Systematic risk and market microstructure in a market under conditions of economic crisis. The case of the Athens Stock Exchange.

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Abstract

The objective of this task is to examine the estimation of systematic risk (often called Beta coefficient) in its relation to some market microstructure phenomena such as thin trading, the so-called intervalling effect, and the effect of changing the starting period in calculating asset returns in a capital market under conditions of economic crisis. The data under consideration are daily closing prices of stocks traded at the Athens Stock Exchange (ASE) covering the period 25/09/2012 – 22/09/2017. That period was particularly intense on the economic and political front of the country, considering the acute economic crisis that was over Greece, thus depicting a turbulent image of the ASE.

It is therefore of particular interest, amongst others, to examine the validity of some stylized facts regarding the effect of friction in the trading process on the estimation of betas for the underlying period of this study. More concretely, the price adjustment delays resulting from friction in the trading process causes beta estimates not to be invariant but to change systematically with respect to the differencing interval over which asset and market index returns are calculated (“intervalling effect”). Furthermore, the abovementioned bias in betas is higher for thinner firms.

Another effect that has been noticed in previous studies and also related with the estimation of systematic risk is the one that arises for the same differencing interval but a different starting day (henceforth “Corhay effect”), but the importance of this phenomenon yet has not been sufficiently assessed quantitatively.

The current study provides evidence for the following: (a) The Corhay effect is intense and fortified further as the differencing interval is lengthened; (b) The
intervalling effect is extremely weak, if any, although it was found strong for the same market at previous time periods; (c) low cap stocks expose clearly stronger Corhay effect as compared to large cap stocks; (d) Corhay effect overwhelmingly dominates over the intervalling effect and it is the determining factor of changes in betas; (e) The importance of the Corhay phenomenon has not been properly assessed in the published research thus far, as it is either ignored completely or smoothed away by taking average betas for the same differencing interval but different starting period.
Περίληψη

Στόχος αυτής της μελέτης είναι η εξέταση της εκτίμησης του συστηματικού κινδύνου (συχνά παρατίθεται ως συντελεστής Βήτα) σε σχέση με μερικά από τα φαινόμενα που σχετίζονται με την μικροδομή της αγοράς, ιδίας δε στην τριβή στις συναλλαγές, η μικρή εμπορευσιμότητα των μετοχών, το επονομαζόμενο «`intervalling effect» και το φαινόμενο που προκαλείται από την αλλαγή της ημέρας εκκίνησης στον υπολογισμό των αποδόσεων κρατώντας σταθερό το μέγεθος αυτού του διαστήματος σε μία αγορά υπό συνθήκες κρίσης.

Τα δεδομένα είναι τιμές κλεισίματος μετοχών που διαπραγματεύονται στο Χρηματιστήριο Αξιών Αθηνών (ΧΑΑ) κατά την περίοδο 25/09/2012 – 22/09/2017. Αυτή η περίοδος υπήρξε ιδιαίτερα έντονη στο οικονομικό-πολιτικό προσκήνιο της χώρας, λαμβάνοντας υπόψη την έντονη οικονομική κρίση στην οποία βρισκόταν η Ελλάδα, αποτυπώνοντας λοιπόν μία ταραχή εικόνα για το ΧΑΑ.

Αποτελεί ιδιαίτερου ενδιαφέροντος, μεταξύ άλλων, η εξέταση φαινομένων που έχουν παρατηρηθεί σε προηγούμενες μελέτες και σχετίζονται με το πως επιδρά η τριβή στις συναλλαγές στις εκτιμήσεις των συντελεστών Βήτα, ως προς την ισχύ τους και για το χρονικό διάστημα που διεξάγεται η συγκεκριμένη μελέτη. Πιο συγκεκριμένα, οι καθυστερήσεις στην αναπροσαρμογή των τιμών που προκύπτουν από την τριβή στις συναλλαγές έχουν ως επακόλουθο τη συστηματική μεταβολή των τιμών των συντελεστών Βήτα με το διάστημα υπολογισμού των αποδόσεων («`intervalling effect»). Επιπλέον, η μεροληψία αυτή στις εκτιμήσεις είναι μεγαλύτερη για μετοχές με μικρότερη εμπορευσιμότητα.
Ένα άλλο φαινόμενο που έχει παρατηρηθεί σε προηγούμενες μελέτες και σχετίζεται με την εκτίμηση του συστηματικού κινδύνου είναι αυτό που προκύπτει για το ίδιο διάστημα υπολογισμού των αποδόσεων αλλά για διαφορετική ημέρα εκκίνησης (από εδώ και έπειτα θα λέγεται «Corhay effect» ή αποτέλεσμα διαφορετικής ημερομηνίας έναρξης υπολογισμού αποδόσεων), η σημαντικότητα του οποίου όμως δεν έχει μέχρι στιγμής εκτιμηθεί επαρκώς.

Η συγκεκριμένη μελέτη συμβάλλει ερευνητικά στα ακόλουθα: (α) Το Corhay Effect είναι ιδιαίτερα έντονο και ενισχύεται περαιτέρω καθώς το διάστημα υπολογισμού των αποδόσεων μεγενθύνεται (β) Το intervalling effect είναι ιδιαίτερα αδύναμο, πρακτικά δεν υπάρχει, παρ’ όλο που ήταν έντονο για την ίδια αγορά σε προηγούμενες χρονικές περιόδους (γ) Η μικρότερης κεφαλαιοποίησης μετοχές παρουσίάζουν εντονότερο Corhay effect σε σχέση με τις μετοχές μεγαλύτερης κεφαλαιοποίησης (δ) Το Corhay effect κυριαρχεί έναντι του intervalling effect και αποτελεί τον καθοριστικό παράγοντα για τις αλλαγές στις τιμές (ε) Η σημασία του Corhay effect δεν έχει εκτιμηθεί κατάλληλα μέχρι στιγμής στις ήδη δημοσιευμένες μελέτες (κατ’ ακρίβεια η σημασία του έχει υποτιμηθεί), καθώς είτε ανοίγεται εντελώς, είτε εξομαλύνεται λαμβάνοντας το μέσο όρο των εκτιμήσεων για το ίδιο διάστημα υπολογισμού των αποδόσεων αλλά για διαφορετική ημέρα εκκίνησης.
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Chapter 1

1. Introduction

One of the most important issues in finance is the relation between risk and return. This is in fact the most widely discussed topic of research for many decades with a lot of studies presenting their arguments regarding the proposed models of pricing assets. The unstable economic conditions especially in Greece but also world-wide underlying the importance of the accurate measurement of risk.

