Patterns and pricing of idiosyncratic volatility in French stock market

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Purpose: The current research is to investigate the time series behavior of idiosyncratic volatility (IVOL) and its role in asset pricing in France in a twenty-year testing period.

Design/methodology/approach: We test for the presence of trends in aggregate idiosyncratic and market volatility using Bunzel and Vogelsang’s (2005) t-dan test. We follow Bekaert et al. (2012) to test for regime shifts of both aggregate idiosyncratic and market volatilities. And then, we employ portfolio level analysis and cross-sectional univariate Fama-MacBeth regressions to examine the relationship between IVOL and cross-sectional stock returns in French stock market.

Findings: First, we find that both idiosyncratic and market volatility do not exhibit long-term trends. Instead, their patterns are consistent with regime switching behavior. Second, though we initially find a strong significant negative IVOL effect in the French stock market which is robust in bi-variate Fama-MacBeth regressions, the negative IVOL effect is becoming marginal significant when we control for SIZE, BM, momentum, and short-term reversal simultaneously. Our new evidence suggests that there is a marginal IVOL effect in the French stock market adding to the increasing number of studies questioning the ubiquity of the negative IVOL puzzle.

Originality/value: First, we present the first empirical evidence on examining the trends of both aggregate idiosyncratic and market volatilities, and the pricing role of IVOL in French stock market. We draw an attention for both academia and practitioners on an individual developed stock market. Second, we add new evidence to the mounting results questioning the ubiquity of the IVOL effect. This highlights the importance of country verification of so called anomalies in the US, even in developed markets. Finally, we confirm earlier evidence both aggregate idiosyncratic and market volatilities in the French stock market exhibits regime switching behavior rather than showing a long-term time trends.

Keywords: Idiosyncratic volatility, regime switch model, asset pricing, France

JEL Classification: G11, G12
Patterns and pricing of idiosyncratic volatility in French stock market

1. Introduction

In a recent study, Ang et al. (2009) confirm the ubiquity of a puzzling negative idiosyncratic volatility (IVOL) effect (Ang et al., 2006) in 23 developed countries including the seven largest developed economies (G7) where high volatility stocks earn low-risk adjusted returns. This is puzzling because traditional finance theory suggests idiosyncratic volatility should not be priced as it could be eliminated at no cost through diversification. In case investors cannot fully diversify, finance theory suggests a positive (not a negative) relationship between idiosyncratic risk and return (Levy, 1978 and Merton, 1987). Ang et al. (2009) report a statistically significant difference in risk-adjusted returns between high and low IVOL portfolios of 1.31% per month across 23 developed markets. However, in their study, they also report that among G7 countries not only did France show a decrease in the magnitude of the idiosyncratic volatility coefficient when idiosyncratic volatility was computed using a local Fama-French model instead of a world Fama-French model, the idiosyncratic volatility coefficient turned insignificant indicating the absence of an IVOL effect. We investigate this further in this study. To the best of our knowledge, this is the first paper to examine the role of IVOL in pricing French stocks. If there is no significant relationship between returns and idiosyncratic volatility in the French stock market, this would add to mounting evidence

2 However, some studies suggest that Ang et al.’s findings are not robust to portfolio weighting schemes (Bali and Cakici, 2008) and controls for short-term reversals (Huang, Liu, Rhee, and Zhang, 2010). Others argue that a positive relationship exists between idiosyncratic volatility and returns using alternative measures of expected idiosyncratic volatility (Malkiel and Xu, 2004; Speigel and Wang, 2006; Divatopolous et al. 2008; Fu, 2009; Chua et al. 2010).
questioning the ubiquity of the so-called idiosyncratic volatility effect (Wei and Zhang, 2006; Bali, et al. 2008; Fu, 2009; Fink et al, 2010; Pukthuantong-Le and Vissalnachotti, 2009; Suss, 2012; Liu et al., 2016).

Campbell et al. (2001) report evidence of an increasing trend in idiosyncratic volatility in the U.S. relative to market volatility in the period 1962 to 1997. This is important since it implies increasing benefits from diversification. Theoretically, if there is an increased trend of IVOL with a flat market volatility, investors would be benefited from the process of the portfolio diversification. If the IVOL is a decreased trend or remaining flat in the historical data, then investors are hard to capture the diversification benefit. In this sense, the IVOL may not be priced in the stock market. However, Brandt, Brav, Graham, and Kumar (2010) dispute this suggesting instead an episodic pattern in idiosyncratic volatility in the U.S. over time that is largely driven by the behavior of retail investors. In a related study Bekaert, et al. (2012) show that instead of a long-term trend, IVOL follows a stationary autoregressive process that occasionally switches to a higher variance regime in the U.S. and in 22 other developed markets. The trend of the IVOL seems an important issue relative to the benefit of portfolio diversification. Therefore, we are also interested in the historical trend of the IVOL in the French stock market, which is also the first evidence on this issue.

