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Sentiment Versus Liquidity Pricing Effects in the Cross-Section of UK Stock Returns

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Abstract

This study examines the asset pricing role of 'sentiment risk' in stock returns in the case of the UK stock market. We define sentiment risk as the sensitivity of stock returns to investor sentiment in financial markets. We incorporate a broad range of financial market variables in measuring financial conditions and use this as a proxy for market-wide investor sentiment. The paper distinguishes between rational and irrational (noisy) investor sentiment. Initial findings indicate a strong role for rational sentiment risk in the returns of FTSE All Share stocks. However, our paper makes a key contribution by identifying that this evidence largely disappears after controlling for the liquidity risk features of stocks. No evidence of sentiment risk pricing is found among the subgroups of FTSE 250 and FTSE 100 stocks. More generally, our findings point to a strong relation between sentiment risk and liquidity risk in returns and the need for careful disentangling of sentiment versus liquidity effects.

Keywords: Sentiment risk, asset pricing, stock returns, financial conditions.

JEL classification: G11, G12, G14.

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I. Introduction and Literature Review

This study examines the role of investor sentiment in stock returns. We examine the case of the United Kingdom (UK). Investor sentiment in financial markets can be fickle and it fluctuates up and down reflecting investors' collective relative optimism versus pessimism. Some of this sentiment is rational and some is noise. Individual stock returns are sensitive to this fluctuating investor sentiment, although the degree of sensitivity varies across stocks. However, investor sentiment can be systematic and persistent. As such stock returns' sensitivity to investor sentiment is difficult to diversify. We refer to this sensitivity as 'sentiment risk'. From asset pricing theory, this prompts the question as to whether sentiment-sensitive stocks command a premium to compensate investors for this difficult-to-diversify risk, i.e., is sentiment risk priced in stock returns.

After first constructing a broad measure of investor sentiment, we then decompose this measure into a 'rational' component and an 'irrational' component. The former is the component of the broad measure that has predictability over future market returns. As such it may be said to be smart and rationally incorporated into the investor's information set in making investment decisions. The latter is the component that is not useful in predicting market returns, i.e., not smart, and may be interpreted as noisy sentiment. Specifically, we examine the role of both rational investor sentiment and irrational investor sentiment in UK stock returns in an asset pricing framework.

There is a growing literature on the role of investor sentiment in stock markets. Baker and Wurgler (2006, 2007) provide both theoretical and empirical evidence that share prices of companies with subjective valuation (such as listed companies that are younger, smaller, unprofitable, non-dividend-paying or with extreme growth potential) are highly sensitive to investor sentiment. More recent studies, including Ho and Hung (2009), Schmeling (2009), Bathia and Bredin (2013), Huang et al. (2015) and Sun et al. (2016), provide additional empirical evidence for the effect of this sentiment. Bathia and Bredin (2013) study the G7 nations and find a negative relationship between stock market returns and investor sentiment. Investigating 18 industrialised countries, Schmeling (2009) obtains similar findings: positive sentiment drives up (down) prices leading to lower (higher) future returns. Baker et al. (2012) construct investor sentiment indices for each of six countries (i.e., US, UK, Canada, Japan, Germany and France). The study finds that when a country's investor sentiment is high, future returns are relatively low. This is particularly the case for small stocks, high volatility stocks, growth stocks and distressed stocks. Corredor et al. (2013) study investor sentiment pricing in the UK, Germany, France and Spain. In the case of the UK, Corredor et al. document a strong relation between local investor sentiment and the stock returns of high minus low portfolios formed on book-to-market, size, volatility and dividends.

An important feature of our study is the distinction between rational versus irrational investor sentiment. This issue receives very little attention in the literature. Verma et al. (2008) first model investor sentiment as a function of several fundamental variables. Rational investor sentiment is taken to be the fitted values from these regressions while irrational investor sentiment is estimated as the regression residuals. Verma et al. report that there are immediate positive responses in stock market returns to irrational sentiment but that these are subsequently corrected. The impact of rational sentiment, however, is greater than that of irrational sentiment.

Our study investigates sentiment risk in an asset pricing framework. Traditional stock pricing models assume that money is smart and therefore rule out fickle investor sentiment in stock pricing. Here, investors are assumed to be rational and unemotional and their actions cause stock prices to reflect fundamental values. However, there is also a well-established literature on the role of noise traders in the market and their impact on stock prices (e.g., De Long et al. (1990), Shleifer and Vishny (1997), Baker and Wurgler (2006, 2007), Edelen et al. (2010)). Noise traders follow trends and are prone to group behaviour that is particularly influenced by market sentiment. The actions of noise traders can cause stock prices to deviate from fundamental value. The smart money investor does not know whether smart money will correct this price deviation, i.e., by forcing market prices to revert to fundamental value, within his/her investment horizon. As such the smart money investor is subject to this market sentiment risk. If there are enough noise traders operating in the market then this risk may be systematic and may require sentiment-sensitive stocks to command a premium.

Since investor sentiment is unobservable directly, it is a challenge to construct a suitable sentiment proxy. Baker and Wurgler (2006) create a proxy for US equity market sentiment that is the first principal component of six equity market variables – the closed-end fund discount, equity market turnover, the number of IPOs, average first-day returns on IPOs, equity share of new issues and the dividend premium. Several studies have used this index to investigate the role of investor sentiment in stock pricing (e.g., Yu and Yuan 2011; Chung et al. 2012; Chau et al. 2016). With a growing interest in investor sentiment among both academics and practitioners, institutions such as Merrill Lynch, Chartcraf and the American Association of Individual Investors began to publish survey data on investor sentiment on a regular basis. Sentiment literature using survey data includes Fisher and Statman (2000), Lee et al. (2002), Lemmon and Portniaguina (2006) and Ho and Hung (2009).

