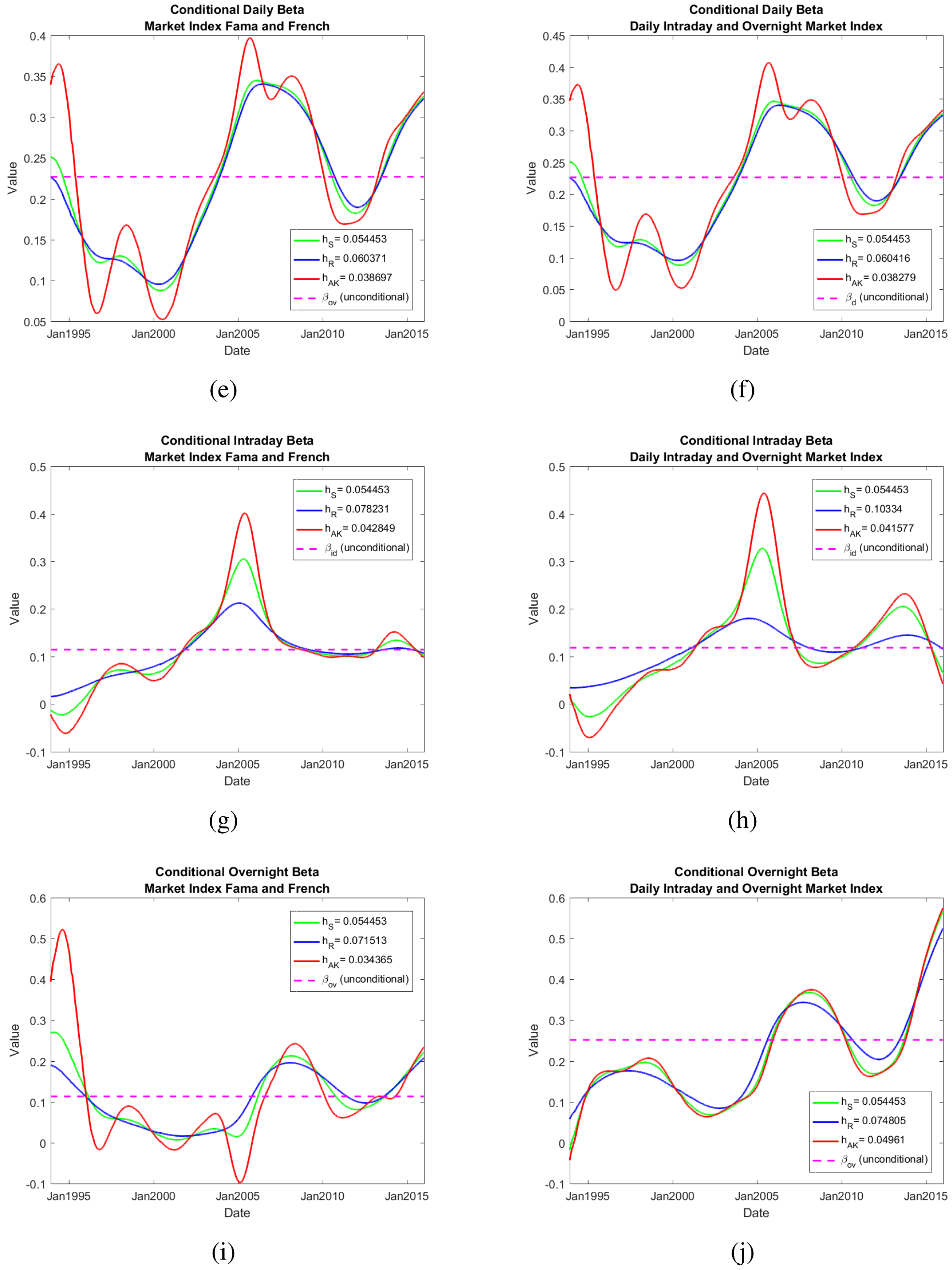


Figure 2.10: Conditional daily intraday and overnight betas values of a generic stock. We plot the beta considering the three different bandwidths: Silverman h_S, modified Ruppert h_R and Ang and Kristensen h_{AK}. On the left we have the values daily (a) intraday (c) and overnight (e) considering the same market index for all the trading periods. On the right we have the values daily (b) intraday (d) and overnight (f) considering three different market index.

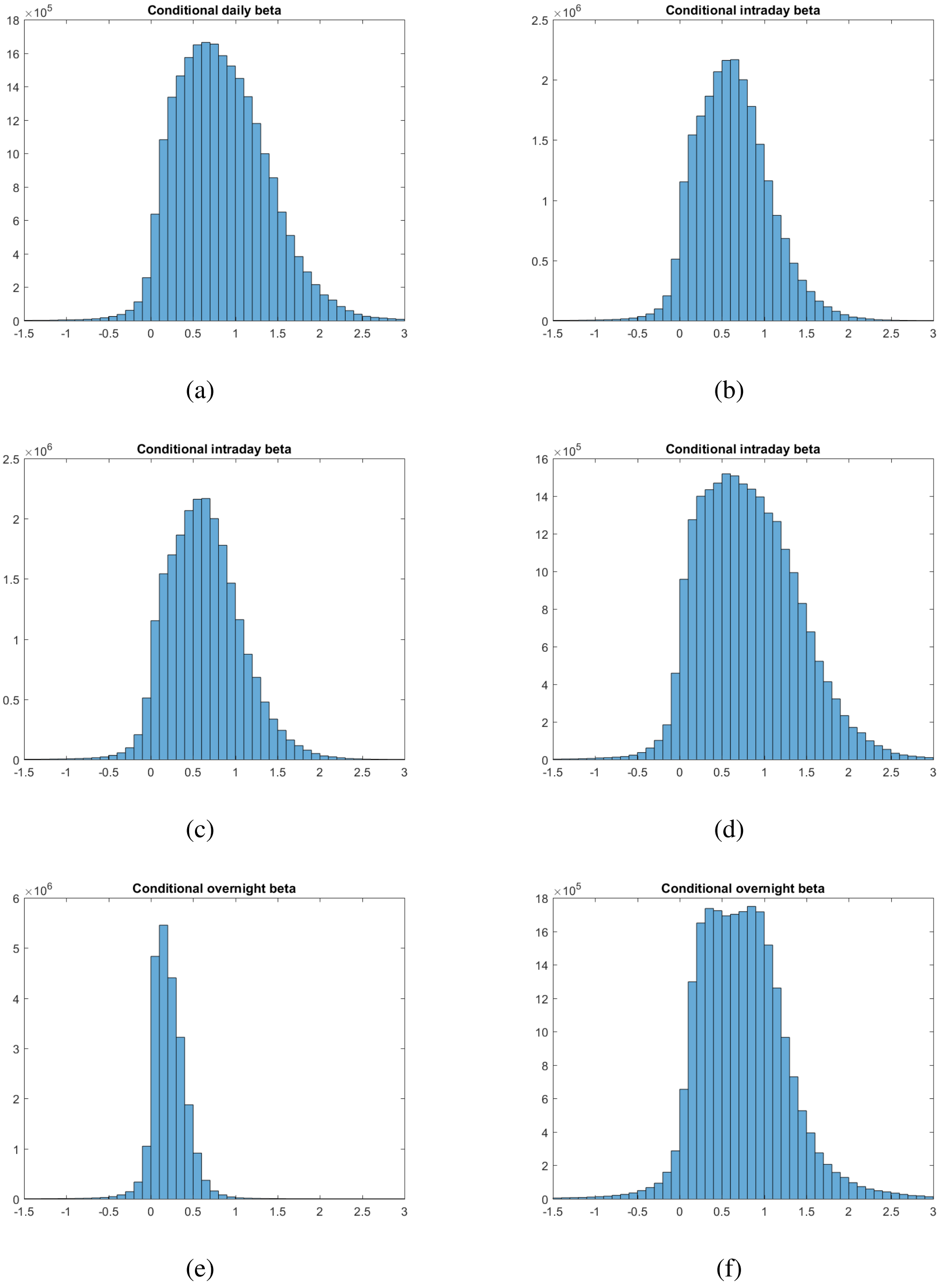


Figure 2.11: Conditional beta distribution across stocks, considering the Silverman bandwidth. On the left daily (a), intraday (c) and overnight (e) betas computed for each stock considering the Fama and French daily market index; on the right daily (b), intraday (d) and overnight (f) computed with weighted market index for each trading period.

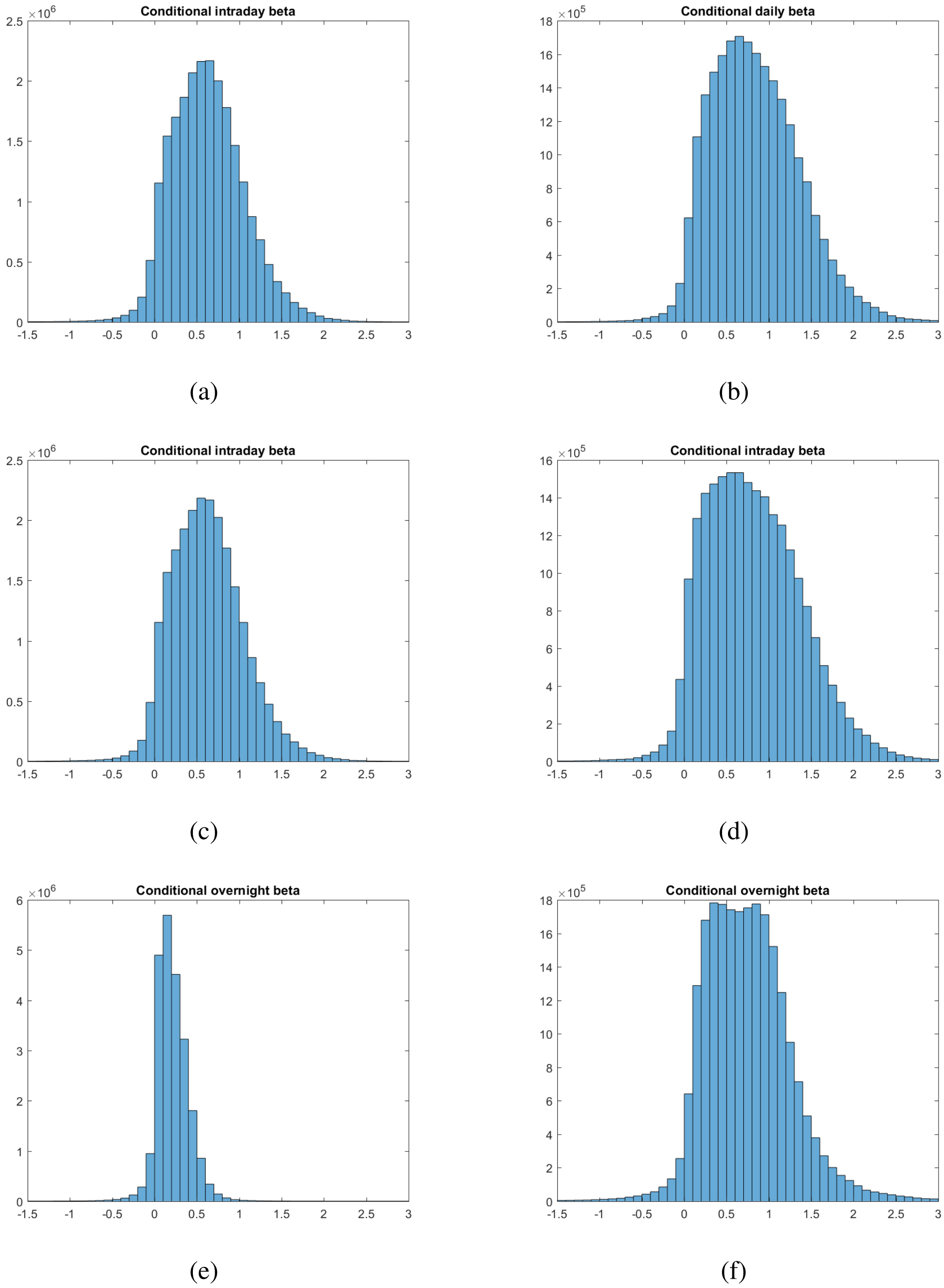
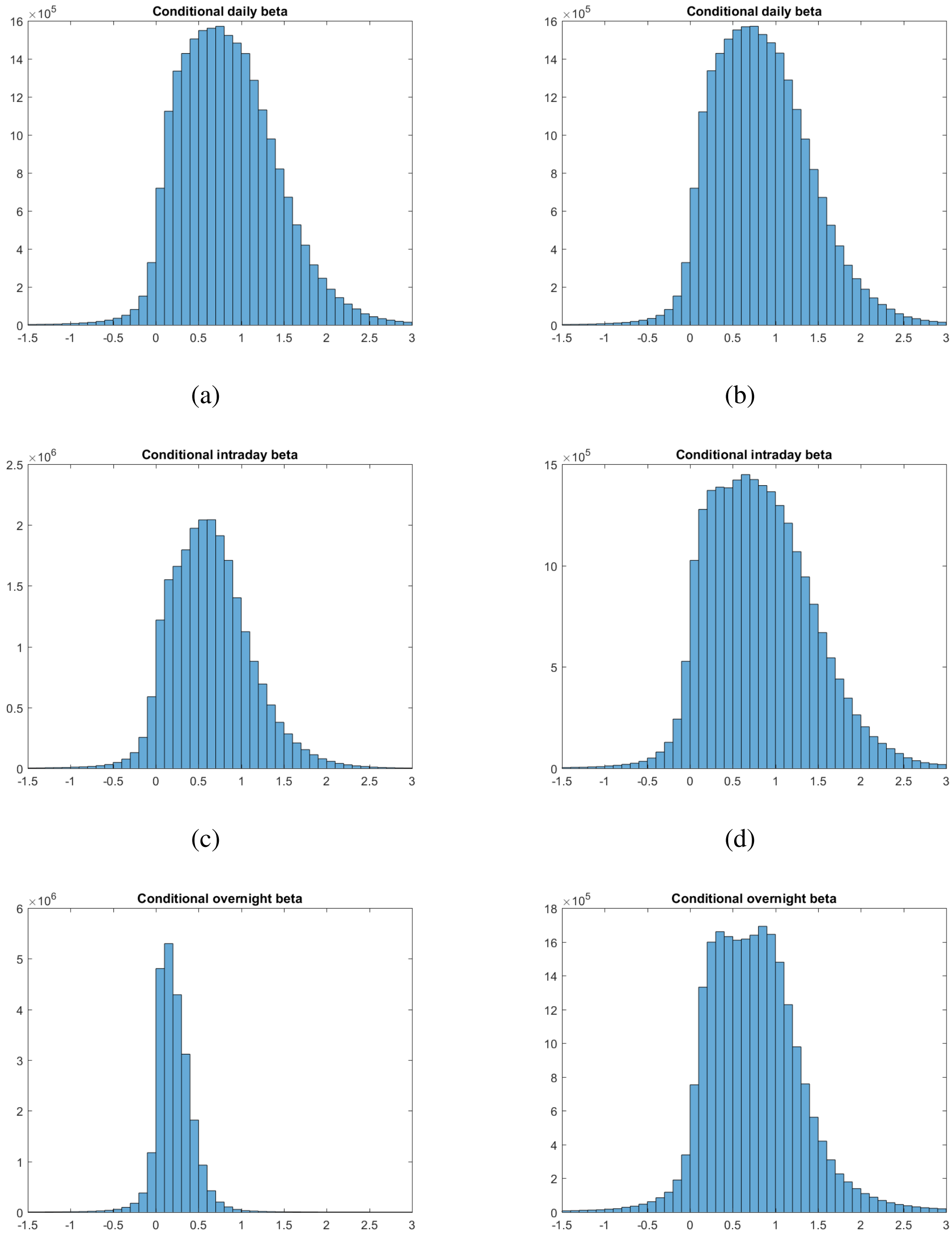


Figure 2.12: Conditional beta distribution across stocks, considering the modified Ruppert bandwidth. On the left daily (a), intraday (c) and overnight (e) betas computed for each stock considering the Fama and French daily market index; on the right daily (b), intraday (d) and overnight (f) computed with weighted market index for each trading period.



(a) (b)

(c) (d)

(e) (f)

Figure 2.13: Conditional beta distribution across stocks considering the Ang and Kristensen bandwidth. On the left daily (a), intraday (c) and overnight (e) betas computed for each stock considering the Fama and French daily market index; on the right daily (b), intraday (d) and overnight (f) computed with weighted market index for each trading period.

Conditional Beta (h_S)												
	Market Index Fama and French						Daily intraday and overnight Market Index					
	α^d	α^{id}	α^{ov}	β^d	β^{id}	β^{ov}	α^d	α^{id}	α^{ov}	β^d	β^{id}	β^{ov}
1	-3.22E-04	9.45E-04	-3.98E-05	0.4350	0.2827	0.1527	-2.91E-04	9.85E-04	-4.99E-05	0.4343	0.3654	0.4989
2	-1.53E-04	4.23E-04	-2.87E-06	0.4874	0.3371	0.1508	-1.18E-04	4.70E-04	-1.74E-05	0.4868	0.4360	0.5097
3	-5.05E-05	1.57E-04	1.25E-04	0.6437	0.4616	0.1822	-3.06E-06	2.25E-04	1.06E-04	0.6434	0.6113	0.6102
4	-2.85E-05	-6.11E-05	2.36E-04	0.8465	0.6189	0.2271	3.48E-05	2.64E-05	2.15E-04	0.8459	0.8285	0.7520
5	-1.03E-05	-1.08E-04	2.32E-04	0.9941	0.7453	0.2490	6.38E-05	-6.08E-06	2.07E-04	0.9932	0.9981	0.8441
6	4.42E-05	-5.91E-05	1.88E-04	1.0363	0.7807	0.2554	1.21E-04	4.80E-05	1.60E-04	1.0355	1.0392	0.8787
7	2.93E-05	-8.01E-06	9.01E-05	1.0481	0.7941	0.2542	1.06E-04	1.02E-04	6.03E-05	1.0476	1.0529	0.8792
8	1.69E-05	4.78E-06	4.24E-05	1.0542	0.8022	0.2519	9.35E-05	1.18E-04	9.58E-06	1.0535	1.0585	0.8870
9	-9.85E-06	-7.08E-05	7.81E-05	1.0133	0.7615	0.2516	6.36E-05	3.56E-05	4.41E-05	1.0123	1.0075	0.8877
10	-8.18E-05	-1.07E-04	3.28E-05	0.9967	0.7133	0.2830	-1.00E-05	-1.60E-05	-6.92E-06	0.9953	0.9959	1.0265

Table 2.12: Mean of conditional alpha and beta on 10 Portfolios. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time varying alpha and beta are evaluated in each portfolio considering the same daily Fama and French market index and daily intraday and overnight market index. Results are from June 30, 1993 to December 31, 2015.

Conditional Beta (h_R)												
	Market Index Fama and French						**Daily intraday and overnight Market Index**					
	α^d	α^{id}	α^{ov}	β^d	β^{id}	β^{ov}	α^d	α^{id}	α^{ov}	β^d	β^{id}	β^{ov}
1	-3.21E-04	9.45E-04	-2.45E-05	0.4342	0.2823	0.1501	-2.90E-04	9.80E-04	-5.00E-05	0.4334	0.3647	0.4986
2	-1.52E-04	4.23E-04	-3.98E-06	0.4868	0.3368	0.1505	-1.16E-04	4.68E-04	-1.71E-05	0.4861	0.4348	0.5101
3	-6.54E-05	1.53E-04	1.21E-04	0.6478	0.4631	0.1823	-1.76E-05	2.18E-04	9.55E-05	0.6476	0.6170	0.6119
4	-4.42E-05	-6.51E-05	2.32E-04	0.8541	0.6211	0.2284	2.00E-05	2.00E-05	2.02E-04	0.8536	0.8351	0.7662
5	-2.31E-05	-1.17E-04	2.28E-04	1.0046	0.7553	0.2498	5.21E-05	-1.01E-05	1.95E-04	1.0037	1.0051	0.8617
6	3.47E-05	-6.83E-05	1.86E-04	1.0476	0.7942	0.2560	1.12E-04	4.45E-05	1.50E-04	1.0468	1.0481	0.8949
7	2.17E-05	-1.58E-05	8.90E-05	1.0596	0.8079	0.2542	9.96E-05	9.89E-05	5.28E-05	1.0591	1.0628	0.8909
8	1.33E-05	-4.89E-08	4.23E-05	1.0604	0.8112	0.2514	9.06E-05	1.17E-04	4.50E-06	1.0597	1.0643	0.8928
9	-9.71E-06	-7.22E-05	7.90E-05	1.0135	0.7637	0.2505	6.38E-05	3.56E-05	4.28E-05	1.0125	1.0078	0.8839
10	-8.17E-05	-1.07E-04	3.29E-05	0.9966	0.7129	0.2829	-9.91E-06	-1.60E-05	-5.27E-06	0.9952	0.9957	1.0268

Table 2.13: Mean of conditional alpha and beta on 10 Portfolios. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying alpha and beta are evaluated in each portfolio considering the same daily Fama and French market index and also with a daily intraday and overnight market index. As bandwidth here we consider the modified Ruppert bandwidth. Results are from June 30 1993 to December 31 2015.

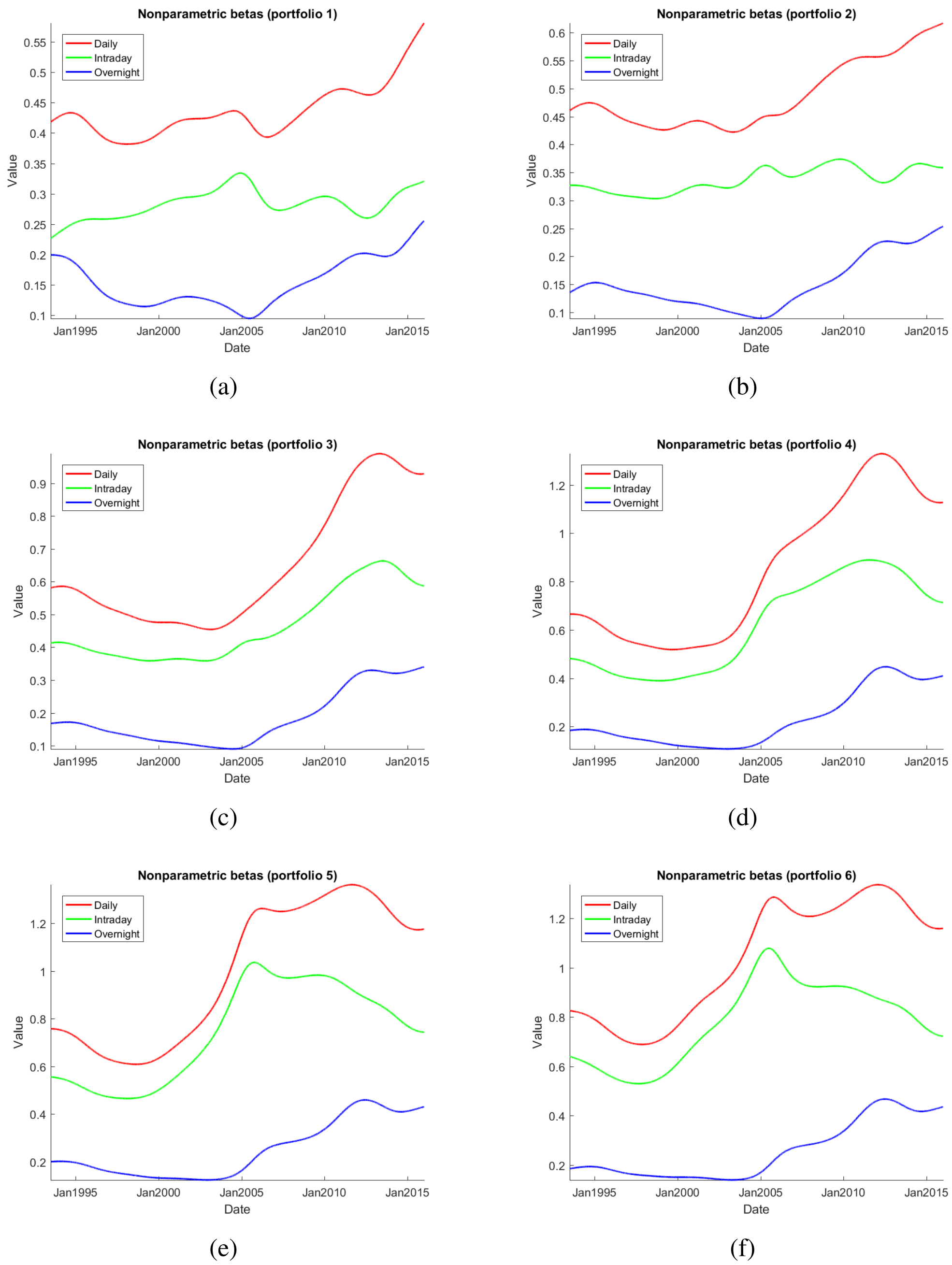
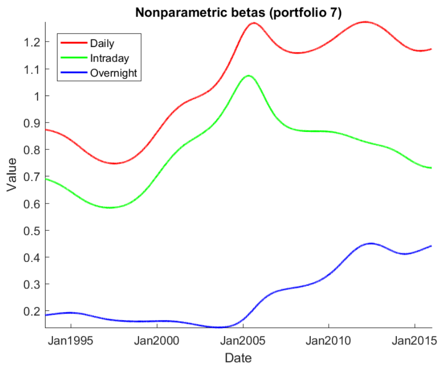
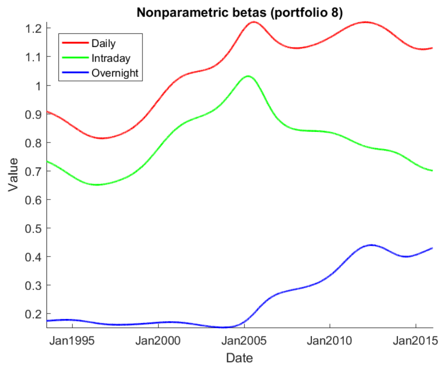


Figure 2.14: Conditional betas on 1-6 portfolios, between June 30, 1993 to December 31, 2015. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying betas are evaluated in each portfolio considering the Fama and French market index and the Silverman bandwidth.



