Stock return autocorrelation, beta, and data frequency

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ABSTRACT

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In this thesis, I empirically test the autocorrelation function of stock returns and how the frequency of data affects the measurement of the beta of stock returns. Different data frequencies, from daily to monthly, of stock and market returns from the Center for Research in Security Prices over a 30-year period from 1983 to 2012 are used in the empirical analysis. I find that infrequent rebalancing generates a certain pattern in the autocorrelation function of stock returns and that return autocorrelations can switch sign and become positive. Furthermore, idiosyncratic risk strongly affects the detection of autocorrelation. In addition, the stock beta increases with the measurement time interval. The findings suggest that beta depends heavily on the shape of stock returns' autocorrelation function due to short-term stock reversal.

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1. Introduction

The autocorrelation of stock returns and systematic risk or beta of securities are always central to contemporary theory in finance, both theoretically and empirically. Autocorrelation in stock returns indicates predictability and can reveal the price movements of the stock. Beta of securities measures the sensitivity to market movements. In this thesis, I investigate the autocorrelation function of stock returns and how the data frequency affects an estimate of the stock beta.

It has been known from the literature that the infrequent trading of investors could cause low liquidity in the market, as well as a slow movement of the capital and short-term price overreacting.[1] Heston, Korajczyk, and Sadka (2010) use the half-hour-interval of intraday returns to run cross-sectional regressions and document a striking intraday patterns of return continuation, which means a statistically significant positive relation between a stock's return over a given interval within a day and its subsequent returns at daily frequencies. It can last for at least 40 trading days. Inspired by this paper, Bogousslavsky (2016) expands the findings, explaining seasonality patterns at different frequencies and revealing the important role of the infrequent rebalancing, which generates the pattern of autocorrelation function of stock returns. The return autocorrelations can switch sign and become positive at the rebalancing horizon.

Isaenko (2020) assumes that traders have high short-term trading incentives and capital delays and studies their impact on the returns of the market. Combining these two effects can cause high volatility and high Sharpe ratio for stock returns. Moreover, his model predicts that volatility of the conditional Sharpe ratio strongly depends on the frequency of time series. Isaenko (2019) develops a linear factor model to study how estimates of measurements of conditional moments of stock return, including stock's beta, are affected by the data frequency. He predicts that if the reversal rate of the stock and the reversal amplitude are smaller than those of the stock market, then the stock's beta increases with the measuring time interval. On the other hand, if the reversal rate and amplitude of the stock are higher than those of the stock market, then the stock's beta decreases with the measuring time interval.

[1] See for example, Duffie (2010) and Isaenko (2020).

Motivated by these papers, it is of interest to determine autocorrelation functions for different stocks empirically and relate these functions to how estimates of the beta are affected by the data frequency. The relation between the shape of the autocorrelation function and measurements of beta at different frequencies is intuitive since the autocorrelation within a given time interval averages out the value of beta. The autocorrelation is defined by its strength and by time scale. Both these characteristics will affect the relations between estimates of beta and data frequency.

I analyze the autocorrelation function pattern of the all-stocks portfolio, the market index (the S&P 500), and 15 industry portfolios with daily data over a 30-year period from January 1983 to December 2012. The all-stocks portfolio includes all stocks with equal weights. The 15 industry portfolios are divided from the stock market based on the Standard Industrial Classification code. I first test the autocorrelation function of the all-stocks portfolio for a comparison with the results in prior studies, as well as to see how common and strong short-term autocorrelation is. And then, I compare the autocorrelation function pattern of the all-stocks portfolio with the autocorrelation function pattern of the market index and 15 industry portfolios. The results show an exponential decay pattern (in absolute value) that is disturbed around the 5th day, and the pattern is similar for the all-stocks portfolio and 15 industry portfolios. Also, the autocorrelations can switch sign and become positive. However, the autocorrelation function pattern of the market index does not show an obvious decay pattern.

I also test the autocorrelation function of an individual stock with returns at intraday and daily frequency. I choose the stock of JPM (JPMorgan Chase & Co.) as the individual stock sample considering it is a large-size firm with high liquidity. For intraday data of individual stock, I choose half-hour frequency to avoid microstructure noise and use data spanning of 5-years from January 2001 to December 2005; for daily data of individual stock, I use three different time horizons: 12-year horizons from January 1991 to December 2002 and January 2001 to December 2012, and 30-year horizon from January 1983 to December 2012. The results suggest that the idiosyncratic risk can strongly affect detecting the autocorrelation for individual stock. Due to a strong effect of idiosyncratic risk on autocorrelation function, most of my study will be concentrated on well-diversified portfolios.

Several important models have been developed, such as the Capital Asset Pricing Model (CAPM), Fama and French three-factor, and five-factor models, which rely on stocks' beta. The stock beta can capture the sensitivity of returns with respect to various systematic risk factors. In this study I consider a classical beta that measures the co-movement of a stock return with the broad market index. In particular, the stock beta will be estimated by regressing the continuously compounded rate of return of the stock on that of a market index, the S&P 500, over a 30-year period from January 1983 to December 2012. I use different data frequencies, from daily to monthly, to estimate the stock beta for the all-stocks portfolio and 15 industry portfolios and find that the beta increases as the frequency decreases at almost all the portfolios. I detect a direct relation between the dependence of a portfolio's beta from a measuring frequency and the shapes of autocorrelation functions of a portfolio and the market. Unfortunately, this dependence is obscured by inconsistencies in the autocorrelations of the stock market, especially at the lags falling on the second week.

The rest of the thesis is organized as follows. Section 2 sheds light on the previous research and introduces the relevant literature review. Section 3 describes the data and the methodology or models that I use for estimating the autocorrelation function and the stock beta of stock returns. Section 4 analyzes and discusses the empirical results. Lastly, section 5 shows the conclusions and discusses what can be studied for further research.

2. Literature Review

2.1 Slow-Moving Capital

The slow-moving capital is always an attractive topic and has been extensively investigated in recent years in many academic articles. These articles build asset pricing models with the assumption that investors trade infrequently. Duffie (2010) uses several examples, such as the financial crisis of 2007-2009, and an illustrative model to address asset price dynamics caused by the slow movement of investment capital due to infrequent trading of investors.

There are various explanations for the capital delays, including but not limited to the opacity of the market, the cost of searching information, the difficulties of fundraising, and the speed of trading. Duffie (2010) shows a detailed explanation from three aspects: search delays, the limited capacity of intermediated investments, and inattention of investors. There are various types of search delays, such as search costs, time to negotiate, and lending fees. The inattention of investors is also a fact that most investors are likely to spend their time on other things instead of only focusing on trading. These can make shocks to supply or demand, then supply shocks cause price impacts and reversals.

Also, opaque OTC markets rely on sequential search and bilateral negotiations. Zhu (2012) offers a dynamic model of opaque over-the-counter markets to address this issue. Likewise, liquidity is also an essential concern for capital movements; the more liquid security often trades at a higher price than its less liquid counterpart. The price premium would also cause shocks, which make the capital move slower.[2] Rinne and Suominen (2016) present evidence that for the mutual funds, on average, the costs of immediacy even exceed returns from providing liquidity. Goldreich, Hanke, and Nath (2005) provide empirical support for the relationship that higher prices go with higher borrowing fees. The higher cost will, in turn, slow the flow of capital. Dow, Han, and Sangiorgi (2019) also use a stochastic dynamic equilibrium model to show how the "liquidity hysteresis" affects the arbitrage capital flow and provide an explanation of why capital moves slowly.

2.2 Short-Term reversal and Autocorrelation

Due to the slow-moving capital, there is a short-term reversal and certain patterns of the autocorrelation function of stock returns. Rinne and Suominen (2011) present a structural model of the stock market where a subset of the investors trade and rebalance infrequently. Their model predicts an exponentially declining autocorrelation function (in absolute terms), and their empirical estimates, using the daily data frequency, also support the model prediction. Boulatov,

[2] For more detailed evidence about the liquidity and price premium, see for example, Duffie (1996) and Banerjee and Graveline (2013).

Hendershott, and Livdan (2013) use daily non-public data and find support for the prediction of positive autocorrelations in portfolio returns. Isaenko (2020) builds a model with the assumption of capital inertia; the difference from other literature is that the investors have high short-term trading incentives. He shows that capital delays lead to a short-term overreaction of stock price and daily aggregate consumption. Additionally, his model explains why the autocorrelation between trading volume and stock returns could be negative or positive.

There are also other explanations for the autocorrelation function of stock returns.[3] For example, since the time series of stock prices are not sampled simultaneously; thus the nonsynchronous trading can induce spurious cross-autocorrelation in individual security and portfolio returns. Atchison, Butler, and Simonds (1987) find that the nonsynchronous trading model cannot sufficiently explain the high observed autocorrelation of the indices. Lo and MacKinlay (1990) use a simple stochastic model indicating that some of the cross-autocorrelations may be due to nonsynchronous trading problems, but it couldn't be the only reason for the autocorrelation patterns; otherwise, the markets would have to be unrealistically thin. Boudoukh, Richardson, and Whitelaw (1994) argue that nonsynchronous trading hypothesis cannot be completely responsible for the observed autocorrelations and that institutional factors may be the possible reason to explain the autocorrelation patterns. A few papers also think that autocorrelation may happen because noise traders tend to trade based on stale information.[4]

But particularly, the infrequent rebalancing and capital delays would make the autocorrelation pattern happen in monthly, weekly, daily, and even the intraday frequencies. Heston and Sadka (2008) find a persistent monthly seasonal pattern in the cross-section of expected stock returns. Lehmann (1990) documents the evidence of market inefficiency in the form of weekly return reversal in individual stocks. Conrad and Kaul (1989) present evidence that stocks' return reversal pattern is exponential at the weekly frequency. Rakowski and Wang (2009) reveal that seasonality in daily mutual fund flows is mean-reverting and specific patterns, such as

[3] See for example, Chowdhury, Rahman, and Sadique (2017). They summarize the reasons of autocorrelation patterns and that would be due to the presence of information asymmetry, uninformed individual investors, non-synchronous trading, underdeveloped financial analysis industry and other behavioral aspects such as tendency to herd. They explore the study of autocorrelation in the emerging markets.

