Can investor profit from the daily timing strategy? Average Stock Variance and Market Returns

by

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Abstract

This paper discusses the predictability of average stock variance on market returns. We find a statistically and economically significant relation between value-weighted market returns and the pre-determined value-weighted average stock variance. This relation persists after we explore the forecasting power on industry classification portfolios other than the market. Further, we interpret how a timing strategy exploiting its variation successfully avoids loses in contractions. Finally, we provide three possible justifications for the relation between average stock volatility and the stock market return.

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Dedication

To my family.

Chapter 1

Introduction

The risk of a portfolio comprises systematic risk and unsystematic risk (also known as idiosyncratic risk). Systematic risk is the risk common to all securities, and idiosyncratic risk refers to the risk associated with individual assets. Idiosyncratic risk can be diversified away to smaller levels by including a greater number of assets in the portfolio. Thus, most asset pricing model takes into account the asset's sensitivity to non-diversifiable risk, which is systematic risk (Sharpe (1964) and Lintner (1965)). However, some asset pricing models allow for the idiosyncratic risk (Levy (1978), Merton (1987), Malkiel and Xu (1997), Mayers (1976), and Barberis and Huang (2001)). There is an ongoing discussion in the empirical literature about the central implication of the asset pricing models. French et al. (1987) show that the stock market return is related with its own lagged volatility in time-series analysis. Goyal and Santa-Clara (2003) find there is a positive relation between value-weighted average return and lagged equally weighted average volatility using monthly data. This paper presents a challenge to the notion that only systematic risk matters in asset pricing. However, Wei and Zhang (2005) dispute that the positive relationship in Goyal and Santa-Clara (2003) does not translate to economic gains for monthly data. Moreover, a recent study by Chen et al. (2010) assesses the economic significance of the predictive relation using a time-varying strategy that exploits its variation over time at the daily frequency and finds this time-varying strategy significantly outperforms the market buy-and-hold strategy in terms of the mean-variance tradeoff.

In this paper, we follow previous work by Goyal and Santa-Clara (2003) and Chen et al. (2010). First, we discuss the measure of average stock risk at the daily frequency. More specifically, Chen et al. (2010) use daily data from 1926/01/04 to 2008/12/31, while our sample period includes an additional year from 2008/01/01 to 2009/12/31. We see that the period 2008-2009 happens to coincide with a stock market crash in which returns tend to be low and volatilities are high. The occurrence of such a bear market might be rare and the information obtained from the data in the period 2008-2009 is statistically important. The positive and significant relationship between future market returns and average stock volatility found by Chen et al.,(2010) shows up in the extended sample period (2008-2009) and in our entire sample period (1926/01/04 - 2009/12/31). We then provide details on further robustness checks and find our results based on daily data are significantly robust.

In the second part, we test the rolling-window timing strategy (Chen et al. (2010)) for four most recent business cycles. At day t, the timing strategy invests all in the stock index if the forecasted market return for day t+1 is positive, and otherwise they invest all in Treasury Bills. For each future day t+1 the forecasts are based on the estimated coefficients from a regression of the value-weighted average return on the lagged value-weighted average variance using the 60 daily observations between days t and t-59 (Chen et al. (2010)). They refer to such trading strategy as "rolling-window timing strategy". Our results illustrate how the strategy switches between the stock index and the Treasury Bills and indicate such strategy performs dramatically better than the market buy-and-hold strategy for contractions. We further explore the forecasting power of rolling-window timing strategy on the industry classification portfolios other than the market. The results show both the statistical and economical significances of the relation between average variance and future returns hold on five industry portfolios. Also, the rolling-window timing strategy dramatically outperforms the market buy-and-hold strategy for all the five portfolios. Moreover, we carry out the exercise for IBM stock and find the results are consistent with those on portfolio 3 which includes IBM stock according to the industry classification.

Finally, we focus on the possible justifications for the positive and significant relation between average stock volatility and further market returns. One possible explanation for our findings is that the instability in the economy's fundamentals is a key source of time-series variation in the parameters of the market return process (Chen et al. (2010)). Thus, the rolling-window timing strategy is potentially capable to capture the time-series variation due to changes in macroeconomic conditions in the predictive relation. Further, we discuss the coexistence of high prices and high price volatility. Scheinkman and Xiong (2003) propose a model of asset trading, based on heterogeneous beliefs generated by agents' overconfidence. They conclude that bubbles are accompanied by large trading volume and high price volatility in equilibrium. As the volatility of the assets increases, the value of the equity goes up at the expense of the debt holders, if we think of the equity in a firm as a call option on the value of the firm's assets

(Goyal and Santa-Clara (2003)). Also, we dispute that average stock variance is a measured variable used to infer the background risk, and affect the risk aversion of investors towards traded assets. We show that our findings are consistent with models based on investor heterogeneity.

The plan of this paper is as follows. In Section I, we first discuss the measure of average stock variance at the daily frequency. We then document the predictability of time-series variation between market returns and average stock volatility and provide details on robustness checks. A discussion of our research design follows in Section II. We examine the impact of average stock variance on further market returns during business cycles and construct portfolios according to the industry classification. To assess the economic significance of the predictability of stock returns we examine regressions that incorporate for time-series variation in the coefficients of the predictive model. Section III focuses on the paper with some possible justifications for the impact of average stock volatility on stock returns. Finally, it is the conclusion.

