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OPACITY AND EVENT STUDY ANALYSIS

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ABSTRACT

This study examines the impact of asset pricing model's misspecification on the power of an event study analysis. Gilbert, Hrdlicka, Kalodimos, and Siegel (2014) show that asset pricing model fails to price asset accurately at high frequency. This is due to uncertainty about the effect of systematic news on firm value, which they address as firm opacity. They propose an additional factor in the market model and empirically show better performance of the augmented model. This study practically investigates the implication of this additional factor on enhanced power of event study analysis. Key findings indicate that an adjusted asset pricing model improves the power of event studies for small stock portfolio. The detection rate increases from 2.9 percent to 15.5 percent based on an induced abnormal return of 1.5 percent to 2 percent. However, there is no improvement in abnormal return detectability in portfolios of random stocks or other characteristic- sorted portfolios.

CHAPTER 1: INTRODUCTION

This study examines the impact of intervalling effect in betas on the event study analysis. The study extends the recent research by Gilbert, Hrdlicka, Kalodimos, and Siegel (2014), in which they point out that betas estimated from daily returns are biased and are different from those estimated from quarterly returns. They attribute beta differences to the uncertainty of how systematic news affects the firm value (firm opacity), which causes the risk structure to alter across frequencies. Moreover, they show that a factor constructed from the difference in beta portfolio returns is associated to firm opacity. The inclusion of this factor, referred to as opacity factor hereafter, improves the performance of the Captical Asset Pricing Model (CAPM).

The standard event study analysis routinely uses a market model as the benchmark to compute the expected return surrounding an event date. However, as pointed out by Gilbert et al. (2014), this model is misspecified given a bias in the beta estimation from daily returns. Consequently, there is potential for biased estimates of abnormal returns and misspecified test statistics in an event study may result (Strong, 1992). It is the key objective of this study to examine whether the bias correction proposed by Gilbert et al. (2014) would seriously impact the findings from an event study analysis in terms of the specification and power of the test. The expectation is that when parameters are free from bias, event study residuals are no longer misestimated, leading to a more precise conclusion regarding to the event.

This study finds that there is enhanced power of event study analysis for the small firm portfolio. The detection rate is from 2.9 percent to 15.5 percent higher compared to the market model when induced abnormal return is from 1.5 percent to 2 percent. However, the augmented model does not benefit in other portfolios.

1.1 Background of intervalling effect and opacity factor

My research starts with replicating the methodology by Gilbert et al. (2014) to construct five Δβ sorted portfolios, with Δβ being the difference between the quarterly and daily beta of a given stock. For all five portfolios, I agree with Gilbert et al. (2014) about the tendency that portfolios' betas change when return intervals change. Literature documents this phenomenon and addresses it as intervalling effect (Brailsford and Josev, 1997; Frankfurter, Leung and Brockman, 1994). Among the other issues around beta estimates such as the method of estimation (Chan and Lakonishok, 1992), the effect of length of estimation period (Baesel, 1974; Kim, 1993) or the effect of outliers (Shalit and Yitzhaki, 2002), the intervalling effect gets most of the attention. Evidences show that it can seriously impact the results obtained from event studies. For example, I refer to studies about beta changes around stock splits by Lamoureux and Poon (1987), Brennan and Copeland (1988) and Wiggins (1992) . Using daily returns, Lamoureux and Poon (1987) and Brennan and Copeland (1988) document a significant permanent increase in average beta subsequent to stock split ex dates. On the contrary, Wiggins (1992) rejects that conclusion due to no statistically significant difference between pre and post split beta estimated from weekly or monthly returns data. This means the wedge between betas before and after the date decays when the measurement interval is lengthened.

The dominant explanation for intervalling effect is non-synchronous trading, which is about the simultaneous treatment of stock prices recorded at different time (Dimson, 1979; Scholes and Williams, 1977). Gilbert et al. (2014), however, rule out this explanation and provide a risk based one. They claim that stocks' opacity, which is the uncertainty about the effect of systematic news on opaque firms, is the source of the betas' change across return frequencies. They use ∆β to proxy for firm's opacity. The higher ∆β, the more opaque the firm is and vice versa. The underlying rational is that while transparent firms respond to information by immediately and fully incorporating it into their stock prices, opaque firms experience a time lag before their stock price fully reflects this information (Gilbert et al., 2014).

Based on underlying cause of intervalling effect, scholars develop various adjustments to improve beta estimates. All of the adjustments aim at daily returns because beta bias gets more severe with this return frequency (Brown and Warner, 1985; Diacogiannis and Makri, 2008; Brailsford and Josev, 1997; Pogue and Solnik, 1974). From the perspective of non-synchronous trading, the most widely known adjustments to correct beta estimates are presented in the works of Dimson (1979), Scholes and Williams (1977), Cohen, Hawawini, Maier, Schwartz, and Whitcomb (1983a). Their common approach is to take covariance between assets returns and lead and lag market returns into consideration. In this way, researchers expect to correct the different trading delays between securities and index, which results in biased and inconsistent ordinary least squares (OLS) estimation (Berry, Gallinger and Henderson, 1990). From the perspective of firm opacity, Gilbert et al. (2014) modify market model with the addition of opacity factor, which is, empirically, the difference between daily returns of portfolio of highest Δβ stocks and that of lowest Δβ stocks. Based from factor formation, Gilbert et al. (2014) also address opacity factor as Δβ factor. They then regress stock returns on both market returns and Δβ factor to obtain stock beta. Gilbert et al.'s (2014) approach is about disentangling the cash flow effects from the discount rate effects in opaque firms at high frequency data.

1.2 Objectives of the research

First, I will address how the Δβ factor helps alleviate bias in betas estimated from daily returns. Second, and more crucially, I investigate its performance in improving event study power. This research expects to add new evidences to existing literature on improved beta estimation and its implications in event study analysis.

1.2.1 Can opacity factor adjust beta biases?

To address whether the opacity factor works effectively or not, this study focuses on observing the following. First, the research documents the ability to correct the bias in the beta estimates, which is the downward bias for opaque firms and upward bias for transparent firms (Gilbert et al., 2014). Second, the research assesses the mean R^2 value in the regression model. Augmented model will have higher R^2 compared to the original OLS model, if the addition of opacity factor in the model provides a better explanatory framework of return variability. Additionally, I anticipate observing the most increase in R^2 in the top opaque groups.

This is a by- product of my research to supplement results reported in Gilbert et al. (2014). They only assess CAPM alpha to review performance of modified model. Therefore, the assessment of model's beta and R^2 will, first, give a detailed view of how the opacity factor adjusts intervalling effect. Second, and more importantly, the possible increased R^2 may predict a more powerful event study test because a higher ability to detect the event effects depends on the R^2 of the model regression (Campbell, Lo and MacKinlay, 1993).

1.2.2 Does opacity factor improve the power of event study analysis?

The thrust of the present research is the examination of the effectiveness of opacity factor in event studies. This test follows Gilbert et al.'s (2014, p.7) suggestion about the "important practical implication for measuring systematic market risk with high frequency returns in event studies". This will enrich literature in the area of fixing beta bias in event studies, where most of the attempts do not seem to succeed. For example, despite extra work to account for nonsynchronous trading by Scholes and Williams (1977) and Dimson (1979) approach, Reinganum (1982) and Theobald (1983) find that Scholes and Williams and Dimson betas are not superior to daily data OLS. They do not eliminate autocorrelation in event study residuals or strengthen the test power in the simulation studies either. In another study, Dyckman, Philbrick and Stephan (1984) apply Scholes and Williams betas and Dimson betas to volume based portfolios in the US equity market. The results are not better. There is no increased ability in abnormal returns detection, even for the lowest volume portfolio, which benefits the most from beta estimates corrected for nonsynchronous trading.

This research will resolve the beta bias in event study in the light of stock opacity rather than nonsynchronous trading. I adopt Brown and Warner's (1980, 1985) simulation approach in event study to examine the specification and power test of both traditional and augmented return generating models. Event study tests with preferable model will be better- specified and display more power in their ability to pick up abnormal returns.

I address both research objectives by conducting tests on portfolios of randomly chosen stocks and opacity clustered stocks. The motivation to work on opacity clustered portfolios comes from Gilbert et al.'s (2014) observation of stronger fixing effect in more opaque stocks. I, therefore, for the first objective, expect to see better improvement of beta and R^2 and for the second object, more powerful event studies in opaque portfolios than transparent portfolios. Furthermore, instead of using Δβ alone, I also use market value and turnover as opacity proxies to form opacity-based portfolios. It is reasonable because of high correlation between high market value and low Δβ stocks or high turnover and low Δβ stocks. Additionally, literature shows that these stock have the similar beta and R^2 patterns when the return interval changes.

I develop my research along the following path. Chapter 2 provides a background of the intervalling effect on beta estimation. Most importantly, I present detailed understanding about opacity factor. Chapter 3 explains the data and methodology. Chapter 4 documents all the empirical findings. Two mainstream results are the performance of opacity factor in estimating betas and in strengthening the power of event study tests. Further, I conduct a test when event date is not known with certainty and then, consider the real event, which is a dividend announcement date. A discussion on explanations for the documented results follows. Chapter 5 remarks conclusions.

My main findings are as follows. For the first objective, there is no improvement in beta estimates or R^2 in portfolios consisting of randomly chosen stocks. For portfolios of opacity clustered stocks, the added factor increases the model R^2 for all portfolios. Furthermore, it fixes the downward bias in betas of low opacity groups. For the second object, the highlight is from the low market value portfolio. In this portfolio, I document the remarkably higher rejection rates for adjusted model. The improved power in event study in low market value portfolio is the first to document in the literature that there is a methodology to challenge the traditional market model. There have been no evidences so far of a model that can over-perform market model in event study analysis in some cases. For portfolio of randomly chosen stocks and other characteristic sorted portfolios, generally, my results demonstrate no improved test power. When the event date is unknown, both the specification and power of the event test dilute considerably across both methodologies and all abnormal return levels introduced. The difference in power of 2 models' performance remains marginal. Finally, using a dividend announcement date as an actual event, I confirm the previous observation that the more complex model does not add more benefits. My results strengthen Brown and Warner's (1985) conclusion that the bias in betas does not necessarily imply misspecification in an event study. A more precise return generating model, therefore, is not sufficient to produce a more powerful test for abnormal returns.

The main contributions of my research are as follows. First, I pioneer a test of the performance of the newly introduced opacity factor in event studies. Second, this work enriches the literature on the interaction between improved beta estimates and event study analysis, where evidence is still limited. Third, this work significantly updates the random sample results from Brown and Warner (1985). Besides widening the data, I add the test of opacity to supplement the traditional nonsynchronous trading test. Fourth, I work on varied sample characteristics to confirm result consistency.

CHAPTER 2: LITERATURE REVIEW

2.1 Sampling frequency and beta estimation- intervalling effect

The phenomenon that stock beta estimate is dependent of different interval length is intervalling effect (Corhay, 1992; Dowen and Isberg, 1988; Fung, Schwartz and Whitcomb, 1985; Schwartz and Whitcomb, 1977). Academic community has given this effect considerable interest, from its first documentation in Pogue and Solnik (1974). In this work, when testing the market model on European common stocks, they present estimated betas for each of four frequencies, namely, weekly, monthly, quarterly and yearly and report the lowest betas for daily returns and highest for monthly returns. They also find that intervalling effects across seven European markets are more significant compared to the US market and tend to be the larger the smaller market (Larson and Morse, 1987).

Although there is no intervalling effect on the whole market as the average beta stays almost unity (Corhay, 1992), this effect is prominent for characteristic-based portfolios. Two commonly used criteria for portfolio formation are stock's size and trading volume. Smith (1978) documents this effect in portfolio sorted by stock betas. Gilbert et al. (2014) extend the previous observations to $\Delta\beta$ sorted portfolios, with $\Delta\beta$ being the difference between stock beta estimated at low frequency and high frequency return intervals. Generally, the major body of the literature documents intervalling effect through alpha and beta behavior patterns and the change in explanatory power of the model.

The core observation in intervalling effect is beta coefficient. Despite differences in markets and their microstructure, studies across markets agree on the direction of beta change in response to different return intervals. The general trend is that beta estimates of high market capitalization or high trading volume firm decrease when the return interval gets longer. The vice versa applies for low market capitalization or low trading volume firm. Especially, the rate of change in beta magnitude is more significant for low market capitalization and low trading volume stocks. Roll (1981) and Hawawini (1983) explain the similar beta changes under intervalling effect of high (low) market value stocks and high (low) trading volume stocks that small firms trade less. Brailsford and Josev (1997) support Roll (1981) and Hawawini (1983) by examining market capitalization and trading volume relationship in Australian equity market. With the samples of 15 lowest and highest market value ranked stocks, they report the percentage of zero returns of 2 portfolios across daily, weekly and monthly return interval. The results show that low market value firms have remarkably higher portion of zero returns. When the return interval gets lengthened, zero return frequencies decline for both portfolios. Additional evidence is the correlation between market capitalization and average daily trading volume, which is 0.74.

