



**UCD GEARY INSTITUTE FOR PUBLIC POLICY  
DISCUSSION PAPER SERIES**

# **Are equity market anomalies disappearing? Evidence from the U.K.**

John Cotter  
University College Dublin

Niall McGeever  
University College Dublin

Geary WP2018/04  
February 19, 2018

UCD Geary Institute Discussion Papers often represent preliminary work and are circulated to encourage discussion. Citation of such a paper should account for its provisional character. A revised version may be available directly from the author.

Any opinions expressed here are those of the author(s) and not those of UCD Geary Institute. Research published in this series may include views on policy, but the institute itself takes no institutional policy positions.

# Are equity market anomalies disappearing? Evidence from the U.K.

John Cotter and Niall McGeever  
University College Dublin

## Abstract

We study the persistence over time of nine well-known equity market anomalies in the cross-section of U.K. stocks. We find strong evidence of diminished statistical significance for most of these anomalies including the return reversal and momentum effects. Two anomalies – firm profitability and stock turnover – remain quite robust throughout our sample period. These results hold for both portfolio sorts and Fama-MacBeth regression analyses and are robust to the use of alternative methods of risk adjustment. Our findings are consistent with improvements in market efficiency over time with respect to well-known anomaly variables.

Keywords: Anomalies, Asset Pricing, Market Efficiency

JEL Classification: G10, G12

---

Corresponding author: Niall McGeever, Smurfit Graduate School of Business, University College Dublin, Blackrock, Co. Dublin, Ireland. Email: niallmcgeever@gmail.com. We thank Abhinav Anand, Michael Brennan, Charlotte Christiansen, Gregory Connor, John J. McConnell, René Stulz, Avanihar Subrahmanyam, Anita Suurlaht, seminar participants at University College Dublin and Xiamen University, and participants at the Irish Economic Association 2016 and European Financial Management Association 2016 for helpful comments and suggestions. We gratefully acknowledge the support of Science Foundation Ireland under grant number 16/SPP/3347.

# Are equity market anomalies disappearing? Evidence from the U.K.

## **Abstract**

We study the persistence over time of nine well-known equity market anomalies in the cross-section of U.K. stocks. We find strong evidence of diminished statistical significance for most of these anomalies including the return reversal and momentum effects. Two anomalies – firm profitability and stock turnover – remain quite robust throughout our sample period. These results hold for both portfolio sorts and Fama-MacBeth regression analyses and are robust to the use of alternative methods of risk adjustment. Our findings are consistent with improvements in market efficiency over time with respect to well-known anomaly variables.

Keywords: Anomalies, Asset Pricing, Market Efficiency

JEL Classification: G10, G12

# 1 Introduction

Equity market anomalies are patterns in historical stock returns which are difficult to reconcile with risk-based models of expected return. The anomalies literature shows that particular categories of stocks earn abnormally high or low average returns. Major contributions to this literature include the observations that small firms tend to have high average returns (Banz, 1981) and that recent stock returns predict future returns (Jegadeesh and Titman, 1993). The documentation of robust anomalies indicates that either average returns are to some extent determined by non-risk firm characteristics or that our benchmark model is failing to capture some important aspect of risk.

In this paper, we investigate the persistence over time of a set of well-known equity market anomalies in the cross-section of U.K. stocks. This market provides an excellent setting in which to study anomaly persistence. First, it is among the most developed and liquid stock markets in the world. Second, trading costs for U.K. stocks have fallen substantially over recent years (Brogaard et al., 2014). Third, many of the most robust anomalies in the literature are also evident in historical U.K. returns.

We examine anomalies which have been found to be robust across time and across international markets. These anomaly characteristics are accruals (Sloan, 1996), asset growth (Cooper et al., 2008), book-to-market ratio (Fama and French, 1992), new equity issuances (Pontiff and Woodgate, 2008), firm profitability (Fama and French, 2006), return reversal (Jegadeesh, 1990), momentum (Jegadeesh and Titman, 1993), firm size (Banz, 1981), and stock turnover (Datar et al., 1998).