Chapter 2

Measure of Risk and Robustness Checks

In this section, we introduce our measure of average stock variance at daily frequency and investigate their relation to the market return. We find that there is a statistically significant positive relationship between average stock variance and further market returns.

2.1 Measure of Risk

As noted in Goyal and Santa-Clara (2003), the variance of a stock on day t can be estimated as the squared value of the realized return of that stock on that day. Then, the value-weighted average variance for date t is calculated. Denoted by AV_{pt} for portfolio *p*, this variance is given by:

$$AV_{pt}^{vw} = \sum_{i=1}^{N_{pt}} \lambda_{it} r_{it}^2 \tag{1}$$

where

λ_{it} = the market value of equity for firm *i* as of the close of trading on date *t* divided by the aggregate market capitalization of all firms in portfolio *p* as of the close of trading on that date,

r_{it} = the realized return of stock *i* on date *t*, and

N_{pt} = the number of firms in portfolio *p* at the close of trading on date *t*.

The reason we value weight rather than equally weight the stocks in each portfolio is that a value weighting allows us to better capture the economic significance of our results, as the individual returns of the larger and more important firms will be more heavily represented in the aggregate return than will those of the smaller firms. Note that when we estimate σ_{it}^2 for each stock using r_{it}^2, we do not demean r_{it} before computing its squared value, and thus avoid estimating μ_{it}.

However, for one day holding period, the impact of subtracting the mean return of the day is minimal. Also, French et al. (1987) and Schwert (1989) find that the squared mean term is irrelevant to calculate variances in daily data.

To better understand the value-weighted average stock variance, following Goyal and Santa-Clara (2003) we assume that the daily returns of each stock are driven by a common factor f and a firm-specific shock ε_{it}. The daily returns are generated by:

$$r_{it} = f_t + \varepsilon_{it} \tag{2}$$

Assume further that the idiosyncratic shocks and the factor shocks are uncorrelated, and that the factor loading for each stock is equal to one. Also, assume that f is normally distributed with mean μ_f and variance σ_f^2, and that ε_{it} is i.i.d. with mean zero and variance σ_ε^2. Those imply that:

$$AV_{pt} = f_t^2 + 2 f_t \sum_{i=1}^{N_{pt}} \lambda_{it}\varepsilon_{it} + \sum_{i=1}^{N_{pt}} \lambda_{it}\varepsilon_{it}^2 \tag{3}$$

$$EV\left(AV_{pt}\right) = \mu_f^2 + \sigma_f^2 + \sigma_\varepsilon^2 \tag{4}$$

$$Var\left(AV_{pt}\right) = 2\sigma_f^2\left(\mu_f^2 + \sigma_f^2\right) + 4A_p\left(\mu_f^2 + \sigma_f^2\right)\sigma_\varepsilon^2 + 2A_p\sigma_\varepsilon^4 \tag{5}$$

where $A_p = \sum_{i=1}^{N_{pt}} \lambda_{it}^2$.

As discussed in Chen et al. (2010), using the same measure of the average stock variance, the idiosyncratic risk constitutes about 90% of the average variance measure and the average variance is measured precisely. Thus, the precision in the measure AV makes it a better variable to use in predictive regressions of the market return.

2.2 Data and Robustness Checks

We compute the value-weighted variance using Center for Research in Security Prices (CRSP) data for the period January 4th, 1926 to December 31st, 2009. We use all the stocks which have a valid return on date t and a valid market capitalization on that day. The value-weighted return on date t, R_t^{vw} is the daily return including all distributions on a value-weighted market portfolio (excluding American Depository Receipts (ADRs)). The main predictor, the value-weighted average stock variance AV_t^{vw}, is defined previously.

To determine whether the average stock volatility can predict the market return, we begin with a simple regression of the expected return conditional on the lagged value-weighted average stock variance. We estimate the following daily time-series regressions:

$$R_t^{VW} = \alpha + \beta AV_{t-1}^{VW} + \varepsilon_t \tag{6}$$

where

R_t^{vw} = the value-weighted market return on date *t*, and

V_{t-1}^{vw} = the value-weighted average stock variance on date *t-1*.

This test yields parameter estimates of α and β.

Second, we employ three more robustness tests using the log value-weighted market return instead of the value-weighted market return and the log value-weighted average stock variance instead of the value-weighted average stock variance. To evaluate the predictive performance of the value-weighted average stock variance, we estimate the following daily time-series regressions:

$$log(1+R_t^{VW}) = \alpha + \beta AV_{t-1}^{VW} + \varepsilon_t \tag{7}$$

$$R_t^{VW} = \alpha + \beta log(AV_{t-1}^{VW}) + \varepsilon_t \tag{8}$$

$$log(1+R_t^{VW}) = \alpha + \beta log(AV_{t-1}^{VW}) + \varepsilon_t . \tag{9}$$