The above conclusion about beta response to intervalling effect is distilled from a range of empirical evidences. Among the most frequently mentioned researches is by Dimson (1979). Retrieving returns from London Share Price Database file, he assigns stocks to portfolios according to their trading frequency. When interval increases from 1 month to 3 months, beta rises for the groups of lowest trading stocks, from 0.5 to 0.72 and falls for the other groups, from 1.15 to 0.99. This conveys the biased upward for large issue stocks and downward for thinner issues (Beer, 1997). Moreover, Dimson (1979) shows that the magnitude of the beta bias is more evident in less frequently traded group. While the two most frequently traded portfolios produce estimates that are 20% too high, the most infrequently traded stocks experience beta that is approximately 40% too low. Another research is by Handa, Kothari, and Wasley (1989). Different from Dimson (1979), they form 20 size sorted portfolios using stocks from US market and estimate their one day, one week, one month, two months, one quarter, four months, six months and one year betas. Beta of low market value portfolios rises from 1.41 to 1.66 when return interval increases from 1 month to 1 year. For high market value portfolio, it falls from 0.67 to 0.56. Researchers also present evidence in thin markets. Brailsford and Josev (1997) perform the investigation on 2 extreme sized portfolios in Australian stock market. Their results indicate that beta estimates of high (low) capitalized firms fall (rise) as the return interval is longer. In details, the mean beta of low market value portfolio increases from 0.633 to 1.229 when the interval increases from daily to monthly returns. The difference between mean beta estimates of daily to monthly and weekly to monthly stays significant. In contrast, for a group of high cap stocks, the mean beta decreases from 1.310 to 1.203 when the return interval increases from daily to monthly returns. Only the difference between daily and monthly betas remains statistically significant. This means the rate of change is more evident for low market value stocks. Corhay (1992) does the examination on both market value and trading volume sorted portfolios from 250 stocks from Brussels Stock Exchange from January 1977 to December 1985 and he finds that the results are not significantly different from each other. By performing statistical tests for the equality between portfolio beta means, he confirms intervalling effect, which is strong at short interval and weaker at longer interval, such as 22 or 30 days. He investigates individual stock betas in 2 extreme market value portfolios and concludes that, for the smallest market value portfolio, individual beta coefficients reveal an upward trend for longer interval. The opposite patterns apply for the largest market capitalization group. Most recently is the research on Athens Stock Exchange by Diacogiannis and Makri (2008), which confirms the intervalling effect and point out that the change in beta is greater for low market value portfolio.

Besides the commonly- used size and trading volume sorted portfolios, intervalling effects are present in portfolios of other characteristics. Smith (1978) performs empirical test and documents an increased beta with lengthened return intervals for stocks with true beta greater than unity and vice versa. In his work, based on estimated systematic risk in a prior period of 200 CRSP stocks, he splits stocks into 10 portfolios. When he extends the interval from 1 to 3 months, across all portfolios, the average beta rises monotonically. When the intervals are more than 12 months, for high beta portfolios, beta continues to increase but those of low beta portfolios level off and then decrease. Gilbert et al. (2014) sort stocks based on the difference between their low and high frequency betas, referred to as $\Delta\beta$. They find that the difference between daily and quarterly beta remains statistically and economically significant across all delta beta portfolios. The opaque firms, which have high $\Delta\beta$, display the similar beta behavior as small firms or low trading volume firms when the return interval changes. That is, high frequency betas are smaller than low frequency betas. In contrast, transparent firms, which have low $\Delta\beta$ are closer to high market value or high trading volume firms in terms of beta change under intervalling effect. In addition, Gilbert et al. (2014) analyze CAPM alpha behaviors. Their comparison is two dimensions, including alpha comparison across portfolios and alpha comparison across estimation frequencies for each portfolio. First, similar to differences in betas, the differences between daily and quarterly alphas are statistically significant for all 5 $\Delta\beta$ portfolios. For the same return frequency, alpha of the least opaque group is smallest and monotonically increases along the increasing $\Delta\beta$. Therefore, the more transparent the portfolio becomes, the more accurately the model price the assets. Second, alpha is insignificant at quarterly frequency, which is a clear indication of better CAPM performance at quarterly interval.

In terms of explanatory power of return generating model, the common documentation is the deterioration in R^2 when the return interval is shortened (Brailsford and Josev, 1997;Cohen et al.,1980; Dimson, 1979). For example, Dimson (1979) observes that with beta estimated from monthly returns rather half year returns, the mean R^2 falls from 36 percent to 21 percent. Another example is Australian market, where low market value portfolio experiences a jump in R^2 from 0.6 percent to 5.4 percent when the return interval goes from daily to monthly return (Brailsford and Josev, 1997) . The rate at which R^2 increases or decreases when the return interval changes is more evident for low market value or low trading volume portfolios. In the same work, Brailsford and Josev (1997) report that for high cap portfolios, the mean R^2 slightly moves from 0.440 to 0.443 when the return interval moves from daily to monthly. On the contrary, for the same interval change, R^2 of low market value portfolio witnesses a surge from 0.006 to 0.054. Finally, R^2 is considerably lower for low market value or low volume stocks. Dimson (1979) reports that very frequently traded shares have R^2 of about 35 percent when he uses monthly data to estimate but for very infrequently traded shares, R^2 stays at 8 percent only.

In short, Cohen et al. (1980) summarize the empirical phenomena for intervalling effect in the following points. First, beta is subject to change when the differencing interval changes. Betas of thin or low market capitalization securities rise when interval is lengthened and vice versa for high value or high volume securities. Second, the explanatory power of the market model regression is on the rise with longer interval. Furthermore, Gilbert et al. (2014) show that the significance of alpha coefficients at high return frequency is indicative of the model misspecification.

2.2 The cause of risk alteration with differencing data interval

Scholars agree that risk alteration with different return intervals stems from price adjustment delay, which is a significant source of cross correlation among security returns, resulting in autocorrelation of market index returns consequently (Chordia and Swaminathan, 2000; Cohen et al., 1980; Roll, 1981). Price adjustment delay is systematically different across issues; therefore, stocks do not have uniform reaction towards intervaling effect. Roll (1981) claims that the higher the return frequencies, the more significant the returns auto correlation, the slower the price adjustment process.

The underlying notion is that price adjustment delay prevents the immediate reflection of full impact of information in prices of some stocks. These stocks fail to incorporate some of recent information that is already contained in the prices of other stocks (Bernhardt, Davies and Hall, 2005). Stock prices deviate from true values; consequently, the unbiased betas are impossible to obtain. However, as the return interval lengthens, the impact of price adjustment delays gets lessened and prices incorporate much of the relevant information (Gilbert et al., 2014). Alternatively stated, this is when the differencing interval increases and gets greater than the delay. No delays are infinite, therefore, extending return interval helps mitigates the intervalling effect (Cohen et al., 1980).

Hawawini (1983) demonstrates a statistical approach to explain how return cross correlation accounts for beta changes in response to different return intervals. The model aims to estimate beta of long return interval from beta of short return interval. He proposes the model as follows.

$$\beta_i(T)=\beta_i(1) * \frac{T+(T-1)qi}{T+(T-1)qm} \quad (1)$$

where

$\beta_i(T)$ is stock beta estimated from T day interval

$\beta_i(1)$ is stock beta estimated from 1 day interval

$$q_i=\frac{\rho_{i,m+1}+\rho_{i,m-1}}{\rho_{i,m}} \quad (2)$$

$$q_m=\frac{\rho_{m,m+1}+\rho_{im,m-1}}{\rho_{m,m}} \quad (3)$$

$(\rho_i \ \rho_m)$ is the serial cross correlation coefficient of returns on security i with returns on the market index.

“qi” ratio is the relative cross correlation coefficients between returns on security “i” and returns on the market index estimated on one period returns and “qm” ratio is the cross correlation coefficient of market index autocorrelation.

The equation clearly shows that beta of longer interval differs from beta of short interval and the change results from the intertemporal cross correlation. In other words, beta changes depend on the serial cross correlation of returns and the autocorrelation of the market index returns with different leads and lags. Beta is invariant to interval length only when (1) security q ratio is non zero and equal to that of the market index or (2) security and market q ratio both stays 0, both of which are unlikely to happen (Hawawini, 1983).

The equation also explains the beta change direction when return interval changes. When return interval gets lengthened (T increases), beta estimates will increase if the security “qi” ratio is greater than the market “qm” ratio. The higher lead and lag serial cross correlation will make the higher than average “qi” ratio (Hawawini, 1983). Therefore, stocks with higher lead and lag serial correlation will have higher beta when the return frequency is lower.

Lag times between the trades result in lead lag correlation (Hasbrouck, 1991) and are exclusive for each stock. Corhay (1992) relates the average time between trades, or the expected magnitude of the price adjustment delay, to the thinness of the stocks: thinner securities take longer to respond than frequently traded ones. Roll (1981) relates stock thinness to its market values as well because small firms trade less. Therefore, low market value or low trading stocks have longer trade lags and greater induced autocorrelation. It explains why the intervalling effect is more prominent for these stocks (Roll, 1981).

Empirically, many researches attempt to illustrate the relationship between stock volume and higher lead lag autocorrelation. Chordia and Swaminathan (2000) empirically prove that the lead lag effects are related to the tendency of low volume stocks to be slower at responding to market wide information compared to high volume stocks. With the speed of adjustment measured based on lagged betas from Dimson regressions, they find that stocks of low trading volume, from 30 to 50 percent contribute the most to portfolio autocorrelations and cross autocorrelations. McQueen, Pinegar, and Thorley (1996) analyze the possibility of asymmetric response to market news as captured by the return on a market index and document that smaller firms take longer to react to market news. Using the market regression model proposed by Dimson (1979) and Chordia and Swaminathan (2000), Marshall and Walker (2002) measure the speed of adjustment to new information for different size quintile and arrive at the similar findings by McQueen, Pinehar and Thorley (1996).

In short, researches have statistically shown that the sensitivity of estimated betas to the return interval is primarily due to auto correlated market indices as well as intertemporal cross correlations between market return and those of individual securities. Therefore, the major effort now lies in explaining the fundamental causes behind those correlations which are referred to as price adjustment delays across securities. From the literature review, there are two mainstreams of explanations, centering on the presence of market friction and opacity-induced risk.

2.2.1 Market friction- nonsynchronous trading

Nonsynchronous trading is about the simultaneous treatment of stock prices recorded at different time (Scholes and William, 1977). This often happens to the infrequently traded issues, which usually have their last recorded price well before the end of the trading day (Fisher, 1966). Therefore, in case of sudden shock in the market, the new information can incorporated first in the prices of thick stocks and it takes a lag for thin stocks to reflect the information in the prices. Returns, calculated from those out of date price, therefore, are spurious and lose its predictability.

Non-synchronous trading is responsible for the observed autocorrelation in stock returns (Karathanassis, Patsos and Glezakos, 1999). Therefore, it causes intervalling effect. Roll (1981) explains that when there is no trade during the day, that day's implicit return will be recorded on the day when its first subsequent trade happens. The price change, therefore, reflect market information for both days (Alles, 1997). This return correlates with the returns of other firms which have their trades registered on the first day, resulting in the auto correlation. The same phenomenon applies if firms trade every day but not continuously. Alles (1997) explains how index autocorrelation occurs as the function of the autocorrelation of its component stocks as well as the cross serial correlation between these returns. When the return of the stock on a day the trade occurs involves in the computation of the index return, information in the stock on no trade day is reflected in the index return. The time span of the information reflected in the stock mismatches with the time span of the information contained in the index. In short, nonsynchronous trading leaves securities and market index, as a consequent, auto-correlated.

To explain beta change direction, Dimson (1979) statistically shows that shares of low trading volume or low market value have their covariance with the market substantially underestimated, resulting in the downwards bias. The opposite applies for more frequently traded or high value shares. Scholes and Williams (1977), by studying the properties of the market model with nonsynchronous data, find that the variance and covariances of reported returns are different from corresponding variances and covariances of true returns. The measured variances for single securities overstate the true variances while the measured cotemporaneous covariance understates in absolute magnitude true covariances.

2.2.2 Risk based explanation for intervalling effect

Studies suspect that stock different price adjustments arise as a result of some other effects, other than nonsynchronous trading alone (Atchison, Butler and Simonds, 1987; Theobald, 2004). Gilbert et al. (2014) shed light on this suspicion by performing robustness check on stocks with high liquidity, high market value and using Dimson (1979) correction. Although their constructed sample is free from non-synchronous trading, intervalling effects remain. Therefore, they propose a risk based explanation. This new approach seems well grounded because when Gilbert et al. (2014) perform the test with risk neutral agents, no difference in betas across frequencies exists. In their opinion, firm opacity, which is the uncertainty about the effect of systematic news on firms' value, causes different price adjustment delay across firms. Developing this idea, Gilbert et al. (2014) address 3 fundamental questions of intervalling effect, including "how intervalling effect happens", "why stocks of different characteristics have different beta changes in response to interval changes" and "why intervalling effects diminish when the return frequency is lower".

First, Gilbert et al. (2014) explain how intervalling effects happen due to firm's opacity. At high frequencies, if investors are risk averse, this uncertainty creates an additional source of uncertainty that risk averse investors take into consideration while no additional uncertainty exists at low frequencies. The additional risk makes the price distribution different across frequencies, driving a wedge between the high and low frequency market betas.

Second, Gilbert et al. (2014) account for the varied behavior patterns of betas of different stocks. They result from the interaction between cashflow effect and discount rate effect on different firm types at high frequency when market information arrives. Risk averse investors demand additional compensation for uncertainty about assets' exposure to the shock. Therefore, in the advent of good news, the net price change of opaque stocks reflects good news about future dividends (cashflow channel) but bad news about temporarily increased uncertainty (discount rate channel). On the contrary, in case of bad news, the net price change of opaque firms reflects negative news about future dividends (cashflow channel) but there is reduced uncertainty (discount rate channel) thanks to zero dividend of the opaque firm. Hence, returns of opaque firms at high frequencies are the combined effect of both discount rate and cash flow channel. Meanwhile, prices of transparent assets respond only to the cash flow effect because those firms respond immediately to market news, carrying no increased risk uncertainty.

At high frequencies, the presence of the additional discount rate effect in the price movement of the opaque firms will dampen the co-movement between returns of the opaque and transparent assets. Since the market is mainly constituted of transparent firms, the co-movement between transparent assets and the market is emphasized. Meanwhile, the opposite happens for the co-movement between the opaque assets and the market. Therefore, unconditional high frequency betas of transparent assets are upward biased and betas of opaque asset are downward biased. This explains the observation of smaller high frequency betas compared to low frequency betas for opaque firms and vice versa.

Third, at sufficiently low frequencies, the effect of systematic news is made known for all firms. Brailsford and Josev (1997) also state that price adjustment delay prevents the full impact of information impounded into prices at high frequency returns. But in case of a lengthened return interval, the reduced impact of price adjustment delay helps prices reflect much of the relevant information. Therefore, opaque firms do not have to carry additional uncertainty risk, resulting in the identical price distribution for both types of firms in the market. Consequently, beta estimated from high frequency catches up with betas estimated from low frequency in values. This explanation accounts for the diminishing intervalling effect in low frequency intervals.

