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The Intervaling Effect on Higher-Order Co-Moments

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Abstract

This paper investigates the sensitivity of higher-order co-moments for different return measurement intervals. The levels of systematic skewness and kurtosis are found to be significantly influenced by the length of return interval. An asset preferred because of its positive co-skewness and low co-kurtosis when measured in one particular interval may have negative co-skewness or high co-kurtosis for another interval. We find the intervaling effect varies according to the level of price adjustment delay as proxied by market capitalization and illiquidity. Findings persist for intervals of up to twelve months, and are consistent during both volatile and stable periods.

Keywords: Return Interval, Co-Skewness, Co-Kurtosis, Price Delay

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1. Introduction

An extensive literature has provided evidence that systematic skewness and systematic kurtosis[1] further characterize the risk of an individual security relative to the market, thus supplementing the capital asset pricing model (CAPM) (see, for example, Hung et al., 2014; Kostakis et al., 2012; Kraus and Litzenberger, 1976). These higher-order co-moments have been widely applied to security pricing (Conrad et al., 2013; Kostakis et al., 2012), and optimal portfolio allocation (Jondeau and Rockinger, 2012; Martellini and Ziemann, 2010). Among current empirical studies, however, minimal consideration is given to the appropriate return interval for the calculation of higher-order moment parameters. In this paper, we find that the return interval plays a central role in the estimation of higher-order co-moments and is also significantly related to the delay of securities in adjusting prices to market wide information.

A long line of research considers the effect of the investment interval on the estimation of financial parameters, often referred to as the intervaling effect.[2] Primarily, the systematic risk (beta or β) of an asset or a portfolio changes as the interval alters, when the single-factor model or Sharpe-Lintner CAPM is applied (Gilbert et al., 2014; Perron et al., 2013; Gençay et al., 2005; Handa et al., 1989; Hawawini, 1980b; Cohen et al., 1980; Levhari and Levy, 1977). A considerable body of work has also yielded similar intervaling effects, for example, in examining common risk factors when the Fama-French three-factor model is considered (Kamara et al., 2015; Brennan and Zhang, 2013), in utilizing the GARCH-M framework through the use of the conditional CAPM (Brailsford and Faff, 1997), and in inspecting the multi-index return generating process underlying the Arbitrage Pricing Theory (Parhizgari et al., 1993).

TABLE 1 ABOUT HERE

Nonetheless, there is little, if any, literature that has considered the impact

[1] Systematic skewness (kurtosis), is defined as the component of an asset's skewness (kurtosis) that is related to the market portfolio's skewness (kurtosis) respectively. Section 2 has more details.

[2] This effect has been named alternatively: the interval effect, the investment interval problem, the holding period problem, etc. In this research we will refer to it as the intervaling effect. The interval is the time frequency of the data, e.g. daily, weekly, monthly, quarterly, annual, etc.

of the return interval on higher-order co-moments.[3] For example, Table 1 describes 24 papers which are published in top peer-reviewed journals covering our sample period. Monthly or daily returns are widely used and without further explanation. We contribute to the literature by considering the intervaling effect on systematic skewness (denoted as co-skewness, gamma or γ) and systematic kurtosis (denoted as co-kurtosis, delta or δ). This is of particular relevance for empirical estimation of higher-order parameters. First, the skewness and kurtosis of financial asset returns have long been shown to display significant variation as a function of the measurement return interval (Hawawini, 1980a; Smith, 1978; Francis, 1975; Fogler and Radcliffe, 1974).[4] Gamma and delta measure the contribution of skewness and kurtosis of the market portfolio to asset returns, respectively. Second, recent literature suggests that most common risk factors, such as the well-known Fama-French factors, are interval dependent (Kamara et al., 2015; Brennan and Zhang, 2013). These risk factors have been found to act as proxies for the higher-order pricing factors, (Nguyen and Puri, 2009; Chung and Schill, 2006), suggesting that the intervaling effect should carry through to higher-order co-moments.

In this paper, we find that systematic skewness and kurtosis are highly sensitive to the length of the return interval. Significant differences between estimated gammas and deltas across distinct sampling intervals are detailed. The intervaling effect on gamma is approximately ten times stronger than that found for delta. Moreover, we find that the parameter sign associated with gamma differs from interval to interval. This finding is consistent with previous empirical evidence on the changing signs of financial returns' skewness, when different sampling intervals are considered (Lau and Wingender, 1989; Hawawini, 1980a).

[3] One exception is Galagedera and Maharaj (2008) who investigate the association between portfolio returns and higher-order co-moments at different time-scales for Australian industry portfolios only. Moreover, they do not consider stock level parameters or the possibility that information delays might be associated with the intervaling effect.

[4] Among these, Hawawini (1980a) identifies the factors that determine the direction and the strength of this effect mathematically, explaining earlier contradictory empirical observations. The author demonstrates that the behavior of skewness in response to changes in the length of the differencing interval is a function of both the signs and magnitudes of the skewness, and coefficient of variation measured over the one-day interval.

The existing literature attributes the intervaling effect to frictions in the trading process, such as price delay (Kamara et al., 2015; Corhay, 1992; Handa et al., 1989; Cohen et al., 1983b). Moreover, the effect has been linked to the frequency of trading on a structural level (Dimson and Marsh, 1983; Dimson, 1979; Scholes and Williams, 1977). Different delays in the adjustment of securities' prices to a change in market wide information induce serial cross-correlation between security returns and market returns. The parameter estimation for higher-order co-moments may be biased due to four underlying aspects. First, there is serial correlation in individual securities' returns. Second, serial correlation also exists in market returns. Third, the relative levels of the two serial correlations may be different. Finally, the level of serial correlation may alter for different sampling intervals. In general, the greater the expected trading delay of a security relative to the (equal or value-) weighted average trading delay in the market index, the greater the sensitivity of co-moments to the measurement interval.

To investigate this for the higher co-moments, we first explore the term structure of estimated gammas and deltas across different intervals, by forming portfolios based on firms' market capitalizations. The speed of pricing adjustment for larger firms is greater than that for small counterparts (Theobald and Yallup, 2004).[5] We find that for all securities whose firm sizes are greater (less) than the market average, the magnitude of the intervaling effect on co-moments are positively (inversely) related to their market capitalization. Moreover, the estimated deltas of securities for relatively smaller firms are found to shrink as return intervals shorten, while the securities of larger companies display generally increasing deltas. Our results are robust to the methods used to construct the market index. Further, the intervaling effect on co-moments computed from using equal-weighted market index is stronger than that using a similarly constructed value-weighted index.

Studies document that the intervaling effect, as a consequence of delays in the

[5]Theobald and Yallup (2004) establish the lead/lag relationship and demonstrate that large firms have higher speeds of adjustment than small firms. Their results are consistent with a number of other papers, such as Jegadeesh and Titman (1995) and Lo and MacKinlay (1990), which have established and investigated the lead/lag effects across size sorted portfolios and shown that large capitalisation stocks lead small capitalisation stocks.

trading process, may also be linked to liquidity. For example, Kamara et al. (2015) and Brennan and Zhang (2013) find that less liquid securities have greater adjustment delays than frequently traded securities. Using Amihud's (2002) illiquidity-sorted portfolios, our results suggest that for all security with greater (less)-than-average liquidity relative to the market portfolio, the magnitude of the intervaling effect on their co-moments are increasing (decreasing) with the level of liquidity.

We also test the robustness of our results to several possible concerns. Previous studies test the intervaling effect using longer intervals (Perron et al., 2013; Handa et al., 1989), using data from different subperiods, or using securities selected on the basis of their continuous presence during the whole period (Corhay, 1992). We find our results are robust in all these situations. We also reveal that the intervaling effect on higher-order co-moments exists during both low-risk and high-risk periods.

Our findings for the impact of the sampling interval on co-moments is important for both portfolio selection and asset pricing. Risk-averse investors prefer stocks with lower betas and deltas (Hung et al., 2014; Kostakis et al., 2012; Dittmar, 2002). We show that an asset which has smaller than average betas and deltas using a particular sampling interval may have larger than average estimates when measured using another interval. Moreover, investors' preference for positive skewness typically leads to a desire for positive and higher gammas, which represent higher probabilities of extreme positive returns in the security relative to market returns. Our findings suggest that an asset which is selected for a portfolio based on its positive gamma using one measurement interval may have negative gamma when using another interval, with resultant implications for asset and portfolio selection. Furthermore, since systematic skewness and kurtosis are interval dependent, the measured risk premia of these moment-related risk factors in the higher-order moment capital asset pricing model and their explanatory power may also be sensitive to the measurement interval.

The remainder of this paper is organized as follows. Section 2 describes the methodology applied to derive the co-moments and measures to capture the magnitude of the intervaling effect. Section 3 introduces data for each test and portfolio formation. Section 4 details the main empirical results and describes some robustness checks. Concluding comments are given in Section 5.

2. Test Methodology

2.1. Construction of Co-moments and Four-moment CAPM

The Sharpe-Lintner CAPM is strongly reliant on a variety of assumptions. Among them, the normality of returns is often argued as the crucial assumption. However, the returns of an asset or a portfolio tend to have negative skewness and their tails are often fatter than those implied by a normal distribution. Thus, moments of returns higher than variance are central to maximizing investors' expected utility. Progressively, Rubinstein (1973) and Kraus and Litzenberger (1976) extend the static CAPM to nonlinear forms of the risk-return trade-off by considering systematic skewness. Building on this, Fang and Lai (1997) and Dittmar (2002) suggest a four-moment capital asset pricing model by including co-kurtosis.

As a starting point, we will also follow Kraus and Litzenberger (1976) theoretical framework. Given $\tilde{W}$ as the end of period wealth, an investor's expected utility ($E[U(\tilde{W})]$) can be expressed by using a Taylor series expansion to the n^{th} order around mean wealth ($\overline{W}$), approximated as:

$$E[U(\tilde{W})] = \sum_{n=0}^{\infty} \frac{U^{(n)}\overline{W}}{n!} E[(\tilde{W} - \overline{W})^n] \tag{1}$$

where $U^{(n)}\overline{W}$ is the n^{th} derivative of the utility $U(\tilde{W})$ evaluated at the mean of the investors terminal wealth. Thus, the expected return of asset i in excess of the risk-free rate R_f is equal to the weighted sum of co-moments, with the weights reflecting measures of an investor's risk aversion:

$$E[R_i] - R_f = \sum_{n=2}^{\infty} \frac{-U^{(n)}}{(n-1)!E[U'(\tilde{W})]} C_{in}(R_i, \tilde{W}) \tag{2}$$

where R_i is the return on risky asset i. $C_{in}(R_i, \tilde{W})$ stands for the n^{th} co-moment of risky asset i with the investor's wealth portfolio, defining the contribution of a marginal increase in the holdings of the security to the corresponding central moments of the investor's future wealth.

In this paper, we consider the first four central moments and adjust them to different sampling interval lengths. At the aggregate market level, the standard deviation, skewness, and kurtosis of the market portfolio M measured by an L-day interval are given by $\sigma_{M,L}$, $S_{M,L}$, and $K_{M,L}$, shown below

$$\begin{aligned}
\sigma_{M,L} &= E[(R_{M,L} - \overline{R}_{M,L})^2]^{1/2} \\
S_{M,L} &= E[(R_{M,L} - \overline{R}_{M,L})^3]^{1/3} \\
K_{M,L} &= E[(R_{M,L} - \overline{R}_{M,L})^4]^{1/4}
\end{aligned} \tag{3}$$

where $R_{M,L}$ is the L-day return on the market portfolio and $\overline{R}_{M,L}$ is the mean value during the sample period. $\beta_{iM,L}$, $\gamma_{iM,L}$, and $\delta_{iM,L}$ are measures of systematic variance, skewness and kurtosis of the risky asset i with respect to the market portfolio M and are given by

$$\begin{aligned}
\beta_{iM,L} = C_{i2}(R_{i,L}, R_{M,L}) &= \frac{E[(R_{i,L} - \overline{R}_{i,L})(R_{M,L} - \overline{R}_{M,L})]}{E[(R_{M,L} - \overline{R}_{M,L})^2]} \\
\gamma_{iM,L} = C_{i3}(R_{i,L}, R_{M,L}) &= \frac{E[(R_{i,L} - \overline{R}_{i,L})(R_{M,L} - \overline{R}_{M,L})^2]}{E[(R_{M,L} - \overline{R}_{M,L})^3]} \\
\delta_{iM,L} = C_{i4}(R_{i,L}, R_{M,L}) &= \frac{E[(R_{i,L} - \overline{R}_{i,L})(R_{M,L} - \overline{R}_{M,L})^3]}{E[(R_{M,L} - \overline{R}_{M,L})^4]}
\end{aligned} \tag{4}$$

The excess return on the i^{th} asset is[6]

$$\overline{R}_{i,L} - R_{f,L} = \lambda_\beta \beta_{iM,L} + \lambda_\gamma \gamma_{iM,L} + \lambda_\delta \delta_{iM,L} \tag{5}$$

where the coefficients λ_β, λ_γ, and λ_δ are the risk premia (factor exposures). Equation 5 is referred to as the four-moment pricing model (hereafter 4M-CAPM) in this paper.