Table I provides the results of ordinary least squares (OLS) estimates of equation (6),(7),(8) and (9) for the full sample period from January 4th, 1926 to December 31st, 2009 . Throughout our analysis, the t-statistics reported in parenthesis are adjusted for autocorrelation and heteroskedasticity using the Newey-West (1987) correction based on one hundred and twenty lags (the daily equivalent of six months). Panel A presents the results using the value-weighted market return and lagged value-weighted average stock variance, Panel B presents the results using the log value-weighted market return and lagged value-weighted average stock variance, Panel C points out the results using the value-weighted market return and log lagged value-weighted average stock variance and Panel D shows the using the log value-weighted market return and lagged log value-weighted average stock variance. Both Panel A and Panel B show that there is a positive and significant relation between value-weighted average variance and further market returns. The estimated coefficient in Panel A is 0.563 and the t-stat is 4.61, while the estimated coefficient in Panel B is 0.484and the t-stat is 4.05. This suggests that log-normal distribution of return does not affect the relation between returns and variance. The R squared of the regression in Panel A and B are 0.24% and 0.18%, respectively, indicating that the value-weighted average variance can predict further market returns well. However, the estimated coefficients in Panel C and Panel D are insignificant, reflecting that the lagged log value-weighted average variance has no predictive power on further market returns.

Table I

Forecasts of Value-Weighted Portfolio Returns Based on the Measure of Average Volatility at daily frequency

This table presents the results of a one-day ahead predictive regression of value-weighted portfolio returns on lagged explanatory variables for the sample period 1926/01/04-2009/12/31. AV^{vw} is the value-weighted average variance and R^{vw} is the value-weighted stock market index return . AV^{vw} is calculated using CRSP daily data for the sample period 1926/01/04-2009/12/31. The first row in each regression is the coefficient, the second row is the Newey-West (1987) adjusted t-statistic based on one hundred and twenty lags.

Panel A: Using R^{vw} and AV^{vw}

Sample Period	Intercept	AV_{t-1}^{vw}	R^2	Obs.
1926/01/04-2009/12/31	0.000	0.563	0.24%	22,126
	(1.43)	(4.61)		

Panel B: Using $\log(1+R^{vw})$ and AV^{vw}

Sample Period	Intercept	AV_{t-1}^{vw}	R^2	Obs.
1926/01/04-2009/12/31	0.000	0.484	0.18%	22,126
	(1.24)	(4.05)		

Panel C: Using R^{vw} and $\log(AV^{vw})$

Sample Period	Intercept	$\log(AV_{t-1}^{vw})$	R^2	Obs.
1926/01/04-2009/12/31	0.002	0.000	0.02%	22,126
	(1.69)	(1.46)		

Panel D: Using $\log(1+R^{vw})$ and $\log(AV^{vw})$

Sample Period	Intercept	$\log(AV_{t-1}^{vw})$	R^2	Obs.
1926/01/04-2009/12/31	0.003	0.000	0.05%	22,126
	(2.33)	(2.08)		

Chapter 3

A Time-Series Trading Strategy

3.1 Trading Strategies

Evidence that the pre-determined value-weighted average variance is statistical robust positive related with further market returns implies that a profitable trading strategy incorporating the information of stock volatility may exist. First, we discuss the predictability under the assumption of a time-invariant relation. In Goyal and Santa-Clara (2003), they examine a trading strategy based on out-of sample forecasts of the value-weighted market return for monthly data. At time t, the trading strategy invests all in the stock index if the forecasted excess return of stocks over the risk free rate is greater than zero; otherwise it invests all in Treasury bills. The forecasts are based on a regression using all the available data up to time t,

$$\hat{R}_{t+1}^{VW} = \hat{\alpha} + \hat{\beta} AV_t^{VW} \tag{10}$$

The parameters are re-estimated every month, which allows for 60 months in the estimation of the first forecasting regression. Also, Chen et al. (2010) test the same trading strategy for daily data and allow for 60 prior days in the estimation of the first forecasting regression. Both of their findings show that the lagged variance of the market has no profitable forecasting power for the market return and suggest the possibility that the predictability relation may vary over time. For this purpose, a rolling-window timing strategy based on out-of-sample forecasts of the value-weighted market return is developed in Chen et al. (2010). At day t the timing strategy invests all in the stock index if the forecasted market return for day t+1 is positive, and otherwise they invest all in Treasury Bills. For day t+1, the forecasts are based on the estimated coefficients from a regression of the value-weighted average return on the lagged value-weighted average variance using the 60 daily observations between days t and t-59. The parameters are re-estimated every day during the sample period from 1926/07/01 to 2008/12/31 (we update the sample period to 2009/12/31 in this paper), which allows for 60 prior days in the estimation of the first forecasting regression. This generates an estimated coefficient on value-weighted average stock variance every day. Then, we obtain a time series of return to the rolling window timing strategy.

Table II

Rolling-Window Timing Strategy Based on Return Forecasts

This table presents descriptive statistics of a rolling-window timing strategy based on out-of-sample forecasts of the value-weighted market return. At time t, the trading strategy invests all in the stock index if the forecasted market return is greater than zero; otherwise it invests all in Treasury bills. The sample period is from 1926/01/04 to 2009/12/31. However, the forecasting exercise starts in 1926/07/01, to allow for 60 daily observations between days t and t-59 in the estimation of the forecasting regression. The parameters are then re-estimated every day. The mean and standard deviation are annualized. N is the number of days the rolling-window timing strategy is invested in the market portfolio.