Most indirect measures of investor sentiment used in the current literature are based on stock market variables. There is vast empirical evidence indicating that sentiment affects other asset markets as well. For example, Clayton et al. (2009) show that investor sentiment plays a role in real estate valuation. Wang (2001) studies six actively traded agricultural futures markets and shows that trader sentiment provides strong signals of futures prices. The 2008-09 subprime mortgage crisis was triggered by a large decline in the real estate prices in the US, leading to negative sentiment in the real estate market that spread quickly to equity markets. We contend that these findings support the need to develop a proxy for investor sentiment that covers a wider range of financial market indicators. Hatzius et al. (2010), a US study, advocate developing a broader financial conditions index (FCI) and select 45 variables to fully represent the financial system. Wacker et al. (2014) develop a FCI based on 16 variables in the case of the UK. Focusing on other industrialised countries, Paries et al. (2014) use a panel of 62 indicators for the Eurozone (EU). In our study, in order to examine the role of investor sentiment in stock pricing, we first develop a broad FCI based on 22 variables for the UK. Such a broad measure is more likely to capture all relevant elements of investor sentiment compared to a narrow range of equity market indicators alone.

Considering a broad range of 18 financial market variables, Koop and Korobilis (2014) provide a detailed discussion of the construction of FCIs. A common approach is to construct a FCI by extracting the co-movement of the selected constituent variables using a conventional principal component analysis (PCA). However, there are some limitations to this baseline PCA approach. First, the conventional PCA assumes that factor loadings are fixed over the full sample period, i.e., assumes that the correlation between financial variables remains unchanged through time. However, Hollo et al. (2012) find that the relationship between five market-specific indices change over time. Contessi et al. (2013) test the correlations between 55 pairs of financial variables and show that almost half of them change significantly during the last financial crisis. Second, many studies using PCA do not distinguish between the rational component in sentiment measures and an irrational component (e.g., Baker and Wurgler, 2006). Huang et al. (2015) define the rational component as that which has some predictive power in forecasting future stock market returns.

Koop and Korobilis (2014) introduce a time-varying factor augmented vector autoregressive (TVP-FAVAR) model that allows factor loadings to change over time. We apply this model to construct an investor sentiment index that best forecasts future market returns.[1] As applied here, the method provides a means of separating the rational from the irrational components in investor sentiment. Specifically, we denote the rational sentiment index as the best predictor of the one period ahead aggregate stock market return. This is because as the optimal predictor of future market returns, this sentiment is of economic relevance and smart investors will rationally incorporate it into their information set. We then derive the irrational (noisy) component of investor sentiment as that which does not predict future market returns. We examine stocks' sensitivity to both rational and irrational sentiment and the role of this sensitivity in stock returns.

To our knowledge Huang et al. (2015) is the first investor sentiment proxy in the literature that separates information in the index constituents that is relevant to aggregate stock market returns from noise. Huang et al. (2015) use partial least squares to extract the forecasting information from investor sentiment proxies. However, Koop and Korobilis (2014) provide evidence that the TVP-FAVAR with stochastic volatility (SV) model is the optimal method to weight constituent financial indicators in a sentiment index and produces an FCI with greater forecasting ability. We adopt the Koop and Korobilis (2014) method in this paper and provide a summary in the next section.

II. Estimates of Market Sentiment

In this section, we employ the Koop and Korobilis (2014) TVP-FAVAR with SV model to construct the rational investor sentiment index. We derive the noise component of investor

[1] Koop and Korobilis (2014) apply the TVP-FAVAR with stochastic volatility model to develop a FCI that best forecasts the inflation rate, the unemployment rate and the growth rate of real GDP in the US. We adopt the method here.

sentiment as the residual in a regression of a conventional PCA based sentiment index on our estimate of rational sentiment.

The TVP-FAVAR model partly features a conventional PCA by estimating a FCI as the co-variation in multiple financial variables. However, distinguishing from this conventional PCA, Koop and Korobilis (2014) allow for time varying factor loadings. In other words, the TVP-FAVAR model has the advantage over the PCA of allowing the relationship between variables to change over time. We consider a p-lagged TVP-FAVAR with SV model as follows:

$$X_t = \lambda_t^f f_t + u_t, \qquad u_t \sim N(0, V_t) \qquad [1]$$

$$\begin{pmatrix} r_t \\ f_t \end{pmatrix} = c_t + B_{t,1} \begin{pmatrix} r_{t-1} \\ f_{t-1} \end{pmatrix} + \cdots + B_{t,p} \begin{pmatrix} r_{t-p} \\ f_{t-p} \end{pmatrix} + \varepsilon_t, \qquad \varepsilon_t \sim N(0, Q_t) \qquad [2]$$

where X_t is a $n \times 1$ vector of normalised financial indicators, which are discussed later in Section III, r_t denotes the monthly return on the FTSE All-share index, λ_t^f represents time-varying loadings, $B_{t,1}$, …, $B_{t,p}$ are VAR parameters and both u_t and ε_t are zero-mean Gaussian errors with covariances V_t and Q_t respectively. The term f_t denotes the first principal component (PC) from X_t taking changes in the correlation structure between financial variables over time into consideration. There is much evidence in the literature that the first PC is sufficient to explain the co-variation in all the observed financial variables and thus is usually considered as an indicator of financial market conditions (e.g., Hatzius et al. 2010; Wacker et al. 2014). In our study, the FCI is used as a comprehensive measure of investor sentiment. An increase in this index corresponds to improving sentiment among investors in financial markets and *vice versa*.

