The Predictability of Low Frequency Volatilities Measures: Evidence from Hong Kong Stock Markets

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This draft on 24th May, 2017[1]

[1] We wish to thank FAN, Xinyan for her excellent research assistant.

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Abstract

We employ low frequency data and long estimation horizon to estimate *realized volatility* measures for Hong Kong stocks and examine the relationship between our *realized volatility* measures and the expected stock returns over the period from 1980 to 2015. First, we find that only long-term idiosyncratic volatility (IV^{Long}) is consistently negatively related to the expected stock returns. Second, we create a long-term MAX (MAX^{Long}) measure, which is the maximum weekly return for a stock in the past three-years. We show that the MAX^{Long} is negatively related to the subsequent stock returns over the study period. More importantly, we find both IV^{Long} and MAX^{Long} co-exist in the Hong Kong stock markets. Finally, the negative relationship between the IV^{Long} and expected stock returns is also robust when we control for the effect of financial crisis, January effect, and tiny stock effect. Our results contribute to the literature by showing that the relationship between volatility measures and expected stock returns is sensitive to changes in data frequency and the estimation horizon for *realized volatilities*.

JEL Classification: **G11, G12**

Keywords: total volatility, idiosyncratic volatility, maximum weekly returns, asset pricing, weekly data, Hong Kong stock markets

1. Introduction

A growing literature in finance examines the relationship between the realized volatility measures and expected stock returns in global stock markets. Ang, Hodrick, Xing and Zhang (2006, 2009) present a new anomaly in the U.S. and other 23 developed stock markets, called the 'idiosyncratic volatility puzzle' (hereafter *IV puzzle*). They find that expected stock return is negatively related to idiosyncratic risk, measured by idiosyncratic volatility (hereafter IV). Ang et al.'s (2006, 2009) findings go against traditional finance theory which posits that high risk should be rewarded by high return. Recent studies show that the predictability of IV is related to the level of diversification of an investor's portfolio. If the number of stocks in an investor's portfolio is less than 30, then the investor would demand an IV premium[2] (Stateman, 1987; Campbell et al., 2001; Kearney and Potì, 2008; Miffre et al., 2013).

The empirical results on the relationship between IV and cross-sectional expected stock return is still mixed in two streams of studies. The first stream relates *expected volatility* to realized return, and find that expected IV is positively related to realized return (Malkiel & Xu, 2006; Fu, 2009; Bradrania et al., 2015). These studies use long term data (i.e. monthly returns) to estimate expected IV. The second stream of studies examines the relationship between *realized volatility* and expected stock return, and find that *realized volatility* is negatively related to expected stock return (Ang et al.,

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[2] Campbell et al. (2001) suggest that a well-diversified portfolio in the U.S. stock markets should contain 50 randomly selected stocks. Kearney and Potì (2008) indicate that the number of stocks in a fully diversified portfolio in European stock markets increased from 35 stock in 1974 to 166 stocks in 2003.

2006, 2009). These studies use short run daily return data to estimate *realized volatility*. However, findings in the second stream of studies are challenged by other researchers. For example, both Bali and Cakici (2008) and Fu (2009) argue that the *IV puzzle* is impacted by the data frequency in estimating IV. Khovansky and Zhylyevskyy (2013) empirically find that the sign of the IV coefficient alters with changes in data frequency in estimating IV, such as using daily, monthly, quarterly and annual data to compute IV for the U.S. stocks for the period 2000 to 2011.

Many researchers have attempted to explain the *IV puzzle* from a variety of economic mechanisms linking IV to expected stock returns. The literature classifies these explanations into three categories (Hou and Loh, 2012). The first category relates the *IV puzzle* to investors' lottery preferences, and several proxies are proposed for a stock's lottery features, such as maximum daily returns and skewness, among others (Barberis and Huang, 2008; Boyer et al., 2010; Bali et al., 2011). The second category states that the *IV puzzle* is caused by various market frictions, such as one-month return reversal, illiquidity and other variables (Bali and Cakici, 2008; Boehme et al., 2009; Fu, 2009; Huang et al., 2010; Han and Lesmond, 2011; Bradrania et al., 2015). The last category argues that the *IV puzzle* is caused by leverage, growth options, financial distress and the variables that are excluded from the previous two categories (Johnson, 2004; Cao et al., 2008; Avramov et al., 2013; Kryzanowski and Mohsni, 2015).

Bali et al. (2011) suggest a significant negative MAX effect in the U.S. stock markets. They find that the MAX effect is the true effect in the U.S. stock markets, and that the idiosyncratic volatility effect is just a proxy of the MAX effect, which is supported by Annaert et al.'s (2013) evidence in the European stock markets and Chan and Chui's (2016) findings in the HK stock markets. However, Bali et al.'s (2011) findings are not supported by other empirical evidence in either developed or emerging stock markets. For example, Aboulamer and Kryzanowski (2016) find that the MAX effect cannot drive out the idiosyncratic volatility effect in the Canadian stock market over the period from 1975 to 2012. In emerging stock markets, Nartea et al. (2017) find that the negative MAX and the idiosyncratic volatility effect co-exist in the China stock markets, supported by Nartea et al.'s (2013) findings in the South Korean stock market. In this paper we examine if the intermediate- and long-term realized volatility measures are also the proxies of the MAX estimated from a long horizon.

Blitz and van Vliet (2007) also find that expected stock returns are negatively related to firms' total volatilities (hereafter TV) in the US, European and Japanese stock markets between 1986 to 2006 and in 30 emerging stock markets for the period 1988 to 2010 (Blitz et al., 2013). They called this as the '*total volatility puzzle*' (thereafter *TV puzzle*), where TV is measured by the standard deviation of past returns. Blitz and van Vliet (2007) further find that the total volatility effect is even stronger than beta when estimated by the capital asset pricing model (CAPM). Thus, when using TV instead of beta to measure risk, the negative relationship between risk and return is even stronger (Blitz et al., 2013). This is well documented by Baker, Bradley and Wurgler (2011) for the US stock markets for the period 1968 to 2008.

Our study attempts to answer two questions using low frequency data (weekly return data) and longer estimation horizon to compute *realized volatility* measures (both TV and IV) for HK stocks for the period 1980 to 2015. First, is there a *IV/TV puzzle* in the HK stock market? Second, does the *IV/TV puzzle* still exists in the HK stock markets after controlling for MAX.

Our study differs from previous studies in several ways. First, we use weekly stock return data to estimate *realized* TV/IV in terms of expected stock returns for HK stocks. Lewis (2006) suggests that the relationship between risk and return changes with the use of weekly stock return data rather than monthly data. The use of weekly stock return data in estimating *realized* TV/IV offers two benefits. On the one hand, we can directly compare our findings in the HK stock markets with results from Blitz and van Vliet (2007) and Blitz et al. (2013) in developed and emerging stock markets. On the other hand, we can test Bali and Cakici's (2008) and Fu's (2009) suggestion that both the *TV puzzle* and *IV puzzle*s are due to the data frequency in estimating *realized volatility* measures. Second, we employ a much longer estimation period (26 weeks and 156 weeks) to compute *realized volatility* measures for HK stocks. Ghysels et al. (2003) suggest that investors pay more attention to realized returns of the distant past than those of the recent when forming expectations about stock market volatility (Guo and Savickas, 2003). Moreover, Boudoukh et al. (2008) prove that long horizon estimation has stronger predictability than short horizon estimation. For example, with a horizon of 1-month, the regression R^2 is never over 2%, and the *t-statistics* are greater than 2 only in the post-World War II; however an increased estimation horizon improved the R^2 to 14% for 2-year horizon and 26% for 4-year horizon for the full sample (Campbell et al., 1997, p.268). Therefore, stock volatility measures might be more precise with the use of a long rather than a short estimation period. Finally, the testing period in our study covers both the 1997 Asian financial crisis and the 2008 global financial crisis, which allows us to investigate the behaviour of the volatility effect in the crisis period.

