Predicting Stock Market Returns and Volatility with Investor Sentiment: Evidence from Eight Developed Countries

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We test the predictive ability of investor sentiment on the return and volatility at the aggregate market level in the U.S., four largest European countries and three Asia-Pacific countries. We find that in the U.S., France and Italy periods of high consumer confidence levels are followed by low market returns. In Japan both the level and the change in consumer confidence boost the market return in the next month. Further, shifts in sentiment significantly move conditional volatility in most of the countries, and in Italy such impacts lead to an increase in returns by 4.7% in the next month.

INTRODUCTION

Financial economists demonstrate that investor sentiment affects stock prices. Shiller (1981) and Leroy and Porter's (1981) show that stock prices are too volatile to be justified by changes in future dividends. Black (1986) terms so-called 'noise traders' who trade on 'noise' as if it were profitable information associated with fundamentals affect stock prices. De Long, Shleifer, Summers, and Waldmann (1990) show that noise traders who have erroneous beliefs drive stock prices away from fundamental values and increase volatility. Fisher and Statman (2003) present evidence showing that monthly *changes* in consumer confidence indexes (MS and CCI) and S&P500 stock returns exhibit a positively *contemporaneous* relationship. Baker and Stein (2004) theoretically show that as investor sentiment increases, liquidity and stock prices increases, and hence subsequent stock returns will be low. Brown and Cliff (2004) document a contemporaneous relation between investor sentiment and U.S. stock market returns. Baker and Wurgler (2006) provide evidence that investor sentiment exerts greater cross-sectional impacts on stocks whose valuations are highly subjective and difficult to arbitrage. Ho and Hung (2009) use various measures of investor sentiment as conditioning information in asset pricing models and find that these model specifications often capture the anomalies including the size, value and momentum effects.

Recent research further shows that investor sentiment predicts the cross-section of stock returns. Lemmon and Portniaguina (2006) document that a measure extracted from the indexes composed by the University of Michigan (MS) and Conference Board (CCI) forecasts the returns on small stocks and those stocks with low institutional ownership. Stambaugh, Yu, and Yuan (2011) argue that, comparing to the stocks in the long leg, the stocks in the short leg of the long-short strategies based on 11 anomalies investigate are relatively overpriced when investor sentiment is high. Chung, Hung and Yeh (2012) demonstrate that investor sentiment predicts the cross-section of stock returns particularly during economic expansionary periods.

This paper contributes to the literature by studying in eight developed markets the predictive relations between investor sentiment, stock market returns and volatility. We explicitly allow for the roles investor sentiment, either the level or the change in the sentiment index, may play in both the mean and volatility equations in a GARCH-M model. We seek to understand whether investor sentiment may influence conditional volatility of stock market returns. This is because shifts in sentiment may exert significant impacts on conditional volatility, and such effects may affect subsequent stock market returns via the risk-return relation. The extant research primarily focuses on examining the relation between sentiment and return patterns, while little has been done in an international context on examining the sentiment-volatility predictive relation, and whether such relation further leads to an impact on aggregate stock market returns. This paper aims to fill this gap.

We consider the stock markets in the U.S., Europe (the U.K., France, Germany and Italy) and the Asia-Pacific countries (Japan, Australia and New Zealand). We remove the possible fundamental information contained in the investor sentiment indicator by controlling for the economic fundamentals including dividend yield, the annual measure of inflation, the change in the short-term risk-free rate, and the 12-month change in the industrial production index in the predictive regression. Pesaran and Timmermann (1994) consider the predictive power for monthly stock market returns of these variables. In our results dividend yield and the inflation rate show statistical significance for most of the countries. We also control for the possible seasonal effects in January and October.

Our study of investor sentiment and international markets is distinctive from prior research in our focus and findings. We consider eight developed markets, unlike many studies that look at only the U.S. market. We examine the relations between sentiment in the current month and the next-month return and volatility. Our use of the monthly frequency of the survey-based sentiment indicators is consistent with the approach widely adopted in recent research such as Chung, Hung and Yeh (2012), Stambaugh, Yu, and Yuan (2011), Yu, and Yuan (2011), Ho and Hung (2009), and Baker and Wurgler (2006), among others. At the levels of daily and weekly frequencies, Wang, Keswani and Taylor (2006) construct their U.S. sentiment indicators (e.g., the ratio of the trading volume or the open interest of put options divided by that of call options— measures that are widely viewed as bearish indicators) and survey indexes, and also calculate realized volatility based on 5-minute S&P 500 index returns. They report that S&P 500 index returns and the volatility measures Granger cause these sentiment indicators. Jansen and Nahuis (2003) find no Granger causality, however, between stock market index returns and consumer confidence, at either monthly or fortnightly frequencies, in the majority of the European countries they examined.

Importantly, we find that shifts in investor sentiment significantly affect conditional volatility of stock market returns in most of the countries. The impact of consumer confidence on stock returns via conditional volatility is present in Italy and the U.S. In Italy such impacts lead to an increase in returns by 4.7% in the next month using the level of consumer confidence. Our results for the U.S. are in line with those of Lee, Jiang and Indro (2002) who utilize the U.S. data and show evidence that investor sentiment influences conditional volatility. We do not find similar effect in the rest of the countries in our sample.

Schmeling (2009) considers the sentiment-returns relation across the long-run horizons in international markets, while we go a step further to test the ways investor sentiment may influence the conditional volatility of returns. Moreover, in addition to examining the level of investor sentiment, we also allow for the role of the change in investor sentiment may play in the formation of the future market return and volatility.

Our results on the return predictive ability of investor sentiment are consistent with prior research. We find that periods of high sentiment level tend to be followed by low aggregate market returns in the countries we examined. The negative relationship between current consumer confidence level and subsequent excess monthly return is statistically significant not only for the U.S. market but also for France and Italy. Fisher and Statman (2003) show a negative relationship between the *level* of the consumer confidence in one month and S&P 500 stock returns over the *next* month. They further find that high consumer confidence level predicts lower future returns on S&P index, Nasdaq index, and small-cap portfolios over the next 6 and 12 months. Brown and Cliff (2005) find that returns on portfolios formed on the basis of size and book/market ratios over future multiyear horizons are negatively related to Investors' Intelligence sentiment index which directly reflects the attitude of stock investors, and that market pricing errors are positively related to sentiment. This evidence suggests that the market is typically overvalued during periods of optimism.

An important exception is Japan where the current consumer confidence level boosts the excess market return in the next month. The observed positive effect of the current investor sentiment level on the subsequent market returns might be due to an extended effect of sentiment on the return of the subsequent month. In other words, stock prices are boosted not only in the current month when the market participants are optimistic, but also prices are affected in the following month. In contrast, the change in consumer confidence exhibits no predictive power for the subsequent excess stock market return in most of the countries except for Japan again where a positive and statistically significant relation exists.

Second, we further distinguish the effects of sentiments of the consumption and production sectors for the European countries by using two separate sentiment indicators: consumer confidence index and the Economic Sentiment Index (ESI) developed by the European Commission. The ESI was originally constructed to track the investment-GDP growth relation. It does not only contain the information on consumer confidence about the economy, but also significantly reflects the opinions of firms about future prospect of the economy and their investment intentions. The traditional consumption CAPM theory claims that stock returns are related to agents' decisions on consumption and investment portfolio allocation. The production-based asset pricing model (Cochrane 1991), in contrast, states that expected returns are high if investment growth is high, and thus variables related to investment growth have predictive power for stock returns. We find that, indeed, the shifts in the European Commission's economic sentiment move the conditional volatility in the U.K. and France.

