J. of Multi. Fin. Manag. xxx (2016) xxx–xxx

Contents lists available at ScienceDirect

Journal of Multinational Financial Management

journal homepage: www.elsevier.com/locate/econbase

Identifying the relative importance of stock characteristics

Declan French[a], Yuliang Wu[b,*], Youwei Li[a]

[a] Queens University Management School, 185 Stranmillis Road, Belfast BT9 5EE, UK
[b] School of Management, The University of Bradford, Emm Ln, Bradford BD9 4JL, UK

ARTICLE INFO

Article history:
Received 2 November 2015
Received in revised form 13 January 2016
Accepted 14 January 2016
Available online xxx

JEl Classification:
G12

Keywords:
Stock characteristics
Factor models

ABSTRACT

There is no consensus in the literature as to which stock characteristic best explains returns. In this study, we employ a novel econometric approach better suited than the traditional characteristic sorting method to answer this question for the UK market. We evaluate the relative explanatory power of market, size, momentum, volatility, liquidity and book-to-market factors in a semiparametric characteristic-based factor model which does not require constructing characteristic portfolios. We find that momentum is the most important factor and liquidity is the least important based on their relative contribution to the fit of the model and the proportion of sample months for which factor returns are significant. Overall, this study provides strong evidence to support that the momentum characteristic can best explain stock returns in the UK market. The econometric approach employed in this study is a novel way to assess relevant investment risk in international financial markets outside U.S. Moreover, multinational institutions and investors can use this approach to identify regional factors in order to diversify their portfolios.

1. Introduction

It is well documented that stock returns are affected by firm size (Fama and French, 1992), book-to-market (Fama and French, 1993), momentum (Jegadeesh and Titman, 1993; Moskowitz and Grinblatt, 1999; George and Hwang, 2004), volatility (Goyal and Santa-Clara, 2003; Ang et al., 2006) and liquidity (Amihud, 2002; Acharya and Pedersen, 2005; Liu, 2006). However, there is no consensus in the literature as to which one of these characteristics best explains returns. Asness et al. (2013) find that momentum and value characteristics significantly influence asset prices across countries and across asset classes. Liu (2006) contend that the illiquidity characteristic for stock trading discontinuity is able to subsume the book-to-market effect. Foran et al. (2014, 2015) show that the liquidity risk premium is reduced when asset pricing models incorporate the momentum factor. Cotter et al. (2015) find that the idiosyncratic volatility characteristic has been the most important priced factor during the recent UK economic downturn. Fama and French (2015) and Hou et al. (2015) find that the book-to-market and momentum factors become unimportant in explaining returns after controlling for the investment and profitability factors. The investigation of the explanatory power of stock characteristics is not only of empirical value

* Corresponding author.
E-mail address: Y.Wu20@bradford.ac.uk (Y. Wu).

http://dx.doi.org/10.1016/j.mulfin.2016.01.002
1042-444X/

for investors in selecting stocks,[1] but is also of theoretical value for academics in understanding the relative importance in priced factors.[2]

This study employs a novel econometric approach, the semiparametric characteristic-based factor model developed by Connor et al. (2012) (CHL hereafter), to evaluate the relative power of stock characteristics to explain returns on the London Stock Exchange (LSE). The widely adopted approach in multi-factor asset pricing models relies on sorting each variable by a predetermined cut-off rate to construct characteristic portfolios which are used to generate factor returns for a given stock characteristic (Fama and French, 1992, 1993, 1995). When more than three characteristics are included in asset pricing models, the total number of characteristic portfolios will increase substantially causing higher correlations between factor returns due to poor diversification of the portfolios (e.g. Fama and French, 2015). Using the traditional sorting method to evaluate the relative explanatory power of a large number of stock characteristics is therefore empirically challenging. The challenge is even greater in a country with fewer listed stocks than in U.S markets. Lee (2011) reports that around 3000 stocks were listed in U.S markets from 1988 to 2008 while the UK market is the largest European market with only one third of this number of stocks. Given that U.S. markets have the largest number of stocks in the world, it can be argued that the characteristic sorting approach is still able to estimate factors there.[3] However, the CHL method which does not rely on characteristic sorting to obtain factors is more suitable for the UK market and other developed and emerging markets which have a smaller number of stocks than in U.S. Thus, the CHL method is an important novel methodology for assessing relevant investment risk in international financial markets outside U.S. Moreover, multinational institutions and investors can use this approach to identify regional factors in order to diversify their portfolios.

Fama and French (2015, p. 19) note that "the most serious problems of asset pricing models are in small stocks". It is therefore important to construct size portfolios that accurately reflect the difference in market capitalisation between small and large firms. However, when a market contains many small stocks and few large stocks the identification of the size portfolios becomes difficult. With 935 stocks on the LSE main board as in August 2014, the FTSE 100 index including 100 largest UK domestic stocks represents 84% of total market capitalisation, indicating that there are a large number of small stocks in the UK market. A 50% cut-off rate to sort firm size according to Fama and French (1993, 1995) can underestimate the large size portfolio's market capitalisation leading to a downward bias in the size factor return. One possible solution is to use a finer sorting on firm size such as a 25% or 20% cut-off rate. Since the size portfolios have to interact with other characteristic portfolios, the finer sorting can significantly increase the total number of characteristic portfolios, some of which will not be well diversified in markets with fewer stocks. The CHL approach overcomes this empirical difficulty because it uses stocks' own market capitalisation to estimate the size factor return. Therefore, the UK market is ideally suited to the application of the CHL method to obtain multiple characteristic factors.

The CHL methodology builds upon an existing literature on characteristic-based factor models. Connor and Linton (2007) employ multivariate kernel methods to obtain returns for factor-mimicking portfolios, which are used as independent variables to estimate factor returns and betas from a parametric nonlinear regression. CHL modify the Connor and Linton (2007) approach by estimating factor returns and beta directly from individual stock characteristics instead of constructing factor-mimicking portfolios. The CHL characteristic-based factor model is a weighted additive regression model in which each beta function is a time-invariant unknown function of one stock characteristic while the corresponding factor return is a time-varying parametric weight for the beta function.

We evaluate the relative importance of five stock characteristics (size, book-to-market ratio, momentum, volatility, and liquidity) in two ways. First, we consider the incremental contribution of the characteristic of interest to the fit of the model. Each of the five stock characteristics is combined with the market factor and the R^2 is then compared to assess explanatory power. In addition, we drop each of the characteristics from the complete model and compare the reduction in R^2 in each case. Second, since the CHL method can generate a time-series of estimates for each factor return, we can test whether the factor return is statistically different from zero in a given month. Then, the percentage of sample months in which each factor return is significant can be a yardstick to evaluate the relative importance among the five characteristics. This approach is similar to the two-step procedure followed in Fama and MacBeth (1973) and Cotter et al. (2015) where the changing explanatory power of each constructed factor over time is observed using a regression based on a backward-looking sample

[1] Barberis and Shleifer (2003) provide a theoretical justification for multi-factor asset pricing models in which investors make style investments based on stock characteristics. Investors classify stocks into these styles to save information processing cost when making their investment decisions among thousands of stocks.