The first model to explain the relation between expected return and risk was the Capital Asset Pricing Model (CAPM). The CAPM (Jack Treynor, 1962; Sharpe, 1964; Lintner, 1965a,b; Jan Mossin, 1966) marks the birth of asset pricing theory. This model is based on the idea that not all risk should affect asset prices and especially provides insight into the kind of risk that is related to return. The model provides a methodology for translating risk into expected returns. The CAPM is considered the backbone of modern price theory for financial markets. The CAPM was built up on the Modern Portfolio Theory (MPT) developed by Markowitz in 1952. The MPT is a theory on how risk-averse investors can construct portfolios to maximize the expected return based on a given level of risk, emphasizing that risk is an inherent part of higher reward. It was intended to illuminate idiosyncratic risk which is the risk inherent in a particular investment due to its unique characteristics. Markowitz’s work on portfolio theory may be regarded as having established financial micro analysis as a respectable research area in economic analysis. The very important studies of Markowitz and
Sharpe were milestones of the modern financial analysis and some years later they were awarded with the Nobel Prize (1990).

Over the years the CAPM has been tested in empirical studies for the credibility of its results dividing many times the scientific community. There is a large literature on the ability of the CAPM to explain the observed returns and there are serious specification issues about the explanatory power of the single – factor model on the expected returns proposing a conditional version of the CAPM (Fama and French , 1992, 1993, 1996, Milionis and Patsouri 2011). For plenty of reasons (Jaganathan and Wang , 1996; Elton et al., 2007, Milionis and Patsouri, 2011) the beta coefficient (the historical measure of the systematic risk which is used in the CAPM) is still the most widely used measure of systematic risk by analysts and financial managers and the CAPM is still widely used on applications.
Chapter 2

2. Description of the model

2.1 What exactly is the CAPM?

The Capital Asset Pricing Model (CAPM) is a model that describes the relationship between expected return and systematic risk inherent in a security’s investment. Practically, the CAPM is used to determine a theoretically appropriate rate of return of an asset, in order to decide whether it is worth or not to add this asset in an already well-diversified portfolio. The systematic risk or market risk is the non-diversifiable risk which is described by the beta coefficient (β). The formula of the CAPM model is the following:

\[ E(R_j) = R_F + \beta_j [E(R_m) - R_F] \]  

(1)

Where, \( R_j \) is the return on the security \( j \), \( R_F \) is the risk-free return which is usually arising from government bonds, \( R_m \) is the return on the market index and \( \beta_j \) is the beta coefficient for security \( j \).

The general idea of the CAPM is that investors should be compensated in two ways: time value of money and risk. The time value of money is represented by the risk free rate (\( R_F \)) in the formula and compensates the investor for placing money in any investment over a period of time. The other half of the formula represents risk and computes the amount of compensation the investor needs for taking on additional risk. This is accomplished by taking a stocks beta, which measures a stock’s volatility in relation to market volatility, and multiplying to risk premium. The risk premium is
calculated by subtracting the risk free rate of return from the expected return of the market, which is represented by a market’s index. So this premium is typically the reward for the excess risk.

2.2 CAPM assumptions

The CAPM is often criticized as being unrealistic because of its assumptions. It is therefore reasonable to quote the assumptions on which it is based on and see why they are criticized.

First, there is the assumption that the investors hold diversified portfolios. This assumption states that investors are only requiring return for the risk that they cannot diversify away, the systematic risk of their portfolio, since unsystematic has been removed and can be ignored. Another one is about the time horizon of the transactions. It states that there is a single holding period in order to make comparable the returns on different securities. Usually a holding period of one year it is used. Consequently it is assumed that investors can borrow and lend at the risk-free rate of return. This is an assumption made from portfolio theory, from which the CAPM was developed, and gives a minimum level of return required by investors.

In fact it is not possible for investors to borrow in the risk-free rate because the risk associated with individual investors is much bigger than that associated with the Government. The CAPM also assumes that there is a perfect capital market. A perfect capital market requires that there are no taxes and transaction costs, that all information is freely available to all investors who as a result have the same expectations, that all investors are risk averse, rational and want to maximize their
utility and that there are a large number of buyers and sellers in the market so no one participant can influence the market.

All these assumptions made by the CAPM although there are not respond to the real world in which investment decisions are made from individuals and companies does allow it to focus on the relationship between return and systematic risk.

### 2.3 Beta coefficient ($\beta$)

In finance the beta coefficient of an investment indicates whether the investment is more or less volatile in comparison to the market as a whole. Beta is a measure of the risk arising from exposure to general market movements, the so called systematic risk, non-diversifiable risk or market risk. Large changes to macroeconomic variables such as interest rates, inflation, foreign exchange, wars, natural disasters, broad changes to government policies and general events that cannot be planned for or avoided are changes that impact the broader market and cannot be avoided or reduced through diversification. Beta is a historical measure which is used in the CAPM model in order to provide estimates of the expected returns of an asset or a portfolio based on its beta and expected market returns. Beta risk is the only kind of risk for which investors should receive an expected return higher that the risk free rate of interest. The Beta coefficient is mathematically defined from the following equation for an asset $i$:

$$\beta_j = \frac{Cov(R_j, R_m)}{Var(R_m)}$$
Since the Beta coefficient measures the degree of exposure of an asset to the market risk it is obvious that the market portfolio of all investable assets has a Beta of exactly 1. A Beta below 1 indicates a lower volatility than the market. These stocks are called defensive and practically if the market returns change by one percentage point the stocks returns will move in the same direction as the market but with a lower percentage change. A Beta greater than 1 generally means that the asset is both volatile and tends to move up and down with the market. More specifically these stocks are called aggressive and they tend to outperform when the market is strong and fall further when the market declines. Negative Betas are possible for investments that tend to go down when the market goes up, and vice versa.