Collectively the HK stock markets are considered a major financial centre in Asia, and ranks as the second largest in Asia in terms of market capitalisation at the end of July 2010. The total market capitalisation of the HK stock markets is over HK$3 trillion, but over 90% of total trading is attributed to unsophisticated retail investors, which contributes to the higher volatility of HK stocks compared with U.S. stocks (Nartea and Wu, 2013). In addition to this, there are three reasons why we choose HK stock markets as our test sample. First, Chang et al. (2007) suggest that only a list of designated stocks can be sold short in the HK stock markets unlike in the U.S stock markets[3]. Gu et al. (2016) find that the limited of arbitrage would affect the role of IV in pricing stocks. Therefore, we could test if the IV is priced in a stock market with short-selling restrictions. Second, Jones and Lipson (2005) find that HK investors' portfolios are extremely under-diversified with less than 7% of total investors holding more than 10 stocks. Moreover, there were about 2.06 million local retail investors in the HK stock

[3] According to the Hong Kong stock exchange, the designated stocks are either indices stocks, or the stocks with market capitalization of more than HKD$3 billion and have a turnover ratio of more than 60% in the last 12 months, or the stocks that have been listed on the stock exchange for more than 60 days (Hong Kong Stock Exchange, 2016).

markets (Hong Kong Exchanges and Clearing Limited, 2010). The literature suggests that the retail investors are more likely to hold under-diversified stock portfolios. Investors who hold under-diversified portfolios are likely to ask for compensation for bearing idiosyncratic risk. Finally, based on a survey conducted by the Chinese University of Hong Kong (2006) more than 70% of the Hong Kong population have a tendency to exhibit a gambling behaviour, which is one the highest proportion in the world. Moreover, there is a growing trend of young people becoming involved in gambling activities (Wong, 2010). This indicates that Hong Kong investors are likely exhibit a risk seeking behaviour. As suggested in the literature, the MAX effect is mainly caused by investors' risk seeking behaviour, whereby the HK stock markets provide a great opportunity to examine both the *Volatility* and *IV puzzles* as well as the MAX effect.

Our study provides a comprehensive analysis of the *TV* and *IV puzzles* in the HK stock markets. We extend the literature in several ways. First, we find that only long-term realized IV is consistently negatively related to expected stock returns. Therefore, our results confirm that the data frequency and estimation horizon used in estimating *realized volatility* measures do indeed have an impact on the relationship between *realized volatility* measures and expected stock returns. To the best of our knowledge, this is the first study that empirically tests the relationship between the *realized volatility* measures and expected stock returns by using low-frequency data and long estimation horizon. Therefore, we empirically support the arguments in Bali and Caciki (2008), Fu (2009), and Khovansky and Zhylyevskyy's (2013).

Second, we present a new variable that we call long-term MAX (as MAX^{Long}), and find that it is consistently negatively related to the subsequent monthly returns for HK stocks. This result is supportive of the existence of a negative MAX effect as in other studies (see for example, Bali et al., 2011; Annaert et al., 2013; Walkshäusl, 2014; Aboulamer and Kryzanowski, 2016; Chan and Chui, 2016; and Nartea et al., 2017). More importantly, we find that both IV^{Long} and MAX^{Long} co-exist in the HK stock markets over the sample period. This result confirms most findings in emerging stock markets (Nartea et al., 2013; and Nartea et al., 2017), but differs from the findings in developed stock markets (Bali et al., 2011; and Annaert et al., 2013).

Finally, our study provides an important out-of-sample empirical evidence in testing the volatility effect in an Asian developed stock market. Though our results support the existence of an IV and MAX effect in the HK stock markets consistent with studies in other markets, part of our results are inconsistent with previous findings in the U.S. and other developed stock markets, such as the missing TV effect and the co-existence of IV^{Long} and MAX^{Long} (Blitz and van Vliet, 2007; Blitz et al., 2013; and Chan and Chui, 2016). Thus, our study emphasizes the necessity to examine by country verification, anomalies which are originally discovered in the U.S. and other developed stock markets.

The rest of this paper is organised as follows. Section 2 introduces the research methods and the data collection. Section 3 discusses the empirical results and Section 4 concludes the study.

2. Data and Methods

Data on both weekly and monthly stock returns as well as accounting information of stocks are obtained from DataStream. The sample includes all common stocks traded on both the main board and Growth Enterprise Market (GEM) of the HK stock exchange from January 1980 to December 2015. The sample also includes both the active stocks and the "dead" stocks listed in DataStream to mitigate survival bias. However, the following investment vehicles are excluded from the sample, i.e. investment trusts, closed-end funds, exchange traded funds and preferred shares, because they are either under different trading arrangements or regulated by different accounting standards compared to common shares. Stocks with negative book-to-market (BM) ratios or with missing accounting data in a particular month are also excluded from the sample to reduce the noise in computing volatility measures for stocks. Finally, sample stocks must continuously have weekly return records in the past 26 weeks, otherwise, they are excluded from the sample in that particular month.

Following Ince and Porter (2006) and Chan and Chui (2016), we take several steps to filter our sample to mitigate any potential data problems caused by DataStream. One problem is dealing with the zero-return for stocks. DataStream computes the stock's returns by the percentage change in stock return index, and carries forward the return index from the previous period to the current period. If a stock has a zero return record in the current period, this could either be due to the fact that there is really no change in the return in the current month, or because there is no trading in the stock. We screen the return index to ensure that only traded stocks are included in our sample. Another problem is the missing return observations in DataStream. We used the price and dividend information to create price-based returns for stocks with missing return observations if at least the price information is available. Finally, we winsorized both weekly and monthly returns at the 0.5% and 99.5% level, wherein we set the largest and smallest 0.5% of the observations on the weekly (monthly) returns to equal to the 0.5th and 99.5th percentiles, respectively. These procedures ensure our empirical results are not unduly influenced by outliers.

This results in 37 stocks in the sample at the beginning of the testing month, and increases to 1488 stocks in the last month of the sample. There are 1,054,907 weekly return observations in the sample during the study period. We use the weekly HK prime rate as the weekly risk free rate.

2.1 Estimating Volatility

We use two estimation periods to compute the volatility measures for our study, 156 weeks (long-term) and 26 weeks (intermediate-term). We use the Fama-French (FF) three-factor model adopted by Ang et al. (2006, 2009) to estimate the IV for HK stocks, which is the standard deviation of the residuals from equation (1)[4]:

$$R_{i,t} - R_{f,t} = \alpha + \beta_{MKT,i,m} (R_m\text{-}R_{ft}) + \beta_{SMB,i,m} SMB_t + \beta_{HML,i,m} HML_t + \varepsilon_{i,t}\,, \quad (1)$$

where $R_{i,t} - R_{f,t}$ is the excess returns of individual stocks at time *t* and $\beta_{MKT,i,m}$, $\beta_{SMB,i,m}$ and $\beta_{HML,i,m}$ are the coefficients of market, SIZE and BM ratio premiums, respectively. R_m-R_f is the excess market returns, SMB is the return difference between small firms and big firms; and HML is the return difference between high and low BM firms. We use equation (1) to estimate the IV for all stocks. IV is computed at the beginning of each month as the standard deviation of the residuals ($\varepsilon_{i,t}$) from equation (1) using weekly return data for the previous *t* trading weeks, where *t* equals either 26 or 156. Both TV and IV computed by past 156-week weekly return data are defined as TV^{Long} and IV^{Long}; otherwise, TV and IV are computed by past 26-week weekly return data, and are called intermediate-term volatility measures.

2.2 Testing the Volatility Effect

We employ a portfolio sorting method to investigate the relationship between *realized volatility* measures and the expected monthly portfolio returns. To do this, stocks are firstly sorted into three portfolios according to one of their *realized volatility* measures at the beginning of each month. Portfolios are rebalanced every month. Portfolios that

[4] The total volatility of a stock is computed as the standard deviation ($\sigma_{i,t}$) of the past weekly returns.

contain the top third of all stocks with the highest volatility measures are named as either HTV or HIV. The portfolios that contain the bottom third of all stocks with the lowest volatility measures are named as either LTV or LIV; other stocks are sorted into either MTV or MIV portfolios. Next, both equal- and value-weighted portfolio raw returns and alphas (refers to the FF three-factor equation (1)) are estimated for each portfolio at the beginning of the current month. Finally, we compare the differences of raw returns and alphas between the high- and low-volatility portfolios.