[2] Stock characteristics, which affect returns, can be formed into priced factors. However, whether these factors represent systematic risk or mispricing attracts much debate in the literature. For example, the disposition effect can cause return momentum as investors are reluctant to sell losers relative to winners, leading to prices slowly reacting to new information (e.g. Grinblatt and Han, 2005; Daniel et al., 1998; Hong and Stein, 2000; Barberis et al., 1998). In this sense, momentum is more likely to be a mispricing factor. However, Liu and Zhang (2008) and Sagi and Seaholes (2007) show that winners have greater growth-related risk (i.e. a greater factor loading on the growth rate of industrial production) than losers, suggesting that return momentum can be a priced risk factor.

[3] One typical example is the work of Daniel et al. (1997) who formulate 125 (i.e. $5 < MML : MO > \times 5 < MML : MO > \times 5$) characteristic-based benchmark portfolios for size, past one-year return and book-to-market ratio. The method needs at least 3750 (i.e. $30 < MML : MO > \times 125$) sample stocks to eliminate idiosyncratic risk in a given characteristic portfolio making this method less implementable to adjust raw returns for stocks outside U.S. equity markets.

Please cite this article in press as: French, D., et al., Identifying the relative importance of stock characteristics. J. Multinatl. Financial Manage. (2016), http://dx.doi.org/10.1016/j.mulfin.2016.01.002

rolled forward one month at a time. In contrast, in the CHL procedure, the characteristic information of the entire sample is used in one step to estimate the loadings and monthly factor returns.[4]

Our primary results show that the relationships between stock characteristics and their factor betas are nonlinear. Consistent with the findings of Connor and Linton (2007), the evidence suggests that factor premia exist in the full spectrum of sample stocks rather than just in stocks with an extreme characteristic. However, the liquidity-beta function has a relatively flat slope among the five characteristic-beta functions, implying that stocks returns are not as sensitive to the liquidity premium as to other characteristics' premia. In the R^2 analysis, the two-factor model that combines the market and momentum factors has the highest R^2.In contrast, the liquidity based two-factor model has the lowest R^2, indicating its relative unimportance. Also our results show that the momentum factor is statistically significant in a higher proportion of sample months than other factors while the liquidity factor is significant least often. We undertake various robustness tests to check the consistency of our results. When we separate sample months according to the state of the economy, the results reveal that the momentum and liquidity characteristics are the most and least important factors respectively even in a downturn of the economy. Finally, we include stock previous month returns, as the month-by-month reversal factor in addition to the six-factor model, to check the robustness of our results. The result shows that the momentum characteristic remains the most important one. Therefore, we conclude that the momentum characteristic can best explain stock returns.

The paper proceeds as follows. Section 2 presents the methodology. Section 3 describes the data. Section 4 reports results and Section 5 concludes.

2. Methodology

Rosenberg (1974) first models expected return as a linear combination of book-to-market ratio and market value of equity. The factor returns are estimated by cross-sectional regression of returns according to the betas. Thus, excess returns y_{it} for stock i at time t is linearly dependent on stock characteristics X_j

$$y_{it} = f_{\mathrm{ut}} + \sum_{j=1}^{J} X_{jit} f_{\mathrm{jt}} + \varepsilon_{it} \tag{1}$$

where f_{jt} is the factor returns for characteristic j and ε_{it} are the mean zero asset specific returns. Fama and French (1993) modify the Rosenberg approach by approximating factor returns by returns of constructed portfolios. Fama and French (1993) estimate the factor betas using a time series regression of stock excess returns on the factor returns.

Connor and Linton (2007) combine the two approaches. They assume the factor betas are smooth nonlinear functions of security characteristics. In a model with factors analogous to Fama and French, they form a grid of equally spaced characteristic pairs. They use multivariate kernel methods (see, e.g., Pagan and Ullah, 1999) to form factor-mimicking portfolios for the characteristic pairs from each point on the grid. Then they estimate factor returns and factor betas simultaneously using bilinear regression on the set of factor-mimicking portfolio returns. More precisely, they specify a model of the form

$$y_{it} = f_{\mathrm{ut}} + \sum_{j=1}^{J} G_j\left(X_{ji}\right) F_{jt} + \varepsilon_{it} \tag{2}$$

where the F_{jt} are factor-mimicking portfolios constructed from a grid of characteristic pairs using multivariate kernel approaches, and each $G_j(\bullet)$ is a smooth time-invariant function of characteristic j, but they do not assume a particular functional form. The curse of dimensionality (see Pagan and Ullah (1999)) limits the number of distinct factors that can be used in Eq. (2). The required portfolio sorting in the Fama and French model to create these factors becomes infeasible for more than three factors with typical sample sizes.

CHL develop a new estimation methodology that efficiently uses both the time series and cross-sectional dimensions of the data. By restricting the factor betas to be non-linear functions of the security characteristics X_{ji}, they specify the following model

$$y_{it} = f_{\mathrm{ut}} + \sum_{j=1}^{J} g_j\left(X_{ji}\right) f_{jt} + \varepsilon_{it}. \tag{3}$$

The univariate nonparametric functions $g_j(\bullet)$ are time-invariant while the factor returns f_{jt} vary over time. Given time period t, Eq. (3) is a weighted additive nonparametric regression model for panel data with time-varying parametric weights $\left(f_{jt}\right)$.

CHL assume that the characteristic J-vectors of the assets X_{ji}, $i = 1, \ldots, n$ are independent and identically distributed across i. Under the identifying restriction that for each factor the cross sectional average beta equals zero and the cross sectional variance of beta equals one, $E[g_j(X_{ji})] = 0$ and $var[g_j(X_{ji})] = 1$, CHL propose an iterative procedure to estimate both

[4] ANOVA has been used previously to identify the relative importance of factors but its theoretical assumptions are often violated in empirical applications (e.g. Basu, 1983; Jaffe et al., 1989).

the characteristic-beta functions and the factor returns in Eq. (3) simultaneously from data. It starts with period-by-period cross-sectional least squares regression of Eq. (1), and next the estimated factor returns f_{ut}, f_{it} are used to solve for $g_j(\bullet)$ by nonparametric regression (see CHL for details). Then the estimated functions $g_j(\bullet)$ are inserted in Eq. (3) and the factor returns f_{ut}, f_{it} are re-estimated by cross sectional regressions. These last two steps iterate until a convergence criterion is satisfied. CHL establish the asymptotic theory for the suggested estimation procedure. In contrast to the traditional portfolio approach, the recursive estimation procedure in CHL does not need any portfolio grouping or multivariate kernels in estimating the model. By avoiding the curse of dimensionality the CHL model allows for any number of factors with no theoretical loss of efficiency.

This methodology has also a number of additional advantages over the procedure of creating factor-mimicking portfolios. Fama and French (1993) estimate the size and value factor returns by double-sorting stocks in terms of size and the book-to-market ratio. Then, factor betas are estimated by running a time-series regression on the factor returns. The factor returns used in the Fama–French procedure lack rigorous statistical theory to justify their consistency and also standard errors do not fully account for all sampling error. In addition, when the estimated factor returns serve as explanatory variables in the time-series regression, there is a potential errors-in-variables problem in the subsequent process of estimating factor betas. In contrast, since the CHL approach uses all sample stocks' characteristics to estimate each factor return and its associated beta, it is able to generate consistent and asymptotically normal estimates for factor returns and betas that are not obtainable by using the Fama–French procedure.