2.3 Fixing intervallig effect for better beta estiamtes

2.3.1 Longer or shorter return interval for beta estimation?

To arrive at the correct beta and keep intervalling effect to a minimum, I consider beta estimated from long interval return. Researches, in the light of R^2 as the measure of asset pricing model accuracy level, shows that betas obtained from longer return frequencies are superior to those from low return frequencies. Some researches even associate the short return interval with CAMP's failure. Brzeszczyński, Gajdka, and Schabek (2011) generalize that the longer the interval, the higher the chance that CAPM holds. For example, Handa et al. (1989) stress CAPM failure in the case of monthly intervals but they do not reject the appropriateness of CAPM in case of yearly interval for stocks in NYSE. Campbell and Clarida (1987) document the existence of predictable time varying excess returns using three- month holding period returns for Eurodollar investment between 1976 and 1982. However, in the related area, Campbell (1987) strongly rejects the model when he uses monthly US data to predict excess returns on bills and bonds. Therefore, for the sake of appropriate return generating model, one suggestion is to estimate betas from longer return intervals.

Since the comprehensive databases with shorter data periods became available, daily frequency has become more popular. First, the daily data carries more information on an asset' risks compared to returns measured over longer periods (Kim, 1999). It is because the information is not lost during the process the stock returns are aggregated from high frequencies (Brzeszczyński et al., 2011). Being information rich, daily data can illustrate daily trends and stocks response to events on specific days, which is helpful for event study application (Berry et al., 1990). Second, daily data furnishes researchers with more observations for an effective regression analysis without lengthening the estimation period, which exposes beta estimates to the risk of instability across time (Brzeszczyński et al., 2011). Third, a large number of observations for a given estimation period help researchers overcome the critical problem of robustness to sampling variation (Warren, 2003). Handa et al. (1989) state that the accuracy of beta estimation is obviously affected by the number of return observations. Finally, Daves, Ehrhardt and Kunkel (2000) recommend betas estimated from daily returns for the greatest accuracy of beta values.

Researchers cannot ignore the huge benefits offered by daily return data. It has become a strong motivation for them to make various adjustments to beta estimated from daily returns.

2.3.2 Corrective methods for beta estimated from daily returns

Scholars apply a variety of alternative corrective techniques for beta estimation at daily return frequency because of severe intervalling effect at this return level (Diacogiannis and Makri, 2008; Brailsford and Josev, 1997; Pogue and Solnik, 1974). Scholes and Williams (1977), Dimson (1979) and Cohen et al. (1983b) are the best known methods for correcting beta bias (Beer, 1997; Kim, 1999). These corrective models deal with the intervalling effect resulting from nonsynchronous trading. In their recent paper, Gilbert et al. (2014) recommend the use of the $\Delta\beta$ factor in a market model to arrive at the correct beta estimates. This has been the only corrective model so far that resolves intervalling effect from risk perspective.

Scholes and Williams (1977) and Dimson (1979)

Scholes and Williams (1977) and Dimson (1979) attempt to correct the implied bias in the OLS beta. These methods focus on dealing with nonsynchronous trading, adjusting beta coefficients by taking information from consecutive period returns into consideration. The goal is to yield a consistent estimator (Fowler and Rorke, 1983).

Scholes and Williams estimator is a variant of the OLS beta estimate in which the market model is run separately with contemporaneous, lead and lagged market returns.

$R_{it}=\alpha_i+\beta_{i,\,t-1}*R_{mkt,t-1}+\xi_{i,t-1}$

$R_{it}=\alpha_i+\beta_i*R_{mkt,t}+\xi_{i,t}$

$R_{it}=\alpha_i+\beta_{i,t+1}*R_{mkt,t+1}+\xi_{i,t+1}$ where

R_{it} is security return at time t

$R_{mkt,t-1}$ is market portfolio's return at time t-1

$R_{mkt,t}$ is market portfolio return at time t

$R_{mkt,t+1}$ is market portfolio's return at time t+1

Then, I obtain the consistent beta estimator by summing the slope coefficient of the individual regression models, adjusted for the auto correlation of the market index

$$\beta = \frac{\beta_{i,t-1}+\beta_i+\beta_{i,t+1}}{1+2r} \quad (4)$$

r is the first order auto correlation coefficient of the market index.

Dimson type models have the general form as

$R_{it}=\alpha_i+\sum_{k=-m}^{m}\beta_k R_{mkt,t+k} + \xi_{it}$ where

R_{it} is security return, $R_{mkt,t+k}$ is market index return with appropriate leads and lags and m is from exogenous information relevant to the marketability frequency of the stocks. Dimson beta coefficient is the total of partial betas $\beta_D=\sum_{k=-m}^{m}\beta_k$.

In a discussion about m, Berglund, Liljeblom and Loflund (1989) and Cohen et al. (1983b) recommend that the number of leads and lags included should be limited to ten to reduce the distortion in the estimate and the loss of statistical efficiency resulting from the excessive number of unnecessary variables.

Dimson's beta, however, does not eliminate all the residues from non-trading (Dimson, 1979). In addition, it might suffer from inconsistency when compared to Scholes and Williams beta (Fowler and Rorke, 1983). Therefore, Fowler and Rorke (1983) suggest a variant of this procedure that uses a weighted rather than an unweighted sum of slope coefficients to yield a more consistent version as follows:

$W_1=\frac{1+\rho_1}{1+2\rho_1}$ for one lag and one lead

$W_2=\frac{1+\rho_1+\rho_2}{1+2\rho_1+2\rho_2}$ for two leads and lags, where

ρ_1 is the first order serial correlation coefficient for the index and

ρ_2 is the second order serial correlation coefficient.

Dimson's beta is superior to Scholes and Williams' beta in terms of efficiency (Dimson, 1979). Even the modified version of Dimson's beta does not prevent the estimation procedure from being more economical and computationally convenient than Scholes and Williams's beta. To illustrate, where there are two leads and two lags, Dimson's procedure only requires one multiple regression for each security and two for the index. Meanwhile, it takes five simple regressions for each security and two for the index for the latter.

Cohen et al. (1983a)

Dimson (1979) and Scholes and Williams (1977) shortcomings stem from their assumptions of short lag structure. First, they assume information loss resulted from non- trading can be reflected immediately in subsequent period because transaction happens in every return measurement period. Second, the process to produce the delay structure in observed betas is independent and identically distributed over time. These assumptions restrict the model's ability to extend the results if at least one transaction does not happen per each period. However, even for frequently traded stocks, there is likelihood that a day goes without any transaction.

Cohen et al. (1983a), on the contrary, observe that beta bias last more than several weeks. Therefore, higher order of lead and lag may display significant power in the regression and omitting them may lead to an inconsistent parameter (Cohen et al., 1983a). It motivates them to develop a model that does not limit number of lead and lag periods to estimate betas.

Cohen et al. (1983a) develop their technique basing on the proposition that as with the enlargement in differencing interval, adjustment delay diminishes and OLS beta approaches true values. Therefore, the first step is to obtain this consistent estimator. This is the value that OLS estimator approaches when interval returns increase without bound, referred to as asymptotic beta. Second, they estimate intervalling effect on beta coefficients. Finally, they estimate the extent to which the difference between a stock's asymptotic beta and its OLSE beta for a given differencing interval is related to the inverse market value of that security's outstanding shares. This relationship helps them obtain inferred betas from betas of some short differencing intervals and market value of shares outstanding.

Δβ factor by Gilbert et al. (2014)

The appeal of opacity factor roots from its ability to disentangle discount rate effect and cashflow effect for opaque stocks. Gilbert et al. (2014) create opacity factor by going long the opaque assets and short the transparent assets. Empirically, opacity factor is the daily return differences between the daily value- weighted returns of portfolios of stocks in the top and bottom of opacity scale distribution, with opacity proxy being the difference between stock's low and high frequency betas. From its construction, Gilbert et al. (2014) address opacity factor as Δβ factor as well. This factor yields a zero investment portfolio that moves only with the discount rate effect. Hence, in augmented model, Δβ factor absorbs the discount rate effect, market beta captures the cashflow effect alone, reflecting the asset's risk fully and correctly. At low frequency, opacity influence is invisible due to a full response by all firms to the information. CAPM prices the assets perfectly. Therefore, opacity factor only plays its role at high frequency returns (Gilbert et al., 2014).

In short, Gilbert et al. (2014) formulate a factor to address the opacity induced risk in the advent of new market information. This factor also satisfies Atchison et al.'s (1987) suspicion about the unknown price adjustment delay factor.

2.3 Correction methods' performance in asset pricing model

Authors of the above mentioned methodologies prove the feasibility of their suggestions empirically.

Scholes and Williams (1977) apply the Scholes and Williams' beta on daily returns of stocks listed on the New York and American Stock Exchange from January 1963 to December 1975. They form five portfolios based on the trading volume with the first portfolio consisting of 20 percent of lowest trading volume securities and so on for the next portfolios. With the first portfolio, portfolio Scholes and Williams' beta is larger than corresponding OLS betas, fixing the downward bias. The difference is reduced when they compared Scholes and Williams' beta and OLS beta of thicker portfolio. At the same time, the coefficient for lagged beta β^- decreases and the lead betas β^+ increase.

Dimson (1979) evaluates his method empirically on returns from the London Share Price Database in the period of 1955 to 1974. First, the beta range for OLS beta is from 0.47 to 1.20 but with the Dimson method, the range is narrower, from 0.85 to 1.13. He observes the higher explanatory power of the regression model, from a mean of 22.1 percent with OLS regression to 23.8 percent with Dimson regression. The aggregated betas of infrequently traded firms are higher than OLS betas and vice versa.

Cohen et al. (1983a) perform analysis on 50 New York Stock Exchange common stocks, ranked by their market value, from January 1970 to December 1973. They show that estimated asymptotic betas tend to unchanged when interval returns are lengthened to infinity. Inferred asymptotic betas are good estimators of estimated asymptotic betas with mean square error of 0.055 and high correlation. Furthermore, the inferred asymptotic betas are reasonably stable over different samples of NYSE in the tested period.

Gilbert et al. (2014) empirically test the $\Delta\beta$ factor on five by $\Delta\beta$ sorted portfolio. Portfolio 1 contains stocks of lowest $\Delta\beta$ and portfolio 5 has stocks of highest $\Delta\beta$. Comparing alphas of CAPM and augmented model across all 5 portfolios, they document the significant drop in high frequency augmented alphas. In details, the model augmented with $\Delta\beta$ has the largest decrease of 59 percent in the sum of squared daily alphas. The sum of squared monthly and quarterly alphas falls by much smaller 19 percent and 30 percent respectively. By comparing different frequencies within a given a portfolio, they observe the most noticeable improvement in alphas in portfolio 4 and 5, the top opaque portfolios. These results evidence the better performance of asset pricing model augmented with $\Delta\beta$ factor.

After above pioneering papers, aside from the newly introduced opacity factor, many researches apply those corrective methods in different markets to test their wide applicability.

McInish and Wood (1986) compare beta estimates of Dimson (1979), Scholes and Williams (1977) and Cohen et al. (1983). They construct five portfolios with a maximum time difference in minutes from the last trade to market close. They keep returns and several other risk related variables approximately in par across the portfolios. Therefore, without bias, five portfolios should display equal beta. Moreover, portfolios and market index are constructed from the same securities; the betas of the market must average 1.0. It follows that beta of each of five portfolios is 1.0. The extent of the OLS beta's divergence from 1.0 reflects how biased the OLS beta is. Empirically, the OLS betas obtained for 5 portfolios vary monotonically from 0.744 to 1.494. Portfolios containing infrequently traded stocks have beta estimates less than 1.0 and vice versa. This result is indicative of the intervalling effect. If the Scholes and Williams, Dimson or Cohen et al. techniques are sufficient to correct beta bias, the corrected estimates should be close to 1.0 for every portfolio. The results show that all the correction methods adjust betas in the positive direction. Among 3 techniques, Dimson beta is the best performer. It reduces the bias by 29 percent in comparison with the spread in OLS beta estimates.

Karathanassis et al. (1999) show that Dimson method corrects intervalling effects in the Athen's stock exchange. First, the majority of stocks display higher explanatory power compared to the corresponding simple market model. Second, Dimson betas are greater than the betas obtained from simple market model. It indicates that Dimson method fixes the downward bias. Additionally, the use of Dimson type model eliminates heteroscedasticity. In details, with the simple market model, 54.5 percent of the shares display heteroscedasticity at 5 percent level of significance. Meanwhile, only 22.7 percent of the stocks appear heteroscedastic when they use Dimson model. Based on the findings, Karathanassis et al. (1999)

conclude that Dimson model provides a more appropriate and efficient estimation of beta in this particular stock market.

According to Fung et al. (1985), estimated asymptotic beta obtained from Cohen et al.'s (1983) model is the most accurate because it explicitly considers different return frequencies, taking largest data demands. Using estimated asymptotic beta as the benchmark, Fung et al. (1985) compare the performance of Scholes and Williams' beta and inferred asymptotic beta from Cohen et al. (1983) in French stock market. Scholes and William's beta does not correct the intervalling effect and are relatively inaccurate predictors of asymptotic beta for any differencing interval. The average Scholes and Williams' beta is less than the average OLS beta, showing the under adjustment effect. Meanwhile, the proper adjustments toward the true betas should make the average Scholes and Williams' betas greater. Alternatively, inferred asymptotic betas display almost no intervalling effect and stay close to the estimated asymptotic betas. Compared to the US market, the inferred asymptotic beta obtained in French market performs even better. For a one day interval, the inferred beta mean square error, for the French sample, is 0.038 compared to 0.055 in US market.