The rest of the paper is organised as follows. Section 2 describes in detail the data and methodology. Section 3 presents the empirical results, and Section 4 concludes.

DATA AND METHODOLOGY

Investor Sentiment Data

We use investor the sentiment indicator in each country to investigate the relationship between investor sentiment and stock price behaviour at the market level. For the U.S. market, we use the consumer confidence indexes compiled by the University of Michigan (MS) and the Conference Board (CCI) [1], respectively. In addition to using consumer confidence indexes, we also consider the Investors Intelligence sentiment index (II) for the U.S. The II sentiment index, published by Chartcraft, reflects the outlook of independent financial market newsletter writers. Each week, the editor of Investors Intelligence reviews approximately 150 market newsletter writers and classifies their opinions into three categories. "Bullish" represents, among the total number of the bullish and bearish newsletter writers, the percentage of the bullish advisors who recommend stock for purchase or predict that the stock market will rise; "Bearish" indicates the proportion of the advisory services that recommend closing long positions or opening short ones because of the prediction that the market will decline; "Correction" denotes the ratio of the newsletter writers who predict a bull market but advises clients to hold off buying, or predicts a bear market but sees a short-term rally in the near future.

For the European countries, we adopt the consumer confidence index for each country developed by the European Commission. We also use the Economic Sentiment Index (ESI) for the European countries, in order to capture the information not contained in consumer confidence indicators. The ESI is constructed as a weighted average of monthly survey results from five sectors: industry (with a weight of 40%), services (30%), consumers (20%), retail trade (5%) and construction (5%). The ESI reflects the confidence of the consumers and manufactures of each EU country. If consumers and manufacturers feel confident about the prospects of the general economic and own financial situation, they are more willing to increase their consumption and production, respectively. As a result, the stock markets should reflect such economic activities if economy-wide sentiment influences stock price behaviour.

We employ consumer confidence indexes as investor sentiment measures for the Asia-Pacific markets, namely, Japan, Australia, and New Zealand. The consumer confidence indexes developed outside of the U.S. adopt questions and score calculation procedures similar to the MS.

Stock Market Indexes and Macroeconomic Variables

We use major stock market indexes to represent the performance of the stock market in each country. Since these market indexes are frequently reported in the headlines of mass media, they not only draw the attention of stock market participants but also the general public. We collect the monthly stock market return indexes from Datastream include S&P500 (the U.S.), FTSE100 (the U.K.), CAC40 (France), DAX30 (Germany), MIB30 (Italy), NIKKEI225 (Japan), ASX20 (Australia), and NZ50CAP (New Zealand). The sample periods start differently across countries, due to the availability of the data, but all end in September 2006. The starting months for the sample periods are January 1985 for US, January 1986 for UK, January 1989 for France, January 1991 for Germany, December 1994 for Italy, March 1993 for Japan, and June 1992 for Australia, and January 2001 for New Zealand.

Pesaran and Timmermann (1994) find that the lagged values of the dividend yield, the annual measure of inflation, the change in the 1-month T-bill rate, and the 12-month change in the industrial production index predict excess stock returns at both the quarterly and monthly horizons. In order to control for the fundamental information contained in the sentiment measures, we collect these data from Global Financial Data and include these macroeconomic variables in our analysis:

DY_t: Dividend yield on stock market index for month *t*, computed as $\frac{Dividend_{t-1}}{Market\ Index_t}$.

PI_t: The 12-month inflation rate for month *t* is calculated as $\log\left(\frac{CPIAV_t}{CPIAV_{t-1}}\right)$, where $CPIAV$ is the annual average of Consumer Price Index.

DI_t: Monthly change in the 1-month T-bill rate, computed as $R_{ft} - R_{ft-1}$.[2]

DIP_t: The 12-month rate of change in industrial production for month *t*, computed as $\log\left(\frac{IPAV_t}{IPAV_{t-1}}\right)$, where $IPAV$ is 12-month average of the industrial production index.

Model Specification

For each country under consideration, we estimate three specifications of the GJR type of GARCH-M model. Our model specification differs from Lee, Jiang, and Indro (2002) in the following aspects. First, we include the macroeconomic variables that represent the fundamental information in the mean equation. Second, instead of using the contemporaneous investor sentiment measures, we lag investor sentiment by 1 month in the mean equation in order to examine the predictive power of investor sentiment for the subsequent stock market returns. Third, apart from the monthly change in the investor sentiment measure, we also consider the impact of investor sentiment level on stock returns.

We start with the base model, Model 1 (equations 1 and 2), where only the macroeconomic variables, dummies for January and October, and the volatility variable are in the specification, without the investor sentiment variable:

$$R_{it} - R_{ft} = \alpha_0 + \alpha_1 \log h_{it} + \alpha_2 Jan_t + \alpha_3 Oct_t + \alpha_4 DY_{t-1} + \alpha_5 PI_{t-2} + \alpha_6 DI_{t-1} + \alpha_7 DIP_{t-2} + \varepsilon_{it},\ \varepsilon_{it} \sim N(0,\ h_{it}) \quad (1)$$

$$h_{it} = \beta_0 + \beta_1 \varepsilon_{it-1}^2 + \beta_2 \varepsilon_{it-1}^2 I_{it-1}^- + \beta_3 h_{it-1} + \beta_4 R_{ft} \quad (2)$$

where R_{it} is the monthly return on a market index, R_{ft} is the risk-free rate. The dummy variable I_{it-1}^- acknowledges the asymmetric response in investors' formation of conditional volatility to positive and negative shocks, that is, $I_{it-1}^- = 1$ if $\varepsilon_{it} < 0$, and $I_{it-1}^- = 0$ otherwise. Glosten, Jagannathan, and Runkle

(1993) find that the magnitude of the change in market volatility is greater for bad news than for good news. The coefficient β_2 captures the sensitivity of conditional volatility on negative shocks. A positive β_2 indicates that a negative shock causes volatility to rise more than a positive shock of the same magnitude[3].

Model 1 allows us to test the risk-return relation (α_1), the seasonal effects (α_2 and α_3) and fundamental effects (α_4 through to α_7) on excess market returns. Pesaran and Timmermann (1994) show that the yield variable has a positive effect on excess return, while the inflation rate, the change in the 1-month T-bill rate, and the rate of change in industrial production have negative effects on the excess return. They find no evidence of a January effect on the S&P500 index.

We test whether investor sentiment exhibits return predictive ability on the stock market index after controlling for the macroeconomics variables. To this end, we specify Model 2 (equations 3 and 4) to incorporate the one-period lagged value of investor sentiment *level* in the mean equation, and allow the impact of the investor sentiment level on the conditional volatility:

$$R_{it} - R_{ft} = \alpha_0 + \alpha_1 \log h_{it} + \alpha_2 Jan_t + \alpha_3 Oct_t + \alpha_4 S_{t-1} + \alpha_5 DY_{t-1} + \alpha_6 PI_{t-2} + \alpha_7 DI_{t-1} + \alpha_8 DIP_{t-2} + \varepsilon_{it},\ \varepsilon_{it} \sim N(0,\ h_{it}) \tag{3}$$

$$h_{it} = \beta_0 + \beta_1 \varepsilon_{it-1}^2 + \beta_2 \varepsilon_{it-1}^2 I_{it-1}^- + \beta_3 h_{it-1} + \beta_4 R_{ft} + \beta_5 (\Delta S_{t-1})^2 D_{t-1} + \beta_6 (\Delta S_{t-1})^2 (1 - D_{t-1}) \tag{4}$$

S_{t-1} is the level of investor sentiment in month *t-1*, either using the consumer confidence index or the ESI as the proxy. A statistically significant coefficient estimate of α_4 on investor sentiment indicates return predictive ability on the aggregate stock market. The variance of the change in sentiment, $\mathrm{Var}(\Delta S_{t-1})$, can be approximated by $(\Delta S_{t-1})^2$ in (4) as the mean of the change in sentiment is close to zero. The coefficients β_5 and β_6 capture the impacts of the shifts in bullish and bearish sentiments on the conditional volatility, respectively. In conjunction with the coefficients β_5 and β_6, the coefficient α_1 reflects the relation between return and volatility. For example, a statistically significant estimate of β_5 indicates an impact of sentiment on volatility, which in turn, translates to the risk-return relation if the coefficient α_1 is statistically significant.