2.3 Robustness Tests for the Volatility Effect

Two major drawbacks of portfolios analysis are losing too much information from individual stocks through aggregation, and its inability to control more than two variables simultaneously. Bali et al. (2011) assert that the method cannot disentangle the true effect between the two variables of interest. Consequently, we use firm-level Fama-MacBeth cross-sectional regressions to test the robustness of the volatility effect by controlling for various known effects in the HK stock markets over the study period. We regress equation (1) and its nested versions as follows:

$$R_{i,t} = \beta_{0,t-1} + \beta_{1,t-1}\, IV_{i,\,t-1} + \beta_{2,t-1}\, TV_{i,\,t-1} + \beta_{3,t-1}\, IV^{Long}_{i,\,t-1} + \beta_{4,t-1}\, TV^{Long}_{i,\,t-1} + \beta_{5,t-1} SIZE_{i,\,t-1} + \beta_{6,t-1}\, BM_{i,\,t-1} + \beta_{7,t-1}\, MOM_{i,\,t-1} + \beta_{8,t-1}\, REV_{i,\,t-1} + \beta_{9,t-1}\, ROE_{i,\,t-1} + \beta_{10,t-1}\, OWNER_{i,\,t-1} + \beta_{11,t-1}\, GO_{i,\,t-1} + \beta_{12,t-1}\, MAX^{Long}_{i,\,t-1} + \varepsilon_{i,t-1} \quad (2)$$

The definitions of the variables in equation (2) are described in Table 1.

[Insert Table 1 here]

3. Empirical Analysis

3.1 Descriptive Statistics Results

Table 2 reports the descriptive statistics of our *realized volatility* measures. Panel A in Table 2 reports the descriptive statistics for ten volatility measures. TV^{Long} and IV^{Long} represent long-term total volatility or idiosyncratic volatility; and TV and IV represent intermediate-term total volatility or idiosyncratic volatility. We use the superscripts of EW or VW to indicate equal- or value-weighted volatility measures. MV^{Long} and MV measures the long- and intermediate-term value-weighted market volatilities. Both intermediate- and long-term equal-weighted TVs have higher means and medians than their corresponding value-weighted TVs, implying that firms with low market capitalization are more volatile than firms with high market capitalization. This is consistent with the results reported in Campbell et al. (2001) for the US stocks and other studies for emerging stock markets (Nartea and Wu, 2013; Nartea et al. 2013). We observe a similar pattern for IV measurements. Moreover, IV accounts for a large part of TV, in which intermediate-term IV^{EW} (IV^{VW}) account for 78% (59%) of TV^{EW} (TV^{VW}) and long-term IV^{EW_Long} (IV^{VW_Long}) account for 87% (66%) of TV^{EW_Long} (TV^{VW_Long}), which supports Goyal and Santa-Clara's (2003) findings in the US stock markets. Finally, both intermediate- and long-term market volatilities (MV) have higher coefficients of variation than their corresponding TV and IV, which indicates that the average MV is more variable than the corresponding TV or IV.

Panel B in Table 2 reports the correlations between each of the volatility measures. As expected, both the intermediate- and long-term value-weighted TVs have the highest correlation coefficients with their corresponding MVs. Furthermore, we also notice that both intermediate- and long-term equal-weighted IVs have the lowest correlation coefficients with their corresponding MVs.

[Insert Table 2 here]

Before performing further analysis, we conduct a preliminary test to examine the predictability of our control variables on the subsequent monthly returns. Table 3 reports the time-series averages of the slope coefficients over 294 months from July 1980 to December 2015 for univariate regressions with the *Newey-West* (1987) t-statistics in parenthesis. The independent variables are each of the control variables used in the study. The dependent variable is the one-month ahead stock returns. First, there are significant positive BM, MOM, ROE, and OWNER effects in the HK stock market, consistent with the literature. Second, we also observe a significant negative coefficient of MABA. This suggests that firms with more growth opportunities suffer lower subsequent returns. Nartea and Wu (2013) suggest that a negative coefficient of MABA could indicate that investors pay a premium for high MABA stocks resulting in a lower return in the future. Next, Table 3 also shows a negative Size effect but it is insignificant. This is consistent with the results in Nartea and Wu (2013) and Chan and Chui (2016). Finally, we create a new variable, called MAX^{Long} by following Bali et al.'s (2011) method, which matches the estimation period of our long-term TV and IV.

MAX^{Long} is a stock's highest weekly return in the past 156 weeks instead of the commonly used maximum daily return in previous month as in Bali et al. (2011) in the U.S. stock markets and other studies in global stock markets, such as the European stock markets (Annaert et al., 2013; and Walkshäusl, 2014), Australian (Zhong and Gary, 2016), Canadian (Aboulamer and Kryzanowski, 2016), and HK stock markets (Chan and Chui, 2016), and China (Nartea et al., 2017). The results in Table 3 shows that our MAX^{Long} is marginally significant and negatively related to the subsequent monthly returns, consistent with Chan and Chui's (2016) findings for HK stocks. The result suggests that MAX^{Long} has some predictability on subsequent monthly returns in the HK stock markets over the study period.

[Insert Table 3 here]

3.2 Long Term Volatility Effects

We investigate the long-term volatility effects by testing the relationships between the TV^{Long} and IV^{Long} and expected portfolio returns. Panel A in Table 4 reports the results when we use 156-week weekly return data to compute the TV for HK stocks. The results show that high TV^{Long} portfolios underperform the low TV^{Long} portfolios by 1.24% per month for the equal-weighted portfolios, but this underperformance is statistically insignificant; or by 2.17% per month for the value-weighted portfolios, which is significant at 1% level. More importantly, the alphas in panel A in Table 3 show that the difference between high- and low-TV^{Long} portfolios is an annualized -5.76% for EW portfolio or -16.44% for VW portfolios, both of which are statistically significant. Our results are generally consistent with those of Blitz and van Vliet (2007) and Blitz et al. (2013), who document corresponding annual alpha spreads of 7% for the US, 7.4% for Europe, 9.8% for Japan and 15.5% for emerging markets.

Panel B in Table 4 shows the long-term IV^{Long} effect, where IV^{Long} is estimated by the past 156-week weekly data. The results show that the high IV^{Long} portfolio generates a lower raw return than the low IV^{Long} portfolios, at -1.19% (-2.52%) per month for equal- (value-) weighted portfolios, but it is only significant for value-weighted portfolios. The alpha spreads between the high IV^{Long} portfolio and low IV^{Long} portfolio are annualized at -5.28% for the EW portfolio or -18.72% for the VW portfolio, both are statistically significant. Both value-weighted raw return and alpha spreads are higher than the corresponding value of TV^{Long} sorted portfolio reported in panel A in Table 4.

[Insert Table 4 here]

Due to the limitations of the portfolio sorting approach, we also perform Fama-MacBeth regressions and estimate equation (2). We examine the *realized volatility* effect and report the time-series averages of the slope coefficients of each variable over 294 months from July 1980 to December 2015, with the *Newey-West* (1987) *t*-statistics reported in parentheses. The univariate, bivariate, and multivariate results of long-term volatility effects are reported in Table 5. Panel A in Table 5 shows that the coefficient of long-term TV^{Long} is significantly negative at all levels in the univariate test. Moreover, Panel A in Table 5 shows that both the bivariate and multivariate regression results indicate that the coefficients of TV are statistically significant, regardless of whether we individually control for certain variables or control for all variables simultaneously. Similarly, we observe that the coefficients of Size, BM, ROE, OWNER, and MABA are statistically significant at all levels with the expected signs. The REV coefficient is negative and marginally significant. The coefficient of MOM is positive but insignificant.

The results in Panel B in Table 5 are similar to the results in Panel A. There is a significant negative long-term IV^{Long} effect in the HK stock markets regardless of whether we control for each variable individually or simultaneously. There is only one exception as that the marginal significant negative REV in the Panel A becomes insignificant.

The results in Table 5 support those in Table 4, with both long term TV^{Long} and IV^{Long} showing significant effects on expected stock returns. Furthermore, the results in Panel A in both Table 4 and 5 support the findings of Blitz and van Vliet (2007) and Blitz et al. (2013) while the results in Panel B in both Table 4 and 5 are consistent with the findings of Ang et al. (2006, 2009) in the US and 23 developed stock markets, and Drew et al.'s (2004) findings in Shanghai Stock Exchange.