[6] The existing literature expands the investor's expected utility of end-of-period wealth to higher moments by using Taylor series expressions. Then, the Lagrangian approach is used to maximize the investor's expected utility of end of period wealth, subject to a budget constraint. Finally, the higher-order risk-return equilibrium conditions are formed. In our study, we follow the same theoretical framework. We assume that the investor's expected utility is the same for a given wealth level measured using different sampling intervals.

2.2. A Correction to Beta, Gamma and Delta Estimates

We estimate individual betas, gammas and deltas based on the definitions provided in Equation 4 using non-overlapping logarithmic returns measured across different intervals. At this stage, a correction approach for co-moment estimation is applied to deal with seasonality.[7] Since a return for a specific interval length is measured as the difference between the first and last logarithm of prices ($R_{i,L} = ln[P_{it}] - ln[P_{i(t-L)}]$), price moves between these two days (e.g. $P_{i(t-1)}, \cdots, P_{i(t-L+1)}$) are wiped out. Hence, a large number of substantial price moves that could have significant impact on the estimates will be ignored, if we use return intervals with longer lengths.

The correction consists in computing each parameter (beta, gamma or delta) in Equation 4 a total of L times for an interval of length L, and then calculating an average estimate. Such a procedure allows us to avoid bias in estimating parameters. Thus, the equations become:

$$\begin{aligned} \overline{\beta}_{iM,L} &= \sum_{n=1}^{L} \beta_{iM,L,n}/L \\ \overline{\gamma}_{iM,L} &= \sum_{n=1}^{L} \gamma_{iM,L,n}/L \\ \overline{\delta}_{iM,L} &= \sum_{n=1}^{L} \delta_{iM,L,n}/L \end{aligned} \tag{6}$$

All co-moments are first computed for returns of interval length L using the complete series of daily returns. Then, the first daily return is deleted, the returns of interval length L are recalculated with the remaining observations and beta, gamma and delta are computed again and so forth until repeated L times.

[7]This method is first suggested by Corhay (1992). Corhay indicates that the estimated betas and their speed of convergence to the asymptotic value depend on which day the differencing interval starts. He demonstrates that betas estimated using Monday to Monday weekly returns are always larger than those estimated using Friday to Friday weekly returns, due to seasonality. Recent studies such as Hong and Satchell (2014) also suggest that a correction of beta is necessary to better discern the convergence of the beta coefficient, if additive returns are used.

2.3. Ordinary Least Squares Coefficients

In the section above, we develop a methodology to calculate higher order moment parameters using individual moment characteristics. However, a portion of empirical tests on the intervaling effect rely on estimates of Ordinary Least Squares (OLS) regressions, instead of using the mathematical definition shown in Equation 4. The literature attempts to represent the higher moments through a simple polynomial functional relation between the returns of an asset or a portfolio and the market index (e.g. Lambert and Hübner, 2013; Doan et al., 2014; Kostakis et al., 2012), given by[8]:

$$R_{i,L} - R_{f,L} = \phi_{0,L} + \phi_{1,t}(R_{M,L} - R_{f,L}) + \phi_{2,L}(R_{M,L} - \overline{R}_{M,L})^2 + \phi_{3,L}(R_{M,L} - \overline{R}_{M,L})^3 + \varepsilon_L \tag{7}$$

Many studies directly use the three coefficients, $\phi_{1,t}$, $\phi_{2,t}$ and $\phi_{3,t}$ in Equation 7, as proxies for the betas, gammas and deltas respectively. However, although this cubic market model is consistent with the 4M-CAPM, the estimated coefficients of the OLS regression for Equation 7 are inherently different from those corresponding systematic measures. If the asset returns conform to Equation 7, the systematic risk measures of the 4M-CAPM, $\beta_{iM,L}$, $\gamma_{iM,L}$, and $\delta_{iM,L}$ respectively,

[8]Although polynomial regressions fit a nonlinear model to the data, as a statistical estimation problem it is linear, in the sense that the regression function $E(y|x)$ is linear in the unknown parameters that are estimated from the data. For this reason, a polynomial regression is considered to be a special case of multiple linear regression. See Lambert and Hübner (2013) for more detail.

are linear combinations of the estimated coefficients $\hat{\phi}_{1,L}$, $\hat{\phi}_{2,L}$, and $\hat{\phi}_{3,L}$[9]

$$\begin{aligned}
\beta_{iM,L} &= \hat{\phi_{1,L}} + \hat{\phi_{2,L}} \frac{E(R_{M,L} - \overline{R}_{M,L})^3}{E(R_{M,L} - \overline{R}_{M,L})^2} + \hat{\phi_{3,L}} \frac{E(R_{M,L} - \overline{R}_{M,L})^4}{E(R_{M,L} - \overline{R}_{M,L})^2} \\
\gamma_{iM,L} &= \hat{\phi_{1,L}} + \hat{\phi_{2,L}} \frac{E(R_{M,L} - \overline{R}_{M,L})^4 - [E(R_{M,L} - \overline{R}_{M,L})^2]^2}{E(R_{M,L} - \overline{R}_{M,L})^3} \\
&\quad + \hat{\phi_{3,L}} \frac{E(R_{M,L} - \overline{R}_{M,L})^5 - E(R_{M,L} - \overline{R}_{M,L})^3 E(R_{M,L} - \overline{R}_{M,L})^2}{E(R_{M,L} - \overline{R}_{M,L})^3} \qquad (8) \\
\delta_{iM,L} &= \hat{\phi_{1,L}} + \hat{\phi_{2,L}} \frac{E(R_{M,L} - \overline{R}_{M,L})^5 - E(R_{M,L} - \overline{R}_{M,L})^2 E(R_{M,L} - \overline{R}_{M,L})^3}{E(R_{M,L} - \overline{R}_{M,L})^4} \\
&\quad + \hat{\phi_{3,L}} \frac{E(R_{M,L} - \overline{R}_{M,L})^6 - [E(R_{M,L} - \overline{R}_{M,L})^3]^2}{E(R_{M,L} - \overline{R}_{M,L})^4}
\end{aligned}$$

For robustness, we further apply the regression approach over the different intervals. We refer to the beta, gamma and delta estimated by this approach as OLS estimated beta, gamma and delta. The OLS regression and linear combination calculations will also be repeated L times for a sampling interval of length L to remove any effect of seasonality.

2.4. Sensitivity to the Measurement Interval

The extant literature considering the intervaling effect has not specified a test to measure the strength of the intervaling effect. The one-way analysis of variance (ANOVA1) is the most commonly used approach. However, tests of significance for ANOVA1 are known to be valid only if the observations are assumed to be normally distributed or have equal variances. Both of these assumptions may be violated in studies related to the intervaling effect.

Therefore, we augment the use of ANOVA1, with a series of parametric and non-parametric tests. First, rather than testing the betas, gammas and deltas directly, we will explore the performance of ratios of estimates. For example, $Ratio^{\gamma}_{1,L_m}$ is the ratio between 1-day gamma and monthly gamma of the same

[9]Hung (2008) and Rubinstein et al. (2006) both document the mathematical proof of Equation 8 and show that the cubic market model is consistent with the four-moment asset pricing model.

firm.[10,11] Using this framework, if there is no intervaling effect, all ratios are equivalent (equal to 1), while the alternative hypothesis is that at least one group of ratios is significantly different from 1.

Second, we use the parametric ANOVA1, the Kruskal-Wallis non-parametric ANOVA1 test, the Wilcoxon-Mann-Whitney rank-sum test, and the Wilcoxon signed-rank test to test the magnitudes of the betas, gammas and deltas. We determine whether there are significant variations across different sampling intervals. Furthermore, we use a sign variation test to check if the signs of gamma also change. We retain the ANOVA1 test due to its wide application in previous literature, but a Bartlett's test for equal variances is also considered.[12] Therefore, if the equality of variance is significantly rejected, we will focus on the non-parametric tests mentioned above to validate findings.

Third, to quantify the magnitude of the intervaling effect, we define an intuitive variable, referred to as *SAD*, as the sum of the absolute differences between

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[10]Using ratios has several advantages. Most importantly, we can easily hypothesise that they are equal to 1 if there is no intervaling effect on the systematic measures. A ratio greater than one indicates an upward intervaling effect, and vice versa. A negative ratio indicates the signs of estimates are affected by the sampling interval used. Moreover, the coefficients estimated across different intervals may not be independent, while even non-parametric tests require independent random samples. We can compare the estimates with a sample of ones instead. Using ratios also allows us to compare the intervaling effect on three systematic measures, even if the magnitudes of the betas, gammas and deltas are considerably different. See Brennan and Zhang (2013) for further details.

[11]The choice of denominator in estimates has no impact in applying the ratio analysis. We use monthly returns in our paper since they are most widely applied in recent asset pricing studies. Moreover, literature on the intervaling effect also suggests that monthly estimates are very close to the "true" values.

[12]Results of the analysis of variance may not change appreciably in the face of moderate violations of the assumptions. However, even if the assumptions are not valid, one may still use the calculated F-statistics as relative measures of the treatments being considered.

other interval estimates and monthly estimates:

$$
\begin{aligned}
SAD_{\beta} &= \sum_{n}^{L} \left| \overline{\beta}_{iM,n} - \overline{\beta}_{iM,L_m} \right| \\
SAD_{\gamma} &= \sum_{n}^{L} \left| \overline{\gamma}_{iM,n} - \overline{\gamma}_{iM,L_m} \right| \\
SAD_{\delta} &= \sum_{n}^{L} \left| \overline{\delta}_{iM,n} - \overline{\delta}_{iM,L_m} \right|
\end{aligned}
\tag{9}
$$

where $\overline{\beta}_{iM,n}$, $\overline{\gamma}_{iM,n}$ and $\overline{\delta}_{iM,n}$ are the corrected beta, gamma and delta measured by $n-day$ interval and L_m stands for the length of a business month. The *SAD* quantitatively captures the aggregate tendency of all estimates of beta, gamma and delta to vary from that measured at a monthly interval. If there is no intervaling effect, the *SAD* should be zero.

2.5. Test Hypotheses

The empirical tests proceed as follows. First, we examine the overall intervaling effect on individual betas, gammas and deltas, regardless of firm characteristics. Second, we sort individual firms into portfolios according to their market capitalization and liquidity, as proxies of price delay, and explore the sensitivities of portfolio mean beta, gamma and delta to the measurement interval.

We test the following hypotheses on examining the intervaling effect, especially on co-skewness and co-kurtosis.