Contrary to above positive results, some researches support the use of OLS betas over adjusted betas. Beer (1997) applies Scholes and Williams' (1977) adjustment method on market value sorted portfolios in Brussels stock exchange and acquires results different from those acquired in US by Scholes and Williams (1977). For example, Scholes and Williams (1977) find that the coefficients and the t test of the lagged component increase with the thinness of the transaction. Because of stock prices' failure to incorporate timely information due to nonsynchronous trading, they emphasize that lagged coefficients are, on average, more important in magnitude than the leading coefficient. However, Beer (1997) observes the opposite, indicating that Scholes and Williams' method under-adjusts the intervalling effect. Beer (1997) assess modified Dimson's beta at the same time. To account for beta inconsistency (Fowler, 1980), Beer (1997) combines Dimson's estimate (1979) with the Bayesian correction by Vasicek (1973), including 1 lead and 1 lag. This combination provides slightly better results with less severe bias, compared to the benchmark of unity beta that the author assigns to each share. However, this augmented Dimson betas deteriorate asymptotically when more leads and lags are included in the measuring period. It supports the assumption that a full adjustment process is between -1 and +1, which cannot satisfactorily capture reality (Beer, 1997). To sum up, she suggests that OLS technique serves as the most highly recommended method to produce beta estimate, at least in thin market such as Belgian market. It is “simple to implement and easily understandable” (Beer, 1997,p9) and arrives at the similar results. The same viewpoint is present in Bartholdy, Olson and Peare (2007), support the use of OLS beta estimated over Dimson’s betas or Scholes and Williams’ betas using New Zealand daily returns or Davidson and Josev (2005), who document the negligible difference between OLS and Scholes and Williams’ betas in Australian market.

2.4 Correction methods’ performance in event study

The possible misspecification in event studies as the result of the biased beta estimates requires some attentions (Campbell and Wesley, 1993) . Cohen et al. (1980) particularly discuss that the bias in beta coefficients might lead to bias in abnormal returns, misleading the event study results. Especially, in the limited evidences about different beta correction methods’ performance in event studies, the expected improvement is consistently negligible, in both actual event and simulation approach.

Among very few attempts to apply corrected betas in an actual event are by Gheyara and Boatsman (1980), Lamoureux and Poon (1987) and Brennan and Copeland (1988).

Gheyara and Boatsman (1980) adjust nonsynchronous trading in daily return by Scholes and Williams method. Their purpose is to determine whether replacement cost disclosure as mandated by the Securities and Exchange Commission’s Accounting Series Release 190 contains any informational content. They carry out the test with both OLS betas and Scholes and Williams betas. The results are insensitive to the methods. The striking similarity between them even leads to the redundancy of the report on Scholes and Williams beta in their research. The conclusion is that there is no information found for the replacement cost disclosure.

Further work on the failure of nonsynchronous adjusted beta is by Lamoureux and Poon (1987) and Bernnan and Copeland (1988). To study the beta changes around stock splits, both papers estimate daily OLS betas, Scholes and Williams adjusted betas and betas from Fowler and Rorke (1983). OLS beta increases about 30 percent in magnitude in the week surrounding the ex date and 18 percent over the 75 days subsequent to the split. The use of the Scholes and Williams (1977) three day and the more general, Fowler (1980) five day beta estimators does not change the conclusion about the risk alteration in the advent of stock split. Therefore, sophisticated beta estimations do not add value for improving event studies.

Brown and Warner (1985) provide a pioneer paper on investigating alternative models for abnormal return measurements by simulation procedures with actual stock return data. Without any specific event, their methodology is of high generalization. Due to the randomness in assigning the securities and the corresponding event date, there should be no abnormal performance on average if the return generating model works correctly. The test focuses on addressing two types of errors, through which they can make conclusions about the specification and the power of the model. First, they assess the chance that the model can commit the rejection of the null hypothesis of no abnormal returns when it is true. Second, the power test is the probability that the model cannot reject the null hypothesis of no abnormal return when it is false. They compare the model power in abnormal return detection among the OLS beta, Scholes and Williams procedures and the Dimson aggregate coefficients method, with three lags and three leads. They use exchange listing as the proxy for trading frequency. Of the New York Stock Exchange (NYSE) and American Stock Exchange (AMEX), the latter is believed to be more thinly traded. The magnitudes and directions of the beta change in all three methodologies are up to expectation. For NYSE stocks, OLS estimates of beta are on average greater than the Scholes and Williams or

Dimson estimates. For AMEX stocks, they observe the reverse relative magnitudes of the average beta estimates. However, procedures other than OLS do not showcase any improvement in either the specification or the power of the tests. In the case of no abnormal return, rejection rates across all methodologies are close to the significance level of the test, ranging from 4.4 percent to 5.6 percent, indicating that all tests are well specified. In the presence of abnormal returns, they do not document any significant difference in the power to detect abnormal performance from the OLS, Scholes Williams and Dimson based procedures. For example, across three estimation approaches, rejection frequencies with 1 percent induced abnormal returns range from 64.4 percent to 65.2 percent for the NYSE samples and from 28.8 percent to 31.2 percent for the AMEX samples.

Dyckman, Philbrick and Stephan (1984) apply OLS betas, Scholes and Williams' betas and Dimson's betas to three trading volume sorted portfolios, namely low-, medium- and high-trading frequency portfolios. On average, for induced abnormal returns of 3 percent, at 5 percent, the rejection rates across 3 portfolios for each beta estimation method are equal to each other and are roughly 7 percent. In high trading frequency portfolio, all three procedures detect the abnormal performance at 10 percent. The insignificant difference is present in the low trading frequency portfolios, where the rejection rate from Dimson procedure is only 1 percent lower than the other procedures, whose rejection rate is 6%. The result suggests that Scholes and Williams and Dimson methods do not enhance the ability to detect abnormal performance on daily returns for thinly traded stocks.

Cowan and Sergeant (1996), after investigating the test specification of volume clustered portfolios, reach the same conclusion. Instead of a normal portfolio t test, they test Scholes and Williams' betas with standardized, standardized cross sectional, rank and generalized sign test. They then compare those results from a combination of OLS beta and above mentioned t tests. The findings show the extension to another t statistics test does not improve test power either.

Despite improvements in asset pricing in the presence of corrected betas by Dimson, Scholes and William or Cohen et al., an enhanced event study power does not result. The emergence of Δβ factor and its proven effectiveness in asset pricing model poses a question: Whether the augmented market model can challenge the traditional event study analysis or its impact on the abnormal return detection is negligible as in previous cases. The following test on the Δβ factor's performance in event study analysis will address this literature gap.

CHAPTER 3: DATA AND METHODOLOGY

3.1 Data

This research uses the same sample as in Gilbert et al. (2014). All stocks listed in NYSE/AMEX/ NASDAQ that have a year- end market capitalization of at least $5 million for every year from 1969 to 2010 are research objects. Daily and monthly stock returns are downloaded from CRSP. Because CRSP provides return data for both mutual funds and real estate as well, this study filters common shares from CRSP database by selecting items with a share code of either 10 or 11.

Daily and monthly excess returns of the market portfolios are available from

Kenneth French's website. I compound monthly returns to obtain quarterly returns of all assets.

3.2 Methodology

The main purpose of this research is to test the impact of opacity factor on event study test power. Therefore, two main tasks to perform are constructing the opacity factor and conducting event studies with that opacity factor.

3.2.1 Methodology for opacity factor formation

Gilbert et al. (2014, p. 29) develop the opacity factor from the concept of "going long the opaque assets and short the transparent assets". Empirically, I will construct this factor as the difference between the daily value- weighted returns of portfolios of stocks in the top and bottom tercile of the opacity proxy, which is $\Delta\beta$ (Gilbert et al., 2014). The preliminary task, therefore, should be forming portfolios based on $\Delta\beta$.

I obtain $\Delta\beta$ by replicating the procedure in Gilbert et al. (2014). First, I estimate CAPM betas at the end of every calendar year from 1969 to 2010 from quarterly returns over the past 5 years (60 months). The regression is

$$R_{it}=\alpha+\beta*R_{mkt,t}+\xi_{it} \quad (5), \text{ where}$$

R_{it} is stock quarterly returns in 5 years

$R_{mit,t}$ is corresponding market quarterly returns in 5 years

To be included in the sample, all the stocks must have at least 15 quarters of data in 5 consecutive years. Those betas are referred to as quarterly betas. To obtain daily CAPM beta, I do the same with daily returns, with the condition that the stock must have at least 945 days of data. I address these as daily betas. For each stock in every year in the period, I calculate the difference between stock's quarterly and daily beta, referring to these as Δβ. I then sort stocks into 5 quintile portfolios based on their lagged Δβ, with portfolio 1 comprising the stocks of lowest Δβ and portfolio 5 with stocks of highest Δβ. I rebalance these portfolios at the end of every year.

For example, to calculate quarterly betas for the year 1969, I will regress the stocks' quarterly returns in year 1965, 1966, 1967, 1968 and 1969 on their corresponding quarterly market returns. Furthermore, for a stock to be included, it must have at least 15 quarters of data between 1965 and 1969. I do the same for daily betas. For each stock, the difference between daily beta and quarter beta, defined as Δβ, is recorded. I repeat the same procedure every year from 1969 to 2010 so that every stock has different a Δβ each year. For every year, I then sort stocks into portfolios conditioned on their lagged Δβ.

I present the summary statistics (pool averages) for the constituents of 5 value weighted portfolios.

Table 1: Summary statistics of Δβ portfolio constituents

	Port 1	Port 2	Port 3	Port 4	Port 5
Number of firms	636	636	636	636	684
Daily Beta	1.04	0.94	0.91	0.94	1.09
Quarterly Beta	0.71	0.98	1.20	1.50	2.55
Δβ	-0.33	0.05	0.29	0.56	1.46
Share price	24.72	43.76	52.81	24.54	12.82
Market Cap ($m)	3,468.67	2,759.48	1,811.02	773.70	340.99
Below $5	16%	11%	12%	19%	34%
Mcap(1st/50th/99th pct. ($m/m/b)	6/343/50	6/257/46	6/159/27	5/96/11	5/56/4

This table reports the summary statistics of 5 value weighted portfolios formed annually based on stocks' lagged Δβ. Number of firms, Daily beta, Quarterly beta, Δβ, share price, market cap ($m) are the average of all firms in the portfolio across the whole sample period. Below $5 is the percentage of month ending with trading price less than $5 for a given stock. The last MCap reported are the 1st percentile (in million dollars), the median (in million dollars) and the 99th percentile (in billions of dollars) of the size of the portfolio constituents. The sample period is from 1969 to 2010.

The target is to reproduce 5 Δβ portfolios that are as similar as portfolios formed in Gilbert et al. (2014), in terms of the trend and values. For all items reported in my portfolios, there are no differences over than 10% compared to portfolios in Gilbert et al. (2014) in terms of values, which is acceptable. More importantly, the trend remains. First, portfolio 1 has the quarterly beta lower than its daily beta (I report the difference of -0.33 while Gilbert et al. (2014) report the difference as -0.38). As Δβ increases, quarterly beta becomes higher compared to daily beta and the largest difference between quarterly and daily beta is in portfolio 5, where Δβ is reported to be 1.46 (compared to 1.49 in the original article). Second, firms in the portfolios have smaller market capitalization and lower liquidity when Δβ increases.

Then, I calculate daily and quarterly value weighted portfolio returns of lagged Δβ portfolios and estimate unconditional full sample daily and quarterly betas as well as the difference between betas across frequencies for each of the 5 portfolios. The report of the differences in portfolio betas across frequencies in table 2 addresses the null hypothesis that beta are frequency independent (Gilbert et al., 2014). I estimate the standard error in beta differences by implementing bootstrapping simulation. First, I randomly select 168 quarters with replacement from all the quarters in the estimation period (I have 42 years of investigation, or 168 quarters). I calculate the quarterly value weighted returns of all portfolios in the chosen quarters and then estimate the unconditional full sample quarterly beta. Second, I obtain the corresponding return dates of the above quarters, calculate portfolio daily value weighted returns in those days and estimate the unconditional full sample daily beta. I record the difference between the quarterly beta and daily beta. I repeat this procedure 10 000 times so as to obtain to distribution of Δβ test statistics and estimate p values for the differences in the betas.

Table 2: Differences in CAPM β across return frequencies

	Port 1	Port 2	Port 3	Port 4	Port 5	Port5-Port1
Daily returns Beta	1.00	0.95	0.95	1.01	1.14	0.14
Quarterly Returns Beta	0.89	0.92	1.02	1.13	1.42	0.53
Quarterly beta-Daily beta	-0.11**	-0.02	0.07**	0.12***	0.28***	0.39***

*This table presents unconditional β estimates of 5 portfolios sorted by lagged Δβ in every year in the sample period from 1969 to 2010. Daily return β is the time series estimates of β for each portfolio at daily frequency. Quarterly return β is the time series estimates of β for each portfolio at quarterly frequency. Quarterly beta- Daily beta is the difference between portfolio quarterly return β and daily return β. Standard errors for the differences in betas are obtained from bootstrapping. ***, **, * indicate significance level at 1%, 5% and 10% respectively.*

Portfolio betas reported in table are comparable to those in Gilbert et al. (2014), in terms of trends and absolute values. There are 2 important observations. First, for low Δβ portfolio, when the interval becomes lengthened, the low frequency beta decreases and the high frequency beta increases. The opposite trend applies to high Δβ portfolio. For example, portfolio 1 exhibits a decrease in beta of 0.11 (compared to 0.14 in Gilbert et al. (2014)) when the interval decreases whereas portfolio 5 exhibits the increase in beta of 0.28 (compared to 0.27 in Gilbert et al. (2014)). Second, the differences in beta across frequencies are both statistically and economically significant. Gilbert et al. (2014) assess the difference between differences in beta by building a 5-1 portfolio that is long Portfolio 5 and short Portfolio 1. I report the difference in beta across frequencies for portfolio 5-1 of 0.39, compared to 0.41 in Gilbert et al. (2014). However, they are both statistically and economically significant. This indicates that portfolio beta is frequency dependent. From literature, this is the intervalling effect.

I agree with Gilbert et al.'s (2014) about investigating frequency dependent betas in portfolios rather than in individual stocks. First, most empirical finance studies of asset markets target portfolios rather individual stocks (Brooks, Faff and Lee, 1994). Second, Theobald and Yallup (2004) argue that intervalling affects are more apparent at the portfolio level. Third, a test on portfolios rather individual stocks will reduce random variation in estimated betas (Berglund et al., 1989). Hence, it is easier to detect beta inconsistency across frequencies. The drawback of this method is that some information is lost in the aggregation of stocks to portfolios. However, this potential loss of data does not pose severe problem due to the large number of stocks listed in three large exchanges NYSE/ AMEX/NASDAQ that I examine (Berglund et al., 1989).