[4] See for example, Shiller (1984), Sentana and Wadhwani (1992), and Bange (2000), they provide evidence that feedback traders might create autocorrelation in stock returns.

day-of-week and day-of-month patterns, are exist. Heston, Korajczyk, and Sadka (2010) show a striking pattern of stock returns with intraday data at half-hour intervals and lasts for at least 40 trading days. The results of this thesis, with daily data of stock returns, are also in line with these articles that the autocorrelation of the stock returns has a certain pattern and it would change its sign from negative to positive.

The results for autocorrelation on individual stocks vary. In particular, Atchison, Butler, and Simonds (1987) find no autocorrelation on average using individual returns. Campbell, Grossman, and Wang (1993) observe that first-order daily return autocorrelation of individual stocks declines with trade volume. Chan (1993) reports autocorrelation in the returns of large firms and develops a model to explain why stock returns are positively cross-autocorrelated. More recently, Xue and Zhang (2017) apply the threshold quantile autoregressive model and use the data from the stock index and individual stocks, showing that the Shanghai A-share stock index has significant negative autocorrelations in the lower regime and has significant positive autocorrelations in the higher regime. My results show that the idiosyncratic risk strongly affects detecting the autocorrelation for individual stocks.

2.3 Beta and Data Frequency

It has been shown by a number of papers that the relation between measuring frequency and estimates of the conditional moments of stock returns, such as the beta, strongly depends on the autocorrelation of stock returns.[5] There are also empirical studies that analyze why the beta could be affected by the measuring frequency.[6]

Isaenko (2019) develops a linear factor model, which based on the predictions of the equilibrium models of a short-term price reversal built by Rinne and Suominen (2011) and Isaenko (2020), to better understand how an estimate of the stock's beta is affected by the data frequency.

[5] See for example, Blume and Stambaugh (1983), Roll (1983), Handa, Kothari, and Wasley (1989), and Lo and MacKinlay (1990) for reviews.

[6] There are different explanations, like effect of firm size, nonsynchronous trading, firm opacity, etc. See for example, Handa, Kothari, and Wasley (1989), Lo and MacKinlay (1990) and Gilbert, Hrdlicka, Kalodimos, and Siegel (2014) for more details.

This relation depends heavily on the shapes of the autocorrelation functions of stock returns and the stock market. He predicts that if the reversal rate and the amplitude of the stock are lower than those of the stock market, then the stock's beta increases with the measuring time interval. On the other hand, if the reversal rate and amplitude of the stock are higher than those of the stock market, then the stock's beta decreases with the measuring time interval.

This thesis studies the dependence of beta from measuring frequency empirically. I consider various portfolios and show that the beta increases as the frequency decreases. This trait will be explained by using the shapes of the autocorrelation function of stock returns and the market returns.

3. Data and Methodology

3.1 Data

I use daily returns and monthly returns from the Center for Research in Security Prices (CRSP) for the all-stocks portfolio and the 15 industry portfolios over the period January 1983 to December 2012. I focus on the last 30 years of data because it needs long-term data to detect the autocorrelation function for stock returns, but it would be an issue for a longer period considering the structural shifts in investors' rebalancing frequencies. The 15 industry portfolios include Mining, Construction; Food; Textiles, Printing; Chemicals; Pharmaceuticals; Extractive Industry; Durable; Computers; Transportation; Utilities; Retail; Financial Institution; Insurance, Real Estate; Services; and Other industry. I divide the stock market into 15 industry portfolios based on variable siccd, which stands for the Standard Industrial Classification code.[7] Bi-daily, weekly, bi-weekly returns are compounded from daily returns for both the stock returns and the market returns. I use

[7] Thanks to the SAS macro code for industry classification into 15 industries (prepared by Yaniv Konchitchki, U.C. Berkeley). The code is based on Konchitchki, Yaniv. 2011."Inflation and Nominal Financial Reporting: Implications for Performance and Stock Prices." The Accounting Review 86 (3), 1045–1085. This classification is also used in Barth, Mary E., Yaniv Konchitchki, Wayne R. Landsman. 2013. "Cost of Capital and Earnings Transparency." Journal of Accounting and Economics 55 (2-3), 206–224.

variable sprtrn in the CRSP database, which is Return on S&P Composite Index, to proxy the market return in the model.

For data cleaning, I retain only firms that are common stocks and traded on NYSE, AMEX or NASDAQ. Each stock is required at least 945 days of data for daily returns and at least 60 months of data for monthly returns. Penny stocks (average price less than one dollar) and returns above 400% are eliminated. Data are winsorized at the 1st and 99th percentile.

I also want to see how the estimate of beta depends on measuring frequency when this frequency is high (intraday). I use intraday data from TAQ (NYSE Trade and Quote) database and daily data from CRSP database to test autocorrelation function for individual stock, specifically, I choose JPM (JPMorgan Chase & Co.) because it is a large-size firm with high liquidity. For intraday data on market return, I use the SPY (SPDR S&P 500 ETF Trust) as the market index proxy. For daily data on market return, I still use variable sprtrn in the CRSP database as the market index proxy. From TAQ, I collect the trading time and price for each trade. Intraday stock prices are calculated as the middle price between the bid and ask prices. I use half-hour-interval frequency to calculate intraday returns and this gives 13 intraday intervals per trading day from 9:30 a.m. to 4:00 p.m. It excludes after-hours trading and overnight open-close price movements. For each time interval, intraday return r is calculated as follows:

$$r_t = \frac{P_t - P_{t-1}}{P_{t-1}} \tag{1}$$

The return provides a measure of price movements of individual stock, specifically JPM, throughout the day.

I test intraday returns with 30-minute frequency to avoid microstructure noise and use data spanning 5-year from January 2001 to December 2005. For daily data, I consider that the time horizon may have certain impact on individual stocks, thus test with three different time horizons: 12-year horizon from January 1991 to December 2002, 12-year horizon from January 2001 to December 2012, and 30-year horizon from January 1983 to December 2012.

3.2 Methodology

3.2.1 Autocorrelation function

For autocorrelation function, I estimate a multiple time-series regression of current returns on lagged returns at each time point with daily data frequency:

$$r_{i,t} = \alpha_t + \gamma_{1,t} r_{i,t-1} + \cdots + \gamma_{L,t} r_{i,t-L} + \gamma_{\mu,t}\mu_{i,t} + \mu_{i,t} + \varepsilon_{i,t} \tag{2}$$

Where $\mu_{i,t}$ is the average same-weekday (the same weekday as day t) return on stock *i* over the previous year, $r_{i,t}$ is the return of stock *i* on day *t*, and $r_{i,t-L}$ is the return of stock *i* on the *L* lags of day *t*. The slope coefficients $\gamma_{m,t}$ represent the response of returns at time t to returns over a previous interval lagged by L periods. I choose the lag L equals 20 when detecting the autocorrelations of stocks. But the results are not sensitive to the exact number of the lags. I use $\mu_{i,t}$ as the weekly fixed effect, which controls for variation in expected returns across days of the week. This is likely to be a concern since prior research documents that average stock returns are not equal across days of the week.

For the autocorrelation function of market return and individual stock, I do not add the variable $\mu_{i,t}$ in the model, and just run the simple autocorrelation model below:

$$r_{i,t} = \alpha_t + \gamma_{1,t} r_{i,t-1} + \cdots + \gamma_{L,t} r_{i,t-L} + \varepsilon_{i,t} \tag{3}$$

However, using simple regressions without variable $\mu_{i,t}$ does not affect the results. For the autocorrelation function of market return and individual stock with daily frequency, I also choose the lag L equals 20 for the comparison with the autocorrelation function of stock returns. For individual stock with intraday frequency, I choose lag L equals 65, which is for the past 5 trading days (a week).

3.2.2 Market Model

For the beta, I use a single index model and estimate a multiple time-series regression of stock returns on market returns with different frequencies (daily, bi-daily, weekly, bi-weekly, and monthly):

$$r_t = \alpha_t + \beta_t r_{M,t} + \varepsilon_t \tag{4}$$

where r_t is the stock return on day *t*, $r_{M,t}$ is the market return on day *t*, and ε_t is regression residuals on day t. The main interest of this thesis is to see how β_t changes with different data frequencies and I analyze this relation for the all-stocks portfolio and 15 industry portfolios.

The reason that I use time-series regressions instead of cross-sectional regressions is because the cross-sectional analysis will determine autocorrelation coefficients (slopes) by using the least-squared regression, so the contribution of each stock to the slope will depend on a data set. This is a problem since the cross-sectional analysis will need to test the beta of well-diversified portfolios versus data frequency, but portfolios will not be well-defined.

4. Results

4.1 Summary Statistics

Table 1 shows that, after the data cleaning, the univariate statistics for the all-stocks portfolio and 15 industry portfolios of daily data.

As can be seen from Table 1 that all sectors and the market are positively skewed, and the kurtoses are around 3. The all-stocks portfolio sample contains the daily stock returns of 12,721 firms within a 30-year period from January 1983 to December 2012. The minimum return is -0.1219512, the maximum return is 0.1428571, and the mean return is 0.00034352.