(a)



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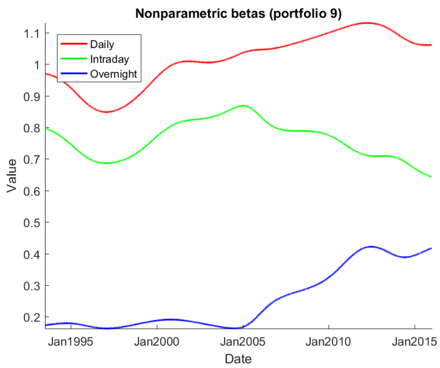

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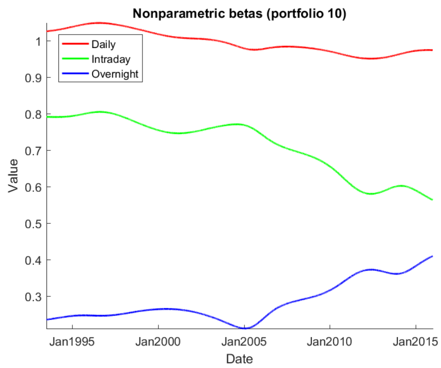


(d)

Figure 2.14: Conditional betas on 7-10 portfolios, between June 30, 1993 to December 31, 2015. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying betas are evaluated in each portfolio considering the Fama and French market index and the Silverman bandwidth.

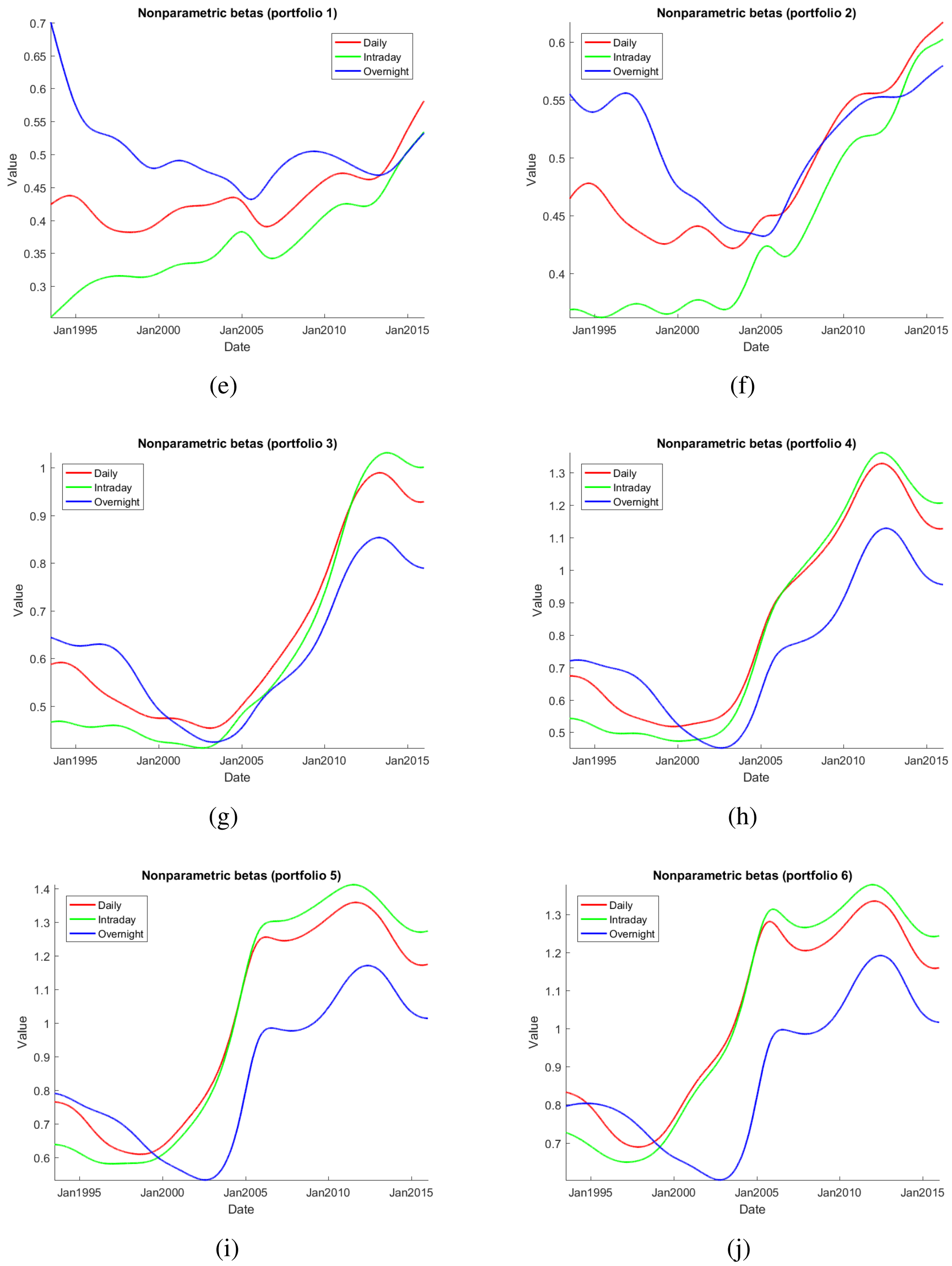


Figure 2.15: Conditional betas on 1-6 portfolios, between June 30, 1993 to December 31, 2015. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying betas are evaluated in each portfolio considering a daily intraday and overnight market index and the Silverman bandwidth.

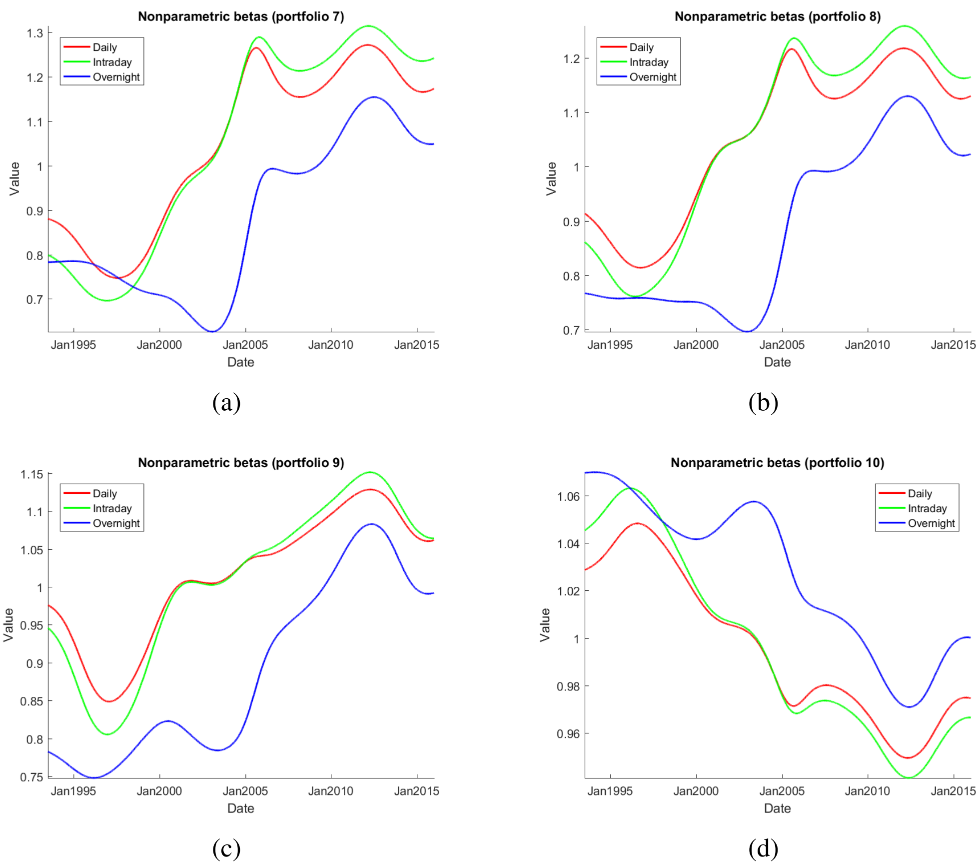
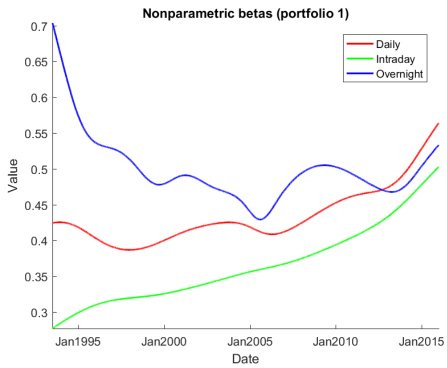
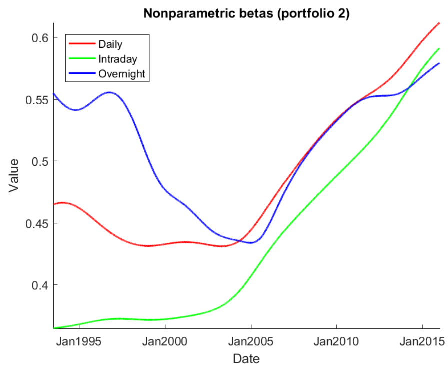


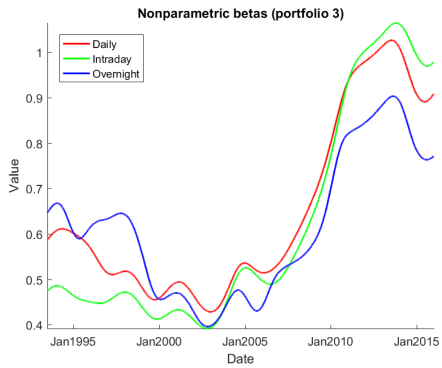
Figure 2.15: Conditional betas on 7-10 portfolios, between June 30, 1993 to December 31, 2015. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying betas are evaluated in each portfolio considering a daily intraday and overnight market index and the Silverman bandwidth.



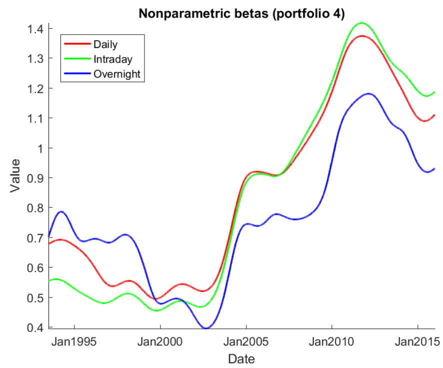
(e)



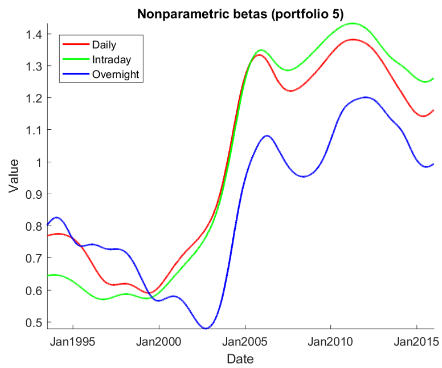
(f)



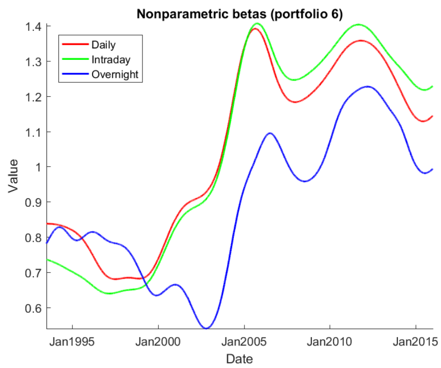
(g)



(h)



(i)



(j)

Figure 2.16: Conditional betas on 1-6 portfolios, between June 30, 1993 to December 31, 2015. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying betas are evaluated in each portfolio considering a daily intraday and overnight market index and the modified Ruppert bandwidth.

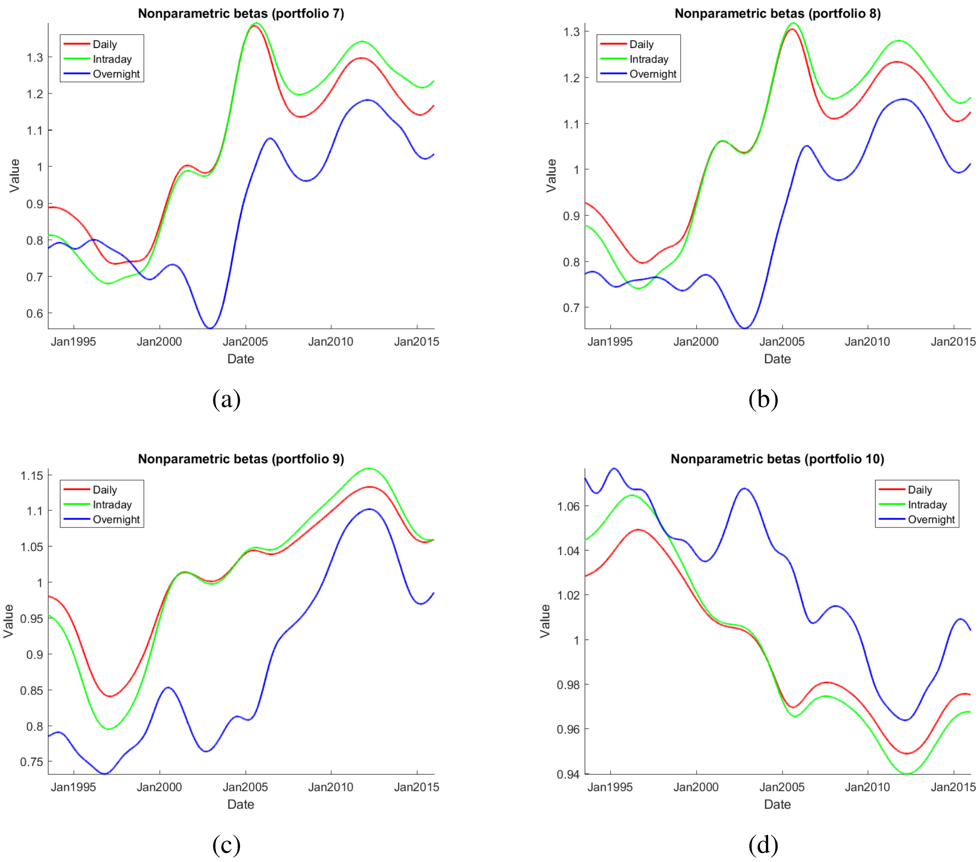
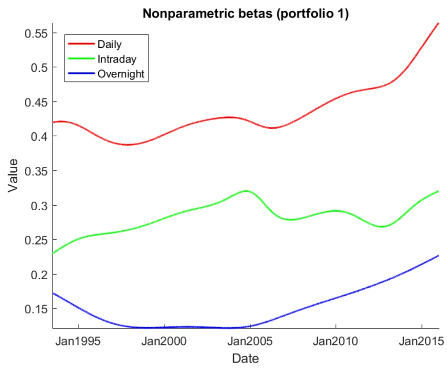
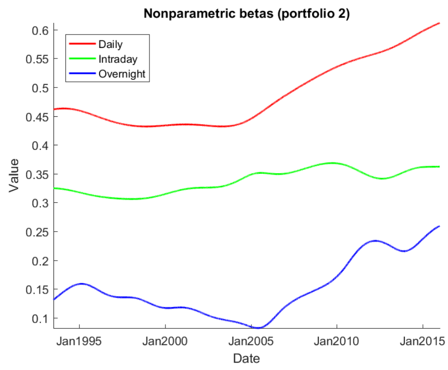


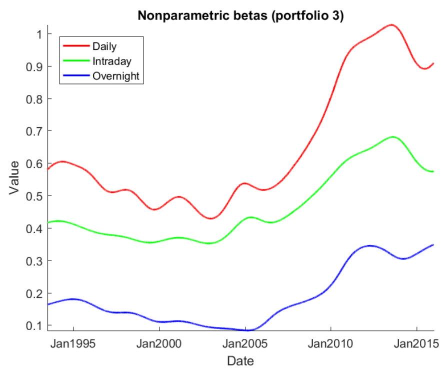
Figure 2.16: Conditional betas on 7-10 portfolios, between June 30, 1993 to December 31, 2015. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying betas are evaluated in each portfolio considering a daily intraday and overnight market index and the modified Ruppert bandwidth.



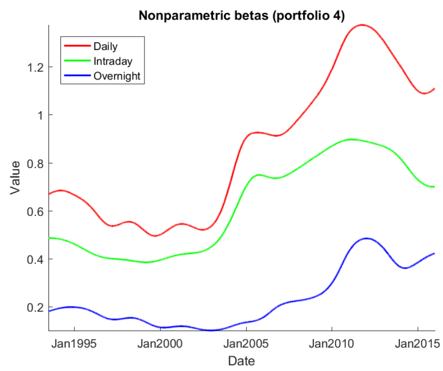
(e)



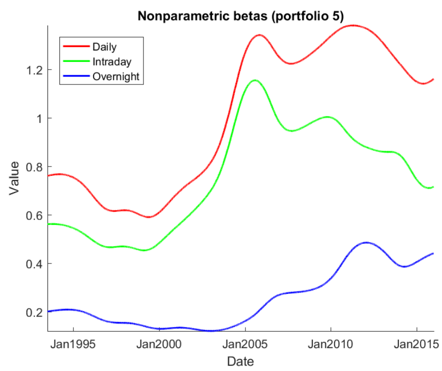
(f)



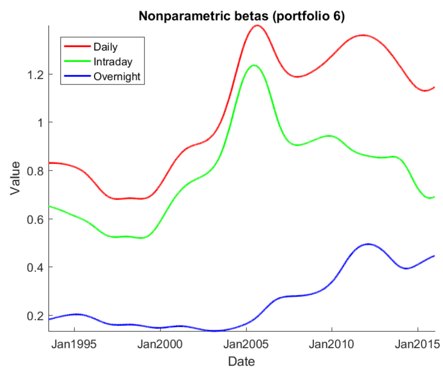
(g)



(h)

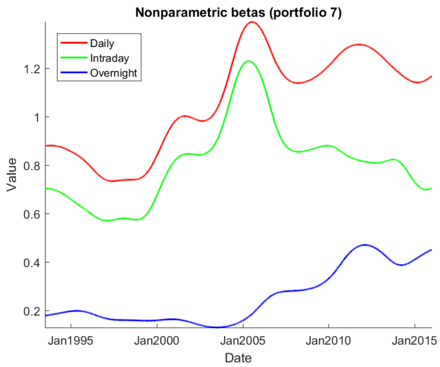


(i)

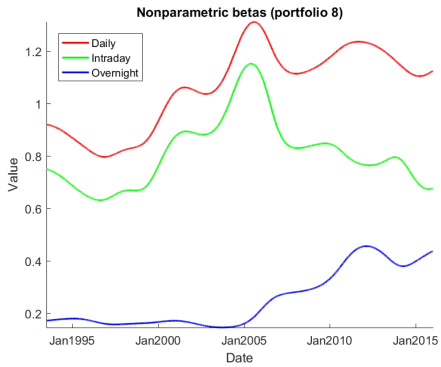


(j)

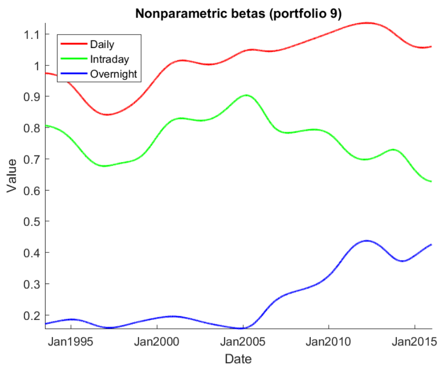
Figure 2.17: Conditional betas on 1-6 portfolios, between June 30, 1993 to December 31, 2015. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying betas are evaluated in each portfolio considering a daily Fama and French market index and the modified Ruppert bandwidth.



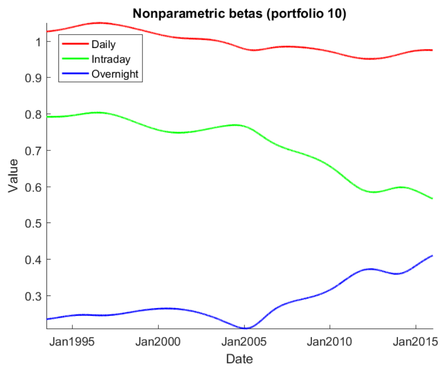
(a)



(b)



(c)

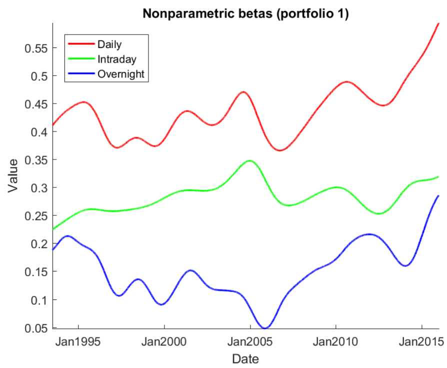


(d)

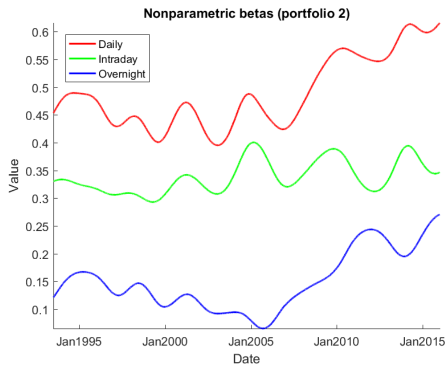
Figure 2.17: Conditional betas on 7-10 portfolios, between June 30, 1993 to December 31, 2015. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying betas are evaluated in each portfolio considering a daily Fama and French market index and the modified Ruppert bandwidth.

Conditional Beta (h_{AK}) Market Index Fama and French						
	α^d	α^{id}	α^{ov}	β^d	β^{id}	β^{ov}
1	-3.25E-04	9.44E-04	-3.97E-05	0.4351	0.2832	0.1498
2	-1.58E-04	4.20E-04	-4.96E-06	0.4884	0.3386	0.1495
3	-8.35E-05	1.40E-04	1.18E-04	0.6529	0.4687	0.1818
4	-5.93E-05	-7.86E-05	2.30E-04	0.8609	0.6287	0.2286
5	-4.02E-05	-1.33E-04	2.25E-04	1.0166	0.7678	0.2501
6	1.96E-05	-8.10E-05	1.85E-04	1.0640	0.8082	0.2562
7	1.18E-05	-2.51E-05	8.92E-05	1.0745	0.8210	0.2537
8	6.41E-06	-7.44E-06	4.47E-05	1.0718	0.8210	0.2495
9	-1.12E-05	-7.56E-05	8.39E-05	1.0148	0.7671	0.2464
10	-7.82E-05	-1.14E-04	4.10E-05	0.9938	0.7176	0.2769

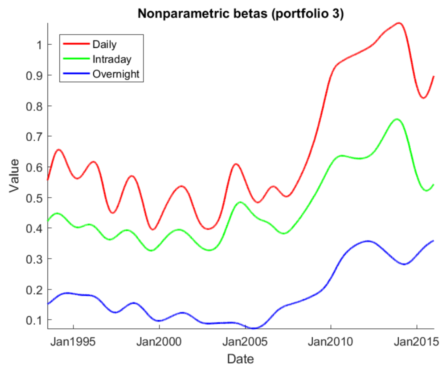
Table 2.14: Mean of conditional alpha and beta on 10 Portfolios. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying alpha and beta are evaluated in each portfolio considering the same daily Fama and French market index. As bandwidth here we consider the Ang and Kristensen bandwidth. Results are from June 30, 1993 to December 31, 2015.