In this study we investigate the behavior of aggregate idiosyncratic and market volatility from 1991 to 2012 in the French stock market, then we examine the relationship between idiosyncratic volatility and cross-sectional stock returns. There are two reasons why we are interested in the IVOL effect in French stock market. First, most of previous literatures investigate the trends and pricing behavior of IVOL in a group of European stock markets, but
French stock market is one of the oldest stock markets in the world, and the 2nd largest stock market ranked by capitalization in Europe following by U.K. stock market. Moreover, the French stock exchange was ranked the 4th largest exchange in the world, which the total marketization was USD$3.5 trillion in November 2014 (Wilipedia.com, 2017). Surprisingly, the French stock market as an individual sample has been far ignored in the literatures, especially in the fields of asset pricing and financial anomalies. Therefore, this study is going to fill the gap in the literatures.

Second, the French stock market, known as the Paris Bourse, has been restructured in September 2000, and it plays a role of regional stock exchange rather than a stock exchange for an individual country. The early stage of the French stock exchange is comprised by three sections, the official list (the Premier Marché), the lists for medium-sized companies (the Second Marché), and the list for fast-growing start-up companies (the Nouveau Marché). In September 2000, the Paris Bourse merged with the Amsterdam, Lisbon and Brussels exchanges to form Euronext NV (Euronext.com, 2017). There are more than 1300 companies listed on the integrated exchange at moment. It might be very interested in testing the IVOL effect for French listed firms only on a universal stock market after the consolidation of independent European markets since our testing period covers both periods.

We can easily summarize our results. First, we test for the presence of trends in aggregate idiosyncratic and market volatility using Bunzel and Vogelsang’s (2005) t-dan test and then we follow Bekaert et al (2012) and test for regime shifts. We find that both idiosyncratic and market volatility do not exhibit long-term trends. Instead their patterns are consistent with regime switching behavior. Second, though we initially find a strong significant
negative IVOL effect in the French stock market which is robust in bi-variate Fama-MacBeth regressions, the negative IVOL effect is becoming marginal significant when we control for SIZE, BM, momentum, and short-term reversal simultaneously. Our new evidence suggests that there is a marginal IVOL effect in the French stock market adding to the increasing number of studies questioning the ubiquity of the negative IVOL puzzle.

We contribute to the literature on the idiosyncratic volatility effect in a number of ways. First, we present the first empirical evidence on examine the trend of IVOL and the pricing role of IVOL in French stock market. Prior studies were mostly focusing on a group of developed stock markets rather than an individual stock market. From this point of view, we draw an attention for both academia and practitioners on an individual developed stock market. Second, we add new evidence to the mounting results questioning the ubiquity of the IVOL effect. This highlights the importance of country verification of so called anomalies in the US, even in developed markets. Finally, we confirm earlier evidence idiosyncratic volatility in the French stock market exhibits regime switching behavior rather than showing a long-term time trend.

The rest of the paper is organized as follows: section 2 describes our data and methods; section 3 presents the empirical results in three parts. First we report volatility patterns over time, then we examine the relation between volatility and market returns, and finally we examine the relation between idiosyncratic volatility and cross-sectional stock returns. Section 4 concludes the paper.

2. Data and Methods

Although the French stock exchange represents a universal stock exchange in Europe which listed firms are from different countries today, the sample of the current study only
convers listed French firms. Daily and monthly stock returns on individual firms were obtained from DataStream. The data set covered the period from August 1991 with 147 firms, to June 2012 with 507 firms, with an average of 443 firms per month. The risk-free rate which is defined as French EU-FRANCE 1 month middle rate was also obtained from the DataStream. Market returns are the value-weighted returns of all firms used in the study.

We exclude investment trusts, closed-end funds, exchange traded funds, and preferred shares. At the beginning of each month, we exclude stocks that do not have continuous return records in the past 22 trading days. In order to reduce noise in computing IVOL for each stock, we also exclude stocks with daily return less than -100% and/or monthly return greater than 200% as well as stocks with negative book-to-market (BM) ratio. Stocks with missing accounting data in a particular month were also excluded from the sample in that month.

2.1. Estimating idiosyncratic volatility

We follow Ang et al., (2006, 2009) and estimate the IVOL of each firm at the beginning of every month. IVOL is the standard deviation of the residuals ($\sigma_{\epsilon}$) from the Fama-French (1993, 1996) 3-factor model (1), henceforth FF3-factor model, using daily data for the previous 22 trading days.

$$R_{i,t} = \alpha + \beta_{MKT,i,m}MKT_t + \beta_{SMB,i,m}SMB_t + \beta_{HML,i,m}HML_t + \epsilon_{i,t}$$ (1)

where day $t$ refers to the 22 trading days ending on the last trading day of month $m-1$. $R_{i,t}$ and MKT are excess returns of firm $i$ and the market, respectively, over the risk-free rate. SMB is the excess return of small firms over big firms, and HML is the excess return of high book-to-market (BM) firms over low BM firms. SMB is the return of the upper half less the return of the lower half of all firms ranked in ascending order according to market capitalization while
HML is the return of the bottom third less the return of the top third of all firms ranked in ascending order according to BM.

2.2. Portfolio analysis and Fama-MacBeth regressions

We use both portfolio-level analysis as well as firm-level Fama-MacBeth cross-sectional regressions to examine the relation between IVOL and expected returns. In portfolio-level analysis, firms are first sorted into tertiles at the start of each month based on IVOL and allocated to groups. We then compute each tertile portfolio’s equal- and value-weighted raw returns for the current month. We also estimate each tertile portfolio’s alpha (α coefficient) from the FF3-factor model (Eq. 1) using each tertile portfolio’s full sample of monthly value- or equal-weighted returns.