Strategy	Mean	Std. Dev.	N	Sharpe Ratio
MBHS	10.08%	16.82%	22,093	0.392
RWTS	11.62%	11.02%	13,968	0.754

Table II presents the annualized mean and standard deviation for the market buy-and-hold strategy (MBHS) and the rolling-window timing strategy (RWTS). The rolling-window timing strategy with a mean return 11.62% of and standard deviation of 11.02% outperforms the market buy-and-hold strategy, which has a mean return of 10.08% and standard deviation of 16.82% annually. This result is similar to that in Chen et al. (2010). The evidence suggests that pre-determined the average stock variance has significant ability to forecast market return under the assumption of a time-variant predictive model.

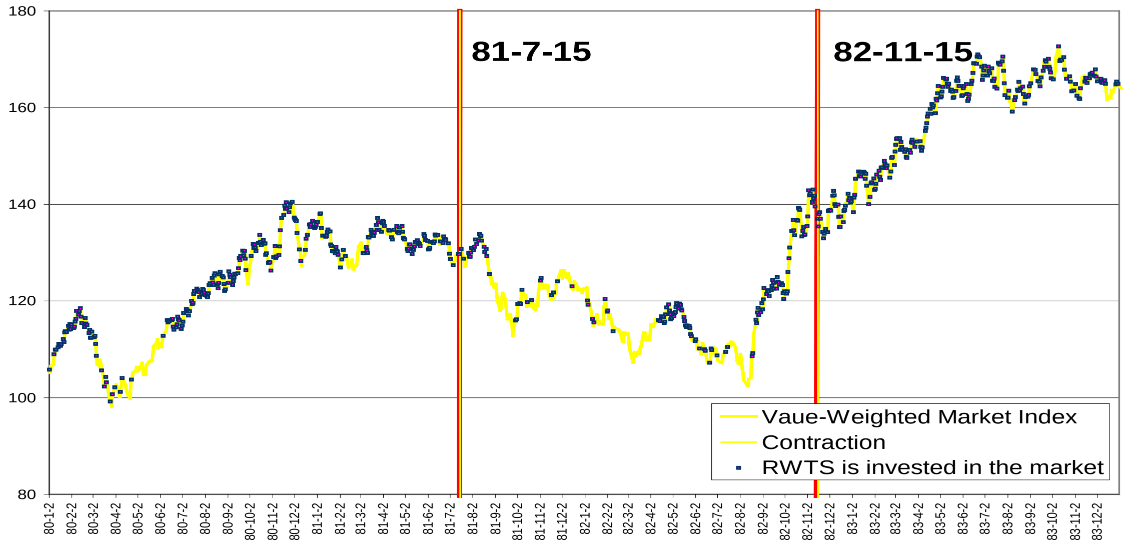
3.2 Business Cycles

The rolling-window timing strategy invests in the market for ^^ out of ^^ trading days. We explore market buy-and-hold strategy, which always invests in the stock index during the entire sample period from 1926/07/01 to 2009/12/31. One might conjecture that the rolling-window timing strategy avoids bad times, as it exits the stock market and invests in Treasury bills when the forecasted excess return of stocks over the risk free rate is less than zero. This is consistent with the conventional wisdom that bad news travels slowly. Think of a firm which is sitting on good news. To the extent that its managers prefer higher to lower stock prices, they will push the news out the door themselves. On the other hand, if the same firm is sitting on bad news, its managers will have much less incentive to bring investors up to date quickly(Hong et al. (2000)). Thus the marginal contribution of average stock volatility in getting the news out is likely to be greater when the news is bad. We examine the rolling-window strategy for the four business-cycle contractions reported by NBER to illustrate how the strategy avoids recessions and how this affects its return.