3. Data and variables

Our sample includes all London Stock Exchange (LSE) listed stocks from October 1986 to December 2011. The stock monthly return series, stock market capitalisation, stock book-to-market ratio, and stock trading volume are extracted from Thomson Reuters Datastream. We include only common stocks listed in LSE and exclude preferred stocks, unit trust, close-end and open-end funds through filtering on data type. In addition, we check stock-quoted currency and remove those that are not quoted in Sterling. This screening procedure filters out stocks with American Depository Receipts traded in the LSE. Finally, we have a total of 311,639 firm-month observations with 1028 stocks in each month on average.

The construction of size and value characteristics follows Fama and French (1993). We require that each sample stock must have valid information for market capitalisation and book-to-market ratio in June of each year. The size characteristic in each month equals the logarithm of the previous June's market value of equity. Likewise, the value characteristic equals the ratio of the book value of equity to the market value of equity in the previous June. In addition to the Fama–French size and value characteristics, we construct three additional characteristics, namely momentum, volatility and liquidity. The effect of the three additional characteristics on cross-sectional stock returns are well documented in the asset pricing literature (e.g. Jegadeesh and Titman, 1993; Goyal and Santa-Clara, 2003; Liu, 2006). The momentum variable is measured as the cumulative twelve month return up to and including the previous month. The volatility variable is defined as the standard deviation of the stock return over twelve months up to and including the previous month. We use Liu's (2006) liquidity measure (*LM12*) which is defined as follows

$$LM12 = \left[\text{number of zero daily trading volumes in prior 12-month} + \frac{1/\text{12-month turnover}}{1,000,000}\right] \times \frac{21 \times 12}{NoTD} \tag{4}$$

The first term in the bracket is the number of non-trading days for a given stock in the previous 12- month period. The 12-month turnover is the sum of daily stock turnover over the prior 12 months ending in the previous month. Daily stock turnover is the ratio of the number of shares traded on a particular day to the number of shares outstanding at the end of the day. The value of 1,000,000 is chosen as a deflator to constrain the term $(\left(1/(\text{12-month turnover})\right)/1,000,000\Big)$ between zero and one.[5] *NoTD* is the number of trading days in prior 12 months. *LM12* incorporates the number of non-trading days with the stock turnover ratio, making it ideal for capturing trading continuity. For each stock, the size and value characteristics are held constant from July to June while the momentum, volatility, and liquidity characteristics change each month based on prior 12- month information. Accordingly, the empirical analysis starts from October 1987, one year after the starting point of the dataset. Finally, when we estimate the factor return function in Eq. (3), the five characteristics are standardised in each month to have zero mean and unit variance.

The construction of traditional factor-mimicking portfolios uses a predetermined cut-off rate on stock characteristics. For example, stocks within the top and bottom 30% of book-to-market ratio are defined as value and growth portfolios respectively in Fama and French (1993). The value premium is the return difference between the value and growth portfolios. The process of our factor return generation as specified in Eq. (3) does not impose any cut-off rate for a given stock characteristic. Rather, the factor return function is estimated simultaneously from all sample stocks not only just from two particular portfolios with strongest and weakest stock characteristics. This approach can potentially improve estimation efficiency.

[5] By using the deflator, the number of non-trading days carries more importance than the stock turnover ratio. It is also equivalent to dependent double-sort on non-trading days first and then on the stock turnover ratio (Liu, 2006).

Table 1
Summary statistics.

	Size (£1,000)	Book-to-market	Mom.	Volatility	LM12
Panel A: the whole sample					
Mean	741.7	0.7036	−0.0399	0.1252	115.13
Median	744.8	0.7015	0.0015	0.1226	101.55
Std.	312.75	0.2461	0.2506	0.0305	58.19
Skewness	0.0165	1.3349	−0.8512	0.9520	0.65
Panel B: October 1987–December 1999					
Mean	490.04	0.6804	0.0115	0.1071	162.77
Median	461.43	0.6692	0.0170	0.1046	148.88
Std.	188.02	0.1088	0.1807	0.0206	42.85
Skewness	0.9834	0.2986	0.1646	0.4016	0.40
Panel C: January 2000–December 2011					
Mean	1002.17	0.7277	−0.0931	0.1440	66.4
Median	1021.08	0.7684	−0.0080	0.1386	64.25
Std.	169.62	0.332	0.2981	0.0278	15.71
Skewness	−0.3514	0.9059	−0.7327	1.4976	0.45

Note: *Size* is a stock's total market capitalisation, *book-to-market* is book value equity over its market value equity, *momentum* (*mom.*) is a stock's cumulative prior twelve monthly returns including the previous month, *volatility* is the standard deviation of the stock return over twelve months up to and including the previous month, *liquidity* (*LM12*) follows definition of Liu (2006) and is given at Eq. (4) (in text. For each of five stock characteristics, we obtain the cross-sectional mean in each month and report their time-series averages across the sample period in the table.

4. Results

In this section, we present summary statistics for our data (Section 4.1), estimate the model and discuss the characteristic-beta functions (4.2), relate the estimated factors to factor-mimicking portfolio returns (4.3) and compare the explanatory power of each characteristic (4.4). The robustness of our findings is examined in Sections 4.4 and 4.5.

4.1. Summary statistics

Table 1 reports firm characteristics for sample stocks from October 1987 to December 2011. For each of five characteristics, we obtain each one's cross-sectional mean in each month and report their time-series averages across the sample period. Panel A is for the whole sample period, while Panel B and C are for two sub-sample periods, October 1987–December 1999 and January 2000–December 2011, respectively. First, the average firm size in the UK stock market has nearly doubled from a half million to one million pounds across the two sub-sample periods. The significant increase of average firm size in the later period reflects the attractiveness of the LSE for world-wide investors and the resulting opportunities for firm growth. In addition, a number of large IPOs took place in the LSE during 2000–2006.[6] The average of the book-to-market ratio remains relatively stable during the two periods (0.68 in the first period and 0.73 in the second period) although, in the later sample period, the book-to-market ratio has a larger variation than in the earlier one (standard deviation is 0.11 in the first period versus 0.33 in the second period). The pattern of past 12-month returns has changed over the two periods. In the earlier period, the average of past 12-month returns is positive (1.15%) and becomes negative (−9.31%) thereafter. Negative past 12-month returns in the second period reflect the impact of the 2007 financial crisis on UK stock returns. Our volatility measure also changes between the two periods for the same reason. Whilst the average of return volatility across all sample months is 0.13, it has also increased from the first period (0.11) to the second period (0.14). Finally, while the overall liquidity measure in the UK stock market is around 115.12, it has significantly decreased in the second sub-period from 162 days in the first sub-period to 66 days in the second sub-period.[7]

4.2. Characteristic-beta functions

Table 2 reports the estimates of the characteristic-beta functions at selected percentiles and the heteroskedasticity-consistent standard errors for each of these estimates.[8] Across size, book-to-market, momentum, volatility, and *LM12*, the standard errors are small in the middle range of standardised characteristics where data is denser and are larger in the two tails where the data is sparser. Estimates for the liquidity characteristic-beta in the bottom and top quintiles do not vary because the data points for *LM12* do not change below the 20th percentile and beyond the 80th percentile. These values of

[6] In 2005, there were 59 new IPOs on the LSE's main market with a total market value of £21,664 million. In contrast, in 1998 there were 63 IPOs with a market value of only £8,798 million (LSE, 2014).