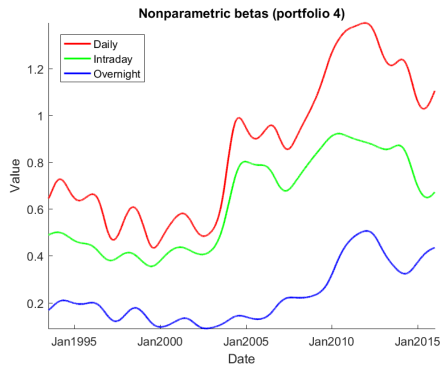
(e)



(f)



(g)



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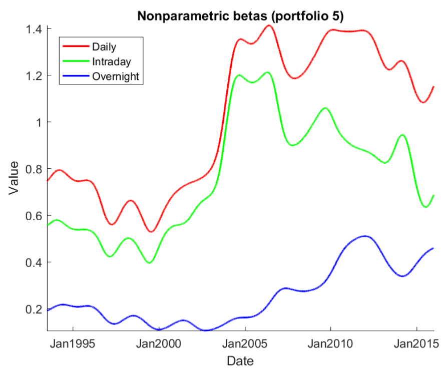

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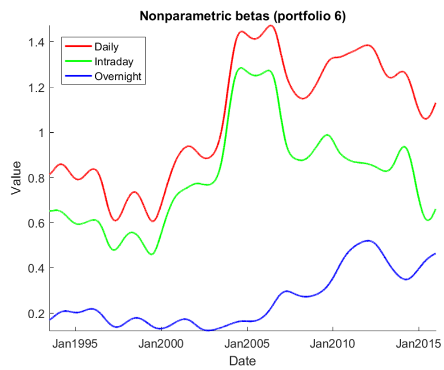

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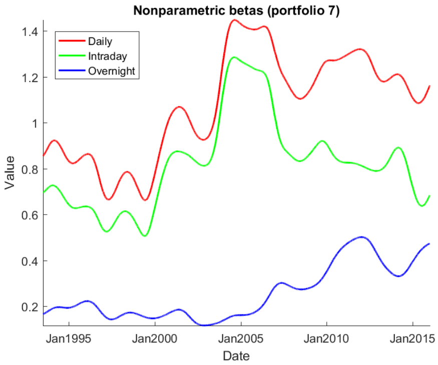
Figure 2.18: Conditional betas on 1-6 portfolios, between June 30, 1993 to December 31, 2015. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying betas are evaluated in each portfolio considering a daily Fama and French market index and the Ang and Kristensen bandwidth.



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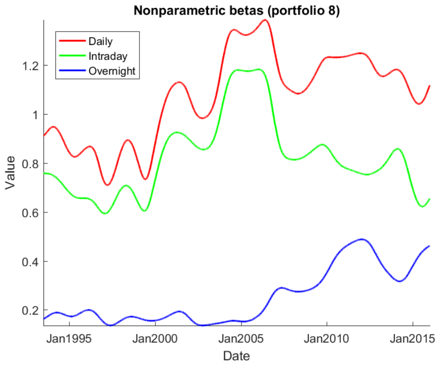

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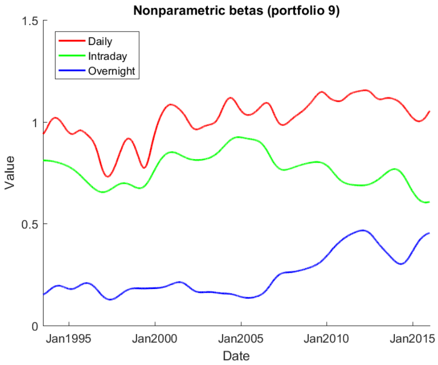

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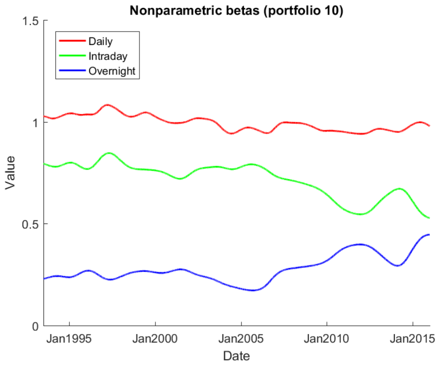

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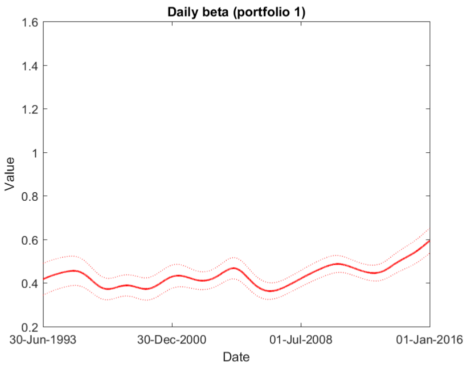
Figure 2.18: Conditional betas on 7-10 portfolios, between June 30, 1993 to December 31, 2015. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying betas are evaluated in each portfolio considering a daily Fama and French market index and the Ang and Kristensen bandwidth.



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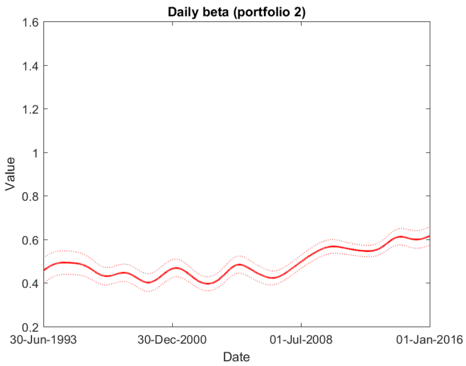

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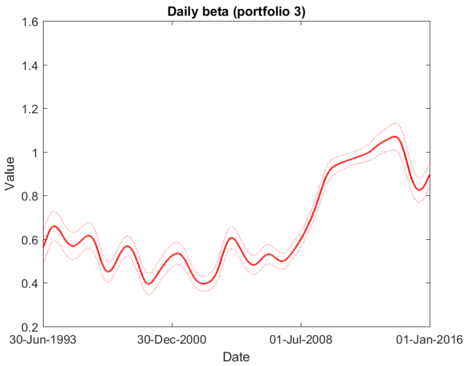

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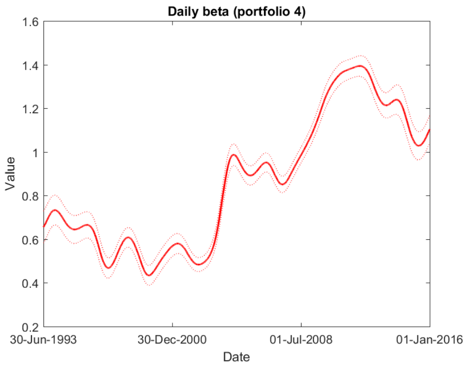

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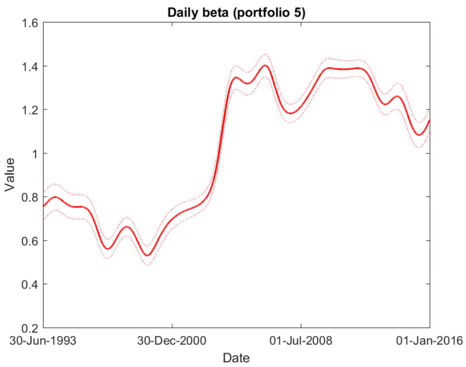

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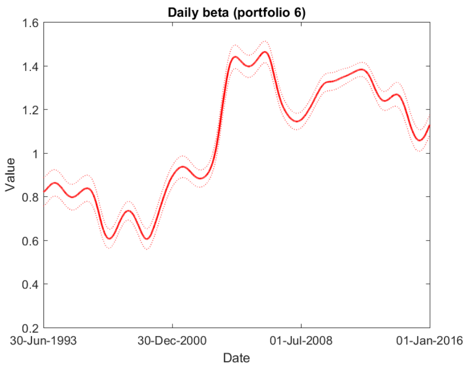

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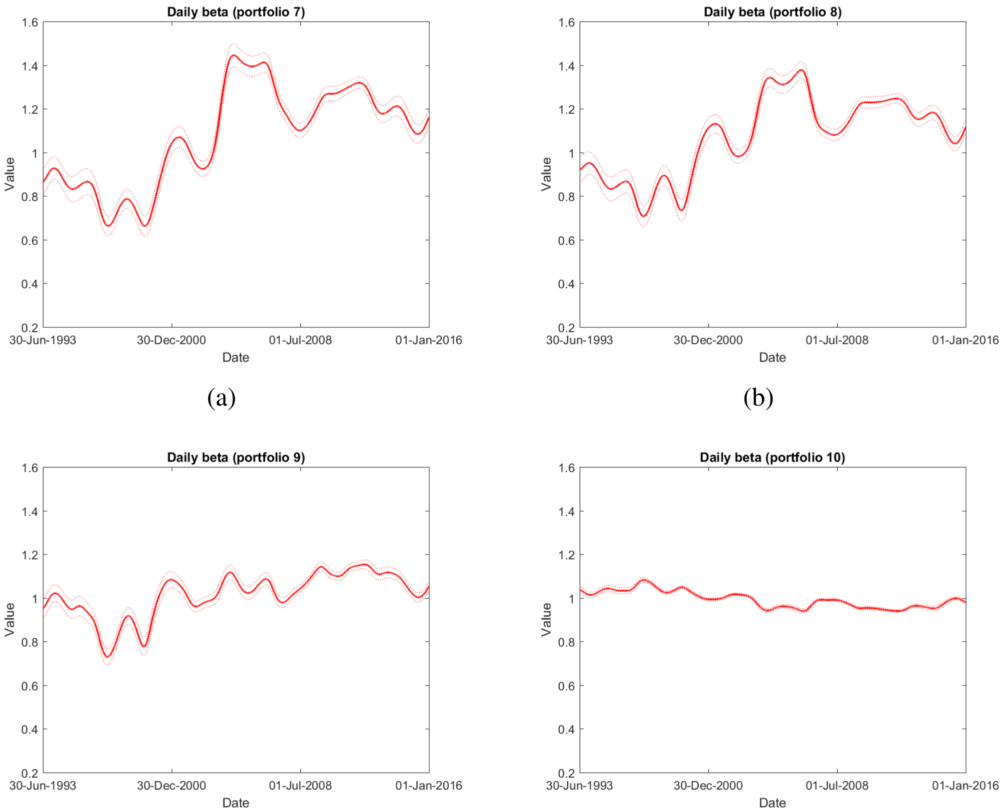
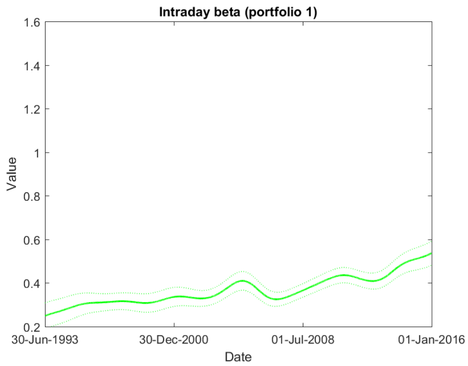
Figure 2.19: Daily conditional betas on portfolios 1-6 between June 30, 1993 to December 31, 2015. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying betas are evaluated in each portfolio considering a daily intraday and overnight market index and the Ang and Kristensen bandwidth. Dashed lines represent the 95% confidence bands.



(a) (b) (c) (d)

Figure 2.19: Daily conditional betas on portfolios 7-10 between June 30, 1993 to December 31, 2015. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying betas are evaluated in each portfolio considering a daily intraday and overnight market index and the Ang and Kristensen bandwidth. Dashed lines represent the 95% confidence bands.



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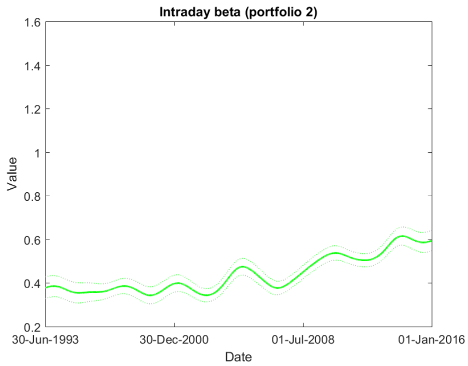

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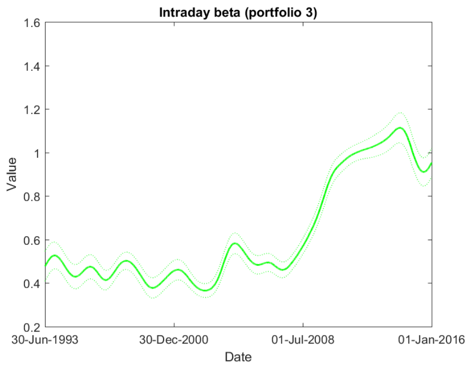

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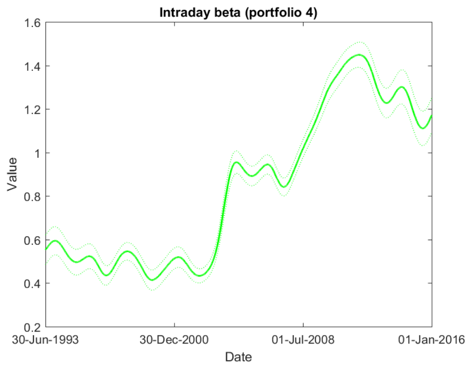

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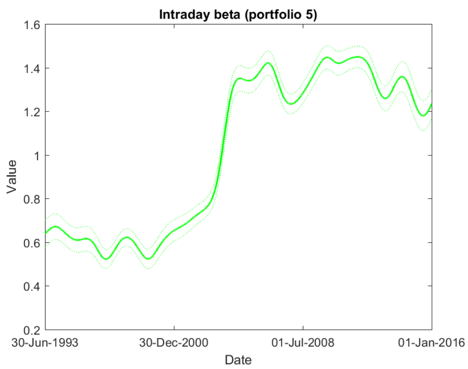

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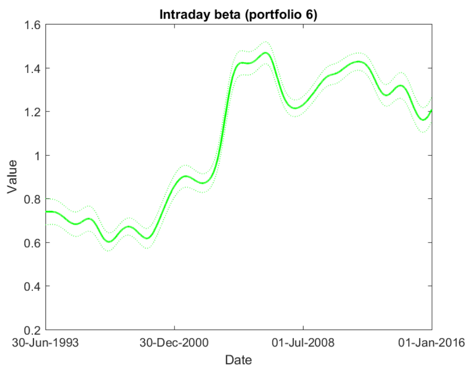

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Figure 2.20: Intraday conditional betas on portfolios 1-6 between June 30, 1993 to December 31, 2015. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying betas are evaluated in each portfolio considering a daily intraday and overnight market index and the Ang and Kristensen bandwidth. Dashed lines represent the 95% confidence bands.

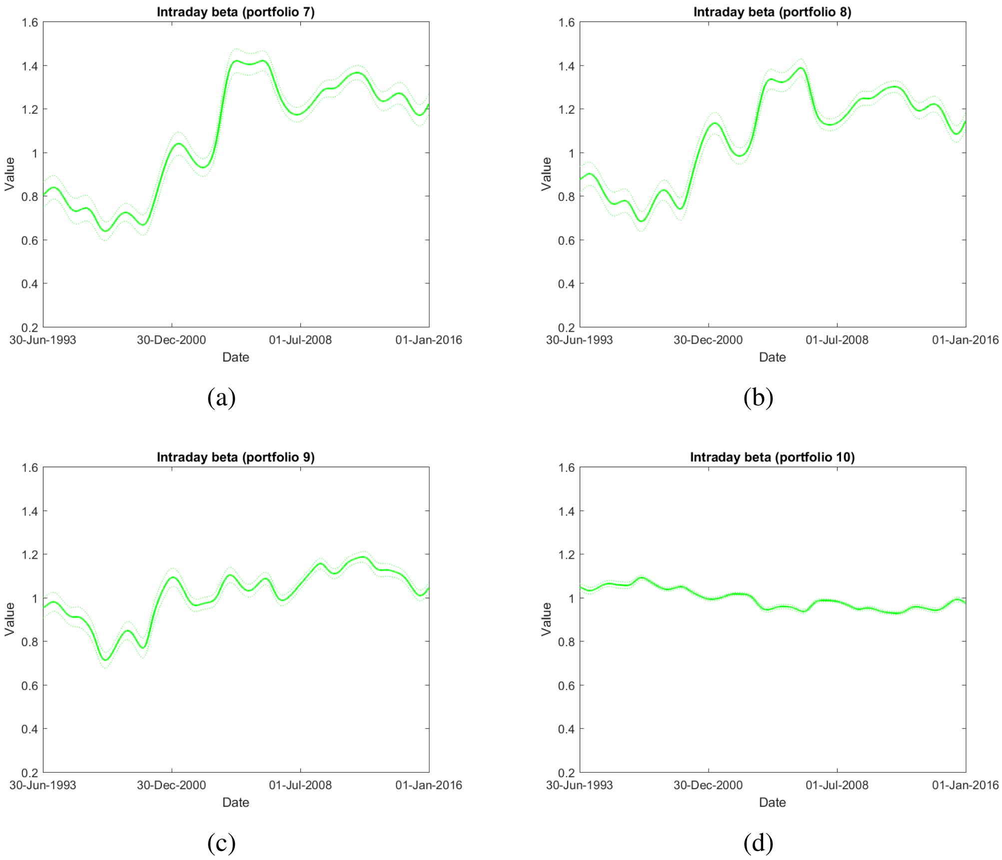
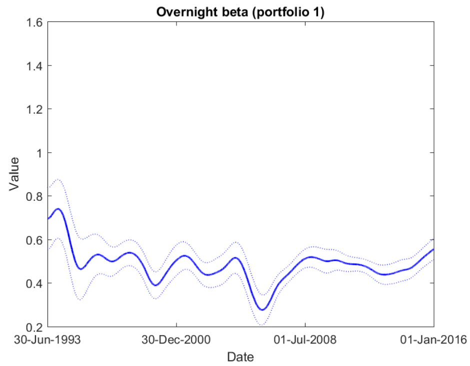


Figure 2.20: Intraday conditional betas on portfolios 7-10 between June 30, 1993 to December 31, 2015. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying betas are evaluated in each portfolio considering a daily intraday and overnight market index and the Ang and Kristensen bandwidth. Dashed lines represent the 95% confidence bands.



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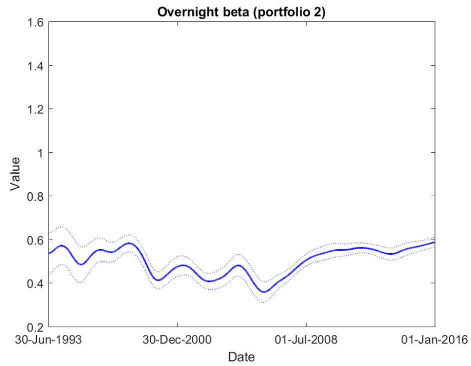

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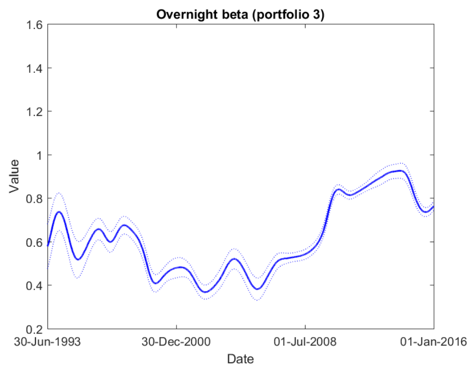

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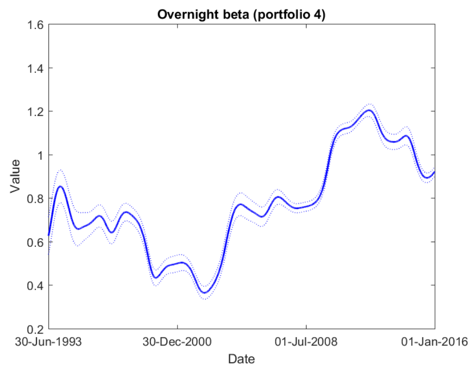

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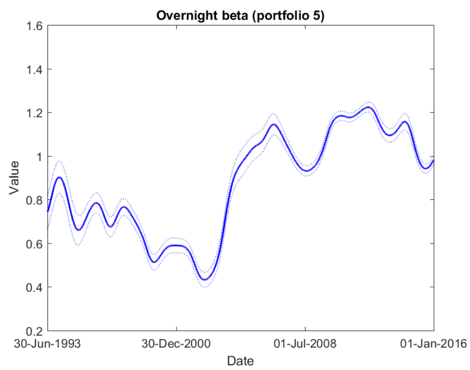

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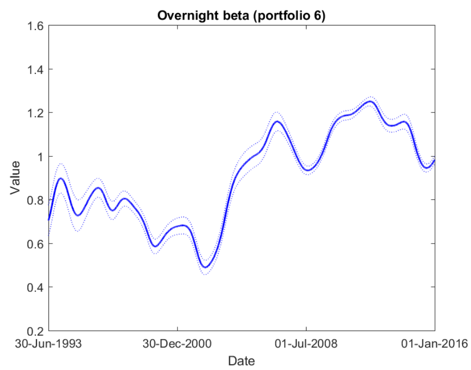

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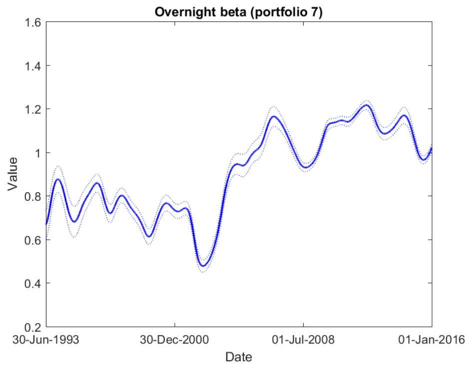
Figure 2.21: Overnight conditional betas on portfolios 1-6 between June 30, 1993 to December 31, 2015. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying betas are evaluated in each portfolio considering a daily intraday and overnight market index and the Ang and Kristensen bandwidth. Dashed lines represent the 95% confidence bands.



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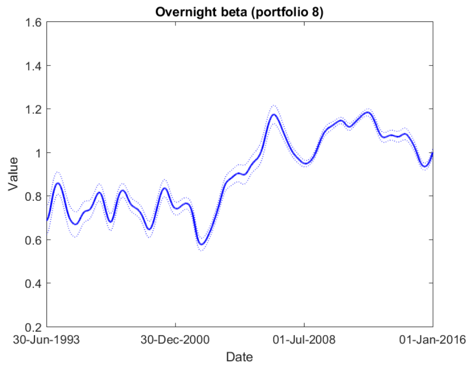

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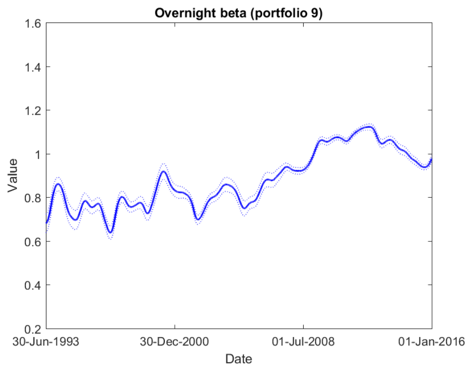

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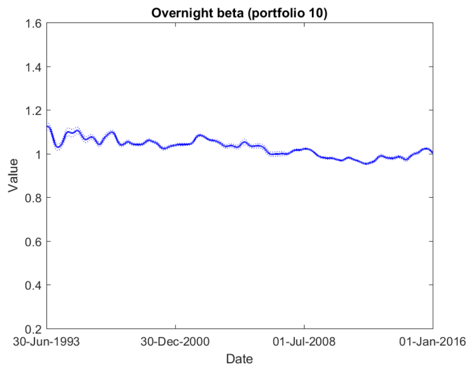

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Figure 2.21: Overnight conditional betas on portfolios 7-10 between June 30, 1993 to December 31, 2015. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying betas are evaluated in each portfolio considering a daily intraday and overnight market index and the Ang and Kristensen bandwidth. Dashed lines represent the 95% confidence bands.