For the 15 industry portfolios, the sample sizes are quite different. The biggest sample is the Durable industry containing 2,906 firms on average, while the smallest sample is the Food industry, which only has 266 firms in total. Basically, there are two ranges of the sample size

Table 1. Summary Statistics of Daily Data

Portfolios	Average return	Std. dev.	Skewness	Kurtosis	Minimum return	Maximum return	Average no. of firms	Jarque–Bera
All-stocks	0.00034352	0.0320981	0.28381284	2.75272591	-0.1219512	0.1428571	12721	12210125.72***
Mining, construction	0.00044185	0.03520114	0.33676626	2.57502850	-0.12857140	0.15384620	347	225445.07***
Food	0.00055308	0.02559050	0.28051691	3.00075112	-0.10000000	0.11428570	266	297746.67***
Textiles, printing	0.00048705	0.02777561	0.31361749	3.16624412	-0.11111110	0.12500000	624	721659.14***
Chemicals	0.00055163	0.02777602	0.31808805	3.17384408	-0.10810810	0.12500000	316	342697.17***
Pharmaceuticals	0.00037918	0.03932323	0.43770300	2.09975658	-0.13140310	0.16666670	637	332642.19***
Extractive Industry	0.00046191	0.03388264	0.32227095	2.83079118	-0.12676060	0.15151520	512	478835.59***
Durable	0.00030789	0.03373643	0.29795180	2.68114777	-0.12500000	0.14605810	2906	2435013.70***
Computers	0.00039091	0.04051248	0.37656447	2.16213463	-0.14084510	0.17170320	1916	945586.09***
Transportation	0.00032347	0.03186745	0.28277397	2.67353159	-0.12056740	0.14285710	750	510456.65***
Utilities	0.00045294	0.01793506	0.11628215	3.52357000	-0.07692308	0.08333330	365	668879.36***
Retail	0.00040379	0.03345869	0.27860202	2.71735698	-0.12500000	0.14457830	1644	1237890.09***
Financial Institution	0.00045070	0.02506871	0.19436303	2.78221720	-0.10000000	0.11111110	2216	1592701.99***
Insurance, Real Estate	0.00060031	0.02474228	0.21854880	2.95273804	-0.09999999	0.11111110	1632	974004.61***
Services	0.00055458	0.03715463	0.40993978	2.90284674	-0.13635320	0.16666670	1825	1374973.04***
Other	0.00036378	0.02995323	0.38180833	3.51064642	-0.11578947	0.14285707	511	172613.17***

Notes: This table contains the summary statistics of daily returns from January 1983 to December 2012 for the all-stocks portfolio and the 15 industry portfolios. I retain only firms which are common stocks (shrcd 10 or 11), and traded on NYSE, AMEX or NASDAQ (exchcd 1, 2 or 3). I require at least 945 days of data for daily returns and at least 60 months of data for monthly returns. Penny stocks (average price less than one dollar) and returns above 400% (or less than -400%) are eliminated. I winsorize stock returns at the 1%/99% level to remove the effect of outliers.

within the 15 industry portfolios. The bigger team contains industry portfolio Durable, Computers, Retail, Financial Institution, Services and Insurance, Real Estate. They have a number of firms ranging from 1,632 to 2,906. On the other side, the smaller range only has a number of firms from 266 to 750. The average number of firms for all industry portfolios is 1,097.

In addition, the biggest return within the 15 industry portfolios is 0.1717032 achieved in the Computers industry, and the smallest return is -0.07692308 from the Utilities industry. The Computers industry's minimum return is the biggest in magnitude among the minimum return of other industries, while the maximum return of the Utilities industry is the smallest in magnitude among the maximum returns in other industries. The Utilities industry also has the smallest standard deviation, the smallest skewness, and the biggest kurtosis. On the contrary, the Computers industry has the biggest standard deviation, high skewness, and low kurtosis. The difference in standard deviation fits the fact that the Utilities industry is relatively low-risk and defensive, while the Computers industry is a high-risk sector. Hence, there are considerable variations among the samples of 15 industry portfolios.

Since the sample size is enormous, I use the Jarque–Bera test to test the normality of each portfolio. The test statistic JB is defined as:

$$JB = \frac{n}{6}\left(S^2 + \frac{1}{4}(K-3)^2\right) \tag{5}$$

Where n is the number of observations (or degrees of freedom in general), S is the sample skewness, and K is the sample kurtosis.

Among all the portfolios, even though the mean returns and standard deviations are near 0 (the highest is 0.00060031 and 0.04051248), the skewness is small (the highest is 0.40993978), and the Kurtoses are around 3; all the Jarque–Bera test statistics are far from zero and strongly reject the null hypothesis of normality, which is consistent with the stylized fact that stock returns are not normally distributed.

4.2 Autocorrelation Function of the All-Stocks Portfolio

This section examines the autocorrelation function of the all-stocks portfolio, which includes all stocks with equal weights. The reason for this consideration is to learn how common and strong the short-term autocorrelation is for daily data. I run the time-series regression of the autocorrelation functions for the all-stocks portfolio from January 1983 to December 2012. I let L equals 20, which stands for the 20 lags in the autocorrelation function. The results are not sensitive to the exact number of lags.

From the coefficient estimates and t-statistics of the autocorrelation function of all-stocks portfolio (column 2 and column 3 in Table 2), I can see that almost all lags are statistically and economically significant, except the lag 15, lag 17, and lag 19. The first nine lags, which stand for short horizons, are the most significant. The table also shows a decay pattern every five lags within the first 15 lags. The first lag is significantly negative and large in absolute value because of bid-ask bounce (-0.0924). As shown in Roll (1984), given a continuous trading market, the observed security returns will be negatively correlated due to transaction prices bouncing between the bid and ask prices. Rhee and Wang (1997) also show that bid-ask errors induce both the bid-ask bounce and the spread size effect, and they each will bias the return behaviour and cause negative first-order autocorrelation. Afterwards, the lag decays exponentially to lag 5 with the value -0.0036. But the following lag 6 (γ_6) equals to -0.0049, which is larger in the absolute value than the lag 5 (γ_5). Then, lag 6 decays exponentially to lag 10 with the positive value 0.0009. Similarly, lag 11 is larger than lag 10 and decays exponentially to lag 15. It indicates the infrequent rebalancing every five trading days (a week), which is in line with the assumption of the slow-moving capital and other empirical studies that the short-term reversal spans at a weekly frequency. Bogousslavsky (2016) also shows the same stock return behaviour for the autocorrelation function of the all-stocks portfolio. In addition, lag 10, lag 11, lag 12, lag 13, lag 16, and lag 20 are all statistically and economically significant positive. The control variable of the weekly fixed effect $\gamma_{\mu,t}$ equals to -0.9702 and is strongly statistically and economically significant at the 1% level.

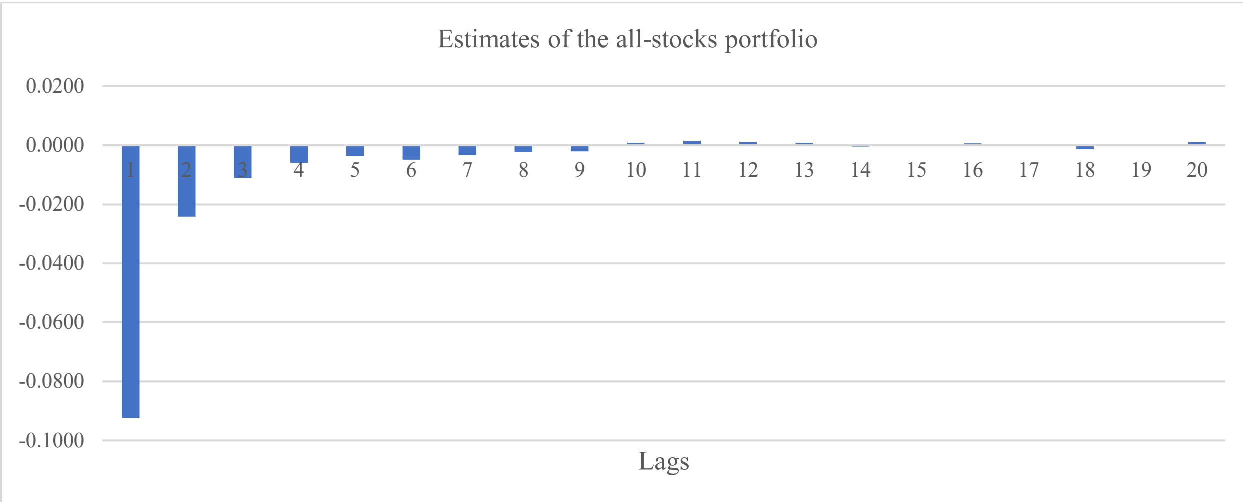
I draw the coefficient estimates and t-statistics of the autocorrelation function of the all-stocks portfolio in Figure 1 for a more intuitive understanding. It illustrates an obvious exponential decay pattern (in absolute value) of infrequent rebalancing over each five trading days (or a week).

Table 2. Autocorrelation Functions of the All-Stocks Portfolio

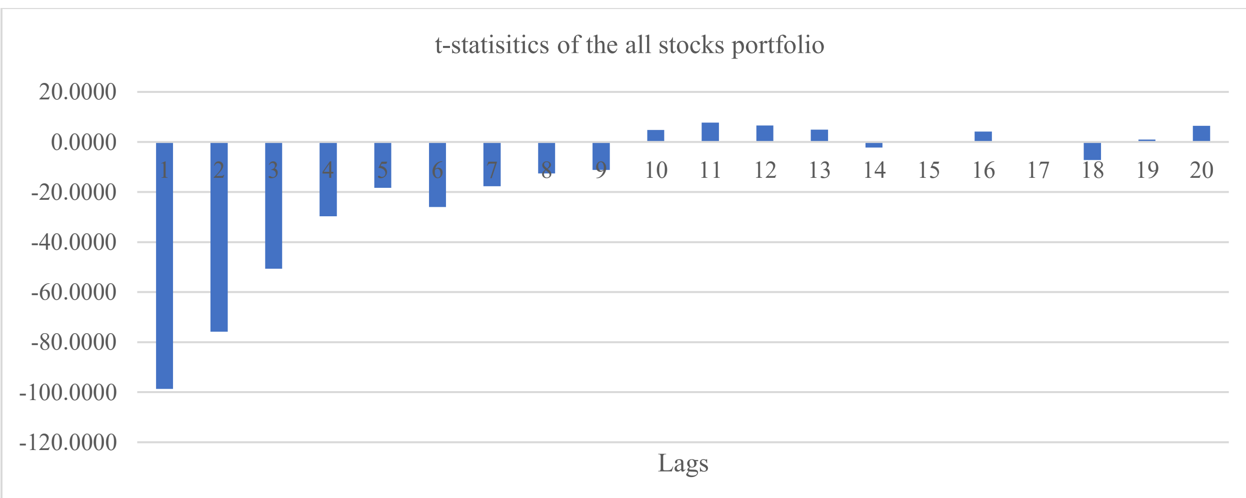
Lags	All stocks (daily)	
	Estimates	t-statistics
γ1	-0.0924***	-98.7246
γ2	-0.0242***	-75.8566
γ3	-0.011***	-50.6225
γ4	-0.006***	-29.6943
γ5	-0.0036***	-18.3622
γ6	-0.0049***	-25.9716
γ7	-0.0033***	-17.6745
γ8	-0.0023***	-12.6300
γ9	-0.0021***	-11.1384
γ10	0.0009**	4.7606
γ11	0.0015***	7.7257
γ12	0.0012***	6.5281
γ13	0.0009***	4.9296
γ14	-0.0004**	-2.2367
γ15	0.0000	-0.2328
γ16	0.0007***	4.1255
γ17	-0.0001	-0.2998
γ18	-0.0013***	-7.1538
γ19	0.0002	0.9344
γ20	0.0011***	6.4207
μ	-0.9702***	-766.5630