Hypothesis 1a. *The magnitudes of estimated beta, gammas and deltas are invariant to the length of the sampling interval used to compute returns.*

This can be formulated as:

$$
\begin{aligned}
&H_0 : \forall L \quad Ratio^{\beta}_{L,L_m} = \frac{\beta_{iM,L}}{\beta_{iM,L_m}} = 1, \;\; Ratio^{\gamma}_{L,L_m} = \frac{\gamma_{iM,L}}{\gamma_{iM,L_m}} = 1 \;\; and \;\; Ratio^{\delta}_{L,L_m} = \frac{\delta_{iM,L}}{\delta_{iM,L_m}} = 1 \\
&H_1 : \exists L \; s.t. \quad Ratio^{\beta}_{L,L_m} = \frac{\beta_{iM,L}}{\beta_{iM,L_m}} \neq 1, \;\; Ratio^{\gamma}_{L,L_m} = \frac{\gamma_{iM,L}}{\gamma_{iM,L_m}} \neq 1 \;\; and/or \;\; Ratio^{\delta}_{L,L_m} = \frac{\delta_{iM,L}}{\delta_{iM,L_m}} \neq 1
\end{aligned}
\tag{10}
$$

where L is the length of one specific interval and L_m stands for the length of a business month (assumed to be 20 business days in this paper). Alternatively, with SADs calculated using individual betas, gammas and deltas, we can also test this hypothesis by assuming a null of

$$H_0: \ SAD_\beta = 0, \quad SAD_\gamma = 0 \ \ and \ \ SAD_\delta = 0 \tag{11}$$

Hypothesis 1b. *The signs of estimated gammas are invariant to the length of the sampling interval used to compute returns.*

Specifically, the literature suggests that the sign of skewness will also change due to different sampling intervals used (Lau and Wingender, 1989; Hawawini, 1980b). Building on this, we test whether the sign of systematic co-skewness changes from one interval to another. For two gammas with opposite signs, the resultant ratio will be negative. Thus, the hypothesis regarding the sign of gamma can also be formulated as:

$$H_1^*: \ \exists L \ \ s.t. \quad Ratio^{\gamma}_{L,L_m} = \frac{\gamma_{iM,L}}{\gamma_{iM,L_m}} < 0 \tag{12}$$

Furthermore, we test whether the intervaling effect is more prevalent among stocks with distinct characteristics. In particular, larger or more liquid firms have relatively less price delay in adjusting to market information (Kamara et al., 2015; Theobald and Yallup, 2004; Corhay, 1992). We then describe our null hypotheses as:

Hypothesis 2. *The magnitude of the intervaling effect on beta, gamma and delta is invariant to the security's price delay (using market capitalization and Amihud illiquidity as proxies).*

Therefore, for any two firms X and Y with different levels of market capitalization or liquidity (or illiquidity), the null hypothesis is:

$$H_0: \ SAD_{\beta,X} = SAD_{\beta,Y}, \quad SAD_{\gamma,X} = SAD_{\gamma,Y} \ \ and \ \ SAD_{\delta,X} = SAD_{\delta,Y} \tag{13}$$

where $SAD_{\beta,X}$, $SAD_{\gamma,X}$ and $SAD_{\gamma,Y}$ correspond to the sum of absolute differences of systematic variance, skewness and kurtosis for Firm X and Y, respectively. A non-zero SAD corresponds to an intervaling effect.

3. Data and Portfolios

3.1. The Sample

To examine the intervaling effect on systematic skewness and kurtosis, we use stocks listed on the Center for Research in Security Prices (CRSP) daily tape with share codes 10 or 11 for the period 01/02/1990 to 12/31/2013[13]. Alongside prices, the total market capitalization and trading volumes of outstanding shares are also collected. Non-overlapping logarithmic returns are calculated for nine sampling intervals: 1, 2, 3, 4, 5, 10, 20, 65 and 125 business days. These intervals encompass the majority of regular measurement intervals used both in practice and in the literature: daily, weekly, monthly, quarterly, and semi-annually.

To test Hypothesis 1a and 1b, we have nine samples corresponding to the nine sampling intervals. For all intervals, we use value-weighted returns as the market index.[14] The risk free rate is the (compounded) three-month T-bill rate, and we will scale the rate for each sampling interval.[15] To ensure a sufficient number of observations for each interval, we drop those stocks with less than five years of daily returns (at least ten observations for all individual stocks measured using the 125-day interval). This results in a total of 8088 securities in our sample.

3.2. Price-delay Sorted Portfolios

The existing literature has documented that prices adjust following the arrival of information, and that adjustment delays are inversely related to the size and trading liquidity of firms (Lin et al., 2014; Hou and Moskowitz, 2005). Larger and more liquid firms have less delay in pricing adjustment to market information. For this reason, we sort all stocks into 20 equally sized portfolios by market

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[13]Daily returns on the CRSP file are recorded since July 1962. However, we mainly use data starting from 1990 since there is a great proportion of data missing for most securities on CRSP daily tape before 1990, which may significantly affected our following constructions and tests on individual securities. The results based on the full data range can be obtained on request.

[14]We do not use the CRSP index as our market index because its returns are not logarithmic, and therefore are not additive. Our daily market returns are reasonable and closely track the daily CRSP index having a correlation coefficient of 0.994.

[15]This may cause a reduction in the accuracy of estimates. However, we focus on the magnitudes of betas, gammas and deltas. The risk free rate is not involved in calculating the estimates based on their definitions (Equation 4.) The risk free rate is used in the OLS regression on the cubic market model, but will be omitted when computing the betas, gammas and deltas as well.

capitalizations (*MC* portfolios) and Amihud (2002) illiquidity ratios (*AR* portfolios), respectively. The Amihud ratio is one of the most widely used illiquidity proxies in recent literature.[16] It is expected to be positively related to the delay in price adjustment. In other words, the intervaling effect is expected to be more evident in more illiquid stocks.

Our set-up for portfolios to test Hypothesis 2 is similar to those in Perron et al. (2013) and Handa et al. (1989). For size sorted portfolios, we reassign securities on an annual base into 20 portfolios according to their average market capitalization ranks.[17] The first, $MC1$, contains the smallest 5% of firms and the last, $MC20$, contains the largest 5%. For each *MC* portfolio, we estimate all individual betas, gammas and deltas using each stock's one-year returns and re-estimate them each year from 1990 to 2013. Then we calculate value or equal-weighted co-moments as the estimates for each portfolio. To ensure an adequate number of observations when using one year of data, we consider the first seven sampling intervals: 1, 2, 3, 4, 5, 10, and 20 days.[18]

The Amihud illiquidity measure captures the daily price response associated with one dollar of trading volume:

$$Amihud = Average \left[\frac{|r_t|}{Dollar\ Volume_t} \right] \tag{14}$$

The average is only calculated over positive-volume days. Thus, for Amihud-ratio sorted portfolios, the first, $AR1$, contains the smallest 5% Amihud ratios (highest liquidity) of the firms and the last, $AR20$, contains the largest 5% (lowest liquidity). We also calculate the annual means of Amihud ratios and reassign *AR* portfolios each year from 1990 to 2013.

[16]The estimates for portfolios formed on the basis of other liquidity measures such as Amivest ratios, bid-ask spreads and volume of trading of the securities are also calculated, but as their results do not significantly differ from those obtained with the market capitalization, they are not presented.

[17]Our portfolio composition changes each year, since firms' average market capitalizations are re-ranked and firms enter and leave the sample as a result of listing, delisting, mergers, and the like.

[18]We also check the robustness of our results by using longer intervals in Section 4.3.

3.3. Normality Tests and Summary Statistics

To get an idea of the statistical properties of the data under examination, Table 2 details Jarque-Bera statistics and corresponding p-values from tests of normality of the returns for the market index, our data sample and for portfolios formed according to market-capitalization or to their Amihud ratios. The results from tests on returns of different intervals suggest that higher frequency returns data tend to be more skewed and leptokurtic, while returns measured by longer-interval data are usually better represented by a normal distribution. This finding is consistent with existing literature (e.g. Hung, 2008; Chung and Schill, 2006).

TABLE 2 ABOUT HERE

The Jarque-Bera test rejects the assumption of normally distributed returns for the market index and weighted average returns for all intervals at a 95% level. Considering portfolios formed using market capitalization and Amihud liquidity, contrasting results are found. For 1-day up to 20-day intervals, the normality of portfolio returns are significantly rejected at the 99% level. At the longest intervals examined, normality cannot be consistently rejected. In particular, for the smallest and least liquid stocks, the assumption of normality cannot be rejected. Moreover, for the portfolios containing the largest and most liquid stocks, normality is not rejected. These findings suggest that security size and liquidity impact the distributional properties of stock returns.

4. Empirical Results

4.1. Sample Means across Measurement Intervals

We first test Hypotheses 1a and 1b on the full set of 8088 securities from 1990 to 2013. Table 3 illustrates market value-weighted averages for individual betas, gammas and deltas, as well as for the sums of absolute differences (SADs). Co-moments (beta, gamma and delta) are all significantly sensitive to the sampling interval. These results suggest that the conclusions of all asset pricing and portfolio selection studies incorporating gamma and delta will substantially depend on the chosen return interval.

TABLE 3 & FIGURE 1 ABOUT HERE

In Panel A of Table 3, we detail the betas, gammas and deltas estimated using the definitions given in Equation 4, while the values in Panel B are calculated as a linear combinations of coefficients of the cubic market model (Equation 7), based on the formulas in Equation 8. The results detailed for each methodology are essentially identical. In the rest of this study, we will rely on estimates formed using the Equation 4 definition, since this approach is parsimonious.

Market value-weighted betas and deltas are shown to display a similar trend, and are both monotonically increasing as the sampling interval is lengthened, from approximately 1.0 using a 1-day sampling interval to 1.190 for beta and 1.290 for delta using a 125-day interval. Findings for estimated gamma suggest a U-shape pattern from short to long intervals. Gamma declines from 1.182 for a 1-day sampling interval to 1.089 for a 4-day interval, and then rebounds to 1.962 for the longest interval considered. This U-shaped pattern may primarily be attributed to changes in sign for a large number of estimated gammas between the 3 day and 4 day interval. Furthermore, SADs indicate that gammas are far more sensitive to the intervaling effect than the other two parameters (approximately 10 times larger).

Panel C in Table 3 presents empirical results found from testing the strength of the intervaling effect in higher order co-moments, using data for 8088 individual stocks from the beginning of 1990 to the end of 2013. On the one hand, ANOVA1 tests give mixed results: the F-test statistics from the analysis of variance among the nine samples of the individual betas and gammas are insignificant, while that for the deltas is 3.809 and is statistically significant at the 99% level. If this is true, only delta is significantly affected by the sampling interval among the three systematic measures, contradicting previous empirical evidence of the intervaling effect on betas (Cohen et al., 1983a; Hawawini, 1980b). However, these statistics are significantly biased by violations of the main assumption of equal variances (significantly rejected by Bartlett's tests).

On the other hand, the results of our non-parametric tests strongly suggest a significant intervaling effect on betas, gammas and deltas. The Kruskal Wallis test indicates that the sampling interval has a significant effect on all three systematic measures. Betas have the largest K statistics (approximately χ^2 distributed with 8 degrees of freedom), while gammas have the lowest. Higher K statistics suggest that among the nine samples of gammas and betas, at least one sample stochastically dominates another sample. The Wilcoxon-Mann-Whitney test and Wilcoxon Signed-rank test also significantly reject the equivalence of the samples at the 95% level. The results of Wilcoxon Signed-rank test provide strong evidence, since this test only compares the individually paired observations.

Finally, testing the variation in the sign of gamma (Hypothesis 1b), we find that there are 5 samples having significantly different signs from estimates using monthly returns. In contrast, when we also test the sign variation in betas and deltas, none of the tests rejects the null hypothesis. These findings suggest that when we use data for all stocks from 1990 to 2013, only the signs of gammas are considerably affected by the sampling intervals used. Our results are particularly important for the recent literature on Mean-Variance-Skewness and higher-order portfolio selection frameworks. Investors' preference for positive skewness typically leads to the selection of securities with positive gammas, which represent higher probabilities of extreme positive returns in the security over market returns. However, according to the results outlined in Table 3 and also later in Table 9, an asset of interest that is identified with positive gamma using a particular sampling interval may have negative gamma using another interval.

The results outlined above, testing Hypotheses 1a and 1b, suggest that estimated gammas and deltas are sensitive to the choice of sampling interval. However, this provides little detail regarding the origins of the intervaling effect. We next test Hypotheses 2 to understand the relation between the delay in pricing adjustment and the intervaling effect on systematic skewness or kurtosis.

