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Net Equity Issuance Effect in the UK

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Abstract

Net equity issuance (NEI) by firms has predictive power for US stock returns. This paper examines the NEI anomaly for UK stocks, using regression on firm characteristics and sorted portfolios with several factor models. The anomaly generalises to the UK only in part. We confirm the existence of a large NEI effect for small and midsize stocks, but not for large stocks. The repurchase effect, of positive abnormal returns following repurchases, is absent in the UK. We also find that the NEI effect in smaller stocks is not exploitable by investors, allowing for transaction costs.

Keywords: net equity issuance, net repurchases, asset pricing anomalies, factor models, abnormal returns

JEL classification: G11, G12, G14, G15, M41

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1. INTRODUCTION

The net equity issuance (NEI) effect is the finding that share issuance by companies net of repurchases forecasts future returns on their shares. Several recent studies find that excess and abnormal returns, over periods from one month up to three years, are negatively related to changes in shares outstanding over the previous year (Daniel and Titman, 2006; Fama and French (FF), 2008 and 2016; Pontiff and Woodgate, 2008; McLean, Pontiff and Watanabe, 2009). The NEI effect is viewed as a first-rank returns anomaly, comparable with other leading anomalies such as momentum. It is not a smallcap phenomenon – it holds across stocks of all sizes – and it has so far proved robust across different models to explain returns, suggesting that it is not a manifestation of some other asset pricing anomaly.

This paper presents a thorough investigation of the NEI effect using UK data. There are several reasons for such an enquiry. First, most of the evidence to date is from the USA. An important means of checking and understanding US evidence is to explore the extent to which it generalises to other markets. The London Stock Exchange is a major stock market, and there is no existing study of the NEI effect that is specific to the UK. The case for a UK study is reinforced by caveats about the NEI effect in the USA, and by existing related evidence for the UK. For the USA, the NEI effect is reduced when a five-factor model is used (FF, 2016), and it is absent in US data before 1970 (Pontiff and Woodgate, 2008). It is not known whether the effect survives after transaction costs. For the UK, existing evidence suggests that the NEI effect might be smaller than in the USA, or different in nature. Studies of long-run average abnormal returns (LRARs) following share issues report mixed results, with debates both about the impact of research design on the results, and about whether LRARs are different following rights issues compared with open offers or placings. There is no consensus that average LRARs are negative following UK SEO announcements, as there is for US SEOs, nor that LRARs are positive following repurchase announcements.[1] The international study of McLean et al. (2009) finds that there is an NEI effect in the UK, but the coefficient on the NEI variable is substantially smaller than it is for the USA. Our much more detailed evidence confirms the partial existence of an NEI effect in the UK, but there are important differences in the nature of the effect, compared with the USA.

The second reason for a UK study is that the results of asset pricing tests are sensitive to the methods used. One point is that the support for a given factor or anomaly variable depends on which other factors are included in the model being tested. Second, there is a debate about whether observed returns are related simply to certain firm characteristics such as size, that matter perhaps for behavioural reasons (Daniel and Titman, 1997), or whether the characteristics cause exposure to risk factors, and the return premia associated with those factors are rewards for risk, as proposed by FF (1993, 1996). In this case differences in average returns across firms are interpreted as arising from differences in covariance risks, i.e. in the sensitivity of a firm's returns to risk factors. Lee, Liu and Strong (2007) test competing hypotheses from these explanations using UK data, and conclude that 'characteristics better explain the UK size and value premiums' (p. 744). Third, results can be sensitive to how the variables are measured, as Michou, Mouselli, and Stark (2014) document for the size and value (or book-to-market) factors using UK data.

The only existing evidence on the NEI effect in the UK is the estimate in McLean et al. (2009). They use one model and method of estimation, namely a regression of future returns on four firm characteristics – size, value, momentum and NEI. We present a much richer set of results. We test NEI effect using three approaches to estimation, and a variety of models.

[1] For SEOs, see Levis (1995), Ho (2005), Armitage (2007), Ngatuni, Capstaff and Marshall (2007), Iqbal, Espenlaub and Strong (2009), Armitage and Capstaff (2009), and Capstaff and Fletcher (2011). For repurchases, see Rau and Vermaelen (2002) and Oswald and Young (2004).

A third reason for our study is that there is a substantial body of academic evidence on asset pricing models that uses UK data (see, for example, Michou et al., 2014, or Foye, 2017, and references therein). To date the UK-specific literature does not encompass tests of the important NEI anomaly, and our paper fills that gap.

The reasons for the NEI effect are uncertain. The effect is related to an earlier finding that average long-run abnormal returns are negative following share issues, at least in the USA (e.g. Loughran and Ritter, 1995). This possibly arises because companies succeed on average in issuing new shares at times when their shares are overvalued. In addition, long-run abnormal returns are positive following repurchases, possibly also due to market timing (e.g. Peyer and Vermaelen, 2009). In the literature on market anomalies, the NEI variable is simply the increase or decrease in the number of shares in issue, whatever the reason for the change, and our tests follow in this tradition. FF (2008) emphasise that the NEI variable, along with other 'anomaly variables', is a rough proxy for expected cash flows: shares issues imply net cash outflows. Li, Livdan & Zhang (2009) present a neoclassical model in which returns are predicted to be lower after share issues because issues are made when discount rates are low, and because of decreasing returns on real investment. McLean et al. (2009) find that the impact of positive NEI on future returns tends to be greater internationally than in the US, and that the impact is 'stronger in countries where it is less costly for firms to issue and repurchase shares' (p. 2). They view this evidence as supportive of a market-timing explanation for the NEI effect, because the market-timing motive for issuance and repurchase should be more prominent in countries where it is easier to take advantage of market mispricing of shares.

We present three sets of results, from three approaches to estimation. First, we conduct regressions of future stock returns over one, six or 12 months, on firm size, value, momentum and NEI variables treated as firm characteristics. This approach is used by most of the previous papers that establish an NEI effect, including Daniel & Titman (2006), FF (2008), Pontiff and

Woodgate (2008) and McLean et al. (2009). We estimate our characteristics-based panel regressions using the Fama-MacBeth (1973) method, and also using standard OLS but with four alternative estimates of the standard errors. We find that the NEI variable has a significant negative coefficient, consistent with an NEI effect, for the full sample and for subsamples of stocks sorted by size. The coefficients on NEI are comparable in importance with the coefficients on the other anomaly variables. These results establish that there is a robust NEI effect in the UK, at least using regressions on firm characteristics.

Second, we report 12-month future average raw and abnormal returns (ARs) for portfolios sorted by size and NEI, controlling for the size and value effects on returns. The benchmark return for a given stock is the return on the sorted portfolio of which the firm is a constituent, where the sorting is done independently by size and book-to-market value. We find that future average ARs are positive for portfolios with zero NEI and for the first two quintiles of positive NEI, before turning negative for the third quintile and beyond. These findings are roughly similar to those in FF (2008) for US firms using the same method, with two notable differences. First, for negative-NEI (net repurchase) portfolios, 12-month average ARs are negative, though mostly not statistically significant. The post-repurchase ARs are lowest for the largest stocks. The non-positive returns following net repurchases differ from the US evidence, in which both repurchase announcements and net-repurchase portfolios are followed by substantial positive and significant LRARs (for repurchases see, for example, Evgeniou et al., 2018). Second, the NEI effect is much weaker among large stocks in our data, and not statistically significant using value weighting. This is not so in FF (2008, Table 2); in their data the NEI effect is similar across subsamples of stocks sorted by size.

To assess whether the NEI effect can be exploited profitably by investors, we estimate the returns on hedge portfolios after transaction costs. The hedge portfolios are long in zero-NEI stocks and short in stocks with the highest quintile of NEI. There is no existing evidence on the NEI effect net of costs. But transaction costs make a huge difference. For the full sample, the hedge returns are –10.1% (equal weighted; t = –4.67) or 1.9% (value weighted; t = 0.73).. For the subsample of small stocks, the hedge-portfolio returns after transactions costs are strongly negative. So we find that, although there is an NEI effect in the UK for small and midsize stocks, it is not exploitable after transaction costs. This finding helps explains the existence of the effect itself.

Third, we assess the NEI effect in the context of several factor models. Average ARs of portfolios sorted by NEI and size are estimated as the alphas from time-series regressions of the portfolio monthly excess returns on factor returns. This approach is used by FF (1993) and many subsequent papers. We report results for the capital asset pricing model, FF three- and five-factor models, and a six-factor model with market, size, value, investment, profitability and liquidity factors. The six-factor model provides the best explanation of returns, according to the average adjusted R^2 measure. The NEI effect survives across all the models, but it is again much stronger among small and midsize stocks. In fact, for large stocks there is no discernible relation between NEI and ARs using the five- and six-factor models. Also, ARs following net repurchases are again not reliably positive. Overall, the results for sorted portfolios from time-series regressions using factor models are similar to those in which ARs are calculated from benchmark returns on portfolios sorted by size and value.