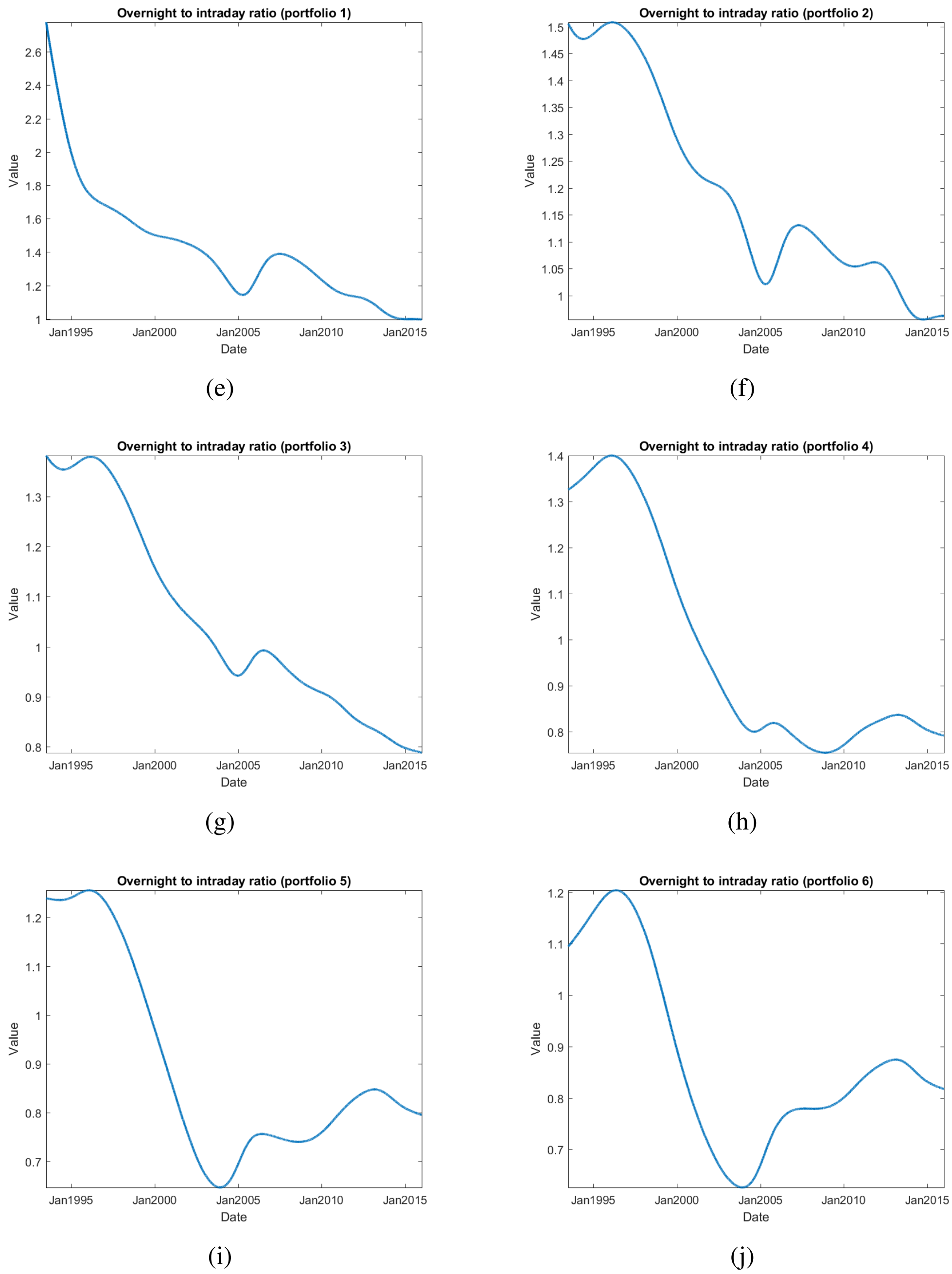
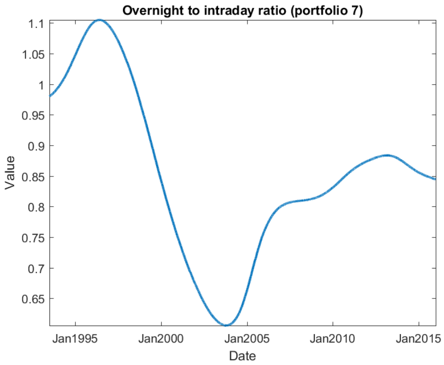


Figure 2.22: Ratio between overnight and intraday betas on 1-6 portfolios, between June 30, 1993 to December 31, 2015. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying betas are evaluated in each portfolio considering a daily intraday and overnight market index and the Silverman bandwidth.



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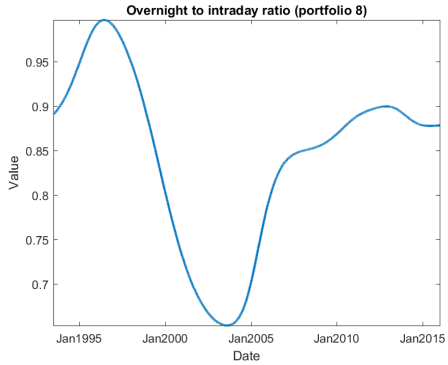

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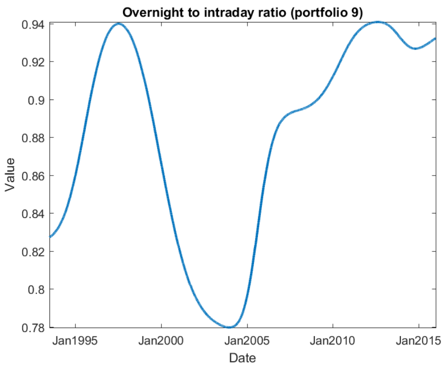

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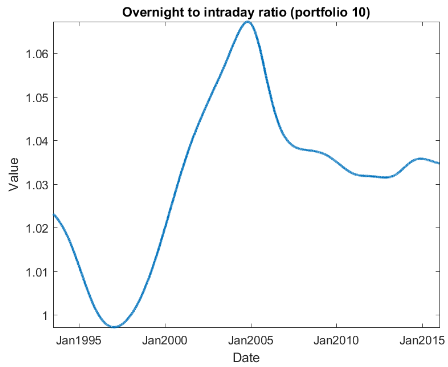

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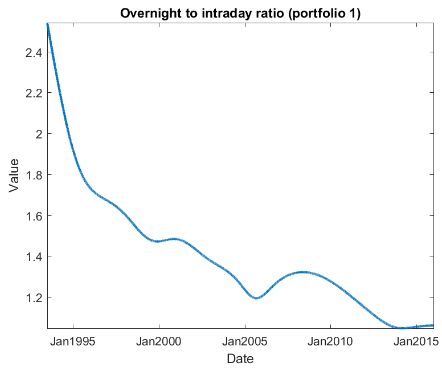
Figure 2.22: Ratio between overnight and intraday betas on 7-10 portfolios, between June 30, 1993 to December 31, 2015. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying betas are evaluated in each portfolio considering a daily intraday and overnight market index and the Silverman bandwidth.



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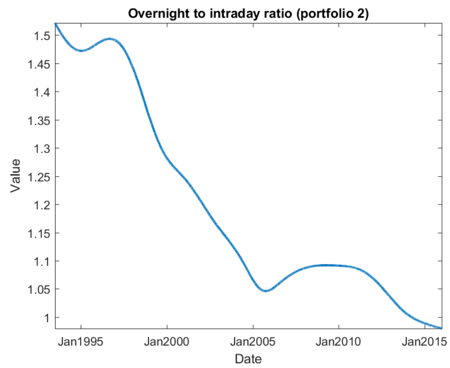

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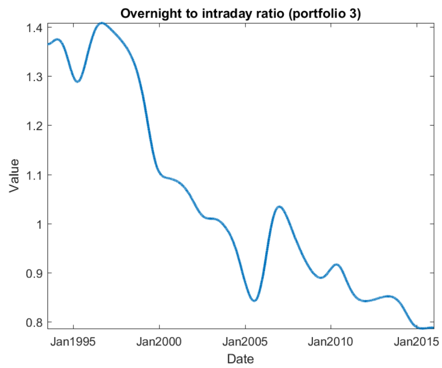

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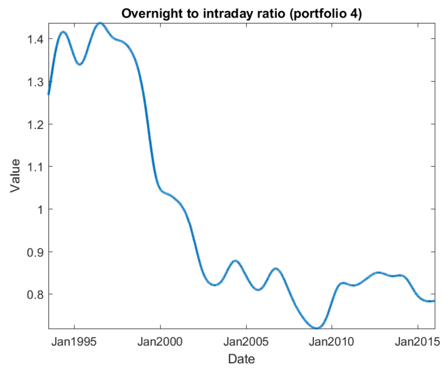

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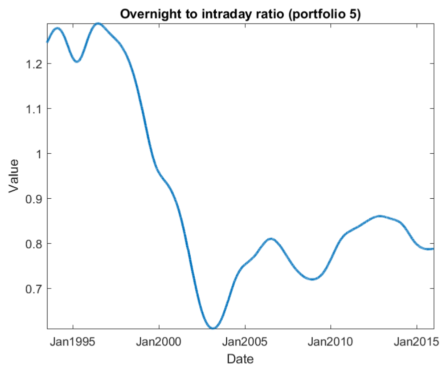

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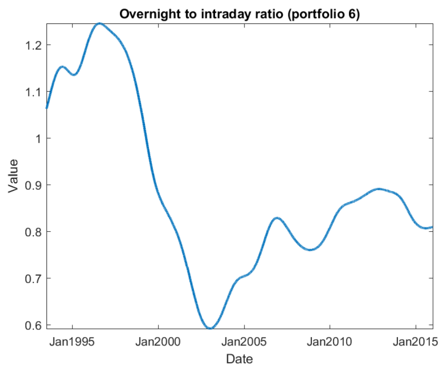

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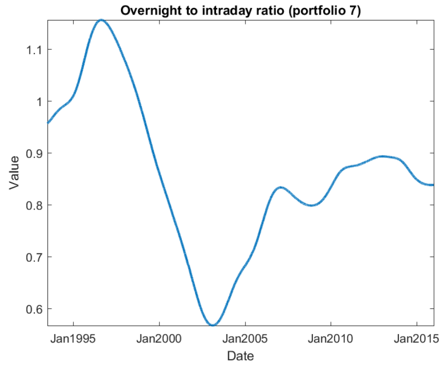
Figure 2.23: Ratio between overnight and intraday betas on 1-6 portfolios, between June 30, 1993 to December 31, 2015. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying betas are evaluated in each portfolio considering a daily intraday and overnight market index and the modified Ruppert bandwidth.



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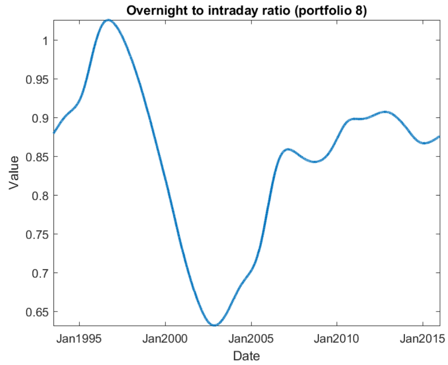

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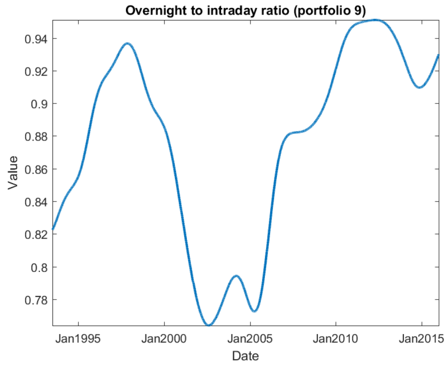

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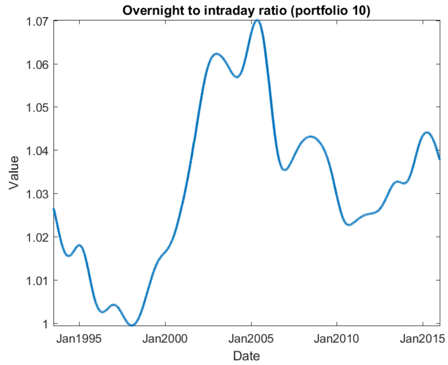

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Figure 2.23: Ratio between overnight and intraday betas on 7-10 portfolios, between June 30, 1993 to December 31, 2015. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying betas are evaluated in each portfolio considering a daily intraday and overnight market index and the modified Ruppert bandwidth.

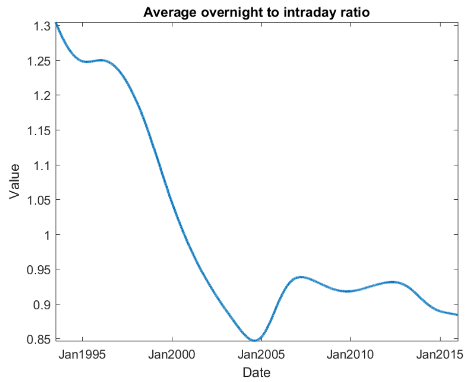


Figure 2.24: Average ratio between overnight and intraday betas on 10 portfolios, between June 30, 1993 to December 31, 2015. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying betas are evaluated in each portfolio considering a daily intraday and overnight market index and the Silverman bandwidth.

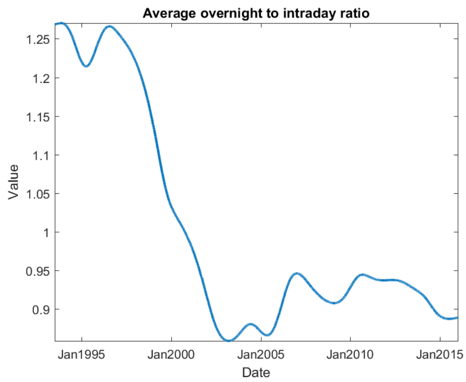


Figure 2.25: Average ratio between overnight and intraday betas on 10 portfolios, between June 30, 1993 to December 31, 2015. Portfolios are divided and sorted considering the market capitalization at the end of each month. Time-varying betas are evaluated in each portfolio considering a daily intraday and overnight market index and the modified Ruppert bandwidth.

Chapter 3

BAB daily, intraday and overnight

Introduction

All rational agents select for their investments portfolios with the highest expected excess return per unit of risk, and so with an higher Sharpe ratio. By the CAPM (Sharpe, 1964; Lintner, 1965; Mossin, 1966) we know that an high beta stock implies more risk respect to the market, and for this reason investor should be compensated with an higher return. As shown by many empirical tests (Black, 1972; Jensen et al., 1972), high-risk stocks do not give the extra returns that the theory predicts, indeed, an high-beta implies a low-return. The security market line, and so the relationship between beta and returns, is flatter than the line suggested by the CAPM. Probably these anomalies are due to the influence of investor to funding restrictions, as leverage constraints and margin requirements. In order to improve returns investors overweight their portfolios toward higher beta assets, and leverage their position. Considering also that the market, usually, overpays for high-beta stocks and underpays for low beta stocks, starting from the Black's (1993) work, Frazzini and Pedersen (2014) develop a statistical arbitrage strategy in which try to take advantage of these anomalies by buying low-beta stocks and shorting high-beta stocks. This strategy is known as Betting Against Beta (BAB). The idea is to consider assets with higher betas and take a short position in them. At the same time, they leverage its position taking a long position in assets with lower betas. Analyzing US stock market, 20 international stock markets and different financial products, as treasury bonds, corporate bonds, future and forward, Frazzini and Pedersen (2014) find that a BAB factor gives significant positive returns and stocks with higher volatility give relatively lower returns. They find that to an higher beta, corresponds a lower alpha and a lower Sharpe ratio. Same results have been obtained by Agarwalla et al. (2014) for the Indian market.

As we have shown in the previous chapter, there are differences in patterns between daily, intraday and overnight betas. Our idea is look at beta as a signal and use these differences on the Frazzini and Pedersen (2014) BAB strategy. We want to compare the BAB returns of three different portfolios sorted and divided considering as weights the value of daily, intraday and overnight pre-ranking betas. Each portfolio is organized with the same methodology of Frazzini and Pedersen (2014) and so it is long-low-beta and short-high-beta. In addition to these three portfolios, we organize ten portfolios for each trading period, considering the value of pre-ranking betas. Finally, in order to evaluate the alpha and so the portfolio performances, we implement a CAPM, a conditional CAPM, a Fama and French (1992) three factor model and a Carhart (1997) four factor model.

In the first two sections we present the work of Frazzini and Pedersen (2014) and explain how they construct their BAB factor, then we show the results obtained considering our strategy.

3.1 The BAB factor

There are many kinds of different agents, each one is subject to portfolio constraints. For example, there could be agents that cannot use leverage and overweight high beta assets, in this case assets will have low returns, agents that cannot use leverage, agents that can use leverage, but face margin constraints and finally unconstrained agents, that underweight high beta assets and buy low beta assets that they lever up.

Following Frazzini and Pedersen (2014) the required return for a security s, when investors face leverage constraints, can be written as:

$$\mathrm{E}_t[r^s_{t+1}] = r^f + \psi_t + \beta^s_t \lambda_t \ ,$$

where $\lambda_t = \mathrm{E}_t[r^M_{t+1}] - r^f - \psi_t$ represents the risk premium and ψ_t the tightness of funding constraints, measured by the average of Lagrange multiplier. The alpha respect to the market is $\alpha^s_t = \psi_t(1-\beta^s_t)$, it is decreasing in the beta β^s_t. The Sharpe ratio is highest for an efficient portfolio, furthermore it decreases for higher betas and increases for lower betas.

In order to show the asset pricing effect of the funding friction, the authors consider the returns on market-neutral Betting Against Beta (BAB) factor.

A BAB factor is a portfolio that is long leveraged on low-beta and short on high-beta securities, it can be expressed as:

$$r^{BAB}_{t+1} = \frac{1}{\beta^L_t}\left(r^L_{t+1} - r^f\right) - \frac{1}{\beta^H_t}\left(r^H_{t+1} - r^f\right) \ , \tag{3.1}$$

where the returns associated to a portfolio of low and high assets, are computed considering some weights, in particular $r^L_{t+1} = r'_{t+1}w_L$ and $r^H_{t+1} = r'_{t+1}w_H$. The betas of these portfolios are $\beta^L_t = \beta'_{t+1}w_L$ and $\beta^H_t = \beta'_{t+1}w_H$ with $\beta^L_t < \beta^H_t$. The portfolio (3.1) is market neutral, this means that its beta is equal to zero. Furthermore leverage and de-leverage of the long and short portfolio respectively, has been done considering a beta of one. The BAB factor provides an excess return on a self-financing portfolio, because it is a difference of excess returns.
The authors give evidence of different aspects related to the BAB factor:

1. A BAB factor has a positive expected return:

$$\mathrm{E}\left[r^{BAB}_{t+1}\right] = \frac{\beta^H_t - \beta^L_t}{\beta^L_t \beta^H_t}\psi_t \geq 0$$

   and it is increasing in the ex ante betas $\frac{\beta^H_t - \beta^L_t}{\beta^L_t \beta^H_t}$ and in the funding tightness ψ_t.

2. When a shock occurs, like a declining in funding liquidity or a credit crises, we will have an increase on the investment constraints, m^k_t, and at the same time the returns on the BAB factor are negative although the future returns rise.
   A tighter portfolio constraint leads to a contemporaneous loss for the BAB factor:

$$\frac{\partial r^{BAB}_{t+1}}{\partial m^k_t} \leq 0$$

   and an increase in its required return:

$$\frac{\partial \mathrm{E}(r^{BAB}_{t+1})}{\partial m^k_t} \geq 0\ .$$

3. When an increase in funding liquidity risk happens the betas of securities in the cross-section are compressed towards one.
   Assuming that over time all random variables are identically and independently distributed (i.i.d.) and δ_t is independent from the other random variables. Further, considering that after the BAB portfolio formation, at time $t-1$, the prices are set, taking into account the new information about m_t and the wealth W_t, we have a rise (fall) in the conditional variance of the discount factor $1/(1+r^f+\psi_t)$. Then,

   (i) We have a compression toward one of the conditional returns betas β^i_{t-1}, related to all securities, this means a greater dispersion;

(ii) Although the BAB portfolio is market neutral respect to the information set used at portfolio formation, its conditional beta becomes positive (negative).

4. Constrained investors overweight high-beta assets and less-constrained investors overweight low-beta asset applying leverage.
Considering the security payoff in the period

$$P_{t+1} + \delta_{t+1} = \mathrm{E}[P_{t+1} + \delta_{t+1}] + b\left(P^M_{t+1} + \delta^M_{t+1} - \mathrm{E}[P^M_{t+1} + \delta^M_{t+1}]\right) + e$$

where b is the vector of market exposures and e the vector of noise, the authors give the following proposition related to the agent's position:
"Unconstrained agents hold a portfolio of risky securities that has a beta less than one; constrained agents hold portfolios of risky securities with higher betas. If securities s and k are identical except that s has a larger market exposure than k, $b^s > b^k$, then any constrained agent j with greater than average Lagrange multiplier, $\psi^j_t > \psi_t$, holds more shares of s than k. The reverse is true for any agent with $\psi^j_t < \psi_t$".

3.2 Methodology

In order to construct the BAB factor and so the BAB portfolio, Frazzini and Pedersen (2014) rank all securities in ascending order, on the basis of their estimated beta at the end of each calendar month. The ex-ante beta, for the generic security i, is obtained by a rolling regression of excess returns on market excess returns:

$$\hat{\beta}^{TS}_i = \hat{\rho}\frac{\hat{\sigma}_i}{\hat{\sigma}_m} \tag{3.2}$$

where $\hat{\sigma}_i$ and $\hat{\sigma}_m$ are the estimated volatilities for the stock and the market, and $\hat{\rho}$ is their correlation. The evaluation of volatilities and correlation occurs over two different periods. In particular the authors consider one-year rolling standard deviation for volatilities, using daily log return. For these computations they require six months of non missing return data (120 trading days). Instead, for correlation they consider a five-years rolling standard correlation, overlapping three days log returns, over three years of non missing data (750 trading days). They decide to overlap three days log returns, in order to overcome the non-synchronous trading,

$$r^{3d}_{i,t} = \sum_{k=0}^{2} \ln(1 + r^i_{t+k}) \quad , \tag{3.3}$$

where $r^i_{t+k} = (P^i_{t+k} + \delta^i_{t+k})/P^i_t - 1$, for $k = 0, 1, 2$ are the daily returns, related to three days, evaluated considering dividends δ^i_{t+k}.

Furthermore, to reduce the influence of outliers, and so improve the accuracy of stock betas, they consider a beta-compression method. In particular, following Vasicek (1973) and Elton et al. (2009), in order to combine the beta related to the market and the beta related to the stock, they use a shrinkage beta estimator. This methodology consists of a simple weighted average of the two betas and it is regarded as the statistically optimal estimator, the beta for a generic stock i can be adjusted by:

$$\hat{\beta}_i = w_i \hat{\beta}_i^{TS} + (1 - w_i)\hat{\beta}_i^{XS} \tag{3.4}$$

where $\hat{\beta}_i^{TS}$ is the time series estimate of beta, $\hat{\beta}_i^{XS}$ represents the market beta, that can be evaluated as the cross sectional mean. w_i represents some weight, it can be evaluated as:

$$w_i = \frac{1}{T} \sum_{t=1}^{T} \frac{\sigma^2_{\beta_t}}{S.E.\beta_{it} + \sigma^2_{\beta_t}}$$

where $\sigma^2_{\beta_t}$ is the cross-sectional variation of betas at time t and $S.E.\ \beta_{it}$ is the standard error of beta related to the stock i at time t. Betas are computed regressing daily returns on market returns considering five years rolling returns. The weight w_i is different for each stock, although usually in literature consider the same value for all the stocks. For the empirical test they assume $w = 0.6$ and $\hat{\beta}_i^{XS}$=1.
Obtained and adjusted, at the end of each calendar month, the ex-ante beta Frazzini and Pedersen (2014) rank securities in ascending order and separate them in two portfolios: low-beta and high-beta. In the first they consider all stocks with a beta less than its asset class median and in the second one the others. Each security in the portfolios is weighed by the ranked betas. In the low beta portfolio lower beta securities have larger weight, in the high beta portfolio higher beta securities have larger weight.
Considering n securities and let $z_i = rank(\beta_{it})$ the vector of ranked beta, with $\bar{z} = 1_n \frac{z}{n}$, they define the weights as:

$$w_H = k(z - \bar{z})^+ , \quad w_L = k(z - \bar{z})^- \quad \text{with} \quad k = \frac{2}{1_n}|z - \bar{z}| \tag{3.5}$$

where $(\cdot)^+$ and $(\cdot)^-$ indicate the positive and negative part of the vectors ($(\cdot)^+ = \max(0, \cdot)$, $(\cdot)^- = \max(0, -\cdot)$). In order to have the sum of the weights equal to one, they consider the normalization factor k. Once we get these quantities, it is possible to compute the BAB factor applying equation (3.1):

$$r^{BAB}_{t+1} = \frac{1}{\beta^L_t}\left(r^L_{t+1} - r^f\right) - \frac{1}{\beta^H_t}\left(r^H_{t+1} - r^f\right) ,$$

where, as we said in the previous paragraph, the returns are $r^L_{t+1} = r'_{t+1} w_L$ and $r^H_{t+1} = r'_{t+1} w_H$ and the betas of these portfolios are $\beta^L_t = \beta'_t w_L$ and $\beta^H_t = \beta'_t w_H$.

3.3 Daily, intraday and overnight BAB factor

Starting from the Frazzini and Pedersen (2014) procedure we estimate the BAB factor (3.1) on three portfolios, ranked and divided considering the high and low values of daily, intraday and overnight pre-ranking betas. We apply, essentially, the same methodology that they use, but considering as signal, instead of daily betas, also intraday and overnight betas.