Notes: This table reports the coefficient estimates and their t-statistics of autocorrelation functions with 20 lags and the weekly fixed effect (daily data) for the all-stocks portfolio. *, **, and *** refer to a 10%, 5%, and 1% level of significance, respectively.

Panel B of Figure 1 plots the t-statistics of $\gamma_{m,t}$ and the t-statistics show the same type of infrequent rebalancing pattern.



Panel A: Coefficient Estimates



Panel B: t-statistics

Figure 1. Coefficient estimates and t-statistics of autocorrelation function of the portfolio with all stocks.

This figure contains the estimates and t-statistics of autocorrelation function of the all-stocks portfolio from January 1983 to December 2012.

In line with the analysis in Bogousslavsky (2016), the infrequent rebalancing generates specific return autocorrelation patterns and offers a plausible explanation for the shape of the short-term autocorrelation function shown in Figure 1. Suppose there is a liquidity shock in the market, and the stock price increase. Since traders rebalance their portfolios infrequently, they will hold an excess position in their portfolios. After some time and when they rebalance their portfolios, traders with excess positions will sell it and cause the stock price to decrease in the market. Hence infrequent rebalancing can result in negative short-term autocorrelation. Isaenko (2020) also assumes that there are a lot of investors who trade rarely even if they have high trading motives. As a result, an informational shock instantly translates into the stock price and then gets adjusted by investors' gradual trading. The adjustment is negative for a positive shock and positive for a negative shock, leading to a negative short-term autocorrelation.

4.3 Autocorrelation Functions of the Market Index

In this section, I run the time-series regression of the autocorrelation function for market index (S&P 500) with daily frequency data from January 1983 to December 2012. The reason for this consideration is to learn how the short-term autocorrelation for the market index and make a comparison with the autocorrelation function of the all-stocks portfolio. I let L equals 20 to keep consistency.

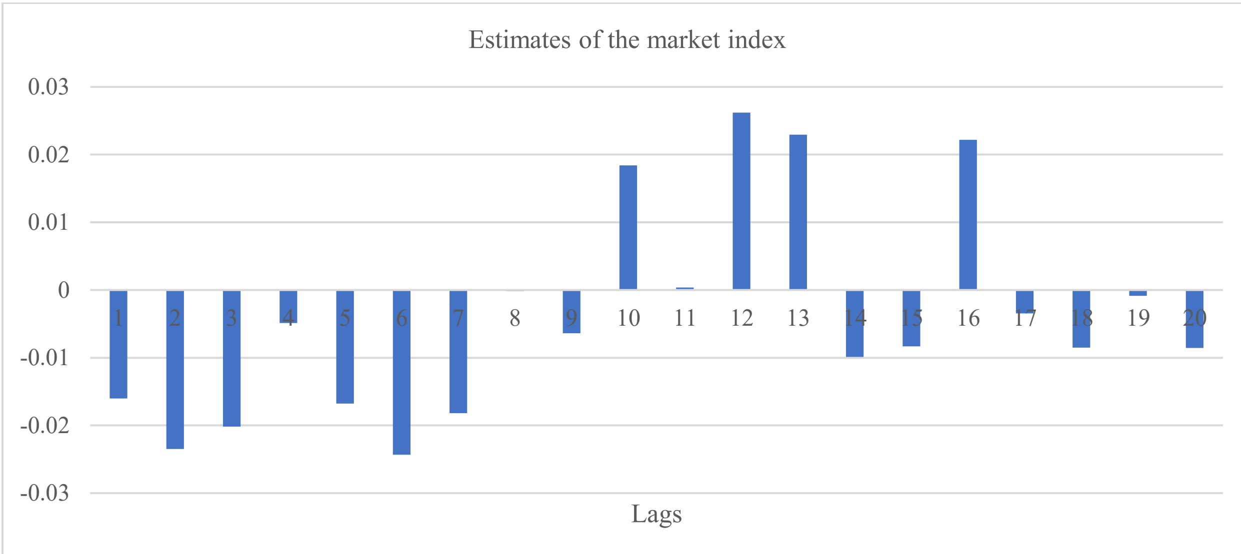
Table 3 shows that the estimates of first 9 lags are negative, revealing return reversals for almost 2 trading weeks. However, surprisingly, the estimate of the first lag is not statistically significant. Baltussen, Bekkum, and Da (2019) show a striking change in the autocorrelation of market index return across 20 major market indexes covering 15 countries in North America, Europe, and Asia. While many studies find market index autocorrelation to be positive until the 1990s, they prove that it switches to negative since the 2000s. This change happens in most stock markets around the world and is both statistically significant and economically meaningful. They explain the decline in the serial dependence due to the increasing popularity of index products (e.g. futures, exchange-traded funds, and index mutual funds) and the arbitrage mechanism between

Table 3. Autocorrelation Functions of the Market

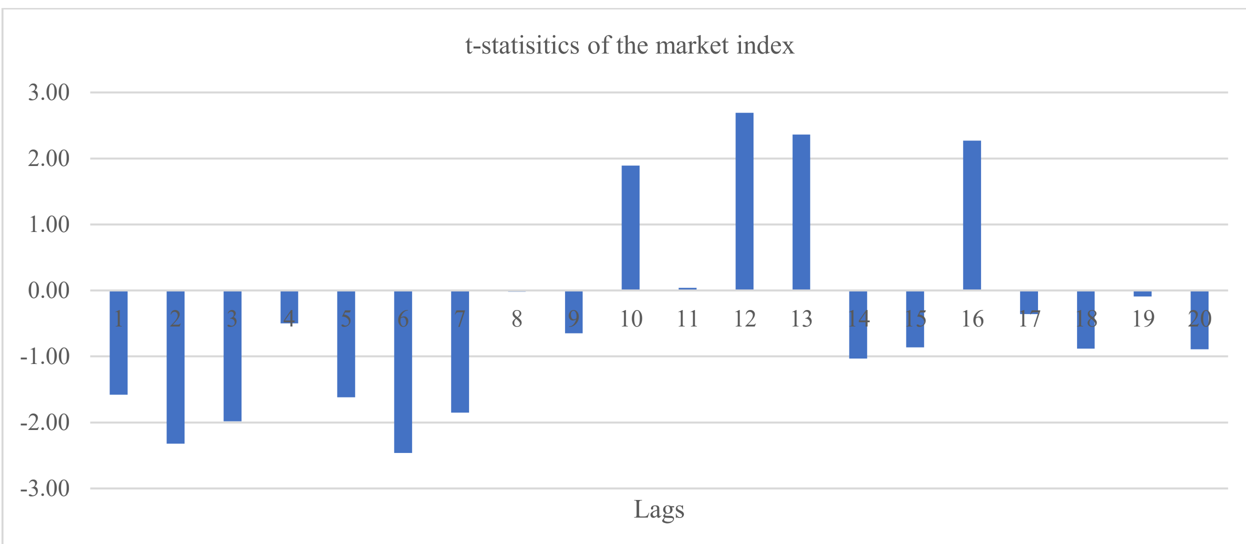
Lags	S&P 500 (Daily data)	
	Estimates	t-statistics
γ1	-0.01601	-1.58
γ2	-0.02348**	-2.32
γ3	-0.02015**	-1.98
γ4	-0.00487	-0.50
γ5	-0.01677	-1.62
γ6	-0.02431**	-2.46
γ7	-0.01819*	-1.85
γ8	-0.00016	-0.02
γ9	-0.00637	-0.65
γ10	0.01842*	1.89
γ11	0.00038	0.04
γ12	0.02619***	2.69
γ13	0.02297**	2.36
γ14	-0.00990	-1.03
γ15	-0.00831	-0.86
γ16	0.02218**	2.27
γ17	-0.00346	-0.36
γ18	-0.00850	-0.88
γ19	-0.00088	-0.09
γ20	-0.00857	-0.89

Notes: This table reports the coefficient estimates and their t-statistics of autocorrelation functions with 20 lags and the weekly fixed effect (daily data) for the market proxy (S&P 500). *, **, and *** refer to a 10%, 5%, and 1% level of significance, respectively.

those index products and their underlying stocks. Since I use daily data with a 30-year horizon from 1983 to 2012, it could explain the loss of significance in the sample.



Panel A: Coefficient Estimates



Panel B: t-statistics

Figure 2. Coefficient estimates and t-statistics of autocorrelation function of the market index.

This figure contains the estimates and t-statistics of autocorrelation function of the market index (SPY) from January 1983 to December 2012.