Taking the evidence together, we conclude that there is an NEI effect in the UK, and that it exists independently of other asset pricing anomalies. But the nature of the anomaly differs from its nature in the US evidence; the anomaly is less pervasive in the UK. Our results from sorted portfolios and factor models show that average ARs following net repurchases are not reliably positive, and that the NEI effect is much weaker or absent among large stocks. In addition, we find that the NEI effect is not exploitable by investors after transaction costs. This means it is questionable whether the effect should be characterised as an anomaly, although, since much of the anomalies literature ignores transaction costs, anomalies tend to be measured gross of costs.

Our evidence supports the view of FF (2008) that reliance should not be put on cross-section regressions on firm characteristics alone. The lack of a robust NEI effect for large stocks in sorted portfolios is not consistent with the results from characteristics-based regressions. Another discrepancy is that there appears to be a size effect in the characteristics-based regressions, yet there is no ‘small minus big’ size premium in our data.

Our evidence that the NEI effect is confined to smaller companies is consistent with market timing of share issues. There is greater information asymmetry for small companies and therefore better opportunities for them to time share issues, though their costs of issue will tend to be higher. However, small early-stage companies also have low profitability and high investment, both of which are anomaly variables. FF (2008, 2016) emphasise that anomalies generally tend to be stronger among small stocks. In additional tests we find that the NEI effect is not related to the number of analysts that follow the company, which does not support the idea that firms with a lower analyst following, and hence higher information asymmetry, are able to time their share issues and repurchases more effectively.

The absence of an NEI effect among large stocks clearly does not support the observation of McLean et al. that the effect is stronger among companies with lower costs of issue and repurchase, since large companies have lower unit costs of issue and repurchase. However, rights issues continue to be used by large companies in the UK. There is less incentive for market timing of rights issues, since many of the new shares are sold to existing shareholders. In addition, the lack of robust positive average ARs following net repurchases does not support timing and suggests that other motives for share repurchase are prevalent (Farre-Mensa, Michaely and Schmaltz, 2014, includes a review of evidence on repurchase motives). Overall, we do not find clear evidence in support of the market-timing explanation, beyond the fact that the NEI effect is larger and more robust for small and midsized companies.

The paper proceeds as follows. Section 2 describes the three methodological approaches we use, and the data. Section 3 presents the results from each approach in turn, and Section 4 concludes.

2. METHODS AND SAMPLE

2.1 Regressions on firm characteristics

Tests of asset pricing anomalies are sensitive to methods of estimation, selection of explanatory variables, and construction of the variables (e.g. FF, 2008; Michou et al., 2014). We therefore use three approaches to estimation. Our first set of results are from regressions of stock returns on firm characteristics that might explain returns, using the Fama-MacBeth method. For each month in the sample period, a cross-section regression is run of future returns on firm characteristics. The coefficient for each characteristic is then estimated by the average of its monthly coefficients. Cross-section regressions provide direct information about the marginal effect that an anomaly variable has on firms' average returns. Our regression for a given month *t* is:

$$R_{t+n}^{i} = \alpha_t + \beta_{1t} NEI_t^i + \beta_{2t} MV_t^i + \beta_{3t} BM_t^i + \beta_{4t} Mom_t^i + e_t \qquad (1)$$

where R_{t+n}^{i} is the sum of ln(1 + return on stock *i*) for months *t*+1 to *t*+*n*. The characteristics are defined as follows:[2]

Net equity issuance, the key variable of interest, is the change in the number of shares outstanding, net of repurchases, adjusted for capital changes, i.e. stock splits and stock dividends, share consolidations, and the scrip element of rights issues. The adjustments are

[2] We also experiment with other explanatory variables in (1), to be consistent with the UK literature (Soares and Stark, 2015): Cash holdings/Price, Earnings/Price, Sales growth, and R&D/Assets. Our results for NEI are robust to inclusion of these variables.

captured using the capital-adjustment factor of the London Share Price Database (LSPD, code C2).[3] Our capital-adjustment index CAI_t^i is given by

$$CAI_t^i = \prod_{\tau=0}^{t} C2_\tau^i \tag{2}$$

where $t = 0$ is the first month the stock was first listed, and $C2_\tau^i$ is the LSPD factor for capital changes in month τ.[4] The adjusted number of shares, $Nshares_t^i$, is the number of ordinary shares outstanding for month t (Datastream code NOSH) multiplied by CAI_t^i. We measure short-term NEI as:[5]

$$NEIS_t^i = ln(Nshares_{t-1}^i) - ln(Nshares_{t-13}^i) \tag{3}$$

We also calculate long-term NEI measured over five years:

$$NEIL_t^i = ln(Nshares_{t-1}^i) - ln(Nshares_{t-61}^i) \tag{4}$$

Size: We follow Daniel and Titman (2006) and Pontiff and Woodgate (2008) in estimating company size by the market value of the equity (*MV*) lagged by 12 months:

$$MV_t^i = ln\left(MV_{t-12}^i\right) \tag{5}$$

As a robustness check, we also run the characteristics-based regressions using *MV* measured with no lag. The results are qualitatively similar, and are available on request.

Book-to-market ratio: BM_t^i is the inverse of market-to-book value (MTBV) from Datastream for 31 December of the year before the year of month *t*.

$$BM_t^i = ln\left(\frac{1}{MTBV_{Dec,t-1}^i}\right) \tag{6}$$

[3] A manual check of annual reports shows that the capital-adjustment information in LSPD is more accurate than in Datastream, the leading alternative source of data. A group of 32 randomly chosen companies are used for this check. Among the total of 141 capital changes by these companies, Datastream has 32 inaccurate data points (22.7%), with 14 missing and 18 incorrect, while LSPD has two missing records (1.4%). At the company level, Datastream's inaccuracies affect 21 companies (65.6%) while LSPD's affect two (6.3%).

[4] LSPD states the adjustment factor multiplied by 1,000. For example, its factor for a one-for-two scrip issue = 0.667 × 1,000 = 667. We divide the LSPD factor by 1,000 in equation (2).

[5] In a previous version of the paper we calculate results using a six-month gap between month *t* and the measurement period for share issuance, as in Pontiff and Woodgate (2008). The results are qualitatively similar.

In this ratio market value is as at 31 December and book value is the most recent available at that date. A lag is necessary to ensure that the book value would be known at time t, and follows Fama and French (1993, 2008) and Hou et al. (2015). We create a dummy variable *BMdum* equal to one if BM_t^i is negative or missing, and zero otherwise.

Momentum: the momentum characteristic, Mom_t^i, is measured as the cumulative stock return for the six months ending one month before the end of month t:

$$Mom_t^i = \sum_{t-7}^{t-1} R_t^i \tag{7}$$

The explanatory variables are winsorized at 1% (both tails) to reduce the influence of extreme observations, following Pontiff and Woodgate (2008). The time-series standard error of β_t for a given characteristic is used to test the significance of the mean of β_t. In the case of future returns over more than one month, overlaps of the holding periods for the shares induce autocorrelation of the error term. Therefore we calculate Newey-West standard errors for the relevant t-statistics (see Wooldridge, 2006, pp. 432-5), adjusting for N–1 orders of autocorrelation, where N refers to the holding period in months.

If the errors in a regression using panel data are not independent and identically distributed, the standard errors of coefficients from standard OLS or the Fama-MacBeth (FM) method are subject to potential biases. Peterson (2009) supports the use of FM estimation when there might be a 'time effect', i.e. correlation across firms of the residuals for a given time period. The unadjusted FM standard error, however, is biased downwards if there is also a 'firm effect', i.e. time-series correlation of the residuals for a given firm. Therefore we follow Peterson's advice and test for firm and time effects in our data. We estimate model (1) using OLS, with four alternative estimates of the coefficient standard errors. These are (i) the White standard error, which is robust to heteroscedasticity but not to time or firm effects; (ii) a firm-clustered standard error; (iii) a time-clustered standard error; (iv) a two-way clustering standard error. The formulas are in Cameron, Gelbach and Miller (2008) and Thompson (2011). The difference between the White and firm-clustered standard errors measures the firm effect, while the difference between the White and the time-clustered standard errors measures the time effect. The two-way clustering standard error provides unbiased estimation where both firm and time effects exist, and thus it can be used as a benchmark for our FM standard errors. Note that, for returns over six or 12 months, the FM standard errors are already incorporate the Newey-West adjustment to reduce bias from autocorrelation of the error term (i.e. the firm effect).

2.2 Sorted portfolios: ARs from size and book-to-market benchmarks

Our second approach is to use sorted portfolios, with benchmark returns from portfolios sorted by size and book-to-market ratio, as in FF (2008). Sorted portfolios provide an explicit picture of the differences in average ARs across values of a given anomaly variable. FF note that cross-section regression results could be affected by extreme individual stock returns, or by numerically dominant small-cap stocks. They recommend sorted-portfolio analysis as a complementary approach.