As a robustness test, we also conduct firm-level Fama-MacBeth regressions to control for various variables. We estimate the following model and its nested versions:

\[ R_{i,t+1} = \beta_{0,t} + \beta_{1,t}IV_{i,t} + \beta_{2,t}SIZE_{i,t} + \beta_{3,t}Value_{i,t} + \beta_{4,t}Reversal_{i,t} + \beta_{5,t}Momentum_{i,t} \quad (2) \]

\( R_t \), is realized stock return in month \( t \). IVOL is realized idiosyncratic volatility as defined previously. SIZE at the end of month \( t \) is defined is the log of the firm’s market capitalization at the end of month \( t \). BM is the firm’s book-to-market ratio six months prior, i.e. at the end of \( t-6 \). Following Jegadeesh and Titman (1993), MOM at time \( t \) is the stock’s 11-month past return lagged one month, i.e. return from month \( t-12 \) to month \( t-2 \). REV in month \( t \) is short-term reversal defined as the return on the stock in month \( t-1 \), following Jegadeesh (1990) and Lehmann (1990).

3. Empirical Results

3.1 Volatility Patterns over Time
3.1.1 Descriptive Statistics

We report the descriptive statistics for three volatility series in Table 1. MVOL is monthly market volatility (MVOL). The MVOL for a given month \( m \) is the standard deviation of the daily value-weighted market returns for the past 22 trading days ending on the last trading day of month \( m \). IVOL\textsuperscript{EW} and IVOL\textsuperscript{VW} are respectively the equal-weighted (EW) and value-weighted (VW) average idiosyncratic volatility across all firms, where IVOL is the standard deviation of residuals from (1). Table 1 shows that both IVOL\textsuperscript{EW} and IVOL\textsuperscript{VW} are 0.0188 and 0.0127 respectively, which is only about half compared to the IVOL in China where is the biggest emerging stock market in the world (Kong and Kong, 2015). The results indicate the stock market in developed countries might be more stable than emerging stock markets. Moreover, the results also indicate that small firms seem to have higher idiosyncratic volatility than big firms as suggested by the higher mean of IVOL\textsuperscript{EW} compared with IVOL\textsuperscript{VW}. This is consistent with results in other markets particularly the U.S. However, IVOL\textsuperscript{EW} is less variable than IVOL\textsuperscript{VW} as indicated by its lower coefficient of variation (CV). MVOL on the other hand is more variable than IVOL\textsuperscript{EW} having a higher CV, but it has a similar CV as IVOL\textsuperscript{VW}.

(Insert Table 1 around here)

As expected, our volatility measures are highly correlated as shown in Panel B, with correlation coefficients ranging from 0.849 to 0.913.

Panel C displays the autocorrelation structure of the three volatility series. As serial correlation is fairly high in all three series, we test for the presence of unit roots using the augmented Dickey and Fuller (1979) test. Panel D shows that we can reject the presence of unit roots for all three series, whether or not a trend is included. Hence our analysis of the
volatility series will be in levels instead of first differences.

3.1.2 Does a time trend exist?

Figure 1 plots IVOL\textsuperscript{EW}, IVOL\textsuperscript{VW}, and MVOL. As indicated in Figure 1, there does not appear to be any long-term trend in any of these volatility series. Instead, the plots suggest episodic behavior in these series. There was an upward trend in all three volatility series from 1991 to 2001, a downward trend until 2006, a spike in 2009 followed by a decreasing trend thereafter. The pattern of our volatility measures in the Figure 1 are very similar to the volatility figures for the French stock market reported by Duncan and Kabundi (2014).

(Insert Figure 1 around here)

As a formal test for the presence of trends, we begin by estimating the following OLS model:

\[
VOL_t = b_0 + b_1 t + b_2 VOL_{t-1} + \epsilon_t
\]

(3)

where \(VOL\) represents IVOL\textsuperscript{EW}, IVOL\textsuperscript{VW}, and MVOL, and \(t\) is time. The estimated time trend \(b_1\) parameter and its t-statistic are reported in Table 2. Over the full sample period from 1991:08 to 2012:06, the standard t-test shows a statistically significant positive trend in IVOL\textsuperscript{EW} but no trend for both IVOL\textsuperscript{VW} and MVOL. However, since Vogelsang (1998) points out that the null hypothesis of no trend is rejected too often when errors in the trend regression are persistent, we also employ the t-dan test developed by Bunzel and Vogelsang (2005). This test is valid whether or not a unit root exists in the error terms. The t-dan test statistics reported in Table 2 confirm the absence of a trend in either IVOL\textsuperscript{VW} or MVOL but a positive trend in IVOL\textsuperscript{EW} which indicates that the IVOL of small stocks have been trending upwards. However, this apparent trend in IVOL\textsuperscript{EW} could be simply due to the spike in volatility towards the end of
2008. Nonetheless, the fact that MVOL and IVOL$^\text{VW}$ are relatively flat over the study period, implies that there is also no trend in correlations among stocks and that the benefits from diversification would have likely remained the same on average over the study period, which also means that the number of stocks needed to attain a certain level of diversification would also have remained the same.