[7] In October 1987, there are 289 firms with trading volume information. In December 2011, this number has increased to 1302.

[8] Bandwidth selection affects the degree of smoothing in the estimates of the characteristic-beta functions. Throughout this paper, semiparametric estimates were calculated using the bandwidth selection approach developed in Mammen and Park (2005) which relies on a penalised least squares framework. On this basis a bandwidth of 0.07 was selected in each application.

Please cite this article in press as: French, D., et al., Identifying the relative importance of stock characteristics. J. Multinatl. Financial Manage. (2016), http://dx.doi.org/10.1016/j.mulfin.2016.01.002

Table 2
Characteristic beta functions.

Characteristic	Size		Book-to-market		Momentum		Volatiltiy		LM12	
Percentile	Coef.	Std. error	Coef.	Std. error	Coef.	Std. error	Coef.	Std. error	Coef.	Std. error
2.5%	−1.856	0.097	−1.817	0.066	−2.636	0.144	−1.140	0.067	−0.917	0.076
5%	−1.445	0.081	−1.122	0.064	−2.513	0.088	−1.052	0.064	−0.917	0.076
10%	−1.182	0.069	−0.871	0.064	−1.406	0.061	−0.960	0.061	−0.917	0.076
20%	−1.080	0.058	−0.606	0.064	−0.837	0.049	−0.831	0.057	−0.917	0.076
30%	−0.593	0.053	−0.393	0.063	−0.345	0.046	−0.715	0.055	−0.919	0.074
40%	−0.354	0.050	−0.189	0.063	−0.126	0.046	−0.517	0.053	−0.812	0.067
50%	−0.225	0.049	0.047	0.063	0.046	0.046	−0.261	0.051	−0.588	0.060
60%	0.113	0.049	0.253	0.063	0.434	0.047	0.002	0.050	0.031	0.059
70%	0.615	0.052	0.488	0.063	0.643	0.048	0.338	0.051	0.570	0.074
80%	1.064	0.058	0.684	0.064	0.769	0.051	0.807	0.053	1.443	0.091
90%	1.634	0.078	0.998	0.065	1.019	0.058	1.677	0.066	1.443	0.091
95%	1.704	0.110	1.191	0.067	1.292	0.069	2.425	0.098	1.443	0.091
97.5%	1.568	0.160	0.768	0.072	1.881	0.090	3.446	0.165	1.443	0.091

Note: The model is estimated by weighted nonlinear regression using a 6-factor model. The factor betas are restricted to have average zero and variance one for identification.

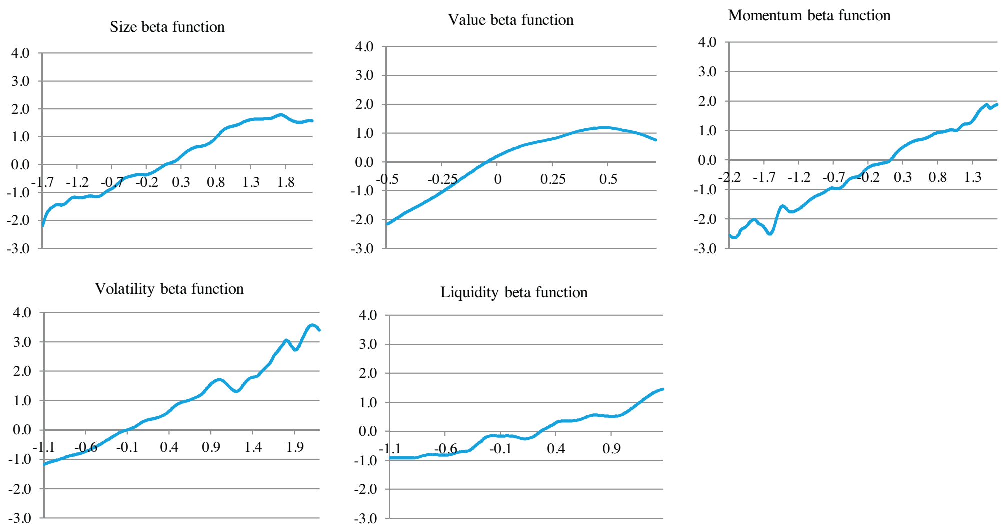

Fig. 1. Non-linear characteristic beta functions.
Note: Results for each function are displayed over a support ranging from 2.5% to 97.5% percentile of the respective stock characteristic.

the *LM12* measure reflect that some stocks have no zero-trading days in the previous 12-months while other stocks were never traded during this period.

The characteristic-beta functions across characteristic points are also plotted in Fig. 1. The functions satisfy the equally-weighted zero mean and unit variance identification conditions (in Section 2). Fig. 1 shows that all five characteristic-beta functions are generally upward-sloping but nonlinear. The positive relationships between book-to-market, liquidity, volatility and momentum and betas are consistent with the existing literature indicating that an increase in one stock characteristic raises its associated beta. The relationship between size and beta is defined inversely to the Fama–French model in which a stock's size beta means its return sensitivity to the size premium between small and large firms. A large firm should have a small size beta in the Fama–French model while in our model large firms have large size betas by construction. The liquidity-beta function tends to have a less steep slope than the other four beta functions. The result suggests that the liquidity premium is not as significant as other characteristics' premia. The value-beta function is downward sloping at the high end of the value characteristic implying that the marginal increase in the value premium is negative in this region. Fama and French (1993, 1996) claim that the book-to-market ratio is a proxy for distress risk which is more prevalent in high book-to-market firms. We find that the value-beta function has a rising slope for most firms but not for extremely high book-to-market firms.[9]

[9] In addition, Dichev (1998) and Griffin and Lemmon (2002) find that most distressed stocks are growth stocks with low book-to-market ratios suggesting that the value feature is not a proxy for distress.

Table 3
Correlations between estimated factor returns and factor mimicking portfolio returns.

	Market	Size	Book-to-market	Mom.	Volatility	LM12	RMRF	SMB	HML	FF_Mom	Liquidity
Market	1										
Size	0.18	1									
Book-to-market	−0.15	0.41	1								
Mom.	−0.42	−0.11	−0.17	1							
Volatility	0.67	0.18	−0.25	−0.17	1						
LM12	−0.34	0.21	−0.02	0.17	−0.27	1					
RMRF	0.77	0.53	−0.01	−0.24	0.57	−0.32	1				
SMB	0.50	−0.21	−0.19	−0.30	0.41	−0.20	0.01	1			
HML	0.07	0.15	0.60	−0.41	−0.19	−0.25	0.05	−0.03	1		
FF_Mom	−0.17	−0.29	−0.30	0.64	−0.06	0.20	−0.15	−0.12	−0.51	1	
Liquidity	0.05	0.60	0.27	−0.06	0.11	0.31	0.41	−0.31	0.14	−0.36	1

Note: This Table provides correlations between the semiparametric approach to estimating factors with the Fama–French (*RMRF*, *SMB*, and *HML*), the liquidity (*liquidity*) and the momentum factor-mimicking portfolio returns(*FF_Mom*). *RMRF* is a market factor which is the value-weighted market return over the 3-month UK Treasury bill rate. *SMB* is the monthly return difference between small capitalisation portfolios and large capitalisation portfolios. *HML* is the monthly return difference between high book-to-market portfolios and low book-to-market portfolios. *FF_Mom* is the monthly return difference between past 12-month winner portfolios and loser portfolios. *Liquidity* is the return difference between low liquidity portfolios and high liquidity portfolios based on zero trading days and the share turnover ratio during past 12 months.