Negro and Otrok (2008) and Eickmeier et al. (2009) suggest a model where the loadings are set as random walks. Primiceri (2005) also assumes a random walk process for VAR parameters. Following these papers, we set λ_t^f and $B_{t,1}$, …, $B_{t,p}$ as:

$$\lambda_t^f = \lambda_{t-1}^f + v_t, \qquad v_t \sim N(0, W_t) \qquad [3]$$

$$\beta_t = \beta_{t-1} + \eta_t, \qquad \eta_t \sim N(0, R_t) \qquad [4]$$

where $\beta_t = \left(c_t', vec\left(B_{t,1}\right)', \ldots, vec\left(B_{t,p}\right)'\right)'$. Nakajima (2011) follows Primiceri (2005) and shows that the use of stochastic volatility improves the performance of a time-varying parameter VAR. Therefore, the covariances V_t and Q_t are allowed to evolve over time. As an identifying assumption in Primiceri (2005) and Koop and Korobilis (2014), the matrix V_t is assumed to be diagonal. This ensures that u_t is a vector of time-varying idiosyncratic shocks.

The system [1] to [4] now constitutes a TVP-FAVAR with SV model. As demonstrated by Koop and Korobilis (2014), this system is an extension of the time-varying parameter VAR and includes two equations, [1] and [2]. The former extracts a latent factor (f_t) from the information set (X_t) and the latter models the dynamic interaction of the rational investor sentiment index with r_t. The estimated f_t from the TVP-FAVAR with SV model is considered as the proxy of rational investor sentiment because it not only summarises the recent relevant information regarding financial market sentiment but also contains rolling updates in relation to the correlations between the constituent variables in X_t. Using the VAR structure of the TVP-FAVAR with SV model, Koop and Korobilis (2014) empirically show that time variation in loadings is important to improve the performance of the estimated principal components to forecast macroeconomic variables.

In order to ensure that the estimated f_t summaries the co-variation in a group of financial conditions indicators in X_t, we opt to follow Koop and Korobilis (2013) and use a recursive steps algorithm: First, update λ_t^f and β_t given an estimate of f_t based on $X_{1:t}$, and then subsequently update f_t with the estimated λ_t^f and β_t. The first PC estimate of f_t based on $X_{1:t}$ is used in estimating λ_t^f and β_t. This process can support large time-variation in loadings λ_t^f, parameters β_t and variances, V_t and Q_t. To summarise

Step (1): Initialise all unknown parameters by having: $f_0 \sim N\left(0, \Sigma_{0|0}^f\right)$, $\lambda_0^f \sim N\left(0, \Sigma_{0|0}^\lambda\right)$, $\beta_0 \sim N\left(0, \Sigma_{0|0}^\beta\right)$, $V_0 \equiv I_n$ and $Q_0 \equiv I_2$. Obtain the principal component estimate of the factor $\hat{f}_t$ based on $X_{1:t}$.

Step (2): With the estimates of $\hat{f}_t$ obtained from Step 1, estimate V_t, Q_t, R_t and W_t using the variance discounting method. With the estimates of V_t, Q_t, R_t and W_t, estimate λ_t^f and β_t using the Kalman filter and smoother algorithm.

Step (3): Estimate and update f_t given λ_t^f using the Kalman filter and smoother algorithm.

Step (4): Repeat Step (2) to Step (3) at each point in time.

Our sample period runs from January 1990 to December 2011. However, due to data availability constraints, not all financial conditions variables are available at the beginning of the period. In the above procedure, each month the sentiment index is comprised of those variables available that month.

In the case of estimating the rational sentiment index and predicting the one-period ahead return on the FTSE All-share index, we compare the forecasting power of two investor sentiment indices, i.e., the first PC of X_t using (i) the TVP-FAVAR with SV model that captures time-varying correlations among the constituent financial indicators and (ii) a conventional standard PCA. First, we calculate the squared forecasting errors (SFE) and absolute forecasting errors (AFE) of the two indices at each point in time and then form two time series of $SFE_t^{PCA}/SFE_t^{TVP-FAVAR}$ and $AFE_t^{PCA}/AFE_t^{TVP-FAVAR}$ by dividing the monthly SFE (and AFE) of the PCA based sentiment index by that of the TVP-FAVAR with

SV model based index. The ratio of $SFE_t^{PCA}/SFE_t^{TVP-FAVAR}$ and/or $AFE_t^{PCA}/AFE_t^{TVP-FAVAR}$ greater than 1.0 indicates the greater predictive power of the sentiment index produced by the TVP-FAVAR with SV model. We perform a Diebold and Mariano (1995) test separately on both the squared forecast errors and the absolute value forecast errors. The tests find that the forecasting errors from the TVP-FAVAR model are significantly lower than that of the PCA method at the 1% significant level in both cases. This strongly motivates our use of the TVP-FAVAR method to construct our rational sentiment index.

To derive our irrational sentiment index, we extract the portion of the PCA based sentiment index that is irrelevant in forecasting the stock market by running the following regression:

$$F_t^{PCA} = \alpha F_t^{Rational} + \tau_t \qquad [5]$$

where F_t^{PCA} denotes the first principal component produced by a conventional PCA (i.e., the broad sentiment index) and the $F_t^{Rational}$ is obtained from the TVP-FAVAR with SV model. As $F_t^{Rational}$ is the optimal predictor of one-period ahead market returns, we take the residual τ_t as a measure of irrational or noisy investor sentiment.

III. Data

In this section, we describe our data set and the selection of financial variables that comprise the financial conditions index (FCI) as a broad measure of investor sentiment. Stock return data are taken from the London Share Price database (LSPD). Our sample period runs from January 1990 to December 2011. We restrict our analysis to stocks which were in the FTSE All Share index historically. The LSPD Archive file records historically when a given stock was a constituent of the FTSE All Share.