(Insert Table 2 around here)

3.1.3 Regime switching behavior in idiosyncratic volatility

In this section, we test for regime-switching behavior in idiosyncratic volatility. We follow Bekaert et al.’s (2012) method to further test whether or not our volatility series in the French stock market is characterized by a stationary process that occasionally switches between high- and low-volatility regimes. Bekaert et al. (2012) argue that the upward trends of idiosyncratic volatility in the U.S. and 22 other developed markets were driven by the chosen starting- and ending time points. For example, if the starting point is in a low volatility period, while the end point is in a high volatility period, then the trend test would easily show a positive trend. Bekaert et al. (2012) thus suggest that idiosyncratic volatility in the U.S. and 22 other developed markets are best characterized by a stationary process that occasionally switches between high- and low-volatility regimes. A regime-switching behavior in idiosyncratic volatility also appears evident in emerging markets with Nartea, et al. (2013) documenting evidence of such behavior in the Chinese stock market, the world’s largest emerging market.

To test for regime switching behavior in idiosyncratic volatility in the French stock market, we let volatility, $y_t$, follow an AR(1) model where all parameters can take on one of two values
depending on the realization of a discrete regime variable, \( s_t \). The regime variable follows a Markov chain with constant transition probabilities. Indexing the current regime by \( i \) the model is

\[
y_t = (1 - b_i)\mu_i + b_i y_{t-1} + \sigma_i e_t, \quad i \in \{0, 1\}
\]  

(4)

with \( e_t \sim N(0,1) \). In the model, we force regime 0 (regime 1) to be the low (high) volatility regime and the mean levels (\( \mu_i \)) of the volatility series of both regimes to be nonnegative (i.e. \( \mu_1 > \mu_0 > 0 \)).

The transition probability matrix, \( \Phi \), is \( 2 \times 2 \), where each probability represents \( P[s_t = i | s_{t-1} = j] \), with \( i, j \in \{1, 2\} \):

\[
\Phi = \begin{pmatrix} p_{11} & 1 - p_{11} \\ 1 - p_{22} & p_{22} \end{pmatrix}
\]

The model has only 8 parameters, \( \{\mu_0, \mu_1, b_0, b_1, \sigma_0, \sigma_1, p_{11}, p_{22}\} \).

The estimation results for each volatility series \( y_t = \text{IVOL}^\text{EW}, \text{IVOL}^\text{VW}, \text{MVOL} \) are reported in Table 3. We use the robust White (1980) covariance matrix to compute the standard errors. Table 3 shows that levels for both EW and VW IVOL in the low volatility regime (\( \mu_0 \)) at 0.0258 (\( \text{IVOL}^\text{EW} \)) and 0.0105 (\( \text{IVOL}^\text{VW} \)) respectively, which are both statistically significant. The corresponding levels in the high volatility regime (\( \mu_1 \)) at 0.0163 and 0.0181 are also both statistically significant. The differences between the levels of the two regimes for both volatility series are also statistically significant as indicated by the results of the Wald test. Our results also show higher volatility in regime 1 (\( \sigma_1 \)) compared with regime 0 (\( \sigma_0 \)) for both EW and VW IVOL. The EW (VW) volatility in regime 1 is 0.0040 (0.0035) compared with 0.0013 (0.0013) for regime 0. Thus we find that idiosyncratic volatility in the French stock
market conforms with a stationary autoregressive process that occasionally switches between high and low-variance regimes. This is consistent with the behavior of idiosyncratic volatility in developed stock markets (Bekaert et al. 2012) and in the world’s largest emerging market (Nartea et al. 2013).

(Insert Table 3 around here)

Figure 2 shows the smoothed probabilities of being in regime 0 for our three volatility series. Unlike the evidence reported by Bekaert et al. (2012) in the U.S. stock market, we find that both high- and low- idiosyncratic volatility regimes in the French stock market have the propensity to stay for a period before switching to another. We observe this phenomenon several times over the study period. For example, Panel a of Figure 2 shows that IVOL$_{EW}$ was in a high volatility regime from 1992 to mid-2000, consistent with Morel’s (2001) findings in the French stock market. And then, it shifts to a low volatility regime until the early of 2006. Furthermore, the IVOL$_{EW}$ remained in a high volatility regime during the 2008 financial crisis, until the beginning of 2009 when it switched again to a low volatility regime. Panel b of Figure 2 shows that IVOL$_{VW}$ switched between high- and low volatility regimes more frequently than IVOL$_{EW}$. IVOL$_{VW}$ stayed in the low volatility regime for most of the 20 year testing period, for example from 1992 to March 1998, January 2003 to January 2008, and September 2009 to the end of the study period. If we define $y_t$ to be in regime 0 if the probability of being in regime 0 is higher than 0.5, and vice versa for regime 1, then there are 4 regime switches in IVOL$_{VW}$ and 3 regime switches in IVOL$_{EW}$ over the 20-year study period. Our results indicate that those big firms become more volatile after the integration of the European stock market, but the volatilities of small firms seem becoming stable. The results are consistent to Bekaert and
Harvey’s (2000) suggestion, which the markets’ liberalization could not only reduce the markets’ volatilities in emerging market, but also in developed stock markets. Panel c of Figure 2 shows that MVOL was switching from low volatility regime to high volatility regime unpredictably over the study period. It is hard to observe a clear pattern for the MVOL, but the regime of the MVOL partly follows the regime of IVOL$^{VW}$ reported in the panel b.