Our finding of the nonlinearity of five characteristic-beta functions has implications for analysis of characteristic-based return premia in equity markets. Our results suggest that stock characteristics can be directly embedded in beta functions to estimate returns. It also implies that the marginal return premium for each characteristic is not linearly proportional to the difference in return premia between firms with extreme characteristics.

4.3. *Factor correlations*

In this subsection, we compare the estimated factors to the factor portfolio returns from the original Fama–French procedure. *RMRF* is a market factor which is the value-weighted market return over the 3-month UK Treasury bill rate. *SMB* is the monthly return difference between small capitalisation portfolios minus large capitalisation portfolios. *HML* is the monthly return difference between high book-to-market portfolios and low book-to-market portfolios (Fama and French, 1993). *FF_Mom* is a momentum factor and is calculated as the monthly return difference between past 12-month winner portfolios and loser portfolios (Carhart, 1997). These factors are provided by Gregory et al. (2013).[10] *Liquidity* is the return difference between the top 30% of stocks and the bottom 30% of stocks in terms of Liu's liquidity measure (Liu, 2006) which is provided for the UK by Wu et al. (2012). The simple correlation analysis can evaluate whether our semiparametric estimated factors are similar to the Fama–French factors and whether the liquidity and volatility factors can provide additional information beyond the Fama–French factors. The correlation matrix in Table 3 shows results.

The estimated market factor has a correlation coefficient of 0.77 with *RMRF*[11] while the estimated momentum factor has a correlation coefficient of 0.64 with *FF_Mom*. The correlation coefficient between the estimated *book-to-market* factor and *HML* is 0.60. *Liquidity* has a correlation coefficient with *LM12* of 0.31. The evidence reveals that although we do not impose any predetermined cut-off rate to define extreme stock characteristics, the semiparametric estimated factors share a large amount of similarities with the factors generated by factor-mimicking portfolios. *SMB* has a negative correlation with *size* at −0.21. This negative correlation is attributable to the model specification that the semiparametric estimation procedure uses standardised firm size information to estimate the premium as explained earlier. The estimated volatility factor has a positive correlation (0.67) with the Fama–French market factor, implying that the volatility premium likely increases in a bull market. However, the volatility factor has negative correlations with *HML* (−0.19) and *FF_Mom* (−0.06). Finally, *LM12* has moderate correlations with *RMRF* (−0.32), *SMB* (−0.20), *HML*(−0.25), and *FF_Mom* (0.20). The correlation analysis reveals that the estimated factors are correlated with the factor-mimicking portfolios and that the two additional factors, volatility and liquidity, contain some information outside the Fama–French three factors.

4.4. *The explanatory power of estimated factors*

4.4.1. *Regression R^2 of characteristic-based factor models*

We use the average R^2 of the cross-sectional regressions after convergence to assess the fit of the model. Then, we evaluate the relative explanatory power of each characteristic in the model in two ways. First, we singly add one of five factors along

[10] We are grateful to Gregory et al. (2013) for providing the UK Fama–French factors on their website, http://business-school.exeter.ac.uk/research/areas/centres/xfi/research/famafrench/files/.

[11] Connor and Korajczyk (1988) show that the dominant statistical factor in a large asset market is approximately identical to the equally-weighted index return. The market factor in our model is derived from the regressions with equal weights amongst a large sample of stocks. It is not surprising that the equally weighted market factor has a high correlation with the value weighted index return.

Table 4
Regression R^2 analysis and statistical significance of factors.

	Six-factor model	Size	Book-to-market	Momentum	Volatility	LM12
Panel A: marginal *R*-square statistics when adding first or dropping first in the model						
Adding first in the one-factor model	4.56%	1.26%	0.78%	1.67%	1.63%	0.85%
Dropping first in the six-factor model		0.60%	0.50%	0.97%	0.70%	0.24%

	Market	Size	Book-to-market	Momentum	Volatility	LM12
Panel B: number of period sig.						
Number of periods statistically sig.	49%	45%	30%	54%	42%	27%
p-Value	0.00	0.00	0.00	0.00	0.00	0.00
95% confidence intervals	(43%, 55%)	(40%, 51%)	(25%, 35%)	(49%, 60%)	(36%, 47%)	(22%, 33%)

Note: This table shows the time-series averages of R^2 statistics as a measure of the explanatory power of the factor model and the percentage of months in which each factor is statistically significant. The six-factor model includes the market, size, book-to-market, momentum, volatility and LM12 factors. The first row in Panel A shows average R^2 from cross-sectional regressions when one factor is combined with the market factor. The second row in Panel A shows changes of average R^2 from cross-sectional regressions when one factor is dropped from the six-factor model. Panel B shows the percentage of months in which each factor is statistically significant. The 95% confidence interval and the associated p-value are based on count statistics with binomial distributions under the null hypothesis that the factor return is zero in each period.

with the market factor to formulate a two-factor model. Second, we take the difference in R^2 between the 6-factor model (by including all five characteristics) and the 5-factor model by dropping one of the five factors except for the market factor. The R^2 difference then can be interpreted as each factor's incremental explanatory power in the full model. Panel A in Table 4 shows results.

The six-factor model that includes all five characteristics and the market factor has R^2 of 4.56%. The two-factor model combining the momentum characteristic with the market factor has R^2 of 1.67% which is higher than that of the market factor with any combination of other characteristics. When the liquidity characteristic combines with the market factor, the model has R^2 of 0.85%. The second row in Panel A shows the reduction in R^2 when one of the characteristics is individually dropped from the six-factor model. The momentum factor has a marginal R^2contribution of 0.97% to the six-factor model, while the liquidity factor only has 0.24%. In terms of R^2, our results reveal that the momentum characteristic is the most important in explaining return variations. In contrast, the liquidity feature has least explanatory power for returns.

4.4.2. Statistical significance of estimated factors

The alternative way to assess the relative importance among five characteristics is to count the number of cross-sectional regressions in which the *t*-statistic for each factor return is significant at a 95% confidence level across all 291 months.[12] Panel B in Table 4 shows results. The momentum factor returns are statistically significantly different to zero in more than half of sample months (54%) suggesting that it is the most important factor. This proportion is even higher than that of the market factor (49%). The liquidity factor is the least important factor only significant in 27% of sample months. The difference between the two proportions is highly significant as the proportion of months for which the liquidity factor is significant is outside the confidence interval for the momentum factor. The book-to-market factor is significant in about one third of the sample months which is outside the 49% lower bound of the 95% confidence interval for the momentum factor indicating that it is also less important than the momentum characteristic. The second row in Panel B tests these overall *p*-values under the null hypothesis that the factor return is zero in each period. The *p*-values are zero for all the six factors implying that they are individually and statistically significant. Consistent with the R^2 results, stock momentum, as one of stock past return patterns, is a relatively more important characteristic, while the liquidity characteristic as proxied by the trading speed is the least important one.