We can obtain beta estimates from the CAPM model by regressing \( R_j - R_F \) on \( R_m - R_F \). The most direct way though of predicting the values of Beta coefficient is estimates using historical data. These estimates result with the Ordinary Least Square method using the so-called Market Model (MM). The Market Model (MM) or Single Index Model (SIM) is a simple asset pricing model to measure both the risk and the return of an asset. The model has been developed by William Sharpe in 1963 and is commonly used in finance. Mathematically the SIM is expressed as:

\[
R_j - R_F = \alpha_j + \beta_j (R_m - R_F) + u_j
\]

According to this model, the return of a stock can be analyzed into the expected excess return of the individual stock due to firm-specific factors, commonly denoted by its alpha coefficient (\( \alpha \)), the return due to macroeconomic events that affect the market, and the unexpected microeconomic events that affect only the firm. The term \( \beta_j (R_m - R_F) \) represents the market movement modified by the stock's Beta and the \( u_j \) denotes
the unsystematic risk of the security j due to firm-specific factors. Firm-specific events are the unexpected microeconomic events that affect the returns of specific firms.

For realistic changes in the value of the risk free rate ($R_f$), there is very little difference in the estimations of Beta, typically in the third decimal place. So, the MM is expressed as follows:

$$R_j = a_j + \beta_j R_m + u_j$$  \hspace{1cm} (2)

where, $u_j$ is the stochastic disturbance and $a_j$ is a constant which measures the change in $R_j$ that is independent of a change in $R_m$. So, practically Betas are obtained by regressing the $R_j$ on $R_m$. According to this model neither $\alpha$ nor $\beta$ depend on the length of the differencing interval used to calculate the returns. The estimates of $\alpha$ and $\beta$ are strongly dependent on the differencing interval as we will analyze bellow.

The basic difference between CAPM model and MM model is that the first is formulated in terms of expectations which are not observable while the second one is based on observations. Assuming that realized returns are on the average equal to the observed ones, we can use the observed returns. Thus, we use for convenience the equation (2) for estimating betas.
Chapter 3

3.1 Theoretical background

In a frictionless market and under the usual MM assumptions Beta estimates should be invariant with the length of the measurement interval. However, a plethora of empirical evidence (Corhay, 1991; Cohen et al., 1983a; Scholes and Williams, 1977; Dimson, 1979) have established that MM Beta estimates vary systematically with the length of the measurement interval (differencing interval) which is used to calculate the index and securities returns. This phenomenon is known as the “intervalling effect”.

Another phenomenon related to the differencing interval is the “Starting day effect” or “Corhay effect”, which is observed for the same differencing interval but for a different starting period. More specifically, the selection of values for a given differencing interval \(L\) in order to calculate the returns is a repeating procedure performed \(L\) times and the first value of each repetition for every differencing interval is deducted. So, for a differencing interval of size \(L\), \(L\) estimates are obtained.

The two abovementioned phenomena are lead to biased estimations of Beta coefficients and result to a wrong assessment of a security’s risk. From previous studies researchers noticed that there is an intervalling effect that affects the estimations of the systematic risk. As for the starting day effect, the importance of this phenomenon has not been sufficiently assessed quantitatively, as it is either completely ignored (Cohen et al., 1984) or, at best, it is smoothed away by taking the average of estimations (Milionis, 2010; 2011).
The characteristic of market microstructure related to the influence of differencing interval in Beta estimations is the friction in the trading process which is caused among others from information and transaction costs. This friction is responsible for the price adjustment delays (Cohen et al., 1983b). Due to the friction in the trading process true returns, which would be observed in a frictionless market, cannot be obtained. The changes in true returns are faster than in observed returns, so in each time period only a part of the true returns incorporated in the observed ones. The abovementioned can be expressed quantitatively by the following model which connects the observed returns ($R^o_{jt}$) with the true returns ($R_j$) and was proposed by Cohen et al. (1983b):

$$R^o_{jt} = \sum_{n=0}^{N} y_{j,t-n,n}R_{j,t-n}$$

With, $E(\sum_{n=0}^{\infty} y_{j,t,n}) = 1 \ \forall j,t$

Where, $y_{j,t-n,n}$ are random variables representing the portion of true returns of security j at time $t - n$ which is reflected in observed returns at time $t$.

So the MM for the true returns and the observed returns respectively is written as:

$$R_{jt} = a_j + \beta_j R_{mt} + u_{jt}$$

$$R^o_{jt} = a^o_j + \beta^o_j R^o_{mt} + u^o_{jt}$$

where $\beta_j$ and $\beta^o_j$ express the systematic risk for the true and the observed returns respectively. The $\beta_j$ and $\beta^o_j$ are related through the following equation (Cohen et al., 1983b):
\[ \beta_j^o = \beta_j (1 + 2 \sum_{n=1}^{N} \beta_{m+n}^o) - \sum_{n=1}^{N} (\beta_{j+n}^o + \beta_{j-n}^o) \]  \quad (3) 

Where, 

\[ \beta_{m+n}^o = \frac{\text{Cov}(R_{m,t+n}^oR_{m,t}^o)}{\text{Var}(R_{m,t}^o)}, \quad \beta_{j \pm n}^o = \frac{\text{Cov}(R_{j \pm n,t}R_{m,t}^o)}{\text{Var}(R_{m,t}^o)} \]

From the equation (3) it is obvious that Beta for the observed returns depends on the Beta for the true returns, on the autocorrelations of the stocks index up to order N and the cross-correlation among the observed returns of the security j and the market index m up to order N. Consequently, the OLSE of Beta for observed returns is an inconsistent estimator while \( \beta_j \) is a consistent estimator of the systematic risk. Provided that N is finite the same will apply for the lags in the readjustment of the values. So, the bias of the estimator will tend to decrease as the differencing interval is lengthened.

### 3.2 Purpose of the study

In this work, some stylized facts established from previous studies will be empirically tested. More specifically, the importance of the intervalling effect in a market under conditions of crisis will be assessed. Thereafter, the importance of the starting day effect in its own right, as well as in comparison to the intervalling effect will also be assessed. Subsequently, the potential effect of the capitalization value on the above will be evaluated. Finally, other features of Beta estimates related to market microstructure and the possible influence of the extreme conditions during the sampling period will be examined.
Chapter 4

4. Some information for the ASE

4.1 The turbulent sampling period

The period under study is very condensed in terms of economic – political events. Some of the most important events are the European and National elections, the failed attempts to elect a President of Democracy, the Referendum and the closure of the Banks and the ASE. These events are presented in Figure 1 along with the variation of the General index of the ASE, while many crucial events of the five years study period are presented in Table 1.