4.2. The Intervaling Effect and Firm Size

Literature suggests that prices adjust following the arrival of information and that adjustment delays are negatively related to firm size (e.g. Lin et al., 2014; Hou and Moskowitz, 2005). Cohen et al. (1980) also show that larger firms have a higher speed of price adjustment results, and consequently smaller serial correlation in returns.

We wish to study how the magnitude of the intervaling effect on a security's higher-order co-moments is influenced by its firm size (market capitalization). Sorted on the basis of securities' market capitalizations, Table 4 and Table 5 illustrate the estimated co-moments using value-weighted and equal-weighted market index, respectively.[19] The intervaling effect on three co-moments of all portfolios are significant at a 99% level in both K-W tests and SAD-related hypothesis tests. Consistently, SAD figures for gammas are still much larger than those of betas and deltas, and the sign of gamma is also found to change significantly for all portfolios, as shown in Table 3.

TABLE 4 & TABLE 5 ABOUT HERE

More precisely, our results make a number of novel contributions. First, for all securities with greater expected trading delays than the weighted average trading delay in the market, the magnitudes of the intervaling effect on their co-moments are inversely related to their market capitalizations. We assume a value-weighted market capitalization at \$29.80 billion and a equal-weighted value at \$3.39 billion are proxies for weighted average trading delay for the value-weighted and equal-weighted market index, respectively. Therefore, using value-weighted returns in Table 4, the first 19 *MV* portfolios all have less market capitalizations than than that of the market. Thus, the magnitude of the intervaling effect, measured using SADs, is found to be inversely related to the market capitalization. Similarly, using equal-weighted returns in Table 5, the SADs of the first 12 portfolios are generally in a decreasing order.

Second, in contrast, if a security has greater-than-average firm size, its expected trading delays are less than the weighted average trading delay in the market. Thus, for these securities, their co-moments' sensitivity to the measurement interval should be positively related to their market capitalizations. Most existing literature only sorts stocks into 20 or fewer portfolios. Thus, usually only one portfolio (such as $MC20$ in Table 4) has much larger averaged market capitalization than those of others' and of the market. We re-sort $MV20$ into 10 sub-portfolios to clarify the pattern of the intervaling effect on these securities, as shown in Table

[19]Table 4 lists estimates for $MC1$ to $MC5$ and $MC16$ to $MC20$, five portfolios containing the smallest firms and five containing the largest firms, for brevity. These ten portfolios have the most important economical and statistical implications for our study. Table 5 selects results of two smallest portfolios, two largest and four portfolios in the middles, since the intervaling effect on estimates show a U shape. Complete tables can be obtained upon request.

6. From $MV20-7$ to $MV20-10$, the intervaling effect on co-moments is positively related to the market capitalization. Consistent results can be found using the equal-weighted market index as shown in Table 5. $MV19$ and $MV20$ both have greater market capitalizations than the market, resulting in all SAD_β, SAD_γ and SAD_δ of $MV19$ being smaller than those of $MV20$.

Third, previous evidence suggests betas of smaller firms are shown to increase, while those for the largest firms decline as the measurement interval lengthens (Cohen et al., 1983a,b). Consistently, we find that estimated deltas of most portfolios in Table 4 and sub-portfolios in Table 6 are monotonically increasing as the sampling interval is lengthened. Exceptionally, deltas and betas of securities with larger market capitalizations than that of the market portfolio, show a downward trend when the sampling interval increases from 1 day to 20 days, with values very close to one. This also confirms the behaviour of the security betas documented in the existing literature. However, we fail to find a similar monotonic relationship between estimated gammas and the sampling interval. Instead, gammas of *MC* portfolios display rough U-shape patterns.

Lastly, given that value-weighted market returns are primarily affected by larger stocks, a value-weighted market index should have smaller serial correlation than a similarly constructed equally-weighted market index. We find that for the same portfolio, SAD_β, SAD_γ and SAD_δ calculated based on an equal-weighted market index (Table 5) are all greater than those using a value-weighted index (Table 4), respectively. Our results confirm the empirical findings on betas in Cohen et al. (1980), and extend these to co-skewness and co-kurtosis.

Therefore, we conclude that for any security, the greater (less) is the expected trading delay of the security relative to the weighted average trading delay in the market index, the more sensitive the co-moments will be to choices of the measurement interval. The estimated betas and deltas of these securities are found to shrink as return intervals shorten. Moreover, higher-order co-moments estimated using a value-weighted market index are less affected by the measurement interval.

Our results contribute to existing studies, by considering the similarities and differences of the weighted average trading delay in the market index between using value-weighted and using equal-weighted market returns. Previous results are not robust to the construction methods of the market index. On the one hand, studies like Corhay (1992) and Hawawini (1983) use a value-weighted market index and indicates that the strength of the intervaling effect on beta is inversely related to the size. On the other hand, Perron et al. (2013) and Handa et al. (1989) apply an equal-weighted market index. They offer evidence that the betas of extreme market-capitalization portfolios (largest and smallest securities) change dramatically. Our results help to reconcile these previous findings.

4.3. The Intervaling Effect and Liquidity

An extensive literature also suggests that liquidity plays a significant role in explaining the delay in price adjustment. Liquidity stimulates arbitrage activity and thus enhances market efficiency. Securities of illiquid firms will be less efficient in adjusting to market information and thus have stronger cross-serial correlation with the market portfolio (for example, see Chung and Hrazdil, 2010; Chordia et al., 2008). We, therefore, sort securities into portfolios using the Amihud illiquidity ratio, which is one of the more widely used liquidity proxies in the finance literature. Table 7 shows the results of empirical tests for Hypothesis 2. We list co-moments estimated using the value-weighted index only.

TABLE 7 ABOUT HERE

Panels A, B and C of Table 7 display sample means of 10 Amihud-ratio sorted (AR) portfolios', $AR1$ to $AR5$ and $AR15$ to $AR20$ for beta, gamma and delta respectively. The greater the Amihud ratios, the less the firm's liquidity and thus the greater delay in adjusting price. The most liquid firms will often have relatively large market capitalizations. Hence, the pattern of estimated betas, gammas and deltas for AR portfolios are similar to those of MC portfolios in Table 4 above, but ranked inversely.

The value-weighted mean betas and deltas of the most liquid portfolio, $AR1$, similar to those of $MC20$, each take value close to one and are inversely related to the lengths of the measurement interval (from approximately 1.0 with 1-day interval to 0.95 with 20-day interval). The gammas of $AR1$ are also found to be less affected by the measurement interval, compared to those of the other 9 portfolios.

The value-weighted Amihud ratio of the market index is 2.456, indicating that only $AR1$ has higher liquidity and likely has less price delay than those of the market. Consistently, according to both K-W statistics and SADs, for all securities with lower liquidity than the market, the magnitude of the intervaling effect is inversely related to liquidity. Moreover, SAD_{δ} of $AR2$ is smaller than that of $AR1$, which is in agreement with our earlier findings on the "ι" shape SADs, using value-weighted returns.

4.4. Implications for Higher-order Asset Pricing and Portfolio Selection

Table 4 and Table 7 have several implications, for higher-order asset pricing and portfolio selection. First, the literature documents some return anomalies such as the Size Effect (Banz, 1981) and Liquidity Effect (Amihud, 2002; Amihud and Mendelson, 1986). Investors may pursue stocks with smaller capitalizations or less liquidity while seeking out opportunities for extra returns. However, regardless of the debate on whether these anomalies are still present currently, our results indicate that the intervaling effect is closely related to both firm size and market liquidity. This suggests that investors in smaller or less liquid firms should pay more attention to choosing the measurement interval in analysing systematic risk exposure of a security.

Second, recent portfolio selection theory suggests that risk-averse investors are attracted to securities with smaller betas and deltas, and with positive gammas (for example, see Kostakis et al., 2012). However, according to our empirical results, the relative ranks of portfolio betas, gammas and deltas alter when the sampling interval is lengthened. In particular, for MC portfolios, the 1-day betas are increasing from 0.637 for $MC1$ to 0.998 for $MC20$, while the 20-day betas are declining from 1.526 for $MC1$ to 0.956 for $MC20$. The estimated deltas also follow this pattern. Moreover, gamma is the most sensitive to the measurement interval, since not only the magnitudes but also the signs of gammas change. An asset that is chosen based on its positive gamma using a particular sampling interval may have negative gamma using another interval. Therefore, our results contend that portfolio allocation using higher-order moments will be significantly influenced by the sampling interval chosen. A security chosen for particular properties at one interval may not be selected for a different choice of interval.

4.5. Robustness Checks

This section complements the evidence detailing the intervaling effect in higher order asset pricing by performing three further robustness checks.

First, as considered in previous literature such as Perron et al. (2013) and Handa et al. (1989), we test the robustness of our findings using intervals longer than one month. Table 8 presents estimated betas, gammas and deltas using returns data for all firms on the CRSP monthly tape. Using intervals from 1 month to 12 months, commonly considered by investors, results are found to be in keeping with those detailed in Table 4. Considering market capitalization as a proxy for price delay, the magnitude of the intervaling effect (measured by K-W tests and SADs) for smaller securities is inversely related to market capitalization, and vice versa. Securities in portfolio $MC1$ are still the most sensitive to the length of intervals used in measuring returns, while those for firms in portfolios $MC19$ are least affected (with smallest SADs). Furthermore, estimated deltas also have a similar pattern to betas, and gammas are the most significantly affected by the measurement interval among the three systematic measures. The U-shape pattern of gamma is even stronger than that witnessed at the shorter intervals detailed earlier. A small caveat is that the results in Table 4 and Table 8 are not strictly comparable because the underlying sample periods (one-year non-overlapping windows v.s. five-year moving windows) and stocks sources (from CRSP daily tape v.s. monthly tape) are different.[20] However, both tables reject our Hypothesis 2, suggesting that the intervaling effect is significant across a large range of measurement intervals and highly related to friction in the trading process. Moreover, it also suggests that investors considering longer intervals when making portfolio allocation decisions are subject to similar estimation issues encountered by those with shorter investment intervals.

[20] For example, those 20-day betas, gammas and deltas in Table 4 of the first five portfolios are much larger than the corresponding 1-month estimates in Table 8, while these two groups of $MC16$ to $MC20$ are actually consistent. This may be caused by two main reasons. First, different measurement horizons may lead to significant difference in estimating parameters, referred to as the horizon effect, which is stronger for securities with smaller market capitalizations (see Kamara et al. (2015) for reference). Second, market-capitalization portfolios formed by stocks on CRSP monthly tape and those on daily tape may be very different, especially for small-capitalization portfolios.

TABLE 8 ABOUT HERE

Second, avoidance of data problems due to the listing and delisting of securities is essential in estimating and analysing systematic risks. We examine securities selected on the basis of their continuous presence during the whole period. We repeat our tests on 989 securities which have consecutive data spanning 24 years from 1990 to 2013. All results, as shown in Panel A of Table 9, still significantly reject our Hypothesis 1. According to the W-M-W and signed rank tests, all 8 samples of ratios are again significantly different from one. Although non-parametric ANOVA1 tests are statistically significant at the 99% level, these figures are much smaller than those found in Table 3. Given that the standard deviations of the magnitudes are similar, this finding suggests that the estimates are less effected by the sampling intervals when only the data of these 989 stocks are used, as opposed to when all the other stocks are included. The lower sensitivity of these stocks to the measurement interval also offers evidence for Hypothesis 2. We expect these 989 continuously traded firms to have relatively stable performances, efficient financial structures, and high liquidity.