[Insert Table 5 here]

3.3 Intermediate Term Volatility Effects

In this section, we examine the robustness of our results by estimating volatility measures from the past 26-week weekly data. The results are reported in Table 6. Panel

A in Table 6 reports the intermediate-term TV effect and panel B shows the intermediate-term IV effect. The results in Table 6 are similar to those in Table 4. For example, the alpha spreads indicate that the EW (VW) high TV portfolio significantly underperforms the low TV portfolio by 0.37% (0.90%) per month, while the EW (VW) high IV portfolio significantly underperforms the low IV portfolio by 0.45% (1.45%) per month.

[Insert Table 6 here]

Table 7 shows the univariate, bivariate and multivariate regression estimations for the intermediate-term TV and IV. First, the univariate results show that both coefficients of intermediate-term TV and IV are significantly negative at all levels. Second, Panel A in Table 7 shows that the intermediate-term TV coefficients are statistically significant at all levels, except when we control for ROE and MABA. Finally, Panel B in Table 7 reports that the coefficients of intermediate-term IV are statistically significant in both bivariate and multi-variate tests.

In summary, we find a significantly negative intermediate-term TV and IV effect in the HK stock markets, which is consistent with the findings reported in Section 3.2.

[Insert Table 7 here]

3.4 Can MAX Drive Out the Volatility Effect?

Since Bali et al. (2011) conclude that the IV effect is only a proxy for the MAX effect in the U.S. stock markets, we examine the robustness of our results after controlling for MAX^{Long}.[5]. Table 8 shows the multi-variate Fama-MacBeth regression results. Model (1) to Model (4) show that the significant negative relationship between our *realized volatility* measures survive after controlling for the MAX^{Long}. Furthermore, the MAX^{Long} is significant and negatively related to the subsequent stock returns in Model (1) to Model (4). Next, Model (5) shows the results of all our *realized volatility* measures together in a regression while controlling for seven variables without controlling for MAX^{Long}. The result of Model (5) in Table 8 shows that only the IV^{Long} is significantly negative with the other three *realized volatility* measures which turned insignificant. Finally, Model (6) shows that the coefficient of IV^{Long} remains significantly negative even when we control for MAX^{Long}, while MAX^{Long} is also significant and negatively related to expected stock returns.

3.5 Three Robustness Tests

We perform three more tests in this section to further examine the robustness of *realized volatility* measures in predicting the expected stock returns.

3.5.1 The Effects of Financial Crises

[5] As indicated in the literature, MAX and IV are highly correlated. Thus, we examine the correlation coefficients between our MAX^{Long} and our *realized volatility* measures before we conduct any further analysis. The result shows that the correlation coefficients between our MAX^{Long} and our *realized volatility* measures are all higher than 0.80, which could potentially create a multicollinearity problem in the Fama-MacBeth regression analysis. Therefore, we orthogonalise these variables before conducting the bivariate and multivariate regressions by regressing MAX^{Long} on each of our *realized volatility* measures and use residuals as a proxy for the MAX^{Long}.

Ang et al. (2006) assert that the *IV puzzle* is immune from the effects of financial crisis in the U.S. stock markets. However, Bekaert et al. (2012) present empirical evidence that the average aggregate IV in G7 countries and 23 developed countries is higher during periods of financial crisis than on average. Thus, we question if both the *TV* and *IV puzzles* in the HK stock markets reported in the previous sections are caused by the effect of the financial crisis. To confirm this, we exclude two periods from our study sample to re-examine both the *Volatility* and *IV puzzles* in the HK stock markets: July 1997 to June 1998 (Asian financial crisis) and September 2008 to April 2009 (2008 global financial crisis)[6].

Table 9 reports the bivariate and multivariate regression results for each of our volatility measures. Model (1) to (4) indicate that all of our volatility measures are statistically significant when we control for eight variables simultaneously. Model (5) shows that only the coefficient of IV^{Long} is significantly negative after controlling for seven control variables except for MAX^{Long}. Model (6) confirms the results in Model (5), that the coefficient of IV^{Long} is still significantly negative even after controlling for all eight variables simultaneously.[7] Moreover, the coefficient of MAX^{Long} is also significantly negative.

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[6] We also perform the tests only including financial crisis periods, July 1997 to June 1998 (Asian financial crisis) and September 2008 to April 2009 (2008 global financial crisis). The results show that only IV^{Long} is significantly negative, but none of the MAX variables are statistically significant at any levels. We do not report these results in detail due to space limitations but they are available upon request.

[7] We perform the same tests for the full sample and a sub-sample from 1993 to 2011. The results, which are similar to those reported in this section, are available upon request.

[Insert Table 9 Here]

3.5.2 The January Effect

Doran et al. (2012) present an interesting finding that the significant negative IV effect is present only in non-January months in the U.S. stock markets, regardless of the weighting scheme. Similar to Huang et al. (2011), they observe a positive relationship between the IV and expected stock returns in January months. Huang et al. (2011) explain the positive relationship between IV and expected stock returns with more loser stocks in the high IV portfolio in December. These loser stocks have a stronger reversal effect in January, and thus the high IV portfolio generates a high return in January. We investigate if Doran et al.'s (2012) findings also apply to the HK stock markets. Table 10 reports the multi-variate regression results for non-January data. The results show that both coefficients of IV^{Long} and MAX^{Long} are statistically significant when all of the variables are simultaneously controlled. Therefore our results only partly support Doran et al.'s (2012) findings in the U.S. stock markets, but we do not observe a positive relationship between IV and expected stock returns[8].

[Insert Table 10 here]

3.5.3 Extreme Price Effect

[8] We also perform multi-variate regression results for a sample contains only January data. The results are similar to results reported in Table 10. We do not observe any significant positive relationship between our *realized volatility* measures and subsequent stock returns. We do not report these results in detail due to space limitations but they are available upon request.

Bali and Cakici (2008) and Fu (2009) assert that the volatility effect in the stock markets might be caused by the stocks with the smallest prices. In addition, Angelidis and Tessaromatis (2008) also find that the negative IV effect only matters for the smallest stocks (small capitalizations), wherein IV could be a proxy for non-traded risk, i.e. human and entrepreneurial capital risk, or reflect the inability of investors to hold undiversified portfolios. We thus test if the volatility effect in the HK stock markets is caused by tiny stocks by removing stocks priced under HK$1. The results are reported in Table 11, which shows that both coefficients of IV^{Long} and MAX^{Long} are statistically significant at all levels even after removing all tiny stocks. Our findings support Ang et al. (2006, 2009), who also report that the IV effect is not due to low-priced stocks.

[Insert Table 11 here]

Our findings have two important implications. First, only the long-term IV^{Long} is consistently priced in the HK stock markets under different scenarios during the study periods. Our findings of a high-risk low-return relationship in the HK stock markets only support Ang et al.'s (2006, 2009) idiosyncratic volatility effect, but do not support the total volatility effect of Blitz and van Vliet (2007) and Blitz et al. (2013) findings. Our results indicate that the negative volatility effect for HK stocks is related to the data frequency and the estimation horizon for the *realized volatility* measures, which empirically supports the arguments of Bali and Cakici (2008), Fu (2009), and Khovansky and Zhylyevskyy's (2013). For example, when we use 26-week weekly data to estimate the realized IV, the intermediate-term IV is no longer significant over the sample period; but when we use 156-week weekly data to estimate the long-term realized IV, the long-term IV^{Long} is consistently significant and negatively related to the expected stock returns. Our results suggest that HK investors prefer stocks with high long-term IV to the extent of paying a premium on them thus resulting in a lower return in the future. Second, we find that both IV^{Long} and MAX^{Long} co-exist in the HK stock markets over the study period. This is contrary to the findings of Bali et al. (2011) in the U.S. stock markets, Annaert et al. (2013) in the European stock markets, and Chan and Chui (2016) in the HK stock markets, who report that the MAX and IV effects do not co-exist. However, our results are supportive of other findings in either developed or emerging stock markets (Nartea et al., 2014; Aboulamer and Kryzanowski, 2016; Zhong and Gary, 2016; and Nartea et al., 2017). Our results suggest risk seeking behaviour among HK investors.

4. Conclusion

Recent empirical evidence shows that both TV and IV are negatively related with expected stock returns, which contradicts traditional asset pricing theory (Ang et al., 2006, 2009; Blitz and van Vliet, 2007; and Blitz et al., 2013). This is the first study to use low frequency data and long horizon estimation period to estimate both realized TV and IV for HK stocks. We compute the *realized volatility* measures using different estimation periods - an intermediate-term volatility measure using past 26-week weekly data and a long-term volatility measure using past 156-week weekly data. We also create a new variable, called MAX^{Long}, which is the maximum weekly stock return in the past three-years (past 156 weeks). We test the predictive ability of our *realized volatility* measures on the expected stock returns in the following month over a thirty-five year period.