In addition, I draw the coefficient estimates and t-statistics of the autocorrelation function of the market index in Figure 2 as a comparison to Figure 1. However, compared to the shape of autocorrelations of the all-stocks portfolio in Figure 1, the autocorrelations of the market index don't show an obvious decay pattern and are positive significant at lag 10, 12, 13, and 16. Considering the S&P 500 index, a market-capitalization-weighted index of 500 of the largest publicly-traded companies in the U.S., only captures the large-cap firms, this might be an issue that would affect the shape of its autocorrelation function.

4.4 Autocorrelation Functions of the Industry Portfolios

In this section, I examine the autocorrelation functions for the 15 industry portfolios with 30-year horizon from January 1983 to December 2012. To keep consistency, I still let *L* equals 20, which stands for the 20 lags in the autocorrelation function. The results in Table 4 are quite similar to the result of the autocorrelation function of the all-stocks portfolio in Table 2.

At short horizons, the coefficients of the autocorrelation function are all negative and significant. Except for the Insurance, Real Estate and the Other industry, the autocorrelations of all the sectors are negatively significant in the first 6 lags. All the coefficient of the lag 1 (γ_1) is the biggest in absolute value, and then the lag starts to decay exponentially to lag 5 (γ_5). Following the lag 5 (γ_5), lag 6 (γ_6) increases in absolute value in almost all industry portfolios, except Food, Insurance, Real Estate, and the other industry. For example, in the Computers industry, lag 6 (γ_6) increases (in absolute value) from lag 5 (γ_5) -0.0028 to -0.0054; it increases from -0.0061 to -0.0075 in the Utilities industry. Afterwards, the coefficients of autocorrelation functions decay exponentially again. However, not all lag 11 (γ_{11}) are bigger than the lag 10 (γ_{10}) in absolute value. This result shows that the short-term reversal happening in weekly frequency also exists in the 15 industry portfolios at short horizons. There is also an exponential decay in all the coefficient estimates and their t-statistics in all the industry portfolios.

The coefficients of the control variable, the weekly fixed effect $\gamma_{\mu,t}$, are all strongly statistically and economically significant at 1% level. All the coefficients ($\gamma_{\mu,t}$) are near the -1 for

Table 4. Autocorrelation Functions of 15 Industry Portfolios

Lags	Mining, construction		Food		Textiles, printing		Chemicals		Pharmaceuticals	
	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
γ1	-0.0954***	0.0000	-0.1059***	0.0000	-0.0935***	0.0000	-0.0933***	0.0000	-0.0602***	0.0000
γ2	-0.0251***	0.0000	-0.0272***	0.0000	-0.0201***	0.0000	-0.0237***	0.0000	-0.0235***	0.0000
γ3	-0.0122***	0.0000	-0.0124***	0.0000	-0.0098***	0.0000	-0.0107***	0.0000	-0.0127***	0.0000
γ4	-0.0085***	0.0000	-0.008***	0.0000	-0.0046***	0.0001	-0.0099***	0.0000	-0.0066***	0.0000
γ5	-0.0049***	0.0061	-0.0053***	0.0013	-0.0026***	0.0038	-0.0032*	0.0651	-0.0057***	0.0000
γ6	-0.0053***	0.0038	-0.0051***	0.0007	-0.0042***	0.0001	-0.0046***	0.0072	-0.0065***	0.0000
γ7	-0.0054***	0.0047	-0.0046***	0.0025	-0.0032***	0.0011	-0.0031	0.1046	-0.0033***	0.0004
γ8	-0.0039**	0.0272	-0.0029**	0.0429	-0.0006	0.5633	-0.0030	0.1021	-0.0006	0.5489
γ9	-0.0014	0.4122	0.0002	0.8882	-0.0021*	0.0555	-0.0038**	0.0487	-0.0032***	0.0004
γ10	0.002	0.2619	0.0017	0.2415	-0.0001	0.9354	0.0026	0.1559	0.003***	0.0028
γ11	0.0009	0.5962	-0.0001	0.9191	0.0018*	0.0610	0.0012	0.5133	0.0018**	0.0388
γ12	0.0002	0.8850	-0.0015	0.2916	0.0000	0.9681	-0.0003	0.8789	0.0001	0.9220
γ13	-0.0028	0.1628	0.0019	0.2129	0.0001	0.8949	-0.0024	0.1461	-0.0011	0.2179
γ14	-0.0031*	0.0943	-0.0031**	0.0475	-0.0008	0.4134	-0.0032*	0.0554	-0.0019**	0.0449
γ15	0.0016	0.4122	-0.0006	0.6745	-0.0007	0.4925	-0.0013	0.4465	0.0015	0.1552
γ16	0.0024	0.1761	0.0007	0.5788	0.0019**	0.0388	0.0019	0.2523	0.0004	0.6505
γ17	0.0011	0.5283	0.0018	0.1917	-0.0005	0.6089	-0.0027	0.1041	-0.0006	0.4834
γ18	-0.0044**	0.0128	0.0005	0.7627	-0.0021**	0.0199	-0.0042***	0.0082	-0.0023***	0.0092
γ19	-0.0003	0.8762	-0.001	0.4849	0.0006	0.4723	-0.0033*	0.0649	0.001	0.2572
γ20	0.0007	0.7038	-0.0002	0.9060	0.0002	0.8350	0.0018	0.2820	0.0012	0.1351
μ	-0.9492***	0.0000	-0.9684***	0.0000	-0.9707***	0.0000	-0.979***	0.0000	-0.9616***	0.0000

Table 4. Continued

Lags	Extractive Industry		Durable		Computers		Transportation		Utilities	
	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
γ1	-0.0931***	0.0000	-0.0962***	0.0000	-0.0760***	0.0000	-0.0659***	0.0000	-0.0780***	0.0000
γ2	-0.0245***	0.0000	-0.0246***	0.0000	-0.0243***	0.0000	-0.0149***	0.0000	-0.0208***	0.0000
γ3	-0.0131***	0.0000	-0.0119***	0.0000	-0.0116***	0.0000	-0.0080***	0.0000	-0.0089***	0.0000
γ4	-0.0062***	0.0001	-0.0074***	0.0000	-0.0055***	0.0000	-0.0038***	0.0000	-0.0079***	0.0000
γ5	-0.0056***	0.0002	-0.0042***	0.0000	-0.0028***	0.0000	-0.0036***	0.0002	-0.0061***	0.0000
γ6	-0.0069***	0.0000	-0.0061***	0.0000	-0.0054***	0.0000	-0.0044***	0.0000	-0.0075***	0.0000
γ7	-0.0057***	0.0003	-0.004***	0.0000	-0.0024***	0.0000	-0.0015	0.1030	-0.0056***	0.0000
γ8	-0.0043***	0.0071	-0.0032***	0.0000	-0.0026***	0.0000	-0.0013	0.1250	-0.0034***	0.0013
γ9	-0.0027*	0.0907	-0.0031***	0.0000	-0.0015***	0.0042	-0.0023***	0.0095	-0.0025**	0.0163
γ10	0.0007	0.6635	-0.0003	0.4390	0.0018***	0.0004	0.0008	0.4033	-0.0016*	0.0981
γ11	-0.0003	0.8319	0.0002	0.7055	0.0021***	0.0001	0.0025***	0.0064	-0.0015	0.1389
γ12	-0.0015	0.3581	0.0011***	0.0059	0.0037***	0.0000	0.0024***	0.0055	-0.0002	0.8185
γ13	0.0005	0.7623	0.0008*	0.0563	0.0048***	0.0000	0.0017*	0.0733	-0.0015	0.2271
γ14	0.0019	0.2092	-0.0011***	0.0069	0.0002	0.7403	0.0000	0.9975	-0.0036***	0.0009
γ15	-0.0007	0.6507	-0.0007*	0.0726	0.0009*	0.0721	0.0000	0.9655	-0.0009	0.4124
γ16	-0.0007	0.6064	-0.0001	0.7946	0.0013***	0.0065	0.0003	0.7664	0.0008	0.4164
γ17	0	0.9988	-0.0002	0.6139	-0.0005	0.3235	0.0006	0.4820	-0.0021**	0.0424
γ18	-0.0016	0.3169	-0.0016***	0.0000	-0.0017***	0.0013	-0.0006	0.4454	-0.0020*	0.0663
γ19	0.0011	0.4932	0.0004	0.3075	-0.0003	0.5980	-0.0004	0.6101	0.0004	0.7329
γ20	0.002	0.1832	0.0008**	0.0347	-0.0002	0.6702	0.0007	0.4419	0.0016*	0.0824
μ	-0.9622***	0.0000	-0.9653***	0.0000	-0.9720***	0.0000	-0.9765***	0.0000	-0.9830***	0.0000