Next, we test whether the *change* in investor sentiment exhibits return predictive ability on the stock market index after controlling for the macroeconomics variables. In Model 3 we use the lagged value of the *change* in investor sentiment, ΔS_{t-1}, in the mean equation, while keeping the same volatility equation as in (4):

$$R_{it} - R_{ft} = \alpha_0 + \alpha_1 \log h_{it} + \alpha_2 Jan_t + \alpha_3 Oct_t + \alpha_4 \Delta S_{t-1} + \alpha_5 DY_{t-1} + \alpha_6 PI_{t-2} + \alpha_7 DI_{t-1} + \alpha_8 DIP_{t-2} + \varepsilon_{it},\ \varepsilon_{it} \sim N(0,\ h_{it}) \tag{5}$$

EMPIRICAL RESULTS

Investor Sentiment and Stock Returns

Table 1 summarizes the descriptive statistics for the sentiment measures and stock returns. Panels A and B report these results for the level and the change of the investor sentiment, respectively. According to Panel A, the level of consumer confidence, on average, is negative for each of the European countries. The consumer confidence level and the ESI level of the U.K. register a slightly higher average score than its European counterparts. Italy shows the smallest variation in consumer confidence, but displays the most volatile producer sentiment among the European countries. The averages of the U.S. consumer confidence indexes are 91.85 for the MS and 101.23 for the CCI. Note that these two indicators have different base periods. The scores for the Asia-Pacific countries are close to each other, centring around

100. The first order autocorrelations of the index levels generally exceed 0.9, and the second order autocorrelations range between 0.80 (consumer confidence for Australia) and 0.93 (the ESI for France), with the only exception of the ESI for Italy.

Panel B reports that the changes in the sentiment measures, on average, are positive in most of the countries in the sample, while the average changes in consumer confidence are negative in Germany, Italy and New Zealand. Panel C shows that during the sample period investors earn positive average returns of about 1% per month in all of the countries, but Japan. MIB30 shows the highest average return of 1.09%, while NIKKEI225 earns the lowest return of 0.14%.

Table 2 reports the correlation coefficients of the sentiment indicators. The consumer confidence indexes of the U.S. exhibit positive and statistically significant correlations with all the European countries, but the correlations with the Asia-Pacific countries are weaker. The correlations between the European and the Asia-Pacific countries are generally low. Japan, for example, shows low correlations (close to zero) with all other countries, except Italy. The consumer confidence indexes of Australia and New Zealand are significantly and positively correlated, and most of the correlations among European countries are positive, possibly due to economy proximity within the geographic region.

Consumer Confidence, Fundamentals, and the U.S. Stock Market

Table 3 reports the empirical evidence of the sentiment-volatility and sentiment-return relations for the U.S. market. The analysis starts with a GARCH-M model that excludes investor sentiment. The findings are reported in the second column of Table 3.

In the absence of investor sentiment in the model, the coefficient estimates of Model 1 show that conditional volatility is negatively associated with the excess return on the S&P500 index. The coefficient estimate on $\log h_{it}$ is statically significant at the 1% level. The negative risk-return relation is consistent with Fama and Schwert (1977), Campbell (1987), Pagan and Hong (1991), Breen, Glosten, and Jagannathan (1989), Turner, Startz, and Nelson (1989), Nelson (1991), and Glosten, Jagannathan, and Runkle (1993).

The direction of the impact of the lagged values of the macroeconomic variables on monthly stock return is generally in line with the findings of Pesaran and Timmermann (1994). Specifically, the yield variable, with a coefficient of 0.809, shows a positive effect on excess return and is statistically significant at the 1% level. The effect of the inflation rate and the change in the 1-month T-bill rate is negative, respectively, although statistically insignificant. Nevertheless, to the contrary of Pesaran and Timmermann's (1994) finding, the result here shows that the rate of change in industrial production on excess market return is positive. The opposite sign might be attributed to the difference in the sample periods. Pesaran and Timermann's (1994) findings is based on the monthly data for the 1954-1990 period, which has only a 6-year overlap with the early sample we use in the analysis.

The result for the conditional volatility equation indicates that the conditional volatility is positively serially correlated, and positively related to the risk-free rate. Investors perceive positive and negative shocks asymmetrically in forming their expectations of conditional volatility.[4]

Columns 3 – 8 in Table 3 report the coefficient estimates of the GARCH-M models augmented by the sentiment measures, namely, MS, CCI, and II, respectively. The results of Model 2 in which investor sentiment is measured by the level of investor sentiment indicator show current high sentiment level is followed by low excess stock market return in the next month, regardless of the different investor sentiment indexes. Among the investor sentiment indicators considered, the significant and negative coefficient of the MS indicates that the consumer confidence index of the University of Michigan in one month predicts the S&P500 excess return in the next month. This finding is consistent with Fisher and Statman (2003) who find a negative relationship between the *level* of the investor sentiment in one month and the stock returns over the *next* month. In contrast, we find no evidence to suggest the return predictive ability of the change in the investor sentiment measure on the stock market index after controlling for the macroeconomics variables.

Table 3 shows that the shifts in investor sentiment can influence the formation of conditional volatility. For consumer confidence (MS and CCI) the shifts in investor sentiment are negatively associated with conditional volatility. Verma and Verma (2007) also document a negative relationship between noise trading and DJIA and S&P 500 return volatilities for both individuals and institutions. Kurov (2008) finds that high investor sentiment has a negative impact on the transitory volatility in the futures market. In contrast, II's impact on stock volatility is positive and only marginally significant at the 10% level for the bullish sentiment measures. The risk-return relation, reflected in α_1, is insignificant at the 5% level. As a result, any change in investor sentiment fails to further impact stock return via its influence on conditional volatility.

Compared to Model 1, the macroeconomic variables that previously demonstrate predictability for the market performance are now different when investor sentiment is included in the mean equation. Dividend yield exhibits positive predictive power for S&P500 only in Model 3; however, according to the *p*-value, its explanatory power is weakened when investor sentiment is present in the model. The rate of change in industrial production maintains its ability to positively forecast excess market return in Model 2. In Model 3 the rate of change in industrial production is significant at the 5% level for MS and CCI, but loses its explanatory power for the market return when we use II. Statistically, inflation rate shows no ability to predict stock return in Model 1 while its predictive power enhances dramatically in Models 2 and 3 in which we observe a negative relationship.

Consumer Confidence, Fundamentals, and the European Stock Markets

Table 4 presents the results for the European markets, namely, the U.K., France, Italy, and Germany using the consumer confidence indexes compiled by the European Commission. The first column under each country in Table 4 reports the coefficient estimates of the GARCH-M model as specified in the base model as in Model 1 which does not consider sentiment.