TABLE 9 ABOUT HERE

Third, we also check the robustness of the intervaling effect during different market conditions. We collect the Chicago Board Options Exchange Market Volatility Index (VIX) and TED spread which is defined as the difference in yields between US Euro-dollar deposits and US Treasury bills. The VIX is widely used to represent market risk and the TED spread is usually regarded as an indicator of perceived credit risk. Simply, we separate our 24-year time window into years with less-than-average risk and years with above average risk.[21] Table 10 illustrates the sum of absolute differences for market-capitalization portfolios during each period. We find that SAD_{β}, SAD_{γ}, and SAD_{δ} are all negatively related to the market capitalization, rejecting H2. However, during high-risk periods, as

[21] According to our calculations, the average VIX and TED spread during 1990 to 2013 are 20.188 and 0.525, respectively. For VIX, high-risk periods consist of 1990, 1991, 1995, 1997, 1998, 1999, 2000, 2007, 2008 and 2009, while the other years belong to low-risk periods. For TED spread, high-risk periods include 1990, 1997, 1998, 1999, 2000, 2001, 2002, 2003, 2008, 2009, 2010 and 2011.

shown in Panel A and Panel C, SADs are large relative to low risk periods. In particular, SAD_δ and SAD_β for securities with larger market capitalizations during low-risk periods are considerably less than those during the other years. These findings suggest that the intervaling effect is present during low risk periods, but it is stronger during high-risk periods perhaps pointing to longer price transmission delays during riskier periods.

TABLE 10 ABOUT HERE

5. Conclusion

Higher-order co-moments extend the Sharpe-Lintner CAPM, allowing for more detailed characterization of individual asset risk. However, previous literature has largely ignored the impact of the choice of return interval on estimation precision for higher-order co-moments. Based on an extensive data sample of stocks from CRSP for 1990 to 2013, this paper details the sensitivity of systematic skewness and kurtosis to the return interval. We develop a system of consistent sequential tests to measure the strength of the intervaling effect. The magnitude of the effect is shown to depend on firm characteristics and relates to price adjustment delay.

Accordingly, this study has shed new light on the literature considering higher-order asset pricing and portfolio selection theories, progressively, in two steps. First, we show evidence that the magnitudes of the third and fourth moment-related pricing factors (gamma and delta) are significantly influenced by the sampling interval. Moreover, the sign of gamma also changes significantly when the interval is lengthened. Second, we further refine the estimation of gammas and deltas by using the returns of market-capitalization sorted portfolios and Amihud-ratio sorted portfolios, respectively, measured over intervals from one day to one month. Increasing firm market capitalizations and Amihud's illiquidity ratio are used as positive and inverse proxies for price adjustment delay. We find significant changes as the return interval is lengthened. Gammas and deltas of securities with similar delay in pricing adjustment, relative to the market portfolio, are usually less affected by the measurement interval. Results are demonstrated to be robust to the use of an equally weighted market index, to longer return intervals of up to twelve months, and to performance during volatile and stable periods.

We conclude with a word of caution to empirical researchers who use higher-order asset pricing or portfolio selection theories in their empirical work. The magnitudes and ranks of gammas and deltas may alter as the sampling interval is changed. An asset which is chosen because of its positive systematic skewness and low systematic kurtosis measured in one particular interval may have negative gamma and larger-than-average delta when another interval is used. The intervaling effect may thus result in potential ambiguity in pricing and selecting assets for different situations.

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APPENDIX: TABLES & FIGURES

Table 1: Structural Empirical Review of Higher-order Moment Asset Pricing and Portofolio Selection Studies,1990-2013

Return Measurement Interval		Reference	Asset Classes	Higher-order Co-moments	Journal	Title
	1	Vanden (2006)	Stocks and Options	Co-skewness	RFS	Option Coskewness and Capital Asset Pricing
	2	Gandhi and Lustig (2015)	Stocks	Coskewness	JF	Size Anomalies in U.S. Bank Stock Returns
	3	Botshekan, Kraeussl and Lucas (2012)	Stocks	Co-skewness	JFQA	Cash Flow and Discount Rate Risk in Up and Down Markets: What Is Actually Priced?
	4	Chabi-Yo (2012)	Stocks	Co-skewness and kurtosis	MS	Pricing Kernels with Stochastic Skewness and Volatility Risk
	5	Bali, Brown and Caglayan (2012)	Hedge funds	Co-skewness	JFE	Systematic risk and the cross section of hedge fund returns
	6	Giroud and Mueller (2011).	Stocks	Co-skewness	JF	Corporate Governance, Product Market Competition, and Equity Prices
	7	Bali, Cakici and Whitelaw (2011)	Stocks	Co-skewness	JFE	Maxing out: Stocks as lotteries and the cross-section of expected returns
	8	Yang, Zhou and Wang (2010)	Stock and Bond	Co-skewness	MS	Conditional Co-skewness in Stock and Bond Markets: Time Series Evidence
Monthly	9	Martellini and Ziemann (2010)	Stocks	Co-skewness and kurtosis	RFS	Improved estimates of higher-order co-moments and implications for portfolio selection
	10	Kumar (2009)	Stocks and portfolio	Coskewness	JF	Who Gambles in the Stock Market?
	11	Chabi-Yo (2008).	Hedge funds	Co-skewness and kurtosis	RFS	Conditioning Information and Variance Bounds on Pricing Kernels with Higher- Order Moments: Theory and Evidence
	12	Guidolin andTimmermann (2008)	MSCI indices	Co-skewness and kurtosis	RFS	International Asset Allocation under Regime Switching, Skew, and Kurtosis Preferences
	13	Ang, Chen and Xing (2006)	Stocks	Co-skewness	RFS	Downside Risk
	14	Post and Levy (2005)	Stocks	Co-skewness	RFS	Does Risk Seeking Drive Stock Prices? A Stochastic Dominance Analysis of Aggregate Investor Preferences ans Beliefs
	15	Dittmar (2002)	20 industry-sorted portfolios,	Co-skewness and kurtosis	JF	Nonlinear Pricing Kernels, Kurtosis Preference, and Evidence from the Cross Section of Equity Returns
	16	Harvey and Siddique (2000)	Stocks	Co-skewness	JF	Conditional Skewness in Asset Pricing Tests
	17	Grinblatt and Titman (1994)	Mutual Fund / Stocks	Co-skewness	JFQA	A Study of Monthly Mutual Fund Returns and Performance Evaluation Techniques
Daily	18	Maheu, McCurdy and Zhao (2013)	Stocks	Co-skewness and kurtosis	JFE	Do jumps contribute to the dynamics of the equity premium?
	19	Briec, Kerstens and Jokung (2007)	Stocks	Co-skewness	MS	Mean-Variance-Skewness Portfolio Performance Gauging: A General Shortage Function and Dual Approach
Daily and monthly	20	Conrad, Dittmar and Ghysels (2013)	Stocks and Options	Co-skewness and kurtosis	JF	Ex Ante Skewness and Expected Stock Returns
Daily and monthly	21	Goyal and Saretto (2009)	Stock option	Co-skewness	JFE	Cross-section of option returns and volatility
Daily, weekly, monthly, quarterly, and semiannual	22	Chung, Johnson and Schill (2006)	Stocks	Co-skewness and kurtosis	JB	Asset Pricing When Returns Are Nonnormal: Fama-French Factors versus Higher-Order Systematic Comoments
Daily, weekly, and monthly	23	Ang and Chen (2002)	Stocks	Co-skewness	JFE	Asymmetric correlations of equity portfolios
Monthly and semiannual	24	Han and Lesmond (2011)	Stocks	Co-skewness	RFS	Liquidity Biases and the Pricing of Cross-sectional Idiosyncratic Volatility

Note: This table illustrates empirical papers published since 1990 on higher-order moment asset pricing and/or portfolio selection on top peer reviewed journals: The Journal of Finance ('JF'), Journal of Financial Economics ('JFE'), Review of Financial Studies ('RFS'), Journal of Financial and Quantitative Analysis ('JFQA'), Journal of Business ('JB'), and Management Science ('MS').

Table 2: Normality Tests across Sampling Intervals, CRSP 1990-2013

	Sampling Intervals																	
	1-Day		2-Day		3-Day		4-Day		5-Day		10-Day		20-Day		65-Day		125-Day	
	Jarque–Bera	Prob.	Jarque–Bera	Prob.	Jarque–Bera	Prob.	Jarque–Bera	Prob.	Jarque–Bera	Prob.	Jarque–Bera	Prob.	Jarque–Bera	Prob.	Jarque–Bera	Prob.	Jarque–Bera	Prob.
Index	15731.933	0.000	1676.653	0.000	1538.059	0.000	841.217	0.000	1536.507	0.000	252.901	0.000	55.856	0.000	74.850	0.000	8.116	0.022
Sample	15861.827	0.000	1690.223	0.000	1564.346	0.000	810.323	0.000	1479.410	0.000	244.165	0.000	51.145	0.000	77.082	0.000	8.063	0.023
market-capitalization sorted Portfolios																		
MC1	6850.902	0.000	2774.473	0.000	2603.450	0.000	1353.232	0.000	1896.967	0.000	777.295	0.000	197.719	0.000	2.826	0.163	1.167	0.335
MC2	10823.794	0.000	2666.988	0.000	2582.183	0.000	1773.086	0.000	1481.073	0.000	310.512	0.000	112.790	0.000	6.364	0.067	0.099	0.999
MC3	13409.214	0.000	3001.829	0.000	3152.623	0.000	2103.831	0.000	1966.313	0.000	512.668	0.000	135.902	0.000	1.288	0.400	0.045	0.902
MC4	7000.853	0.000	2320.281	0.000	2944.071	0.000	1498.833	0.000	1973.842	0.000	524.168	0.000	120.542	0.000	8.073	0.034	0.099	0.753
MC5	12012.360	0.000	2427.912	0.000	2127.031	0.000	1491.345	0.000	2088.294	0.000	478.776	0.000	183.421	0.000	2.685	0.175	0.746	0.690
MC16	10582.958	0.000	2004.940	0.000	1878.247	0.000	1061.537	0.000	1918.699	0.000	346.840	0.000	171.074	0.000	63.842	0.000	6.468	0.034
MC17	11991.377	0.000	2088.934	0.000	2175.914	0.000	1335.099	0.000	2064.525	0.000	352.982	0.000	154.166	0.000	43.446	0.000	5.220	0.050
MC18	14477.147	0.000	2277.238	0.000	2170.980	0.000	1809.569	0.000	3181.282	0.000	509.369	0.000	384.198	0.000	77.370	0.000	18.969	0.003
MC19	17547.317	0.000	3457.257	0.000	1784.750	0.000	2521.145	0.000	3775.772	0.000	1393.383	0.000	568.555	0.000	74.308	0.000	13.286	0.005
MC20	9528.078	0.000	1312.953	0.000	871.565	0.000	459.315	0.000	717.744	0.000	214.828	0.000	87.823	0.000	78.648	0.001	1.454	0.284
Amihud-ratio sorted Portfolios																		
AR1	8360.818	0.000	1202.655	0.000	782.533	0.000	458.266	0.000	614.329	0.000	216.645	0.000	120.278	0.000	93.562	0.001	0.807	0.446
AR2	11931.246	0.000	1780.741	0.000	1275.338	0.000	1120.610	0.000	2403.256	0.000	838.685	0.000	240.147	0.000	63.983	0.000	20.591	0.002
AR3	15133.767	0.000	2318.931	0.000	2073.223	0.000	1722.390	0.000	2277.501	0.000	552.077	0.000	237.104	0.000	92.927	0.000	28.041	0.001
AR4	10439.544	0.000	1884.936	0.000	1756.282	0.000	1023.423	0.000	1992.181	0.000	421.966	0.000	221.377	0.000	25.912	0.001	4.999	0.055
AR5	12767.332	0.000	1884.153	0.000	2192.499	0.000	1399.887	0.000	2115.440	0.000	483.169	0.000	156.261	0.000	67.653	0.000	23.059	0.001
AR16	14254.823	0.000	2227.143	0.000	1953.447	0.000	1357.728	0.000	1810.059	0.000	705.149	0.000	145.294	0.000	10.174	0.012	0.004	0.927
AR17	75140.104	0.000	13879.951	0.000	4982.232	0.000	3274.826	0.000	2746.621	0.000	647.755	0.000	134.233	0.000	13.635	0.005	0.561	0.816
AR18	12897.777	0.000	4238.441	0.000	6222.397	0.000	3843.849	0.000	5804.310	0.000	2107.909	0.000	481.060	0.000	12.539	0.009	0.325	0.862
AR19	19283.452	0.000	4671.680	0.000	3111.044	0.000	2562.554	0.000	2438.904	0.000	844.410	0.000	240.742	0.000	1.885	0.278	0.101	0.742
AR20	79429.852	0.000	12411.018	0.000	4054.017	0.000	3909.340	0.000	3042.208	0.000	1537.989	0.000	376.058	0.000	3.643	0.109	0.308	0.946

Note: Value-weighted returns of all stocks on the CRSP daily tape from 1990 to 2013 are used as the market index. Our sample consists of 8088 securities with more than 5-year returns. The logarithmic returns of individual stocks are calculated for nine sampling intervals: 1, 2, 3, 4, 5, 10, 20, 65 and 125 days. Each year the securities are reassigned to 20 portfolios according to their average market capitalization ranks or Amihud ratios, for MC and AR portfolios. The first, $MC1$ ($AR1$), contains the smallest 5% of firms by market capitalizations (Amihud ratios) and the last, $MC20$ ($AR20$), contains the largest 5%. The Jarque–Bera normality test is employed to test whether stock returns are normally distributed. The Jarque-Bera test statistic is: $JB_L = N_L * [\frac{S_L^2}{6} + \frac{(K_L-3)^2}{24}]$, where N_L, S_L and K_L are the number of observations, skewness and kurtosis of returns measured by the interval with length L days.