Table 4. Continued

Lags	Retail		Financial Institution		Insurance, Real Estate		Services		Other	
	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
γ1	-0.1053***	0.0000	-0.1259***	0.0000	-0.1427***	0.0000	-0.0920***	0.0000	-0.0501***	0.0000
γ2	-0.0267***	0.0000	-0.0330***	0.0000	-0.0385***	0.0000	-0.0246***	0.0000	-0.0061**	0.0406
γ3	-0.0122***	0.0000	-0.0097***	0.0000	-0.0101***	0.0000	-0.0111***	0.0000	-0.0082***	0.0006
γ4	-0.0069***	0.0000	-0.0039***	0.0000	-0.0024**	0.0443	-0.0054***	0.0000	-0.0052**	0.0121
γ5	-0.0037***	0.0000	-0.0035***	0.0000	0.0004	0.6574	-0.0031***	0.0000	-0.0039*	0.0740
γ6	-0.0048***	0.0000	-0.0033***	0.0000	-0.0001	0.9043	-0.0039***	0.0000	-0.0021	0.3325
γ7	-0.0039***	0.0000	-0.0022***	0.0000	-0.0008	0.3100	-0.0039***	0.0000	-0.0045**	0.0132
γ8	-0.0020***	0.0004	-0.0027***	0.0000	-0.0006	0.5257	-0.0030***	0.0000	-0.0049**	0.0118
γ9	-0.0017***	0.0051	-0.0006	0.2354	0.0009	0.2678	-0.0022***	0.0001	-0.0014	0.4500
γ10	-0.0004	0.4978	0.0023***	0.0001	0.0029***	0.0000	0.0012*	0.0552	-0.0001	0.9421
γ11	0.0012**	0.0462	0.0023***	0.0000	0.0038***	0.0000	0.0005	0.4545	0.0001	0.9475
γ12	0.0012**	0.0444	0.0015***	0.0082	0.0037***	0.0000	0.0001	0.9062	0.0019	0.4081
γ13	0.0004	0.5076	0.0024***	0.0000	0.0017**	0.0314	-0.0005	0.4473	-0.0030*	0.0721
γ14	-0.0001	0.8642	-0.0011**	0.0392	0.0029***	0.0002	0.0002	0.6769	0.0006	0.7510
γ15	0.0015***	0.0100	-0.0012**	0.0206	0.0002	0.8376	-0.0006	0.2939	0.0015	0.4718
γ16	0.0019***	0.0010	0.0006	0.2454	-0.0003	0.6698	0.0000	0.9653	0.0008	0.6639
γ17	0.0009	0.1339	0.0010*	0.0601	-0.0003	0.6693	-0.0002	0.7009	-0.0019	0.3162
γ18	0.0002	0.7095	0.0007	0.1470	-0.0004	0.5517	-0.0013**	0.0228	-0.0002	0.9353
γ19	0.0012**	0.0301	0.0000	0.9694	0.0007	0.3871	0.0001	0.8287	-0.0012	0.5185
γ20	0.0027***	0.0000	0.0005	0.3420	0.0019***	0.0064	0.0018***	0.0016	0.0036*	0.0707
μ	-0.9696***	0.0000	-0.9700***	0.0000	-0.9670***	0.0000	-0.9694***	0.0000	-0.9368***	0.0000

Notes: This table reports the coefficient estimates and their t-statistics of autocorrelation functions with 20 lags and the weekly fixed effect (daily data) for 15 industry portfolios. *, **, and *** refer to a 10%, 5%, and 1% level of significance, respectively.

the all-stocks portfolio and the industry portfolios. Using simple regressions without $\gamma_{\mu,t}$ does not affect the results for all industry portfolios either.

Notably, the results are correct for all-stocks portfolio and all the industry portfolios. The short-term reversal pattern and the autocorrelation decay are similar for different industries, so it does not appear to be sensitive to the way portfolios are formed.

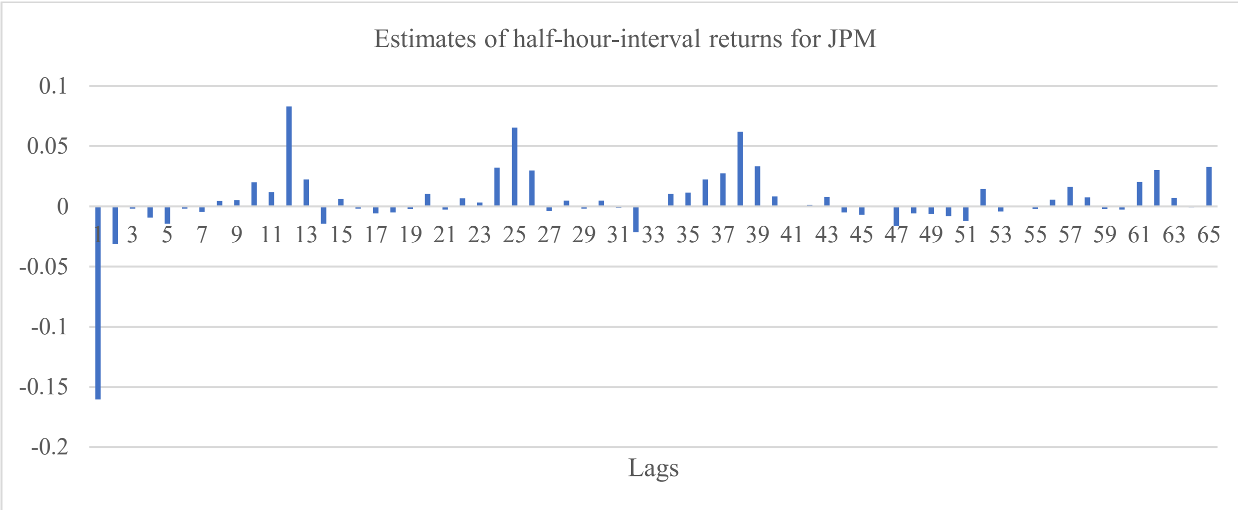
Similarly, there are positive coefficients in every industry portfolio. For example, coefficients of lag 10 to lag 16 in the Computers industry are all positive and statistically significant at 1% or 10% level, except lag 14 (γ_{14}). Coefficients of lag 10 to lag 13 in the Financial Institution industry are all positive and statistically significant at 1% level. Coefficients of lag 10 to lag 14 in Insurance, Real Estate industry are all positive and statistically significant at 1% or 5% level. It indicates that the autocorrelation function will change its sign from negative to positive with the slow-moving capital and the infrequent rebalancing.

However, there is a difference between industry portfolios. For high-risk sectors, like Computers, Retail, Financial Institution, and Insurance, Real Estate industry, there are more positive and significant autocorrelations; while traditional and low risk-sectors, like Mining, Construction, Food, Chemicals, and Extractive Industry, there are positive autocorrelations, but none of them are statistically significant. Hence, I conclude that the risk of portfolios has an impact on the significance of return autocorrelations.

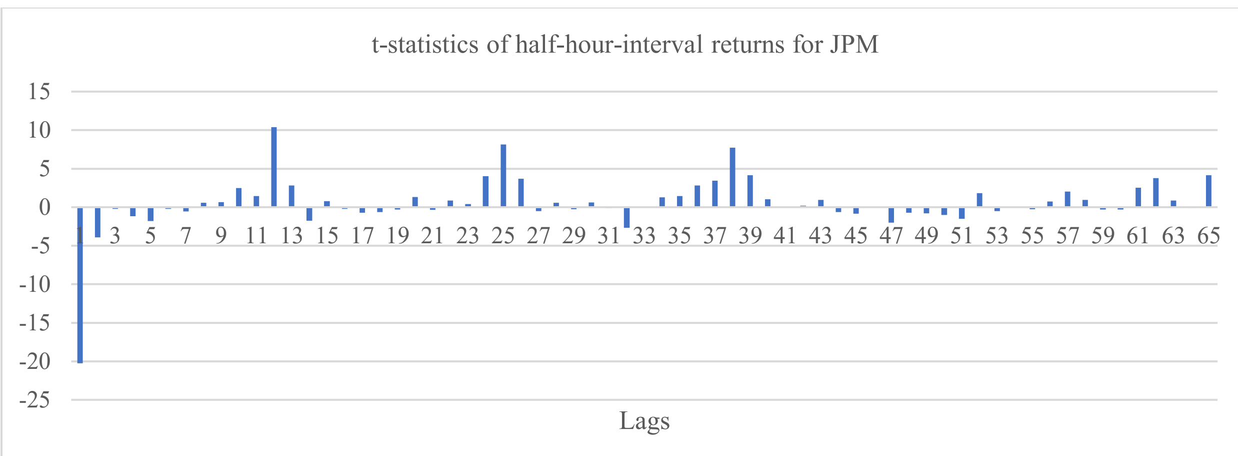
4.5 Autocorrelation Functions of the Individual Stock (JPM)

Naturally, I am also interested in the autocorrelations for individual stocks. In this thesis, I choose the stock of JPM, considering it is a large-size firm with high liquidity. I test it with both intraday and daily frequency at different horizons.

Firstly, for intraday frequency, I test with 30-minute interval to avoid microstructure noise for a 5-year horizon from January 2001 to December 2005. Figure 3 presents the estimates of the autocorrelation function of intraday half-hour-interval returns for lags up to 1 week for individual



Panel A: Coefficient Estimates



Panel B: t-statistics

Figure 3. Coefficient Estimates and t-statistics of Autocorrelation Function of half-hour-interval returns for JPM.

This figure contains the estimates of autocorrelation function of intraday half-hour-interval returns from January 2001 to December 2005 for individual stock JPM.

Stock JPM. Since there are 13 half-hour intervals per day and five trading days per week, I choose L equals 65 and produces 65 lagged intervals. Consistent with prior studies, such as Lehmann (1990) and Lo and Mackinlay (1990), the first several estimates of autocorrelations are negative, showing a reversal period lasting several hours for the stock returns. From Figure 3, I can see that autocorrelations become positive after the reversal period for a few lags (momentum effect). This pattern repeats with slowly diminishing amplitudes roughly every 13 trading intervals. Panel B of Figure 3 plots the t-statistics of the estimates and shows a similar type of periodicity. Within every 13 trading intervals, the return effects remain mostly negative but become statistically significant positive at lags 13, 26, 39, 52 and 65, which is multiples of 13 lags. It appears that temporary price effects firstly reverse at future times and then rebound at the same time on subsequent days in short horizons.

The autocorrelation pattern starts to decay after the third trading day. The statistical significances of estimates are not as good as the significances of estimates when I run regressions over the all-stocks portfolio and industry portfolios. Only one-third of estimates are statistically significant above the 10% level. And these estimates, which are statistically significant, are concentrate on the beginning and the end of each trading days. Namely lag 1, lag 2, lag 12, and lag 13 in the first trading day; lag 14, lag 24, lag 25, and lag 26 in the second trading day; lag 36, lag 37, lag 38, and lag 39 in the third trading day; lag 52 in the fourth trading day; lag 61, lag 62 and lag 65 in the fifth trading day. Over the first week, the smallest t-statistics at the daily frequency (lags 13, 26, 39, 52, and 65) is 1.81 (lag 52) and significant at 10% level, while the highest t-statistics at the daily frequency is 4.15 and significant at 1% level .