After establishing 5 Δβ sorted portfolios, Δβ factor is constructed as "the difference between the value- weighted returns of portfolios of stocks in the top and bottom terciles of the Δβ distribution" (Gilbert et al., 2014, p30), which are portfolio 5 and portfolio 1 respectively. Due to the similarities between my 5 constructed portfolios and those by Gilbert et al. (2014), I can later perform the event study test with the recently constructed Δβ factor. The purpose is to address Gilbert et al.'s (2014) implication of systematic risk for event study analysis.

Gilbert et al. (2014) propose the use of 2 factor CAPM model augmented with the Δβ factor to estimate the opacity- adjusted beta.

$$R_{i,t}=\alpha+\beta_{i,1}*R_{mkt,\,t}+\beta_{i,2}*R_{\Delta\beta,t}+\xi_{i,t} \quad (6),\text{ where}$$

$R_{i,t}$ is stock daily return during estimation period

$R_{mkt,t}$ is market portfolio daily return during estimation period

$R_{\Delta\beta,t}$ is the difference in daily return between the portfolio comprising the highest Δβ stocks and portfolio comprising the lowest Δβs stocks during estimation period

$\beta_{i,1}$ is the opacity adjusted beta.

3.2.2 Methodology for event study test

3.2.2.1 Sample construction

To assess the opacity factor performance in event study, I replicate the well-known simulation approach from Brown and Warner (1985) , who study the daily returns for stocks in the NYSE and ASE stock exchanges. With the use of actual stock return data, the simulation procedure exploits data from “the true generating process” and is the “direct way to summarize event study performance” (Brown and Warner, 1985, p.6). I will apply the same simulation to both return generating models for a direct comparison.

First, I randomly select 200 securities without replacement from the population of all securities with available daily return in CRSP. Second, for each chosen security, an event date (Day 0) between 1 January 1970 and 31st December 2010 is randomly generated. To allow for estimation, the securities are required to have at least 250 days of continuous returns before Day 0 and 10 days of continuous returns following day 0. As long as this constraint is satisfied, each day has an equal probability of being picked. I extract a time series of 261 daily returns around the random event date. Day -250 through -11 comprise a 240 day estimation period from which market model parameter result are obtained. Later, these parameters will be used in conjunction with market portfolio returns and other factor (if the opacity factor is considered) to estimate the expected return. The event period is from day -10 to day +10.

I replicate this procedure 1000 times to obtain 1000 portfolios of 200 stocks each.

3.2.2.2 Abnormal return and t statistics calculation

Abnormal return is defined as the difference between securities’ actual ex post return and what is expected under the assumed return generating process.

While I can obtain the actual ex- port return from CRSP database, it is necessary to specify a model to generate the expected returns. Two models I will consider in this research are the OLS market model and the two factor model which takes opacity factor into consideration. I refer to them as one- factor model and two-factor model, respectively.

(1) One factor model

Among choices for commonly used return generating model in event studies, for simplicity and efficiency, I prefer the use of the OLS market model. Brown and

Warner (1985) prove that there is no evidence of more advances by more complicated methodologies than one factor market model. They also affirm that a methodology based on the market model performs well under a wide variety of conditions. The 1 factor model is

$$R_{i,t}= \alpha_i+\beta_i*R_{mkt,t}+\xi_{i,t}, \text{ (7) where}$$

$R_{i,t}$ is the daily stock return in the estimation period

$R_{mkt,t}$ is the daily market portfolio return in the estimation period.

The abnormal return is calculated as

$$AR=R_i-\hat{\alpha}-\hat{\beta}*R_{mkt}, \text{ (8) where}$$

R_i is the stock return on event date

R_{mkt} is the market return on event date

$\hat{\alpha}$ and $\hat{\beta}$ are OLS values from the estimation period.

(2) Two factor model

When I take the opacity factor into consideration, the return generating process becomes

$$R_{it}= \alpha_i+\beta_{1i}*R_{mkt,t}+ \beta_{2i}* R_{\Delta\beta,t} +\xi_{it}, \text{ (9) where}$$

R_{it} is the daily stock return during estimation period

$R_{mkt,t}$ is the daily market portfolio return during estimation period

$R_{\Delta\beta,t}$ is the difference in the daily return between the portfolios of the highest Δβ and portfolio of the lowest Δβ during estimation period.

The abnormal return is calculated as

$$AR= R_{i,}-\hat{\alpha}-\hat{\beta}_1*R_{mkt} -\hat{\beta}_2*R_{\Delta\beta}, \text{ (10) where}$$

R_i is the stock return on event date

R_{mkt} is the market return on event date

$R_{\Delta\beta}$ is the difference in the daily return between the portfolio of the highest Δβ and portfolios of the lowest Δβ on event date

$\widehat{\alpha}, \widehat{\beta_1}, \widehat{\beta_2}$ are estimated values from the estimation period.

In terms of test statistics, following Brown and Warner's (1985) methodology, which is further discussed by Corrado (1989), Boehmer, Masumeci and Poulsen (1991) or Campbell and Wasley (1991), I use the "portfolio" test statistic. For 1 day event period, the t statistics is the ratio of the portfolio mean abnormal return divided by its estimated standard deviation. If abnormal returns are independent, identically distributed and normal, the test statistic is distributed as student t and it is approximately standard normal under the null hypothesis.

By using a time series of average abnormal returns for computing the standard deviation, the test statistic takes into account cross sectional dependence in the security specific excess returns. However, ignoring the dependence adjustments does not harm the results and benefits the researchers through less complex calculations (Brown and Warner, 1985).

3.2.2.3 Null hypothesis, specification test and power test

With a random date chosen to be the event date, I expect that no abnormal performance is exhibited in any portfolio. Therefore, the null hypothesis is that the mean day 0 abnormal return is 0. Alternatively stated, Ho: Abnormal Return=0.

By testing this hypothesis, I examine the frequency of Type I error (rejecting the null hypothesis when it is true) through the specification test and Type II error (failure to reject the null hypothesis when it is false) through the power test, both of which reveal the effectiveness of the event study analysis. Providing an error is systematic takes a lot of time (Brown and Warner, 1985), I repeatedly test the null hypothesis for all 1000 portfolios to confirm that the results I obtain are systematic rather than by chance.

Out of the 1000 portfolios, I record the number of portfolios that reject the hypothesis, a Type I error. For a well specified test, the actual rejection rate under the null hypothesis of no abnormal return should be close to set nominal significance level. In this research, the expected rejection rate is close to 5 percent as I set the significance level at 5 percent. If the null hypothesis happens to be rejected too frequently, it results in a rejection rate greater than 5 percent and vice versa. In both cases, the test is not reliable and it is futile to exercise the power test later.

To undertake the power test, I inject the abnormal return to the actual return on each security on a hypothetical event date and test the null hypothesis of no abnormal return again. Now, the returns of the sample securities have been transformed to reflect an abnormal return; therefore, if the null hypothesis fails to be rejected, Type II error occurs. This method allows the examination of the power of the methodologies and the likelihood of detecting abnormal performance when it is present. A higher chance of detecting the abnormal return reflects the more a powerful test.

3.2.2.4 Uncertain event date

Following Brown and Warner (1980), Dyckman et al. (1984) and Saens and Sandoval (2005) , I examine the impact of uncertain event date on the event study analysis. This is a common problem as it is sometimes difficult to identify the exact date that investors receive new information (Cowan, 1993). There are two different approaches to deal with this issue. Brown and Warner (1980) allow the abnormal return to affect the test statistics only if the randomly selected event date from the uncertain period happens to coincide with the actual event date. Alternatively, Dyckman et al. (1984) accumulate the residuals over the uncertain event period and the test statistics reflects the information event, although it is diluted by the inclusion of non- event residuals. I adopt the method by Dyckman et al. (1984), who state that accumulating residuals has an advantage when uncertainty exists about the event date. In addition, Morse (1984) also prefers to accumulate residuals over the uncertain event period rather than attempting to select a particular event day under uncertainty.

To serve the event date uncertainty, I use the multi day Market Model, where beta is obtained from the returns of a multiday period. I use three- day period to estimate beta to account for three- day event uncertainty. Similarly, Dann (1981), Shane and Spicer (1983) and DeAngelo and Rice (1983) utilize multi day model when examining event date uncertainty. In the three- day market model, I utilize three- day returns, rather than single day return. These returns are calculated consistently with the equation

$$R_{3day}= (1+R_{-1})*(1+R_0)*(1+R_{+1})-1 \quad (11),$$

where the product is taken over consecutive days from -1 to +1.

Therefore, the three- day market model is

$$R_{it,3day}=\alpha_{3day} +\beta_{i,3day}*R_{mktt,3day}+\xi_{it,3day} \quad (12).$$

Similarly, the augmented three- day market model is

$$R_{it,3day}=\alpha_{3day} +\beta_{1,3day}*R_{mktt,3day}+ \beta_{2,3day}*R_{\Delta\beta t,3day} +\xi_{it,3day} \quad (13).$$

The test period three day residual is the difference between the actual three- day return as computed using equation (10) and the expected return based on the three- day market model (12) and augmented model (13).

For 1 factor model,

$$AR=R_{i,\ 3day}-\widehat{\alpha_{3day}}-\hat{\beta}_{3day}*R_{mkt,3day} \quad (14)$$

For 2 factor model,

$$AR= R_{i,\ 3day}-\widehat{\alpha_{3day}}-\hat{\beta}_{1,3day}*R_{mkt,3day} -\hat{\beta}_{2,3day}*R_{\Delta\beta,3day} \quad (15).$$

Once I obtain firm's residual, I add abnormal returns to the residuals, as in the case of certain event date. The standard deviation is calculated using the 83 three- day residuals in the original 250 day test period. I divide the firm's residual by firm's standard deviation to obtain t statistics and conduct the similar procedure for the specification and power test of event study analysis.

CHAPTER 4: RESULTS AND DISCUSSION

4.1 Initial results- random stocks selection

4.1.1 Intervalling effect correction

Table 3: Descriptive statistics of Betas using alternative estimation techniques

By random stocks	1 factor model	2 factor model	Difference (significant at 1%)
Beta estimates	0.659	0.659	0.000
R^2	0.063	0.076	0.014
Mean Durbin Watson	1.970	2.056	
% Durbin Watson significance- Accept	67.500	67.800	
% Durbin Watson significance- Reject	30.000	29.900	

This table reports descriptive statistics of betas and R^2 in return generating models. Beta and R^2 are estimated from estimation period. Reported beta and R^2 are the mean based on 200 000 observations of randomly chosen stocks. Accept or reject of Durbin Watson is the percentage that Durbin Watson statistics accept or reject the null hypothesis of zero first order autocorrelation in the residuals at 5 percent level of significance.

No intervalling effect proves to be fixed because betas obtained from 2 models do not differ. There is a marginal increase in R^2 with the addition of $\Delta\beta$ factor. The autocorrelation of two methods are similar and does not pose any significant problem to parameter estimations in event study. In short, the two factor model does not contribute to correcting the bias.

4.1.2 Properties of estimation period returns and daily excess returns

Table 4: Properties of estimation period returns and excess returns on day 0

Panel A

By random stocks	Mean	SD	Skewness	Kurtosis
1 factor model	0.000	0.50	3.346	98.229
2 factor model	0.000	0.50	3.345	98.369

This table reports properties of daily performance measures for individual stocks' excess returns based on time series data in the estimation period. Stocks and event dates are randomly selected. The number reported is the mean of 200 000 estimates. The time period is from 1969 to 2010 and no abnormal return is injected.

Panel B

By random stocks	Mean	SD	Skewness	Kurtosis
1 factor model	0.000	0.57	3.608	78.628
2 factor model	0.000	0.57	3.599	78.556

This table reports cross sectional properties of sample wide mean performance measure at day 0 of 1000 portfolios, with 200 randomly chosen stocks in each portfolio. The event date is chosen by random. Each number reported in the table is mean based on 1000 values, one for each portfolio. For a given sample, the mean performance measure is the mean of all the performance measure of individual securities in the sample.

In accordance with other researches such as Ahern (2009) or Brown and Warner (1980), individual stock returns and abnormal returns are non- normal. Although the mean is close to those from normal distribution, which is 0, the large positive kurtosis indicates the presence of fat tail. This means more frequent extreme positive values exist when compared to a normal distribution.

Since hypothesis tests typically focus on mean abnormal return, I am more concerned with the distribution of portfolio abnormal return to determine the extent that the abnormal returns deviate from normality. This step does not overlap with the investigation of normality of underlying asset returns because non normality of asset returns does not necessarily imply non normality of the model residuals (Brown and Warner, 1985).

The residuals based on the OLS market model and two factor model regressions are non- normal. Mean, standard deviation and skewness are positive and close in absolute value in comparison with returns during estimation period. The kurtosis becomes less extreme. The standard deviations are similar for 2 methodologies, suggesting that the alternative measure might display a similar ability to detect the abnormal performance when it is present. Furthermore, the mean of residuals from two factor model regression is the same as those from OLS regression, being equal to 0. This indicates that the estimate bias in betas is compensated for by the bias in alphas, resulting in no clear cut impact of the new return generating model in residual estimates (Brown and Warner, 1985).

4.1.3 Test statistics properties

Table 5: Properties of test statistics of portfolios of randomly chosen stocks

By random stocks	Mean	SD	Kurtosis	Skewness
1 factor model	0.006	0.013	6.017	-0.216
2 factor model	0.019	0.008	6.242	0.024

This table reports summary measure for actual distribution of test statistics based on 1000 portfolios, one for each portfolio, sample size is 200 stocks, randomly selected stocks and event dates. No abnormal return is induced. Time period is from 1969 to 2010.

These descriptive statistics are helpful in evaluating the specification of the test statistics when I introduce no abnormal performance into the data. With no abnormal return on day 0, well specified test statistics should stay in conformity with standard normal random variables. Both the skewness and the kurtosis are different from the theoretical value under the normal distribution, which are 0 and 3 respectively. Especially, the deviation of skewness from 0 implies the difference in rejection frequencies for positive and negative excess returns. However, because I employ 2 tail portfolio t test, this non normality is not a hindrance.