Table 3: Sample Means of Individual Betas, Gammas and Deltas across Different Intervals, CRSP 1990-2013

	Sampling Intervals									SAD
	1-D	2-D	3-D	4-D	5-D	10-D	20-D	65-D	125-D	
Panel A: Definition Betas, Gammas and Deltas										
Beta	1.007	1.020	1.029	1.035	1.041	1.066	1.092	1.144	1.190	1.267***
Gamma	1.182	1.182	1.095	1.089	1.129	1.161	1.225	1.340	1.962	14.512***
Delta	1.022	1.034	1.045	1.057	1.060	1.102	1.136	1.223	1.290	1.798***
Panel B: OLS Betas, Gammas and Deltas										
Beta	1.007	1.020	1.029	1.035	1.041	1.066	1.093	1.144	1.190	1.266***
Gamma	1.182	1.182	1.095	1.088	1.129	1.161	1.225	1.341	1.963	14.514***
Delta	1.022	1.034	1.045	1.057	1.061	1.102	1.135	1.223	1.289	1.799***

	Number of Stocks	ANOVA1	Bartlett's	W-M-W 95%	W-M-W 90%	Signed Rank 95%	Signed Rank 90%	Sign Variance 95%	Sign Variance 90%	K-W
Panel C: Measures for the Intervaling Effect										
Beta	8088	0.633	0.000	8/8	8/8	8/8	8/8	0/8	0/8	11648.444***
Gamma	8088	0.665	0.000	8/8	8/8	8/8	8/8	5/8	5/8	12886.066***
Delta	8088	3.809***	0.000	8/8	8/8	8/8	8/8	0/8	0/8	8142.973***

Note: The intervaling effect is tested for 8088 securities from 1990 and 2013 with a minimum of five years of continuous data. Panel A illustrates the averages of individual betas, gammas and deltas across all nine intervals, calculated using the definitions in Equation 4. In Panel B, individual estimates across all nine intervals based on the linear combinations (Equation 8) of the estimated coefficients in OLS regressions on the cubic market model (Equation 7) are listed. SAD is the sum of the absolute differences between other interval estimates and monthly estimates as shown in Equation 9. It will be calculated for individual betas, gammas and deltas, respectively. One-tailed tests are run to check whether SAD in each case is significantly different from zero, according to Equation 11. Panel C documents tests on the sensitivity of the intervaling effect. ANOVA1 tests the variations of the magnitudes due to the different sampling intervals, while "$Bartlett's\ \ P-value = 0.000$" indicates the equal variances assumption is significantly rejected. We then use four non-parametric tests. The Wilcoxon-Mann-Whitney test and Wilcoxon Signed-rank test compare the differences in medians of each sample of ratios and the sample of ones. For each 8 samples of ratios, the portions of significantly different observations are displayed under 95% and 90% confidence levels. A simple sign variation test is used to identify whether the signs are also vary significantly. We compare the signs of estimators measured by the monthly returns and those in the other eight samples. The Kruskal Wallis test is a non-parametric version of ANOVA1 to test the differences in medians among each nine samples. Chi-squared statistics with the significant stars are presented. *, **, *** indicate statistical significance at the 90%, 95% and 99% levels, respectively.

Table 4: Estimated Co-moments of Market-Capitalization Sorted Portfolios across Different Return Measurement Intervals, CRSP Daily Tape, 1990:1 - 2013:12.

Portfolio	Mkt. Cap. (10^7\$)	1-D	2-D	3-D	4-D	5-D	10-D	20-D	K-W	SAD
Panel A: Value-weighted Betas across Intervals										
MC1	2.972	0.637	0.752	0.845	0.919	0.994	1.270	1.526	1147.938***	3.740***
MC2	5.942	0.725	0.828	0.903	0.964	1.017	1.227	1.459	1889.666***	3.092***
MC3	8.804	0.778	0.876	0.946	1.004	1.056	1.234	1.431	1908.751***	2.691***
MC4	12.041	0.922	0.994	1.054	1.103	1.149	1.327	1.511	1210.728***	2.518***
MC5	15.440	1.070	1.119	1.165	1.202	1.234	1.359	1.492	666.433***	1.804***
MC16	191.260	1.078	1.130	1.154	1.167	1.178	1.217	1.275	534.733***	0.729***
MC17	272.091	1.049	1.094	1.112	1.121	1.127	1.151	1.182	290.955***	0.438***
MC18	433.541	1.085	1.116	1.130	1.138	1.144	1.163	1.202	148.145***	0.433***
MC19	852.800	1.061	1.073	1.076	1.077	1.080	1.085	1.103	16.163***	0.164***
MC20	4371.724	0.998	0.981	0.975	0.971	0.969	0.964	0.956	88.457***	0.122***
Market	2979.998									
Panel B: Value-weighted Gammas across Intervals										
MC1	2.972	8.645	1.407	2.233	-1.576	2.185	1.513	1.550	1694.338***	11.719***
MC2	5.942	13.252	1.465	2.242	-2.266	2.278	1.787	1.397	1515.836***	17.702***
MC3	8.804	11.976	1.497	1.929	-0.680	1.931	1.654	1.213	1488.520***	14.813***
MC4	12.041	7.838	1.429	1.946	0.018	1.941	1.548	1.669	1343.736***	8.730***
MC5	15.440	9.698	1.474	1.596	0.534	1.755	1.688	1.487	1267.144***	9.754***
MC16	191.260	6.304	1.285	1.382	0.600	1.303	1.370	1.254	983.390***	6.029***
MC17	272.091	5.373	1.191	1.370	0.776	1.082	1.321	1.490	1088.959***	5.592***
MC18	433.541	4.286	1.115	1.417	0.724	1.131	1.292	1.090	942.970***	4.156***
MC19	852.800	2.963	1.086	1.166	1.385	0.897	1.170	1.236	955.271***	2.501***
MC20	4371.724	0.672	0.933	0.923	0.018	0.994	0.960	1.004	1057.655***	1.521***
Market	2979.998									
Panel C: Value-weighted Deltas across Intervals										
MC1	2.972	0.715	0.780	0.896	0.974	1.019	1.247	1.507	321.520***	3.413***
MC2	5.942	0.798	0.856	0.949	1.017	1.054	1.224	1.461	624.154***	2.869***
MC3	8.804	0.835	0.898	0.979	1.040	1.074	1.229	1.416	724.417***	2.439***
MC4	12.041	0.954	1.000	1.077	1.134	1.174	1.321	1.523	552.743***	2.474***
MC5	15.440	1.102	1.117	1.183	1.214	1.245	1.352	1.501	254.872***	1.791***
MC16	191.260	1.073	1.125	1.156	1.176	1.178	1.210	1.274	331.874***	0.723***
MC17	272.091	1.048	1.087	1.114	1.126	1.123	1.146	1.181	159.103***	0.439***
MC18	433.541	1.084	1.113	1.129	1.140	1.139	1.157	1.196	78.831***	0.416***
MC19	852.800	1.056	1.069	1.072	1.076	1.075	1.086	1.089	9.939***	0.099***
MC20	4371.724	0.999	0.986	0.975	0.970	0.970	0.958	0.950	106.212***	0.161***
Market	2979.998									

Note: The value-weighted returns of all stocks during 1990 to 2013 on CRSP daily tape are used as the market index. Each year securities are reassigned to 20 portfolios according to their average market capitalization rank. The first, $MC1$, contains the smallest 5% of firms and the last, $MC20$, contains the largest 5%. For each MC portfolio, we compute all individual estimates using each stock's one-year returns and re-estimate them every year from 1990 to 2013 across seven intervals. This table illustrates the averages of individual betas, gammas and deltas of the securities. The Kruskal Wallis test (Chi-squared statistics) and the sums of absolute differences (see Equation 9) are used to test the magnitudes of the intervaling effect. SADs are calculated for individual betas, gammas and deltas, respectively. One-tailed tests are run to check whether SAD in each case is significantly different from zero, according to Equation 11. *, **, *** indicate statistical significance at the 90%, 95% and 99% levels, respectively.

Table 5: Estimated Co-moments of Market-Capitalization Sorted Portfolio by Using Equal-weighted Returns as the Market Index, CRSP Daily Tape, 1990:1 - 2013:12.

Portfolio	Mkt. Cap. (10^7)	1-D	2-D	3-D	4-D	5-D	10-D	20-D	K-W	SAD
Panel A: Equal-weighted Betas across Intervals										
MC1	2.972	0.992	1.080	1.147	1.192	1.237	1.390	1.483	816.428***	1.579***
MC2	5.942	1.084	1.153	1.204	1.237	1.270	1.371	1.449	825.471***	1.178***
MC3	8.804	1.129	1.189	1.228	1.255	1.282	1.359	1.410	644.757***	0.951***
MC9	35.842	1.439	1.405	1.382	1.366	1.349	1.298	1.253	894.613***	0.580***
MC10	44.400	1.405	1.369	1.343	1.325	1.308	1.252	1.207	999.506***	0.623***
MC11	54.382	1.399	1.362	1.337	1.316	1.295	1.221	1.174	1220.336***	0.692***
MC12	67.659	1.376	1.343	1.316	1.296	1.274	1.204	1.145	1434.739***	0.679***
MC18	433.541	1.192	1.152	1.115	1.089	1.064	0.972	0.902	2379.484***	0.857***
MC19	852.800	1.119	1.059	1.018	0.989	0.963	0.870	0.796	2865.091***	1.017***
MC20	4371.724	1.028	0.958	0.912	0.881	0.853	0.753	0.672	3831.174***	1.135***
Market	338.755									
Panel B: Equal-weighted Gammas across Intervals										
MC1	2.972	1.502	1.283	7.679	1.422	1.074	-0.438	1.025	593.303***	9.320***
MC2	5.942	1.012	1.467	6.310	1.571	1.443	0.510	0.619	472.286***	7.639***
MC3	8.804	1.047	1.397	4.161	1.322	1.274	0.756	1.055	484.534***	4.262***
MC9	35.842	1.369	1.198	-1.576	1.165	1.176	0.912	0.987	455.124***	4.354***
MC10	44.400	1.364	1.153	-1.446	1.032	1.125	0.922	0.977	429.402***	4.423***
MC11	54.382	1.518	1.177	-2.122	1.175	1.167	0.956	1.347	377.148***	5.406***
MC12	67.659	1.544	1.150	0.321	1.159	1.122	0.753	1.587	376.583***	3.259***
MC18	433.541	2.180	0.986	-1.182	1.024	0.943	0.991	0.853	314.312***	9.464***
MC19	852.800	1.506	0.915	-0.309	1.029	0.907	1.645	1.141	384.753***	3.985***
MC20	4371.724	1.606	0.795	-1.886	0.882	0.761	1.584	1.136	628.865***	6.365***
Market	338.755									
Panel C: Equal-weighted Deltas across Intervals										
MC1	2.972	1.035	1.119	1.173	1.209	1.236	1.366	1.457	151.760***	1.349***
MC2	5.942	1.142	1.196	1.231	1.251	1.276	1.357	1.430	162.180***	0.890***
MC3	8.804	1.172	1.219	1.241	1.257	1.278	1.357	1.399	162.729***	0.718***
MC9	35.842	1.409	1.373	1.358	1.342	1.328	1.295	1.269	510.320***	0.493***
MC10	44.400	1.371	1.338	1.321	1.306	1.292	1.243	1.212	625.701***	0.515***
MC11	54.382	1.358	1.326	1.308	1.297	1.282	1.226	1.176	612.740***	0.537***
MC12	67.659	1.324	1.302	1.282	1.273	1.259	1.204	1.152	744.738***	0.469***
MC18	433.541	1.164	1.111	1.081	1.075	1.056	0.988	0.921	1413.596***	0.749***
MC19	852.800	1.099	1.019	0.987	0.978	0.957	0.892	0.814	1684.049***	0.948***
MC20	4371.724	1.015	0.918	0.882	0.873	0.856	0.778	0.696	2647.580***	1.090***
Market	338.755									