In our multifactor pricing models the risk factor portfolios to proxy market, size, value and momentum risks are as follows: FTSE All Share returns are used to represent the market portfolio (source: LSPD). The size factor portfolio, small minus big (SMB), is calculated from the sample by each month forming a portfolio that is long the smallest decile of stocks and short the largest decile of stocks by market capitalisation and holding for one month before reforming. Market value data are taken from the LSPD. The value factor portfolio, high book to market minus low book to market stocks (HML), is the return on the Morgan Stanley Capital International (MSCI) Value Index minus the return on the MSCI Growth Index. The Momentum factor portfolio (MOM) is formed by ranking stocks each month based on returns over the previous 11 months. A factor mimicking portfolio is formed by going long the top performing 1/3 of stocks and taking a short position in the worst performing 1/3 of stocks over the following month (Cuthbertson et al. 2008). Stock return data are taken from the LSPD. All portfolios are equally weighted. The risk free rate is the yield on 3 month sterling denominated gilt (source: Bank of England).

In constructing our sentiment index, we include 22 measures of financial conditions across money, equity, bond (sovereign and corporate), housing, commodity and currency markets. The choice of variables in this study is broadly in line with previous literature on FCIs (e.g., Hatzius et al. 2010; Wacker et al. 2014; Paries et al. 2014). The categories and list of financial conditions indicators are presented in Table 1.

[Table 1 Here]

As indicators of stock market conditions we include returns, earnings and volatility. Specifically, we include the UK FTSE All Share index, the FTSE All Share P/E ratio and the FTSE 100 volatility index. In addition, following Baker, Wurgler and Yuan (2012) and Corredor et al. (2013), we include stock market turnover as a proxy for stock market liquidity, measured as total dollar volume over the month divided by total capitalisation at the end of the previous month.

Credit spreads measure the relative prices at which financing is available to various market participants and are a keen gauge of changing perceptions of risk and investor sentiment in the market place. For this reason, we include several measures of credit spread from a variety of credit markets including the sovereign, corporate, non-financial corporate and inter-bank markets. For example, we include the yield spread between government and corporate bonds, between general corporate bonds and financial sector corporate bonds (in order to capture changing investor sentiment towards the financial sector around the financial crisis period) and between high quality versus low quality corporate bonds. As an indicator of credit risk closer to the retail level of the economy, we also include in our analysis the spread between fixed interest rates in the mortgage market (considered as the rate for secured loans) and the fixed rate on unsecured personal loans. In money markets, we capture the volatility in interest rate expectations as a measure of investor sentiment around interest rate risk. Here, we use the Driffill et al. (2006) interest rate futures spread. This is the spread between the short-term LIBOR (London Interbank Offered Rate) interest rate futures contract at quarter *t-1* and the current short-term interest rate (i.e., the three-month treasury bill discount rate at time *t*).

On housing and lending market indicators, we include UK gross mortgage lending as well as UK net lending to individuals and house associations (seasonally adjusted). UK gross mortgage lending includes all lending secured from active lenders. As a direct measure of investor sentiment towards the property market (housing market in particular), we include the UK house price index (i.e., the Nationwide Building Society index).

From the commodity market, we select a broad indicator, i.e., the Reuters commodity index returns. We also incorporate currency market sentiment and include the sterling effective exchange rate index. Finally, we incorporate two direct survey-based estimates of investor sentiment, namely the GfK (Growth from Knowledge) consumer confidence index and the Royal Institution of Chartered Surveyors business confidence index (both obtained from Datastream).

IV. Sentiment Risk and Pricing

We now turn to examining the pricing of investor sentiment risk among stocks. To do this we attempt to capture this risk in a sentiment risk mimicking portfolio. For each investor sentiment factor, i.e., for the rational sentiment factor (first extracted principal component from the Koop and Korobalis (2014) method, [1] – [4]) and the irrational sentiment factor (residual from the TVP-FAVAR with SV model, [5]), each month individual stock (excess) returns are regressed on the sentiment factor as well as factors for market, size, value and momentum risk. We estimate this regression over the previous 36 months (minimum 24 month requirement for stock inclusion). Stocks are then sorted into fractile portfolios (we examine vigintiles, deciles, quintiles and terciles) according to their sentiment risk, i.e., their estimated beta relative to the sentiment factor as follows.

$$r_{i,t} = \theta_i + \beta_i * F_t^S + \gamma_i * F_t^O + \varepsilon_{i,t} \qquad [6]$$

where F_t^S is the relevant sentiment factor. F_t^O is a matrix of the other risk factors for market, size, value and momentum risk, $r_{i,t}$ is the excess return on stock *i* at time *t*. Stocks are assigned to a portfolio based on $\hat{\beta}_i$, which measures the stock's sensitivity to the sentiment factor, in ascending order, e.g., portfolio 1 contains low sentiment risk (low beta) stocks while portfolio 20 contains high sentiment risk (high beta) stocks. Each portfolio return is the equal weighted average return of its constituent stocks for the following month. Portfolios are reformed monthly. The sentiment risk mimicking portfolio is taken to be the difference between the high minus low portfolios, e.g., 20-1. We then estimate the performance alpha of these sentiment risk mimicking portfolios by regressing their returns on the following four-factor performance attribution model

$$r_{p,t} = \alpha_i + \beta_1 * r_{m,t} + \beta_2 * SMB_t + \beta_3 * HML_t + \beta_4 * MOM_t + \varepsilon_t \qquad [7]$$

where $r_{p,t}$ are the returns on the high minus low sentiment risk fractile portfolios, α_i is the risk-adjusted performance measure of interest, β_j, j=1..4 are the risk factor loadings and SMB_t, HML_t and MOM_t are the benchmark factor portfolios for size risk, value risk and momentum risk respectively.