We construct 21 portfolios as at 30 June each sample year, based on seven categories of *NEIS*, and three of *MV*. Stocks with positive NEI are allocated into quintiles from 5 (largest NEI) to 1; stocks with zero NEI are in group 0, and stocks with negative NEI are in group –1. The stocks are also sorted independently by size into three groups; the break points are the 30th and 70th percentiles of *MV* for the largest 350 stocks. This independent sorting results in portfolios with different numbers of stocks.[6] Cumulative value- and equal-weighted ARs are calculated for each portfolio over the next 12 months. The AR for a given stock *i* following portfolio-formation month *t* is calculated as:

[6] As a robustness test we also conduct the analysis using consecutive sorting (e.g. by NEI and then within each NEI group, by size). The results are similar. See Berk (2000) for more on consecutive sorting.

$$AR_{t+12}^{i} = R_{t+12}^{i} - R_{t+12}^{Bi} \tag{8}$$

where R_{t+12}^{Bi} is the cumulative return on a matching benchmark portfolio for the stock. To create the benchmark portfolios, sample stocks are sorted into quartiles by *MV* measured as at 30 June each year, and independently sorted into quartiles by *BM* measured as at 31 December in the previous year. Each stock is a constituent of its benchmark portfolio, one of 16 for each year. For example, suppose for a given month *t* that stock *i* is in the portfolio consisting of stocks in quartile 4 by *MV* (largest) and quartile 1 by *BM* (lowest). Stock *i*'s benchmark return is then the cumulative value-weighted return for the next 12 months on the portfolio formed from stocks that are in both quartile 4 by *MV* and quartile 1 by *BM*.

We also investigate returns net of transaction costs, which consist of bid-ask spread, broker's commission, and stamp duty (a tax on trading). The bid-ask spread is calculated as:

$$Spread_{t}^{i} = Av_{t}^{i}\frac{Ask_{\tau}-Bid_{\tau}}{(Ask_{\tau}+Bid_{\tau})/2} \tag{9}$$

where τ denotes a trading day, and the average is taken over trading days in the 12 months preceding month *t*. Commissions are assumed to be 0.13% of the midpoint price. This follows the estimate of commissions paid by market intermediaries in Agyei-Ampomah (2007) and Soares and Stark (2009). Their source is a survey of transactions costs by the London Stock Exchange, which is no longer available. We also show results for other categories of investor which pay higher commissions, according to the survey. Stamp duty, on purchases only, was 0.5% during the sample period. The roundtrip cost of normal trading is therefore:

$$Cost_{t}^{i} = Spread_{t}^{i} + 0.26 + 0.50 \tag{10}$$

Selling and covering short is at least as expensive, but there is no stamp duty. The total percentage transaction cost TC to create and liquidate a position in a long-short hedge portfolio p is estimated as:

$$TC_{t}^{p} = 2 \times \sum_{i=1}^{n}\left(W_{t}^{i} \times Cost_{t}^{i}\right) - 0.50 \tag{11}$$

where n is the number of stocks in portfolio p and W_t^i is the weight of stock i in the portfolio, and the holding period starts at the end of month t.

2.3 Sorted portfolios: ARs from factor models

Our third set of tests explores the NEI effect in the context of factor models. The cross-section regression approach described in Section 2.1 tests for an NEI effect under the assumption that returns are explained by firm characteristics. But much of the empirical asset pricing literature assumes that returns are explained by exposure to risk, measured by covariances of a stock's returns with factor returns where each factor is assumed to proxy for an undiversifiable source of risk. Following this approach, we take the 21 portfolios sorted by NEI and size, as in Section 2.2, and run time-series regressions in which the monthly portfolio excess return is regressed on the monthly return for each factor. The average return over time for portfolio p that is not explained by the factors, and is potentially attributable to NEI, is measured by the intercept α_p:

$$R_t^p - R_{Ft} = \alpha_p + \beta'_{p,n}(Factor_t^n) + e_t^p \tag{12}$$

where R_t^p is the value-weighted return for portfolio p in month t, R_{Ft} is the rate on three-month Treasury bills, $\beta'_{p,n}$ is a vector of coefficients on the n factors (factor loadings for p), and $Factor_t^n$ is a vector of factor returns. The factors we include are as follows.

Market factor: $MKT_t = R_{Mt} - R_{Ft}$, where R_{Mt} is the return on the market, proxied by the FTSE-Allshare index.

Size factor: SMB_t = return on small (low MV_t^i) stock minus return on large stocks.

Value factor: HML_t = return on high book-to-market (high BM_t^i) stocks minus return on low book-to-market stocks.

Profitability factor: RMW_t = return on robust-profitability stocks minus return on weak-profitability stocks. We measure profitability by return on equity (Hou et al., 2015):

$$ROE_t^i = Net\ income_{fy,t-1}^i / Book\ value_{fy,t-2}^i \tag{13}$$

where net income (Datastream WC01551) is before extraordinary items and net of preferred dividends, book value is shareholders' funds, and *fy*,*t*–1 denotes the financial year ending in the calendar year before month *t*.[7]

Investment factor: CMA_t = return on conservative-investment stocks minus return on aggressive-investment stocks. We measure investment by growth in assets (Hou et al., 2015):

$$Inv_t^i = (Assets_{fy,t-1}^i - Assets_{fy,t-2}^i)/Assets_{fy,t-2}^i \tag{14}$$

Liquidity factor: LIQ_t = return on low-liquidity (high $Spread_t^i$) stocks minus return on high-liquidity stocks.[8]

Insert Table 1 about here

Calculation of the factor returns follows the procedures applied to UK data in Gregory, Harris and Michou (2001) and Gregory, Tharayan and Christidis (2014). Specifically, at the end of June of each year, we use the median of the largest 350 stocks to split our sample into two groups, small and big based on size (the group with small stocks is larger because the sample includes companies below the top 350 by size). This is consistent with Fama and French (1993, 1996) who use the median NYSE company in order to split the sample of NYSE, AMEX and NASDAQ stocks into small and large groups. Stocks are also sorted independently into three groups by each of *BM*, *ROE* and *Inv*, using the 30th and 70th percentiles of the largest 350 stocks as breakpoints. We then form four sets of six portfolios, each set formed from the

[7] We also measure profitability using $Book\ value_{fy,t-1}^i$ as the denominator in (13), as in FF (2015). The results are similar.

[8] In unreported analysis we use three alternative measures of liquidity: share turnover (Datar, Naik and Radcliffe, 1998; Brennan, Chordia and Subrahmanyam, 1998), the return-to-volume metric of Amihud (2002), and the LM12 measure in Liu (2006). The results using these measures are qualitatively similar to those using *Spread*, and are available on request.

intersections of the size groups and one of *BM*, *ROE* and *Inv*. The portfolios are re-formed annually as at 30 June, except the momentum portfolios which are re-formed monthly. The factor returns are obtained from value-weighted monthly returns on the relevant portfolios, according to the formulas in Table 1. The factor returns mix value and equal weighting; the return for a given portfolio is value-weighted, but each factor return is constructed from portfolio returns that have equal weights, as in FF (2015 and elsewhere).

We follow Liu (2006) in constructing the liquidity factor. Stocks are sorted into two size groups; the largest 350 stocks, and the remaining stocks. Each group is then sorted in terms of liquidity. The low-liquidity portfolio is constructed using the 15% lowest liquidity (highest *Spread*) stocks from the large-size group and the 35% lowest liquidity stocks from the small-size group. The high-liquidity portfolio is constructed using the 35% highest liquidity stocks from large-size group and the 15% highest liquidity stocks from the small-size group.

We report results for models with: the market factor only (capital asset pricing model, CAPM); market, size and value factors (three-factor model, FF 1993); market, size, value, profitability and investment (five-factor model, FF 2015); and a six-factor model with market, size, value, profitability, investment and liquidity. We include the CAPM and three-factor models to provide benchmark results. The FF five-factor model is included because of its recent prominence, and the six-factor model because it has the greatest explanatory power measured by the average adjusted R^2 measure.[9]

The profitability, investment and liquidity factors, which are additional to those in the FF three-factor model, have potential to account for the NEI effect. A four-factor model in

[9] In addition to the reported models, we calculate results for (i) a two-factor model with only market and liquidity factors (Liu, 2006); the FF three-factor model plus (ii) an investment factor (Lyandres, Sun and Zhang, 2008) and (iii) momentum and liquidity factors (Eckbo and Norli, 2005); (iv) a four-factor model that includes market, value, momentum and profitability factors (Novy-Marx, 2013), and (v) a model that includes market, value, profitability and investment factors (Hou, Xue and Zhang, 2015). The results from these models regarding NEI are qualitatitvely similar to those reported below; there is evidence for an NEI effect, though it is not always present across all categories of stock by size. These additional results are available on request.