Figure 1. The Athens General Index movement during the sampling five years period.
Table 1. The most important economic – political events during the sampling period.

<table>
<thead>
<tr>
<th>Date</th>
<th>Event</th>
</tr>
</thead>
<tbody>
<tr>
<td>7/11/2012</td>
<td>Over vote medium term program 2013-2016</td>
</tr>
<tr>
<td>11/2013</td>
<td>Downgrade of the Athens Stock Exchange by MSCI (Emerging market)</td>
</tr>
<tr>
<td>25/5/2014</td>
<td>European elections (success of SYRIZA)</td>
</tr>
<tr>
<td>17/12/2014</td>
<td>Parliament failed to elect President of the Republic (First)</td>
</tr>
<tr>
<td>23/12/2014</td>
<td>Parliament failed to elect President of the Republic (Second)</td>
</tr>
<tr>
<td>29/12/2014</td>
<td>Parliament failed to elect President of the Republic (Third)</td>
</tr>
<tr>
<td>25/1/2015</td>
<td>National elections</td>
</tr>
<tr>
<td>20/2/2015</td>
<td>First agreement between the new (SYRIZA-ANEL) government and the lenders</td>
</tr>
<tr>
<td>29/6/2015</td>
<td>Imposition of bank holiday and restrictions on capital movements</td>
</tr>
<tr>
<td>5/7/2015</td>
<td>Referendum, Closure of banks and imposition of a takeover cash limit. Closure of the Athens Stock Exchange</td>
</tr>
<tr>
<td>14/8/2015</td>
<td>Resolution of the third memorandum</td>
</tr>
<tr>
<td>20/11/2015</td>
<td>Recapitalization of the banks</td>
</tr>
<tr>
<td>21/3/2016</td>
<td>Downgrade of the Athens Stock Exchange by FTSE</td>
</tr>
</tbody>
</table>
(Advanced Developing market)

*The list is indicative but not exhaustive

The extreme volatility of the General Index is even more apparent from Figure 2 where for the sampling period the variation of the Index in comparison to other three indices, the FTSE100, the DAX and the DOW JONES, is shown in standardized values.

Brief description of these indices: The FTSE100 is a share index of the 100 companies listed in the London Stock Exchange with the highest capitalization, the DAX is a blue chip stock market index consisting of the 30 major German companies trading on the Frankfurt Stock Exchange and the DOW JONES INDUSTRIAL AVERAGE (DJIA) is a price-weighted average of the 30 significant stocks traded on the New York Stock Exchange (NYSE).

Figure 2. The variation of the Athens Stock General Index in comparison to FTSE100, DAX and DJIA, using standardized values.
4.2 Value of Transactions of the ASE

The total value of transactions of the Athens Stock Exchange during the sampling period has ranged along its maximum value of 4.890.258.146,27 euro to its minimum value 662.965.713,41 euro. The variation of the total value of transactions per month of the ASE is presented in Figure 3 along with the movement of biggest stocks of the market, represented as Large Cap. Figure 4 represents the ratio of the value of transactions of Large Cap over total value of transactions for the market. From these two figures we observe that Large Cap stocks contribute a large part of the total stock market value of transactions. That means that the activity is concentrated in only a few large stocks.

Figure 3. Total value of transactions for ASE and Large Cap stocks.
Figure 4. The ratio of value of transactions of Large Cap stocks over the total value of transactions of the ASE.
Chapter 5

5. Empirical analysis

5.1 Data description

Two time scales important for the empirical determination of Beta coefficients are:

1. The total time interval covered by the data which is called the sampling time (T) and
2. The smoothing time that is the differencing interval which is used for the calculation of returns (L).

From a purely statistical approach in order to obtain accurate measurements we need a sampling time as much long as possible and a smoothing time as small as we can get. From a financial approach though the opposite is required. Taking a big T increases the probability in this time period for events such as acquisitions, mergers and other events that affect the Beta coefficient to occur. Furthermore, a small smoothing time increases the bias of the estimations as described before. The most common approach of most institutions is to use data for a five years period and monthly returns in order to estimate Beta coefficients.

The data are daily closing prices of stocks traded in the Main Market of the Athens Stock Exchange (ASE) during the five years period from 25/09/2012 to 22/09/2017. The ASE started trading in 1876. There are the following markets operating in the ASE:

1. Regulated Securities Markets
2. Alternative Market

The stocks of the Securities Market are divided into five categories:

1. Main Market
2. Low Dispersion,
3. Surveillance
4. Under Suspension
5. Under Deletion

From May 31 2001, the ASE joined the Mature Financial Markets according to the classification of Morgan Stanley Capital International (MSCI). Until that day the ASE belonged to the European Emerging Markets. In November 2013 the same institution downgraded the ASE in the Emerging Market. The ASE was also downgraded from the FTSE on March 21 2016 in the Advanced Developing Market. The current capitalization of the ASE is approximately 43 billion euros, further details about the ASE and its institutional and operational evolution are given in many papers (see for instance Milionis et al., 1998, Milionis and Papanagiotou, 2009).

Returns are expressed as the logarithmic difference of price relatives, using the unit differencing interval. The smoothing time is varied from one to thirty days. The Athens General Index (Gen) is used as the market index. The data were collected from the site www.naftemporiki.gr.
5.2 Methodological approach and results for the two phenomena

The empirical results of previous studies have shown that the effect of the differencing interval used to calculate the securities and market returns on the estimations of systematic risk for the same market but with a different smoothing time is quite intense.

More specifically, the Betas are obtained through regressions using as an independent variable the returns of the Gen and as a dependent variable the returns of each stock. The total number of stocks is 122, the stocks traded in the Main Market as mentioned before for the whole sampling time. As it is proven by Corhay in 1992 the estimations of Beta coefficients resulting for a differencing interval L but for a different starting day of returns calculation are different. So in order to obtain all these estimations the above regressions for every L, varying from one to thirty days, and for every different starting day in L are carried out. Continuing, the average value of Beta estimates in every L is calculated. From these regressions the t-statistic values and p-values are also obtained in order to test the following hypothesis:

\[ H_0: Beta = 0 \quad H_1: Beta \neq 0 \]

The results of this test show that from the whole sample only 93 stocks have statistically significant values for returns calculated using L=1, meaning that the Gen effect is statistically significant. In the following figure we can see the number of statistically significant Beta estimations for every L and every different starting day in that L, moving from L=1 to L=30.