The liquidity factor has been well documented as an important priced risk factor affecting returns in US markets (e.g. Pastor and Stambaugh, 2003; Amihud, 2002; Liu, 2006). However, our empirical results provide less support for this argument in the UK market. Our evidence suggests that the liquidity factor may not be a systematic risk factor. When investors are in the process of selecting stocks, the features of size, momentum and growth are likely to act as first line criteria in making investment decisions rather than stock liquidity. It can be argued that there is less variation in liquidity in LSE compared to US markets explaining our result. Stock prices are generally positively correlated with liquidity (Amihud, 2002). In the UK, the majority of stock prices are less than £3 ($5) indicating little variation in liquidity.[13] In contrast, US stock prices exhibit much larger variations (Weld et al., 2009). Consistent with our results, Mazouz et al. (2010) also find that stock liquidity is not a priced factor in the UK market. Also, recent findings of Foran et al., 2014 show that the level of liquidity as a characteristic has very limited power to explain UK stock returns. The result that the momentum characteristic is the most significant

[12] The CHL methodology allows for general temporal and cross-sectional dependence in the error terms (see Assumption 1 p. 728, CHL for further information). The factor returns cannot be averaged in a similar fashion to the two-stage procedure used in Fama and MacBeth (1973) as the sampling distribution of the factor returns is not assumed to be independently and identically distributed across time.

[13] According to Wu et al. (2012), 30% of LSE listed stocks had a price of £0.50 or less at the end of 2009.

Table 5
Sub-period analysis.

	Market	Size	Book-to-market	Momentum	Volatility	LM12
Panel A: GDP growth						
Upturns % significant	57%	50%	43%	50%	45%	33%
p-Value	0.00	0.00	0.00	0.00	0.00	0.00
95% confidence intervals	(44%, 69%)	(37%, 63%)	(31%, 56%)	(37%, 63%)	(32%, 58%)	(21%, 45%)
Downturns % significant	52%	50%	32%	67%	42%	37%
p-Value	0.00	0.00	0.00	0.00	0.00	0.00
95% confidence intervals	(39%, 64%)	(37%, 63%)	(20%, 43%)	(55%, 79%)	(29%, 54%)	(24%, 49%)
Panel B: industrial production growth						
Upturns % significant	45%	53%	33%	58%	45%	32%
p-Value	0.00	0.00	0.00	0.00	0.00	0.00
95% confidence intervals	(32%, 58%)	(41%, 66%)	(21%, 45%)	(46%, 71%)	(32%, 58%)	(20%, 43%)
Downturns % significant	53%	41%	33%	53%	38%	29%
p-Value	0.00	0.00	0.00	0.00	0.00	0.00
95% confidence intervals	(41%, 66%)	(29%, 54%)	(21%, 45%)	(41%, 66%)	(25%, 50%)	(18%, 41%)
Panel C: term spread						
Upturns % significant	47%	47%	36%	56%	34%	24%
p-Value	0.00	0.00	0.00	0.00	0.00	0.00
95% confidence intervals	(35%, 60%)	(35%, 60%)	(23%, 48%)	(43%, 69%)	(22%, 46%)	(13%, 35%)
Downturns % significant	52%	53%	36%	50%	47%	33%
p-Value	0.00	0.00	0.00	0.00	0.00	0.00
95% confidence intervals	(39%, 65%)	(41%, 66%)	(24%, 49%)	(37%, 63%)	(34%, 59%)	(21%, 45%)
Panel D: two sample periods						
10/1987–12/1999	52%	47%	37%	53%	36%	30%
p-Value	0.00	0.00	0.00	0.00	0.00	0.00
95% confidence intervals	(43%, 60%)	(39%, 55%)	(29%, 45%)	(45%, 61%)	(28%, 44%)	(23%, 38%)
01/2000–12/2011	46%	44%	23%	56%	47%	25%
p-Value	0.00	0.00	0.00	0.00	0.00	0.00
95% confidence intervals	(38%, 54%)	(36%, 52%)	(16%, 29%)	(48%, 64%)	(39%, 56%)	(18%, 32%)

Note: The Table reports the percentage of months in which each characteristic-based factor is statistically significant at the 5% level. We use GDP growth, industrial production growth and term spread to define up and downturns of the economy in panels A, B, and C respectively. 'Upturns' and 'downturns' are the top and bottom 20% of months according to one of the above macro-economic variables. In panel D, we further separate the sample into the earlier period (10/1987–12/1999) and the later period (01/2000–12/2011). The 95% confidence interval and the associated *p*-value are based on count statistics with binomial distributions under the null hypothesis that the factor return is zero in each period.

factor affecting returns is consistent with the recent finding of Asness et al. (2013) which shows that the momentum effect exists across countries and across asset classes (i.e. futures, and commodity markets).

4.4.3. Sub-period analysis

The impact of stock characteristics on stock returns can also depend on economic conditions. For example, Zhang (2005) contends that high book-to-market firms behave as distressed firms in a downturn of the economy when the price of risk is high implying that the value effect should be more pronounced in economic downturns rather than upturns. Petkova and Zhang (2005) provide further empirical evidence that the value premium is higher in bad times in support of Zhang (2005). Thus, it is worth examining whether the relative importance among the factors will be affected by economic conditions. To shed light on this issue, we re-test the relative importance amongst the characteristics in different states of the economy. We define up and downturns of the economy in three different ways as the top and bottom quintile of sample months based on the UK GDP growth rate, the UK industrial production growth rate and the UK term spread defined as the yield difference between 10-year UK government bonds and T-bill respectively.[14]The three macro-economic variables are widely used to indicate macro-economic conditions (e.g. Fama and French, 1988, 1989). Our choice of a cut-off rate of 20% to define the up- and down-turn of the economy is consistent with Petkova and Zhang (2005). Table 5 shows results.

In terms of the GDP growth rate in Panel A, the market characteristic is significant in 57% of the economy upturn months, while the momentum and size characteristics are significant in exactly half of the economy upturns, followed by the volatility (45%), the book-to-market (43%) and the liquidity (33%) characteristics. In times of economy downturns, the momentum characteristic is statistically significant in 67% of months which is higher than the market factor (52%). The difference of 15% is also statistically significant because 67% is outside the upper bound of the 95% confidence interval for the market factor. Inconsistent with Zhang (2005)'s explanations for the book-to-market effect, we find that the book-to-market characteristic is more significant in economy upturns than in downturns (43% against 32%). The characteristic of stock liquidity is significant only in 37% of the downturn months which is roughly the same as that of the upturn months (33%). The result suggests that liquidity is relatively less important for stock returns regardless of the state of the economy.

[14] The information on the three variables was downloaded from datastream.

Table 6
Robustness check.