For comparison, Heston, Korajczyk, and Sadka (2010) run cross-sectional regressions of half-hour-interval returns with an all-stock sample (1,715 firms) and document pronounced intraday return reversals due to bid-ask bounce. Also, they find a significant continuation of returns. There is a statistically significant positive relationship between a stock's return over a given interval within a day and its subsequent returns at daily frequencies (i.e., lags of 13, 26, 39, ... periods). That is, knowing that the return of one stock is high between a certain time today has explanatory power for the return on the stock at the same time tomorrow and on subsequent days. The continuation effect is statistically significant for at least 40 trading days. Moreover, the smallest t-statistics at the daily frequency (lags 13, 26, 39, 52, and 65) over the first week is 9.62,

Table 5. Autocorrelation Functions of JPM (daily frequency)

Lags	1991-2002		2001-2012		1983-2012	
	Estimates	t-statistics	Estimates	t-statistics	Estimates	t-statistics
γ1	-0.01372	-0.74	-0.0399**	-2.12	-0.00483	-0.41
γ2	-0.00824	-0.45	-0.02137	-1.14	-0.00348	-0.30
γ3	-0.04224**	-2.29	-0.01429	-0.76	-0.02236*	-1.91
γ4	-0.03596*	-1.95	-0.01967	-1.05	-0.04004***	-3.42
γ5	-0.00095911	-0.05	-0.03476*	-1.85	-0.01184	-1.01
γ6	-0.0075	-0.41	-0.01055	-0.56	-0.00628	-0.54
γ7	-0.02569	-1.39	0.02165	1.15	0.00267	0.23
γ8	0.01727	0.93	-0.01946	-1.04	-0.01289	-1.10
γ9	-0.01684	-0.91	0.02463	1.32	0.00704	0.60
γ10	0.02004	1.08	0.04288**	2.29	0.02787**	2.38
γ11	-0.00737	-0.4	0.02104	1.13	0.00859	0.73
γ12	0.03911**	2.11	0.05356***	2.87	0.02156*	1.84
γ13	-0.01384	-0.75	-0.03377*	-1.81	-0.01873	-1.60
γ14	0.01973	1.07	-0.00549	-0.29	0.00116	0.10
γ15	-0.00872	-0.47	-0.02634	-1.41	-0.02329**	-1.99
γ16	0.00396	0.21	0.04172**	2.23	0.00374	0.32
γ17	0.03842**	2.07	0.02849	1.52	0.01747	1.49
γ18	-0.03252*	-1.76	0.05206***	2.79	0.00414	0.35
γ19	0.02537	1.37	-0.01466	-0.78	-0.00505	-0.43
γ20	0.01134	0.61	0.00464	0.25	0.00167	0.14

Notes: This table reports the coefficient estimates and their t-statistics of autocorrelation function with 20 lags for individual stock JPM with daily frequency. *, **, and *** refer to a 10%, 5%, and 1% level of significance, respectively.

which is even higher than the highest t-statistics for JPM, and significant at 1% level. Their estimates and t-statistics of autocorrelations show much more significance as well. It suggests that the idiosyncratic risk can affect the significance of autocorrelations for individual stocks.

Secondly, following the intraday frequency, I also run regressions of autocorrelation function with daily frequency over three different time-horizons: 12-year horizons from January 1991 to December 2002 and January 2001 to December 2012, and 30-year horizon from January 1983 to December 2012. I find that the autocorrelation function of individual stock depends on the time horizons and is time varying.

From Table 5, I can see that the first 6 lags have negative autocorrelation estimates for all three horizons. It shows a one-week price reverse effect. Afterwards, the price effect starts to fluctuate and turns positive or negative without a certain pattern. In addition, the estimates of lag 12 are positive and statistically significant for all three horizons. Except for these common points, the estimates and t-statistics of the autocorrelation function for JPM over the three different horizons are quite different, both the magnitude and the statistical significance. The estimate of lag 1 is significant at 5% level only on the horizon 2001 to 2012. The results of the longer horizon (30-year horizon from 1983 to 2012) also show much more decay in autocorrelations compare to the results at shorter horizons.

Moreover, when we compare the results of intraday and daily frequency, it is interesting that the shape of the autocorrelation with intraday data is positive at most lags, and the shape of the autocorrelation with daily lags is mostly negative. This comparison suggests that the momentum effect is more robust in shorter time intervals (e.g. half-hour interval) with intraday data while the reversal effect is stronger for daily frequency.

Overall, the results of intraday returns with half-hour-intervals and daily returns suggest that the idiosyncratic risk can strongly affect detecting the autocorrelation for individual stocks. Individual stock returns are very sensitive to both firm-level or macro news in the stock market, and it will have a substantial impact on autocorrelations or betas.

4.6 Estimates of Beta of the All-Stocks Portfolio and the Industry Portfolios versus Data Frequencies

Finally, I analyze how the data frequencies affect an estimate of the stock beta. I run time-series regressions on 15 industry portfolios and the all-stocks sample, using the market model with a 30-year horizon from January 1983 to December 2012 at different frequencies: daily, bi-daily, weekly, bi-weekly, and monthly.

Table 6 shows that the estimated betas are all significant at higher than the 1% level. Additionally, the beta increases as the frequency decreases at almost all the portfolios. Exceptionally, the betas of the Extractive and Financial Institution industry measured with monthly are almost the same as the betas estimated with bi-weekly frequency. The beta of the Utilities industry measured with monthly is even smaller than its beta measured with weekly and bi-weekly frequency.

For the all-stocks portfolio, the beta increases from 0.5899 (daily data) to 0.8177 (monthly frequency). Over the entire 15 industry portfolios sample, the highest beta was Computers industry frequencies, confirming the sector's high-risk profile as discussed in Section 4.4. However, the high-risk sectors of Insurance, Real Estate industry has the lowest beta in daily, bi-daily, and weekly frequency. Then it rises sharply in bi-weekly frequency. It is worth to notice that all the beta of every portfolio rises sharply from weekly to bi-weekly frequency. For example, the beta of the Food industry increases 12% in magnitude from weekly to bi-weekly frequency while it only increases 2.6% and 3% in magnitude from daily to bi-daily and bi-daily to weekly frequency. Also, the beta of the Computer industry rises 20.6% in magnitude from weekly to bi-weekly frequency while it only increases by 9% and 3% in magnitude from daily to bi-daily and bi-daily to weekly frequency.

The increasing of a portfolio's beta with decreasing measuring frequency can be explained based on the comparison of the autocorrelation coefficient of the market portfolio (see Figure 2) with the autocorrelation coefficient of a portfolio (see Figure 4). Figure 4 plots the autocorrelation functions of the Retail, Computers, and Utilities industry portfolios. In particular, the co-

Table 6. Beta of the All-Stocks Portfolio and the 15 Industry Portfolios with Different Data Frequencies

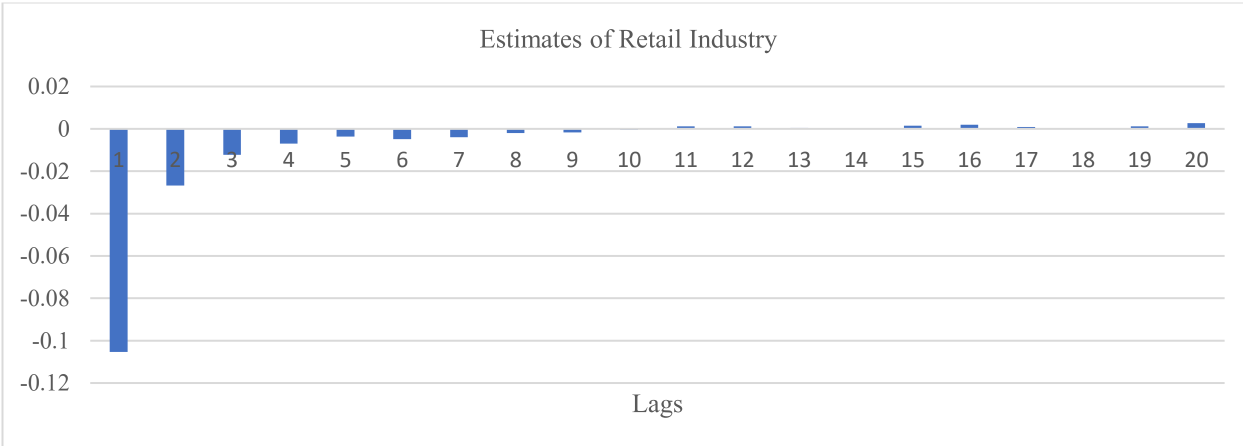
Portfolios	Industry portfolios' beta results									
	Daily		Bi-daily		Weekly		Bi-weekly		Monthly	
	Beta	t-statistics	Beta	t-statistics	Beta	t-statistics	Beta	t-statistics	Beta	t-statistics
Mining, construction	0.5993***	17.2699	0.6454***	18.2942	0.6894***	15.2207	0.7449***	16.3284	0.7452***	10.6348
Food	0.4451***	25.2379	0.4565***	26.0122	0.4703***	22.2466	0.5271***	22.7444	0.5465***	14.1708
Textiles, printing	0.5647***	29.4896	0.5997***	31.6496	0.6541***	25.7747	0.7479***	27.3555	0.8013***	16.9849
Chemicals	0.6190***	25.6989	0.6506***	27.4268	0.6820***	23.6349	0.7549***	25.5467	0.8121***	17.4029
Pharmaceuticals	0.7319***	40.1303	0.8044***	43.7016	0.8298***	24.4588	0.9942***	24.4732	1.0179***	11.8790
Extractive Industry	0.5896***	26.0174	0.6363***	27.0732	0.6396***	15.6426	0.7018***	15.9782	0.7000***	8.9386
Durable	0.6018***	50.6632	0.6515***	54.1557	0.6947***	30.2022	0.8072***	32.1948	0.8795***	18.4776
Computers	0.8447***	48.0555	0.9204***	51.6767	0.9480***	27.6405	1.1429***	29.9249	1.2711***	16.4709
Transportation	0.7179***	40.5165	0.7717***	43.5670	0..8008***	31.0693	0.9144***	32.7906	1.0007***	21.0917
Utilities	0.4209***	33.5037	0.4258***	33.1874	0.4328***	22.7950	0.4674***	19.0471	0.4305***	11.8984
Retail	0.5839***	42.0433	0.6233***	44.8123	0.6591***	28.3946	0.7557***	30.0212	0.8077***	15.7138
Financial Institution	0.4808***	36.9494	0.4895***	39.8014	0.5085***	26.6062	0.5475***	25.7879	0.5466***	11.9046
Insurance, real estate	0.3346***	28.5338	0.3820***	31.6804	0.4203***	21.3286	0.5269***	21.9453	0.5822***	13.5462
Services	0.6057***	44.1346	0.6486***	47.5243	0.6777***	27.6863	0.8030***	30.6847	0.8608***	15.8434
Other	0.4400***	19.3234	0.5103***	20.9073	0.5669***	16.3877	0.7086***	13.1126	0.7519***	8.9543
All stocks	0.5899***	70.1127	0.6319***	76.2229	0.6642***	35.6024	0.7679***	38.8925	0.8177***	20.1837