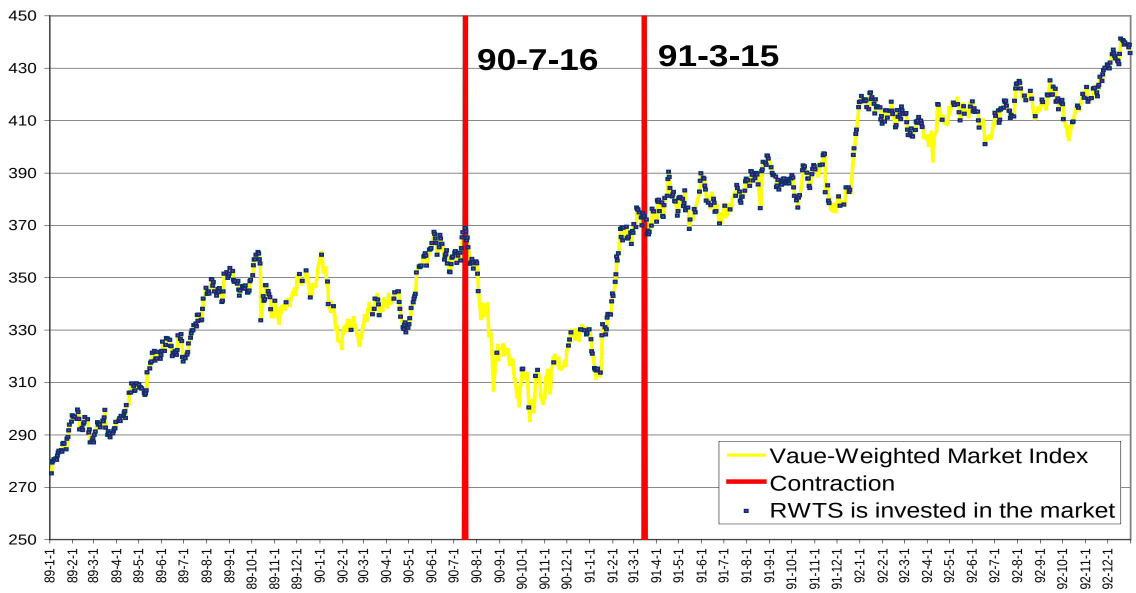
Figure I

Daily loading of Rolling-Window Timing Strategy on the Market over the Contraction Periods dated by the NBER