A standard deviation of each test statistic should be 1 under null hypothesis. The null hypothesis of no abnormal returns in specification test is subject to too frequent rejections if the standard deviation is less than 1 whereas a standard deviation more than 1 results in less frequent rejections (Bartholdy et al., 2007). From the results in the table 5, both factors tend to reject the null hypothesis more frequently than the set significance level of 5%. Meanwhile, one factor model suffers from higher rejection rate, indicating the more severe misspecification compared to the other model.

4.1.4 Specification and power test

Table 6: Specification and power test of portfolio of randomly chosen stocks

	Test level α=0.05							
	Actual level of abnormal performance in day 0							
By random stocks	**0%**	**0.50%**	**0.75%**	**1.00%**	**1.25%**	**1.50%**	**1.75%**	**2.00%**
1 factor model	5.40%	26.30%	52.10%	76.10%	92.30%	97.70%	99.40%	99.90%
2 factor model	5.20%	26.30%	52.00%	75.40%	92.20%	97.80%	99.30%	99.90%

This table reports a comparison of alternative performance measures by percentage of 1000 portfolios, with 200 stocks each portfolio, where the null hypothesis is rejected. This is a two tailed test and the null hypothesis is Ho: mean abnormal performance in day 0 is 0. The results reported are for portfolios of random stocks using one day event period. The level of induced abnormal performance ranges from 0 percent to 2 percent. Rejection rates are reported based on 5 percent significance test.

Type I error allows conclusion about the correctness of the statistics. Irrespective of the methods employed, for a statistics test to be well specified, t test rejects the null hypothesis at approximately the significance level of the test. Therefore, on average, I expect to detect abnormal performances in approximately 50 out of 1000 portfolios. From the table 6, I conclude that tests using each of the models are well specified in rejecting the existence of abnormal performance when it is not present. In detail, the rejection rates for one factor model and two factor model are 5.2 percent and 5.4 percent respectively.

Types II error allows the conclusion about the power of the test, regarding the ability to detect the abnormal returns when they are induced into the data. The model that leads to higher rejection rates is preferable as it indicates a more powerful technique. Results in table 6 show that across all the abnormal returns levels, the results of better models are quite mixed. However, the differences between the rejection rates at each level of induced abnormal returns are consistently negligible, ranging from 0.1 percent to 0.3 percent. For example, with 1 percent abnormal performance, one factor model rejects the null hypothesis in 76.10 percent of 1000 replications when I test at 5 percent level of significant. This compares to 75.4 percent with 2 factor model. This indicates two methodologies display similar power. Therefore, for a given test statistic in this setting, abnormal return generating model choice is of no importance. These findings echo those reported by Brown and Warner (1980, 1985) when they perform the event study on portfolios formed from random stocks in the exchange.

The rejection frequencies monotonically increase with the increase in abnormal performance levels. When abnormal return is 2 percent in each sample security, both models detect the abnormal returns almost all of the time. At 5 percent significance level, the rejection rates are 99.90 percent. Hence, both tests are quite powerful when there is a 2 percent or more abnormal return.

In short, the result shows that the effect of a more complicated method to calculate the abnormal returns seems invisible. However, it is not a striking result because the $\Delta\beta$ factor does not significantly improve either beta estimates or the explanatory power of the model when the random stocks are selected.

4.2 Opacity clustering

The lack of $\Delta\beta$ factor effect on event study is because the tested sample is from randomly chosen stocks in the market, which almost represent the entire market. The addition factor may only be suitable for opaque stocks only, as a large fraction of the market is transparent assets, which do not benefit much from the function of new factor (Gilbert et al., 2014). This rationale also accounts for the reported result in table 3 that betas of randomly chosen stocks obtained from augmented model are not different from normal OLS betas.

From five $\Delta\beta$ sorted portfolios, Gilbert et al. (2014) empirically document better α performance across all 5 portfolios and the most prominent reduction in alphas is from groups of higher opaque stocks (high $\Delta\beta$). This indicates that 2 factor model impact more effectively on opaque stocks than transparent stocks at daily return interval. Therefore, it is reasonable to develop a hypothesis about the likelihood of a more powerful test for high as opposed to low opaque securities if I account for opacity induced risk.

To address this question, I perform event study analysis with opacity clustered portfolios. The expectation is that two factor model will display higher ability to detect abnormal returns in high opaque portfolios. This intuition is simply that with the involvement of the ∆β factor, a given level of abnormal performance should be easier to detect when the opacity level in the sample security returns are high rather than low.

4.2.1 Interaction between ∆β and value/ turnover effect

Gilbert et al. (2014) proxy opacity by Δβ, which is the difference between betas estimated from low and high frequencies. Firms with high Δβ are opaque and vice versa. However, I also attempt to proxy stock opacity by stock market value and stock turnover due to following observations. First, from Table 1, I agree with Gilbert et al. (2014) that the more Δβ increases, the more opaque the firms are, the smaller market capitalization and lower liquidity they have. Second, literature demonstrates similar behavior patterns of betas of stocks with low market value, low turnover or high opacity when return interval alters. They all suffer from downward bias at high return frequency. Therefore, examining the performance of portfolios formed based on different opacity proxies will not limit the use of the ∆β factor in ∆β sorted portfolios, but extend it to different stock picking strategies with shared characteristics.

In order to perform event study on market value clustered portfolios, I rank stocks in increasing order of their year- end market value and assign them to five portfolios, each with approximately the same number of securities. Portfolio 1 comprises stocks of lowest market value and portfolio 5 comprises stocks of highest market value. I rebalance these portfolios at the end of each year. I employ the same procedure to create five turnover- clustered portfolios. In this research, I choose to use turnover, defined as the ratio of the number of shares traded in a day to the number of shares outstanding at the end of the day (Chordia and Swaminathan, 2000), rather than trading volume or dollar trading volume. The rationale is that the superiority of turnover, compared to raw trading volume or dollar trading volume, lies in its ability to disentangle the effect of firm size from trading volume because the latters have high correlation with firm size (Chordia and Swaminathan, 2000). Gilbert et al. (2014) also use turnover when they test the relationship of opacity proxies and betas estimated from different frequencies.

After forming five sets of portfolios based on size, turnover and $\Delta\beta$, I adopt Reinganum's (1981) method to investigate the relationship between each pair of size- and opacity- portfolios, turnover- and opacity- portfolios. I classify firms according to which value and $\Delta\beta$ quintile the stocks jointly belong to study the interaction between market value and $\Delta\beta$. I employ the same procedure to work on the pair of stock turnover and stock $\Delta\beta$. Table 7 contains two- way classification scheme averaged over the portfolios formation in 31 consecutive periods.

Table 7: Average numbers of firms jointly belong to 2 quintiles.

Quintile	Opacity				
	Transparent	Port 2	Port 3	Port 4	Opaque
Market value					
Smallest	91.3	92.9	109.9	142.1	197.9
Port 2	91.6	102.1	125.0	149.4	166.5
Port 3	108.1	116.6	131.6	141.0	137.3
Port 4	128.2	142.7	148.0	129.0	86.8
Largest	213.2	189.6	129.0	74.1	28.2
Turnover					
Lowest	58.0	99.0	83.4	121.9	122.3
Port 2	76.8	92.0	108.0	126.7	125.8
Port 3	92.1	100.5	113.6	127.8	141.7
Port 4	131.5	134.0	130.8	126.3	141.2
Highest	267.2	203.0	148.4	114.4	111.3

This table reports the average of firms jointly belong to 2 quintiles from 1969 to 2010.

First, I consider the interaction between market value and opacity quintile: the number of firms jointly belonging to opacity quintile and market value quintile monotonically increases, from portfolio one to five of market value quintile. The largest number of stocks jointly belonging to two quintiles belongs to the largest market value portfolio and the lowest opacity portfolio, at an average of 213 stocks. The opposite applies when going along opacity quintile, from portfolio 1 to portfolio 5. The number of firms jointly belonging to opacity quintile and market value quintile monotonically decreases when the market value increases. The highest interaction is from the smallest market value portfolio and the highest opacity portfolio, at 198 stocks. This casual observation reveals market value negatively correlates with Δβ. Second, I consider the interaction between turnover quintile and opacity quintile. I arrive at the same conclusion of the negative correlation between stocks' turnover and Δβ. These observations may support the idea that opacity may indirectly proxy for the same factor that generates the intervalling effect in size and turnover based portfolios.

A possible explanation for the negative relationship between firm size and firm opacity is that the bigger size the firms have, the more transparent they become and vice versa. Zhang (2006) posits that small firms are opaque because they are unattractive to customers, suppliers and shareholders, resulting in investors' underreact in the presence of new information. Because large firms trade more (Roll, 1981; Hawawini, 1983), consequently, there is high correlation between low turnover stocks and high opacity stocks and vice versa.

As explained in previous part, it is reasonable to expect a more powerful test for high as opposed to low opaque securities if I account for opacity induced risk. Hence, I predict a higher detection rates for portfolios of small or low turnover or high Δβ stocks. For brevity, I only report the results of two extreme groups for each proxy because they will display the most remarkable and noticeable differences in the power, if any.

4.2.2 Intervalling effect correction

Similar to the analysis of beta estimates in portfolios of randomly chosen stocks, I focus on how Δβ factor helps alleviate the bias through the assessment of 2 models' R^2 and beta. Moreover, I report Durbin Watson test to reflect the level of autocorrelation in the excess returns that can impact the inference of statistics.

Table 8: Descriptive statistics of Betas using alternative estimation techniques for opacity clustered portfolio

	1 factor model	**2 factor model**	**Difference (significant at 1%)**
By ∆β			
High ∆β			
Beta estimates	0.810	0.816	0.006
R squared	0.069	0.087	0.019
Mean Durbin Watson	1.959	1.969	
% Durbin Watson significance-Accept	68.80	69.80	
% Durbin Watson significance-Reject	27.00	26.90	
Low ∆ β			
Beta estimates	0.791	0.754	-0.036
R squared	0.114	0.126	0.012
Mean Durbin Watson	1.968	1.979	
% Durbin Watson significance-Accept	70.42	71.06	
% Durbin Watson significance-Reject	27.40	27.24	

By Market Value			
High Market value			
Beta estimates	1.051	1.030	-0.021
R squared	0.202	0.221	0.019
Mean Durbin Watson	1.970	1.980	
% Durbin Watson significance-Accept	68.40	69.30	
% Durbin Watson significance-Reject	26.47	25.90	
Low Market value			
Beta estimates	0.542	0.758	0.649
R squared	0.028	0.087	0.078
Mean Durbin Watson	1.979	1.995	
% Durbin Watson significance-Accept	78.53	80.02	
% Durbin Watson significance-Reject	11.60	9.90	
By Turnover			
High turnover			
Beta estimates	1.137	1.093	-0.044
R squared	0.125	0.144	0.019
Mean Durbin Watson	1.982	1.989	
% Durbin Watson significance-			

Accept	70.10	70.50	
% Durbin Watson significance-Reject	28.60	28.58	
Low turnover			
Beta estimates	0.488	1.137	0.216
R squared	0.048	0.125	0.059
Mean Durbin Watson	1.968	1.798	
% Durbin Watson significance-Accept	88.60	89.04	
% Durbin Watson significance-Reject	10.40	9.38	

This table reports descriptive statistics of betas and R^2 in two return generating models. Beta and R^2 are estimated from estimation period. Reported beta and R^2 are the mean based on 200 000 observations of randomly chosen stocks. Accept or reject of Durbin Watson is the percentage that Durbin Watson statistics accept or reject the null hypothesis of zero first order autocorrelation in the residuals at 5 percent significance.

Overall, there is a common trend in terms of R^2, beta change and autocorrelation in the portfolios of same opacity characterized by market value, turnover or $\Delta\beta$.

Between groups of high and low opacity, R^2 in two factor model are consistently appreciably lower for groups of high opacity stocks (portfolios with high $\Delta\beta$, low market value or low turnover). The second dimension is the comparison between 2 models for given portfolios. Generally, there is an increase in the R^2, which is statistically significant at 1percent, when opacity factor is involved. This means the inclusion of the opacity factor supplies useful incremental information in explaining the cross section of returns. Furthermore, I observe the higher rate of R^2 increase in high opacity groups. This alteration in R^2 indicates the likelihood of better event study power for high opacity stocks when the new model is used (Campbell, Lo and MacKinlay, 1993). Especially, the largest R^2 increase in is 7.8 percent for low market value portfolio, indicating the most improved performance of event study in this portfolio.

The differences between OLS betas adjusted betas are all significant at 1 percent. For low opacity groups, the mean betas estimates decline in the presence of new factor. The opposite beta pattern applies to high opacity group. This is indicative of downward bias fixing for opaque stocks and upward bias fixing for transparent stocks. These findings are consistent with previously work in beta corrected for intervaling effect by Larson and Morse (1987),Brailsford and Josev (1997), Karathanassis et al. (1999) or Alles (1997). As expected, opaque as opposed to transparent stocks experience a more noticeable beta change. For example, while the rate for beta change in high turnover portfolio is 4 percent, it is 57 percent for low turnover portfolio. This evidences that beta of low opacity group is not sensitive to the addition of the new factor. Among high opaque portfolios, I observe the most significant difference in beta estimates in low market value portfolio. This serves as an indication that this portfolio might have biggest differences in pattern in excess returns between two methods, which can lead to the higher chance of detecting the abnormal performance.