Note: The equal-weighted returns of all stocks during 1990 to 2013 on CRSP daily tape are used as the market index. Each year the securities are reassigned to 20 portfolios according to their average market capitalization rank. The first, $MC1$, contains the smallest 5% of firms and the last, $MC20$, contains the largest 5%. For each MC portfolio, we compute all individual estimates using each stock's one-year returns and re-estimate them every year from 1990 to 2013 across seven intervals. This table illustrates the averages of individual betas, gammas and deltas of the securities. The Kruskal Wallis test (Chi-squared statistics) and the sums of absolute differences (see Equation 9) are used to test the magnitudes of the intervaling effect. SADs are calculated for individual betas, gammas and deltas, respectively. One-tailed tests are run to check whether SAD in each case is significantly different from zero, according to Equation 11. *, **, *** indicate statistical significance at the 90%, 95% and 99% levels, respectively.

Table 6: Estimated Co-moments of Sub-portfolio of MC19 and MC20 across Different Return Measurement Intervals, CRSP Daily Tape, 1990:1 - 2013:12.

Portfolio	Mkt. Cap. (10^7\$)	1-D	2-D	3-D	4-D	5-D	10-D	20-D	SAD
Panel A: Value-weighted Betas across Intervals									
MV20 -1	852.21	1.125	1.103	1.078	1.065	1.062	1.062	1.063	0.120^{***}
MV20 -2	1094.935	1.086	1.092	1.085	1.082	1.081	1.085	1.092	0.041^{***}
MV20 -3	1281.516	1.087	1.093	1.090	1.098	1.105	1.130	1.145	0.269^{***}
MV20 -4	1481.352	1.061	1.061	1.056	1.059	1.065	1.085	1.098	0.201^{***}
MV20 -5	1957.334	1.119	1.115	1.121	1.128	1.136	1.165	1.178	0.283^{***}
MV20 -6	2426.516	1.009	1.000	0.990	0.991	0.991	1.005	1.000	0.044^{***}
MV20 -7	3035.294	1.049	1.040	1.031	1.030	1.029	1.040	1.051	0.088^{***}
MV20 -8	3503.364	0.970	0.953	0.943	0.936	0.927	0.926	0.947	0.086^{***}
MV20 -9	4048.152	0.960	0.947	0.949	0.944	0.942	0.927	0.919	0.154^{***}
MV20 -10	7195.334	1.030	1.000	0.993	0.985	0.978	0.970	0.953	0.239^{***}
Market	2979.998								
Panel B: Value-weighted Gammas across Intervals									
MV20 -1	852.21	1.621	1.521	0.274	0.683	0.811	1.463	1.917	5.130^{***}
MV20 -2	1094.935	1.467	0.994	1.014	1.305	0.822	2.245	0.344	5.786^{***}
MV20 -3	1281.516	1.174	1.142	1.295	1.331	0.827	1.124	0.829	1.923^{***}
MV20 -4	1481.352	1.141	1.761	1.517	1.135	1.312	0.024	2.164	6.092^{***}
MV20 -5	1957.334	1.174	1.419	-0.165	1.122	1.114	2.749	0.234	6.808^{***}
MV20 -6	2426.516	0.750	0.920	1.164	0.928	0.948	1.512	2.188	6.905^{***}
MV20 -7	3035.294	1.122	0.563	1.336	1.051	0.939	1.468	0.919	1.675^{***}
MV20 -8	3503.364	0.877	1.029	1.183	0.945	1.351	-0.268	0.672	2.966^{***}
MV20 -9	4048.152	0.674	1.033	1.488	0.880	0.844	-0.213	1.401	3.875^{***}
MV20 -10	7195.334	1.442	0.744	1.734	0.973	1.154	-0.911	1.747	5.344^{***}
Market	2979.998								
Panel C: Value-weighted Deltas across Intervals									
MV20 -1	852.21	1.096	1.062	1.027	1.006	1.016	1.029	1.062	0.202^{***}
MV20 -2	1094.935	1.090	1.108	1.094	1.105	1.099	1.122	1.151	0.289^{***}
MV20 -3	1281.516	1.105	1.105	1.086	1.106	1.116	1.170	1.201	0.519^{***}
MV20 -4	1481.352	1.080	1.083	1.063	1.074	1.086	1.125	1.133	0.285^{***}
MV20 -5	1957.334	1.132	1.120	1.128	1.138	1.150	1.209	1.213	0.400^{***}
MV20 -6	2426.516	1.029	0.990	0.980	0.985	0.990	1.024	1.026	0.163^{***}
MV20 -7	3035.294	1.062	1.060	1.055	1.050	1.050	1.051	1.048	0.041^{***}
MV20 -8	3503.364	0.976	0.970	0.953	0.924	0.903	0.900	0.916	0.188^{***}
MV20 -9	4048.152	0.968	0.972	0.979	0.961	0.952	0.940	0.911	0.307^{***}
MV20 -10	7195.334	1.051	1.048	1.028	1.021	0.998	0.979	0.932	0.535^{***}
Market	2979.998								

Note: The value-weighted returns of all stocks during 1990 to 2013 on CRSP daily tape are used as the market index. Securities of $MV19$ and $MV20$ in Table 4 are reassigned into 5 sub-portfolios, respectively, according to their average market capitalization rank. For each sub-portfolio, we compute all individual estimates using each stock's one-year returns and re-estimate them every year from 1990 to 2013 across seven intervals. This table illustrates the averages of individual betas, gammas and deltas of the securities. The Kruskal Wallis test (Chi-squared statistics) and the sums of absolute differences (see Equation 9) are used to test the magnitudes of the intervaling effect. SADs are calculated for individual betas, gammas and deltas, respectively. One-tailed tests are run to check whether SAD in each case is significantly different from zero, according to Equation 11. *, **, *** indicate statistical significance at the 90%, 95% and 99% levels, respectively.

Table 7: Estimated Co-moments of Amihud-Ratio Sorted Portfolio across Different Return Measurement Intervals, CRSP Daily Tape, 1990:1 - 2013:12.

Portfolio	Amihud Ratio (10^{-10})	1-D	2-D	3-D	4-D	5-D	10-D	20-D	K-W	SAD
Panel A: Value-weighted Betas across Intervals										
AR1	1.589	0.999	0.981	0.974	0.970	0.968	0.961	0.950	87.343***	0.152***
AR2	4.298	1.042	1.047	1.048	1.046	1.047	1.052	1.078	7.723***	0.182***
AR3	7.743	1.097	1.130	1.148	1.154	1.161	1.181	1.217	155.131***	0.432***
AR4	12.002	1.100	1.143	1.162	1.169	1.174	1.193	1.224	374.794***	0.402***
AR5	17.561	1.098	1.151	1.179	1.190	1.200	1.224	1.269	396.734***	0.570***
AR16	474.763	1.094	1.111	1.137	1.164	1.187	1.290	1.381	410.080***	1.302***
AR17	688.935	1.039	1.071	1.106	1.138	1.171	1.329	1.465	732.619***	1.934***
AR18	1092.841	0.959	1.005	1.041	1.078	1.110	1.248	1.425	990.758***	2.106***
AR19	1999.162	0.850	0.909	0.963	1.007	1.042	1.208	1.393	1309.335***	2.381***
AR20	8176.243	0.703	0.773	0.841	0.904	0.967	1.228	1.510	899.863***	3.641***
Market	2.456									
Panel B: Value-weighted Gammas across Intervals										
AR1	1.589	0.690	0.935	0.923	0.049	0.983	0.973	0.995	1031.853***	2.040***
AR2	4.298	3.429	1.076	1.047	1.103	1.070	1.069	1.216	1021.187***	2.926***
AR3	7.743	5.870	1.143	1.455	0.517	1.087	1.273	1.366	940.328***	6.037***
AR4	12.002	8.716	1.207	1.450	0.918	0.876	1.419	0.859	1032.803***	9.431***
AR5	17.561	6.680	1.344	1.291	1.193	1.201	1.266	1.438	975.655***	6.136***
AR16	474.763	6.802	1.345	1.351	0.832	1.465	1.528	1.340	1334.230***	6.299***
AR17	688.935	7.537	1.290	1.182	0.077	1.480	1.699	1.906	1384.758***	9.435***
AR18	1092.841	12.724	1.306	1.627	0.521	1.393	1.498	1.785	1412.509***	13.517***
AR19	1999.162	11.937	1.227	1.673	-1.712	1.760	1.593	1.311	1579.507***	14.826***
AR20	8176.243	11.081	1.377	1.977	-2.156	1.803	1.331	1.865	1756.659***	14.433***
Market	2.456									
Panel C: Value-weighted Deltas across Intervals										
AR1	1.589	1.000	0.985	0.974	0.969	0.969	0.956	0.944	89.673***	0.191***
AR2	4.298	1.042	1.051	1.045	1.046	1.044	1.050	1.067	8.356***	0.127***
AR3	7.743	1.091	1.125	1.143	1.152	1.154	1.185	1.223	94.249***	0.488***
AR4	12.002	1.084	1.130	1.158	1.171	1.171	1.196	1.231	200.869***	0.479***
AR5	17.561	1.094	1.140	1.177	1.194	1.195	1.213	1.249	238.008***	0.483***
AR16	474.763	1.101	1.105	1.136	1.155	1.185	1.278	1.369	175.356***	1.256***
AR17	688.935	1.061	1.058	1.104	1.133	1.171	1.359	1.482	285.924***	2.003***
AR18	1092.841	0.998	1.014	1.070	1.097	1.129	1.251	1.422	362.497***	1.973***
AR19	1999.162	0.891	0.923	0.991	1.041	1.063	1.202	1.395	396.362***	2.259***
AR20	8176.243	0.781	0.792	0.874	0.938	0.980	1.191	1.479	235.174***	3.315***
Market	2.456									

Note: The value-weighted returns of all stocks during 1990 to 2013 on CRSP daily tape are used as the market index. Each year securities are reassigned to 20 portfolios according to their average Amihud (2002) ratio rank. The first, *AR*1, contains the most liquid 5% of firms and the last, *AR*20, contains the least liquid 5%. For each *AR* portfolio, we compute all individual estimates using each stock's one-year returns and re-estimate them every year from 1990 to 2013 across seven intervals. This table illustrates the averages of individual betas, gammas and deltas of the securities. The Kruskal Wallis test (Chi-squared statistics) and the sums of absolute differences (see Equation 9) are used to test the magnitudes of the intervaling effect. SADs are calculated for individual betas, gammas and deltas, respectively. One-tailed tests are run to check whether SAD in each case is significantly different from zero, according to Equation 11. *, **, *** indicate statistical significance at the 90%, 95% and 99% levels, respectively.

Table 8: Robustness Checks: Estimated Co-moments of Market-Capitalization Sorted Portfolio across Longer Return Measurement Intervals, CRSP Monthly Tape, 1990:1 - 2013:12.