Novy-Marx (2013), that includes profitability, subsumes various anomalies including the NEI effect (for research on profitability and returns, see also Haugen and Baker, 1996; Cohen, Gompers and Vuolteenaho, 2002; FF, 2006). There is evidence that an investment factor can explain the puzzling negative ARs after share issues. Lyandres, Sun and Zhang (2008) use an investment-augmented three-factor model and partially explain the negative ARs after SEOs (75% explained), IPOs (80%), convertible debt offerings (50%), and net equity issuance in general (40%) (for research on investment and returns, see also Titman, Wei and Xie, 2004; Cooper, Guel and Schill, 2008; Polk and Sapienza, 2009). Hou, Xue and Zhang (2015) report that a model with market, size, profitability and investment factors subsumes the NEI effect. The evidence in FF (2015, 2016) suggests that most market anomalies, including the NEI effect, shrink when profitability and investment are added to the original FF three factors.

Regarding stock liquidity, equity issuance potentially affects expected returns because it increases the liquidity of the shares. Eckbo and Norli (2005) document that firms that conduct IPOs and SEOs subsequently tend to be more liquid than their matched firms, which reduces their expected returns. Bilinski, Liu and Strong (2012) confirm that SEOs increase liquidity and thus reduce liquidity risk, which could explain the negative ARs following SEOs. Liu (2006) proposes a two-factor model which includes liquidity and outperforms the FF three-factor model.

2.4 Sample

The sample period is from January 1980 December 2017. Both live and delisted UK-registered companies are included, to avoid survivorship bias. Financial-sector companies are excluded. The sample includes companies listed on both the Main Market and Alternative Investment Market of the London Stock Exchange. The minimum number of companies with data by year is 1,008 for 1993, the maximum is 1,326 for 2007. There are 606,036 firm-month observations in total.

Stock returns and capital adjustments are from LSPD. Returns include any dividend, adjusted to a month-end basis, including special dividends which are important for some firms. Datastream is the source of all accounting information, and also the bid and ask share prices. We use SEDOL numbers to match companies in these two databases, supplemented by matching by company name.[10]

Insert Table 2 about here

Table 2 shows descriptive statistics about the firm characteristics. The distributions for NEI are highly positively skewed; a small proportion of firm-months have large increases in shares. For NEIS, 7.1% of firm-months have a negative value, i.e. shares in issue fell between t–12 and t, 43.1% have zero issuance (similar to the 45% proportion of zero-NEI months in McLean et al., 2009), and 49.8% have positive net issuance. The correlation table indicates a high correlation between short-term and longer-term net issuance activities (0.36). Correlations between 12-month future return and the explanatory variables are consistent with expectations, except for size: higher book-to-market ratio stocks tend to have higher returns, which is the value effect; higher momentum shares also tend to offer higher future returns; both short- and long-term NEI are negatively correlated with future returns, consistent with the NEI effect.

3. RESULTS

3.1 Regressions on firm characteristics

[10] SEDOL stands for Stock Exchange Daily Official List. Matching by SEDOL number results in a total of 5,266 companies, including the financial sector. Matching by name increases this total to 6,434.

Insert Table 3 about here

Table 3 shows coefficients from regressions of future returns on firm characteristics. The first monthly regression is for January 1981, the last for December 2017. If there is an NEI effect, future returns should be negatively related to our measures of net share issuance, *NEIS* and *NEIL*. The coefficients on *MV*, *BM* and *Mom* are positive and mostly statistically significant, although *MV* is barely significant for 12-month future returns. These results are consistent with previous research for the UK (Gregory et al. 2001, Gregory et al. 2014; Michou et al. 2014). For NEI, the slope coefficient is negative and significant for both *NEIS* and *NEIL*, confirming the existence of an NEI effect. A one-standard-deviation increase (0.309) in NEIS would on average reduce the one-month future return by 0.13 percentage points, the six-month return by 0.62 points, and the 12-month return by 2.1 points. The equivalent figures for *NEIL* are slightly larger. The coefficients on both NEI measures are significant in all cases except for *NEIS* with one-month returns. Their significance is similar to the *t*-statistics for the momentum characteristic and book-to-market ratio. The dummy variables *NEISzero* and *NEILzero* are usually significant but their signs are not consistent; *NEISzero* is positive except for one-month returns, and *NEILzero* is negative.

The fourth results column shows *NEIS* along with the size, value and momentum characteristics. These results are comparable with those for the UK in McLean et al. (2009, Table 7); their data are from 1981-2006. They use the same model and estimation technique, but with no zero-NEI dummy variable included. For one-month (12-month) future returns, our coefficient is –0.004 (–0.095), compared with –0.012 (–0.104) in McLean et al. Our results therefore suggest a somewhat weaker NEI effect than they find.

To check whether the NEI effect is a smallcap phenomenon, we follow FF (2008) and conduct regressions on characteristics for subsamples of small, medium and large companies using *MV* percentiles of 30% and 70% among the largest 350 stocks as breakpoints. The results are not reported to conserve space, but we find that the regression coefficients for NEI are similar across the three size samples (these results are available on request). For example, using the specification which includes size, value, momentum and both NEI measures, the coefficient on NEIS for 12-month future returns is –0.079 (t = –7.28) for small stocks, and –0.078 (t = –2.90) for large stocks. Hence, the NEI effect does not seem to be a smallcap phenomenon, using regressions on firm characteristics. We shall see that the NEI effect in large stocks is much less apparent using sorted portfolios.

Insert Table 4 about here

Alternative estimates of standard errors. For robustness we also present standard OLS estimates of model (1), with t-statistics from four alternative methods of calculating the standard errors, as described in Section 2.1. Table 4 presents the OLS coefficients for the specification that includes the size, value and momentum characteristics, and four different t-statistics. The relevant FM results from Table 3 are shown alongside to aid comparison. For one-month returns, we observe a significant time effect, indicated by the smaller t-statistics from time- and two-way clustered standard errors than from White standard errors. No material firm effect is apparent. FM regression is designed to avoid underestimation of standard errors when there are time effects, and the FM t-statistics are indeed similar to or below the t-statistics from time- and two-way clustering, except for *Mom*. For six- and 12-month returns, we see that both time and firm effects are present; both the time- and firm-clustered t-statistics are much smaller than the White t-statistics. This shows that both directions of residual dependence need to be controlled for in the regression. The autocorrelation-adjusted FM *t*-statistics are close to those from two-way clustering; they are not inflated by the existence of a firm effect. The Newey-West adjustment appears to be effective.

Regarding NEI, the OLS coefficients on *NEIS* and *NEIL* are negative and at least as large as the coefficients from FM estimation, confirming the NEI effect. Overall, the results in Table 4 show that the *t*-statistics for firm characteristics can be seriously biased upwards without adjustment for firm and time effects. But the results in Table 3 are robust with respect to these problems of residual dependence.

3.2 Sorted portfolios: ARs from size and book-to-market benchmarks

Insert Table 5 about here

We next present ARs from sorted portfolios, first using benchmark returns controlling for size and book-to-market ratio. Table 5 presents descriptive statistics for portfolios independently sorted into seven *NEIS* and three size groups. The data for each portfolio include the raw value- and equal-weighted 12-month future returns, the average values for *NEIS* and *MV*, and the number of firms. As a result of independent sorting, the number of firms varies across the portfolios. The minimum number is 15, indicating that more refined sorting would not be feasible. Positive average NEI in quintiles 1 to 4 is miniscule or small compared with NEI in quintile 5 (in which NEI is 7,500 times larger than in quintile 4, for the full sample). The size distribution of firms is also highly skewed to the right; the difference in market capitalisation between small and medium-size firms is less than ten times, whereas the difference between medium-size and big firms exceeds three hundred times.

The size data show that the net-repurchase portfolio has the largest stocks, with an average market capitalisation £2.17bn for the full sample, while the zero-NEI group has the lowest average size, of £0.26bn. Also, average size decreases from NEI quintiles 1 to 5. So firms with no issuance activity, and firms with the most issuance activity, tend to be small, whereas net repurchases tend to be large.

Regarding returns, we see that from zero-NEI to quintile 5, the raw value- and equal-weighted returns have a decreasing trend, across all three size categories. The trend is stronger using equal-weighted returns, and in the small-firms category. For the full sample the value- (equal-) weighted return is 16.3% (17.4%) for NEI quintile 1 (smallest positive NEI) and 9.5% (3.4%) for quintile 5. The zero-NEI portfolios show returns similar to those of the quintile 1. But the negative-NEI (net repurchase) portfolios show returns that are appreciably below the returns for the zero-NEI portfolios. Hence, the sorted portfolios show that the relation between raw returns and NEI is not monotonic, when net-repurchase firms are taken into account.