However, in what proves to be important in our study, we augment the specification in [7] by adding two liquidity risk factors that control for two liquidity risk attributes of stocks that are known to be priced in stock returns. First, “characteristic liquidity risk” refers to a stock’s own liquidity as a driver of its return. Amihud (2002) argues that illiquid stocks should earn a premium over liquid stocks to compensate investors for the trading costs incurred which reduce returns, e.g., wider bid-offer spreads. Second, “systematic liquidity risk” refers to the sensitivity of a stock’s return to changes in *market* liquidity that may not be diversifiable and hence commands a premium (Korajczyk and Sadka, (2008)). In the UK, there is strong evidence indicating that liquidity risk plays a role in asset pricing (Foran et al. 2015, 2014).

There are several measures of stock liquidity in the literature including quoted spread, effective spread, turnover and order imbalance. Other measures of liquidity include price impact measures, which focus on the impact of trades on stock prices. In order to capture the role of liquidity risk in stock returns we add risk mimicking factors for both characteristic liquidity risk and systematic liquidity risk to [7]. We briefly describe the construction of these risk factors here:

(i) Characteristic Liquidity Risk Factor

We begin by constructing a characteristic liquidity risk mimicking portfolio. This can be constructed for each liquidity measure. However, in this study (in order to avoid generating overly-voluminous results) we select the representative and intuitive quoted spread measure. As in Foran et al. (2014), in order to calculate the quoted spread for each stock, we first calculate the daily closing bid-ask spread divided by the mid-point of the bid and ask prices. We then calculate the time series average of this daily series each month for each stock. Each month all FTSE All share constituent stocks are sorted into decile portfolios based on this quoted spread measure where decile 1 represents high liquidity stocks while decile 10 represents low liquidity stocks. Equally weighted decile portfolio returns are calculated over the following one month holding period and the process is repeated over a one month rolling window. The liquidity characteristic risk mimicking portfolio is the difference between the returns of the top decile (decile 10) and bottom decile (decile 1) portfolios, or illiquid minus liquid stocks. We denote this control variable as 'IML'.

(ii) Systematic Liquidity Risk Factor

Systematic liquidity risk refers to the sensitivity of a stock's return to changes in market liquidity. Hence in constructing a systematic liquidity risk benchmark factor we must first construct a measure of market liquidity. Liquidity is multidimensional where alternative measures of stock liquidity may capture different facets of liquidity. Following the approach of Foran et al. (2014), we first estimate seven measures of liquidity for each stock in our sample. In a procedure similar to that of Korajczyk and Sadka (2008) and Foran et al. (2014), we then use PCA to construct the market liquidity variable. Our PCA captures the commonality in liquidity both across stocks and also across the seven liquidity measures. We use the first principal component as the proxy for overall market liquidity.

We then construct the systematic liquidity risk benchmark factor as follows: each month individual stock (excess) returns are regressed on the market liquidity variable as well as factors for market, size, value and momentum risk. We estimate this regression over the previous 36 months (minimum 24 month requirement for stock inclusion). Stocks are then sorted into deciles according to their systematic liquidity risk, i.e., their estimated beta (sensitivity) relative to the market liquidity variable as follows:

$$r_{i,t} = \theta_i + \beta_i * F_t^L + \gamma_i * F_t^O + \varepsilon_{i,t} \qquad [8]$$

where F_t^L is the market liquidity variable above, F_t^O is a matrix of the other risk factors, $r_{i,t}$ is the excess return on stock *i* at time *t*. Stocks are assigned to a decile based on $\hat{\beta}_i$, which measures sensitivity to market liquidity, in ascending order, e.g., decile 1 contains low liquidity risk (low beta) stocks while decile 10 contains high liquidity risk (high beta) stocks. Each decile portfolio return is the equally weighted average return of its constituent stocks for the following month. Deciles are reformed monthly. The systematic liquidity risk benchmark factor is the difference between the high minus low decile portfolios, i.e., 10-1. We denote this control variable by 'HMLLR' or 'high minus low liquidity risk'.

In order to investigate the role of a possible inter-relation between liquidity risk and sentiment risk in stock returns, we include the IML and HMLLR risk factors in our final portfolio performance attribution model as follows:

$$r_{p,t} = \alpha_i + \beta_1 * r_{m,t} + \beta_2 * SMB_t + \beta_3 * HML_t + \beta_4 * MOM_t + \beta_5 * IML_t + \beta_6 * HMLLR_t + \varepsilon_t \qquad [9]$$

V. Empirical Results

The results of our sentiment risk pricing tests are presented in Table 2. In Panel A, we present findings on the pricing of rational sentiment risk in stock returns while Panel B reports the results on the pricing of irrational sentiment risk. The first row of results in each Panel presents the alpha (and t-statistic of alpha in parentheses) of the sentiment risk mimicking portfolios regressed against the CAPM, Fama-French (1993) and Carhart (1997) risk factors. The second row of results in each Panel presents results where the CAPM, Fama-French and Carhart factor models are augmented with the characteristic liquidity risk factor (IML) and the systematic liquidity risk factor (HMLLR). If stocks are exposed to investor sentiment risk and this risk is priced in stock returns, then we expect these portfolios to yield a positive and significant alpha.

[Table 2 Here]

In Table 2, we present findings relating to the broad set of FTSE All Share stocks. From Panel A, we see that the high decile minus low decile rational sentiment risk mimicking portfolio yields a CAPM alpha of 0.97% per month (pm) over the sample period (January 1990 – December 2011) that is statistically significant at 1% significance, denoted by ***. The equivalent Fama-French alpha is 1.07% pm (also significant at 1% significance) while the Carhart alpha is 0.80% pm (significant at 5% significance). Results are also reported for vigintile, quintile and tercile portfolios denoted “20-1”, “5-1” and “3-1” respectively. It is noteworthy that across almost all models and fractile portfolios, alpha is statistically significant by at least the 10% significance level (denoted by *). These results provide evidence that stocks that are sensitive to rational investor sentiment, defined previously as investor sentiment that predicts one period ahead market returns, yield a higher return compared to those that are relatively insensitive to this sentiment – controlling for other well established risk factors.