Our results show that only the coefficient of long-term IV^{Long} is consistently significant and negatively related to expected stock returns over the study period. The results are robust even when we control for eight variables, such as Size, BM, MOM, REV, ROE, OWNER, and MABA. Our results provide out-of-sample empirical support to the findings reported in Ang et al. (2006, 2009), but do not support findings in Blitz and van Vliet (2007) and Blitz et al. (2013) in the US stock markets and international developed stock markets. Second, we show a significant and negative coefficient of MAX^{Long} over the study period. More importantly, we find that both coefficients of IV^{Long} and MAX^{Long} are significantly negative during the study period. Therefore, we suggest that both IV^{Long} and MAX^{Long} co-exist in the HK stock markets. Finally, we show that the significant negative long-term IV effect is robust even when we control for the financial crises, January effect, and tiny stocks. Our findings support the suggestion of Bali and Cakici (2008), Fu (2009), and Khovansky and Zhylyevskyy (2013) that the volatility effect is sensitive to data frequency in estimating volatility measures.

Our results underscore the importance of examining in other markets, anomalies that are originally discovered in the U.S. stock markets. Our results imply that HK investors prefer to pay a premium for stocks with high long-term specific risk rather than intermediate-term specific risk, and thus their preference results in a low return for these stocks in the following month. Consequently, we suggest that the investors should carefully choose their measures of volatilities when they adopt a volatility trading strategy in the HK stock markets.

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Table 1. Definition of Variables

Variable	Symbol	Definition
Realised Return	R_t	Realised stock return in month *t*
Firm Size	SIZE	Log of the firm's market capitalisation at the end of month *t*
Book-to-market Ratio	BM	The firm's book-to-market ratio with six months lagged period, i.e. the BTM in month *t-6*;
Momentum	MOM	The stock's 11-month past return lagged one month, i.e. return from month *t-12* to month *t-2*
Short-term Reversal	REV	The return of a stock in month *t-1*
Return on Equity	ROE	Returns on equity
Institutional Ownership	Owner	The total percentage of shares that a firm has been controlled by institutional investors, i.e. both central and local government, investment companies, mutual funds, insurance companies, and pension funds;
Growth Options	MABA	The market-to-book ratio of assets (Total assets – Total common equity + Market capitalisation)/Total Assets
The Maximum Returns	MAX^{Long}	the highest maximum weekly returns in the previous 156 weeks

Table 2. Descriptive Statistics of Volatility Measures in the Hong Kong Stock Market

The table presents the descriptive statistics for all monthly variables of our volatility measures. TV and IV refer to aggregate total volatility and aggregate idiosyncratic volatility across all firms, respectively. The superscript of *EW* and *VW* refer to equal- and value-weighted, respectively. The superscript *Long* indicates that the measures are computed by the past 156-week return (long-term measures), otherwise the measures are computed by the past 26-week return (intermediate-term measures). MV is monthly aggregate market volatility computed using weekly value-weighted market returns. The sample period is 1980.07-2015.12.

Panel A: Summary Statistics

	Mean	Median	Stdev	CV	Max	Min
TV^{EW}	0.0715	0.0671	0.0207	0.2888	0.1517	0.4001
TV^{VW}	0.0479	0.0431	0.0156	0.3260	0.1091	0.0257
IV^{EW}	0.0570	0.0540	0.0155	0.2718	0.1079	0.0322
IV^{VW}	0.0295	0.0276	0.0078	0.2630	0.0598	0.0181
$MVOL$	0.0329	0.0288	0.0155	0.4706	0.1041	0.0130
TV^{EW_Long}	0.0779	0.0763	0.0155	0.1989	0.1155	0.0514
TV^{VW_Long}	0.0463	0.0447	0.0082	0.1764	0.0656	0.0319
IV^{EW_Long}	0.0657	0.0625	0.0171	0.2603	0.0994	0.0400
IV^{VW_Long}	0.0302	0.0283	0.0062	0.2048	0.0487	0.0204
$MVOL^{Long}$	0.0356	0.0345	0.0096	0.2707	0.0533	0.0169

Panel B: Correlation Table

	TV^{EW}	TV^{VW}	IV^{EW}	IV^{VW}	$MVOL$	TV^{EW_Long}	TV^{VW_Long}	IV^{EW_Long}	IV^{VW_Long}	$MVOL^{Long}$
TV^{EW}	1.0000									
TV^{VW}	0.8061	1.0000								
IV^{EW}	0.8317	0.4777	1.0000							
IV^{VW}	0.7307	0.7562	0.7483	1.0000						
$MVOL$	0.6914	0.9365	0.2398	0.4938	1.0000					
TV^{EW_Long}	0.6064	0.3417	0.7505	0.4948	0.2096	1.0000				
TV^{VW_Long}	0.3102	0.4588	0.2034	0.3412	0.4478	0.5783	1.0000			
IV^{EW_Long}	0.5482	0.2121	0.8164	0.5056	0.0231	0.9023	0.3083	1.0000		
IV^{VW_Long}	0.4267	0.3490	0.5928	0.6113	0.1564	0.7712	0.6740	0.7806	1.0000	
$MVOL^{Long}$	0.1906	0.4068	-0.0624	0.0801	0.5154	0.3172	0.8510	-0.0712	0.2275	1.0000

Table 3 Predictabilities of Control Variables

Each month from 1980:07 to 2015:12 we run a firm-level univariate Fama–MacBeth cross-sectional regression of the return on that month with 1-month lagged values of each control variables. We report the time-series averages of the slope coefficients and their associated Newey–West t-statistics, each variable is independently regressed on stock returns. Each control variables are defined in Table 1.

Intercept	SIZE	BM	MOM	REV	ROE	OWNER	MABA	MAX^{Long}
0.0116 (1.2440)	-0.0012 (-1.4400)							
-0.0003 (-0.0570)		0.0036 (4.6994)						
0.0025 (0.4780)			0.0662 (2.2135)					
0.0011 (0.1923)				0.0010 (0.1303)				
0.0020 (0.3722)					0.0002 (4.2824)			
-0.0004 (-0.0373)						0.0001 (2.7761)		
0.0081 (1.4581)							-0.0088 (-3.3755)	
0.0102 (2.2740)								-0.0136 (-1.6995)

Table 4. Risk-return Relationship of Portfolios Sorted by Long-term Volatility Measures

The table reports results for stocks sorted into portfolios by their long-term total (idiosyncratic) volatility at the beginning of every month during the period Jul. 1980 to Dec. 2015. We compute long-term total volatility as the standard deviation (σi,t) of the stock's weekly return in the past 156-week, whereas the long-term idiosyncratic volatility is the standard deviation of the residuals of the FF3-factor model. The table reports both equal- and value-weighted portfolios' raw returns for the current month, whereas the estimated equal- and value-weighted portfolios' alphas (α coefficient) from the FF3-factor model (Equation. 1) are also reported. T-statistics are reported in brackets. The last row of each panel presents the difference between high and low long-term volatility portfolios, including raw return, alpha, Size, and BM. [a] Market capitalisation in million HK$.