Insert Table 6 about here

The raw returns in Table 5 are suggestive of an NEI effect. Table 6 presents average 12-month ARs, where the benchmark return for each stock is the return on a portfolio matched by *MV* and *BM* (Section 2.2). In these tests the prediction from an NEI effect is that average AR becomes more negative for portfolios of companies with higher net issuance. The results in Table 6 confirm that an NEI effect exists in the UK, though it is weak for large stocks. Average ARs decrease monotonically across NEI levels from 3.2% (t = 4.05) for zero-*NEIS*, to –3.4% (t = –1.33) for quintile 5, for the full sample. For small stocks the figures are 1.2% (t = 1.20) for zero-*NEIS*, and –13.2% (t = –4.63) for quintile 5. The results are more pronounced for equal-weighted ARs, consistent with a stronger NEI effect in smaller firms. For the full sample, average AR is 2.2% (t = 3.65) for zero-*NEIS*, and –9.21% (t = –5.62) for quintile 5. The results for net repurchases show that ARs tend to be negative, though they are not robustly significantly different from zero.

The results in Table 6 are comparable with those for the USA in FF (2008, Table 2). There are two key differences. First, the non-positive average AR following net repurchases is a notable difference from the US evidence, which shows positive and statistically significant average ARs following repurchases and net repurchases, over periods of one year and longer, using several estimation methods (e.g. Evgeniou et al., 2018; FF, 2016; Pontiff and Woodgate 2008). Previous UK evidence is limited but does not show robust positive LRARs following repurchases. [11] In addition, McLean et al. (2009) use regressions of future returns on firm characteristics, as in our Section 3.1. For an international sample they report insignificant coefficients on dummy variables that indicate firms with net repurchases, suggesting that the US evidence of positive ARs following net repurchases does not generalise to other countries.

Second, a pronounced NEI effect is a feature of smaller stocks in the UK, according to the sorted-portfolios approach (and the results from factor models below). Average ARs for NEI quintiles 4 and 5 are much more negative for small and medium stocks than for large stocks, using both value- and equal- weighting. In FF (2008), there is no difference in the strength of the NEI effect between small and large stocks. A possible explanation for the different UK result for large companies lies in their choices of SEO method. Compared with open offers and placings, rights issues tend to be chosen by larger companies in the UK, and to be larger in relation to the market capitalisation of the company (Barnes and Walker, 2006; Armitage, 2010). A higher proportion of the new shares is sold to existing shareholders in a

[11] There is no previous UK evidence on ARs for net-repurchase portfolios. Rau and Vermaelen (2002) report negative average ARs for up to one year following repurchase announcements. However, Oswald and Young (2004) show that Rau and Vermaelen's sample seriously understates the incidence of repurchases in the UK. For an enlarged sample, Oswald and Young find a positive average AR of 4.3% over one year following announcement or completion dates, though it is only marginally significant (p-value = 0.07).

rights issue, which reduces the incentive to time issues for when the company is overvalued. Consistent with this point, Capstaff and Fletcher (2011) find that average long-run buy-and-hold and calendar-time ARs following rights issues are not significantly different from zero, whereas average LRARs are negative and significant following SEOs by other methods, especially placings which are the dominant method for small companies. Rights issues are rare in the USA and are not used by large companies, so market timing of SEOs might be more prevalent among large US than UK companies.

Insert Figure 1 about here

Table 6 also shows returns for a hedge portfolio consisting of a long position in one unit of the zero-NEI portfolio and a short position in one unit of the quintile-5 portfolio, for each stock-size category. The hedge portfolios are re-formed as at 30 June each year. They generate positive average returns across all size categories, and the average returns are all statistically significant except for large stocks using value-weighting. But the returns are much higher for small and midsize portfolios. For example, the average value-weighted hedge return is 18.4% per year for small stocks, and 7.2% for large stocks. Figure 1 shows the performance of the hedge portfolios constructed from the full sample. The equal-weighted annual returns are positive for all 36 years of sample period; the value-weighted returns are less consistent, with 19 positive returns.

Insert Table 7 about here

Results net of transaction costs. The results so far suggest a potential opportunity for making additional raw or abnormal returns from a trading strategy using information on firms' recent net equity issuance. To assess whether the NEI effect can be exploited by investors in practice, we estimate returns from the hedge portfolios net of transaction costs. These costs consist of the bid-ask spread, as measured by the daily bid and ask prices in Datastream, plus an estimate of the commission paid for each trade. We assume that commissions are 13bp for intermediaries, 15bp for investing institutions, 25bp for corporate investors, and 67bp for individuals, following Soares and Stark (2009).

The results are in Table 7.[12] The estimated costs of implementing the hedge strategy are enormous. Equal-weighted costs exceed 30 percentage points per year for small stocks and 15 points per year for midsize stocks. Most of the costs arise from the bid-ask spread; the differences in cost due to differences in assumed commission are small. Hedge returns net of costs are negative for almost all portfolios, using either value or equal weighting. In particular, the large and significant positive hedge return before costs for small stocks becomes a large and significant negative return after costs. The only positive hedge return after costs is the value-weighted return for the largest stocks, which is 2.4% per year and not statistically significant (t = 0.85). The hedge returns after costs for the full sample are –10.1% (equal weighted; t = –4.67) or 1.9% (value weighted; t = 0.73). We conclude that the NEI effect cannot be exploited, allowing for transaction costs.

3.3 Sorted portfolios: ARs from factor models

Insert Tables 8 and 9 about here

[12] Data on transaction costs are limited to 1991-2017. But we note that the hedge-portfolio returns before transaction costs for this sub-period are similar to those presented in Table 6 for the full period, 1981-2017.

This section examines the NEI effect in the context of the factor models outlined in Section 2.3, namely the CAPM, FF three- and five-factor models, and a six-factor model that adds liquidity to the FF five factors. The sample period for these tests is restricted to 1992-2013, due to lack of some of the requisite data for earlier years. Table 8 shows the factor premia, i.e. average monthly factor returns. All are positive except *SMB* which is –0.01% (t = –0.06).[13] The liquidity factor has the largest premium, of 0.66% per month (t = 2.72).

Using factor models, ARs are estimated as the intercepts (α_p) from regressions in which the dependent variable is the monthly value-weighted portfolio return in excess of the Treasury-bill rate, and the explanatory variables are monthly factor returns. Table 9 shows the results for the same 21 sorted portfolios we use in Section 3.2. As before, the NEI effect predicts that ARs become more negative for portfolios with higher net issuance. If a factor model is successful in explaining the excess returns, the intercepts from the model should be approximately zero across the 21 portfolios. To test the null hypothesis that, for a given model, $\alpha_p = 0$ for each portfolio p, we calculate the GRS F-statistic of Gibbons, Ross and Shanken (1989), together with its corresponding p-value showing the probability that the differences in the alphas could have arisen by chance. The GRS results reject all the models as explanations of the observed excess returns on the 21 NEI-size portfolios: the intercepts are not jointly equal to zero for any model.

The results in Table 9 show that the NEI effect exists across all the models, for small and midsize stocks. In fact for such stocks the extra factors in the five- and six-factor models do not reduce the differences between the alphas for zero- or low-NEI portfolios, and high-NEI portfolios, compared with the differences in alphas using the CAPM and three-factor model. For large stocks, though, the decrease in alphas as NEI increases is not monotonic and is

[13] Though some studies report a significant size effect for the UK (e.g. Lee et al., 2007), Michou et al. (2014) find that neither the size nor value premia are reliably positive and significantly different from zero, across various methods of estimating these factors.

scarcely apparent. This is consistent with the average ARs from the sorted portfolios controlling for size and value effects, in Section 3.2. The net-repurchase portfolios show a mixture of positive and negative alphas using the three-, five- and six-factor models, with the lowest alphas for large stocks. The results for net repurchases are also consistent with those in Section 3.2.

The results from sorted portfolios are reasonably consistent with each other, but are not entirely consistent with the cross-section regressions on anomaly variables treated as firm characteristics (Section 3.1). Specifically, the NEI effect is as strong in the cross-section regressions for large as for small stocks, whereas this is clearly not the case in the sorted portfolios. In addition, there appears to be a size effect in the cross-section regressions, though it is not always statistically significant. Yet the average premium for the 'small minus big' size factor is –0.01% per month (t = –0.06) (Table 8). FF (2008, p. 1655) caution that extreme returns on individual stocks can distort regression results, and that 'if the regressions and the sorts suggest contradictory inferences, influential observation problems are a likely culprit'.

FF (2016, p. 19) conclude for US stocks that 'the net issues anomaly survives in the five-factor model'. We find that the anomaly survives for small and midsize stocks, but not for large stocks. FF also note that the US repurchase anomaly, of positive average ARs following net repurchases, disappears using the five-factor model. But in the UK there is no robust repurchase anomaly in the first place.

Finally, in unreported analysis we examine the regression coefficients (factor loadings) of the 21 portfolios using the six-factor model, in order to determine whether the NEI effect is linked to any of the other factors. There are no very clear patterns, but high-NEI stocks (quintiles 4 and 5) have consistently negative loadings on the profitability and investment factors, across all three size categories. These loadings suggest the firms in quintiles 4 and 5 have low profitability and high investment (since the investment factor is returns on ‘conservative minus aggressive’ investment firms). The loadings make sense for high equity issuers; many will presumably be small early-stage firms with high asset growth and low current profitability. FF (2015, 2016) note that the unexplained low average ARs for small firms with strongly negative loadings on the investment and profitability factors are ‘lethal’ for their otherwise-successful five-factor model.