In Panel B, we present the results around the pricing of irrational investor sentiment risk, defined as the element of investor sentiment that is noise, i.e., has no predictability over future market returns. Across the columns of Panel B it is clear that the alpha of a portfolio comprised of high minus low irrational sentiment risk stocks is not statistically significant across all models and fractile portfolios. This risk is not priced in stock returns.

As described, the second row in each Panel presents results where the CAPM, Fama-French and Carhart factor models are augmented with the two liquidity risk factors. Here, our findings are very different. The evidence that rational sentiment risk is priced in stocks (found previously in Panel A) is no longer present after controlling for these liquidity risks. This indicates that sentiment risk is strongly related to liquidity risk. In some cases the alpha of high minus low irrational sentiment risk stocks in Panel B are negative and statistically significant at 5% significance.

The results presented and discussed so far in Table 2 relate to the broad group of FTSE All Share stocks. It is interesting to probe whether the above findings apply equally to higher profile stocks that attract greater investor scrutiny. It may be the case that such stocks exhibit less sensitivity to fickle market sentiment and/or exhibit smaller deviations in prices from fundamental value that are corrected more quickly by smart money. In this case we would expect to find less evidence (if any) that investor sentiment risk is priced in these stock returns. To investigate this further we repeat the previous analysis separately for the subset of FTSE 250 stocks and FTSE 100 stocks. The results are interesting.

In Table 3 and Table 4 we present findings for FTSE 250 stocks and FTSE 100 stocks respectively. Scanning the results in Panel A of Table 3 for FTSE 250 stocks, we see that rational sentiment risk is no longer priced in stock returns according to the CAPM, Fama-

French and Carhart factor models across fractiles (except for two marginal exceptions at the 10% significance level). Similarly, from Panel B irrational sentiment risk does not play a role in stock returns as was also the case for the broader group of FTSE All Share stock previously. In the liquidity augmented factor models (Panels A & B), all rational and irrational sentiment risk sorted fractile portfolios yield insignificant alphas. Moving to Table 4 for FTSE 100 stocks, from both Panel A and Panel B, we clearly see that investor sentiment risk is not priced among these stocks – both in the case of rational and irrational sentiment risks.

[Table 3 Here]

[Table 4 Here]

Overall, among the broad set of FTSE All Share stocks we find strong initial evidence that rational sentiment risk is priced in stock returns. That is, stocks that are relatively highly sensitive to rational investor sentiment command a return premium to compensate investors. This evidence is supported by CAPM, Fama-French and Carhart performance attribution models. This finding is consistent with past literature generally as well as specifically in relation to the UK market (Baker at al. (2012); Corredor et al. (2013)). However, further analysis reveal interesting results.

Firstly, when we examine the subset of FTSE 250 and FTSE 100 stocks separately, we find that rational sentiment risk is no longer priced in these stocks. This suggests that the finding that sentiment-sensitive stocks command a return premium among the FTSE All Share group as a whole is driven by smaller stocks within the index. Note, however, that while sentiment risk pricing may be more prevalent among small stocks, it remains evident even after controlling for the size risk features of stocks (by the size risk factor) in the Fama-French and Carhart model specifications.

Second, while we find evidence that rational sentiment risk is priced in the returns of smaller stocks in the FTSE All Share index, this evidence disappears when we control for the liquidity risk features of the stocks. This points to a strong relation between investor sentiment risk and liquidity risk in stock markets. Specifically, stocks that are sensitive to rational investor sentiment as measured here by financial conditions, are also less liquid stocks and are stocks whose returns are sensitive to market liquidity.

Third, we find no evidence that irrational sentiment risk is priced among UK stocks.

VI. Conclusion

The role of investor sentiment in stock markets, as well as other asset markets, is attracting increasing attention in the literature in recent years. A consistent finding is that positive (negative) investor sentiment is associated with future lower (higher) stock market returns. However, our paper contributes to a smaller literature on the asset pricing impact of investor sentiment risk. Specifically, we investigate whether stocks that are sensitive to investor sentiment command a premium in the cross-section of stock returns. We document that rational sentiment risk is priced in stock returns in the broad class of FTSE All Shares stocks but not among the subgroups of FTSE 250 and FTSE 100 stocks - suggesting that it is more prevalent among smaller stocks - even after controlling for size risk. However, our study makes a key contribution by identifying that sentiment risk pricing is eliminated altogether after controlling for the liquidity risk features of the stocks. This points a strong relationship between investor sentiment and liquidity and highlights the need for these closely related phenomena to be disentangled in sentiment studies. That we find no evidence of sentiment risk pricing among FTSE 250 stocks and FTSE 100 stocks, again points to a liquidity issue: Stocks that are traded more frequently, in higher volume and that attract greater investor scrutiny are either less sensitive to market sentiment or deviations in their prices from fundamental value are quickly corrected within the investment horizon of smart investors and hence do not command a premium in equilibrium. Finally, we find that irrational sentiment is not priced in returns suggesting a dominant role of smart money in stock markets.