The impacts of the macroeconomic variables on stock returns in the European countries differ from the results reported in Table 3 for the U.S. market. First, inflation is statistically significant and negatively related to the subsequent stock market returns in the U.K., France, Germany and Italy, unlike the U.S. market where inflation rate is statistically insignificant. Second, dividend yield shows predictive power for returns on the U.K. stock market as in the U.S. market, but not in other European countries. Third, industrial production exhibits significant predictive power for returns on the Germany stock market in which a high industrial production in one month is followed by low stock market return in the next month. Finally, the change in the 1-month T-bill rate is statistically insignificant in all the European countries, similar to the result for the U.S.

The results for Model 2 where the level of the consumer confidence enters the predictive regression model, in second column under each country in Table 4, show that high investor sentiment is followed by low excess stock returns in France and Italy. The coefficient estimates for the lagged sentiment level of these two markets are both negative and statistically significant at the 1% level. We find that the shift in investor sentiment impacts the conditional volatility. In Model 2, bearish shifts in sentiment affect volatility in all the European countries but France where bullish shifts in sentiment in the current month result in statistically significant upward revisions in the volatility of future returns.

In Model 3 where the change in the consumer confidence enters the predictive regression model, we find no evidence to suggest a predictive power of the change in consumer confidence for the subsequent stock returns, consistent with the U. S. evidence. In the U.K. market the direction of shifts in sentiment have asymmetric impacts on conditional volatility whereby bullish sentiment shifts cause downward revisions of volatility, while bearish sentiment shifts result in upward revisions of volatility. In Italy, shifts in sentiment, either the level or the change in consumer confidence, significantly impact conditional volatility, leading to a return increase in the next month. Such return increases are not only statistically significant, but also economically significant at 4.7% per month using the level or 3.8% per month using the change in consumer confidence.

The macroeconomic variables in Models 2 and 3 show a very similar overall pattern in the return predictive ability test to those in Model 1. In the U.K. stock market a high dividend yield of the current month strongly predicts a high stock market return in the next mint. In general, high inflation rates are followed by low future returns in the European stock markets. Germany is the only European country where the industrial production change rate negatively and statistically significantly predicts subsequent stock market returns in both Models 1 and 3.

Consumer Confidence, Fundamentals, and the Asia-Pacific Stock Markets

Table 5 presents the results for Japan, Australia and New Zealand. In Model 1, New Zealand is the only country where seasonal patterns are present in which the stock market exhibits superior performance during January and October, and is also the only country where an increase in the 1-month T-bill rate leads to a statically significant decrease in the subsequent excess market return. Consistent with the U.S. and European evidence, the coefficient on dividend yield is positive and statistically significant for Japan and Australia. On the other hand, a high inflation rate predicts a low market return in Australia and New Zealand.

The empirical outcomes of the conditional volatility equation show that high conditional volatility in the current month in these countries is primarily associated with high conditional volatility in the previous month. In Australia, the coefficient estimate on $\log h_{it}$ is negative and statically significant at the 1% level, similar to the U.S. evidence.

Turning to the predictive ability of investor sentiment on the stock market return, the second and third columns under each country show that both the level and change in the consumer confidence in Japan positively predict subsequent market returns. Moreover, in Model 2 for Japan, bullish shifts in consumer confidence cause upward revisions in the volatility of future returns, together with a statistically significant and positive risk-return relation reflected in the mean equation, a bullish sentiment shift in the current month leads to high excess market return in the next month. By contrast, consumer confidence shows no effect on either their market returns or volatilities in the stock markets of Australia and New Zealand. In all the three models, dividend yield remains its positive predictive relation with stock market returns in both Japan and Australia, and inflation rate negatively predict market returns in Australia.

Economic Sentiment Indicator, Fundamentals, and the European Stock Markets

We now use the ESI as a proxy for investor sentiment to explore to what extent the public's sentiment that reflects both the producers' and consumers' perceptions of the economy predict the stock market performance in the European countries. Table 6 reports the test results. We find no evidence that the ESI has a profound predictive ability for the excess returns in the four European countries[5], even for the countries like France and Italy where consumer confidence exhibits significant capability to predict the subsequent excess stock returns. Compared to the evidence for France and Italy reported in Tables 4 where consumer confidence is used to proxy for sentiment, Table 6 suggests that stock returns in these two European countries are more sensitive to the consumption decisions of the consumers than the investment decisions of the producers.

By contrast, the ESI exhibits some degree of influence on the formation of the conditional volatility for the U.K. and France. Table 6 shows that the bullish shifts in the ESI lead to upward revisions in the conditional volatility for these two countries. Furthermore, the bearish shifts in the ESI cause upward revisions of a larger magnitude for the U.K. Because the risk-return relation in these countries is statistically insignificant, the impact of the ESI on the conditional volatility is not transmitted to affect returns.

Empirical studies that examine the relation between investor sentiment and stock market performance uniformly adopt either consumer confidence (like the MS or CCI) or investor sentiment indictor (like the Investors Intelligence Index) to gauge market sentiment. The implicit rationale underlying these studies is that stock return is related to the consumption decisions of the investing public. According to the production-based (or investment-based) asset pricing models (Cochrane, 1991& 1996), however, stock returns are also related to the investment decisions of firms. Our results here seems to suggest that consumption-based asset pricing model might be more appropriate than production/ investment-based asset pricing model in describing the aggregate stock price behaviour in these countries.

CONCLUSION

In this paper we test the predictive ability of investor sentiment for stock market returns in eight developed countries. We use consumer confidence index in each country as the primary proxy for investor sentiment, and control for fundamental variables and allow for the GARCH dynamics in residuals. We also investigate whether the European Commission's economic sentiment index, a sentiment measure that primarily reflects the perceptions of the producers about the prospect of economy, predicts stock market returns for the European countries.

We find that consumer confidence exhibits predictive power for the subsequent stock market returns in the U.S., France and Italy whereby high consumer confidence predicts low excess stock market returns. In Japan both the level and change in current consumer confidence positively predict the excess market return in the next month. Shifts in consumer confidence impact conditional volatility of stock returns in all the countries but Australia and New Zealand; In Italy such impacts lead to an increase in returns by 4.7% in the next month using the level of consumer confidence. Among the fundamental variables, dividend yield and inflation rate exhibit the most prevalent predictive ability for stock returns. Finally, unlike consumer confidence, we do not find evidence that the European Commission's economic sentiment index shows predictive ability for returns on the European stock markets, although the shifts in the ESI move the conditional volatility in the U.K. and France.

ENDNOTES

1. We thank Lynn Franco for providing the Conference Board Consumer Confidence Index.
2. We also use the level of the short-term interest rate as in Ang and Bekaert (2007) in our tests. The results are very similar and do not change our conclusions.
3. The literature gives different explanations for the asymmetric return-volatility relation. The traditional view is that of the leverage effect (see Bollerslev (2008) for detailed discussion), while a behavioral explanation is offered by Hibbert, Daigler and Dupoyet (2008).
4. Empirical studies on the contemporaneous risk-return relation have shown mixed results. French, Schwert, and Stambaugh (1987) and Campbell and Hentschel (1992), for example, find a positive relationship between conditional expected excess return and conditional variance, and Chan, Karolyi, and Stulz (1992), however, find no evidence of a relationship between risk and return for the U.S. market. Yu and Yuan (2011) find a strong positive trade-off when the investor sentiment index constructed by Baker and Wurgler (2006) is low, but little, if any, when investor sentiment is high.
5. We also explore whether this observed relatively weak link between the ESI and stock returns could be attributed to the lag effect of investment decisions on stock returns. To address this issue, we repeat the analysis by lagging the sentiment variables by 3, 6, 9, 12, 18, and 24 months, respectively. The empirical evidence in general fails to support this conjecture.