	Seven-factor model	Size	Book-to-market	Momentum	Volatility	LM12	Lag_ret
Panel A: marginal *R*-square statistics when adding first or dropping first in the model							
Adding first in the one-factor model	4.95%	1.27%	0.79%	1.68%	1.62%	0.89%	0.80%
Dropping first in the seven-factor model		0.56%	0.54%	0.85%	0.64%	0.26%	0.35%

	Market	Size	Book-to-market	Momentum	Volatility	LM12	Lag_ret
Panel B: number of period sig.							
% number of periods statistically sig.	49%	47%	31%	53%	39%	28%	13%
p-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00
95% confidence intervals	(43%, 55%)	(41%, 53%)	(26%, 36%)	(47%, 59%)	(34%, 45%)	(22%, 33%)	(9%, 17%)

Note: This Table shows the time-series averages of R^2 statistics as a measure of the explanatory power of the factor model and the percentage of months in which each factor is statistically significant. The seven-factor model includes the market, size, book-to-market, momentum, volatility, LM12 and monthly reversal factors. The monthly reversal factor (*Lag_ret*) is a stock's previous monthly return which is used to control for month-by-month return reversals. The first row in Panel A shows average R^2 from cross-sectional regressions when one factor is combined with the market factor. The second row in Panel A shows changes of average R^2 from cross-sectional regressions when one factor is dropped from the seven-factor model. Panel B shows the percentage of months in which each factor is statistically significant. The 95% confidence interval and the associated p-value are based on count statistics with binomial distributions under the null hypothesis that the factor return is zero in each period.

We then use an alternative definition of states of the economy. Panel B separates the sample months according to the industrial production growth rate. The momentum factor is significant in 58% of the upturn months and 53% for the downturn months. For the book-to-market characteristic, there is no statistical difference between up and downturns. The liquidity characteristic is only significant in 32% and 29% of the upturn and downturn months, respectively, which are the two lowest ratios among the six characteristics. It should be noted that the momentum effect is significantly different to the liquidity effect (58% against 32%) indicating that the momentum characteristic is more important than liquidity in explaining stock returns. When we use the term spread to define up and downturns in Panel C, our main results are nearly unchanged. The momentum characteristic is of similar importance to that of the market, while the liquidity characteristic remains the least important.

Since datastream provides few firms' information on trading volume at the start of sample period, we separate the whole sample into the earlier period (10/1987–12/1999) and the later period (01/2000–12/2011) when the trading volume information has a wide coverage. Panel D reports results. In the earlier period, the momentum characteristic is significant in 53% of the sub-period months and this ratio is roughly the same as that of the market factor. In the later period, the momentum effect seems to be more important than the market effect, since the ratio of 56% is significantly higher than 46%. In both periods, the liquidity characteristic is significant in less than one-third of sample months. We also find that the book-to-market effect is also relatively weaker in the second sample period. Overall, our results indicate that the characteristics of book-to-market and liquidity are less important than other four characteristics, while the momentum characteristic is the most important one in the two periods.

4.5. Robustness check

Our primary result shows the importance of the momentum characteristic to explain stock returns, implying that past price information may affect investor behaviour in making investments. To check the robustness of the importance of momentum, we include the lagged monthly return as an additional control factor together with previous factors. We call the new factor the monthly reversal factor.[15] If investors are more responsive to the most recent return information, the momentum effect, as an aggregate of past 12-month information, may become weak. Jegadeesh and Titman (1993) show that momentum profits are reduced if one month is skipped between the portfolio formation and the portfolio holding period. We repeat the previous analysis in Table 4 by including the new monthly reversal factor, and our full model is the seven-factor model. Results are reported in Table 6.[16]

Panel A reports that R^2 for the full model is 4.95%, which is slightly higher than the six-factor model of 4.56% in Table 4. In the second row, if one of factors is dropped from the seven-factor model, the R^2 is less affected by liquidity (0.26%) and lagged returns (0.35%) and more by momentum. Therefore, by including the new monthly reversal factor as a control, the importance of momentum remains the same as in our previous results. Panel B shows the percentage of months in which each factor is statistically significant. The market factor is significant in 49% of sample months. Amongst other characteristics, the momentum factor has the highest percentage ratio at 53% indicating that it is more important than others. In contrast, the characteristics of liquidity and lagged returns are significant in only 28% and 13% of sample months respectively. The

[15] Stock returns also exhibit a negative autocorrelation across two consecutive months (Jegadeesh, 1990; Da et al., 2013), which is called month-by-month return reversals. This return irregularity implies that a stock's previous month return is also an important characteristic in influencing the next month's returns.

[16] Results based on the state of the economy are omitted to save space. These results are generally consistent with our main results and are available upon request.

Please cite this article in press as: French, D., et al., Identifying the relative importance of stock characteristics. J. Multinatl. Financial Manage. (2016), http://dx.doi.org/10.1016/j.mulfin.2016.01.002

second last row tests the null hypothesis that each of the monthly factor returns is zero. The results show that we can reject this null hypothesis for all seven factors.

The results in this section reveal that the importance of momentum characteristic is robust to the inclusion of the monthly reversal factor. Despite the fact that past one-month returns are new information relative to past 12-month returns, our results show monthly reversals are one of the weakest factors affecting returns. Investors have difficulty implementing a reversal strategy perhaps since reversals are largely driven by unexpected liquidity shocks (Da et al., 2014; Hameed and Mian, 2015).

5. Conclusions

Stock returns are driven by firms' own characteristics. We address an important empirical question as to which firm characteristic can best explain stock returns in the UK market. To answer this question, we employ a semiparametric approach to estimate the characteristic-based factor model first introduced by CHL. While this study is the first out-of-sample analysis to apply the new method, we also augment the CHL model by including the liquidity characteristic (Liu, 2006) along with the market, size, book-to-market, volatility and momentum factors. Following the CHL methodology, we find that factor betas exhibit nonlinear relationships with stock characteristics consistent with Connor and Linton (2007) and CHL. The nonlinearity implies that the marginal return premium for each characteristic is not linearly proportional to the difference in return premia between firms with extreme characteristics. We also find that the liquidity-beta function is relatively flat compared to other characteristic-beta functions suggesting that stock returns are not as sensitive to the liquidity premium as to other characteristics' premia.

We evaluate the relative importance among stock characteristics in terms of the fit of the model and the percentage of months in which each factor is significant. We find that the momentum characteristic is relatively more important and gives a greater contribution to R^2 than other characteristics. In contrast, the liquidity characteristic contributes least to R^2. The momentum factor is significant in half of the sample months, while the liquidity factor is significant in less than one third of the sample months. The result that the momentum and liquidity characteristics are most and least important holds when we separate the sample months according to the economy downturns and upturns and the earlier and later sample periods. Finally, when we add the monthly reversal factor to check the robustness of the momentum effect, we still find strong return explanatory power for momentum and relatively weak explanatory power for liquidity.

Our evidence supports that past return patterns are the most salient characteristic in explaining stock returns in the UK market (Hong and Lim, 2000; Asness et al., 2013). However, the liquidity characteristic proxied by stock trading continuity is shown to be relatively unimportant in explaining stock returns after controlling for other characteristics. This perhaps can be attributed to a lack of variation in liquidity in the UK market. These results imply that investors use past return patterns as one of their first line criteria when making investments rather than the speed with which they can sell stocks.

Acknowledgements

We are grateful to Gregory Connor and Oliver Linton for providing helpful comments. Declan French would like to acknowledge funding for this research through the Centre of Excellence for Public Health, Queen's University, Belfast MRC Grant # MR/K023241/1. Youwei Li acknowledges the support of National Natural Science Foundation of China (No. 71571197).