The clearest pattern in the factor loadings for 21 portfolios is that the liquidity loading decreases monotonically across the three size groups. Portfolios of small stocks are strongly positively related to low-liquidity stock returns, while large stocks are negatively related, as would be expected. Exposure to the liquidity factor is unrelated to NEI. We infer that the improvement in the adjusted R^2 of the six- over the five-factor model (Table 7) is largely because the additional liquidity factor helps explain differences in returns across the three size categories, rather than across NEI categories.

3.4. Controlling for analyst following

Our results indicate that the NEI effect in the UK arises in small and midsize companies. A possible explanation is that information asymmetry and hence mispricing of shares are greater among small companies, which enables them to time share issues and repurchases more effectively than large companies. To explore this further, with use the number of analysts that follow the company as a proxy for information asymmetry. A larger number of analysts implies that the market is better informed. We use the IBES database to obtain the analyst following for each firm-month, and match each company on Datastream using the SEDOL number (we cannot match about 5% of the IBES sample). The IBES sample starts in 1995. If the NEI effect arises because firms exploit information asymmetry to time their share issues, we expect the NEI effect to be more pronounced for firms with low analyst following.

We implement the test in the characteristics-based regressions (Table 4) by including interaction terms of *NEIS* and *NEIL*, both multiplied by analyst following. For sorted portfolios, Tables 6 and 9, we take the sample with a non-zero following, and calculate results for 'high analyst' and 'low analyst' portfolios, where the breakpoint is the median number of analysts.[14] In none of these analyses does analyst following make a clear difference. The interaction terms in the regressions are rarely statistically significant, and they do not have a consistent sign. In the sorted portfolios both the low- and high-analyst samples show weak evidence of an NEI effect, with no consistent difference between the sub-samples. These results do not support the idea that market timing is more effective for companies followed by fewer analysts. We do not report the results but they are available on request.

4. Conclusions

Net equity issuance is one of a number of 'anomaly variables' that have been discovered to have predictive power for future stock returns. We present a thorough examination of the NEI effect in the UK, using several methods of estimation. We first measure the NEI effect as the coefficient on a firm-specific NEI variable, in cross-section regressions that include other firm characteristics known to forecast future returns. This approach is used in several recent papers that document an NEI effect in the USA and internationally. We confirm that there is a material and robust NEI effect using characteristics-based regressions, and the effect exists within subsamples of stocks sorted by size.

Our second approach uses annual future returns on portfolios of stocks sorted by NEI and size. The benchmark returns are from portfolios of stocks sorted by size and book-to-market ratio. Here we uncover some differences from the US evidence. First, the NEI effect is

[14] We also construct portfolios where 'low analyst' = zero or number of analysts is unavailable in IBES, and 'high analyst' = any positive number. The results using this breakdown also show no consistent difference between the low- and high-analyst subsamples.

almost absent among the largest stocks, which we count as stocks with a market value above the 70th percentile of the largest 350 stocks. Second, there is no reliable ‘repurchase anomaly’, whereby average ARs are positive following repurchases or net repurchases. We also estimate that it would be prohibitively costly to implement a trading strategy designed to profit from the NEI effect. Average returns on hedge portfolios that are long in zero-NEI shocks and short in high-NEI stocks are negative, net of transaction costs.

Our third approach examines the NEI effect in the setting of several factor models. Average ARs on the portfolios sorted by NEI and size are measured by the intercept in time-series regressions of portfolio excess returns on factor returns. If a model is successful in explaining the excess returns across the NEI-size portfolios, the intercept terms should all be approximately zero. The results for the factor models are similar to those for the sorted portfolios controlling for size and book-to-market ratio. There is a clear NEI effect for small and midsize stocks, but not for large stocks. In addition, average ARs for net-repurchase portfolios are not reliably positive.

Our evidence shows that the NEI effect as found in the USA does not entirely generalise to the UK. The results suggest that the timing motive for repurchases is weak in the UK. Future research could explore further the role of repurchases in the UK, about which there is limited existing evidence. Another question is whether the large NEI effect for smaller companies that we find in the UK is due to SEOs, or share issues in connection with takeovers, or whether it persists even after these events are removed.

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Table 1
Factor portfolios

The table summarises how the portfolios are created from which factor returns are calculated. Portfolio formation is as at 30 June each year. The sorts of stocks to form portfolios are independent, except for liquidity. The breakpoints under 'Sort criteria for stocks' are based on the largest 350 sample stocks. Factor returns are calculated from value-weighted returns of the constituent portfolios (e.g. *SL*). *MV* = ln(market value as at *t*–12), where *t* is the month the portfolio is formed; *BM* = ln(book-to-market ratio as at 31 December before month *t*); *ROE* = return on equity, measured by net income in the financial year ending in the calendar year before *t*, divided by shareholders' funds for the previous financial year; *Inv* = investment, measured by the percentage change in assets in the financial year ending the year before *t, Spread* = average daily bid-ask spread for the 12 months to the end of month *t*.

Factor	**Sort criteria for stocks**	**Portfolios from which factor returns are calculated**
Size	Small (*S*) = < median *MV* Big (*B*) = > median *MV* Value: High (*H*) = *BM* > 70th percentile by *BM* Medium (*M*) = 30th < *BM* < 70th percentile Low (*L*) = *BM* < 30th percentile	'Small minus big': $SMB = (SL + SM + SH)/3 - (BL + BM + BH)/3$
Value	Value: as above Size: as above	'High minus low': $HML = (SH + BH)/2 - (SL + BL)/2$
Profitability	Robust (*R*): = *ROE* > 70th percentile by *ROE* Weak (*W*): = *ROE* < 30th percentile by *ROE* Size: as above	'Robust minus weak': $RMW = (SR + BR)/2 - (SW + BW)/2$
Investment	Conservative (*C*): = *Inv* < 30th percentile by *Inv* Aggressive (*A*): = *Inv* > 70th percentile by *Inv* Size: as above	'Conservative minus aggressive': $CMA = (\mathrm{SC} + \mathrm{BC})/2 - (\mathrm{SA} + \mathrm{BA})/2$
Liquidity	Low liquidity (*LL*): = 15% highest *Spread* among largest 350 stocks by *MV* + 35% highest *Spread* among stocks smaller than largest 350 High liquidity (*HL*): = 35% smallest *Spread* among largest 350 stocks by *MV* + 15% smallest *Spread* among stocks smaller than largest 350	'Low liquidity minus high liquidity': $LL - HL$

Table 2
Descriptive statistics: firm characteristics

Panel A shows summary statistics for the firm-level variables in the characteristics-based regressions in Table 3. The sample period is January 1980 to December 2017 (456 months); the number of firm-months is 606,036. *Return* = cumulative log return for months t+1 to t+12 for a given firm in relation to a given month t; *MV* = ln(market value as at t–12); *BM* = ln(firm's book-to-market ratio as at 31 December before month t); *Mom* = cumulative log return for months t–7 to t–1; *NEIS* [*NEIL*] = ln(shares outstanding at t) – ln(shares outstanding at t–12) [ln(shares at t) – ln(shares at t–60)]. Data for *MV*, *BM*, *NEIS* and *NEIL* in Panel A are shown in raw form, before taking logs. Panel B shows Pearson correlation coefficients for the variables after taking logs. Sources for all data: Datastream and London Share Price Database.

Panel A: Summary statistics

Variables	Mean	25th percentile	Median	75th percentile	Standard deviation
Return	-0.032	-0.270	0.045	0.311	0.678
MV	£470m	£7m	£27m	£133m	£2,106m
BM	0.97	0.40	0.81	1.00	2.29
Mom	-0.015	-0.177	0.014	0.200	0.421
NEIS	38.6m	0	0	0.001m	4610m
NEIL	213m	0	0.002m	0.023m	14300m

Panel B: Correlations

	Return	***MV***	***BM***	***Mom***	***NEIS***
MV	0.020				
BM	0.019	-0.043			
Mom	0.088	0.012	0.024		
NEIS	-0.104	-0.055	0.085	-0.074	
NEIL	-0.105	-0.058	0.015	-0.082	0.362

Table 3
Regressions of future returns on firm characteristics

Results are based on monthly cross-sectional regressions of future returns on firm characteristics, for the period January 1981 to December 2017. The coefficients are averages from the monthly regressions, following the Fama-MacBeth method. *t*-statistics are in italics. The *t*-statistics for regressions with six- and 12-month future returns use standard errors with a Newey-West adjustment for autocorrelation of the coefficients. *BMdum* = 1 when *BM* is missing, and 0 otherwise; *Mom* = ln(cumulative return on the stock during months *t*–5 to *t*), *NEISzero* (*NEILzero*) = 1 when *NEIS* (*NEIL*) is zero, and 0 otherwise. See Table 2 for other definitions. R^2 is the average adjusted R^2 from the cross-sectional regressions. *** (**) (*) = significant at the 1% (5%) (10%) level.