Table 1: Categories of Financial Variables and Sample Periods

Name	Sample
1. Stock Market Indicators	
FTSE All Share Index	1990:1-2011:12
The FTSE All Share PE ratio	1993:3-2011:12
The FTSE 100 Volatility Index	2000:2-2011:12
Equity market turnover	1990:1-2011:12
2. Credit Spreads	
Spread between 3m Gilt yield and 3m LIBOR rate	1996:1-2011:12
Spread between 3m TBill yield and the 3m LIBOR rate	1990:1-2011:12
Spread between Sonia and 1yr mean interbank lending rate	1997:1-2011:12
Spread between 10yr Gov Bond and 10yr+ Corporate Bond yields	2004:3-2011:12
Spread between Corporate Bond and Financial Corporate Bond yields	2004:3-2011:12
Spread between AA-corporate Bond and BBB-corporate Bond yields	2004:3-2011:12
Spread between 3m futures interest rate and current 3m TBill	1990:1-2011:12
Spread between 3m Gilt and 3m Commercial Paper yields	2003:3-2011:12
Spread between fixed mortgage rate and unsecured lending rate	1995:1-2011:12
Spread between 3m Gilt yield and private NFC interest rate	2004:1-2011:12
4. Housing and Lending	
Gross mortgage lending	2001:9-2011:12
Net lending to individuals and House Associations	1990:1-2011:12
Housing Price Index	1991:1-2011:12
3m TBill yield	1990:1-2011:12
5. Commodities	
Reuters Commodity Index	1990:1-2011:12
6. Foreign Exchange Rate Markets	
The effective exchange rate index	1990:1-2011:12
7. Sentiment Surveys	
Consumer Confidence Index	1990:1-2011:12
Business Confidence Index	1990:1-2011:12

Table 2: Pricing of Sentiment Risk: FTSE All Share Stocks

For all stocks in the FTSE All Share index, each month sentiment risk for stock *i* is estimated by regressing stock *i*'s (excess) returns over the previous 36 months on the investor sentiment factor along with market, size, value and momentum factors. A stock's sentiment risk is the beta on this sentiment factor. Stocks are sorted into either 20, 10, 5 or 3 equal weighted portfolios based on beta and held for 1 month before reforming the portfolios. The time series of the high sentiment beta portfolio minus the low sentiment beta portfolio is tested against the CAPM, Fama French (1993) 3-factor and Carhart (1997) 4-factor models. In liquidity augmented version of these models we also specify (i) a characteristic liquidity benchmark factor and (ii) a systematic liquidity risk benchmark factor. These are described in the text. Table 2 reports the alphas of these regressions with t-statistics in parentheses. Results in Panel A relate to the rational investor sentiment factor. Results in Panel B relate to the irrational investment sentiment factor. * represents significance at the 10% significance level, ** represents significance at 5% and *** represents significance at 1%. t-stats are Newey West (1987) adjusted for autocorrelation lag order 2.

Panel A: Rational Sentiment Risk											
20-1	**10-1**	**5-1**	**3-1**	**20-1**	**10-1**	**5-1**	**3-1**	**20-1**	**10-1**	**5-1**	**3-1**
CAPM				**Fama-French 3-Factor**				**Carhart 4-Factor**			
1.28**	0.97***	0.55*	0.34	1.42***	1.07***	0.76***	0.53***	1.10**	0.80**	0.50*	0.33*
(2.54)	(2.65)	(1.94)	(1.64)	(3.16)	(3.13)	(2.88)	(2.74)	(2.45)	(2.31)	(1.90)	(1.73)
CAPM + Liquidity Factors				**Fama-French 3-Factor + Liquidity Factors**				**Carhart 4-Factor + Liquidity Factors**			
0.57	0.69	0.51	0.39	0.73	0.92*	0.58	0.44	0.83	0.81	0.44	0.37
(0.74)	(1.27)	(1.32)	(1.39)	(1.03)	(1.70)	(1.45)	(1.48)	(1.18)	(1.51)	(1.08)	(1.24)
Panel B: Irrational Sentiment Risk											
20-1	**10-1**	**5-1**	**3-1**	**20-1**	**10-1**	**5-1**	**3-1**	**20-1**	**10-1**	**5-1**	**3-1**
CAPM				**Fama-French 3-Factor**				**Carhart 4-Factor**			
-0.19	0.05	0.01	0.01	0.01	0.15	0.07	0.06	-0.49	-0.40	-0.33	-0.23
(-0.42)	(0.15)	(0.03)	(0.06)	(0.02)	(0.48)	(0.30)	(0.36)	(-1.28)	(-1.42)	(-1.63)	(-1.56)
CAPM + Liquidity Factors				**Fama-French 3-Factor + Liquidity Factors**				**Carhart 4-Factor + Liquidity Factors**			
-1.30**	-0.94**	-0.75**	-0.54**	-0.28	-0.11	-0.15	-0.07	-0.49	-0.53	-0.48	-0.27
(-2.21)	(-2.01)	(-2.28)	(-2.23)	(-0.45)	(-0.22)	(-0.42)	(-0.26)	(-0.95)	(-1.25)	(-1.56)	(-1.21)

Table 3: Pricing of Sentiment Risk: FTSE 250 Stocks

For all stocks in the FTSE 250 index, each month sentiment risk for stock *i* is estimated by regressing stock *i*'s (excess) returns over the previous 36 months on the investor sentiment factor along with market, size, value and momentum factors. A stock's sentiment risk is the beta on this sentiment factor. Stocks are sorted into either 20, 10, 5 or 3 equal weighted portfolios based on beta and held for 1 month before reforming the portfolios. The time series of the high sentiment beta portfolio minus the low sentiment beta portfolio is tested against the CAPM, Fama French (1993) 3-factor and Carhart (1997) 4-factor models. In liquidity augmented version of these models we also specify (i) a characteristic liquidity benchmark factor and (ii) a systematic liquidity risk benchmark factor. These are described in the text. Table 2 reports the alphas of these regressions with t-statistics in parentheses. Results in Panel A relate to the rational investor sentiment factor. Results in Panel B relate to the irrational investment sentiment factor. * represents significance at the 10% significance level, ** represents significance at 5% and *** represents significance at 1%. t-stats are Newey West (1987) adjusted for autocorrelation lag order 2.