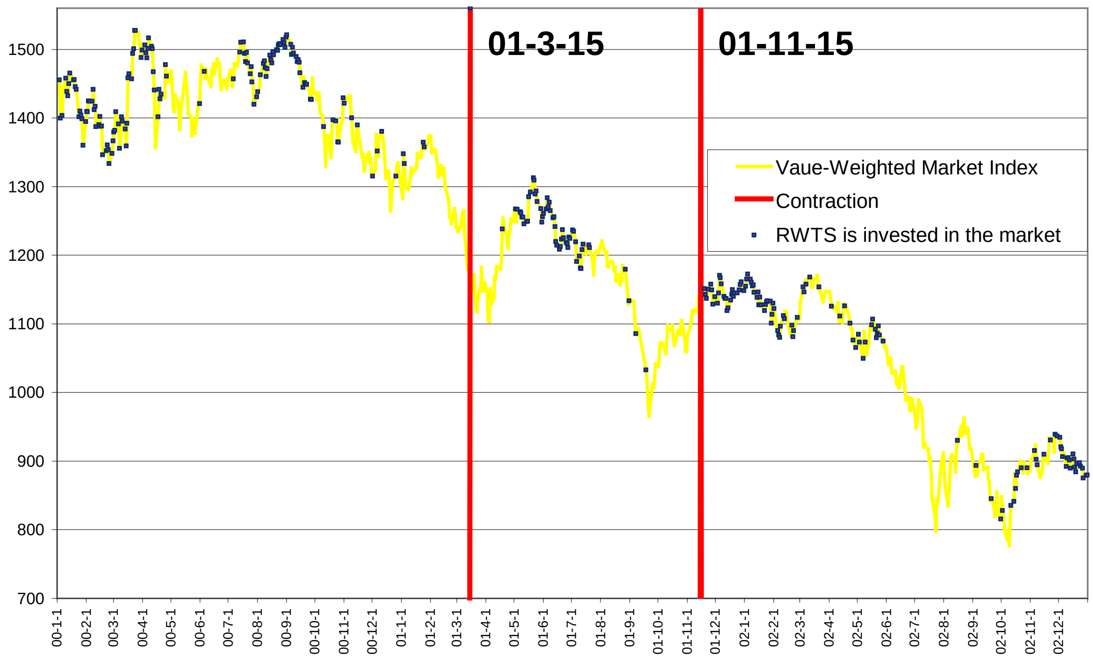
Panel A: Sample Period 1980-1983



Panel B: Sample Period 1989-1992



Panel C: Sample Period 2000-2002



Panel D: Sample Period 2007-2009

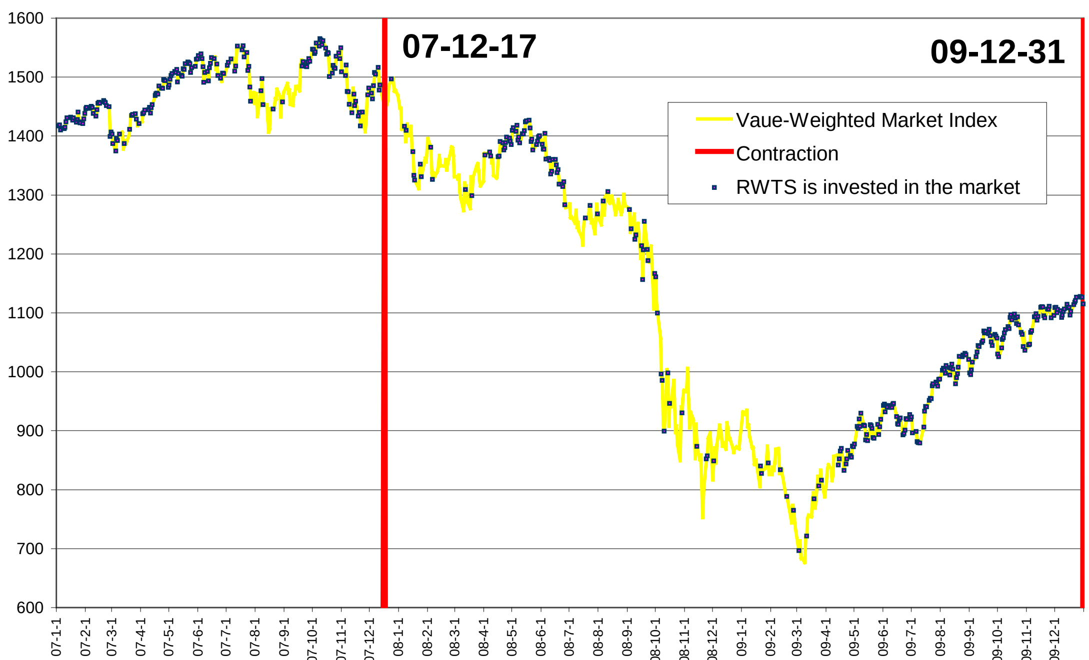


Figure I plots the daily value-weighted stock market index in yellow; the dark dots represent that the investor is in the market at that time following a rolling-window timing strategy. The period between two red lines indicates the market is in contraction. The time line is centered on the recession periods, those are, July 1981-Nov 1982, July 1990- Mar 1991, Mar 2001- Nov 2001 and Dec 2007- Dec 2009, respectively. We can see that the strategy invests in the market before the recession, switches to the risk free asset when (Panel C and D) the recession starts or almost 15 days later (Panel A and B) and then switches back to the market index when the expansion starts.

To investigate the predictability of the average variance over the business cycle, in Table II we examine how our trading strategy based on forecasting coefficients that vary daily performs in contractions. The results show that the rolling-window timing strategy has dramatically higher means and Sharpe ratios as well as lower deviations comparing to the market buy-and-hold strategy. For example, during the most recent contraction (Dec 2007 to Dec 2009), the trading strategy attaining a mean of +6.07% and a Sharpe ratio of +0.259 dramatically outperforms the market buy-and-hold strategy (which has a mean of -4.20% and a Sharpe ratio of -0.163). Our results are similar as those obtained by Chen et al. (2010), where they take all the contractions and expansions in history as two separated samples. They find during business-cycle expansions the rolling-window timing strategy still outperforms the market buy-and-hold strategy, but the difference in performance is significantly lower. Thus, we can generate the conclusion the rolling-window strategy significantly more profitable than the market buy-and-hold strategy based on the results from Chen et al. (2010) and our Table II.

Table II

Rolling-Window Timing Strategy Based on Four Recent Contractions

This table presents descriptive statistics of a rolling-window timing strategy based on out-of-sample forecasts of the value-weighted market return. At time t, the trading strategy invests all in the stock index if the forecasted market return is greater than zero; otherwise it invests all in Treasury bills. The sample period is from 1926/01/04 to 2009/12/31, However, the forecasting exercise starts in 1926/07/01, to allow for 60 daily observations between days t and t-59 in the estimation of the forecasting regression. The parameters are then re-estimated every day. The mean and standard deviation are annualized. N is the number of days the rolling-window timing strategy is invested in the market portfolio. The sample periods are dated by the NBER.

Contraction Period		Mean	Std. Dev	N	Sharpe Ratio
July 1981-Nov 1982	MBHS	9.51%	15.68%	359	-0.113
	RWTS	21.19%	11.45%	164	0.863
July 1990- Mar 1991	MBHS	10.47%	16.32%	188	0.217
	RWTS	25.97%	10.49%	98	1.815
Mar 2001- Nov 2001	MBHS	-6.99%	22.13%	188	-0.478
	RWTS	1.02%	10.41%	64	-0.247
Dec 2007- Dec 2009	MBHS	-4.20%	34.23%	525	-0.163
	RWTS	6.07%	18.17%	291	0.259

3.3 Sorted Portfolios by the Industry Classification

We further explore the forecasting power of our trading strategy on portfolios other than the market. We use five portfolios sorted by the industry classification and assign each NYSE, AMEX, and NASDAQ stock to an industry portfolio at the end of June of year t based on its four-digit SIC code at that time.[1] The first portfolio consists of the companies in the field of Consumer Durables, NonDurables, Wholesale, Retail, and Some Services (Laundries, Repair Shops). The Manufacturing, Energy, and Utilities companies are placed into the second portfolio. The third portfolio contains Business Equipment, Telephone and Television Transmission, Healthcare, Medical Equipment, and Drugs companies. The fifth one includes all the other companies, which are Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment and Finance. To test how the rolling-window timing strategy performs among the five industry portfolios, we report the results of the forecasting regression of the market return conditional on lagged value-weighted average stock variance on Portfolio *i* during the full sample period from 1926/07/01 to 2009/12/31. Notice that we calculate the value-weighted average stock variance based on the stocks included by Portfolio *i* other than the stocks in the market. Table III reports that, for all the five portfolios, there is a highly significant positive impact of average variance on future returns (the estimated coefficients are all positive ranging from +0.372 for Portfolio 3 to0.725 for Portfolio 1, and the t-stat is significant between a low of 1.90 for Portfolio 4and a high of 4.89 for Portfolio 2), where the average portfolio variance is obtained by the stocks within a specific industry classification portfolio. The results interpret the statistical significant relation between pre-determined average industry classification portfolio variance and market returns.