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TABLE 1
DESCRIPTIVE STATISTICS OF SENTIMENT AND STOCK RETURN

	Mean	Standard deviation	Min	Max	Autocorrelation ρ_1	Autocorrelation ρ_2
Panel A: Sentiment						
MS	91.848	9.350	63.900	112.000	0.916	0.838
CCI	101.231	22.135	47.320	144.710	0.964	0.927
UK CC	-7.712	7.628	-28.100	6.900	0.928	0.876
France CC	-17.491	8.585	-34.100	3.700	0.938	0.876
Germany CC	-11.216	8.357	-27.700	6.300	0.957	0.911
Italy CC	-10.975	5.593	-21.300	2.000	0.904	0.827
Japan	98.823	2.367	94.297	102.879	0.974	0.923
Australia	101.309	2.242	95.167	105.791	0.924	0.795
New Zealand	101.975	1.405	98.863	104.118	0.943	0.844
UK ESI	102.267	12.040	68.700	132.200	0.953	0.913
France ESI	99.926	10.122	71.700	118.500	0.971	0.933
Germany ESI	98.121	9.017	78.700	118.900	0.965	0.919
Italy ESI	101.232	19.096	-107.700	121.300	0.104	0.082
Panel B: Change in sentiment						
ΔMS	-0.041	3.801	-12.200	17.300		
ΔCCI	0.015	5.949	-23.010	21.680		
UK ΔCC	0.018	2.872	-11.200	9.600		
France ΔCC	0.016	2.968	-10.600	9.900		
Germany ΔCC	-0.025	2.395	-6.300	6.400		
Italy ΔCC	-0.043	2.419	-7.600	5.900		
Japan	0.027	0.471	-1.278	0.964		
Australia	0.023	0.729	-2.032	1.755		
New Zealand	-0.013	0.373	-1.109	0.837		
UK ΔESI	-0.005	3.709	-10.400	10.200		
France ΔESI	0.506	8.128	-4.800	114.000		
Germany ΔESI	0.559	8.831	-5.000	118.900		
Italy ΔESI	0.763	10.071	-8.900	114.800		
Panel C: Index return (%)						
S&P500	0.868	4.295	-21.763	13.177		
FTSE100	1.009	4.592	-25.946	14.530		
CAC40	0.937	5.536	-17.490	13.415		
DAX30	0.972	6.243	-25.422	21.378		
MIB30	1.091	6.016	-17.553	21.391		
NIKKEI225	0.136	5.783	-16.731	16.144		
ASX20	1.012	3.761	-8.791	9.360		
NZ50CAP	0.846	3.377	-7.507	7.099		

This table presents the summary statistics for investor sentiment level, change in investor sentiment, and index return over the sample period for each country in the sample. CC is the consumer confidence index. ESI denotes the Economic Sentiment Indicator. Δ denotes the change in the investor sentiment. Panel C reports the statistics for each market index: S&P500 (the U.S.), FTSE100 (the U.K.), CAC40 (France), DAX30 (Germany), MIB30 (Italy), NIKKEI225 (Japan), ASX20 (Australia), and NZ50CAP (New Zealand).

TABLE 2
CORRELATION COEFFICIENTS BETWEEN SENTIMENT INDICATORS

	US(MS)	US(CCI)	UK	France	Germany	Italy	Japan	Australia	New Zealand
Panel A: Consumer Confidence									
US(MS)	1.000	0.868	0.530	0.539	0.351	0.189	-0.086	0.263	0.538
		(<.01)	(<.01)	(<.01)	(<.01)	(0.024)	(0.278)	(<.01)	(<.01)
US(CCI)	0.868	1.000	0.594	0.683	0.550	0.291	-0.007	0.171	-0.049
	(<.01)		(<.01)	(<.01)	(<.01)	(<.01)	(0.931)	(0.025)	(0.689)
UK	0.530	0.594	1.000	0.337	0.191	-0.206	-0.007	0.280	0.491
	(<.01)	(<.01)		(<.01)	(<.01)	(0.014)	(0.933)	(<.01)	(<.01)
France	0.539	0.683	0.337	1.000	0.781	0.334	0.034	0.124	-0.073
	(<.01)	(<.01)	(<.01)		(<.01)	(<.01)	(0.664)	(0.105)	(0.551)
Germany	0.351	0.550	0.191	0.781	1.000	0.541	0.020	0.017	-0.400
	(<.01)	(<.01)	(<.01)	(<.01)		(<.01)	(0.798)	(0.820)	(<.01)
Italy	0.189	0.291	-0.206	0.334	0.541	1.000	-0.409	-0.412	-0.132
	(0.024)	(<.01)	(0.014)	(<.01)	(<.01)		(<.01)	(<.01)	(0.279)
Japan	-0.086	-0.007	-0.007	0.034	0.020	-0.409	1.000	0.124	-0.062
	(0.278)	(0.931)	(0.933)	(0.664)	(0.798)	(<.01)		(0.116)	(0.615)
Australia	0.263	0.171	0.280	0.124	0.017	-0.412	0.124	1.000	0.597
	(<.01)	(0.025)	(<.01)	(0.105)	(0.820)	(<.01)	(0.116)		(<.01)
New Zealand	0.538	-0.049	0.491	-0.073	-0.400	-0.132	-0.062	0.597	1.000
	(<.01)	(0.689)	(<.01)	(0.551)	(<.01)	(0.279)	(0.615)	(<.001)	
Panel B Economic Sentiment Indicator									
UK	0.487	0.534	1.000	0.408	0.255	0.106			
	(<.01)	(<.01)		(<.01)	(<.01)	(0.211)			
France	0.485	0.659	0.408	1.000	0.633	0.216			
	(<.01)	(<.01)	(<.01)		(<.01)	(<.01)			
Germany	0.403	0.551	0.255	0.633	1.000	0.192			
	(<.01)	(<.01)	(<.01)	(<.01)		(0.022)			
Italy	0.187	0.158	0.106	0.216	0.192	1.000			

This table shows the Pearson correlation coefficients between the investor sentiment measures of the countries in the sample. Panel A reports the outcomes using the consumer confidence index of each country as an investor sentiment measure. Panel B reports the outcomes using the Economic Sentiment Indicator as an investor sentiment measure. The figures in parentheses are the significance levels of the correlation coefficients.