I estimate Durbin Watson statistics from daily residuals of the estimation period, testing whether the autocorrelation is zero. If serial correlation exists in the residual estimates, alpha and beta estimates are inefficient and false inferences may result regarding information effects (Brown and Warner, 1980). The findings of the Durbin Watson tests reveal three important points. First, auto correlation, as measured by Durbin Watson statistics does not pose a significant problem because all Durbin Watson statistics are approximately 2. Karathanassis et al. (1999) share the same point that that the autocorrelation in the residual returns is not a big concern. In their samples of 22 shares in the Athen stock market, only 9 percent in the simple market model and 4.5 percent in the selected Dimson models are reported with significant autocorrelation at 5 percent. As a result, no severe serial correlation will condition reliable R^2. Second, in spite of negligible auto correlation, there is still evidence that the correlation is consistently positive, resulting in a slightly higher rejection rate than the test's significance level in specification test. Third, the significance of the first order serial correlation is less pronounced in the residuals returns of augmented model. Schwartz and Whitcomb (1977) attribute the low R^2 to residual and market index returns autocorrelation. Hence, this explains the reported deterioration of R^2 when one factor model is used.

4.2.3 Estimation period returns

Table 9: Properties of estimation period returns of opacity clustered portfolios

	Mean	SD	Skewness	Kurtosis
By ∆ β				
High ∆ β				
1 factor model	0.000	0.049	3.223	93.441
2 factor model	0.000	0.048	3.220	93.188
Low ∆ β				
1 factor model	0.000	0.041	2.967	98.808
2 factor model	0.000	0.041	2.977	99.454
By Market value				
High Market value				
1 factor model	0.000	0.025	1.852	102.861
2 factor model	0.001	0.029	1.522	69.973
Low Market value				
1 factor model	0.000	0.054	2.779	71.515
2 factor model	0.000	0.046	3.103	96.607
By Turnover				
High Turnover				
1 factor model	0.000	0.049	4.011	124.606
2 factor model	0.000	0.048	4.056	127.407

Low Turnover				
1 factor model	0.000	0.052	2.975	80.754
2 factor model	0.000	0.052	2.965	80.728

This table reports properties of daily performance measures for individual stock excess returns based on time series data in the estimation period. Securities belong to 2 extreme portfolios sorted by ∆β, market value or turnover. The number reported is the mean of 200 000 estimates. The time period is from 1969 to 2010 and no abnormal return is injected.

Table 9 displays useful information in assessing the degree of non- normality of the data.

Stock excess returns are not normally distributed although the mean is close to 0, the hypothetic value under the assumption of normal distribution. This result is similar to the case of randomly selected stocks. Both the skewness and kurtosis are positive. The positive kurtosis indicates the presence of fat tail, indicating more frequent extreme positive values than in a normal distribution.

Across all portfolios, performances have a similar mean and standard deviation. These results suggest that the alternative measures of excess returns will exhibit similar ability to detect abnormal performance when it is present. The market value sorted portfolio showcase the highlight. This portfolios has lowest standard deviation (0.025 for 1 factor model and 0.029 for 2 factor model), entitling the highest probability to detect abnormal returns compared to other portfolios (Brown and Warner, 1985). For the group of low market value stocks, difference in standard deviation between 2 methods stands out at 0.009. This is the only observed difference in each pair of the methods across all the clustered portfolios. This can be potentially interpreted as the only case where two factor model remarkably increases the power of event study analysis.

4.2.4 Cross sectional properties for portfolios on day 0

Table 10: Properties of excess returns on day 0 of opacity clustered portfolio

	Mean	SD	Skewness	Kurtosis
By Δβ				
High Δβ				
1 factor model	0.000	0.053	5.656	194.437
2 factor model	0.000	0.053	5.642	194.659
Low Δβ				
1 factor model	0.000	0.045	3.986	109.586
2 factor model	0.000	0.045	3.983	109.196
By Market value				
High Market value				
1 factor model	0.000	0.026	2.199	89.750
2 factor model	0.000	0.025	2.196	91.329
Low Market value				
1 factor model	0.000	0.058	2.984	67.006
2 factor model	0.000	0.049	2.949	83.058
By Turnover				
High Turnover				
1 factor model	-0.001	0.053	5.878	215.898
2 factor model	-0.001	0.053	5.916	217.587

Low Turnover				
1 factor model	0.000	0.057	3.848	114.772
2 factor model	0.000	0.057	3.843	114.498

This table reports the cross sectional properties of sample wide mean abnormal performance measures on day 0 using 2 return generating models without the presence of abnormal returns. Securities belong to 2 extreme portfolios sorted by ∆ β, market value or turnover. Each number is the mean of 1000 values, one for each portfolio. For a given portfolio, the mean performance measure is the simple average of the individual securities performance measure. The time period is from 1969 to 2010 and no abnormal return is injected.

The behaviors of the mean, standard deviation, skewness and kurtosis are the same as those in the estimation period. All portfolios show the similar pattern in terms of all test statistics. Especially, for each portfolio, the striking similarity of all the statistics between each pair of methods raises the possibility that the degree of misspecification in the event study is insensitive to the methodology employed. The noticeable performance is from market value portfolios. Among all characteristic based portfolios, the large firm portfolio has the lowest standard deviation, manifesting itself in increased power in event test. At the same time, for small firm portfolio, the lower standard deviation from two factor model compared to the one factor model signals the better event study performance.

Furthermore, similar to randomly chosen stocks, the mean of residuals from two factor model regression and OLS regression are both 0. This means the effect of opacity factor may not be visible in the characterized portfolios. The bias in alpha compensates for the bias in betas. Hence, unchanged power in event study might result, regardless of methodologies I employ (Brown and Warner, 1985).

4.2.5 Test statistics properties

Table 11: Properties of test statistics of opacity clustered portfolios

	Mean	SD	Kurtosis	Skewness
By ∆β				
High ∆β				
1 factor model	0.096	0.043	27.682	-0.318
2 factor model	0.086	0.040	25.705	-0.295
Low ∆β				
1 factor model	0.084	0.043	19.913	-0.087
2 factor model	0.078	0.038	18.901	-0.099
By Market value				
High Market value				
1 factor model	0.020	0.010	5.918	-0.082
2 factor model	0.019	0.004	5.938	-0.062
Low Market value				
1 factor model	0.042	0.042	4.877	-0.123
2 factor model	0.028	0.034	4.608	-0.192
By Turnover				
High Turnover				
1 factor model	0.015	0.023	9.837	-0.163
2 factor model	0.004	0.024	9.800	-0.200
Low Turnover				

1 factor model	-0.282	1.011	0.018	-0.254
2 factor model	-0.268	1.011	0.068	-0.245

This table reports the summary measures for distribution of test statistics, based on 1000 values, one for each extreme portfolio, sample size=200. Portfolios constitute extreme characterized stocks of market value, turnover and $\Delta\beta$. No abnormal performance is seeded into returns. Time period is from 1969 to 2010.

I report the descriptive statistics properties to assess the specification of the statistics in the absence of induced abnormal returns.

Without the presence of an abnormal performance on day 0, well specified test statistics should conform to standard normal random variables. That is, the mean and the skewness are approximately 0, the standard deviation close to 1 and the kurtosis about 3.

I will perform mainly two dimensions of the comparison. The first dimension is the comparison between the groups of opaque and transparent stocks. The second dimension, which is more important, is between statistics from 2 methodologies employed in each portfolio.

For the first dimension of the comparison, means of the opaque groups deviate more from 0. For example, given that high $\Delta\beta$ portfolio is more, the means of $\Delta\beta$ are 0.096 and 0.086 for one and two factor model respectively. In contrast, the low $\Delta\beta$ portfolio has the mean of 0.042 for the one factor model and has it improved to 0.028 for two factor model. As a result, researchers will be prone to incorrectly identify significant effects in samples of a large proportion of opaque stocks. Moreover, the positive means indicate the over rejection in the specification test. Only for low turnover portfolio, means are negative, signaling the under rejection of the null hypothesis. A standard deviation of each test statistic should be 1 under null hypothesis. Under “rule of thumb” of analyzing the standard deviation, I conclude that for both types of portfolios, the null hypothesis is rejected too often because the standard deviation is less than 1. Only low turnover portfolio has less than unity standard deviation. The standard deviation is smallest for large firm portfolio, indicating the highest detection rate. When opacity factor is added, standard deviations tend to lower. However, more reduction is for group of opaque stocks. For example, standard deviation reduces by 0.003 versus 0.005 for high $\Delta\beta$ and low $\Delta\beta$ portfolios respectively with the addition of $\Delta\beta$.

For the second dimension of the comparison, except for low market value portfolio, means and standard deviations obtained from both models for each portfolio are not significantly different. The largest mean difference is from small firm portfolio. Similarly, this portfolio also has the most substantial dispersion between standard deviations when opacity factor is considered. These observations support the higher abnormal return detection rates of two factor model for small firm portfolio.

Skewness should be 0 and kurtosis should be 3 under the null hypothesis. With nonzero skewness, the rejection frequencies for the null hypothesis differ for positive and negative events. However, the use of two tailed portfolio t test is not seriously impacted by the nonzero skewness.

4.2.6 Specification and power test

Table 12: Specification and power test of opacity clustered portfolios

	Test level α=0.05							
	Actual level of abnormal performance in day 0							
	0%	**0.50%**	**0.75%**	**1.00%**	**1.25%**	**1.50%**	**1.75%**	**2.00%**
By $\Delta\beta$								
High $\Delta\beta$								
1 factor model	5.90%	28.20%	58.20%	81.60%	93.40%	98.10%	99.50%	99.90%
2 factor model	5.60%	28.00%	57.40%	81.20%	93.90%	97.90%	99.50%	99.90%
Low $\Delta\beta$								
1 factor model	5.90%	39.70%	71.80%	90.70%	97.90%	99.80%	100.00%	100.00%
2 factor model	5.70%	38.90%	71.50%	91.00%	98.20%	99.90%	100.00%	100.00%
By Market value								
High Market value								
1 factor model	5.60%	81.90%	98.10%	100.00%	100.00%	100.00%	100.00%	100.00%
2 factor model	5.50%	82.60%	98.30%	100.00%	100.00%	100.00%	100.00%	100.00%

Low Market value								
1 factor model	6.00%	22.40%	46.10%	70.90%	89.70%	96.00%	100.00%	100.00%
2 factor model	6.00%	30.60%	61.60%	83.90%	95.70%	98.90%	100.00%	100.00%
By Turnover								
High Turnover								
1 factor model	5.90%	22.00%	48.89%	76.10%	91.50%	97.80%	99.70%	99.90%
2 factor model	5.80%	23.10%	49.50%	77.10%	91.70%	98.10%	99.50%	99.90%
Low Turnover								
1 factor model	4.30%	26.70%	51.20%	76.60%	91.00%	96.80%	99.10%	99.70%
2 factor model	4.90%	26.80%	50.10%	76.40%	90.90%	96.80%	99.10%	99.70%

This table reports results for extreme portfolios based on $\Delta\beta$, market value and turnover using one day event period. The level of induced performance ranges from 0 percent to 2 percent. The numbers reported are rejection rate of 1000 portfolios of 200 stocks each where the null hypothesis Ho: mean abnormal performance in day 0 is 0 is rejected. Rejection rates are reported based on 5 percent significance test and 2 tail test.

In terms of specification test, on average, approximately 5 percent of 1000 portfolios in each category show abnormal performance. Because I set the significance level at 5%, all the tests prove to be well specified. Moreover, while all of the portfolios over reject the null hypothesis, the low turnover portfolio under rejects with both models applied. This observation agrees with my above prediction about the specification test when I analyze the properties of the statistics.

When abnormal return is injected, across different levels of abnormal returns introduced, the rejection frequencies indicate some difference in the power of 2 methodologies. I will analyze 2 main dimensions. The first dimension is across portfolios. The second dimension, which is more crucial, is the performances of two methods in a given portfolio.

First, transparent portfolios always exhibit a higher rejection rates. For example, with 0.75 percent injected abnormal returns, the rejection rates for transparent portfolios range from 49.50 percent to 98.50 percent. Meanwhile, the rejections rates for opaque groups are only from 50.10 percent to 61.60 percent.

Second, when I inject abnormal performance, two factor model proves its superiority to the other model in small firm portfolio. I document a substantial higher power between these two models. For example, when I inject 0.50 percent to 1.50 percent abnormal return, the rejection rate from two factor model is from 2.9 percent to 15.5 percent higher. For other characteristic sorted portfolio, there is little impact on the rejection frequencies, even in opaque groups, where I reasonably expect to observe the visible positive impact of $\Delta\beta$ factor. Generally, the rejection rate is higher with the adjustment of opacity factor but the magnitude of the improvement is marginal, from 0.1 percent to 1 percent. In some cases, the effect of augmented model is totally invisible. This is the case of low turnover portfolio, where the rejection rates are the same under both models when I inject the abnormal returns of 1.5 percent to 2.0 percent.

For all portfolios, the rejection frequencies increase as the abnormal performance level rises. When the level of abnormal return reaches 2 percent, both methods detect the abnormal returns at least 99.90 percent of the time at 5 percent significance level. This means, both tests for abnormal performance are quite powerful when there is 2 percent or more abnormal return, irrespective of the characteristics of the portfolios.

My findings stand out from the common stream in literature with the enhanced event study power for the low market value portfolio. This is the only documented methodology that can challenge the traditional market model in event study analysis. Practically, it motivates portfolio managers to consider the pros and cons between the ease of constructing the Δβ factor and the benefits of more power event study test in small stock portfolios to apply two factor model. Generally, for other portfolios, my results show that the simple method as 1 factor model works no less powerfully than other sophisticated method to detect the presence of abnormal performance. This is similar to conclusion in previous researches. For example, Dyckman et al. (1984) conduct an event study with adjustment to nonsynchronous trading separately on low, medium and high trading volume populations. They conclude that Scholes and Williams and Dimson Aggregated Coefficient methods do not show any improvement in either the specification test or the power of the event studies. At the same time, my results echo Brown and Warner (1985) findings when they integrate non synchronous trading into beta estimation. They affirm that presence of beta biases does not necessarily imply misspecification in event study. Strong (1992) generalizes that although the OLS market model abnormal return may be biased for an individual security, in an event study, the bias in conditional abnormal returns may average out to zero in the sample.