As in Frazzini and Pedersen (2014), in order to evaluate pre-ranking betas, we use formula (3.2), a standard rolling regression of excess return on market return. It decomposes the betas in two parts: the correlation between returns of each stock and market and the ratio of the standard deviation of returns on the market. The daily, intraday and overnight pre-ranking betas, of a generic security i, can be written as:

$$\hat{\beta}_i^d = \hat{\rho}^d \frac{\hat{\sigma}_i^d}{\hat{\sigma}_m}, \qquad \hat{\beta}_i^{id} = \hat{\rho}^{id} \frac{\hat{\sigma}_i^{id}}{\hat{\sigma}_m}, \qquad \hat{\beta}_i^{ov} = \hat{\rho}^{ov} \frac{\hat{\sigma}_i^{ov}}{\hat{\sigma}_m}, \tag{3.6}$$

where correlations and volatilities are evaluated as in Frazzini and Pedersen (2014). Considering that correlations are very slow moving, and volatilities have faster windows (De Santis et al., 1997), we need more data to estimate the first one. So, also in our case, we use five years horizon to calculate correlations and one year rolling standard deviation for volatilities.

The excess log returns, are computed starting by the simple returns of each trading period:

$$\begin{gathered} r_{i,t}^d = \frac{p_{i,t}^{close}}{p_{i,t-1}^{close}} - 1\,, \\ r_{i,t}^{id} = \frac{p_{i,t}^{close}}{p_{i,t}^{open}} - 1\,, \quad r_{i,t}^{ov} = \frac{p_{i,t}^{open}}{p_{i,t-1}^{close}} - 1\,. \end{gathered} \tag{3.7}$$

Also in this chapter, following Bogousslavsky (2016), for the excess returns evaluation we subtract the daily risk-free rate, just from our daily and overnight returns. As in the paper of Frazzini and Pedersen (2014), for the correlation, we want to take into account the financial market micro structure noise, which, in this case, it is due to non synchronous trading. For example, if we have a stock that is very liquid, and considering that the market, by definition, is very liquid, as effect we have that the covariance is by toward zero. In order to mitigate this problem, for daily data in the correlation we employ an averaging of three daily returns as in (3.3), and for intraday and overnight values we overlap, for each security, three periods:

$$\begin{aligned} r_{i,t}^{3id} &= \ln(1+r_{i,t}^{id}) + \ln(1+r_{i,t+1}^{ov}) + \ln(1+r_{i,t+1}^{id})\,, \\ r_{i,t}^{3ov} &= \ln(1+r_{i,t}^{ov}) + \ln(1+r_{i,t}^{id}) + \ln(1+r_{i,t+1}^{ov})\,. \end{aligned} \tag{3.8}$$

To reduce the influence of outliers on betas, we apply on our pre-ranking betas the formula (3.4), assuming w=0.6 and $\hat{\beta}_i^{XS}$=1.
Obtained the daily, intraday and overnight pre-ranking betas, for each trading period we evaluate the rank vectors as:

$$z_i^d = rank(\beta_{i,t}^d)\,, \qquad z_i^{id} = rank(\beta_{i,t}^{id})\,, \qquad z_i^{ov} = rank(\beta_{i,t}^{ov})\,,$$

now we can evaluate the weights for short and long portfolio like in (3.5). At the beginning of each month the three different portfolios are ranked and splitted on two portfolios, low and high beta, considering the values and the weights on the last day of the previous month. The three portfolios have the same number of stocks. Each low beta portfolio is levered up to a daily beta of 1. Each high beta portfolio is levered down to a daily beta of 1. Weights inside each portfolio are proportional to inverse of rank. Applying the (3.1) we obtain our daily, intraday and overnight BAB returns. For the computation of β_t^H, β_t^L and r_{t+1}^H, r_{t+1}^L, at each trading period, in the formula we have to change just the value of the corresponding weights, the returns and betas have to be evaluate considering always daily values, because the portfolios have to be beta neutral.

3.4 Results

For our empirical analysis we consider the US stock market. Daily data have been taken from CRSP (Center of Research in Security Price)[1]. As we explained in the previous chapter, in the data set, there is a lack of open price between July 1962 and June 1992 so, we consider just data from June 15, 1992 to December 30, 2016. We examine the whole cross-section of stocks, deleting that with more than 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation. Furthermore, in order to obtain daily, intraday and overnight portfolios with the same number of stocks we consider stocks with open and close prices. Open and close prices are adjusted for dividends and splits by the cumulative adjustment factor (CFACPR) of the CRSP database. This is a difference with the paper of Frazzini and Pedersen (2014), in which probably they adjust returns considering explicitly the dividends values. Excess returns are evaluated using as risk free rate the treasury bill rate provided by the Kenneth French's database[2]. As proxy for the market, used for pre-ranking betas evaluation, we consider for all the trading periods the same daily weighted index given by the CRSP database (vwretd). We evaluate pre-ranking betas also considering a

[1] `http://www.crsp.com/`

[2] `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

daily, intraday and overnight weighted market index, using the methodology of the previous chapter. In the BAB strategy we obtain very similar results (Table 3.4 in Appendix B) and so for simplicity we decide to use always the same market index for all the three trading periods. In daily, intraday and overnight BAB portfolio

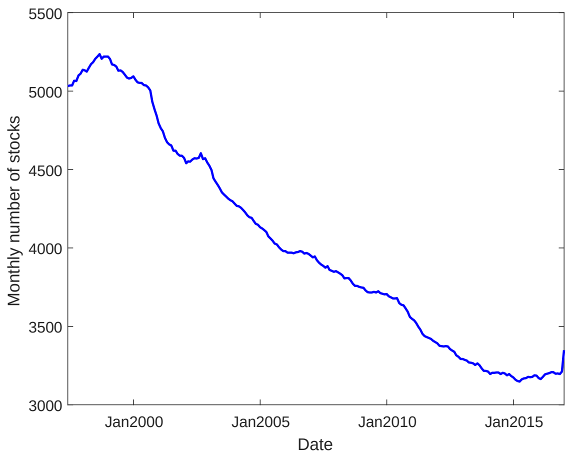
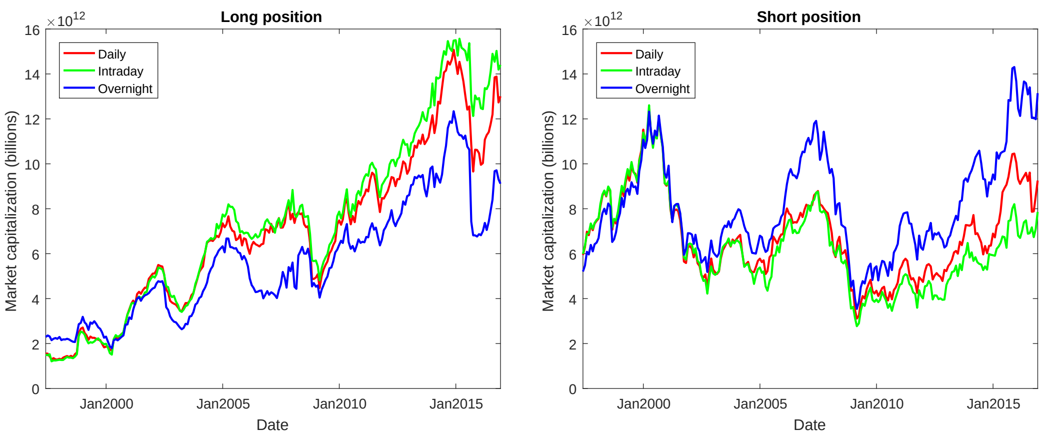


Figure 3.1: Number of stocks traded each month in the BAB portfolio, between June 2, 1997 and December 30, 2016. We consider all the stocks in the database with at last 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation. We have on average for each trading period, in each month, 4024 stocks, 2012 that go long and 2012 that go short. Daily intraday and overnight portfolios have the same number of stocks.



(a) (b)

Figure 3.2: Market capitalization, between June 2, 1997 and December 30, 2016, of long (low betas) (a) and short (high betas) (b) position at daily, intraday and overnight portfolio formation. We trade all the stocks in the database with at last 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation. We have on average for each trading period, in each month, 4024 stocks, 2012 that go long and 2012 that go short.

we have, a monthly average of 4024 stocks, 2012 that go long and 2012 that go short. As we show in Figure 3.1, the monthly number of stocks traded on US stock market is decreasing on the last period. Although the stocks value, and so the market capitalization, increases. This phenomenon could be due to different factors, like the simple delisting of small firms from US market or the increasing of company acquisitions (Doidge et al., 2017; Kahle and Stulz, 2017).
Plotting in Figure 3.2 the value of market capitalization related to our long and short position, at monthly portfolio formation, we notice that at the beginning of the series short stocks, and so that with an high beta, have a greater value. Instead, at the end of the period, all portfolios have a similar market capitalization, with an increasing trend for the long portfolio. Furthermore, the stocks that go short organized considering the overnight pre-ranking betas, have an higher market capitalization respect to daily and intraday, but they are the lower in long position.

Comparing our three BAB portfolios in Table 3.1, we observe similar values for volatility, and so the same level of risk in both portfolios, but we have a pretty much higher returns for intraday BAB portfolio. It seems, also considering the annualized value of the Sharpe ratio, that on intraday we have a kind of improvement in the strategy returns although the risk level remains the same. Also looking at the equity line of these strategies (Figure 3.3) we find that to use intraday betas for portfolio organization give us a better returns on BAB strategy.

BAB Returns			
	Daily	Intraday	Overnight
Number of stocks	4024	4024	4024
Returns	0.1281	0.1417	0.0611
Volatility	0.1159	0.1173	0.0955
Sharpe	1.1053	1.2080	0.6392

Table 3.1: Values of annualized returns, annualized volatility and Sharpe ratio of the BAB returns on our three portfolios: daily, intraday and overnight, between June 2, 1997 and December 30, 2016. We trade the whole cross-section, considering stocks with at last 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation. We have on average for each trading period, in each month, 4024 stocks, 2012 that go long and 2012 that go short.

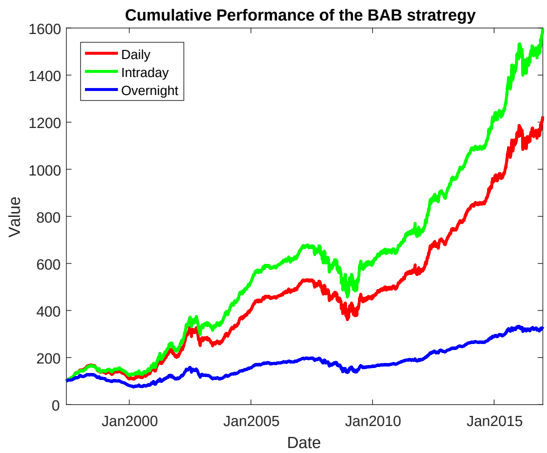


Figure 3.3: Cumulative values of BAB daily, intraday and overnight strategy, between June 2, 1997 and December 30, 2016. We trade the whole cross-section, considering stocks with at last 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation. We have on average for each trading period, in each month, 4024 stocks, 2012 that go long and 2012 that go short.

Considering the values of the daily, intraday and overnight pre-ranking betas we organize, for each trading period, ten unweighted portfolios. At the end of each calendar month we sort and divide stocks considering the value of our pre-ranking betas. Portfolio 1 contains stocks with lower betas and portfolio 10 contains stocks with higher betas. As we can see in Table 3.2 each portfolio includes about 424 stocks for each month, the mean of annualized returns is very similar, but volatility increases with beta (Figure 3.4). We find, as in Frazzini and Pedersen (2014), that the annualized Sharpe ratio decreases for higher beta portfolios (Figure 3.5). There are not significant differences between the values of the daily and intraday portfolios. Instead, looking at overnight portfolios we observe lower values for returns, furthermore, the volatility is not decreasing by beta.

Daily Portfolios										
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Number of stocks	424.52	424.59	424.52	424.55	424.34	424.84	424.49	424.58	424.51	424.60
Mkt Cap.	1.51E+09	3.91E+09	4.16E+09	4.57E+09	4.61E+09	4.47E+09	3.69E+09	3.55E+09	3.21E+09	2.19E+09
Returns	0.2009	0.1647	0.1927	0.1788	0.1805	0.1740	0.1825	0.1866	0.2062	0.1781
Volatility	0.0824	0.1107	0.1367	0.1562	0.1784	0.1987	0.2211	0.2475	0.2844	0.3680
Sharpe	2.4393	1.4876	1.4103	1.1449	1.0118	0.8759	0.8257	0.7538	0.7252	0.4840
Intraday Portfolios										
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Number of stocks	424.52	424.59	424.52	424.55	424.34	424.84	424.49	424.58	424.51	424.60
Mkt Cap.	1.33E+09	4.33E+09	4.55E+09	4.92E+09	4.99E+09	4.07E+09	3.49E+09	3.30E+09	2.95E+09	1.98E+09
Returns	0.2292	0.1718	0.1810	0.1803	0.1745	0.1752	0.1795	0.1856	0.1827	0.1869
Volatility	0.0900	0.1100	0.1341	0.1559	0.1783	0.1976	0.2200	0.2470	0.2820	0.3662
Sharpe	2.5477	1.5624	1.3494	1.1562	0.9787	0.8868	0.8158	0.7513	0.6480	0.5103
Overnight Portfolios										
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Number of stocks	424.52	424.59	424.51	424.56	424.34	424.84	424.49	424.58	424.51	424.60
Mkt Cap.	8.35E+08	3.10E+09	3.34E+09	3.67E+09	4.19E+09	4.39E+09	4.44E+09	4.53E+09	4.19E+09	3.22E+09
Returns	0.2268	0.1379	0.1445	0.1504	0.1680	0.1764	0.1784	0.1990	0.2175	0.2538
Volatility	0.1069	0.1284	0.1492	0.1689	0.1860	0.2028	0.2199	0.2399	0.2632	0.3127
Sharpe	2.1220	1.0739	0.9689	0.8904	0.9030	0.8699	0.8114	0.8298	0.8262	0.8118

Table 3.2: Values of annualized returns, annualized volatility and Sharpe ratio of ten beta sorted portfolios for each trading period, between June 2, 1997 and December 30, 2016. Stocks are sorted and divided, in ten portfolios, considering the value, at the end of each calendar month, of daily intraday and overnight pre-ranking betas. Portfolio 1 contains stocks with lower betas and portfolio 10 contains stocks with higher betas. Results are obtained considering all the stocks in the database with at last 120 trading days of non missing data for volatilities and 750trading days of non missing data for correlation.

Using the daily excess return of our three BAB portfolios and of the ten daily, intraday and overnight portfolios, we evaluate alpha and beta by simple regression

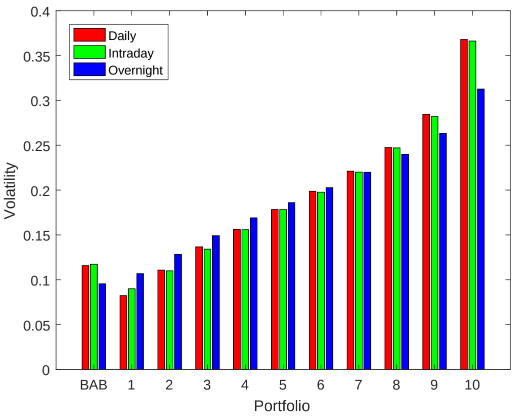


Figure 3.4: Annualized volatility of daily, intraday and overnight BAB factors and ten beta sorted portfolios related to each trading period. Stocks are sorted and divided in ten portfolios considering the value, at the end of each calendar month, of daily intraday and overnight pre-ranking betas. Portfolio 1 contains stocks with lower betas and portfolio 10 contains stocks with higher betas. Results are from June 2, 1997 to December 30, 2016 and are obtained considering all the stocks in the database with at last 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation.

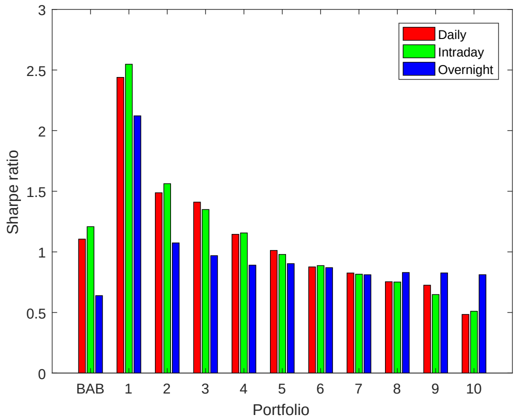


Figure 3.5: Annualized Sharpe ratio of daily, intraday and overnight BAB factors and ten beta sorted portfolios for each trading period. Stocks are sorted and divided in ten portfolios considering the value, at the end of each calendar month, of daily intraday and overnight pre-ranking betas. Portfolio 1 contains stocks with lower betas and portfolio 10 contains stocks with higher betas. Results are from June 2, 1997 to December 30, 2016 and are obtained considering all the stocks in the database with at last 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation.

methods. First of all we adopt a classical CAPM and so we consider as explanatory variable the excess market return (Mkt). Then a Fama and French (1992) three factor model, where the factors are excess market return (Mkt), value (SMB) and book to market (HML). We evaluate also a Carhart (1997) four factor model adding to the previous regressors the daily values related to momentum (MOM). The daily data factors are provided by the Kenneth French's library. In particular Small Minus Large (SML) is the difference in returns of a portfolio of small stocks and large stocks and so the difference on market capitalization. High Minus Low (HML) is the difference in returns of a portfolio of high book-to-market value and a portfolio of low book-to-market value. Momentum (MOM) represents the tendency trend related to the stock. The factor is given by the difference in returns of a portfolio of winners stock, and so with high returns, and losers stock, with a low returns. Finally, using the same methodology of the previous chapter, we evaluate alpha and beta also by a conditional CAPM.

We display the results obtained in Table 3.3, where below the coefficient estimates, in parenthesis, we write the t-statistics and in bold we report the values with a 5% statistical significance. Considering our daily and intraday portfolios we find, as Frazzini and Pedersen (2014), a decreasing in alpha when the beta increases. This result is highlighted by Figure 3.6 in which we represent the alpha associated to the classical CAPM. Furthermore, we note that this kind of relation is not true for overnight portfolios, in which alpha is greater for higher beta stocks portfolios. In almost all regressions we find positive and statistically significant in alphas, this should imply abnormal returns for portfolios.

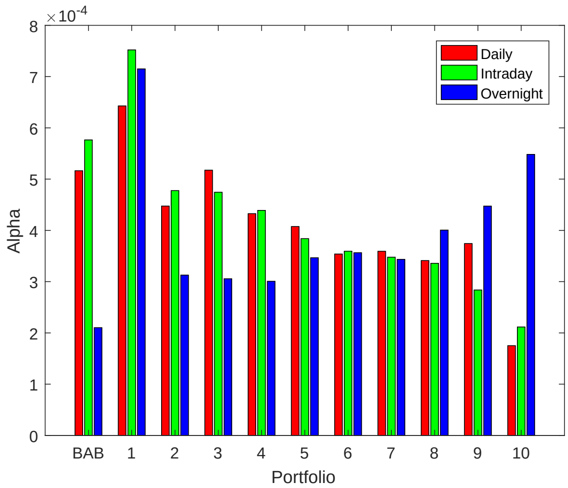


Figure 3.6: CAPM alpha of daily, intraday and overnight BAB factors and ten beta sorted portfolios for each trading period. Stocks are sorted and divided in ten portfolios considering the value, at the end of each calendar month, of daily intraday and overnight pre-ranking betas. Portfolio 1 contains stocks with lower betas and portfolio 10 contains stocks with higher betas. Results are from June 2, 1997 to December 30, 2016 and are obtained considering all the stocks in the database with at last 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation.

We conduct the same analysis also applying some kind of filters for the stocks selection in our BAB portfolios and beta sorted portfolios construction. As we said before, from a computational point of view, related to the model used for pre-ranking beta estimation, we need always to consider stocks with at last 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation. Furthermore, we delete from our portfolios first the stocks with a price less than 5 USD and then stocks with a market capitalization lower than 10^{th} percentile breakpoints of the NYSE market equity, finally we organize portfolios applying both filters. For the NYSE market equity benchmark we adopt the ME breakpoints of the Kenneth French's database.
As we can see, from Table 3.5 and Figure 3.9 in Appendix B excluding stocks with a price less than 5 USD does not give us significant change on the strategy. Of course, we have a lower return due to the lower number of stocks. In this case

	BAB	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Daily Portfolios											
CAPM α	**5.16E-04**	**6.43E-04**	**4.47E-04**	**5.17E-04**	**4.33E-04**	**4.08E-04**	**3.54E-04**	**3.59E-04**	**3.41E-04**	**3.74E-04**	1.75E-04
	(5.89)	(11.13)	(7.35)	(8.03)	(6.42)	(5.64)	(4.55)	(4.12)	(3.50)	(3.25)	(1.03)
CAPM β	**-0.3151**	**0.2606**	**0.4433**	**0.5888**	**0.6935**	**0.8059**	**0.9050**	**1.0056**	**1.1261**	**1.2850**	**1.5946**
	(-44.70)	(56.16)	(90.66)	(113.74)	(128.15)	(138.77)	(144.75)	(143.60)	(143.84)	(138.86)	(116.20)
Three-Factor α	**5.36E-04**	**6.09E-04**	**3.96E-04**	**4.52E-04**	**3.56E-04**	**3.20E-04**	**2.54E-04**	**2.45E-04**	**2.18E-04**	**2.43E-04**	2.74E-05
	(6.26)	(11.25)	(7.66)	(9.09)	(7.58)	(6.67)	(5.29)	(4.75)	(3.71)	(3.28)	(0.20)
Four-Factor α	**4.39E-04**	**6.05E-04**	**3.88E-04**	**4.46E-04**	**3.52E-04**	**3.27E-04**	**2.72E-04**	**2.78E-04**	**2.81E-04**	**3.41E-04**	**2.25E-04**
	(5.68)	(11.17)	(7.51)	(8.98)	(7.49)	(6.83)	(5.71)	(5.54)	(5.21)	(5.33)	(2.03)
Cond. CAPM α	3.77E-04	5.59E-04	3.84E-04	4.71E-04	3.83E-04	3.58E-04	3.34E-04	3.44E-04	3.27E-04	3.86E-04	2.26E-04
Cond. CAPM β	-0.230	0.2761	0.4899	0.6482	0.7560	0.8556	0.9420	1.0353	1.1453	1.2914	1.5667
Intraday Portfolios											
	BAB	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
CAPM α	**5.76E-04**	**7.52E-04**	**4.78E-04**	**4.74E-04**	**4.39E-04**	**3.84E-04**	**3.59E-04**	**3.48E-04**	**3.36E-04**	**2.84E-04**	2.12E-04
	(5.89)	(11.59)	(7.79)	(7.45)	(6.51)	(5.31)	(4.70)	(4.06)	(3.55)	(2.50)	(1.25)
CAPM β	**-0.3151**	**0.2714**	**0.4363**	**0.5763**	**0.6918**	**0.8051**	**0.9028**	**1.0037**	**1.1315**	**1.2756**	**1.5888**
	(-44.70)	(52.08)	(88.52)	(112.59)	(127.69)	(138.53)	(146.97)	(145.84)	(149.08)	(139.61)	(116.77)
Three-Factor α	**5.36E-04**	**7.19E-04**	**4.27E-04**	**4.09E-04**	**3.63E-04**	**2.96E-04**	**2.61E-04**	**2.36E-04**	**2.15E-04**	**1.50E-04**	6.13E-05
	(7.08)	(11.76)	(8.10)	(8.32)	(7.60)	(6.20)	(5.58)	(4.67)	(3.85)	(2.09)	(0.47)
Four-Factor α	**5.02E-04**	**7.17E-04**	**4.17E-04**	**4.01E-04**	**3.61E-04**	**3.03E-04**	**2.79E-04**	**2.70E-04**	**2.73E-04**	**2.48E-04**	**2.59E-04**
	(6.59)	(11.72)	(7.94)	(8.16)	(7.54)	(6.35)	(6.02)	(5.53)	(5.34)	(4.03)	(2.41)
Cond. CAPM α	5.47E-04	6.77E-04	4.12E-04	4.18E-04	3.94E-04	3.44E-04	3.27E-04	3.24E-04	3.25E-04	2.90E-04	2.76E-04
Cond. CAPM β	-0.2555	0.2847	0.4836	0.6344	0.7489	0.8504	0.9395	1.0324	1.1512	1.2859	1.5663
Overnight Portfolios											
	BAB	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
CAPM α	**2.10E-04**	**7.15E-04**	**3.13E-04**	**3.06E-04**	**3.01E-04**	**3.47E-04**	**3.56E-04**	**3.43E-04**	**4.01E-04**	**4.47E-04**	**5.48E-04**
	(2.63)	(10.17)	(4.93)	(4.73)	(4.36)	(4.72)	(4.60)	(4.02)	(4.23)	(4.13)	(3.65)
CAPM β	**-0.1728**	**0.3683**	**0.5426**	**0.6617**	**0.7619**	**0.8456**	**0.9289**	**1.0032**	**1.0909**	**1.1847**	**1.3375**
	(-26.86)	(65.20)	(106.46)	(127.48)	(137.49)	(143.14)	(149.24)	(146.01)	(143.54)	(136.20)	(110.94)
Three-Factor α	**2.21E-04**	**6.73E-04**	**2.53E-04**	**2.34E-04**	**2.17E-04**	**2.55E-04**	**2.55E-04**	**2.30E-04**	**2.81E-04**	**3.24E-04**	**4.24E-04**
	(2.78)	(10.53)	(4.98)	(5.08)	(4.79)	(5.48)	(5.58)	(4.77)	(4.95)	(4.55)	(3.46)
Four-Factor α	1.30E-04	**6.68E-04**	**2.44E-04**	**2.30E-04**	**2.20E-04**	**2.65E-04**	**2.83E-04**	**2.70E-04**	**3.46E-04**	**4.10E-04**	**6.07E-04**
	(1.81)	(10.45)	(4.80)	(4.99)	(4.86)	(5.72)	(6.37)	(5.88)	(6.76)	(6.51)	(6.04)
Cond. CAPM α	1.26E-04	6.66E-04	2.66E-04	2.51E-04	2.47E-04	3.17E-04	3.18E-04	3.24E-04	3.88E-04	4.63E-04	5.64E-04
Cond. CAPM β	-0.0971	0.3963	0.5933	0.7171	0.8068	0.8896	0.9588	1.0310	1.1070	1.1958	1.3253

Table 3.3: Considering the values of daily, intraday and overnight pre-ranking betas we organize for each trading period 10 portfolios and one BAB portfolios. For the ten portfolios formation we sort and divide the stocks considering the value, at the end of each calendar month, of daily intraday and overnight pre-ranking betas. Portfolios are unweighted and are update at each month. Portfolio 1 contains stocks with lower betas and portfolio 10 contains stocks with higher betas. BAB portfolios are long on low beta stocks and short on high beta stocks. They are ranked and divided considering the values of daily intraday and overnight betas. Stocks are weighted by the ranked betas and rebalanced at the begin of each month. For the estimates we consider all the stocks, between June 2, 1997 and December 30, 2016, with at last 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation. We evaluate alpha and beta in regression of daily excess returns. First we consider as explanatory variable the excess market return and so a classical CAPM. Then a Fama and French (1992) three factor model, where the factors are excess market return(Mkt), value (SMB) and book to market (HML). We evaluate also a four factor model adding at the previous regressors the daily values related to momentum (MOM). In parenthesis, below the coefficient estimates, we display t-statistics. The values with a 5% statistical significance are represented in bold. At the end we give also the mean, on the period, of alpha and beta obtained applying a conditional CAPM.

returns are half of the previous one, indeed the average number of stocks, traded each month, is 2638, 1319 that go long and 1319 that go short. Also in this case we have an higher return and Sharpe ratio for the intraday BAB strategy.
If we evaluate the BAB strategy considering at portfolio formation stocks with a market capitalization greater than the 10^{th} percentile breakpoints of the NYSE market equity, we have on average 2314 stocks, 1157 that go long and 1157 that go short. The values of the daily and intraday strategies are pretty similar (Table 3.8 Appendix B). Applying all the two filters we have a monthly average of 1730 stocks, 865 that go long and 865 that go short and as showed by Table 3.11 Appendix B we obtain similar results to the previous case.