Portfolio	Mkt. Cap. (10^7)	1-M	2-M	3-M	4-M	5-M	6-M	12-M	K-W	SAD
Panel A: Value-weighted Betas across Intervals										
MC1	1.070	0.888	1.078	1.201	1.308	1.382	1.409	1.511	700.945***	2.482***
MC2	2.204	0.896	1.054	1.151	1.233	1.289	1.284	1.372	473.960***	2.047***
MC3	3.431	0.926	1.085	1.186	1.265	1.327	1.343	1.373	465.160***	1.877***
MC4	4.853	0.995	1.128	1.219	1.283	1.341	1.355	1.444	522.592***	1.604***
MC5	6.557	1.072	1.218	1.300	1.354	1.397	1.387	1.398	393.959***	1.154***
MC16	142.297	1.213	1.273	1.269	1.252	1.256	1.209	1.237	134.405***	0.651***
MC17	210.980	1.173	1.224	1.217	1.206	1.217	1.194	1.258	54.529***	0.493***
MC18	343.880	1.140	1.191	1.185	1.171	1.178	1.163	1.224	58.334***	0.385***
MC19	714.240	1.068	1.102	1.103	1.099	1.109	1.103	1.142	22.466***	0.125***
MC20	3820.635	0.985	0.969	0.972	0.981	0.978	1.006	1.029	46.446***	0.173***
Panel B: Value-weighted Gammas across Intervals										
MC1	1.070	1.376	2.810	1.065	0.912	1.246	2.160	1.144	669.114***	44.557***
MC2	2.204	1.346	2.348	1.290	0.774	-1.147	2.033	1.662	492.418***	72.609***
MC3	3.431	1.325	2.394	1.232	0.536	-1.476	2.278	0.475	580.221***	64.310***
MC4	4.853	1.449	2.368	1.175	0.983	0.354	1.505	2.377	545.321***	38.476***
MC5	6.557	1.494	2.117	1.234	0.607	-0.886	1.559	0.928	578.784***	49.653***
MC16	142.297	1.367	1.636	1.280	1.101	0.572	1.359	1.100	427.090***	30.628***
MC17	210.980	1.370	1.667	1.211	0.886	0.703	1.224	1.464	436.658***	25.009***
MC18	343.880	1.319	1.322	1.162	1.103	1.208	1.010	1.507	326.281***	18.944***
MC19	714.240	1.259	1.302	0.988	1.030	1.005	0.792	1.142	326.742***	10.838***
MC20	3820.635	0.970	0.381	0.759	1.014	1.668	1.003	1.595	338.154***	2.107***
Panel C: Value-weighted Deltas across Intervals										
MC1	1.070	0.962	1.148	1.243	1.320	1.378	1.448	1.525	87.282***	2.136***
MC2	2.204	0.949	1.136	1.208	1.258	1.302	1.320	1.380	41.429***	1.775***
MC3	3.431	0.988	1.151	1.226	1.281	1.327	1.381	1.375	45.235***	1.625***
MC4	4.853	1.050	1.199	1.261	1.298	1.341	1.380	1.451	38.461***	1.502***
MC5	6.557	1.137	1.294	1.336	1.356	1.378	1.406	1.401	48.522***	0.997***
MC16	142.297	1.265	1.335	1.329	1.300	1.288	1.251	1.226	155.622***	0.683***
MC17	210.980	1.241	1.287	1.289	1.260	1.254	1.239	1.253	41.249***	0.487***
MC18	343.880	1.208	1.248	1.254	1.219	1.209	1.206	1.221	75.403***	0.372***
MC19	714.240	1.127	1.155	1.164	1.151	1.139	1.135	1.146	62.070***	0.131***
MC20	3820.635	1.001	0.977	0.985	1.008	0.992	1.014	1.033	102.242***	0.185***

Note: This table tests the robustness of results using longer intervals. The value-weighted returns of all stocks during 1990 to 2013 on CRSP monthly tape are used as the market index. Each year the securities are reassigned to 20 portfolios according to their average market capitalization rank. The first, $MC1$, contains the smallest 5% of firms and the last, $MC20$, contains the largest 5%. For each MC portfolio, we compute all individual estimates using a five-year moving window from 1990 to 2013 across seven intervals (30 estimations in total). This table illustrates the averages of individual betas, gammas and deltas of the securities. The Kruskal Wallis test (Chi-squared statistics) and the sums of absolute differences (see Equation 9) are used to test the magnitudes of the intervaling effect. SADs are calculated for individual betas, gammas and deltas, respectively. One-tailed tests are run to check whether SAD in each case is significantly different from zero, according to Equation 11. *, **, *** indicate statistical significance at the 90%, 95% and 99% levels, respectively.

Table 9: Robustness Results for Testing the Intervaling effect on Individual Betas, Gammas and Deltas of Securities with Continuous Presence, CRSP 1990-2013

	Sampling Intervals									SAD
	1-D	2-D	3-D	4-D	5-D	10-D	20-D	65-D	125-D	
Panel A: Value-weighted Betas, Gammas and Deltas										
Beta	0.881	0.868	0.866	0.870	0.873	0.881	0.894	0.910	0.963	0.209***
Gamma	1.162	1.028	0.909	0.904	0.940	0.996	1.024	1.145	1.178	0.763***
Delta	0.930	0.918	0.915	0.929	0.937	0.963	0.988	1.001	1.100	0.459***

	Number of Stocks	ANOVA1	Bartlett's	W-M-W 95%	W-M-W 90%	Signed Rank 95%	Signed Rank 90%	Sign Variance 95%	Sign Variance 90%	K-W
Panel B: Measures for the Intervaling Effect										
Beta	989	65.252***	0.000	8/8	8/8	8/8	8/8	0/8	0/8	450.703***
Gamma	989	0.503	0.000	8/8	8/8	8/8	8/8	0/8	0/8	292.597***
Delta	989	17.852***	0.000	8/8	8/8	8/8	8/8	0/8	0/8	513.913***

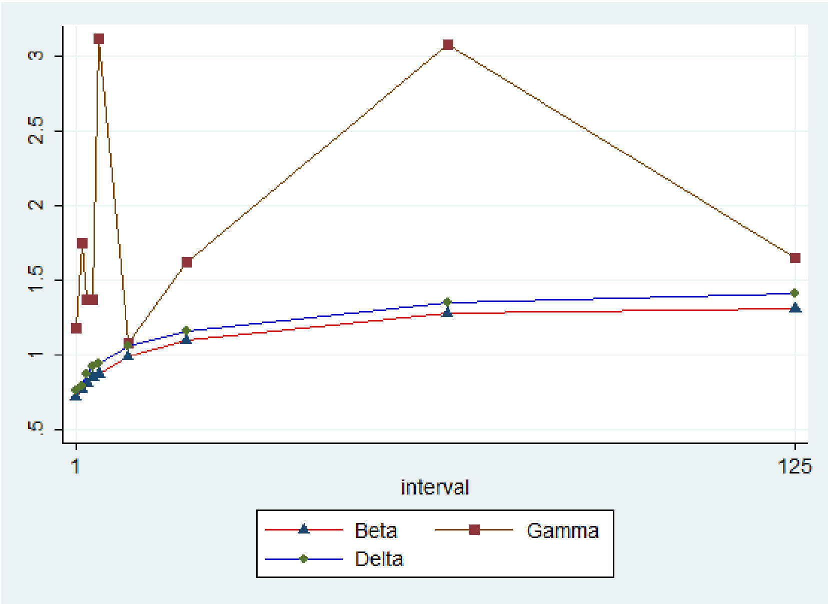
Note: This table illustrates the robustness of results for stocks with continuous presence and for differing cohorts. Panel A tests the intervaling effect on 989 stocks with continuous presence from 1990 through 2013. Nine sampling intervals: 1, 2, 3, 4, 5, 10, 20, 65 and 125 days are formed using daily data from CRSP. Panel B Panel C documents tests on the sensitivity of the intervaling effect. ANOVA1 tests the variations of the magnitudes due to the different sampling intervals, while "$Bartlett's\ \ P-value = 0.000$" indicates the equal variances assumption is significantly rejected. We then use four non-parametric tests. The Wilcoxon-Mann-Whitney test and Wilcoxon Signed-rank test compare the differences in medians of each sample of ratios and the sample of ones. For each 8 samples of ratios, the portions of significantly different observations are displayed under 95% and 90% confidence levels. A simple sign variation test is used to identify whether the signs are also vary significantly. We compare the signs of estimators measured by the monthly returns and those in the other eight samples. The Kruskal Wallis test is a non-parametric version of ANOVA1 to test the differences in medians among each nine samples. Chi-squared statistics with the significant stars are presented. *, **, *** indicate statistical significance at the 90%, 95% and 99% levels, respectively.

Table 10: Robustness Results for Testing the Intervaling Effect during High-Risk versus Low-Risk Periods: SADs for Market-Capitalization Portfolios

SAD	MC1	MC2	MC3	MC4	MC5	MC16	MC17	MC18	MC19	MC20
Panel A: High-VIX Period: an average VIX of 25.389										
Mkt. Cap. (10^7)	2.9	5.6	8.2	11.0	14.4	171.2	241.3	378.5	768.4	4030.0
SAD_β	3.756	3.807	3.302	2.927	2.445	1.133	0.685	0.820	0.342	0.212
SAD_γ	23.773	37.545	32.917	24.794	27.130	14.294	13.895	10.611	5.021	3.381
SAD_δ	3.771	3.946	3.256	2.974	2.433	1.155	0.752	0.831	0.261	0.345
Panel B: Low-VIX Period: an average VIX of 14.994										
Mkt. Cap. (10^7)	3.0	6.2	9.2	12.7	16.1	204.5	292.4	469.9	908.7	4600.0
SAD_β	3.731	2.660	2.329	2.283	1.426	0.506	0.303	0.228	0.064	0.071
SAD_γ	5.805	7.635	4.705	2.676	1.959	3.739	1.711	1.279	1.632	1.003
SAD_δ	3.185	2.218	1.955	2.188	1.411	0.484	0.268	0.195	0.022	0.055
Panel C: High-TED Period: an average TED of 0.792										
Mkt. Cap. (10^7)	2.9	5.7	8.3	11.4	14.6	179.0	255.9	411.0	821.4	4590.0
SAD_β	3.734	3.312	2.985	2.701	2.107	0.834	0.653	0.614	0.251	0.139
SAD_γ	19.513	29.220	25.092	21.523	22.045	10.630	9.133	8.486	3.672	2.183
SAD_δ	3.466	3.228	2.775	2.682	2.115	0.837	0.679	0.647	0.210	0.217
Panel D: Low-TED Period: an averaged TED at 0.333										
Mkt. Cap. (10^7)	3.1	6.2	9.3	12.8	16.4	204.7	289.9	458.4	887.4	4130.0
SAD_β	3.747	2.868	2.400	2.338	1.508	0.628	0.229	0.255	0.075	0.102
SAD_γ	13.319	16.913	14.202	10.612	6.630	5.244	2.148	3.870	1.882	2.324
SAD_δ	3.358	2.503	2.106	2.271	1.472	0.613	0.205	0.187	0.042	0.095

Note: This table checks the robustness of the intervaling effect, measured by the Sum of Absolute Differences, during high-risk and low-risk periods. Seven sampling intervals: 1, 2, 3, 4, 5, 10, and 20 days are used to form returns. Each year the securities are reassigned to 20 portfolios according to their average market capitalization rank. The first, $MC1$, contains the smallest 5% of firms and the last, $MC20$, contains the largest 5%. For each MC portfolio, we compute all individual estimates using each stock's one-year returns and re-estimate them every year from 1990 to 2013 across seven intervals. SAD is our measure for the magnitude of the intervaling effect, as the sum of the absolute differences between other interval estimates and monthly estimates as shown in Equation 9.

Figure 1: Sample Means of Definition Betas, Gammas and Deltas across Different Intervals, all stocks 1990-2013



Note: This figure displays the values in Table 3. In order to avoid data problems due to the listing and delisting of securities, 8088 securities with more than 5-year returns are selected. The logarithmic returns of individual stocks are calculated for nine sampling intervals: 1, 2, 3, 4, 5, 10, 20, 65 and 125 days using the data on the CRSP daily tape from 1990 to 2013. We compute individual beta, gamma and delta for each stock using returns of each sampling interval, based on the definitions in Equation 4. Then, we compute the averages of individual betas, gammas and deltas across all nine intervals.