(Figure 2 around here)

Figure 2 confirms an insignificant time series trend in IVOL in the French stock market consistent with results reported in Table 2. For example, the absence of a trend in both IVOL$^{VW}$ and MVOL reported in Table 2 is consistent with both panel b and c in Figure 2, where both series start and end in the low volatility regimes over our study period. Panel a of Figure 2 shows that our testing period starts from a high-level of IVOL and ends in a low-level of IVOL, which indicates that the significant positive trend in IVOL$^{EW}$ reported in Table 2 is not due to the choice of sample period. However, results reported in Table 3 still suggest a significant regime-switching behavior of the IVOL$^{EW}$.

We also find it interesting that IVOL$^{VW}$ and IVOL$^{EW}$ exhibit a divergence in the period from 1992 to 1999, with IVOL$^{EW}$ being on a high-volatility regime while IVOL$^{VW}$ was on a low-volatility regime. We suggest that this could be due to the boom in high-tech stocks over this period. As high-tech stocks are normally smaller in size and more volatile than traditional listed firms, we expect IVOL$^{EW}$ to be more volatile than IVOL$^{VW}$ before the high-tech bubble burst around year 2000. We also find that both IVOL$^{VW}$ and IVOL$^{EW}$ were on a high volatility regime during the recent 2008 financial crisis. This is consistent with previous findings in the literature wherein stock markets are more volatile during the financial crisis period than other
periods (Nartea et al., 2013). Finally, we find that both IVOL$^\text{VW}$ and IVOL$^\text{EW}$ show a convergent behavior after 2002 in the French stock market.

In sum, results from Table 3 and Figure 2 indicate evidence of episodic behavior in all three volatility series, consistent with occasional regime shifts throughout the study period.

3.2. Can idiosyncratic volatility predict cross-sectional expected stock returns?

3.2.1 Portfolio-level analysis

In this section we examine the presence of an IVOL effect in the French stock market. Table 4 shows the average monthly returns and FF-3 alpha of EW and VW portfolios sorted according to idiosyncratic volatility. Though both the EW and VW return spreads between high and low IVOL portfolios are consistently negative at -0.91% and -0.71% per month respectively, they are not statistically significant. We only report the FF-3 alpha of each portfolios on the third column. Stotz et al. (2010) report that there are not a big differences between Fama and French’s alpha and Jensen’s alpha. The EW alpha spread is likewise negative at -0.34% per month but also statistically insignificant. The exception is the statistically significant VW alpha spread at -0.58% per month. This appears to be consistent with the anomalous and puzzling evidence documented by Ang et al. (2006, 2009) and Brockman and Yan (2006) for the U.S. market. However it is not as high as the -1.31% per month reported by Ang et al. (2006) for the U.S.

(Insert Table 4 around here)

Before we test the robustness of this apparent negative IVOL effect in the French stock market, we report the average of the monthly averages of various characteristics of the IVOL-sorted portfolios in Table 5. We report values for IVOL, size (SIZE), BM (Value), momentum
(MOM), and short-term reversal (REV). These variables are as defined previously. The high IVOL portfolio has three times as much IVOL as the low IVOL portfolio and the difference is highly statistically significant as expected. High (low) IVOL stocks also tend to be small (big) stocks. This results are consistent to Drew et al.’s (2006) findings in the German and UK stock markets, which authors find that small firms have higher IVOLs than big firms. High (low) IVOL stocks also tend to be previous losers (winners) in the past 11 months. However, there is no significant difference in the value and short-term reversal variables between high and low IVOL portfolios. We formally control these variables using firm-level cross-sectional regressions in the next section.

(Insert Table 5 around here)

3.2.2 Firm-level cross-sectional regressions

We begin with univariate regressions on IVOL and our control variables. Table 6 reports the time-series averages of the slope coefficients over the 251 months from 1991:08 to 2012:06 with Newey-West (1987) t-statistics in parenthesis. The univariate regression shows a statistically significant negative relation between IVOL and the cross-section of one-month ahead stock returns. The results also show significant momentum and BM effects with previous winners and stocks with high BM exhibiting higher returns. However we find no size and short-term reversal effects. The absence of a size effect is consistent with Morel (2001) who reports a significant size effect from March 1996 to July 1996 which disappears thereafter.

(Insert Table 6 around here)

Next we control the size, BM, reversal, and momentum effects individually with bi-variate Fama-MacBeth cross-sectional regressions and then simultaneously in a multivariate
regression. We report the results in Table 7. The bivariate regressions show that none of our control variables can individually explain the negative IVOL effect. However if we control for all four variables simultaneously, the IVOL coefficient becomes insignificant! Therefore, firm-level cross-sectional regression results indicate that the apparent negative IVOL effect in the French stock market is not robust and can be explained by our control variables.