Applying factor models, to these filtered portfolio returns, we note that the exclusion of stocks with a market capitalization lower than the 10^{th} percentile breakpoints give negative alphas. The differences in results due to this kind of filter maybe are due to the different behavior of small and large stocks. We know by literature that micro-cap stocks, and so all the stocks with a market capitalization below, more or less, USD 250 million, have a different performance. It seems that the exclusion of these stocks reduces portfolio returns and so small cap outperform large cap (Banz, 1981; Fama and French, 1992, 1995).

Conclusion

We use the differences in behaviors of daily, intraday and overnight betas in the Frazzini and Pedersen (2014) BAB strategy. Our three BAB portfolios are long on low beta stocks and short on high beta stocks. Stocks are ranked and divided considering the values of daily, intraday and overnight betas, they are weighted by the ranked betas and rebalanced at the beginning of each month. We observe an improvement in this methodology if we consider as signal, for the BAB portfolio construction, the intraday betas. In particular we find higher returns and higher Sharpe ratio. We organize also, for each trading period, ten beta sorted portfolios, considering the value of daily, intraday and overnight preranking betas. Portfolio 1 contains lower beta stocks, portfolio 10 higher beta socks. Portfolios are unweighted and are updated at each month. We find that Sharpe ratio decreases and volatility increases in beta, independently from the trading period. Implementing a CAPM, a conditional CAPM, a Fama and French (1992) three factor model and a Carhart (1997) four factor model, we find that our strategy give abnormal returns and, as in the paper of Frazzini and Pedersen (2014), alpha decreases with beta. Although we find that it is not true for portfolios sorted by overnight betas, in which we have an higher alpha for portfolios with higher beta. We obtain same results if we delete, before portfolios formation, all stocks with a price lower than 5 USD. If instead, we exclude securities with lower market cap, we note that intraday and overnight BAB portfolios have more similar values and beta sorted portfolios present negative alpha. Probably the micro cap stocks influence more beta values and so this kind of strategy.

Appendix B

BAB Returns			
	Daily	Intraday	Overnight
Number of stocks	4023	4023	4023
Returns	0.1302	0.1433	0.0432
Volatility	0.1181	0.1252	0.1046
Sharpe	1.1024	1.1453	0.4135

Table 3.4: Values of annualized returns, annualized volatility and Sharpe ratio of the BAB returns on our three portfolios: daily, intraday and overnight, between June 2, 1997 and December 30, 2016. We use a daily intraday and overnight weighted market index for the pre-ranking beta. We trade the whole cross-section, considering stocks with at last 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation. We have on average for each trading period, in each month, 4024 stocks, 2012 that go long and 2012 that go short.

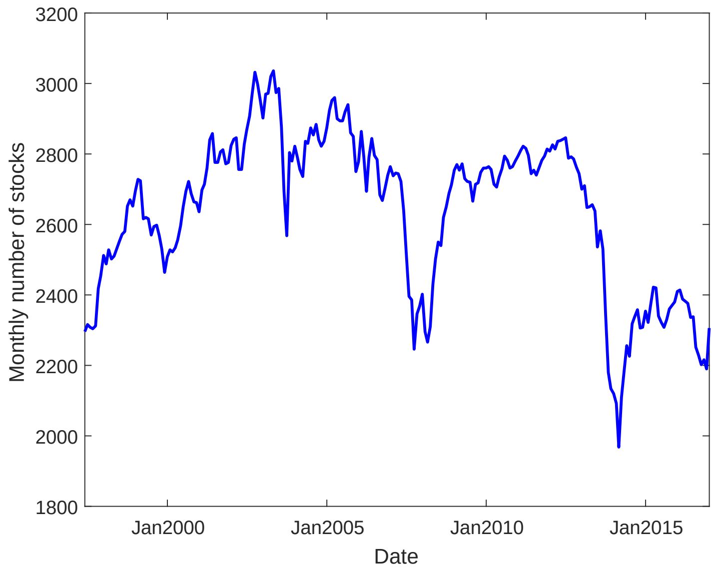


Figure 3.7: Number of stocks traded each month in the BAB portfolio, between June 2, 1997 and December 30, 2016. We consider all the stocks in the database with at last 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation and all the stock with a price greater of 5 USD. We have on average for each trading period, in each month, 2638 stocks, 1319 that go long and 1319 that go short. Daily intraday and overnight portfolios have the same number of stocks.

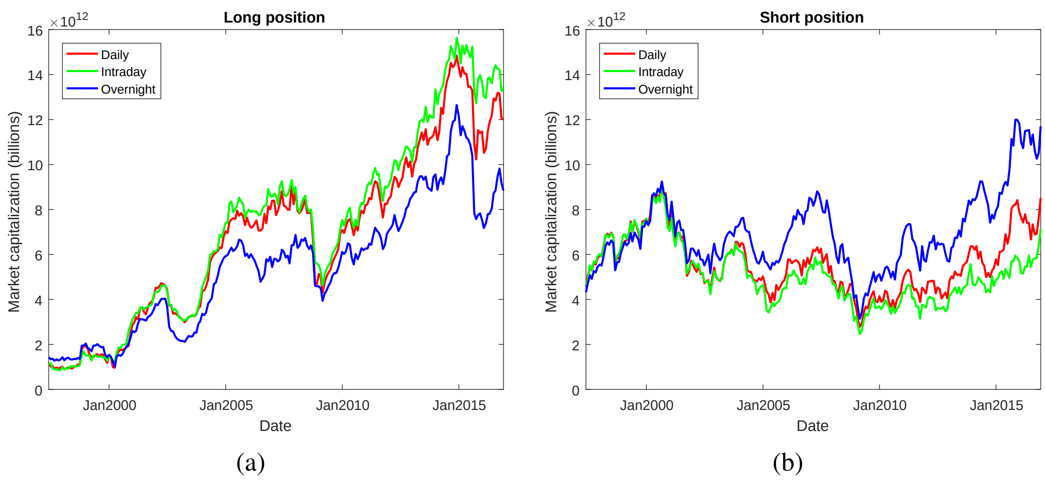


Figure 3.8: Market capitalization, between June 2, 1997 and December 30, 2016, of long (low betas) (a) and short (high betas) (b) position at daily, intraday and overnight portfolio formation. We trade all the stocks in the database with at last 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation and all the stock with a price greater of 5 USD. We have on average for each trading period, in each month, 2638 stocks, 1319 that go long and 1319 that go short.

BAB Returns			
	Daily	Intraday	Overnight
Number of stocks	2638	2638	2638
Returns	0.0877	0.0979	0.0361
Volatility	0.1199	0.1212	0.0994
Sharpe	0.7314	0.8082	0.3630

Table 3.5: Values of annualized returns, annualized volatility and Sharpe ratio of the BAB returns on our three portfolios: daily, intraday and overnight, between June 2, 1997 and December 30, 2016. We trade the whole cross-section, considering stocks with at last 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation and all the stock with a price greater of 5 USD. We have on average for each trading period, in each month, 2638 stocks, 1319 that go long and 1319 that go short.

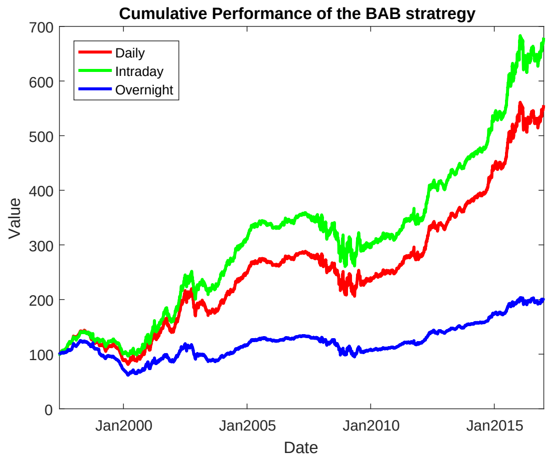


Figure 3.9: Cumulative values of BAB daily, intraday and overnight strategy, between June 2, 1997 and December 30, 2016. We trade the whole cross-section, considering stocks with at last 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation and all the stock with a price greater of 5 USD. We have on average for each trading period, in each month, 2638 stocks, 1319 that go long and 1319 that go short.

Daily Portfolios										
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Number of stocks	276.45	276.61	276.50	276.54	276.30	276.81	276.45	276.59	276.48	276.58
Mkt Cap.	2.76E+09	5.69E+09	5.79E+09	5.96E+09	5.87E+09	5.11E+09	4.58E+09	4.22E+09	4.39E+09	3.13E+09
Returns	0.1563	0.1370	0.1550	0.1597	0.1367	0.1507	0.1561	0.1554	0.1674	0.1544
Volatility	0.0806	0.1119	0.1397	0.1609	0.1816	0.2010	0.2220	0.2433	0.2818	0.3662
Sharpe	1.9401	1.2247	1.1096	0.9925	0.7524	0.7500	0.7033	0.6389	0.5941	0.4215
Intraday Portfolios										
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Number of stocks	276.45	276.61	276.51	276.53	276.30	276.81	276.45	276.59	276.48	276.58
Mkt Cap.	2.86E+09	6.31E+09	6.28E+09	6.83E+09	5.69E+09	4.62E+09	4.17E+09	3.98E+09	4.11E+09	2.72E+09
Returns	0.1754	0.1414	0.1499	0.1463	0.1540	0.1459	0.1426	0.1601	0.1583	0.1557
Volatility	0.0850	0.1109	0.1382	0.1592	0.1818	0.1994	0.2210	0.2437	0.2806	0.3641
Sharpe	2.0636	1.2745	1.0843	0.9189	0.8474	0.7317	0.6454	0.6571	0.5641	0.4277
Overnight Portfolios										
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Number of stocks	276.45	276.61	276.49	276.55	276.30	276.81	276.45	276.59	276.48	276.58
Mkt Cap.	1.91E+09	4.46E+09	4.38E+09	4.89E+09	5.29E+09	5.40E+09	5.53E+09	5.68E+09	5.50E+09	4.47E+09
Returns	0.1671	0.1211	0.1233	0.1336	0.1412	0.1440	0.1372	0.1807	0.1779	0.2061
Volatility	0.1012	0.1279	0.1522	0.1714	0.1900	0.2048	0.2194	0.2374	0.2635	0.3132
Sharpe	1.6511	0.9471	0.8099	0.7798	0.7431	0.7031	0.6251	0.7611	0.6750	0.6581

Table 3.6: Values of annualized returns, annualized volatility and Sharpe ratio of ten beta sorted portfolios for each trading period, between June 2, 1997 and December 30, 2016. Stocks are sorted and divided, in ten portfolios, considering the value, at the end of each calendar month, of daily intraday and overnight pre-ranking betas. Portfolio 1 contains stocks with lower betas and portfolio 10 contains stocks with higher betas. Results are obtained considering all the stocks in the database with at last 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation and all the stock with a price greater of 5 USD.

Daily Portfolios

	BAB	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
CAPM α	**3.64E-04**	**4.66E-04**	**3.34E-04**	**3.62E-04**	**3.49E-04**	**2.28E-04**	**2.59E-04**	**2.53E-04**	**2.22E-04**	2.21E-04	8.11E-05
	(4.09)	(8.33)	(5.62)	(5.65)	(5.18)	(3.17)	(3.26)	(2.92)	(2.34)	(1.99)	(0.48)
CAPM β	**-0.3418**	**0.2583**	**0.4572**	**0.6076**	**0.7207**	**0.8251**	**0.9136**	**1.0122**	**1.1090**	**1.2816**	**1.5939**
	(-47.84)	(57.42)	(95.86)	(117.81)	(133.05)	(142.65)	(143.09)	(145.46)	(145.18)	(143.62)	(118.13)
Three-Factor α	**3.87E-04**	**4.34E-04**	**2.81E-04**	**2.91E-04**	**2.70E-04**	**1.36E-04**	**1.54E-04**	**1.34E-04**	9.39E-05	8.42E-05	-8.57E-05
	(4.45)	(8.20)	(5.54)	(6.03)	(5.65)	(2.83)	(3.07)	(2.54)	(1.62)	(1.16)	(-0.65)
Four-Factor α	2.82E-04	**4.30E-04**	**2.69E-04**	**2.82E-04**	**2.68E-04**	**1.45E-04**	**1.72E-04**	**1.72E-04**	**1.52E-04**	**1.82E-04**	1.15E-04
	(3.65)	(8.11)	(5.33)	(5.86)	(5.61)	(3.01)	(3.47)	(3.39)	(2.85)	(2.94)	(1.08)
Cond. CAPM α	2.41E-04	3.87E-04	2.63E-04	3.07E-04	3.03E-04	1.77E-04	2.39E-04	2.21E-04	1.84E-04	2.02E-04	1.09E-04
Cond. CAPM β	-0.2484	0.2699	0.5123	0.6741	0.7848	0.8742	0.9528	1.0405	1.1332	1.2896	1.5649

Intraday Portfolios

	BAB	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
CAPM α	**4.10E-04**	**5.41E-04**	**3.53E-04**	**3.44E-04**	**2.98E-04**	**2.97E-04**	**2.41E-04**	**2.00E-04**	**2.39E-04**	1.86E-04	8.90E-05
	(4.65)	(8.97)	(5.93)	(5.43)	(4.47)	(4.10)	(3.10)	(2.34)	(2.57)	(1.69)	(0.53)
CAPM β	**-0.3603**	**0.2640**	**0.4505**	**0.6018**	**0.7132**	**0.8245**	**0.9091**	**1.0100**	**1.1164**	**1.2780**	**1.5854**
	(-50.93)	(54.49)	(94.19)	(118.32)	(133.22)	(141.65)	(145.26)	(147.16)	(149.26)	(144.53)	(118.35)
Three-Factor α	**4.36E-04**	**5.07E-04**	**3.00E-04**	**2.75E-04**	**2.21E-04**	**2.06E-04**	**1.36E-04**	8.28E-05	**1.12E-04**	**4.58E-05**	**-7.94E-05**
	(5.07)	(8.88)	(5.87)	(5.67)	(4.64)	(4.25)	(2.81)	(1.60)	(2.02)	(0.65)	(-0.62)
Four-Factor α	3.31E-04	**8.88E+00**	**5.87E+00**	**5.67E+00**	**4.64E+00**	**4.25E+00**	**2.81E+00**	**1.60E+00**	**2.02E+00**	**6.50E-01**	-6.20E-01
	(4.35)	(8.84)	(5.66)	(5.47)	(4.56)	(0.41)	(3.26)	(2.45)	(3.34)	(2.42)	(1.15)
Cond. CAPM α	2.93E-04	4.66E-04	2.82E-04	2.84E-04	2.48E-04	2.67E-04	1.98E-04	1.59E-04	2.09E-04	1.69E-04	1.21E-04
Cond. CAPM β	-0.2735	0.273	0.507	0.662	0.772	0.868	0.949	1.041	1.141	1.286	1.568

Overnight Portfolios

	BAB	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
CAPM α	1.21E-04	**4.80E-04**	**2.45E-04**	**2.17E-04**	**2.31E-04**	**2.35E-04**	**2.26E-04**	**1.79E-04**	**3.30E-04**	**2.87E-04**	**3.55E-04**
	(1.49)	(7.47)	(4.01)	(3.33)	(3.31)	(3.13)	(2.85)	(2.15)	(3.59)	(2.74)	(2.41)
CAPM β	**-0.2079**	**0.3624**	**0.5483**	**0.6778**	**0.7735**	**0.8637**	**0.9350**	**1.0067**	**1.0845**	**1.1957**	**1.3511**
	(-31.82)	(70.20)	(111.74)	(129.85)	(138.06)	(143.18)	(146.29)	(150.45)	(147.03)	(141.81)	(114.26)
Three-Factor α	**1.34E-04**	**4.36E-04**	**1.84E-04**	**1.40E-04**	**1.43E-04**	**1.37E-04**	**1.17E-04**	**6.39E-05**	**2.05E-04**	**1.59E-04**	2.15E-04
	(1.66)	(7.49)	(3.76)	(3.00)	(3.05)	(2.82)	(2.44)	(1.31)	(3.74)	(2.29)	(1.80)
Four-Factor α	3.76E-05	**4.34E-04**	**1.71E-04**	**1.37E-04**	**1.46E-04**	**1.49E-04**	**1.45E-04**	**1.05E-04**	**2.67E-04**	**2.50E-04**	**3.95E-04**
	(0.52)	(7.45)	(3.51)	(2.93)	(3.11)	(3.07)	(3.11)	(2.27)	(5.38)	(4.18)	(4.07)
Cond. CAPM α	2.79E-05	4.08E-04	1.82E-04	1.61E-04	1.89E-04	1.92E-04	1.91E-04	1.43E-04	3.11E-04	2.69E-04	3.61E-04
Cond. CAPM β	-0.1272	0.39	0.61	0.73	0.82	0.90	0.97	1.04	1.10	1.21	1.34

Table 3.7: Considering the values of daily, intraday and overnight pre-ranking betas we organize for each trading period 10 portfolios and one BAB portfolio. For the ten portfolios formation we sort and divide the stocks considering the value, at the end of each calendar month, of daily intraday and overnight pre-ranking betas. Portfolios are unweighted and are update at each month. Portfolio 1 contains stocks with lower betas and portfolio 10 contains stocks with higher betas. BAB portfolios are long on low beta stocks and short on high beta stocks. They are ranked and divided considering the values of daily intraday and overnight betas. Stocks are weighted by the ranked betas and rebalanced at the begin of each month. For the estimates we consider all the stocks, between June 2, 1997 and December 30, 2016, with at last 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation and all the stock with a price greater of 5 USD. We evaluate alpha and beta in regression of daily excess returns. First we consider as explanatory variable the excess market return and so a classical CAPM. Then a Fama and French (1992) three factor model where the factors are excess market return(Mkt), value (SMB) and book to market (HML). We evaluate also a four factor model adding at the previous regressors the daily values related to momentum (MOM). In parenthesis, below the coefficient estimates, we display t-statistics. The values with a 5% statistical significance are represented in bold. At the end we give also the mean, on the period, of alpha and beta obtained applying a conditional CAPM.

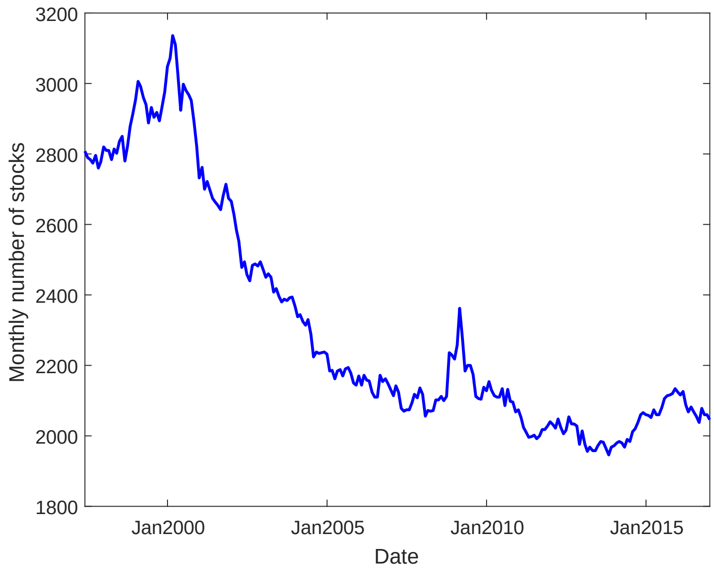


Figure 3.10: Number of stocks traded each month in the BAB portfolio, between June 2, 1997 and December 30, 2016. We consider all the stocks in the database with at last 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation and all the stocks with a market capitalization greater than 10^{th} percentile breakpoints of the NYSE ME. We have on average for each trading period, in each month, 2314 stocks, 1157 that go long and 1157 that go short. Daily intraday and overnight portfolios have the same number of stocks.

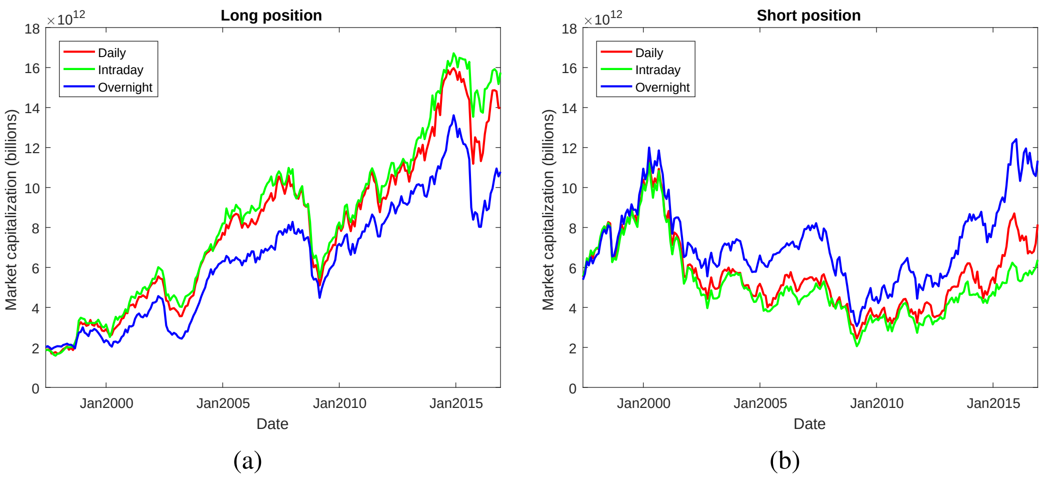


Figure 3.11: Market capitalization, between June 2, 1997 and December 30, 2016, of long (low betas) (a) and short (high betas) (b) position at daily, intraday and overnight portfolio formation. We trade all the stocks in the database with at last 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation and all the stock with a market capitalization greater than 10^{th} percentile breakpoints of the NYSE ME. We have on average for each trading period, in each month, 2314 stocks, 1157 that go long and 1157 that go short.