TABLE 3
THE U.S.: INVESTOR SENTIMENT, EXCESS RETURN, AND CONDITIONAL VOLATILITY

Coefficients	Model 1	MS		CCI		II	
		Model 2	Model 3	Model 2	Model 3	Model 2	Model 3
α_0	-0.046***	0.130**	0.026	0.033	0.025	0.030	0.064
	(<.01)	(0.05)	(0.16)	(0.40)	(0.50)	(0.41)	(0.22)
$\log(h_t)$	-0.004***	0.007	0.004*	0.0007	0.003	-0.0002	0.010
	(<.01)	(0.24)	(0.08)	(0.85)	(0.53)	(0.94)	(0.20)
Jan_t	0.010	0.009	0.003	0.015*	-0.001	0.007	0.011
	(0.32)	(0.40)	(0.78)	(0.09)	(0.87)	(0.51)	(0.26)
Oct_t	0.002	-0.010	-0.006	0.005	-0.0009	-0.003	0.003
	(0.76)	(0.30)	(0.55)	(0.52)	(0.94)	(0.72)	(0.82)
S_{t-1}		-0.001**		-0.0003		-0.0005	
		(0.03)		(0.12)		(0.21)	
ΔS_{t-1}			0.0004		0.0004		-0.001
			(0.36)		(0.37)		(0.35)
DY_{t-1}	0.809***	0.609	0.798**	0.063	0.631*	0.255	0.725*
	(<.01)	(0.18)	(0.05)	(0.84)	(0.09)	(0.52)	(0.06)
PI_{t-2}	-0.048	-0.645*	-0.483	-0.2311	-0.533*	-0.444	-0.612*
	(0.85)	(0.06)	(0.11)	(0.47)	(0.07)	(0.26)	(0.06)
DI_{t-1}	-3.231	-2.423	-3.083	-2.423	-3.076	-7.841	-2.836
	(0.51)	(0.68)	(0.60)	(0.60)	(0.60)	(0.15)	(0.62)
DIP_{t-2}	0.148**	0.277**	0.097	0.247**	0.092	0.121	0.153*
	(0.04)	(0.02)	(0.32)	(0.03)	(0.36)	(0.27)	(0.09)
β_0	-0.0001***	0.0004	0.0004	0.0001***	0.0003	-0.0001**	0.0003*
	(<.01)	(0.18)	(0.12)	(<.01)	(0.16)	(0.04)	(0.08)
ε^2_{t-1}	0.093***	0.066	0.025	0.021**	-0.110***	0.034	-0.101***
	(<.01)	(0.65)	(0.83)	(0.02)	(<.01)	(0.67)	(<.01)
$\varepsilon^2_{t-1} I^-_{t-1}$	-0.116***	0.088	0.232	-0.032***	0.486***	0.113	0.247***
	(<.01)	(0.59)	(0.18)	(0.01)	(<.01)	(0.17)	(0.01)
h_{t-1}	0.968***	0.511*	0.496***	1.000***	0.530***	0.834***	0.559***
	(<.01)	(0.06)	(0.01)	(<.01)	(<.01)	<.01)	(<.01)
$R_{f,t}$	0.030***	0.096*	0.089	-0.001	0.085**	0.032**	0.021
	(<.01)	(0.10)	(0.05)	(0.77)	(0.05)	(0.04)	(0.50)
$(\Delta S_{t-1})^2 D_{t-1}$		-0.000005	-0.00001*	-0.000004***	<.00001	0.00001*	0.00001**
		(0.19)	(0.08)	(<.01)	(0.67)	(0.10)	(0.05)
$(\Delta S_{t-1})^2 (1-D_{t-1})$		-0.00001**	-0.0001***	-0.000002***	-0.000002	<.00001	<.00001
		(0.05)	(<.01)	(<.01)	(0.44)	(0.91)	(0.35)
Ljung-Box *Q*-statistic	6.89	9.97	8085	10.61	7.18	7.67	8.794
	(0.87)	(0.62)	(0.72)	(0.56)	(0.85)	(0.81)	(0.72)
Bera-Jarque statistic	21.07***	77.89***	78.71***	21.05***	82.10***	50.39***	50.95***
	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)

This table reports the GARCH-in-mean models, described in Section II. MS, CCI and II are the confidence indexes compiled by University of Michigan and Consumer Conference Board and the Investors' Intelligence sentiment index, respectively. Model 1 denotes the model that does not include the effect of investor sentiment. Model 2 and Model 3 represent the models that incorporate the effect of sentiment level and changes in investor sentiment (ΔS), respectively. DY_{t-1} denotes the dividend yield. PI_{t-2} denotes the inflation rate. DI_{t-1} represents the change in the 1-month T-bill rate. PI_{t-2} is the rate of change in industrial production. Dummy variables D_{t-1} and 1- D_{t-1} are used to indicate the direction of changes towards more bullish and more bearish sentiment. The Ljung-Box *Q*-statistics tests for serial correlation in standardized residuals for lags up to twelfth order autocorrelation. Normality tests are based on the Bera-Jarque statistics. *** significant at 1% level. ** significant at 5% level. * significant at 10% level.

TABLE 4
EUROPEAN COUNTRIES: CONSUMER CONFIDENCE INDEX, EXCESS RETURN, AND CONDITIONAL VOLATILITY

Coefficients	UK (FTSE100)			France (CAC40)			Germany (DAX30)			Italy (MIB30)		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
α_0	-0.043	-0.057***	-0.043	0.003	-0.034	-0.049	-0.077	-0.027	-0.001	0.160**	0.317***	0.277***
	(0.29)	(<.01)	(0.32)	(0.94)	(0.50)	(0.38)	(0.26)	(0.67)	(0.97)	(0.04)	(<.01)	(<.01)
$\log(h_t)$	-0.001	-0.002	-0.001	0.00007	-0.005	-0.009	-0.015	-0.004	-0.004	0.021*	0.047***	0.038***
	(0.78)	(0.18)	(0.81)	(0.99)	(0.54)	(0.25)	(0.16)	(0.74)	(0.58)	(0.09)	(<.01)	(<.01)
Jan_t	-0.007	-0.005	-0.001	0.012	0.009	0.007	0.019	0.015	0.025	0.020	0.030*	0.030*
	(0.45)	(0.60)	(0.93)	(0.38)	(0.47)	(0.55)	(0.29)	(0.52)	(0.11)	(0.27)	(0.07)	(0.07)
Oct_t	-0.007	-0.005	-0.005	0.003	-0.001	-0.003	0.003	0.009	0.008	-0.011	-0.013	-0.004
	(0.51)	(0.61)	(0.61)	(0.84)	(0.95)	(0.83)	(0.86)	(0.70)	(0.69)	(0.39)	(0.38)	(0.84)
S_{t-1}		0.001			-0.001***			-0.001			-0.002***	
		(0.13)			(0.01)			(0.13)			(<.01)	
ΔS_{t-1}			-0.001			-0.001			-0.003			0.004
			(0.67)			(0.59)			(0.17)			(0.11)
DY_{t-1}	1.738***	1.862***	1.660***	0.951	0.504	0.746	1.037	0.527	0.411	0.841	0.315	-0.641
	(<.01)	(<.01)	(<.01)	(0.20)	(0.52)	(0.43)	(0.29)	(0.60)	(0.68)	(0.28)	(0.39)	(0.43)
PI_{t-2}	-0.572***	-0.474**	-0.600***	-1.209*	-1.521***	-1.093*	-1.532**	-1.004	-1.167*	-1.824**	-2.559***	-1.111
	(0.01)	(0.02)	(<.01)	(0.06)	(0.01)	(0.09)	(0.03)	(0.22)	(0.06)	(0.02)	(<.01)	(0.11)
DI_{t-1}	2.122	-5.664	-4.374	10.653	4.738	3.137	-14.457	-16.905	4.131	-4.715	14.049	14.955
	(0.80)	(0.44)	(0.50)	(0.49)	(0.73)	(0.83)	(0.69)	(0.70)	(0.90)	(0.86)	(0.58)	(0.49)
DIP_{t-2}	-0.166	-0.035	-0.016	-0.179	0.255	-0.019	-0.328**	-0.032	-0.400***	-0.142	-0.123	-0.24
	(0.23)	(0.77)	(0.88)	(0.32)	(0.28)	(0.93)	(0.05)	(0.89)	(0.01)	(0.51)	(0.58)	(0.22)
β_0	-0.0002	0.0001	0.0005***	0.0001	0.0001	0.0002	0.0002	0.003***	0.0005	-0.0004	-0.00001	0.001
	(0.25)	(0.65)	(<.01)	(0.51)	(0.61)	(0.50)	(0.20)	(<.01)	(0.24)	(0.36)	(0.68)	(0.12)
ε^2_{t-1}	0.293**	0.262*	0.30*	0.173	0.004	-0.026	0.148	0.091	0.188	-0.102*	-0.16***	-0.045
	(0.05)	(0.09)	(0.08)	(0.17)	(0.97)	(0.72)	(0.20)	(0.53)	(0.24)	(0.06)	(<.01)	(0.21)
$\varepsilon^2_{t-1} I^-_{t-1}$	0.238	0.239	0.12	0.080	0.340**	0.293**	0.055	0.213	0.114	0.322**	0.249***	0.215
	(0.32)	(0.32)	(0.59)	(0.47)	(0.03)	(0.03)	(0.57)	(0.23)	(0.49)	(0.05)	(<.01)	(0.19)
h_{t-1}	0.330***	0.243***	0.28**	0.669***	0.592***	0.662***	0.768***	0.412**	0.637***	0.407	0.814***	0.480**
	(0.01)	(0.01)	(0.03)	(<.01)	(<.01)	(<.01)	(<.01)	(0.02)	(<.01)	(0.16)	(<.01)	(0.05)
$R_{f,t}$	0.156***	0.087*	0.02	0.058	0.087	0.057	-0.0001	-0.176*	-0.069	0.575	0.247***	0.130
	(<.01)	(0.10)	(0.48)	(0.26)	(0.14)	(0.18)	(0.99)	(0.08)	(0.21)	(0.05)	(<.01)	(0.20)
$(\Delta S_{t-1})^2 D_{t-1}$		-0.00001	-0.00002***		0.0001*	0.0001***		-0.000003	0.00002		-0.00003	-0.0001***
		(0.28)	(<.01)		(0.06)	(0.05)		(0.94)	(0.65)		(0.35)	(0.01)
$(\Delta S_{t-1})^2 (1-D_{t-1})$		0.00001**	0.00006**		-0.00002	-0.00002		-0.00001***	0.0001		-0.00005**	<.00001
		(0.03)	(0.04)		(0.40)	(0.40)		(<.01)	(0.21)		(0.05)	(0.86)
Ljung-Box *Q*-statistic	5.29	3.25	4.71	12.34	11.31	10.97	10.32	11.32	10.51	20.27*	15.82	21.01**
	(0.95)	(0.99)	(0.97)	(0.42)	(0.50)	(0.53)	(0.59)	(0.50)	(0.57)	(0.06)	(0.20)	(0.05)
Bera-Jarque statistic	56.27***	41.80***	43.69***	2.73	2.82	0.93	7.53**	8.63***	1.52	6.77**	20.12***	7.16**
	(<.01)	(<.01)	(<.01)	(0.25)	(0.24)	(0.63)	(0.02)	(0.01)	(0.47)	(0.03)	(<.01)	(0.03)