(Insert Table 7 around here)

4. Concluding Remarks

In a recent study, Ang et al. (2009) confirm the ubiquity of a puzzling negative idiosyncratic volatility (IVOL) effect (Ang et al., 2006) in 23 developed countries including the seven largest developed economies (G7). However, in their study, they also report that among G7 countries not only did France show a decrease in the magnitude of the idiosyncratic volatility coefficient when idiosyncratic volatility was computed using a local Fama-French model instead of a world Fama-French model, the idiosyncratic volatility coefficient turned insignificant indicating the absence of an IVOL effect. We investigate this further in this study. We also investigate the behavior of aggregate idiosyncratic and market volatility in the French stock market in as much as Campbell, et al. (2001) report evidence of an increasing trend in idiosyncratic volatility in the U.S. relative to market volatility which is disputed by both Brandt, et al. (2010) and Bekaert, et al. (2010).

We find that both idiosyncratic and market volatility do not exhibit long-term trends. Instead their patterns are consistent with regime switching behavior similar to that in the U.S. and other developed countries. Though we initially find a negative IVOL effect in the French stock market which is robust in bi-variate Fama-MacBeth regressions the negative IVOL effect
promptly disappears when we control for these well-known effects simultaneously.

We add new evidence to the mounting results questioning the ubiquity of the IVOL effect which highlights the importance of country verification of so-called anomalies in the US, even in developed markets.
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**Table1.** Descriptive statistics

$I_{\text{IVOL}}^{\text{EW}}$, $I_{\text{IVOL}}^{\text{VW}}$ and $M_{\text{VOL}}$, are respectively the equal- and value-weighted idiosyncratic volatility and market volatility. The sample period is 1991:08-2012:06. At the beginning of every month, we compute IVOL of each firm as the standard deviation of the residuals of the FF3-factor model by using previous 22 trading daily return data. We use the standard deviation of daily value-weighted market returns for the past 22 trading days ending on the last trading day of month to represent the MVOL. The Augmented Dickey-Fuller test for unit roots in Panel D are based on regressions with a constant, and regressions with a constant and a trend. The 1% critical values for the unit root test are -3.47 with a constant, and -4.01 with constant and a trend respectively.

| Panel A: Summary statistics | Mean     | Median | Stdev   | CV     | MAX    | Min     |
|-----------------------------|----------|--------|---------|--------|--------|---------|
| $I_{\text{IVOL}}^{\text{EW}}$ | 0.0188   | 0.0174 | 0.0048  | 0.2553 | 0.0397 | 0.0120  |
| $I_{\text{IVOL}}^{\text{VW}}$ | 0.0127   | 0.0113 | 0.0043  | 0.3386 | 0.0322 | 0.0074  |
| $M_{\text{VOL}}$            | 0.0184   | 0.0165 | 0.0067  | 0.3641 | 0.0582 | 0.0098  |

| Panel B: Correlation Table | $I_{\text{IVOL}}^{\text{EW}}$ | $I_{\text{IVOL}}^{\text{VW}}$ | $M_{\text{VOL}}$ |
|----------------------------|-------------------------------|-------------------------|------------------|
| $I_{\text{IVOL}}^{\text{EW}}$ | 1.0000                        |                         |                  |
| $I_{\text{IVOL}}^{\text{VW}}$ | 0.8528                        | 1.0000                  |                  |
| $M_{\text{VOL}}$              | 0.8489                        | 0.9130                  | 1.0000           |

| Panel C: Autocorrelation structure | $I_{\text{IVOL}}^{\text{EW}}$ | $I_{\text{IVOL}}^{\text{VW}}$ | $M_{\text{VOL}}$ |
|-----------------------------------|-------------------------------|-------------------------|------------------|
| $\rho_1$                          | 0.843                         | 0.815                   | 0.775            |
| $\rho_2$                          | 0.748                         | 0.727                   | 0.607            |
| $\rho_3$                          | 0.702                         | 0.681                   | 0.504            |
| $\rho_4$                          | 0.621                         | 0.615                   | 0.422            |
| $\rho_6$                          | 0.545                         | 0.552                   | 0.371            |
| $\rho_{12}$                       | 0.451                         | 0.373                   | 0.224            |

| Panel D: Unit root test t-statistics | Constant | Constant and Trend |
|-------------------------------------|----------|--------------------|
| $I_{\text{IVOL}}^{\text{EW}}$      | -4.6134  | -4.6588            |
| $I_{\text{IVOL}}^{\text{VW}}$      | -3.9604  | -3.9728            |
| $M_{\text{VOL}}$                   | -5.5268  | -5.5271            |
Table 2. Time trend of volatility series

We run the following model by regressing the volatility measure on its first lag and a time trend to test by regressing the volatility measure on its first lag and a time trend: $VOL_t = b_0 + b_1 t + b_2 VOL_{t-1} + \epsilon_t$, where $VOL$ represents $IVOL^{EW}$, $IVOL^{VW}$, and $MVOL$, and $t$ is time. The estimated time trend $b_1$ parameter and its t-statistic and the Bunzel and Vogelsang (2005) t-dan test statistic for the full sample period are reported in Table 2. The 5% critical value (two-sided) for t-dan is 1.726.

|                      | Linear Trend (x 10^{-5}) | t-stat | t-dan  |
|----------------------|--------------------------|--------|--------|
| $IVOL^{EW}$          | 1.6107                   | 3.9417 | 1.8160 |
| $IVOL^{VW}$          | -2.2946                  | -0.6191| -0.2712|
| $MVOL$               | 0.9200                   | 1.5750 | 1.0494 |
Table 3. Regime switching model estimation results