BAB Returns			
	Daily	Intraday	Overnight
Number of stocks	2314	2314	2314
Returns	0.0521	0.0477	0.0335
Volatility	0.1156	0.1142	0.1045
Sharpe	0.4508	0.4178	0.3209

Table 3.8: Values of annualized returns, annualized volatility and Sharpe ratio of the BAB returns on our three portfolios: daily, intraday and overnight, between June 2, 1997 and December 30, 2016. We trade the whole cross-section, considering stocks with at last 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation and all the stocks with a market capitalization greater than 10^{th} percentile breakpoints of the NYSE ME. We have on average for each trading period, in each month, 2314 stocks, 1157 that go long and 1157 that go short.

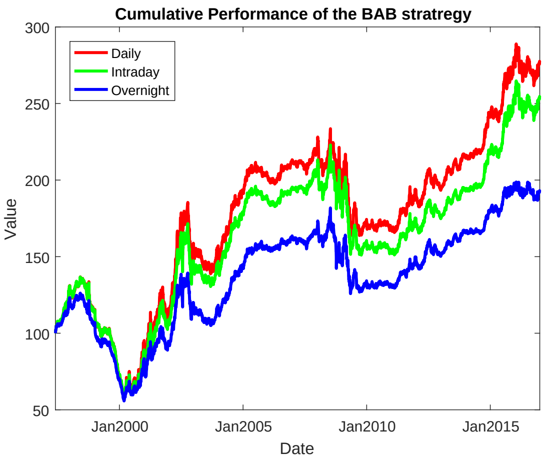


Figure 3.12: Cumulative values of BAB daily, intraday and overnight strategy, between June 2, 1997 and December 30, 2016. We trade the whole cross-section, considering stocks with at last 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation and all the stocks with a market capitalization greater than 10^{th} percentile breakpoints of the NYSE ME. We have on average for each trading period, in each month, 2314 stocks, 1157 that go long and 1157 that go short.

Daily Portfolios

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Number of stocks	232.92	233.00	232.91	233.00	232.67	233.23	232.92	232.98	232.89	233.03
Mkt Cap.	9.53E+09	7.18E+09	7.04E+09	6.62E+09	6.13E+09	5.80E+09	5.17E+09	5.34E+09	4.79E+09	3.22E+09
Returns	0.1019	0.1245	0.1266	0.1271	0.1160	0.1192	0.1350	0.1259	0.1328	0.1165
Volatility	0.1294	0.1560	0.1753	0.1930	0.2097	0.2260	0.2476	0.2721	0.3128	0.4049
Sharpe	0.7878	0.7982	0.7221	0.6586	0.5531	0.5276	0.5454	0.4626	0.4246	0.2876

Intraday Portfolios

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Number of stocks	232.92	233.00	232.90	233.00	232.67	233.23	232.92	232.98	232.89	233.03
Mkt Cap.	1.03E+10	7.73E+09	7.82E+09	6.89E+09	5.98E+09	5.10E+09	4.74E+09	5.06E+09	4.33E+09	2.88E+09
Returns	0.1019	0.1238	0.1160	0.1331	0.1197	0.1150	0.1381	0.1326	0.1247	0.1204
Volatility	0.1291	0.1554	0.1749	0.1937	0.2097	0.2261	0.2454	0.2721	0.3121	0.4055
Sharpe	0.7892	0.7968	0.6632	0.6875	0.5709	0.5083	0.5629	0.4875	0.3996	0.2970

Overnight Portfolios

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Number of stocks	232.92	233.00	232.88	233.02	232.67	233.23	232.92	232.98	232.89	233.03
Mkt Cap.	6.42E+09	5.52E+09	5.53E+09	6.05E+09	5.85E+09	6.27E+09	6.34E+09	6.71E+09	6.58E+09	5.53E+09
Returns	0.1000	0.1204	0.1154	0.1182	0.1282	0.1240	0.1240	0.1393	0.1270	0.1291
Volatility	0.1519	0.1701	0.1878	0.2012	0.2145	0.2262	0.2422	0.2635	0.2980	0.3634
Sharpe	0.6586	0.7080	0.6146	0.5874	0.5975	0.5481	0.5122	0.5286	0.4262	0.3553

Table 3.9: Values of annualized returns, annualized volatility and Sharpe ratio of ten beta sorted portfolios for each trading period, between June 2, 1997 and December 30, 2016. Stocks are sorted and divided, in ten portfolios, considering the value, at the end of each calendar month, of daily intraday and overnight pre-ranking betas. Portfolio 1 contains stocks with lower betas and portfolio 10 contains stocks with higher betas. Results are obtained considering all the stocks in the database with at last 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation and all the stocks with a market capitalization greater than 10^{th} percentile breakpoints of the NYSE ME.

	BAB	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Daily Portfolios											
CAPM α	**1.77E-04**	**1.67E-04**	**2.15E-04**	**1.94E-04**	1.71E-04	1.04E-04	9.42E-05	1.27E-04	5.67E-05	3.43E-05	-1.28E-04
	(1.79)	(2.70)	(3.34)	(2.90)	(2.42)	(1.39)	(1.20)	(1.52)	(0.63)	(0.31)	(-0.74)
CAPM β	**-0.1798**	**0.5552**	**0.7016**	**0.8032**	**0.8917**	**0.9738**	**1.0546**	**1.1620**	**1.2802**	**1.4570**	**1.8009**
	(-22.67)	(112.05)	(135.69)	(149.23)	(156.75)	(161.67)	(166.75)	(173.35)	(176.80)	(164.88)	(129.10)
Three-Factor α	1.76E-04	**1.11E-04**	**1.42E-04**	**1.13E-04**	7.98E-05	4.35E-06	-1.36E-05	1.18E-05	-5.86E-05	-7.67E-05	-2.60E-04
	(1.82)	(2.11)	(3.03)	(2.46)	(1.73)	(0.09)	(-0.30)	(0.26)	(-1.19)	(-1.08)	(-1.87)
Four-Factor α	6.45E-05	8.35E-05	**1.21E-04**	**1.02E-04**	7.64E-05	6.67E-06	-1.73E-07	4.08E-05	-4.95E-06	1.99E-05	-5.64E-05
	(0.74)	(1.62)	(2.62)	(2.22)	(1.66)	(0.15)	(0.00)	(0.91)	(-0.11)	(0.33)	(-0.49)
Cond. CAPM α	6.80E-05	9.50E-05	1.51E-04	1.52E-04	1.27E-04	6.96E-05	5.04E-05	1.05E-04	5.66E-05	7.68E-05	-4.35E-05
Cond. CAPM β	-0.0948	0.6199	0.7628	0.8583	0.9364	1.0152	1.0890	1.1888	1.3005	1.4671	1.7858
Intraday Portfolios											
	BAB	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
CAPM α	1.63E-04	**1.66E-04**	**2.12E-04**	**1.53E-04**	**1.94E-04**	1.18E-04	7.63E-05	1.41E-04	8.39E-05	2.63E-06	-1.12E-04
	(1.69)	(2.73)	(3.36)	(2.29)	(2.75)	(1.60)	(0.98)	(1.72)	(0.93)	(0.02)	(-0.64)
CAPM β	**-0.1934**	**0.5565**	**0.7015**	**0.8021**	**0.8963**	**0.9765**	**1.0579**	**1.1533**	**1.2790**	**1.4555**	**1.7997**
	(-24.92)	(114.05)	(138.39)	(149.90)	(158.26)	(164.27)	(169.64)	(175.12)	(175.66)	(166.01)	(127.84)
Three-Factor α	1.68E-04	**1.11E-04**	**1.41E-04**	7.16E-05	**1.05E-04**	2.07E-05	-3.00E-05	2.93E-05	-3.26E-05	-1.13E-04	-2.49E-04
	(1.77)	(2.15)	(3.06)	(1.58)	(2.26)	(0.45)	(-0.67)	(0.64)	(-0.65)	(-1.63)	(-1.80)
Four-Factor α	5.45E-05	**8.37E-05**	**1.18E-04**	5.96E-05	**9.98E-05**	2.37E-05	-1.47E-05	5.62E-05	2.33E-05	-1.50E-05	-4.57E-05
	(0.65)	(1.65)	(2.62)	(1.32)	(2.15)	(0.52)	(-0.33)	(1.27)	(0.52)	(-0.26)	(-0.40)
Cond. CAPM α	5.53E-05	9.35E-05	1.51E-04	1.01E-04	1.53E-04	8.11E-05	5.04E-05	1.18E-04	7.51E-05	3.99E-05	-2.36E-05
Cond. CAPM β	-0.1183	0.6178	0.7623	0.8554	0.9367	1.0078	1.0897	1.1806	1.3038	1.4699	1.7982
Overnight Portfolios											
	BAB	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
CAPM α	7.86E-05	1.28E-04	**1.80E-04**	1.33E-04	1.25E-04	1.46E-04	1.11E-04	8.93E-05	1.21E-04	2.89E-05	-2.74E-05
	(0.85)	(1.87)	(2.62)	(1.87)	(1.70)	(1.91)	(1.46)	(1.11)	(1.39)	(0.28)	(-0.18)
CAPM β	**-0.0936**	**0.6653**	**0.7692**	**0.8617**	**0.9299**	**0.9975**	**1.0616**	**1.1390**	**1.2410**	**1.3946**	**1.6235**
	(-12.62)	(121.18)	(139.39)	(150.68)	(157.02)	(162.85)	(173.34)	(176.25)	(177.79)	(170.09)	(131.70)
Three-Factor α	6.87E-05	5.99E-05	**1.00E-04**	4.62E-05	2.84E-05	4.08E-05	4.72E-06	-2.03E-05	9.37E-06	-7.87E-05	-1.39E-04
	(0.75)	(1.13)	(2.02)	(0.96)	(0.62)	(0.93)	(0.12)	(-0.48)	(0.20)	(-1.20)	(-1.09)
Four-Factor α	-3.85E-05	3.07E-05	8.20E-05	3.60E-05	2.71E-05	5.11E-05	2.12E-05	7.38E-06	6.34E-05	1.13E-05	5.88E-05
	(-0.47)	(0.59)	(1.67)	(0.75)	(0.59)	(1.16)	(0.53)	(0.18)	(1.49)	(0.20)	(0.57)
Cond. CAPM α	8.43E-07	7.12E-05	1.32E-04	9.35E-05	9.26E-05	1.09E-04	7.47E-05	4.50E-05	1.13E-04	5.71E-05	5.03E-05
Cond. CAPM β	-0.0214	0.7356	0.8238	0.9068	0.9703	1.0359	1.1036	1.1766	1.2641	1.4080	1.6027

Table 3.10: Considering the values of daily, intraday and overnight pre-ranking betas we organize for each trading period 10 portfolios and one BAB portfolios. For the ten portfolios formation we sort and divide the stocks considering the value, at the end of each calendar month, of daily intraday and overnight pre-ranking betas. Portfolios are unweighted and are update at each month. Portfolio 1 contains stocks with lower betas and portfolio 10 contains stocks with higher betas. BAB portfolios are long on low beta stocks and short on high beta stocks. They are ranked and divided considering the values of daily intraday and overnight betas. Stocks are weighted by the ranked betas and rebalanced at the begin of each month. For the estimates we consider all the stocks, between June 2, 1997 and December 30, 2016, with at last 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation and all the stock with a market capitalization greater than 10^{th} percentile breakpoints of the NYSE ME. We evaluate alpha and beta in regression of daily excess returns. First we consider as explanatory variable the excess market return and so a classical CAPM. Then a Fama and French (1992) three factor model where the factors are excess market return (Mkt), value (SMB) and book to market (HML). We evaluate also a four factor model adding at the previous regressors the daily values related to momentum (MOM). In parenthesis, below the coefficient estimates, we display t-statistics. The values with a 5% statistical significance are represented in bold. At the end we give also the mean, on the period, of alpha and beta obtained applying a conditional CAPM.

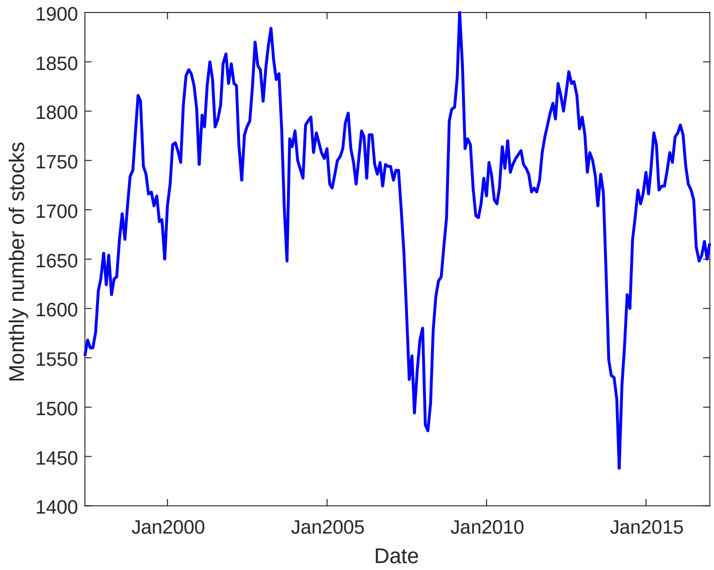


Figure 3.13: Number of stocks traded each month in the BAB portfolio, between June 2, 1997 and December 30, 2016. We consider all the stocks in the database with at last 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation. Furthermore we trade all the stocks with a price greater of 5 USD and with a market capitalization greater than 10^{th} percentile breakpoints of the NYSE ME. We have on average for each trading period, in each month, 1730 stocks, 865 that go long and 865 that go short. Daily intraday and overnight portfolios have the same number of stocks.

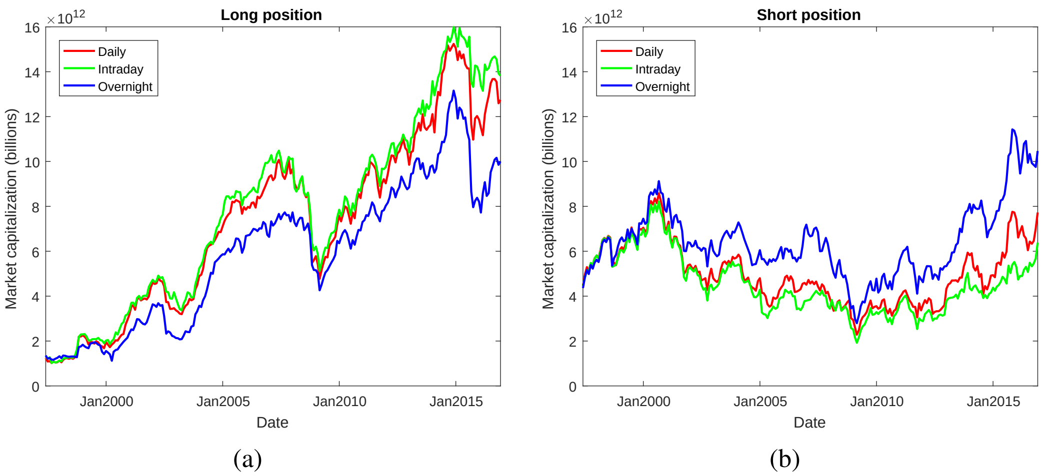


Figure 3.14: Market capitalization, between June 2, 1997 and December 30, 2016, of long (low betas) (a) and short (high betas) (b) position at daily, intraday and overnight portfolio formation. We trade all the stocks in the database with at last 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation. Furthermore we trade all the stocks with a price greater of 5 USD and with a market capitalization greater than 10^{th} percentile breakpoints of the NYSE ME. We have on average for each trading period, in each month, 1730 stocks, 865 that go long and 865 that go short.

BAB Returns			
	Daily	Intraday	Overnight
Number of stocks	1730	1730	1730
Returns	0.0490	0.0447	0.0304
Volatility	0.1185	0.1179	0.1059
Sharpe	0.4137	0.3792	0.2867

Table 3.11: Values of annualized returns, annualized volatility and Sharpe ratio of the BAB returns on our three portfolios: daily, intraday and overnight, between June 2, 1997 and December 30, 2016. We trade the whole cross-section, considering stocks with at last 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation. Furthermore we trade all the stocks with a price greater of 5 USD and with a market capitalization greater than 10^{th} percentile breakpoints of the NYSE ME. We have on average for each trading period, in each month, 1730 stocks, 865 that go long and 865 that go short.

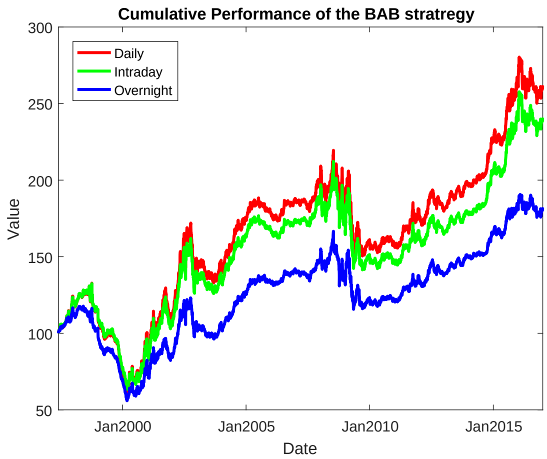


Figure 3.15: Cumulative values of BAB daily, intraday and overnight strategy, between June 2, 1997 and December 30, 2016. We trade the whole cross-section, considering stocks with at last 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation. Furthermore we trade all the stocks with a price greater of 5 USD and with a market capitalization greater than 10^{th} percentile breakpoints of the NYSE ME. We have on average for each trading period, in each month, 1730 stocks, 865 that go long and 865 that go short.

Daily Portfolios

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Number of stocks	173.93	174.07	173.93	174.03	173.75	174.22	173.92	174.03	173.94	174.06
Mkt Cap.	1.15E+10	8.50E+09	7.83E+09	7.44E+09	6.96E+09	6.40E+09	6.04E+09	5.82E+09	6.34E+09	4.32E+09
Returns	0.0964	0.1186	0.1171	0.1131	0.1145	0.1033	0.1169	0.1120	0.1181	0.1093
Volatility	0.1252	0.1503	0.1698	0.1888	0.2040	0.2193	0.2400	0.2596	0.2975	0.3908
Sharpe	0.7693	0.7891	0.6895	0.5991	0.5613	0.4712	0.4869	0.4315	0.3970	0.2797

Intraday Portfolios

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Number of stocks	173.93	174.07	173.94	174.02	173.75	174.22	173.92	174.03	173.94	174.06
Mkt Cap.	1.24E+10	9.11E+09	9.18E+09	7.69E+09	6.49E+09	5.66E+09	5.46E+09	5.44E+09	5.89E+09	3.79E+09
Returns	0.0963	0.1148	0.1094	0.1256	0.1114	0.0979	0.1194	0.1210	0.1165	0.1071
Volatility	0.1242	0.1490	0.1700	0.1881	0.2044	0.2204	0.2364	0.2612	0.2978	0.3915
Sharpe	0.7751	0.7705	0.6431	0.6679	0.5451	0.4439	0.5051	0.4631	0.3912	0.2736

Overnight Portfolios

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Number of stocks	173.93	174.07	173.93	174.03	173.75	174.22	173.92	174.03	173.94	174.06
Mkt Cap.	7.95E+09	6.34E+09	6.36E+09	6.88E+09	6.57E+09	7.00E+09	7.32E+09	7.54E+09	7.93E+09	7.23E+09
Returns	0.0960	0.1053	0.1115	0.1108	0.1139	0.1160	0.1133	0.1202	0.1166	0.1158
Volatility	0.1437	0.1628	0.1831	0.1965	0.2089	0.2207	0.2334	0.2541	0.2836	0.3490
Sharpe	0.6683	0.6465	0.6087	0.5641	0.5452	0.5256	0.4854	0.4729	0.4113	0.3319

Table 3.12: Values of annualized returns, annualized volatility and Sharpe ratio of ten beta sorted portfolios for each trading period, between June 2, 1997 and December 30, 2016. Stocks are sorted and divided, in ten portfolios, considering the value, at the end of each calendar month, of daily intraday and overnight pre-ranking betas. Portfolio 1 contains stocks with lower betas and portfolio 10 contains stocks with higher betas. Results are obtained considering all the stocks in the database with at last 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation. Furthermore we trade all the stocks with a price greater of 5 USD and with a market capitalization greater than 10^{th} percentile breakpoints of the NYSE ME.

	BAB	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Daily Portfolios											
CAPM α	1.77E-04	**1.53E-04**	**2.01E-04**	**1.65E-04**	1.23E-04	1.08E-04	4.28E-05	6.74E-05	1.99E-05	-6.57E-06	-1.42E-04
	(1.80)	(2.43)	(3.10)	(2.48)	(1.72)	(1.42)	(0.53)	(0.79)	(0.23)	(-0.07)	(-0.87)
CAPM β	**-0.2249**	**0.5247**	**0.6671**	**0.7732**	**0.8657**	**0.9395**	**1.0134**	**1.1159**	**1.2159**	**1.3954**	**1.7516**
	(-28.40)	(103.44)	(127.79)	(144.18)	(150.07)	(153.67)	(156.62)	(162.78)	(171.00)	(172.58)	(133.67)
Three-Factor α	1.86E-04	1.04E-04	**1.30E-04**	8.53E-05	3.22E-05	7.96E-06	-6.76E-05	-5.15E-05	-1.03E-04	-1.27E-04	**-2.96E-04**
	(1.92)	(1.82)	(2.58)	(1.78)	(0.65)	(0.16)	(-1.34)	(-0.99)	(-1.96)	(-1.93)	(-2.29)
Four-Factor α	7.27E-05	7.69E-05	**1.11E-04**	7.38E-05	3.25E-05	1.53E-05	-4.91E-05	-2.03E-05	-5.28E-05	-3.69E-05	-9.80E-05
	(0.83)	(1.37)	(2.22)	(1.55)	(0.65)	(0.31)	(-0.98)	(-0.40)	(-1.08)	(-0.66)	(-0.93)
Cond. CAPM α	7.85E-05	8.48E-05	1.32E-04	1.12E-04	8.32E-05	5.93E-05	8.40E-06	2.19E-05	-1.15E-05	2.93E-06	-9.60E-05
Cond. CAPM β	-0.1383	0.5817	0.7276	0.8303	0.9100	0.9812	1.0533	1.1418	1.2440	1.4068	1.7388
Intraday Portfolios											
	BAB	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
CAPM α	1.64E-04	**1.53E-04**	**1.87E-04**	**1.34E-04**	**1.73E-04**	9.43E-05	1.93E-05	8.16E-05	5.37E-05	-1.30E-05	-1.50E-04
	(1.69)	(2.48)	(2.94)	(2.02)	(2.46)	(1.26)	(0.24)	(0.98)	(0.60)	(-0.13)	(-0.91)
CAPM β	**-0.2394**	**0.5238**	**0.6631**	**0.7750**	**0.8663**	**0.9440**	**1.0193**	**1.1012**	**1.2226**	**1.3955**	**1.7492**
	(-30.72)	(105.65)	(129.50)	(145.15)	(153.63)	(156.48)	(157.41)	(164.94)	(170.09)	(171.54)	(131.81)
Three-Factor α	1.79E-04	1.05E-04	**1.18E-04**	5.45E-05	8.48E-05	-3.50E-06	-9.11E-05	-3.36E-05	-7.04E-05	**-1.38E-04**	**-3.10E-04**
	(1.88)	(1.88)	(2.36)	(1.14)	(1.74)	(-0.07)	(-1.80)	(-0.66)	(-1.34)	(-2.13)	(-2.41)
Four-Factor α	6.45E-05	7.83E-05	9.75E-05	4.23E-05	8.36E-05	5.69E-06	-7.18E-05	-2.02E-06	-2.22E-05	-4.53E-05	-1.14E-04
	(0.76)	(1.43)	(1.97)	(0.89)	(1.71)	(0.11)	(-1.43)	(-0.04)	(-0.45)	(-0.83)	(-1.08)
Cond. CAPM α	6.70E-05	8.38E-05	1.21E-04	7.89E-05	1.28E-04	5.27E-05	-1.35E-05	4.63E-05	2.18E-05	-2.12E-05	-1.01E-04
Cond. CAPM β	-0.1643	0.5780	0.7228	0.8239	0.9051	0.9818	1.0534	1.1352	1.2513	1.4095	1.7526
Overnight Portfolios											
	BAB	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
CAPM α	7.94E-05	1.24E-04	1.31E-04	1.26E-04	1.04E-04	9.93E-05	8.93E-05	5.97E-05	5.87E-05	5.95E-06	-6.63E-05
	(0.87)	(1.86)	(1.92)	(1.75)	(1.40)	(1.27)	(1.14)	(0.75)	(0.69)	(0.06)	(-0.47)
CAPM β	**-0.1408**	**0.6227**	**0.7289**	**0.8340**	**0.9017**	**0.9612**	**1.0263**	**1.0929**	**1.1930**	**1.3299**	**1.5748**
	(-19.10)	(116.25)	(132.99)	(144.48)	(150.60)	(153.07)	(163.10)	(170.80)	(173.91)	(172.64)	(137.96)
Three-Factor α	7.71E-05	6.03E-05	5.48E-05	3.77E-05	7.84E-06	-8.61E-06	-1.93E-05	-5.15E-05	-6.01E-05	-1.12E-04	-1.96E-04
	(0.84)	(1.09)	(1.05)	(0.74)	(0.16)	(-0.18)	(-0.40)	(-1.10)	(-1.23)	(-1.81)	(-1.67)
Four-Factor α	-3.14E-05	3.26E-05	3.61E-05	3.05E-05	8.61E-06	5.23E-06	7.09E-09	-1.98E-05	-7.91E-06	-2.68E-05	-6.94E-06
	(-0.38)	(0.60)	(0.69)	(0.60)	(0.17)	(0.11)	(0.00)	(-0.44)	(-0.18)	(-0.51)	(-0.07)
Cond. CAPM α	9.75E-06	6.46E-05	7.69E-05	8.14E-05	6.91E-05	4.47E-05	5.19E-05	5.23E-06	2.93E-05	-3.70E-06	-2.58E-05
Cond. CAPM β	-0.0675	0.6843	0.7884	0.8779	0.9433	1.0034	1.0684	1.1352	1.2160	1.3460	1.5560

Table 3.13: Considering the values of daily, intraday and overnight pre-ranking betas we organize for each trading period 10 portfolios and a BAB portfolios. For the ten portfolios formation we sort and divide the stocks considering the value, at the end of each calendar month, of daily intraday and overnight pre-ranking betas. Portfolios are unweighted and are update at each month. Portfolio 1 contains stocks with lower betas and portfolio 10 contains stocks with higher betas. BAB portfolios are long on low beta stocks and short on high beta stocks. They are ranked and divided considering the values of daily intraday and overnight betas. Stocks are weighted by the ranked betas and rebalanced at the begin of each month. For the estimates we consider all the stocks, between June 2, 1997 and December 30, 2016, with at last 120 trading days of non missing data for volatilities and 750 trading days of non missing data for correlation. Furthermore we trade all the stocks with a price greater of 5 USD and with a market capitalization greater than 10^{th} percentile breakpoints of the NYSE ME. We evaluate alpha and beta in regression of daily excess returns. First we consider as explanatory variable the excess market return and so a classical CAPM. Then a Fama and French (1992) three factor model where the factors are excess market return(Mkt), value (SMB) and book to market (HML). We evaluate also a four factor model adding at the previous regressors the daily values related to momentum (MOM). In parenthesis, below the coefficient estimates, we display t-statistics. The values with a 5% statistical significance are represented in bold. At the end we give also the mean, on the period, of alpha and beta obtained applying a conditional CAPM.