As the differencing interval is lengthened the number of returns decreases leading to a reduction on the degrees of freedom. Consequently, the t statistic value
decreases making the rejection of the null hypothesis harder. That’s why the number of statistically significant estimations of Beta reduces as the L is lengthened.

Figure 5. The number of statistically significant estimations of systematic risk (Beta coefficients) for every differencing interval varying from L=1 to L=30.

5.2.1 Examination of the intervalling effect

In order to evaluate the intervalling effect on Beta estimations the following fraction is calculated and multiplied by 100 so to calculate the percentage change on Betas:

\[
\left( \frac{\text{Beta}(L) - \text{Beta}(1)}{\text{Beta}(1)} \right) \times 100 \quad (4)
\]

Where, \( \text{Beta}(1) \) is the Beta estimation for \( L=1 \) and \( \text{Beta}(L) \) is the average Beta estimation for every \( L \) varying from 1 to 30. After computing the percentage change of Betas the average for every \( L \) is taken and the results are presented in Figure 6 as follows.
Figure 6. The average percentage change of Betas as a function of the differencing interval.

As it is obvious from the above figure the intervalling effect during the sampling period is very weak, if any at all. Because of its weakness the intervalling effect is unable to affect the estimations of systematic risk. The Beta estimations as noticed before and as it also seems from Figure 7 vary as the differencing interval is lengthened.

5.2.2 Starting day effect

The abovementioned evidence for the intervalling effect demonstrates that another phenomenon first considered by Corhay, the so-called Corhay effect, is needed to be examined. The examination intends to determine whether or not the changes on Beta estimates are caused by the Corhay effect as well as its strength, something that hasn’t been taken under consideration in previous studies.
For the evaluation of the Corhay effect the median and standard deviation of Beta estimations in every differencing interval are calculated.

The Corhay effect is assessed using the following fraction:

\[
\frac{\text{Stdev(Beta}(L))}{\text{Median}} \times 100
\]  

(5)

The median is used instead of the average in order to avoid the changes in Beta estimations that come from the outliers. After this computation the average value for every L is computed and the results are presented in Figure 8. For a differencing interval up to 1 the standard deviation equals to zero so the plot starts from L=2.

It is clear that there is a very pronounced starting day effect. The same picture is obtained by splitting the whole sample into stock categories according to their capitalization. These categories will be: Large Cap, Mid Cap and the Rest of the stocks as shown in Figure 9. Smaller stocks which are included in the Rest stocks class have a
Figure 8. The Strength of Corhay effect as a function of the differencing interval.

Figure 9. The intensity of Corhay effect as a function of the differencing interval for the categories according to assets capitalization.

clearly stronger Corhay effect than the others with extremely high intensity values of the phenomenon in bigger differencing intervals.
The intensity of the Corhay effect for smaller stocks becomes even more clear in Figure 10 where the regression between the logarithm of the fraction \( \frac{\text{Stdev}}{\text{Median}} \) and the logarithm of the mean capitalization is carried out over the five years period. Smaller Cap stocks expose a more intense Corhay effect than the others. In Figure 10 we also see the R squared of the regression analysis. The R squared or the Coefficient of Determination is a statistical measure that represents the proportion of the variance in the dependent variable that is predictable from the independent variable. R squared values vary from 0 to 1 and are commonly stated as percentages from 0 to 100%. An R squared of 100% means all movements of a security are completely explained by movements in the index. The obtained R squared is up to 60%.

**Figure 10. The strength of the Corhay effect in relation to capitalization.**
5.3 Intervalling versus starting day effect

At this point, the importance of the Corhay effect in comparison to the intervalling effect will be assessed. In order to succeed this, the following fraction is constructed of which the numerator represents a measure of the intervalling effect and the dominator a measure of the starting day effect:

\[
\left( \frac{\text{Beta}(L) - \text{Beta}(1)}{\text{Stdev}} \right) / \left( \frac{\text{Median}}{\text{Stdev}} \right) * 100
\]

(6)

After computing this fraction the average value for every L is calculated and the results are represented in Figure 11. The conclusion that is driven from this representation is that the intervalling effect has no power over the Corhay effect, as the values are too close to zero to practically conclude that there is any at all.

Figure 11. The relative importance of the intervalling effect as compared to the Corhay effect.
Something very interesting and worth labeling is the conclusion drawn from the following two graphs.

**Figure 12.** The average percentage change of Betas due to the intervalling effect using the maximum of Beta estimations for every L.

![Figure 12](image1)

**Figure 13.** The average percentage change of Betas due to the intervalling effect using the minimum of Beta estimations for every L.

![Figure 13](image2)

The calculation process of the intervalling effect is the same as described previously by using the equation (4). But this time for the first case the maximum of Beta estimations for every L is used, instead of the average, and for the second one the
minimum of Beta estimations for every L is taken. From these two last figures it is clear that there is an intense intervalling effect when using the Beta max or Beta min, but the character of the effect is completely the opposite when Beta min is used. This is in fact another facet of the predominance of the Corhay effect over the intervalling effect. This result is also a topic of conjecture and further study on what is the appropriate way to manage Beta estimates in every differencing interval.

5.4 The effect of Capitalization

As we have seen at an earlier stage of the study the capitalization is related to the intensity of the abovementioned phenomena. First, it is going to be examined the relation between Beta estimates and capitalization. From the graphical representation of the average values of Beta estimates for every stock category of capitalization in relation to L it is observed that there is a strong dependence between Beta estimations and capitalization. More specifically, the Large Cap stocks have on the average larger Betas as demonstrated by Corhay (1992) and it is presented in Figure 14.

As it is already established by Cohen et al. the expected magnitude of the price-adjustment delays is related to the thinness of the securities, meaning that thinner securities have greater adjustment delays than frequently traded securities. Corhay connected the price-adjustment delays of a security with its volatility of Beta estimations. He found out that smaller firms are more volatile in comparison to the other stock categories of capitalization due to thin trading. Small firm returns are more sensitive for any interval length to the way prices are juxtaposed to calculate returns that those of larger firms, which in turn affect the estimated values of Betas.
Figure 14. The average value of Beta estimations for every category of capitalization in relation to $L$.