Panel A: Rational Sentiment Risk											
20-1	**10-1**	**5-1**	**3-1**	**20-1**	**10-1**	**5-1**	**3-1**	**20-1**	**10-1**	**5-1**	**3-1**
CAPM				**Fama-French 3-Factor**				**Carhart 4-Factor**			
0.55 (1.02)	0.06 (0.16)	0.12 (0.49)	0.22 (1.11)	0.73 (1.31)	0.60 (1.59)	0.41* (1.67)	0.35* (1.82)	0.46 (0.97)	0.31 (0.85)	0.19 (0.79)	0.07 (0.41)
CAPM + Liquidity Factors				**Fama-French 3-Factor + Liquidity Factors**				**Carhart 4-Factor + Liquidity Factors**			
0.37 (0.51)	-0.05 (-0.10)	0.13 (0.37)	0.06 (0.24)	0.61 (0.74)	0.69 (1.26)	0.47 (1.28)	0.32 (1.11)	0.50 (0.70)	0.49 (0.92)	0.17 (0.47)	0.04 (0.14)
Panel B: Irrational Sentiment Risk											
20-1	**10-1**	**5-1**	**3-1**	**20-1**	**10-1**	**5-1**	**3-1**	**20-1**	**10-1**	**5-1**	**3-1**
CAPM				**Fama-French 3-Factor**				**Carhart 4-Factor**			
0.47 (0.86)	0.14 (0.37)	-0.03 (-0.09)	0.11 (0.49)	-0.08 (-0.17)	0.07 (0.19)	0.05 (0.19)	0.05 (0.28)	-0.35 (-0.81)	0.02 (0.06)	0.06 (0.24)	0.01 (0.05)
CAPM + Liquidity Factors				**Fama-French 3-Factor + Liquidity Factors**				**Carhart 4-Factor + Liquidity Factors**			
-0.49 (-0.73)	-0.66 (-1.30)	-0.47 (-1.26)	-0.37 (-1.31)	-0.21 (-0.31)	-0.50 (-1.01)	0.08 (0.21)	0.00 (0.00)	-0.61 (-0.95)	-0.23 (-0.49)	0.13 (0.40)	0.14 (0.57)

Table 4: Pricing of Sentiment Risk: FTSE 100 Stocks

For all stocks in the FTSE 100 index, each month sentiment risk for stock *i* is estimated by regressing stock *i*'s (excess) returns over the previous 36 months on the investor sentiment factor along with market, size, value and momentum factors. A stock's sentiment risk is the beta on this sentiment factor. Stocks are sorted into either 20, 10, 5 or 3 equal weighted portfolios based on beta and held for 1 month before reforming the portfolios. The time series of the high sentiment beta portfolio minus the low sentiment beta portfolio is tested against the CAPM, Fama French (1993) 3-factor and Carhart (1997) 4-factor models. In liquidity augmented version of these models we also specify (i) a characteristic liquidity benchmark factor and (ii) a systematic liquidity risk benchmark factor. These are described in the text. Table 2 reports the alphas of these regressions with t-statistics in parentheses. Results in Panel A relate to the rational investor sentiment factor. Results in Panel B relate to the irrational investment sentiment factor. * represents significance at the 10% significance level, ** represents significance at 5% and *** represents significance at 1%. t-stats are Newey West (1987) adjusted for autocorrelation lag order 2.

Panel A: Rational Sentiment Risk											
20-1	**10-1**	**5-1**	**3-1**	**20-1**	**10-1**	**5-1**	**3-1**	**20-1**	**10-1**	**5-1**	**3-1**
CAPM				**Fama-French 3-Factor**				**Carhart 4-Factor**			
0.20 (0.35)	0.16 (0.39)	-0.06 (-0.19)	-0.17 (-0.77)	0.65 (1.11)	0.27 (0.68)	0.13 (0.45)	0.02 (0.07)	0.24 (0.42)	0.20 (0.52)	-0.21 (-0.73)	-0.23 (-1.05)
CAPM + Liquidity Factors				**Fama-French 3-Factor + Liquidity Factors**				**Carhart 4-Factor + Liquidity Factors**			
0.61 (0.67)	0.13 (0.21)	0.14 (0.32)	0.01 (0.03)	0.24 (0.26)	0.21 (0.32)	-0.08 (-0.18)	-0.14 (-0.39)	-0.20 (-0.22)	0.18 (0.28)	0.07 (0.16)	-0.22 (-0.64)
Panel B: Irrational Sentiment Risk											
20-1	**10-1**	**5-1**	**3-1**	**20-1**	**10-1**	**5-1**	**3-1**	**20-1**	**10-1**	**5-1**	**3-1**
CAPM				**Fama-French 3-Factor**				**Carhart 4-Factor**			
0.24 (0.44)	0.18 (0.46)	0.19 (0.66)	0.01 (0.03)	0.22 (0.44)	0.38 (0.96)	0.23 (0.80)	0.05 (0.22)	-0.03 (-0.05)	0.08 (0.21)	0.07 (0.25)	-0.03 (-0.14)
CAPM + Liquidity Factors				**Fama-French 3-Factor + Liquidity Factors**				**Carhart 4-Factor + Liquidity Factors**			
-0.91 (-0.17)	-0.67 (-1.30)	-0.36 (-0.93)	-0.22 (-0.80)	0.94 (1.24)	0.40 (0.66)	0.04 (0.09)	0.06 (0.18)	0.65 (0.79)	0.14 (0.22)	0.04 (0.09)	0.12 (0.36)

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