[1] We follow the industry definition from Fama French's web site http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Table III

Forecasts of Value-Weighted Portfolio Returns Based on the Measure of Average Volatility for five Industry Classification Portfolios

This table presents the results of a one-day ahead predictive regression of value-weighted stock returns on lagged explanatory variables for the industry classification portfolio variance during the sample period 1926/01/04-2009/12/31. AV_i^{vw} is the value-weighted average variance of portfolio i and R^{vw} is the value-weighted stock market index return . $AV_{p_i t}^{vw}$ is calculated using CRSP daily data for the sample period 1926/01/04-2009/12/31 for each industry classification portfolio . The first row in each regression is the coefficient, the second row is the Newey-West (1987) adjusted t-statistic based on one hundred and twenty lags.

Panel A: Regression on Portfolio 1

Sample Period	Intercept	$AV_{p_1 t-1}^{vw}$	R^2	Obs.
1926/01/04-2009/12/31	0.000	0.725	0.25%	22,126
	(0.89)	(3.07)		

Panel B: Regression on Portfolio 2

Sample Period	Intercept	$AV_{p_2 t-1}^{vw}$	R^2	Obs.
1926/01/04-2009/12/31	0.000	0.384	0.22%	22,126
	(2.53)	(4.89)		

Panel C: Regression on Portfolio 3

Sample Period	Intercept	$AV_{p_3 t-1}^{vw}$	R^2	Obs.
1926/01/04-2009/12/31	0.000	0.372	0.09%	22,126
	(2.51)	(2.74)		

Panel A: Regression on Portfolio 4

Sample Period	Intercept	$AV_{p_4 t-1}^{vw}$	R^2	Obs.
1926/01/04-2009/12/31	0.000	0.396	0.12%	22,126
	(1.66)	(1.90)		

Panel A: Regression on Portfolio 5

Sample Period	Intercept	$AV_{p_5 t-1}^{vw}$	R^2	Obs.
1926/01/04-2009/12/31	0.000	0.410	0.16%	22,126
	(1.75)	(3.31)		

In every case of the five industry portfolios, table IV reports the annualized mean and standard deviation for the market buy-and-hold strategy (MBHS) and the rolling-window timing strategy (RWTS), the number of days each strategy invests in the market portfolio (N), and the corresponding Sharpe ratios. The rolling-window timing strategy has a mean return varying from a high of 11.76% for Portfolio 4 and a low of 10.75% for Portfolio 1. The standard deviation ranges from 10.98% for Portfolio 3 to 11.19% for Portfolio 2 annually, with a Sharpe ratio of 0.658 for Portfolio 2 to 0.752 for Portfolio 4 (the lowest value of which is almost twice the Sharpe ratio of the market buy-and-hold strategy (0.392)). The key result in the table is that both the statistical and economical significances of the relation between average variance and future returns are holding for five industry classification portfolios. Thus, the rolling-window timing strategy intensely outperforms the market buy-and-hold strategy even for the industry sorted portfolios.

Table IV

Rolling-Window Timing Strategy for Portfolios Sorted by the Industry Classification

This table presents descriptive statistics of a rolling-window timing strategy based on Portfolios Sorted by the Industry Classification. At time t, the trading strategy invests all in the stock index if the forecasted market return is greater than zero; otherwise it invests all in Treasury bills. The forecasting exercise allows for 60 daily observations between days t and t-59 in the estimation of the forecasting regression. The parameters are then re-estimated every day. The mean and standard deviation are annualized. N is the number of days the rolling-window timing strategy is invested in the market portfolio.

Sample Period: 1926/07/01 to 2009/12/31

	Mean	Std. Dev	N	Sharpe Ratio
MBHS	10.08%	16.82%	22,093	0.392
RWTS on Portfolio 1	10.75%	11.02%	14,098	0.667
RWTS on Portfolio 2	10.77%	11.19%	14,056	0.658
RWTS on Portfolio 3	11.28%	10.98%	14,118	0.718
RWTS on Portfolio 4	11.76%	11.11%	14,271	0.752
RWTS on Portfolio 5	11.49%	11.06%	14,081	0.731

3.4 Individual Stocks

We also carry out the exercise for an individual stock, for example IBM stock, which is included in Portfolio 3 as sorted by the industry classification in previous section. We choose IBM stock as a representative of individual stocks, as it is a large and important firm with data source available for the same sample period from 1926/07/01 to 2009/12/31. We then calculate the performance of the rolling-window timing strategy described above for stock IBM over the entire sample period. It has a mean return of 11.99% and a standard deviation of 11.27%, with a

Sharpe ratio of 0.421. Comparing these numbers with those in Table II, we obtain similar results as those of Portfolio 3. Thus, the rolling-window timing strategy for stock IBM outperforms the market buy-and-hold strategy for an individual stock. In Chapter I, we discuss that the measure of average stock variance, we defined, largely captures idiosyncratic risk, which is the company specific risk and cannot be diversified for a single stock. Our results for IBM stock are consistent with the issue that idiosyncratic risk matters (Goyal and Santa-Clara (2003)). Further research that accounts for this time-series variation can be developed for more individual stocks and portfolios sorted by book-to-market and size, etc.