Panel A. Dependent variable: one-month future return							
Constant	0.00	0.00	0.00	-0.031***	-0.030***	-0.024***	-0.023***
	0.67	-0.35	-1.34	-7.47	-7.10	-6.76	-6.44
MV				0.003***	0.003***	0.002***	0.002***
				6.66	6.37	5.40	5.35
BM				0.004***	0.005***	0.003***	0.003***
				6.46	6.75	5.09	5.20
BMdum				0.016***	0.016***	0.015***	0.015***
				9.72	9.66	8.98	8.95
Mom				0.030***	0.030***	0.028***	0.028***
				11.43	11.50	10.90	11.02
NEIS	-0.004**		-0.017***		-0.003*		-0.004**
	-2.03		-8.11		-1.73		-1.97
NEISzero	-0.007***		-0.007***		-0.002**		-0.003**
	-5.09		-5.28		-2.03		-2.55
NEIL	-0.010***	-0.010***				-0.006***	-0.007***
	-10.32	-10.80				-7.88	-8.24
NEILzero	-0.016***	-0.013***				-0.009***	-0.010***
	-8.17	-7.25				-5.74	-6.09
R^2	0.009	0.005	0.004	0.021	0.024	0.024	0.027
N	621,701	723,235	621,701	606,274	606,036	606,274	606,036

Table 3 cont.

Panel B. Dependent variable: 12-month future return							
Constant	0.017	0.026	-0.012	-0.121***	-0.119***	-0.050*	-0.070**
	0.78	*1.23*	*-0.44*	*-3.25*	*-3.22*	*-1.72*	*-2.29*
MV				0.012***	0.011***	0.005	0.006**
				3.55	*3.34*	*1.52*	*1.97*
BM				0.046***	0.044***	0.034***	0.034***
				6.94	*6.71*	*5.63*	*5.46*
BMdum				0.092***	0.088***	0.074***	0.075***
				8.85	*8.67*	*7.62*	*7.68*
Mom				0.150***	0.144***	0.132***	0.132***
				8.41	*8.44*	*7.88*	*8.02*
NEIS	-0.095***		-0.182***		-0.127***		-0.068***
	-7.78		*-9.69*		*-9.52*		*-6.53*
NEISzero	0.029***		0.027***		0.041***		0.037***
	4.77		*4.32*		*8.70*		*8.17*
NEIL	-0.065***	-0.078***				-0.066***	-0.054***
	-9.20	*-9.57*				*-10.46*	*-9.63*
NEILzero	-0.115***	-0.108***				-0.097***	-0.089***
	-5.84	*-5.10*				*-5.43*	*-5.23*
R^2	0.034	0.025	0.015	0.052	0.061	0.066	0.072
N	560,807	658,208	560,807	549,938	549,714	549,938	549,714

Table 4
Regressions on firm characteristics using OLS, with alternative *t*-statistics

The specification includes all the explanatory variables, as in the last column of Table 3. Coefficients are estimated using OLS. *t*-statistics are in italics, using different methods of estimating standard errors. The Fama-MacBeth results from the last column of Table 3 are reproduced for convenience. We omit results for six-month returns to save space.

Panel A. Dependent variable: one-month future return					
	t White robust	*t* Firm clustered	*t* Time clustered	*t* Two-way clustered	Fama-MacBeth results
Constant			-0.024		-0.023
	-11.72	*-11.27*	*-6.40*	*-6.33*	-4.74
MV			0.002		0.002
	9.62	*9.23*	*4.28*	*4.25*	4.93
BM			0.002		0.003
	10.91	*10.66*	*5.56*	*5.52*	1.86
BMdum			0.019		0.015
	11.41	*10.59*	*9.08*	*8.66*	4.77
Mom			0.034		0.028
	17.69	*17.29*	*6.69*	*6.67*	14.1
NEIS			-0.002		-0.004
	-1.32	*-1.30*	*-0.97*	*-0.96*	-3.08
NEISzero			0.000		-0.003
	0.35	*0.34*	*0.24*	*0.24*	-1.02
NEIL			-0.010		-0.007
	-11.57	*-11.22*	*-8.91*	*-8.75*	-5.13
NEILzero			-0.009		-0.010
	-9.73	*-9.31*	*-3.27*	*-3.25*	-4.56
R^2					0.027
N			606,036		606,036

Table 4 cont.

Panel B. Dependent variable: 12-month future return					
	t White robust	*t* Firm clustered	*t* Time clustered	*t* Two way clustered	Fama-MacBeth results
Constant			-0.058		-0.053
	-14.61	*-5.30*	*-3.63*	*-3.06*	*-0.99*
MV			0.002		0.006
	3.71	*1.14*	*0.87*	*0.71*	*1.97*
BM			0.067		0.034
	54.83	*18.92*	*13.90*	*11.44*	*5.46*
BMdum			0.100		0.075
	31.73	*11.07*	*19.71*	*10.14*	*7.68*
Mom			0.105		0.132
	31.60	*16.59*	*4.54*	*4.43*	*8.02*
NEIS			-0.126		-0.068
	-29.61	*-12.55*	*-17.78*	*-10.93*	*-6.53*
NEISzero			0.069		0.037
	34.12	*12.83*	*11.89*	*9.02*	*8.17*
NEIL			-0.074		-0.054
	-43.36	*-15.18*	*-21.43*	*-12.93*	*-9.63*
NEILzero			-0.074		-0.089
	-35.07	*-12.16*	*-6.22*	*-5.61*	*-5.23*
R^2			0.036		0.072
N			549,714		549,714

Table 5
Descriptive statistics of portfolios sorted by *NEIS* and *MV*

The average annual return, NEI value, size and number of firms for portfolios independently sorted by *NEIS* and *MV*. *NEIS* is shown in millions of shares. We sort stocks as at 30 June each year into seven groups by *NEIS*; negative-NEI stocks are in level –1, zero-NEI stocks are in level 0, and positive NEI stocks are sorted into five quintiles, levels 1 to 5. Independently, we sort stocks sorted into three groups by *MV*. The breakpoints are the 30th and 70th percentiles for the largest 350 stocks. The 21 portfolios are formed based on the intersections between the two sets of sorted groups. VW = value weighted; EW = equal weighted.

				NEI level			
Size	-1	0	1	2	3	4	5
				Value-weighted average annual return			
Small	12.3%	18.7%	19.1%	12.4%	13.4%	6.3%	0.3%
Middle	14.5%	17.1%	17.2%	14.4%	10.7%	7.4%	4.2%
Big	11.2%	17.7%	16.4%	12.3%	14.0%	10.2%	10.5%
All	11.4%	17.6%	16.3%	12.3%	13.8%	9.8%	9.5%
				Equal-weighted average annual return			
Small	13.3%	20.6%	34.5%	14.8%	12.6%	9.0%	3.7%
Middle	15.4%	16.6%	16.5%	14.4%	10.6%	6.2%	3.9%
Big	13.0%	17.1%	16.1%	15.3%	11.4%	7.2%	9.0%
All	14.8%	18.4%	17.4%	15.2%	10.9%	6.2%	3.8%
				NEIS			
Small	-1100.53	0.00	1.43	6.94	41.95	190.10	1077.86
Middle	-151.52	0.00	1.20	7.00	39.96	181.74	841.33
Big	-44.64	0.00	1.28	6.54	38.54	165.64	1131.96
All	-291.96	0.00	1.26	6.75	39.85	182.79	995.09
				MV			
Small	£5m	£5m	£6m	£6m	£6m	£5m	£5m
Middle	£42m	£40m	£50m	£49m	£47m	£42m	£38m
Big	£4,350m	£1,411m	£2,143m	£1,999m	£1,699	£1,300m	£1,475m
All	£2,171m	£264m	£1,215m	£1,079m	£617m	£353m	£267m
				N			
1	16	241	15	16	26	36	50
2	30	225	47	48	61	63	61
3	39	101	76	73	50	38	26

Table 6
Abnormal returns on portfolios sorted by *NEIS* and *MV*

Average ARs for the 21 sorted portfolios in Table 5. The expected return on a given stock is the value-weighted return on the stock's benchmark portfolio, controlling for size and book-to-market ratio. To create the benchmark portfolios, sample stocks are sorted into quartiles by *MV* measured as at 30 June each year, and independently sorted into quartiles by *BM* as at 31 December in the previous year. Each stock is a constituent of its benchmark portfolio. The hedge portfolio consists of a long position in one unit of the zero-*NEIS* portfolio, and a short position in one unit of *NEIS* quintile 5. The hedge portfolio is re-formed as at 30 June each year. Newey-West *t*-statistics are in italics. Bold indicates statistical significance at the 1% level.