4.3 When event date is unknown

Table 13: Specification and power tests when event date is unknown

Test level α=0.05										
	Actual level of abnormal performance in day 0									
	0%	**0.50%**	**0.75%**	**1.00%**	**1.25%**	**1.50%**	**1.75%**	**2.00%**	**2.25%**	**2.50%**
By random stocks										
1 factor model	6.00%	12.40%	24.60%	40.20%	56.80%	73.50%	86.30%	92.20%	96.50%	99.10%
2 factor model	5.80%	11.80%	24.30%	39.30%	56.70%	72.90%	85.00%	91.60%	96.40%	98.60%
By $\Delta\beta$										
High $\Delta\beta$										
1 factor model	6.20%	11.60%	25.50%	39.90%	60.00%	75.90%	87.50%	94.10%	97.80%	99.40%
2 factor model	6.30%	11.80%	25.30%	39.70%	59.40%	74.80%	86.20%	93.80%	97.60%	99.50%
Low $\Delta\beta$										
1 factor model	4.10%	14.30%	33.40%	56.90%	75.80%	88.50%	96.30%	98.80%	99.90%	100.00%
2 factor model	4.60%	14.50%	33.50%	57.20%	76.00%	88.45%	96.60%	98.90%	99.00%	100.00%
By Market value										
High Market value										
1 factor model	6.10%	41.20%	71.50%	89.90%	97.90%	99.30%	99.90%	100.00%	100.00%	100.00%

2 factor model	6.90%	39.50%	71.80%	88.70%	97.60%	99.20%	99.80%	100.00%	100.00%	100.00%
Low Market value										
1 factor model	6.80%	10.40%	19.80%	33.50%	50.40%	66.10%	78.70%	89.60%	94.50%	97.00%
2 factor model	7.00%	10.00%	20.10%	33.50%	49.50%	65.60%	77.80%	89.10%	94.70%	97.00%
By Turnover										
High Turnover										
1 factor model	6.70%	5.20%	12.90%	26.20%	44.80%	61.70%	77.50%	88.30%	95.40%	97.90%
2 factor model	6.40%	5.30%	12.80%	25.60%	44.50%	61.70%	76.80%	89.20%	95.10%	97.80%
Low Turnover										
1 factor model	4.80%	9.60%	24.60%	20.40%	30.50%	55.70%	69.20%	80.60%	93.30%	96.60%
2 factor model	4.90%	9.50%	24.70%	20.30%	30.50%	55.90%	69.10%	80.60%	93.30%	96.60%

This table reports a comparison of alternative performance measures by percentage of 1000 portfolios, with 200 stocks each portfolio, where the null hypothesis is rejected. Abnormal return is generated in the event period of (-1, +1) interval. This is a two tailed test and the null hypothesis is Ho: mean abnormal performance in day 0 is 0. The results reported are for portfolios of extreme stocks of market value, turnover and Δβ. The level of induced abnormal performance ranges from 0 percent to 2 percent. Rejection rates are reported based on 5 percent significance test.

In term of size, the test shows to be less specified when the rejection rates across the portfolios ranges from 4.1 percent to 7.0 percent. They have greater deviation from the significance level of 5 percent compared to when the event date is known with certainty.

In terms of the power of the test, they are all diluted considerably. Even at high levels of abnormal performance, the hypothesis of no abnormal returns often fails to be rejected when abnormal returns are present. For example, when the induced abnormal return reaches 2.0 percent when the event date is known with certainty, the rejection rates are around 100 percent. However, when the event date is unknown, the abnormal return is only fully detected when I inject 2.5 percent. Across all portfolios, the rejection rates obtained from two factor model is similar to or marginally better than those from one factor model. This confirms Dyckman et al.'s (1984) observation that more uncertainty about the event date makes it more difficult to detect abnormal performance and no methods seem to mitigate the problem of event date uncertainty. In contrast to when the event date is known, for small firm portfolio, both methodologies offer the same power.

4.4 Actual event- Dividend announcement

Table 14: Rejection rates in an actual event test

Test level α=0.05			
Actual level of abnormal performance in day 0			
	0%	**0.50%**	**0.75%**
By random stocks			
1 factor model	64.90%	99.10%	99.80%
2 factor model	66.10%	99.30%	99.80%
By $\Delta\beta$			
High $\Delta\beta$			
1 factor model	85.70%	99.80%	100.00%
2 factor model	86.30%	99.80%	100.00%
Low $\Delta\beta$			
1 factor model	86.60%	99.80%	100.00%
2 factor model	86.70%	99.80%	100.00%
By Market value			
High Market value			
1 factor model	66.20%	99.70%	100.00%
2 factor model	66.70%	99.80%	100.00%
Low Market value			
1 factor model	65.10%	99.10%	99.80%
2 factor model	65.20%	99.50%	99.80%

By Turnover			
High Turnover			
1 factor model	61.70%	99.80%	100.00%
2 factor model	62.00%	99.80%	100.00%
Low Turnover			
1 factor model	62.30%	99.20%	100.00%
2 factor model	63.30%	99.40%	100.00%

This table reports a comparison of alternative performance measures by percentage of 1000 portfolios, with 200 stocks each portfolio, where the null hypothesis is rejected. Abnormal return is generated in the event period of (-1, +1) interval. This is a two tailed test and the null hypothesis is Ho: mean abnormal performance in day 0 is 0. The results reported are for portfolios of extreme stocks of market value, turnover and Δβ, using dividend announcement date as actual event. The level of induced abnormal performance ranges from 0 percent to 2 percent. Rejection rates are reported based on 5 percent significance test.

Literature shows that a company's dividend policy has a non-trivial impact on the wealth of its shareholders. Empirical evidence indicates that the corporate announcements of dividend payouts are typically associated with significant price effects (Gurgul, Mestel, & Schleicher, 2003). Commonly, an announcement of higher dividends induces an average increase in stock price and an announcement of shrinking dividends strides along with average decreasing prices. In case of an announcement of unchanged dividend payouts, researchers report no price reaction. For US stock market, Haw and Kim (1991) empirically examine the size sorted portfolio behavior around dividend announcement date and observe the positive and statistically significant abnormal return around the announcement date, confirming that announcement dates have information content. They also extend the observation by stating the average abnormal return on day 0 is greater for smaller firms than for larger firms. Eades, Hess and Kim (1985) also find positive stock returns and a significant increase in beta around dividend announcement date.

I, therefore, consider dividend announcement an event and perform the test to assess which method more frequently identify this announcement as an event. Under the null hypothesis, the higher the rejection rates, the more powerful the method is.

I download the list of all stocks and their corresponding dividend announcement dates and dividend amount from CRSP for the period 1969 to 2010. I only include stocks with a change in announced dividends to make sure all the included announcement dates have informational content. I employ the same procedures to sort stocks into portfolios of random stocks, high/low market value stocks, high/low $\Delta\beta$ stocks and high/low turnover stocks. All the portfolios are rebalanced each year. Finally, I run 1000 replications to see the percentages of portfolios that recognize dividend announcement date as an event.

The results using dividend announcement dates reasonably reflect my findings from simulation test. The detection rates between 2 models are slightly different, indicating the similar power of two models. The benefits of augmented model that I observe in small firm portfolio appear invisible.

In conclusion, the two factor model does not offer significant improvement in abnormal performance detection in case of an actual event.

4.5 Discussion

Brown and Warner (1980) explain the unchanged power in event study test irrespective of return generating model employed. I will infer to these explanations to account for the general observation of no enhancement in event study power in the presence of opacity factor.

First, measurement error exists in each of the variables used to estimate abnormal returns. The hindrance is that I cannot directly observe a security’s risk as well as the market portfolio, which leads to measurement error. Such measurement error should not introduce any systematic bias in event studies. However, with small samples, the measurement error in these variables may large enough to subdue any inconsequential, potential efficiency gains from a better return generating process.

Second, the efficiency of using a particular model for the return generating process is critically subject to the appropriateness of the additional peripheral assumption about the $\varepsilon_{it.}$ This assumption is made in order to test the hypothesis of no abnormal performance of a particular event. For instance, with each model, a test statistic such as a t statistic must be computed and compared to the theory distribution of test statistics under the null hypothesis. In the context that the assumed sampling distribution under the hypothesis differs from the true distribution, false inferences can result. That is, if the assumed properties of the test statistic under the one factor model are more appropriate than those under the two factor model, one factor model is still chosen even if the second method is precise.

Furthermore, following Dowen and Isberg (1988), I consider the correlation of the residuals obtained from the two methods to ascertain the impact of model choices. I show that the pattern of the abnormal return basically remains irrespective of the addition of new factor.

If the new return generating model changes the pattern of abnormal returns, I expect to see the insignificant correlation of residuals generated by both models for the same event. However, in the case that the impact of new return generating model is weak or nonexistent, the correlation should be positive and significant. The greater the correlation, the more negligible the impact of the new factor in event study analysis.

I calculate Pearson correlation coefficients to test the relative pattern of residual returns and Spearman correlation coefficients to test the degree of preservation in ranking of the residuals. Lastly, I conduct a test to determine the impact of the adjusted return generating model on the absolute magnitude of the residual returns.

Table 15: Relationship of residuals obtained from two models

	Pearson Corr	**Spearman Corr**	**Alpha**	**Beta**	R^2
By random stocks	0.994	0.972	0.000***	0.994***	0.988
By $\Delta\beta$					
High $\Delta\beta$	0.992	0.975	0.000***	0.993***	0.984
Low $\Delta\beta$	0.994	0.981	0.000***	0.993***	0.987
By Market value					
High Market value	0.981	0.973	0.000***	0.995***	0.962
Low Market value	0.995	0.980	0.000***	0.992***	0.989
By Turnover					
High Turnover	0.989	0.973	0.000***	0.993***	0.979
Low Turnover	0.995	0.978	0.000***	0.994***	0.990

This table reports the Pearson correlation and Spearman correlation of residual returns obtained from 2 return generating model. Alpha, Beta and R^2 are regression results from equation

$R_{i,\,1factor}=\alpha+\beta*R_{i,\,2factor}+\xi_i$.

The Pearson correlation of residuals is highly positive and significant. This result supports the negligible change that the new factor has on the relative pattern of residual return. It implies that in case of an event study, choice of different models for estimating market model parameters should not affect the relative pattern of residual returns.

The Spearman rank correlation coefficients present a test of the preservation of the ranking of residual returns. The results provide some insight to the likelihood that the choice of a return differencing interval in calculating market model parameters will affect the ranking of observed residual returns. The results show that the choice of models will have a negligible impact upon the relative ranking of residual returns because the correlation coefficient is highly positive and significant.

Lastly, I perform the regression

$R_{i,\ 1factor}=\alpha+\beta^{*}R_{i,\ 2factor}+\xi_i$ (16), where

$R_{i,1factor}$ is the residual returns for stock i calculated from one factor model

$R_{i,2factor}$ is the residual returns for stock i calculated from two factor model

I test whether the choice of different models may affect the absolute magnitude of residual returns in an event study. In case of no effect, alpha is not significantly different from 0 and beta is close to unity. My findings show that alpha coefficients in each of the regressions are significantly 0. However, the beta estimates are different from 1. This means there is a slight difference in the performance of 2 models. The most noticeable difference in absolute magnitude of residual returns in the 2 return generating models is for low market value portfolio. This regression arrives at the lowest beta of 0.992. This is consistent with the evidence documented in the power test that two factor model's performance is substantially better than that of one factor model at some given levels of abnormal returns.

The above examinations of residuals estimated from two methods help explain an improved power in low market value portfolio and general unchanged power in other portfolios in event study analysis in the presence of opacity factor.

CHAPTER 5: SUMMARY AND CONCLUSION

In their recent paper, Gilbert et al. (2014) prove that normal market asset pricing model is misspecified at daily returns. They provide a better model augmented with opacity factor and empirically show its improved performance. My study provides another aspect, addressing the issue whether the better return generating model can enhance the power of the event study.

There are two mainstreams of results in this research. First, I report the direction and magnitude of beta estimates and model R^2 change. This part supplements the model assessment results in Gilbert et al. (2014), where they only assess alpha performance. Second, I report the specification test and power test of event study analysis on portfolios of random stocks and opacity clustered stocks. This is the focus of this study.

In terms of intervalling effect correction, opacity factor shows no impact on either beta or model R^2 on the sample of randomly chosen stocks. However, when I apply the augmented model into characterized portfolios, I agree with Gilbert et al. (2014) about its fixing effects. The addition of opacity factor fixes the downward bias in beta for opaque stocks and results in higher explanatory power. The improvement is the most prominent in most opaque portfolios and gets deteriorated when stocks become transparent.

In terms of event study, I report the simulation results for portfolios of random stocks, portfolios of opacity clustered stocks for 1 day event and when the event date is uncertain. For portfolios of opacity clustered stocks, I examine high market value, high turnover and low $\Delta\beta$ portfolios as low opacity portfolios and vice versa.

The highlight is the remarkable improvement of event study power for the portfolio of small firms. 2 factor model results in increased detection rate of abnormal returns by 2.9% to 15.5% when the abnormal returns are from 0.5 percent to 1.5 percent. This has been the only evidence so far of a methodology that can over-perform traditional market model in event study analysis.

When portfolio consists of randomly chosen stocks, I witness the unchanged size and power of event study analysis with the presence of the opacity factor. When portfolio consists of opacity clustered stocks, both models show to be acceptably specified across all portfolios. However, there are some deviations in the powers compared to the case of random stocks. For all portfolios except small firm one, with opacity factor, the power of event study is increased, yet, humble.

When the event date is unknown, both the specification and power of the event test dilute considerably. Across all portfolios, the rejection rates obtained from 2 factor model are similar to or marginally higher than those from 1 factor model.

I apply these 2 models in actual event dates, which is dividend announcement dates to examine their power. The results show that the more complex model does not add more benefits.

I refer to Brown and Warner (1980) to discuss the possible underlying reasons why a more precise return generating model does not result in a more powerful event study power. First, the measurement error in variables used to estimate abnormal returns may be so large in small samples. Therefore, it conquers the gains from a better return generating model. Second, the difference between the assumed sampling distribution and the actual distribution leads to false inferences. Through the examination of Pearson and Spearman correlation, I also show that the relative pattern and the degree of preservation in ranking of residuals remains irrespective of the model employed. Additionally, I show that the choice of different models does not seriously affect the absolute magnitude of residual returns obtained in the event study. The greatest change in magnitude of residual returns is from low market value portfolio.

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