Panel A. Returns of Portfolios Sorted by Long-term Total Volatility

	Raw Return		Size[a]	B/M	Alpha	
	Mean	Std. Dev			Mean	Std. Error
Panel A: Equal-weighted						
High TV^{Long}	-0.0019 (-0.3043)	0.0062	989.97 (30.8448)	0.8732 (33.2651)	-0.0024 (-1.1338)	0.0021
Medium TV^{Long}	0.0058 (1.1498)	0.0051	3298.19 (34.1554)	1.2278 (38.5863)	0.0003 (0.2190)	0.0016
Low TV^{Long}	0.0105 (2.9724)	0.0035	17211.29 (36.6420)	1.1482 (41.5510)	0.0024 (2.1054)	0.0011
High- Low	-0.0124 (-1.7328)	0.0072	-16222.33 (-34.4564)	-0.2749 (-7.2136)	-0.0048 (-1.9955)	0.0024
Panel B: Value-weighted						
High TV^{Long}	-.0.0115 (-1.7454)	0.0066	989.97 (30.8448)	0.8732 (33.2651)	-0.0128 (-4.0256)	0.0032
Medium TV^{Long}	0.0054 (1.0059)	0.0053	3298.19 (34.1554)	1.2278 (38.5863)	-0.0025 (-1.3553)	0.0018
Low TV^{Long}	0.0102 (2.5919)	0.0039	17211.29 (36.6420)	1.1482 (41.5510)	0.0009 (1.3840)	0.0007
High- Low	-0.0217 (-2.8249)	0.0077	-16222.33 (-34.4564)	-0.2749 (-7.2136)	-0.0137 (-4.2220)	0.0032

Panel B. Returns of Portfolios Sorted by Long-term Idiosyncratic Volatility

	Raw Return		Size[a]	B/M	Alpha	
	Mean	Std. Dev			Mean	Std. Error
Panel A: Equal-weighted						
High IV^{Long}	-0.0020 (-0.3348)	0.0061	791.57 (29.9624)	0.8627 (35.0871)	-0.0031 (-1.5620)	0.0020
Medium IV^{Long}	0.0049 (0.9816)	0.0050	2139.83 (27.3643)	1.1651 (33.3492)	0.0002 (0.1585)	0.0016
Low IV^{Long}	0.0098 (2.5238)	0.0039	18709.25 (39.6504)	1.2410 (46.4469)	0.0014 (1.1415)	0.0012
High- Low	-0.0119 (-1.6424)	0.0072	-17917.68 (-37.9135)	-0.3783 (-10.4171)	-0.0044 (-1.9274)	0.0023
Panel B: Value-weighted						
High IV^{Long}	-0.0152 (-2.3324)	0.0065	791.57 (29.9624)	0.8627 (35.0871)	-0.0146 (-4.4051)	0.0033
Medium IV^{Long}	0.0027 (0.5387)	0.0051	2139.83 (27.3643)	1.1651 (33.3492)	-0.0031 (-1.6651)	0.0019
Low IV^{Long}	0.0101 (2.4525)	0.0041	18709.25 (39.6504)	1.2410 (46.4469)	0.0010 (1.7829)	0.0005
High- Low	-0.0252 (-3.2813)	0.0077	-17917.68 (-37.9135)	-0.3783 (-10.4171)	-0.0156 (-4.6355)	0.0034

Table 5. Univariate, Bivariate and Multivariate Fama-Macbeth Regression Results for Long-term Volatilities

We perform a firm-level Fama-MacBeth regression of the expected individual stock returns with monthly control variables over the full sample period, from 1980:07 to 2015:12. The time-series averages of the slope coefficients and their associated Newey-West t-statistics are reported on each row. TV^{Long} is the realized long-term total volatility computed as the standard deviation of the weekly stock return in the last 156-week, whereas the IV^{Long} is the realised long-term idiosyncratic volatility computed by as the standard deviation of the residuals of the FF3-factor model. Other control variables are defined in the Table 1, including SIZE, BM, MOM, REV, ROE, OWNER, and MABA.

Panel A. Total volatility estimated by weekly data from the past 156 weeks

Intercept	TV^{Long}	SIZE	BM	MOM	REV	ROE	OWNER	MABA
0.0196	-0.1647							
(4.8278)	(-2.3266)							
0.0398	-0.2004	-0.0025						
(5.2823)	(-3.0068)	(-2.9441)						
0.0161	-0.2020		0.0035					
(3.8622)	(-2.6556)		(3.7588)					
0.0161	-0.1348			0.0045				
(4.2833)	(-2.0222)			(1.5903)				
0.0188	-0.1881				-0.0150			
(4.6293)	(-2.5443)				(-1.7119)			
0.0149	-0.1219					0.0002		
(3.4163)	(-2.5392)					(4.2612)		
0.0150	-0.1475						0.0001	
(2.8697)	(-2.0264)						(3.2120)	
0.0243	-0.1774							-0.0081
(5.6557)	(-2.4047)							(-3.3133)
0.0467	-0.2075	-0.0046	0.0024	0.0684	-0.0280	0.0000	0.0001	0.0024
(3.9262)	(-3.2382)	(-3.9923)	(3.2747)	(2.3829)	(-3.3928)	(4.3277)	(5.0397)	(0.7532)

Table 5 (continued) Panel B. Idiosyncratic volatility estimated by weekly data from the past 156 weeks

Intercept	IV^{Long}	SIZE	BM	MOM	REV	ROE	OWNER	MABA
0.0172 (4.1899)	-0.1820 (-2.5882)							
0.0457 (5.1933)	-0.2550 (-3.4850)	-0.0033 (-3.5390)						
0.0147 (3.4540)	-0.2234 (-2.8957)		0.0033 (3.3825)					
0.0152 (3.7689)	-0.1556 (-2.3019)			0.0431 (1.4654)				
0.0163 (3.8472)	-0.1935 (-2.7025)				-0.0108 (-1.3023)			
0.0153 (3.4561)	-0.1746 (-2.2747)					0.0002 (4.2663)		
0.0136 (2.4124)	-0.1482 (-2.0628)						0.0001 (3.3121)	
0.0222 (4.7822)	-0.1857 (-2.4557)							-0.0091 (-3.2746)
0.0486 (3.9725)	-0.2190 (-3.5391)	-0.0050 (-4.3164)	0.0023 (3.1657)	0.0695 (2.3314)	-0.0276 (-3.3613)	0.0000 (4.2214)	0.0001 (5.1494)	0.0022 (0.7055)

Table 6. Risk-return Relationship of Portfolios Sorted by Intermediate-term Volatility Measures

The table reports results for stocks sorted into portfolios by their intermediate-term total (idiosyncratic) volatility at the beginning of every month during the period Jul. 1980 to Dec. 2015. We compute intermediate-term total volatility as the standard deviation (σi,t) of the stock's weekly return in the past 26-week, whereas the long-term idiosyncratic volatility is the standard deviation of the residuals of the FF3-factor model. The table reports both equal- and value-weighted portfolios' raw returns for the current month, whereas the estimated equal- and value-weighted portfolios' alphas (α coefficient) from the FF3-factor model (Equation. 1) are also reported. T-statistics are reported in parentheses. The last row of each panel presents the difference between high and low intermediate-term volatility portfolios, including raw return, alpha, Size, and BM.

Panel A. Returns of Portfolios Sorted by Intermediate-term Total Volatility

	Raw Return		Size[a]	B/M	Alpha	
	Mean	Std. Dev			Mean	Std. Error
Panel A: Equal-weighted						
High TV	-0.0024 (-0.4052)	0.0060	1265.31 (24.6270)	0.8548 (27.8222)	-0.0026 (-1.3721)	0.0019
Medium TV	0.0025 (0.4964)	0.0049	4628.76 (29.4487)	0.9555 (34.1431)	-0.0010 (-0.7548)	0.0013
Low TV	0.0064 (1.8645)	0.0034	12401.68 (30.0120)	0.9194 (40.9780)	0.0011 (0.9673)	0.0012
High- Low	-0.0088 (-1.2759)	0.0069	-11136.37 (-26.7440)	-0.0646 (-1.6969)	-0.0037 (-1.6758)	0.0022
Panel B: Value-weighted						
High TV	-0.0058 (-0.9473)	0.0061	1265.31 (24.6270)	0.8548 (27.8222)	-0.0084 (-3.0580)	0.0027
Medium TV	0.0049 (0.9656)	0.0051	4628.76 (29.4487)	0.9555 (34.1431)	-0.0010 (-0.6804)	0.0014
Low TV	0.0090 (2.4481)	0.0037	12401.68 (30.0120)	0.9194 (40.9780)	0.0007 (0.7629)	0.0009
High- Low	-0.0148 (-2.0708)	0.0072	-11136.37 (-26.7440)	-0.0646 (-1.6969)	-0.0090 (-3.1447)	0.0029

Panel B. Returns of Portfolios Sorted by Intermediate-term Idiosyncratic Volatility

	Raw Return		Size[a]	B/M	Alpha	
	Mean	Std. Dev			Mean	Std. Error
Panel A: Equal-weighted						
High IV	-0.0044 (-0.7650)	0.0058	935.30 (27.8320)	0.8387 (27.6880)	-0.0036 (-2.2064)	0.0016
Medium IV	0.0017 (0.3384)	0.0050	2836.86 (24.9994)	0.9225 (31.4572)	0.0008 (0.5490)	0.0014
Low IV	0.0061 (1.6416)	0.0037	14582.14 (33.8275)	0.9745 (45.8426)	0.0009 (0.8170)	0.0011
High- Low	-0.0105 (-1.5291)	0.0069	-13646.84 (-31.5621)	-0.1358 (-3.6684)	-0.0045 (-2.2818)	0.0020
Panel B: Value-weighted						
High IV	-0.0120 (-2.0309)	0.0059	935.30 (27.8320)	0.8387 (27.6880)	-0.0132 (-5.0477)	0.0026
Medium IV	0.0021 (0.4235)	0.0049	2836.86 (24.9994)	0.9225 (31.4572)	-0.0012 (-0.7271)	0.0017
Low IV	0.0085 (2.1080)	0.0040	14582.14 (33.8275)	0.9745 (45.8426)	0.0013 (2.7244)	0.0005
High- Low	-0.0204 (-2.8648)	0.0071	-13646.84 (-31.5621)	-0.1358 (-3.6684)	-0.0145 (-5.4456)	0.0027

[a] Market capitalisation in million HK$.