	NEI level							Hedge portfolio
Size	-1	0	1	2	3	4	5	0 - 5
				Value-weighted AR				
Small	-5.9%	1.2%	4.4%	-1.5%	-1.0%	**-8.1%**	**-13.2%**	**18.4%**
	-1.74	*1.20*	*1.01*	*-0.42*	*-0.31*	***-3.85***	***-4.63***	***6.77***
Middle	0.7%	**1.8%**	1.7%	0.7%	-2.3%	**-6.1%**	**-9.3%**	**12.9%**
	0.36	***2.57***	*1.01*	*0.58*	*-1.19*	***-2.94***	***-4.57***	***5.73***
Big	-2.7%	**3.5%**	2.4%	-0.7%	0.0%	-2.4%	-2.7%	**7.2%**
	-1.83	***3.82***	*1.71*	*-0.78*	*0.01*	*-1.30*	*-0.89*	***2.17***
All	-2.6%	**3.2%**	2.3%	-0.7%	0.0%	-2.8%	-3.4%	**8.1%**
	-1.88	***4.05***	*1.74*	*-0.76*	*-0.02*	*-1.75*	*-1.33*	***2.74***
				Equal-weighted AR				
Small	-3.5%	2.9%	20.2%	1.3%	-2.2%	-5.1%	**-11.0%**	**16.9%**
	-0.82	*1.94*	*1.27*	*0.22*	*-0.58*	*-1.61*	***-3.62***	***7.60***
Middle	1.4%	1.3%	1.5%	1.0%	-2.0%	**-6.9%**	**-9.1%**	**12.7%**
	0.72	*1.72*	*0.83*	*0.68*	*-1.26*	***-3.25***	***-4.38***	***4.96***
Big	-1.5%	**3.2%**	1.9%	1.6%	-2.1%	**-6.1%**	**-5.3%**	**8.1%**
	-0.68	***2.21***	*1.77*	*1.52*	*-1.68*	***-3.78***	***-2.42***	***3.36***
All	-0.4%	**2.2%**	3.0%	1.4%	-1.8%	**-6.5%**	**-9.2%**	**14.5%**
	-0.25	***3.65***	*1.78*	*1.23*	*-1.83*	***-3.87***	***-5.62***	***7.93***

Table 7
Hedge-portfolio returns net of transaction costs

Average annual returns on the hedge portfolio in Table 6, i.e. a long position in one unit of the zero-*NEIS* portfolio, and a short position in one unit of *NEIS* quintile 5. The sample period in this table is 1991 to 2017. Returns are shown before and after transaction costs, which are calculated according to equation (11). Commissions are assumed to be 13 basis (bp) for intermediaries, 15bp for investing institutions, 25bp for corporate investors, and 67bp for individuals. The column headed Transactions costs shows the percentage-point difference in returns gross and net of costs. Newey-West *t*-statistics are in italics. Bold indicates statistical significance at the 1% level.

	Panel A. Returns by size category, for intermediaries					
	Equal weighted			Value weighted		
Size	Average return before costs	Transaction costs	Average return after costs	Average return before costs	Transaction costs	Average return after costs
Small	**15.9%**	34.7%	**-18.8%**	**16.5%**	29.3%	**-12.8%**
t	***5.96***		***-6.26***	***5.40***		***-3.62***
Middle	**10.6%**	15.3%	-4.7%	**11.5%**	12.9%	-1.4%
t	***3.33***		*-1.52*	***4.35***		*-0.77*
Big	5.8%	6.5%	-0.7%	**6.9%**	4.5%	2.4%
t	*2.09*		*-0.23*	***2.50***		*0.85*
	Panel B. Returns by category of investor, full sample					
Intermediaries	**12.0%**	22.1%	**-10.1%**	**8.0%**	6.1%	1.9%
t	***5.82***		***-4.67***	***2.32***		*0.73*
Institutions	**12.0%**	22.1%	**-10.1%**	**8.0%**	6.1%	1.9%
t	***5.82***		***-4.67***	***2.32***		*0.73*
Corporates	**12.0%**	22.3%	**-10.3%**	**8.0%**	6.3%	1.7%
t	***5.82***		***-4.76***	***2.32***		*0.65*
Individuals	**12.0%**	23.2%	**-11.2%**	**8.0%**	7.2%	0.8%
t	***5.82***		***-5.18***	***2.32***		*0.31*

Table 8
Summary statistics for the factors

The data are calculated from monthly factor returns for the period July 1992 to December 2013. *RM* = market factor, return on FTSE Allshare Index minus the rate of three-month Treasury bills; *SMB* = size factor, 'small minus big'; *HML* = book-to-market factor, 'high minus low'; *RMW* = profitability factor, 'robust minus weak'; *CMA* = investment factor, 'conservative minus aggressive'; *LIQ* = liquidity factor, high-spread stocks minus low-spread stocks. Table 1 explains the construction of the portfolios used to calculate factor returns.

	RM	*SMB*	*HML*	*RMW*	*CMA*	*LIQ*
Mean	0.49	-0.01	0.38	0.40	0.51	0.66
Median	0.94	-0.14	0.27	0.34	0.15	0.55
Maximum	9.90	17.43	11.62	12.78	12.35	22.55
Minimum	-13.61	-14.54	-13.53	-12.64	-8.76	-10.21
Std. dev.	3.89	3.51	2.89	3.14	2.47	3.87
Newey-West *t*	2.14	-0.06	2.08	2.02	3.34	2.72
N	306	306	306	306	306	306

Table 9
Intercepts from factor models

Abnormal returns on the 21 portfolios sorted by NEI and size, as in Table 5. ARs are measured by intercepts from time-series regressions (eq. 11) of monthly portfolio excess returns on factor returns, for the period July 1992 to December 2017. The corresponding *t*-statistics are in italics. The last column reports GRS *F*-statistics with the corresponding *p*-value for joint significance of the intercepts. Factors in the models are: CAPM: market ($R_M - R_F$); FF three-factor model: market, size (*SMB*), book-to-market (*HML*); FF five-factor model: market, size, book-to-market, profitability (*RMW*), investment (*CMA*); five factors plus liquidity: market, size, book-to-market, profitability, investment, liquidity (high spread minus low spread). Table 1 explains the construction of the portfolios used to calculate factor returns.

	NEIS level														GRS
Size	-1	0	1	2	3	4	5	-1	0	1	2	3	4	5	*F*-stat
	Capital asset pricing model														
1	0.13	0.83	0.52	1.15	0.29	-0.04	-0.24	*0.35*	***3.41***	*1.25*	***2.33***	*0.76*	*-0.11*	*-0.63*	5.07
2	0.48	0.27	0.36	0.07	0.04	-0.61	-0.82	***1.99***	*1.31*	*1.51*	*0.29*	*0.15*	***-2.12***	***-2.48***	<0.01
3	0.07	0.47	0.27	0.06	-0.17	-0.17	-0.12	*0.48*	***3.29***	***2.38***	*0.52*	*-0.92*	*-0.70*	*-0.42*	
	Fama-French three-factor model														
1	0.14	0.82	0.50	1.13	0.22	-0.01	-0.22	*0.42*	***4.93***	*1.34*	***2.54***	*0.71*	*-0.04*	*-0.67*	4.81
2	0.43	0.22	0.30	0.00	0.05	-0.59	-0.80	***2.31***	***2.00***	***1.98***	*0.01*	*0.31*	***-3.21***	***-3.46***	<0.01
3	-0.02	0.47	0.29	0.05	-0.21	-0.18	-0.16	*-0.11*	***3.23***	***2.55***	*0.48*	*-1.19*	*-0.78*	*-0.59*	
	Fama-French five-factor model														
1	0.07	0.91	0.48	1.44	0.38	0.22	0.12	*0.20*	***5.41***	*1.24*	***3.19***	*1.16*	*0.65*	*0.37*	4.36
2	0.39	0.28	0.36	-0.01	0.08	-0.40	-0.60	***2.03***	***2.40***	***2.30***	*-0.06*	*0.49*	***-2.11***	***-2.53***	<0.01
3	-0.09	0.46	0.35	0.01	0.01	0.09	0.21	*-0.60*	***3.07***	***3.02***	*0.06*	*0.07*	*0.40*	*0.78*	
	Five factors plus liquidity factor														
1	-0.25	0.38	0.07	0.96	-0.16	-0.66	-0.80	*-0.69*	***2.75***	*0.19*	***2.08***	*-0.51*	***-2.22***	***-2.72***	3.99
2	0.36	0.12	0.30	0.00	-0.02	-0.55	-1.05	*1.79*	*1.07*	*1.81*	*-0.02*	*-0.14*	***-2.85***	***-4.55***	<0.01
3	-0.06	0.44	0.34	0.09	0.16	0.24	0.31	*-0.42*	***2.77***	***2.81***	*0.76*	*0.90*	*1.02*	*1.11*	

Figure 1
Annual returns on hedge portfolio, 1981-2017

The hedge portfolio consists of a long position of one unit in the zero-*NEIS* portfolio and a short position of one unit in *NEIS* quintile 5 (largest positive NEI). The *NEIS* and hedge portfolios are re-formed as at 30 June each year.