In order to examine the abovementioned notations the standard deviation of Beta estimates in every $L$ as computed before is needed, and also the separation of the whole sample in the three stock capitalization categories as shown in Figure 15. It is obvious that indeed there is a larger variability of Beta estimates for smaller stocks. Furthermore, as the differencing interval increases so does the variability with much larger values for $L=30$ as expected and also quoted in Corhay (1992).
5.5 Mean $R^2$ as a function of $L$

The next step of this study is to inspect the explanatory power of the Market Model in relation to firms capitalization. To do so, the variation of the coefficient of determination along with $L$ is presented for all three stock categories of capitalization as shown in Figure 16.

As it is presented in figure 16 the explanatory power of the model is much bigger for larger firms, with a great distance of $R$ squared values between large and small cap stocks. It is also shown that the explanatory power of the MM increases for all stock categories as the differencing interval is lengthened, as expected by microstructure theory (Cohen et al, 1983). But even for large stocks the values of the $R$ squared are on average low, in every $L$ which raises concerns about the interpretative capacity of the one factor model as noted in previous studies (Fama and French, 1992, 1993, 1996, Milionis and Patsouri 2011).
5.6 Convergence – Divergence of Betas estimations

Another interesting topic is the comparison of the estimations of systematic risk for two different sampling periods over the same market. For this task the Beta estimations for the period 1999 – 2004 are going to be used, (taken from Milionis 2010).

The main idea behind this task is to examine the variation of the estimators with reference to unity. More practically, we want to inspect if the Beta estimations converge or diverge from unity. In Blume’s (1971-75) and Vasicek’s (1973) studies they developed a theory on the movement of the estimators of systematic risk. The essence of this theory lies on the distance of Betas from unity and in convergence or divergence of these estimations moving from the first sampling period to the second one. They supported that estimations that are far from unity tend to approach it. This theory however, refers to adjacent time periods.
estimations from the first sampling period covering from 1999 to 2004 to the second one during the 2012 to 2017 is graphically presented.

The findings of this task show that for most stocks there is a divergence from 1, with only seven converging stocks of the total 53. Also, the values of Beta estimations for the second period are much smaller on average than the values of the first sampling period with an exception mainly for banks. The difference of the estimations is much bigger for smaller stocks as shown in Figure 18 where the average value of capitalization for the five years sampling period is being regressed with the difference of Beta values from the two underlying periods of this task. From this, it is concluded that smaller values of Betas are observed especially for smaller stocks.

Figure 17. Convergence – Divergence of Beta estimation from the unit from two sampling periods.
Figure 18. The difference of Beta estimations for the two sampling periods as a function of mean capitalization of the total five years period.

This empirical evidence seems not to be in line with the theory of Blume, Levi and Vasicek as described below. But it is essential to mention that the sampling periods used in this task are not adjacent time periods as were the periods they used in their studies.
Chapter 6

6. Conclusions

The main purpose of this empirical study was to examine the estimations of systematic risk in relation to some phenomena caused by market microstructure. The study is carried out for stocks traded in the Main Market of the Athens Stock Exchange for a five years period. The current study provides counterevidence for many stylized facts about Beta estimation in its relation to market microstructure. As it emerged the effect of the differencing interval, used to calculate the returns on securities and market index, on the estimations of systematic risk also called Beta estimations, the so-called intervalling effect, is very weak for the underlying period in comparison to previous studies for the same market but in different time periods. As it seems the current economic and political conditions of the country have an effect on the Beta estimations.

One phenomenon that provokes interest and hasn’t been assessed properly in previous studies is the starting day effect also known as the Corhay effect. In most studies this effect was either ignored either smoothed away by taking the average of Beta estimations, not correctly assessing the importance of this phenomenon to risk estimation. Contrary on the ongoing the current results reveal a very pronounced Corhay effect which is fortified further as the differencing interval is lengthened. Also the relation of this effect with stocks capitalization provides insight about the intensity of the Corhay effect for smaller cap stocks.
The study of the strength of the intervalling effect compared to Corhay effect showed that the last overwhelmingly dominates over the intervalling effect so that it is the determining factor of changes in Betas.

Consequently, the relation of the capitalization with the Beta estimations showed that larger stocks have larger values of Betas and also that the explanatory power of the Market Model is way better for larger firms. In comparison to previous study carried out in most quiet economic and political conditions of the country the estimations of the systematic risk are generally low for most stocks with an exception of a small part of stocks which mainly contains banks. The Beta values are particularly small for smaller firms.

Another result of this study is that the values of the coefficient of determination (R squared) are larger for larger stocks. Generally, low values of the coefficient of determination in Market Model, particularly for small stocks, are associated with much smaller trading volume. It is also observed that the values of the R squared increases with the differencing interval, mainly for smaller stocks. However, the number of statistically significant estimations of the systematic risk reduces as the L is lengthened. Even for larger firms the results of the R squared in this study where especially low.

It seems that a single factor model such as the Market Model may not sufficiently capture the correlation structure of security returns. For that specific reason there is existing studies proposing conditional versions of the CAPM, introducing additional risk premia to the model such as the one derived from a GARCH-in-mean-model (Milionis 2011; Milionis 2012).
References

English Bibliography


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Appendix

# R-studio is used in order to obtain the estimations of systematic risk and other useful results.

R scripts

#Reading data
install.packages("openxlsx")
library(openxlsx)
xa<-read.xlsx("C:/File.xlsx")

#disable scientific notation
options(scipen = 999)

# Estimating Betas for every l and every starting day in l, storing t-statistics, p-values and r squared values
Final<-c() # supportive matrix for storing Beta estimates
B<-c() # supportive matrix for storing Beta estimates from every regression
Final1<-c() # supportive matrix for storing t-statistics and p-values
B1<-c() # supportive matrix for storing t-statistics and p-values
RSquared<-c() # the final matrix with all t-statistics and p-values
B2<-c() # supportive matrix for storing the r squared values