Bibliography

Adrian, T. and Franzoni, F. (2009). Learning about beta: Time-varying factor loadings, expected returns, and the conditional capm. *Journal of Empirical Finance*, 16(4):537–556.

Agarwalla, S., Jacob, J., Varma, J., and Vasudevan, E. (2014). Betting against beta in the indian market.

Alp, A. and Bilir, H. (2015). Beta calculation and robust regression methods: An example from the istanbul stock exchange. *International Research Journal of Marketing and Economics*, 2(11).

Altman, E. I., Jacquillat, B., and Levasseur, M. (1974). Comparative analysis of risk measures: France and the united states. *The Journal of Finance*, 29(5):1495–1511.

Andersen, T. G. and Bollerslev, T. (1998). Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. *International economic review*, pages 885–905.

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Ebens, H. (2001). The distribution of realized stock return volatility. *Journal of financial economics*, 61(1):43–76.

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Wu, J. (2006). Realized beta: Persistence and predictability. *Advances in econometrics*, 20(2):1–39.

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Wu, J. G. (2005). A framework for exploring the macroeconomic determinants of systematic risk. Technical report, National Bureau of Economic Research.

Andersen, T. G., Bollerslev, T., and Meddahi, N. (2011). Realized volatility forecasting and market microstructure noise. *Journal of Econometrics*, 160(1):220–234.

Ang, A. and Kristensen, D. (2012). Testing conditional factor models. *Journal of Financial Economics*, 106(1):132–156.

Baesel, J. B. (1974). On the assessment of risk: Some further considerations. *The Journal of Finance*, 29(5):1491–1494.

Bali, T. G., Engle, R. F., and Tang, Y. (2016). Dynamic conditional beta is alive and well in the cross section of daily stock returns. *Management Science*, 63(11):3760–3779.

Bandi, F. M. and Russell, J. R. (2005). Realized covariation, realized beta and microstructure noise. *Unpublished paper, Graduate School of Business, University of Chicago*.

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of financial economics*, 9(1):3–18.

Barndorff-Nielsen, O. E., Hansen, P. R., Lunde, A., and Shephard, N. (2011). Multivariate realised kernels: consistent positive semi-definite estimators of the covariation of equity prices with noise and non-synchronous trading. *Journal of Econometrics*, 162(2):149–169.

Barndorff-Nielsen, O. E. and Shephard, N. (2004). Econometric analysis of realized covariation: High frequency based covariance, regression, and correlation in financial economics. *Econometrica*, 72(3):885–925.

Basu, S. (1977). Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis. *The journal of Finance*, 32(3):663–682.

Basu, S. (1983). The relationship between earnings' yield, market value and return for nyse common stocks: Further evidence. *Journal of financial economics*, 12(1):129–156.

Berkman, H., Koch, P. D., Tuttle, L., and Zhang, Y. (2009). Dispersion of opinions, short sale constraints, and overnight returns. *University of Auckland, University of Kansas, American University of Sharjah, Dubai, and Missouri State University Working Paper*.

Bhandari, L. C. (1988). Debt/equity ratio and expected common stock returns: Empirical evidence. *The Journal of Finance*, 43(2):507–528.

Black, A., Fraser, P., and Power, D. (1992). Uk unit trust performance 1980–1989: A passive time-varying approach. *Journal of Banking & Finance*, 16(5):1015–1033.

Black, F. (1972). Capital market equilibrium with restricted borrowing. *The Journal of business*, 45(3):444–455.

Blair, B. J., Poon, S.-H., and Taylor, S. J. (2010). Forecasting s&p 100 volatility: the incremental information content of implied volatilities and high-frequency index returns. In *Handbook of Quantitative Finance and Risk Management*, pages 1333–1344. Springer.

Blume, M. E. (1970). Portfolio theory: a step toward its practical application. *The Journal of Business*, 43(2):152–173.

Blume, M. E. (1975). Betas and their regression tendencies. *The Journal of Finance*, 30(3):785–795.

Bodurtha, J. N. and Mark, N. C. (1991). Testing the capm with time-varying risks and returns. *The Journal of Finance*, 46(4):1485–1505.

Bogousslavsky, V. (2016). The cross-section of intraday and overnight returns. *Browser Download This Paper*.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of econometrics*, 31(3):307–327.

Bollerslev, T. (1990). Modelling the coherence in short-run nominal exchange rates: a multivariate generalized arch model. *The review of economics and statistics*, pages 498–505.

Bollerslev, T., Engle, R. F., and Wooldridge, J. M. (1988). A capital asset pricing model with time-varying covariances. *The Journal of Political Economy*, pages 116–131.

Bollerslev, T., Tauchen, G., and Zhou, H. (2009). Expected stock returns and variance risk premia. *Review of Financial studies*, 22(11):4463–4492.

Bos, T. and Newbold, P. (1984). An empirical investigation of the possibility of stochastic systematic risk in the market model. *Journal of Business*, pages 35–41.

Bowman, A. W. (1984). An alternative method of cross-validation for the smoothing of density estimates. *Biometrika*, 71(2):353–360.

Branch, B. and Ma, A. (2012). Overnight return, the invisible hand behind intraday returns? *Journal of Applied Finance*, 22(2):90.

Branch, B. S. and Ma, A. (2006). The overnight return, one more anomaly. *Available at SSRN: https://ssrn.com/abstract=937997 or http://dx.doi.org/10.2139/ssrn.937997*.

Braun, P. A., Nelson, D. B., and Sunier, A. M. (1995). Good news, bad news, volatility, and betas. *The Journal of Finance*, 50(5):1575–1603.

Brooks, R. D., Faff, R., and McKenzie, M. (2002). Time varying country risk: An assessment of alternative modelling techniques. *The European Journal of Finance*, 8(3):249–274.

Brooks, R. D., Faff, R. W., and Lee, J. H. (1992). The form of time variation of systematic risk: Some australian evidence. *Applied Financial Economics*, 2(4):191–198.

Brooks, R. D., Faff, R. W., and McKenzie, M. D. (1998). Time-varying beta risk of australian industry portfolios: A comparison of modelling techniques. *Australian journal of management*, 23(1):1–22.

Campbell, J. Y. (2000). Asset pricing at the millennium. *The Journal of Finance*, 55(4):1515–1567.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of finance*, 52(1):57–82.

Chan, L. K. and Lakonishok, J. (1992). Robust measurement of beta risk. *Journal of financial and quantitative analysis*, 27(02):265–282.

Choudhry, T. (2002). The stochastic structure of the time–varying beta: Evidence from uk companies. *The Manchester School*, 70(6):768–791.

Choudhry, T. (2005). Time-varying beta and the asian financial crisis: Evidence from malaysian and taiwanese firms. *Pacific-Basin Finance Journal*, 13(1):93–118.

Choudhry, T. and Wu, H. (2008). Forecasting ability of garch vs kalman filter method: evidence from daily uk time-varying beta. *Journal of Forecasting*, 27(8):670–689.

Cloete, G., de Jonah, P., and De Wet, T. (2002). Combining vasicek and robust estimators for forecasting systematic risk. *Investment Analysts Journal*, 31(55):37–44.

Collins, D. W., Ledolter, J., and Rayburn, J. (1987). Some further evidence on the stochastic properties of systematic risk. *Journal of Business*, pages 425–448.

Cooper, M. J., Cliff, M. T., and Gulen, H. (2008). Return differences between trading and non-trading hours: Like night and day. *Working Paper. Available at SSRN: https://ssrn.com/abstract=1004081 or http://dx.doi.org/10.2139/ssrn.1004081*.

Darolles, S., Francq, C., and Laurent, S. (2018). Asymptotics of cholesky garch models and time-varying conditional betas. *Journal of Econometrics*, 204(2):223–247.

De Santis, G., Gerard, B., et al. (1997). International asset pricing and portfolio diversification with time-varying risk. *Journal of Finance*, 52(5):1881–1912.

Doidge, C., Karolyi, G. A., and Stulz, R. M. (2017). The us listing gap. *Journal of Financial Economics*, 123(3):464–487.

Ebens, H. et al. (1999). Realized stock volatility. *Department of Economics, Johns Hopkins University*.

Ebner, M. and Neumann, T. (2005). Time-varying betas of german stock returns. *Financial Markets and Portfolio Management*, 19(1):29–46.

Elton, E. J., Gruber, M. J., Brown, S. J., and Goetzmann, W. N. (2009). *Modern portfolio theory and investment analysis*. John Wiley & Sons.

Engel, C. and Rodrigues, A. P. (1989). Tests of international capm with time-varying covariances. *Journal of Applied Econometrics*, 4(2):119–138.

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, 20(3):339–350.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of united kingdom inflation. *Econometrica: Journal of the Econometric Society*, pages 987–1007.

Engle, R. F. (2016). Dynamic conditional beta. *Journal of Financial Econometrics*, 14(4):643–667.

Esteban, M. V. and Orbe-Mandaluniz, S. (2010). A nonparametric approach for estimating betas: the smoothed rolling estimator. *Applied Economics*, 42(10):1269–1279.

Faff, R. W., Hillier, D., and Hillier, J. (2000). Time varying beta risk: An analysis of alternative modelling techniques. *Journal of Business Finance & Accounting*, 27(5-6):523–554.

Fama, E. F., Fisher, L., Jensen, M. C., and Roll, R. (1969). The adjustment of stock prices to new information. *International economic review*, 10(1):1–21.

Fama, E. F. and French, K. R. (1992). The cross-section of expected stock returns. *the Journal of Finance*, 47(2):427–465.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of financial economics*, 33(1):3–56.

Fama, E. F. and French, K. R. (1995). Size and book-to-market factors in earnings and returns. *The journal of finance*, 50(1):131–155.

Fama, E. F. and French, K. R. (2004). The capital asset pricing model: Theory and evidence. *The Journal of Economic Perspectives*, 18(3):25–46.

Fama, E. F. and MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *The journal of political economy*, pages 607–636.

Fang, H. and Lai, T.-Y. (1997). Co-kurtosis and capital asset pricing. *Financial Review*, 32(2):293–307.

Ferreira, E., Gil-Bazo, J., and Orbe, S. (2011). Conditional beta pricing models: A nonparametric approach. *Journal of Banking & Finance*, 35(12):3362–3382.

Foster, D. P. and Nelson, D. B. (1994). Continuous record asymptotics for rolling sample variance estimators.

Frazzini, A. and Pedersen, L. H. (2014). Betting against beta. *Journal of Financial Economics*, 111(1):1–25.

French, K. R. and Roll, R. (1986). Stock return variances: The arrival of information and the reaction of traders. *Journal of financial economics*, 17(1):5–26.

Fuertes, A.-M. and Olmo, J. (2013). Optimally harnessing inter-day and intra-day information for daily value-at-risk prediction. *International Journal of Forecasting*, 29(1):28–42.

Gallo, G. M. (2001). Modelling the impact of overnight surprises on intra-daily volatility. *Australian Economic Papers*, 40(4):567–580.

Gao, H. and Yao, H. (2004). Shape insensitive optimal adhesion of nanoscale fibrillar structures. *Proceedings of the National Academy of Sciences of the United States of America*, 101(21):7851–7856.

Genton, M. G. and Ronchetti, E. (2008). Robust prediction of beta. In *Computational Methods in Financial Engineering*, pages 147–161. Springer.

Giannopoulos, K. (1995). Estimating the time varying components of international stock markets' risk. *The European Journal of Finance*, 1(2):129–164.

Goyal, A. (2012). Empirical cross-sectional asset pricing: a survey. *Financial Markets and Portfolio Management*, 26(1):3–38.

Güner, N. and Önder, Z. (2002). Information and volatility: Evidence from an emerging market. *Emerging Markets Finance & Trade*, pages 26–46.

Hansen, P. R. and Lunde, A. (2004). An unbiased measure of realized variance. *Available at SSRN 524602*.

Hansen, P. R. and Lunde, A. (2005). A realized variance for the whole day based on intermittent high-frequency data. *Journal of Financial Econometrics*, 3(4):525–554.

Harvey, C. R. and Siddique, A. (2000). Conditional skewness in asset pricing tests. *The Journal of Finance*, 55(3):1263–1295.

Hawawini, G. A., Michel, P. A., and Corhay, A. (1985). New evidence on beta stationarity and forecast for belgian common stocks. *Journal of Banking & Finance*, 9(4):553–560.

Heston, S. L., Korajczyk, R. A., and Sadka, R. (2010). Intraday patterns in the cross-section of stock returns. *The Journal of Finance*, 65(4):1369–1407.

Hillier, J. (2002). The stochastic properties of systematic risk for us mutual funds. *EFMA 2002*.

Hull, J. (2012). *Risk Management and Financial Institutions,+ Web Site*, volume 733. John Wiley & Sons.

Hwang, S. and Satchell, S. E. (1999). Modelling emerging market risk premia using higher moments. *Return Distributions in Finance*, 75.

Jagannathan, R., Schaumburg, E., and Zhou, G. (2010a). Cross-sectional asset pricing tests. *Annu. Rev. Financ. Econ.*, 2(1):49–74.

Jagannathan, R., Skoulakis, G., and Wang, Z. (2010b). The analysis of the cross section of security returns. *Handbook of financial econometrics*, 2:73–134.

Jagannathan, R. and Wang, Z. (1996). The conditional capm and the cross-section of expected returns. *The Journal of finance*, 51(1):3–53.

Jensen, M. C. (1968). The performance of mutual funds in the period 1945–1964. *The Journal of finance*, 23(2):389–416.

Jensen, M. C., Black, F., and Scholes, M. S. (1972). The capital asset pricing model: Some empirical tests.

Jiang, C. (2011). On the robustness of beta risk in the cross-sectional regressions of stock return. *Working paper*.

Kahle, K. M. and Stulz, R. M. (2017). Is the us public corporation in trouble? *Journal of Economic Perspectives*, 31(3):67–88.

Kelly, M. A. and Clark, S. P. (2011). Returns in trading versus non-trading hours: The difference is day and night. *Journal of Asset Management*, 12(2):132–145.

Klemkosky, R. C. and Martin, J. D. (1975). The adjustment of beta forecasts. *The journal of Finance*, 30(4):1123–1128.

Koopman, S. J., Jungbacker, B., and Hol, E. (2005). Forecasting daily variability of the s&p 100 stock index using historical, realised and implied volatility measurements. *Journal of Empirical Finance*, 12(3):445–475.

Kraus, A. and Litzenberger, R. H. (1976). Skewness preference and the valuation of risk assets. *The Journal of Finance*, 31(4):1085–1100.

Lettau, M. and Ludvigson, S. (2001a). Consumption, aggregate wealth, and expected stock returns. *the Journal of Finance*, 56(3):815–849.

Lettau, M. and Ludvigson, S. (2001b). Resurrecting the (c) capm: A cross-sectional test when risk premia are time-varying. *Journal of Political Economy*, 109(6):1238–1287.

Levy, R. A. (1971). On the short-term stationarity of beta coefficients. *Financial Analysts Journal*, 27(6):55–62.

Lewellen, J. and Nagel, S. (2006). The conditional capm does not explain asset-pricing anomalies. *Journal of financial economics*, 82(2):289–314.

Li, X. (2003). On unstable beta risk and its modelling techniques for new zealand industry portfolios. *Massey University Commerce Working Paper*.

Li, Y. and Yang, L. (2011). Testing conditional factor models: A nonparametric approach. *Journal of Empirical Finance*, 18(5):972–992.

Lie, F., Brooks, R., and Faff, R. (2000). Modelling the equity beta risk of australian financial sector companies. *Australian economic papers*, 39(3):301–311.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The review of economics and statistics*, pages 13–37.

Linton, O. B. and Wu, J. (2017). A coupled component garch model for intraday and overnight volatility.

Liu, C. and Maheu, J. M. (2009). Forecasting realized volatility: a bayesian model-averaging approach. *Journal of Applied Econometrics*, 24(5):709–733.

Liu, Q. (2003). Estimating betas from high-frequency data. *Unpublished manuscript, Northwestern University*.

Lockwood, L. J. and Linn, S. C. (1990). An examination of stock market return volatility during overnight and intraday periods, 1964–1989. *The Journal of Finance*, 45(2):591–601.

Luoma, M., Martikainen, T., and Perttunen, J. (1996). A pseudo criterion for security betas in the finnish stock market. *Applied Economics*, 28(1):65–69.

Mallows, C. L. (1973). Some comments on c p. *Technometrics*, 15(4):661–675.

Martens, M. (2002). Measuring and forecasting s&p 500 index-futures volatility using high-frequency data. *Journal of Futures Markets*, 22(6):497–518.

Martin, R. D. and Simin, T. T. (2003). Outlier-resistant estimates of beta. *Financial Analysts Journal*, 59(5):56–69.

McClain, K. T., Humphreys, H. B., and Boscan, A. (1996). Measuring risk in the mining sector with arch models with important observations on sample size. *Journal of Empirical Finance*, 3(4):369–391.

Mergner, S. and Bulla, J. (2008). Time-varying beta risk of pan-european industry portfolios: A comparison of alternative modeling techniques. *The European Journal of Finance*, 14(8):771–802.

Merton, R. C. (1973). An intertemporal capital asset pricing model. *Econometrica: Journal of the Econometric Society*, pages 867–887.

Mossin, J. (1966). Equilibrium in a capital asset market. *Econometrica: Journal of the econometric society*, pages 768–783.

Murray, L. (1995). An examination of beta estimation using daily irish data. *Journal of Business Finance & Accounting*, 22(6):893–906.

Nieto, B., Orbe, S., and Zarraga, A. (2014). Time-varying market beta: does the estimation methodology matter? *SORT-Statistics and Operations Research Transactions*, 38(1):13–42.

Patton, A. J. and Verardo, M. (2012). Does beta move with news? firm-specific information flows and learning about profitability. *Review of Financial Studies*, 25(9):2789–2839.

Polk, C., Lou, D., and Skouras, S. (2018). A tug of war: overnight versus intraday expected returns. *Journal of Financial Economics*.

Pong, S., Shackleton, M. B., Taylor, S. J., and Xu, X. (2004). Forecasting currency volatility: A comparison of implied volatilities and ar (fi) ma models. *Journal of Banking & Finance*, 28(10):2541–2563.

Pooter, M. d., Martens, M., and Dijk, D. v. (2008). Predicting the daily covariance matrix for s&p 100 stocks using intraday databut which frequency to use? *Econometric Reviews*, 27(1-3):199–229.

Robinson, P. M. (1989). Nonparametric estimation of time-varying parameters. In *Statistical Analysis and Forecasting of Economic Structural Change*, pages 253–264. Springer.

Roenfeldt, R. L., Griepentrog, G. L., and Pflaum, C. C. (1978). Further evidence on the stationarity of beta coefficients. *Journal of Financial and Quantitative Analysis*, 13(01):117–121.

Roll, R. (1977). A critique of the asset pricing theory's tests part i: On past and potential testability of the theory. *Journal of financial economics*, 4(2):129–176.

Roll, R. and Ross, S. A. (1994). On the cross-sectional relation between expected returns and betas. *The Journal of Finance*, 49(1):101–121.

Rosenberg, B., Reid, K., and Lanstein, R. (1985). Persuasive evidence of market inefficiency. *The Journal of Portfolio Management*, 11(3):9–16.

Ross, S. A. (1977). The capital asset pricing model (capm), short-sale restrictions and related issues. *The Journal of Finance*, 32(1):177–183.

Rudemo, M. (1982). Empirical choice of histograms and kernel density estimators. *Scandinavian Journal of Statistics*, pages 65–78.

Ruppert, D., Sheather, S. J., and Wand, M. P. (1995). An effective bandwidth selector for local least squares regression. *Journal of the American Statistical Association*, 90(432):1257–1270.

Ryu, A. (2011). Beta estimation using high frequency data. *Available on the Internet: https://econ.duke.edu/uploads/assets/Ryu.pdf.*

Sarker, M. R. (2013). Forecast ability of the blumes and vasiceks technique: Evidence from bangladesh. *Journal of Business and Management*, 9(6):22–27.

Shalit, H. and Yitzhaki, S. (2002). Estimating beta. *Review of Quantitative Finance and Accounting*, 18(2):95–118.

Shanken, J. (1990). Intertemporal asset pricing: An empirical investigation. *Journal of Econometrics*, 45(1-2):99–120.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The journal of finance*, 19(3):425–442.

Sharpe, W. F. (1971). Mean-absolute-deviation characteristic lines for securities and portfolios. *Management Science*, 18(2):B–1.

Sheather, S. J. and Jones, M. C. (1991). A reliable data-based bandwidth selection method for kernel density estimation. *Journal of the Royal Statistical Society. Series B (Methodological)*, pages 683–690.

Shiller, R. J., Fischer, S., and Friedman, B. M. (1984). Stock prices and social dynamics. *Brookings papers on economic activity*, 1984(2):457–510.

Silverman, B. W. (1986). *Density estimation for statistics and data analysis*, volume 26. CRC press.

Stattman, D. (1980). Book values and stock returns. *The Chicago MBA: A journal of selected papers*, 4(1):25–45.

Subrahmanyam, A. (2010). The cross-section of expected stock returns: What have we learnt from the past twenty-five years of research? *European Financial Management*, 16(1):27–42.

Taylor, S. J. and Xu, X. (1997). The incremental volatility information in one million foreign exchange quotations. *Journal of Empirical Finance*, 4(4):317–340.

Todorov, V. and Bollerslev, T. (2010). Jumps and betas: A new framework for disentangling and estimating systematic risks. *Journal of Econometrics*, 157(2):220–235.

Tofallis, C. (2008). Investment volatility: A critique of standard beta estimation and a simple way forward. *European Journal of Operational Research*, 187(3):1358–1367.

Tsai, K.-T., Lih, J.-S., and Ko, J.-Y. (2012). The overnight effect on the taiwan stock market. *Physica A: Statistical Mechanics and its Applications*, 391(24):6497–6505.

Vasicek, O. A. (1973). A note on using cross-sectional information in bayesian estimation of security betas. *The Journal of Finance*, 28(5):1233–1239.

Wang, F., Shieh, S.-J., Havlin, S., and Stanley, H. E. (2009). Statistical analysis of the overnight and daytime return. *Physical Review E*, 79(5):056109.

Wells, C. (1994). Variable betas on the stockholm exchange 1971-1989. *Applied Financial Economics*, 4(1):75–92.