This table reports the GARCH-in-mean models, described in Section II for the European markets. Model 1 denotes the model that does not include the effect of investor sentiment. Model 2 and Model 3 represent the models that incorporate the effect of sentiment level and changes in investor sentiment (ΔS), respectively. DY_{t-1} denotes the dividend yield. PI_{t-2} denotes the inflation rate. DI_{t-1} represents the change in the 1-month T-bill rate. PI_{t-2} is the rate of change in industrial production. Dummy variables D_{t-1} and 1- D_{t-1} are used to indicate the direction of changes towards more bullish and more bearish sentiment. The Ljung-Box *Q*-statistics tests for serial correlation in standardized residuals for lags up to twelfth order autocorrelation. Normality tests are based on the Bera-Jarque statistics. *** significant at 1% level. ** significant at 5% level. * significant at 10% level.

TABLE 5
ASIA-PACIFIC COUNTRIES: CONSUMER CONFIDENCE INDEX, EXCESS RETURN, AND CONDITIONAL VOLATILITY

Coefficients	Japan (NIKKEI225)			Australia (ASX2)			New Zealand (NZ5CAP)		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
α_0	0.463	-0.402	0.253	-0.130***	-0.132	-0.039	0.338***	1.521	0.302*
	(0.58)	(0.19)	(0.28)	(<.01)	(0.47)	(0.45)	(<.01)	(0.76)	(0.09)
$\log(h_t)$	0.091	0.035**	0.052	-0.013***	0.009	0.006	0.021	-0.014	0.039*
	(0.53)	(0.04)	(0.19)	(<.01)	(0.29)	(0.44)	(0.12)	(0.73)	(0.09)
Jan_t	0.012	0.005	0.006	0.002	0.005	0.004	0.021***	0.044	0.004
	(0.51)	(0.76)	(0.78)	(0.88)	(0.68)	(0.73)	(0.01)	(0.86)	(0.85)
Oct_t	-0.017	-0.021	-0.014	0.001	0.0005	-0.0003	0.050***	0.610***	0.027
	(0.41)	(0.23)	(0.48)	(0.87)	(0.96)	(0.97)	(<.01)	(<.01)	(0.53)
S_{t-1}		0.005*			0.001			-0.009	
		(0.06)			(0.59)			(0.85)	
ΔS_{t-1}			0.072***			0.0004			0.004
			(<.01)			(0.93)			(0.85)
DY_{t-1}	6.337*	9.426***	4.801*	1.509**	3.069***	2.842***	-1.592	-4.641	-0.008
	(0.10)	(<.01)	(0.07)	(0.05)	(0.01)	(0.01)	(0.18)	(0.30)	(0.99)
PI_{t-2}	0.318	0.440	0.444	-0.231*	-0.507**	-0.493***	-5.437***	-16.707	-1.201
	(0.63)	(0.46)	(0.47)	(0.06)	(0.03)	(0.03)	(<.01)	(0.13)	(0.45)
DI_{t-1}	-26.089	-58.218	-64.925	-12.019	-38.086*	-34.918*	-110.601**	-23.195	-55.149
	(0.61)	(0.33)	(0.33)	(0.47)	(0.06)	(0.09)	(0.04)	(0.94)	(0.42)
DIP_{t-2}	0.090	-0.090	0.067	-0.196	-0.216	-0.184	-0.102	-3.266***	0.227
	(0.46)	(0.46)	(0.54)	(0.16)	(0.22)	(0.27)	(0.82)	(<.01)	(0.48)
β_0	0.0006	0.004***	0.003***	0.0003***	0.001	0.0007	-0.008*	0.023	-0.0001
	(0.48)	(<.01)	(<.01)	(<.001)	(0.27)	(0.25)	(0.06)	(0.78)	(0.85)
ε^2_{t-1}	0.048	0.117	0.011	0.118	0.193	0.165	0.268	-0.093	-0.335
	(0.59)	(0.13)	(0.75)	(0.12)	(0.22)	(0.28)	(0.52)	(0.94)	(0.02)
$\varepsilon^2_{t-1} I_{t-1}$	-0.023	-0.111	0.038	-0.236***	-0.103	-0.087	-0.806	-0.111	0.481**
	(0.74)	(0.18)	(0.70)	(<.01)	(0.55)	(0.64)	(0.12)	(0.93)	(0.04)
h_{t-1}	0.756***	-0.843***	-0.018	0.859***	0.581**	0.574**	0.621***	-0.132	0.456
	(<.01)	(<.01)	(0.90)	(<.01)	(0.02)	(0.04)	(<.01)	(0.92)	(0.21)
$R_{f,t}$	0.0811	2.669**	-0.262	-0.021	-0.079	-0.093	1.969*	2.295	0.105*
	(0.57)	(0.02)	(0.36)	(0.32)	(0.37)	(0.33)	(0.06)	(0.88)	(0.06)
$(\Delta S_{t-1})^2 D_{t-1}$		0.004**	-.001*		-0.000002	0.00001		0.0001	-0.0004
		(0.04)	(0.08)		(0.99)	(0.95)		(0.99)	(0.43)
$(\Delta S_{t-1})^2 (1-D_{t-1})$		0.001	0.007**		0.0004	0.0003		-0.007	0.0006
		(0.20)	(0.05)		(0.37)	(0.41)		(0.82)	(0.48)
Ljung-Box *Q*-statistic	32.38***	6.62	8.99	7.76	11.92	12.48	7.67	108.24***	26.14***
	(<.01)	(0.88)	(0.70)	(0.80)	(0.45)	(0.41)	(0.81)	(<.01)	(0.01)
Bera-Jarque statistic	6.23**	0.82	0.92	0.99	1.61	1.98	1.33	3.54	2.71
	(0.04)	(0.66)	(0.63)	(0.61)	(0.45)	(0.37)	(0.51)	(0.17)	(0.26)