# m for stocks, l for the differencing interval and j for the starting day
for (m in 1:122) # selection of stocks
{ for (l in 1:30) # selection of values of stocks for each differencing interval
    { for (j in 1:30) # selection of the starting day
        { if (j<=l) # for every differencing interval chooses a different starting day
            X<-xa[seq(from=j,to=1215,by=l),c(m)]
            GD<-xa[seq(from=j,to=1215,by=l),c(123)]
        } } }
model<- lm(X ~ GD, data=xa)
A<-model$coefficients
B<-cbind(B,A[2])
tstat<-summary(model)$coef[2,"t value"]
pvalue<-summary(model)$coef[2,"Pr(>|t|)""]
B1<-cbind(B1,tstat,pvalue)
summary.out<-summary(model)
R<-summary.out$r.squared
B2<-cbind(B2,R)
B<-c()
B1<-c()
RSquared<-rbind(RSquared,B2)
B2<-c()

# print results as an excel file
write.csv(file="C:/FileName.csv",x=Final)
write.csv(file="C:/FileName.csv",x=Final1)
write.csv(file="C:/FileName.csv",x=RSquared)

# Creating matrix with the average value of the estimations for every differencing interval
M1<-Final[,1] # for l=1 there is only one value for every stock

# from l=2 to l=30 there are more than one estimation, depending on l, so the mean value of those estimations is required
# selecting the estimations and calculating the average value of the estimations for every l

l2<-c()
Corh<-c()
F<-cbind(Final[,2],Final[,3])
for (r in 1:122){
    Corh<-mean(F[r,])
    l2<-rbind(l2,Corh) }
l3<-c()
Corh<-c()
F<-cbind(Final[,4],Final[,5],Final[,6])
for (r in 1:122){
    Corh<-mean(F[r,])
    l3<-rbind(l3,Corh) }
l4<-c()
Corh<-c()
F<-cbind(Final[,7],Final[,8],Final[,9],Final[,10])
for (r in 1:122){
    Corh<-mean(F[r,])
    l4<-rbind(l4,Corh) }
l5<-c()
Corh<-c()
F<-cbind(Final[,11],Final[,12],Final[,13],Final[,14],Final[,15])
for (r in 1:122){
    Corh<-mean(F[r,])
    l5<-rbind(l5,Corh) }
l6<-c()
Corh<-c()

F<-cbind(Final[,16],Final[,17],Final[,18],Final[,19],Final[,20],Final[,21])
for (r in 1:122){
    Corh<-mean(F[r,])
    l6<-rbind(l6,Corh)
}

l7<-c()
Corh<-c()

F<-cbind(Final[,22],Final[,23],Final[,24],Final[,25],Final[,26],Final[,27],Final[,28])
for (r in 1:122){
    Corh<-mean(F[r,])
    l7<-rbind(l7,Corh)
}

l8<-c()
Corh<-c()

F<-cbind(Final[,29],Final[,30],Final[,31],Final[,32],Final[,33],Final[,34],Final[,35],Final[,36])
for (r in 1:122){
    Corh<-mean(F[r,])
    l8<-rbind(l8,Corh)
}

l9<-c()
Corh<-c()

F<-cbind(Final[,37],Final[,38],Final[,39],Final[,40],Final[,41],Final[,42],Final[,43],Final[,44],Final[,45])
for (r in 1:122){
    Corh<-mean(F[r,])
    l9<-rbind(l9,Corh)
}
l10<-c()
Corh<-c()

F<-cbind(Final[,46],Final[,47],Final[,48],Final[,49],Final[,50],Final[,51],Final[,52],Final[,53],Final[,54],Final[,55])
for (r in 1:122){
  Corh<-mean(F[r,])
  l10<-rbind(l10,Corh) }

l11<-c()
Corh<-c()

F<-cbind(Final[,56],Final[,57],Final[,58],Final[,59],Final[,60],Final[,61],Final[,62],Final[,63],Final[,64],Final[,65],Final[,66])
for (r in 1:122){
  Corh<-mean(F[r,])
  l11<-rbind(l11,Corh) }

l12<-c()
Corh<-c()

F<-cbind(Final[,67],Final[,68],Final[,69],Final[,70],Final[,71],Final[,72],Final[,73],Final[,74],Final[,75],Final[,76],Final[,77],Final[,78])
for (r in 1:122){
  Corh<-mean(F[r,])
  l12<-rbind(l12,Corh) }

l13<-c()
Corh<-c()

F<-cbind(Final[,79],Final[,80],Final[,81],Final[,82],Final[,83],Final[,84],Final[,85],Final[,86],Final[,87],Final[,88],Final[,89],Final[,90],Final[,91])
for (r in 1:122) {
    Corh <- mean(F[r,])
    l13 <- rbind(l13, Corh)
}
l14 <- c()
Corh <- c()

F <- cbind(Final[,92], Final[,93], Final[,94], Final[,95], Final[,96], Final[,97], Final[,98], Final[,99], Final[,100], Final[,101], Final[,102], Final[,103], Final[,104], Final[,105])

for (r in 1:122) {
    Corh <- mean(F[r,])
    l14 <- rbind(l14, Corh)
}
l15 <- c()
Corh <- c()

F <- cbind(Final[,106], Final[,107], Final[,108], Final[,109], Final[,110], Final[,111], Final[,112], Final[,113], Final[,114], Final[,115], Final[,116], Final[,117], Final[,118], Final[,119], Final[,120])

for (r in 1:122) {
    Corh <- mean(F[r,])
    l15 <- rbind(l15, Corh)
}
l16 <- c()
Corh <- c()

F <- cbind(Final[,121], Final[,122], Final[,123], Final[,124], Final[,125], Final[,126], Final[,127], Final[,128], Final[,129], Final[,130], Final[,131], Final[,132], Final[,133], Final[,134], Final[,135], Final[,136])

for (r in 1:122) {
    Corh <- mean(F[r,])
    l16 <- rbind(l16, Corh)
}
l17<-c()
Corh<-c()

F<-cbind(Final[137],Final[138],Final[139],Final[140],Final[141],Final[142],Final[143],Final[144],Final[145],Final[146],Final[147],Final[148],Final[149],Final[150],Final[151],Final[152],Final[153])
for (r in 1:122){
  Corh<-mean(F[r,])
  l17<-rbind(l17,Corh) }

l18<-c()
Corh<-c()

F<-cbind(Final[154],Final[155],Final[156],Final[157],Final[158],Final[159],Final[160],Final[161],Final[162],Final[163],Final[164],Final[165],Final[166],Final[167],Final[168],Final[169],Final[170],Final[171])
for (r in 1:122){
  Corh<-mean(F[r,])
  l18<-rbind(l18,Corh) }

l19<-c()
Corh<-c()