The regime-switching model results for volatility series. The model is:

\[ y_i = (1 - b_i)\mu_i + b_i y_{i-1} + \sigma_i e_i, \quad i \in \{0, 1\} \]

The transition probability matrix is:

\[ \phi = \begin{pmatrix} p_{11} & 1-p_{11} \\ 1-p_{22} & p_{22} \end{pmatrix} \]

The transition probability parameters, \( p_{11} \) and \( p_{22} \), are constrained to be in \((0, 1)\) over the study period. We also reparameterize to ensure \( \mu_2 > \mu_1 > 0 \). The estimation period is over 1991.08 to 2012.06. T-statistics are reported in parenthesis.

|        | \( IVOL^{EW} \) | \( IVOL^{1W} \) | \( MVOL \) |
|--------|----------------|----------------|----------|
|        | Coeff. | Stan.Error | Coeff. | Stan.Error | Coeff. | Stan.Error |
| \( p_{11} \) | 0.9566 | 0.0184 | 0.9359 | 0.0457 | 0.5898 | 0.1096 |
|         | (51.9802)|           | (20.4997)|         | (5.3824)|          |
| \( p_{22} \) | 0.8497 | 0.0741 | 0.9762 | 0.0167 | 0.8974 | 0.0317 |
|         | (11.4633)|           | (58.2982)|         | (28.3458)|          |
| \( \sigma_0 \) | 0.0013 | 0.0001 | 0.0013 | 0.0001 | 0.0018 | 0.0001 |
|         | (14.8685)|           | (16.4254)|         | (14.7378)|          |
| \( \sigma_1 \) | 0.0040 | 0.0004 | 0.0035 | 0.0003 | 0.0064 | 0.0007 |
|         | (9.4579)|           | (11.7100)|         | (9.4864)|          |
| \( b_0 \) | 0.4815 | 0.1335 | 0.6497 | 0.0589 | 0.6357 | 0.0236 |
|         | (3.6061)|           | (11.0250)|         | (26.9328)|          |
| \( b_1 \) | 0.7600 | 0.0394 | 0.4810 | 0.1119 | 0.6902 | 0.2049 |
|         | (19.2827)|           | (4.2974)|         | (3.3680)|          |
| \( \mu_0 \) | 0.0258 | 0.0013 | 0.0105 | 0.0003 | 0.0147 | 0.0004 |
|         | (20.1068)|           | (36.1627)|         | (34.8796)|          |
| \( \mu_1 \) | 0.0163 | 0.0004 | 0.0181 | 0.0010 | 0.0355 | 0.0087 |
|         | (36.0971)|           | (19.0951)|         | (4.0839)|          |

Likelihood: \(-1205.3056\), \(-1216.8193\), \(-1103.8582\)
Table 4. Returns of portfolios sorted by idiosyncratic volatility

Stock portfolios have been sorted by IVOL at the beginning of every month, i.e., high IVOL (HIV), medium IVOL (MIV) and low IVOL (LIV). The table thus reports each portfolio’s equal- and value-weighted raw returns for the current month. Each portfolio’s alpha (α coefficient) is also included in the table, which is from the FF3-factor model estimated using the full sample of monthly value- or equal-weighted returns for each portfolio. The last row presents the difference in monthly raw returns and differences in alpha between the high and low IVOL portfolios. T-statistics are reported in parenthesis.

| Portfolio | Raw Return | FF-3 Alpha |
|-----------|------------|------------|
|           | Mean       | Std. Dev   | Mean       | Std. Error |
|           | Equal-weighted |          | Value-weighted |              |
| High IVOL | -0.0030    | 0.0059     | -0.0003    | 0.0026      |
|           | (-0.6170)  |            | (-1.1118)  |            |
| Medium IVOL | 0.0027   | 0.0030     | 0.0010     | 0.0018      |
|           | (0.7707)   |            | (0.5384)   |            |
| Low IVOL  | 0.0061     | 0.0016     | 0.0031     | 0.0013      |
|           | (2.3879)   |            | (2.3995)   |            |
| High- Low | -0.0091    |            | -0.0034    | 0.0029      |
|           | (-1.6526)  |            | (-1.1696)  |            |
| High IVOL | -0.0019    | 0.0070     | -0.0039    | 0.0019      |
|           | (-0.3658)  |            | (-2.0721)  |            |
| Medium IVOL | 0.0028   | 0.0038     | -0.0008    | 0.0011      |
|           | (0.7288)   |            | (-0.7252)  |            |
| Low IVOL  | 0.0051     | 0.0026     | 0.0019     | 0.0006      |
|           | (1.5867)   |            | (3.4614)   |            |
| High- Low | -0.0071    |            | -0.0058    | 0.0020      |
|           | (-1.1363)  |            | (-2.9109)  |            |
Table 5. Characteristics of portfolios sorted by idiosyncratic volatility