This table reports the GARCH-in-mean models, described in Section II for the Asia-Pacific markets. Model 1 denotes the model that does not include the effect of investor sentiment. Model 2 and Model 3 represent the models that incorporate the effect of sentiment level and changes in investor sentiment (ΔS), respectively. DY_{t-1} denotes the dividend yield. PI_{t-2} denotes the inflation rate. DI_{t-1} represents the change in the 1-month T-bill rate. PI_{t-2} is the rate of change in industrial production. Dummy variables D_{t-1} and 1- D_{t-1} are used to indicate the direction of changes towards more bullish and more bearish sentiment. The Ljung-Box *Q*-statistics tests for serial correlation in standardized residuals for lags up to twelfth order autocorrelation. Normality tests are based on the Bera-Jarque statistics. *** significant at 1% level. ** significant at 5% level. * significant at 10% level.

TABLE 6
EUROPEAN COUNTRIES: ECONOMIC SENTIMENT INDEX, EXCESS RETURN, AND CONDITIONAL VOLATILITY

Coefficients	UK		France		Germany		Italy	
	Model 2	Model 3	Model 2	Model 3	Model 2	Model 3	Model 2	Model 3
α_0	-0.019	-0.070**	0.056	0.006	-0.034	-0.045	0.094	0.083
	(0.61)	(0.03)	(0.45)	(0.87)	(0.76)	(0.40)	(0.06)	(0.11)
$\log(h_t)$	-0.005	-0.005	-0.002	0.0004	-0.010	-0.010	0.013	0.011
	(0.03)	(0.18)	(0.74)	(0.92)	(0.35)	(0.29)	(0.08)	(0.14)
Jan_t	-0.010	-0.007	0.011	0.013	0.020	0.020	0.014	0.006
	(0.200	(0.41)	(0.39)	(0.29)	(0.28)	(0.30)	(0.49)	(0.68)
Oct_t	(-0.003	-0.004	-0.003	-0.001	0.004	0.004	-0.022**	-0.022*
	(0.66)	(0.65)	(0.85)	(0.92)	(0.83)	(0.84)	(0.03)	(0.06)
S_{t-1}	-0.005		-0.001		-0.0005		-0.0001	
	(0.11)		(0.28)		(0.95)		(0.89)	
ΔS_{t-1}		-0.001		-0.0005		0.001		-0.001
		(0.15)		(0.82)		(0.70)		(0.37)
DY_{t-1}	1.635***	1.712***	0.785	0.991	0.839	1.002	0.688	0.682
	(<.01)	(<.01)	(0.32)	(0.23)	(0.40)	(0.34)	(0.18)	(0.06)
PI_{t-2}	-0.508**	-0.464**	-1.376***	-1.342***	-1.492*	-1.505*	-1.001**	-0.957**
	(0.03)	(0.05)	(0.01)	(0.01)	(0.07)	(0.07)	(0.03)	(0.03)
DI_{t-1}	11.396	4.443	14.214	11.222	-24.231	-24.192	0.069	0.083*
	(0.15)	(0.47)	(0.29)	(0.42)	(0.49)	(0.48)	(0.15)	(0.08)
DIP_{t-2}	0.022	-0.092	0.119	-.053	-0.308	-0.289	-0.085	-0.107
	(0.89)	(0.46)	(0.64)	(0.80)	(0.15)	(0.13)	(0.46)	(0.32)
β_0	-0.005***	-0.0003**	0.0001	0.0001	0.0003	0.0002	0.0001	0.0001
	(<.01)	(0.05)	(0.70)	(0.61)	(0.24)	(0.24)	(0.51)	(0.51)
ε^2_{t-1}	0.384***	0.403***	-0.090	-0.100	0.107	0.108	-0.171***	-0.192***
	(<.01)	(0.01)	(0.42)	(0.31)	(0.26)	(0.25)	(<.01)	(<.01)
$\varepsilon^2_{t-1} I^-_{t-1}$	-0.024	0.100	0.344	0.351	0.090	0.087	0.532***	0.562***
	(0.87)	(0.67)	(0.02)	(0.02)	(0.34)	(0.35)	(<.01)	(0.01)
h_{t-1}	0.487***	0.308***	0.565***	0.550***	0.797***	0.798***	0.628***	0.636***
	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)
$R_{f,t}$	0.092***	0.104**	0.072	0.069	0.018	0.021	0.090	0.075
	(<.01)	(0.02)	(0.17)	(0.22)	(0.72)	(0.65)	(0.25)	(0.34)
$(\Delta S_{t-1})^2 D_{t-1}$	0.00002**	0.00002	0.0002***	0.0002***	-0.00005	-0.00005	0.00001	0.00002
	(0.02)	(0.21)	(0.01)	(<.01)	(0.37)	(0.40)	(0.56)	(0.43)
$(\Delta S_{t-1})^2 (1-D_{t-1})$	0.00003***	0.00004***	0.00005	0.0001	-0.00005	-0.00005	0.00002	0.00002
	(<.01)	(<.01)	(0.31)	(0.29)	(0.17)	(0.19)	(0.51)	(0.51)
Ljung-Box *Q*-statistic	7.73	5.67	10.55	10.59	10.05	10.72	11.61	14.39
	(0.81)	(0.93)	(0.57)	(0.56)	(0.61)	(0.55)	(0.48)	(0.28)
Bera-Jarque statistic	10.22***	13.79***	2.74	1.48	4.03	4.50	2.13	2.65
	(<.01)	(<.01)	(0.25)	(0.48)	(0.13)	(0.11)	(0.35)	(0.27)

This table reports the GARCH-in-mean models, described in Section II for the European markets using the Economic Sentiment Indicator to proxy for investor sentiment. Model 2 and Model 3 represent the models that incorporate the effect of sentiment level and changes in investor sentiment (ΔS), respectively. DY_{t-1} denotes the dividend yield. PI_{t-2} denotes the inflation rate. DI_{t-1} represents the change in the 1-month T-bill rate. PI_{t-2} is the rate of change in industrial production. Dummy variables D_{t-1} and 1- D_{t-1} are used to indicate the direction of changes towards more bullish and more bearish sentiment. The Ljung-Box *Q*-statistics tests for serial correlation in standardized residuals for lags up to twelfth order autocorrelation. Normality tests are based on the Bera-Jarque statistics. *** significant at 1% level. ** significant at 5% level. * significant at 10% level.