F<-cbind(Final[172],Final[173],Final[174],Final[175],Final[176],Final[177],Final[178],Final[179],Final[180],Final[181],Final[182],Final[183],Final[184],Final[185],Final[186],Final[187],Final[188],Final[189],Final[190])
for (r in 1:122){
  Corh<-mean(F[r,])
  l19<-rbind(l19,Corh) }

l20<-c()
Corh<-c()
F<-cbind(Final[,191],Final[,192],Final[,193],Final[,194],Final[,195],Final[,196],Final[,197],Final[,198],Final[,199],Final[,200],Final[,201],Final[,202],Final[,203],Final[,204],Final[,205],Final[,206],Final[,207],Final[,208],Final[,209],Final[,210])
for (r in 1:122){
  Corh<-mean(F[r,])
  l20<-rbind(l20,Corh)
}
l21<-c()
Corh<-c()
F<-cbind(Final[,211],Final[,212],Final[,213],Final[,214],Final[,215],Final[,216],Final[,217],Final[,218],Final[,219],Final[,220],Final[,221],Final[,222],Final[,223],Final[,224],Final[,225],Final[,226],Final[,227],Final[,228],Final[,229],Final[,230],Final[,231])
for (r in 1:122){
  Corh<-mean(F[r,])
  l21<-rbind(l21,Corh)
}
l22<-c()
Corh<-c()
F<-cbind(Final[,232],Final[,233],Final[,234],Final[,235],Final[,236],Final[,237],Final[,238],Final[,239],Final[,240],Final[,241],Final[,242],Final[,243],Final[,244],Final[,245],Final[,246],Final[,247],Final[,248],Final[,249],Final[,250],Final[,251],Final[,252],Final[,253])
for (r in 1:122){
  Corh<-mean(F[r,])
  l22<-rbind(l22,Corh)
}
l23<-c()
Corh<-c()
F<-cbind(Final[,254],Final[,255],Final[,256],Final[,257],Final[,258],Final[,259],Final[,260],Final[,261],Final[,262],Final[,263],Final[,254],Final[,265],Final[,266],Final[,267],Final[,268]
for (r in 1:122){
  Corh<-mean(F[r,])
  l23<-rbind(l23,Corh) }

l24<-c()
Corh<-c()

F<-cbind(Final[,269],Final[,270],Final[,271],Final[,272],Final[,273], Final[,274], Final[,275], Final[,276])
for (r in 1:122){
  Corh<-mean(F[r,])
  l24<-rbind(l24,Corh) }

l25<-c()
Corh<-c()

F<-cbind(Final[,277],Final[,278],Final[,279],Final[,280],Final[,281],Final[,282],Final[,283],Final[,284],Final[,285],Final[,286],Final[,287],Final[,288],Final[,289],Final[,290],Final[,291],Final[,292],Final[,293],Final[,294],Final[,295],Final[,296], Final[,297], Final[,298], Final[,299],Final[,300])
for (r in 1:122){
  Corh<-mean(F[r,])
  l25<-rbind(l25,Corh) }

l26<-c()
Corh<-c()

F<-cbind(Final[,301],Final[,302],Final[,303],Final[,304],Final[,305],Final[,306],Final[,307],Final[,308],Final[,309],Final[,310],Final[,311],Final[,312],Final[,313],Final[,314],Final[,315],Final[,316],Final[,317],Final[,318],Final[,319],Final[,320], Final[,321], Final[,322], Final[,323],Final[,324],Final[,325])
for (r in 1:122){
  Corh<-mean(F[r,])
  l26<-rbind(l26,Corh) }

l27<-c()
Corh<-c()

F<-cbind(Final[,326],Final[,327],Final[,328],Final[,329],Final[,330],Final[,331],Final[,332],Final[,333],Final[,334],Final[,335],Final[,336],Final[,337],Final[,338],Final[,339],Final[,340]
for (r in 1:122)
  Corh<-mean(F[r,])
  l26<-rbind(l26,Corh)

l27<-c()
Corh<-c()

F<-cbind(Final[352],Final[353],Final[354],Final[355],Final[356],Final[357],Final[358],Final[359],Final[360],Final[361],Final[362],Final[363],Final[364],Final[365],Final[366],Final[367],Final[368],Final[369],Final[370],Final[371],Final[372],Final[373],Final[374],Final[375],Final[376],Final[377],Final[378])

for (r in 1:122)
  Corh<-mean(F[r,])
  l27<-rbind(l27,Corh)

l28<-c()
Corh<-c()

F<-cbind(Final[379],Final[380],Final[381],Final[382],Final[383],Final[384],Final[385],Final[386],Final[387],Final[388],Final[389],Final[390],Final[391],Final[392],Final[393],Final[394],Final[395],Final[396],Final[397],Final[398],Final[399],Final[400],Final[401],Final[402],Final[403],Final[404],Final[405],Final[406])

for (r in 1:122)
  Corh<-mean(F[r,])
  l28<-rbind(l28,Corh)

l29<-c()
Corh<-c()

F<-cbind(Final[407],Final[408],Final[409],Final[410],Final[411],Final[412],Final[413],Final[414],Final[415],Final[416],Final[417],Final[418],Final[419],Final[420],Final[421]
for (r in 1:122)
    Corh<-mean(F[r,])

l29<-rbind(l29,Corh) }
l30<-c()
Corh<-c()

F<-cbind(Final[,422],Final[,423],Final[,424],Final[,425],Final[,426], Final[,427], Final[,428], Final[,429],Final[,430],Final[,431],Final[,432],Final[,433],Final[,434],Final[,435])
for (r in 1:122)
    Corh<-mean(F[r,])

l30<-rbind(l30,Corh) }

# configuration of the matrix with the average estimates for every l
Corhay<-c()

Corhay<-cbind(M1,l2,l3,l4,l5,l6,l7,l8,l9,l10,l11,l12,l13,l14,l15,l16,l17,l18,l19,l20,l21,l22,l23,l24,l25,l26,l27,l28,l29,l30)
for (l in 1:30)
    colnames(Corhay)[l] <-"L=

# print results as an excel file
write.csv(file="C:/FileName.csv",x=Corhay)