The table shows that average firm’s characteristics of each IVOL sorted portfolio over the full sample period, i.e., high IVOL (HIV), medium IVOL (MIV) and low IVOL (LIV). IVOL is the standard deviation of the residuals of the FF3-factor model computed using the past 22 trading daily returns data. SIZE is the firms’ capitalization at the end of month $t$; Value is the firm’s book-to-market ratio six months prior, i.e. at the end of $t-6$. Momentum represents the stock’s 11-month past return lagged one month by following Jegadeesh and Titman (1993), i.e. return from month $t-12$ to month $t-2$. REV in month $t$ is short-term reversal defined as the return on the stock in month $t-1$, following Jegadeesh (1990) and Lehmann (1990). T-statistics are reported in parenthesis.

|          | IVOL   | SIZE    | Value | Momentum | REV |
|----------|--------|---------|-------|----------|-----|
| High IVOL| 0.0303 | 575.82  | 0.8218| -0.0394  | 0.0044 |
|          | (55.7154) | (23.9111) | (37.8627) | (-1.5912) | (0.7793) |
| Medium IVOL| 0.0166 | 1810.59 | 0.7864| 0.0638  | 0.0022 |
|          | (61.3300) | (32.4654) | (48.2870) | (4.1401) | (0.6770) |
| Low IVOL | 0.0095 | 3717.68 | 0.8385| 0.0924  | 0.0004 |
|          | (69.2589) | (33.1339) | (76.4216) | (8.9538) | (0.2133) |
| High- Low | 0.0208 | -3141.86 | -0.0200 | -0.1318 | 0.0040 |
|          | (37.1756) | (-27.3784) | (-0.8192) | (-4.9116) | (0.6716) |
We perform firm-level Fama-MacBeth cross-sectional regressions on the return on that month with values of the control variables in previous month for the full sample period. The time-series averages of the slope coefficients and their associated t-statistics are reported in the table. IVOL is the standard deviation of the residuals of the FF3-factor model computed using the past 22 trading daily returns data. SIZE is the firms’ capitalization at the end of month $t$; Value is the firm’s book-to-market ratio six months prior, i.e. at the end of $t$-6. Momentum represents the stock’s 11-month past return lagged one month by following Jegadeesh and Titman (1993), i.e. return from month $t$-12 to month $t$-2. REV in month $t$ is short-term reversal defined as the return on the stock in month $t$-1, following Jegadeesh (1990) and Lehmann (1990). Newey-West T-statistics are reported in parenthesis.

$$R_{t+1} = \beta_{0,t} + \beta_{1,t}IVOL_t + \beta_{2,t}VALUE_t + \beta_{3,t}MV_t + \beta_{4,t}Value_t + \beta_{5,t}Reversal_t + \beta_{5,t}Momentum_t$$

| Intercept | IVOL  | SIZE  | Value   | Reversal | Momentum |
|-----------|-------|-------|---------|----------|----------|
| 0.0117    | -0.6322 |       |         |          |          |
| (3.10)    | (-3.08) |       |         |          |          |
| 0.0017    |        | 1.16E-7 |         |          |          |
| (0.48)    |       | (0.68) |         |          |          |
| -0.0035   |        |       | 0.0072  |          |          |
| (-0.72)   |       |       | (3.75)  |          |          |
| 0.0022    |        |       |         | -0.0135 |          |
| (0.53)    |       |       |         | (-1.02) |          |
| 0.0005    |        |       |         |          | 0.0159   |
| (0.15)    |       |       |         |          | (4.21)   |
Table 7. Bivariate and multivariate Fama-Macbeth regression results

We perform a firm-level Fama-MacBeth cross-sectional regression of the return on that month with values of the control variables in previous month for the full sample period. The time-series averages of the slope coefficients and their associated t-statistics are reported in the table. IVOL is the standard deviation of the residuals of the FF3-factor model computed using the past 22 trading daily returns data. SIZE is the firms’ capitalization at the end of month $t$; Value is the firm’s book-to-market ratio six months prior, i.e. at the end of $t-6$. Momentum represents the stock’s 11-month past return lagged one month by following Jegadeesh and Titman (1993), i.e. return from month $t-12$ to month $t-2$. REV in month $t$ is short-term reversal defined as the return on the stock in month $t-I$, following Jegadeesh (1990) and Lehmann (1990). Newey-West T-statistics are reported in parenthesis.

\[ R_{i,t+1} = \beta_{0,t} + \beta_{1,t} IVOL_{it} + \beta_{2,t} MV_{it} + \beta_{3,t} Value_{it} + \beta_{4,t} Reversal_{it} + \beta_{5,t} Momentum_{it} \]

| Intercept | IVOL  | SIZE  | Value | Reversal | Momentum |
|-----------|-------|-------|-------|----------|----------|
| 0.0130    | -0.7141 | -5.93E-8 |       |          |          |
| (3.03)    | (-2.92) | (-0.35)  |       |          |          |
| 0.0056    | -0.5235 |          | 0.0063 |          |          |
| (1.52)    | (-3.14) |          |        | (3.99)   |          |
| 0.0098    | -0.4504 |          | -0.0164|          |          |
| (2.83)    | (-3.12) |          |        | (-1.39)  |          |
| 0.0093    | -0.5830 |          |        |          | 0.0142   |
| (2.35)    | (-2.82) |          |        |          | (3.87)   |
| 0.0021    | -0.4454 | 4.97E-9 | 0.0063 | -0.0495  | 0.0210   |
| (0.49)    | (-1.75) | (0.03)  | (4.99) | (-3.68)  | (5.07)   |