References

Acharya, V.V., Pedersen, L.H., 2005. Asset pricing with liquidity risk. J. Financ. Econ. 77 (2), 375–410.
Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. J. Financ. Markets 5 (1), 31–56.
Ang, A., Hodrick, R.J., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. J. Finance 61 (1), 259–299.
Asness, C.S., Moskowitz, T.J., Pedersen, L.H., 2013. Value and momentum everywhere. J. Finance 68 (3), 929–985.
Barberis, N., Shleifer, A., 2003. Style investing. J. Financ. Econ. 68 (2), 161–199.
Barberis, N., Shelifer, A., Vishy, R., 1998. A model of investor sentiment. J. Financ. Econ. 49 (3), 307–343.
Basu, S., 1983. The relationship between earnings yield, market value and return for NYSE common stocks: further evidence. J. Financ. Econ. 12 (1), 129–156.
Carhart, M.M., 1997. On persistence in mutual fund performance. J. Finance 52 (1), 57–82.
Connor, G., Korajczyk, R.A., 1988. Risk and return in an equilibrium APT: application of a new test methodology. J. Financ. Econ. 21 (2), 255–289.
Connor, G., Linton, O., 2007. Semiparametric estimation of a characteristic-based factor model of common stock returns. J. Empir. Finance 14 (5), 694–717.
Connor, G., Hagmann, M., Linton, O., 2012. Efficient semiparametric estimation of the Fama–French model and extensions. Econometrica 80 (2), 713–754.
Cotter, J., O' Sullivan, N., Rossi, F., 2015. The conditional pricing of systematic and idiosyncratic risk in the UK equity market. Int. Rev. Financ. Anal. 37, 184–193.
Da, Z., Liu, Q., Schaumburg, E., 2013. A closer look at the short-term return reversal. Manage. Sci. 60 (3), 658–674.
Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. J. Finance 52 (3), 1035–1058.
Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under- and overreaction. J. Finance 53, 1839–1886.
Dichev, I.D., 1998. Is the risk of bankruptcy a systematic risk? J. Finance 53 (3), 1131–1147.
Fama, E.F., French, K.R., 1988. Dividend yields and expected stock returns. J. Financ. Econ. 21 (1), 3–25.
Fama, E.F., French, K.R., 1989. Business conditions and expected returns on stocks and bonds. J. Financ. Econ. 25 (1), 23–49.
Fama, E.F., French, K.R., 1992. The cross-section of expected stock returns. J. Finance 47 (2), 427–465.
Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. J. Financ. Econ. 33 (1), 3–56.

Fama, E.F., French, K.R., 1995. Size and book-to-market factors in earnings and returns. J. Finance 50 (1), 131–155.
Fama, E.F., French, K.R., 1996. Multifactor explanations of asset pricing anomalies. J. Finance 51 (1), 55–84.
Fama, E.F., French, K.R., 2015. A five-factor asset pricing model. J. Financ. Econ. 116 (1), 1–22, forthcoming.
Fama, E.F., MacBeth, J.D., 1973. Risk, return, and equilibrium: empirical tests. J. Political Economy, 607–636.
Foran, J., Hutchinson, M.C., O'sullivan, N., 2014. The asset pricing effects of UK market liquidity shocks: evidence from tick data. Int. Rev. Financ. Anal. 32, 85–94.
Foran, J., Hutchinson, M.C., O'sullivan, N., 2015. Liquidity commonality and pricing in UK equities. Res. Int. Bus. Finance 34, 281–293.
George, T.J., Hwang, C.-Y., 2004. The 52-week high and momentum investing. J. Finance 59 (5), 2145–2176.
Goyal, A., Santa-Clara, P., 2003. Idiosyncratic risk matters! J. Finance 58 (3), 975–1008.
Gregory, A., Tharyan, R., Christidis, A., 2013. Constructing and testing alternative versions of the Fama–French and Carhart models in the UK. J. Bus. Finance Account. 40 (1–2), 172–214.
Griffin, J.M., Lemmon, M.L., 2002. Book-to-market equity, distress risk, and stock returns. J. Finance 57 (5), 2317–2336.
Grinblatt, M., Han, B., 2005. Prospect theory, mental accounting, and momentum. J. Financ. 78, 311–339.
Hameed, A., Mian, G.M., 2015. Industries and stock return reversals. J. Financ. Quant. Anal. 50 (1), 89–117.
Hong, H., Lim, T., Stein, J.C., 2000. Bad news travel slowly: size, analyst coverage, and the profitability of momentum strategies. J. Finance 55 (1), 265–295.
Hong, H., Stein, J., 2000. A unified theory of underreaction, momentum trading and overreaction in asset markets. J. Finance 54, 2143–2184.
Hou, K., Xue, C., Zhang, L., 2015. Digesting anomalies: an investment approach. Rev. Financ. Stud. 28 (3), 650–705.
Jaffe, J., Keim, D.B., Westerfield, R., 1989. Earnings yields, market values, and stock returns. J. Finance, 135–148.
Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. J. Finance 48 (1), 65–91.
Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. J. Finance 45 (3), 881–898.
LSE (2014). London Stock Exchange—New Issues and IPO summary. http://www.londonstockexchange.com/statistics/new-issues-further-issues/new-issues.xls (accessed 02.09.14.).
Lee, K.-H., 2011. The world price of liquidity risk. J. Financ. Econ. 99 (1), 136–161.
Liu, L.X., Zhang, L., 2008. Momentum profits, factor pricing and macroeconomic risk. Rev. Financ. Stud. 21, 2417–2448.
Liu, W., 2006. A liquidity-augmented capital asset pricing model. J. Financ. Econ. 82 (3), 631–671.
Mammen, E., Park, B.U., 2005. Bandwidth selection for smooth backfitting in additive models. Ann. Stat., 1260–1294.
Mazouz, K., Alrabadi, W.H.D., Freeman, M., Yin, S., 2010. Systematic liquidity risk and asset pricing: evidence from London stock exchange. Int. J. Bank. Account. Finance 2 (4), 387–403.
Moskowitz, T.J., Grinblatt, M., 1999. Do industries explain momentum? J. Finance 54 (4), 1249–1290.
Pagan, A., Ullah, A., 1999. Nonparametric Econometrics. Cambridge University Press.
Pastor, L., Stambaugh, R.F., 2003. Liquidity risk and expected stock returns. J. Political Econ. 111 (3), 642–685.
Petkova, R., Zhang, L., 2005. Is value riskier than growth? J. Financ. Econ. 78 (1), 187–202.
Rosenberg, B., 1974. Extra-market components of covariance in security returns. J. Financ. Quant. Anal. 9 (02), 263–274.
Sagi, J.S., Seaholes, M.S., 2007. Firm-specific attributes and the cross section of momentum. J. Financ. Econ. 84, 389–434.
Weld, W.C., Michaely, R., Thaler, R.H., Benartzi, S., 2009. The nominal share price puzzle. J. Econ. Perspect. 23 (2), 121–142.
Wu, Y., Li, Y., Hamill, P., 2012. Do low-priced stocks drive long-term contrarian performance on the London stock exchange? Financ. Rev. 47 (3), 501–530.
Zhang, L., 2005. The value premium. J. Finance 60 (1), 67–103.