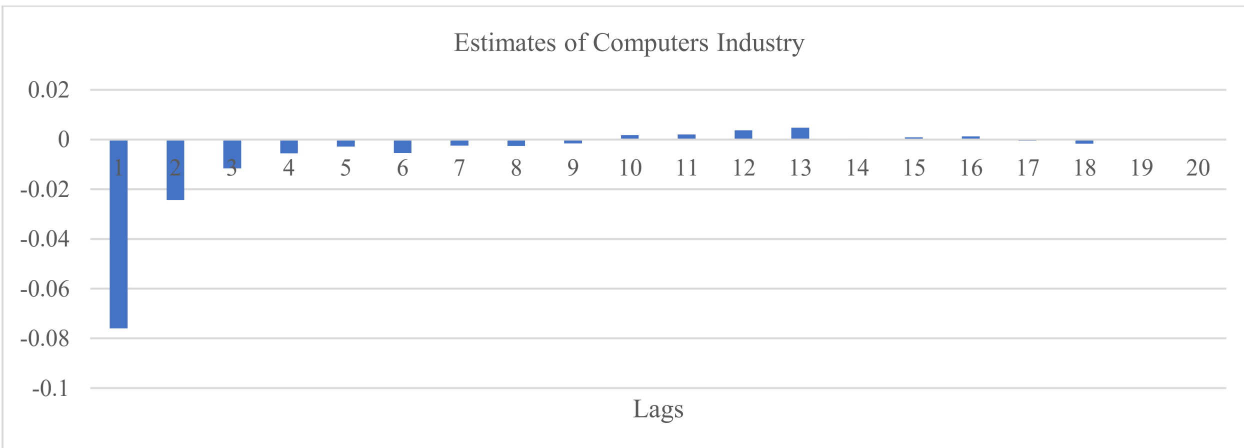
Notes: This table reports the coefficient estimates and their t-statistics of beta with daily, bi-daily, weekly, bi-weekly, and monthly frequency for 15 industry and all-stocks portfolios. *, **, and *** refer to a 10%, 5%, and 1% level of significance, respectively.

movement between the stock returns and returns on the market portfolio is affected by the presence of short-term reversals. A reversal in stock will decrease the covariance of their returns and, therefore, of the beta if returns are measured over a sufficiently long-time-interval. On the other hand, a reversal in the stock market should make beta increase with measuring time interval, since the variance of the stock market returns is attenuated by the reversal more significantly than the co-movement of returns.

Consider, for example, the autocorrelation coefficient of the all-stocks portfolio (see Figure 1) is negative, increases very quickly and becomes very close to zero over a few lags (days). This implies that covariance between the returns of the market portfolio and the all-stocks portfolio will decrease very quickly as the measuring frequency decreases from very high intraday to daily. The covariance will continue to decrease but at a much slower pace as the frequency continues to decrease from daily to bi-daily and weekly. This decrease is mostly due to a significantly negative autocorrelation of the market portfolio. On the other hand, the variance of the stock market will decrease rather slowly as the data frequency decreases from intraday to daily, and so on. Still, it will decrease faster than the covariance between the all-stocks portfolio and the market portfolio, since the variance is quadratic in the market returns. Taking into account that the portfolio's beta is the ratio of the covariance to the variance, I conclude that the portfolio beta should be increasing as the data frequency goes from daily to bi-daily, and to weekly. Going to the frequency below weekly (bi-weekly and monthly) is less straightforward since the autocorrelation of the stock market becomes mostly positive, starting from the lag of 10 days while the autocorrelation of the all-stocks portfolio becomes negligible. Nonetheless, the variance of the stock market return continues to make a leading impact on the portfolio's beta. Based on a positive autocorrelation for lags in the second week, one would expect a slightly decreasing beta for bi-weekly data. However, the latter is not the case, perhaps due to inconsistency in the autocorrelation coefficient. In the 15 industry portfolios, only beta of the Extractive, Utiulities and Financial Institution industry decrease from bi-weekly to monthly.

Based on the comparison of the autocorrelations and betas for all the portfolios, I can see that the Retail industry portfolio matches best with the all-stocks portfolio in both aspects. The





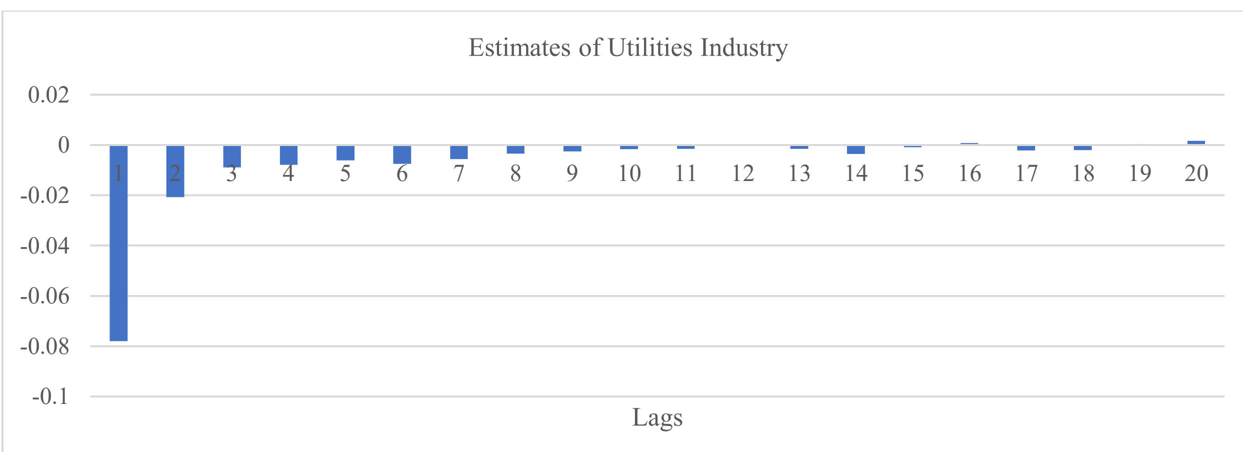


Figure 4. Coefficient estimates of autocorrelation function of three industry portfolios.

This figure contains the estimates of autocorrelation function of the Retail, Computers and Utilities industry portfolios from January 1983 to December 2012.

magnitude and change pattern of its autocorrelation function are almost the same as those of all-stocks portfolio; hence its beta is also nearly the same as the beta for all stocks. Similarly, the Mining, Construction industry portfolio also shows a similar autocorrelation pattern, but it lost significance on positive autocorrelations. This leads to a smaller positive influence on the covariance between the portfolio and the market returns, and its beta with monthly frequency does not increase much from beta with bi-weekly frequency. In addition, I find that the monthly beta of portfolios, which do not have significance in positive autocorrelations, does not increase a lot or barely increase from the bi-weekly frequency beta.

For high-risk sectors, for example, the Computers industry portfolio has higher risk and better liquidity than the all-stocks portfolio. From Table 4, its estimate of lag 5 bounces back with greater magnitude to lag 6 compared to the all-stocks portfolio. It also has more significant positive autocorrelations. Table 6 confirms that it has higher beta and increases more as the frequency decreases. For Insurance, Real Estate industry portfolio, Table 4 shows it has the biggest (absolute in value) estimate of lag 1 and decay much more exponentially than other portfolios. It is the only portfolio that lost significance in both lag 5 and lag 6. However, it bounces back in lag 10 and displays consistent positive significance from lag 10 to lag 14. It has the lowest beta in daily, bi-daily, and weekly frequency and rises sharply from weekly frequency beta to bi-weekly frequency beta.

For low-risk sectors, for example the Utilities industry portfolio, I see from Table 4 that it decays much slower than the autocorrelations of all-stocks portfolios. Also, its autocorrelations are almost negative and only have one significant positive estimate in lag 20. Its beta is relatively small compared to other industry portfolios. Table 6 reveals that the increasing magnitude of its beta is very small and decreases from 0.4674 with bi-weekly frequency to 0.4305 with monthly frequency, which is even smaller than the weekly frequency beta (0.4328).

Overall, findings in this section suggest that beta increases with the frequency interval and is affected by the shape of the autocorrelation function of stock returns due to the short-term reversal of stock returns.

5. Conclusions and Further Research

This thesis shows that the slow-moving capital and the infrequent rebalancing generate a short-term reversal pattern in the autocorrelation function of stock returns. However, the idiosyncratic risk can strongly affect detecting the autocorrelation for individual stocks. And this short-term overreaction in the stock returns leads to a high sensitivity measuring the beta of stock returns. The results display that the stock beta increases with the measuring time interval.

There are two aspects that can be analyzed as further research in this study. In this thesis, I only explore stock portfolios; it would be of interest to see the impact of different data frequencies on the beta of individual stocks. In addition, it would be a trend to use intraday data with higher frequency, such as 1-minute or 5-minute, to investigate how to control the microstructure frictions such as price discreteness and bid-ask bounce, and what is the effect of high frequency trading on the beta of stock returns.

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