Table 7. Univariate, Bivariate and Multivariate Fama-Macbeth Regression Results for Intermediate-term Volatilities

We perform a firm-level Fama-MacBeth regression of the expected individual stock returns with monthly control variables over the full sample period, from 1980:07 to 2015:12. The time-series averages of the slope coefficients and their associated Newey-West t-statistics are reported on each row. TV is the realized intermediate-term total volatility computed as the standard deviation of the weekly stock return in the last 26 weeks, whereas the IV is the realised intermediate-term idiosyncratic volatility computed by as the standard deviation of the residuals of the FF3-factor model. Other control variables are defined in the Table 1, including SIZE, BM, MOM, REV, ROE, OWNER, and MABA.

Panel A. Total volatility estimated by weekly data from the past 26 weeks

Intercept	TV	SIZE	BM	MOM	REV	ROE	OWNER	MABA
0.0102 (2.6363)	-0.1128 (-2.4772)							
0.0249 (3.4372)	-0.1313 (-3.0720)	-0.0018 (-2.3462)						
0.0079 (2.0105)	-0.1250 (-2.3718)		0.0037 (5.1692)					
0.0088 (2.4366)	-0.1022 (-2.3394)			0.0835 (3.1454)				
0.0096 (2.3693)	-0.1242 (-2.5782)				-0.0111 (-1.3442)			
0.0073 (1.7622)	-0.0670 (-1.1598)					0.0002 (4.3519)		
0.0067 (0.9578)	-0.0941 (-1.7139)						0.0001 (3.0442)	
0.0147 (3.4633)	-0.0862 (-1.5078)							-0.0084 (-3.0304)
0.0300 (1.9038)	-0.1338 (-2.5797)	-0.0037 (2.8898)	0.0031 (4.1333)	0.0810 (2.6768)	-0.0255 (-3.2211)	0.0000 (4.1287)	0.0001 (5.5805)	0.0038 (1.0150)

Table 7 (continued)

Panel B. Idiosyncratic volatility estimated by weekly data from the past 26 weeks

Intercept	IV	SIZE	BM	MOM	REV	ROE	OWNER	MABA
0.0092 (2.3187)	-0.1415 (-3.0802)							
0.0263 (3.5377)	-0.1720 (-3.8956)	-0.0021 (-2.5144)						
0.0089 (2.0836)	-0.1934 (-3.3679)		0.0038 (3.7642)					
0.0090 (2.3027)	-0.1327 (-2.9272)			0.0657 (2.5088)				
0.0083 (1.9909)	-0.1496 (-3.2788)				-0.0079 (-1.0694)			
0.0088 (1.8631)	-0.1230 (-1.7780)					0.0002 (4.4778)		
0.0060 (0.8222)	-0.1018 (-1.8050)						0.0001 (3.0804)	
0.0150 (3.3060)	-0.1295 (-2.1265)							-0.0081 (-3.1550)
0.0309 (1.9461)	-0.1454 (-2.7804)	-0.0040 (-3.0661)	0.0031 (4.1425)	0.0797 (2.5068)	-0.0246 (-3.1139)	0.0000 (4.1419)	0.0001 (5.5866)	0.0038 (1.0025)

Table 8 Multivariate Fama-Macbeth Regression Results with MAX^{LONG}

We perform a firm-level Fama-MacBeth regression of the expected individual stock returns with monthly control variables over the full sample period, from 1980:07 to 2015:12. The average of the time-series slope coefficients and their associated Newey-West t-statistics are reported in each row. TV^{Long} (TV) is the realized long-term (intermediate-term) total volatility computed as the standard deviation of the weekly stock return in the last 156 weeks (26 weeks), whereas the IV^{Long} (IV) is the realised long-term (intermediate-term) idiosyncratic volatility computed by as the standard deviation of the residuals of the FF3-factor model. Other control variables are defined in the Table 1, including MAX, SIZE, BM, MOM, REV, ROE, OWNER, and MABA.

Model	Intercept	IV	TV	IV^{Long}	TV^{Long}	MAX^{LONG}	SIZE	BM	MOM	REV	ROE	OWNER	MABA
1	0.0382	-0.1098				-0.0044	-0.0027	0.0770	0.0254	-0.0000	0.0001	0.0020	-0.0131
	(2.7716)	(-2.3123)				(-3.7350)	(-3.7212)	(2.5010)	(3.1988)	(-4.5294)	(5.4424)	(0.6213)	(-2.8114)
2	0.0376		-0.1012			-0.0042	-0.0027	0.0779	0.0262	-0.0000	0.0001	0.0021	-0.0132
	(2.7233)		(-2.1656)			(-3.6057)	(-3.7135)	(2.6400)	(3.2601)	(-4.5695)	(5.3876)	(0.6528)	(-2.9007)
3	0.0493			-0.2707		-0.0050	-0.0023	0.0646	0.0275	-0.0000	0.0001	0.0020	0.0083
	(4.1336)			(-3.6895)		(-4.3992)	(-3.1611)	(2.1032)	(3.3312)	(-4.1099)	(5.0793)	(0.6332)	(1.6813)
4	0.0470				-0.2437	-0.0045	-0.0024	0.0630	0.0282	-0.0000	0.0001	0.0020	0.0056
	(4.1027)				(-2.9994)	(-3.9611)	(-3.2391)	(2.1847)	(3.4124)	(-4.2043)	(4.9993)	(0.6571)	(1.0543)
5	0.0509	-0.0609	-0.0039	-0.1824	0.4129		-0.0052	0.0023	0.0762	-0.0291	0.0000	0.0001	0.0020
	(3.4367)	(-1.3706)	(-0.0259)	(-4.3573)	(1.2392)		(-3.9322)	(3.1960)	(3.0392)	(-3.3931)	(4.2922)	(5.1780)	(0.6378)
6	0.0512	-0.0568	-0.0107	-0.2292	0.4019	-0.0052	-0.0023	0.0706	0.0288	-0.0000	0.0001	0.0018	0.0072
	(3.5656)	(-1.2394)	(-0.0723)	(-4.3560)	(1.2212)	(-3.9816)	(-3.1354)	(2.7868)	(3.3495)	(-4.1686)	(5.1609)	(0.5765)	(1.5307)

Table 9. Multivariate Fama-Macbeth Regression Results Hedged by the Effects of Financial Crises

We perform a firm-level Fama-MacBeth regression of the expected individual stock returns with monthly control variables over the selected sample periods for controlling the effect of financial crisis. The sample period excludes the periods from 1997.07 to 1998.06 and from 2008.09 and 2009.04, which are Asian financial crisis and 2008 Financial Crisis. The average of the time-series slope coefficients and their associated Newey-West t-statistics are reported in each row. TV^{Long} (TV) is the realized long-term (intermediate-term) total volatility computed as the standard deviation of the weekly stock return in the last 156 weeks (26 weeks), whereas the IV^{Long} (IV) is the realised long-term (intermediate-term) idiosyncratic volatility computed by as the standard deviation of the residuals of the FF3-factor model. Other control variables are defined in the Table 1, including MAX, SIZE, BM, MOM, REV, ROE, OWNER, AGE and MABA.