Table V

Rolling-Window Timing Strategy for IBM Stock

This table presents descriptive statistics of a rolling-window timing strategy based on IBM Stock by the Industry Classification. At time t, the trading strategy invests all in the stock index if the forecasted market return is greater than zero; otherwise it invests all in Treasury bills. The forecasting exercise allows for 60 daily observations between days t and t-59 in the estimation of the forecasting regression. The parameters are then re-estimated every day. The mean and standard deviation are annualized. N is the number of days the rolling-window timing strategy is invested in the market portfolio.

Sample Period: 1926/07/04 to 2009/12/31

	Mean	Std. Dev	N	Sharpe Ratio
RWTS for IBM Stock	11.99%	11.27%	14,314	0.421
MBHS for IBM Stock	10.08%	16.82%	22,093	0.392

Chapter 4

Possible Justifications for the Relation between Average Stock Volatility and the Stock Market Return

4.1 Macroeconomics Conditions

The rolling-window timing strategy exploits the time-series variation in the predictive relation between average stock variance and future market returns. Why the relation varies over time is discussed in Chen et al.(2010)). Their explanation is that the instability in the economy's fundamentals is a key source of time-series variation in the parameters of the market return process. They develop a fictitious "two-state full information timing strategy", in which, the investor distinguishes the economy state as a recession or an expansion. Then, they predict the market return one day ahead using the estimated coefficients generated by regressing the market return on pre-determined average stock variance for all the recessions and expansions periods. According to their results, the two-state full information timing strategy performs much stronger in bad times than in good times. Thus, they suggest changes in macroeconomic conditions are a major factor incorporating the information of the time-series variation in the predictive relation. It is consistent with our results for business cycle reported in Table II. In sum, the rolling-window timing strategy is potentially capable to capture the time-series variation due to changes in macroeconomic conditions.

4.2 Volatility of Assets and Speculative Bubbles

The average stock volatility is a key predictor in the rolling-window timing strategy. We find the market return (which contains all the daily returns) is correlated with pre-determined average stock variance with a positive estimated value of 0.562 and a significant t-stat of 4.61 according to table I. We raise the question how this correlation exists. We think of the equity in a firm as a call option on the value of the firm's assets (Black and Scholes (1973) and Merton (1974)). Then, the value of the equity for the debt holders has a positive correlation with the volatility of the assets. We argue the relation between average stock variance and market return may follow from this idea since average stock variance mostly reflects the variance of the assets (Goyal and Santa-Clara (2003)). Also, Scheinkman and Xiong (2003) propose a model of asset trading based on heterogeneous beliefs generated by agents' overconfidence. They find bubbles are accompanied by large trading volume and high price volatility in equilibrium, which is an evidence for the coexistence of high prices and high price volatility.

4.3 Non-Traded Assets and Idiosyncratic Risk

Since the measures of average stock variance largely capture idiosyncratic risk. We examine the relation between asset prices and idiosyncratic risk rather than average stock variance. Some theoretical models including considerations of non-traded assets, human capital and idiosyncratic income shocks are potential drivers of the positive significant relationship between the average return and the average volatility reported in Table I (Wei and Zhang (2005)). For an investor, holding non-traded assets adds background risk to their traded portfolio decisions. A tradeoff between market returns and average stock risk can be generated if the riskiness of non-traded assets is related to the total risk of individual stocks (Goyal and Santa-Clara (2003)). The two widely studied prominent examples of non traded assets are human capital and private businesses. By Storesletten et al. (2001), the idiosyncratic risk in labor income helps to explain equity returns. Also, Constantines and Duffie (1996) show that for idiosyncratic income shocks are highly persistent and become more volatile during economic contractions. Our results in Table II are consistent with that conclusion.

Chapter 5

Conclusion

This paper is an extension research based on the author's paper "Average Stock Variance and Market Returns: Evidence of Time-Varying Predictability at the Daily Frequency" (Chen et al. (2010)). We follow the risk measure in Goyal and Santa-Clara (2003) and show that the lagged variance of the market has forecasting power for the market return by expanding the sample period to the year 2009, when a worldwide economic crash and economic depression occurred. Based on the "a rolling-window timing strategy" developed by (Chen et al. (2010), we interpret how such a strategy successfully avoids loses during contractions. We further explore the forecasting power of average variance of industry classification portfolios other than the market and find the time-series relation between average stock risk and the market return is statistically and economically significant. The results from examining the performance of "rolling-window timing strategy" on a single stock chosen from one of the industry classification portfolios support the relation in an economic perspective.

Finally, we argue the possible justifications for the relation between average stock volatility and the stock market return in three points of view. First, we suggest the variation is partially caused by changes in macroeconomic conditions over time. Second, we show that our results are consistent with capital structure models from an option perspective. Third, we discuss idiosyncratic income shocks are possible drivers of the positive significant relationship between the average return and the average volatility.

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