Model	Intercept	IV	TV	IV^{Long}	TV^{Long}	MAX^{Long}	SIZE	BM	MOM	REV	ROE	OWNER	MABA
1	0.0429 (2.9468)	-0.1014 (-2.2713)				-0.0046 (-3.7012)	-0.0029 (-3.8148)	0.0915 (4.2428)	0.0218 (2.7785)	-0.0000 (-4.5645)	0.0001 (5.2000)	0.0019 (0.5775)	-0.0133 (-2.9699)
2	0.0424 (2.9486)		-0.0944 (-2.1370)			-0.0044 (-3.5763)	-0.0029 (-3.8133)	0.0918 (4.3371)	0.0223 (2.8402)	-0.0000 (-4.6006)	0.0001 (5.1434)	0.0020 (0.6088)	-0.0134 (-3.0530)
3	0.0532 (4.3144)			-0.2488 (-3.5533)		-0.0051 (-4.3570)	-0.0025 (-3.4319)	0.0804 (4.0467)	0.0240 (2.9264)	-0.0000 (-4.0462)	0.0001 (4.9134)	0.0019 (0.5844)	0.0063 (1.2276)
4	0.0515 (4.4248)				-0.2287 (-3.0056)	-0.0047 (-3.9320)	-0.0026 (-3.4702)	0.0789 (4.3455)	0.0246 (2.9942)	-0.0000 (-4.2188)	0.0001 (4.8169)	0.0020 (0.6074)	0.0042 (0.7723)
5	0.0546 (3.5883)	-0.0546 (-1.2218)	0.0184 (0.1183)	-0.1794 (-4.4973)	0.3669 (1.1079)		-0.0053 (-3.7181)	0.0025 (3.4428)	0.0884 (4.8149)	-0.0250 (-2.9587)	0.0000 (4.3233)	0.0001 (4.9479)	0.0020 (0.6007)
6	0.0546 (3.7092)	-0.0526 (-1.1741)	0.0112 (0.0739)	-0.2116 (-4.0687)	0.3527 (1.0834)	-0.0052 (-3.7528)	-0.0025 (-3.4084)	0.0832 (4.7862)	0.0246 (2.9147)	-0.0000 (-4.1977)	0.0001 (4.9557)	0.0018 (0.5342)	0.0054 (1.1295)

Table 10. Multivariate Fama-Macbeth Regression Results Hedged for the January Effect

We perform a firm-level Fama-MacBeth regression of the expected individual stock returns with monthly control variables over the full sample period, from 1980:07 to 2015:12. The sample excludes all January returns. The average of the time-series slope coefficients and their associated Newey-West t-statistics are reported on each row. TV^{Long} TV) is the realized long-term (intermediate-term) total volatility computed as the standard deviation of the weekly stock return in the last 156 weeks (26 weeks), whereas the IV^{Long} (IV) is the realised long-term (intermediate-term) idiosyncratic volatility computed by as the standard deviation of the residuals of the FF3-factor model. Other control variables are defined in the Table 1, including MAX, SIZE, BM, MOM, REV, ROE, OWNER, and MABA.

Model	Intercept	IV	TV	IV^{Long}	TV^{Long}	MAX^{Long}	SIZE	BM	MOM	REV	ROE	OWNER	MABA
1	0.0381	-0.1012				-0.0044	-0.0026	0.0861	0.0228	-0.0000	0.0001	0.0020	-0.0136
	(2.7037)	(-2.0888)				(-3.6184)	(-3.2098)	(3.2098)	(2.5030)	(-3.6293)	(5.1805)	(0.6499)	(-2.6612)
2	0.0376		-0.0950			-0.0043	-0.0026	0.0870	0.0235	-0.0000	0.0001	0.0022	-0.0135
	(2.6837)		(-1.9145)			(3.5211)	(-3.2134)	(2.9417)	(2.5636)	(-3.6729)	(5.1095)	(0.6852)	(-2.7176)
3	0.0481			-0.2472		-0.0049	-0.0022	0.0729	0.0245	-0.0000	0.0001	0.0019	0.0056
	(3.9379)			(-3.0103)		(-4.2049)	(-2.7628)	(2.4018)	(2.6472)	(-3.2578)	(4.5382)	(0.6090)	(0.9451)
4	0.0462				-0.2259	-0.0045	-0.0022	0.0704	0.0252	-0.0000	0.0001	0.0020	0.0036
	(3.8297)				(-2.4991)	(-3.8251)	(-2.7504)	(2.4841)	(2.7132)	(-3.3274)	(4.4561)	(0.6422)	(0.5628)
5	0.0494	-0.0546	-0.0620	-0.1772	0.3543		-0.0051	0.0022	0.0838	-0.0269	0.0000	0.0001	0.0022
	(3.2332)	(-1.2037)	(-0.3993)	(-3.8328)	(0.9732)		(-3.7441)	(2.7621)	(3.3594)	(-2.7809)	(3.4446)	(4.8864)	(0.7188)
6	0.0494	-0.0503	-0.0681	-0.2140	0.3464	-0.0050	-0.0022	0.0781	0.0264	-0.0000	0.0001	0.0019	0.0056
	(3.3420)	(-1.1092)	(-0.4482)	(-3.5524)	(0.9639)	(-3.7626)	(-2.6951)	(3.0710)	(2.7394)	(-3.3533)	(4.6131)	(0.6228)	(0.9823)

Table 11. Multivariate Fama-Macbeth Regression Results Hedged for the Small-Size Effect

We perform a firm-level Fama-MacBeth regression of the expected individual stock returns with monthly control variables over the full sample period, from 1980:07 to 2011:12. The sample excludes share with price under HKD$1. The average of the time-series slope coefficients and their associated Newey-West t-statistics are reported on each row. TV^{Long} (TV) is the realized long-term (intermediate-term) total volatility computed as the standard deviation of the weekly stock return in the last 156 weeks (26 weeks), whereas the IV^{Long} (IV) is the realised long-term (intermediate-term) idiosyncratic volatility computed by as the standard deviation of the residuals of the FF3-factor model. Other control variables are defined in the Table 1, including MAX, SIZE, BM, MOM, REV, ROE, OWNER, and MABA.

Model	Intercept	IV	TV	IV^{Long}	TV^{Long}	MAX^{Long}	SIZE	BM	MOM	REV	ROE	OWNER	MABA
1	0.0177 (1.6240)	-0.1690 (-2.4836)				-0.0015 (-1.7151)	-0.0021 (-2.2189)	0.1525 (3.6658)	0.0073 (0.7324)	-0.0001 (-2.1143)	0.0001 (3.7974)	0.0041 (1.1484)	-0.0248 (-3.9364)
2	0.0161 (1.4715)		-0.1553 (-2.5490)			-0.0012 (-1.3808)	-0.0022 (-2.2249)	0.1551 (3.8726)	0.0090 (0.9045)	-0.0001 (-1.8614)	0.0001 (3.6888)	0.0044 (1.2163)	-0.0251 (-4.0037)
3	0.0293 (3.1190)			-0.3792 (-4.5019)		-0.0021 (-2.3949)	-0.0016 (-1.7449)	0.1297 (3.2842)	0.0082 (0.8529)	-0.0001 (-1.9135)	0.0001 (2.8683)	0.0047 (1.3270)	0.0044 (0.5409)
4	0.0252 (2.6832)				-0.3224 (-3.4441)	-0.0015 (-1.6486)	-0.0018 (-1.8909)	0.1318 (3.4956)	0.0102 (1.0411)	-0.0001 (-1.8954)	0.0001 (2.7794)	0.0048 (1.3584)	-0.0023 (-0.2683)
5	0.0494 (3.2332)	-0.0546 (-1.2037)	-0.0620 (-0.3993)	-0.1772 (-3.8328)	0.3543 (0.9732)		-0.0051 (-3.7441)	0.0022 (2.7621)	0.0838 (3.3594)	-0.0269 (-2.7809)	0.0000 (3.4446)	0.0001 (4.8864)	0.0022 (0.7188)
6	0.0327 (2.8918)	-0.1117 (-1.7270)	-0.0548 (-0.2457)	-0.2647 (-3.8303)	0.3709 (0.9685)	-0.0026 (-2.5965)	-0.0016 (-1.6952)	0.1500 (4.0242)	0.0084 (0.7836)	-0.0001 (-2.4005)	0.0001 (3.1538)	0.0046 (1.2944)	-0.0009 (-0.1229)