We find evidence of a general decline in the significance of these equity market anomalies in the period 1990 to 2013. Most of the anomalies we examine have attenuated or are absent from the data in the second half of our sample period. Perhaps most notably, we find no evidence of the “momentum effect” (Jegadeesh and Titman, 1993) in recent years. Two anomalies – firm profitability and stock turnover – remain rather robust throughout the sample period and show only weak evidence of attenuation over time. Our results hold for both hedge portfolio sorts and Fama-MacBeth regressions.

Understanding the economic implications of our results requires a consideration of the vast anomalies literature. Figure 1 illustrates the process of interpreting anomalies. All contributions to the literature fit at one or more stages of the tree. The first stage

is to determine the statistical significance of an anomaly. Data mining is the practice of repeatedly using the same dataset to test many different hypotheses. The distortionary impact of this practice on anomalies research has been stressed repeatedly in the literature. Recently, Harvey et al. (2016) consider the impact data mining has on the rate of anomaly discovery in the cross-section of stock returns. They argue that many anomalies lose their significance when we account for the intensive search researchers have conducted. Hou et al. (2017) provide a similar critique.

Importantly, the nine anomalies we examine in this study have previously been shown to be robust to out-of-sample testing. This is strong evidence against a data mining explanation and tallies with the view of Fama (1991) that predictable and economically meaningful anomalies should not disappear in out-of-sample testing.

The second stage of the process is to acknowledge that anomalies are relative phenomena; robust anomalies may be evidence of abnormal returns or simply that we have not fully accounted for the assets' risk. However, theorists have struggled to provide ex-post risk-based explanations for many anomalies. In our empirical work, we find that our results are robust to the use of different established models of expected return. This is consistent with the view that anomalies like these represent profitable trading opportunities rather than compensation for risk.

A central argument in the literature is that the discovery of a profitable anomaly will lead to its disappearance. Smart investors should, it is argued, exploit the abnormal returns on offer by constructing appropriate investment portfolios. Anecdotal evidence abounds of academic discoveries informing investors. Recently, McLean and Pontiff (2016) provide systematic evidence that the publication of academic papers is directly related to the disappearance of anomalies. Akbas et al. (2015) also present evidence suggesting that aggregate fund flows are related to variations in anomaly strength. Mutual fund flows – “dumb money” – can result in anomalies becoming more pronounced, while hedge fund flows – “smart money” – lead to anomaly attenuation. Our results are consistent with these recent findings and suggest that recent years have seen an improvement in market efficiency with respect to well-known anomalies.

The last stage of the process is consider whether investors can profit from anomalies in practice. This is the subject of a growing literature on the limits to arbitrage (Gromb and Vayanos, 2010). Investors seeking to exploit anomalies face the basic challenges of

trading costs, short-selling restrictions, and other position limits. In addition, investors may face significant non-fundamental limits to arbitrage. De Long et al. (1990) and Shleifer and Vishny (1997) develop models in which arbitrageurs are concerned about irrational behaviour on the part of other investors. Such behaviour may make arbitrageurs unwilling to target clearly identifiable anomalies. The main implication of this literature is that well-known equity market anomalies may persist over time – even in the presence of sophisticated arbitrageurs. Interestingly, our findings suggest that such limits to arbitrage are not fully preventing anomaly disappearance in the U.K. stock market.

In summary, our results show a general decline in the significance of well-known anomalies in the U.K. stock market. This is consistent with an improvement in market efficiency over time with respect to well-known anomaly variables. Our paper thus makes an important contribution to the literature on cross-sectional asset pricing in the U.K. stock market and also provides important international evidence on equity market anomaly persistence over time.

The remainder of the paper is organised as follows. Section 2 provides an overview of the anomalies we examine in this paper. Section 3 describes our data and Section 4 reviews our methodology. Section 5 presents the results of our analysis and discusses their economic significance. Section 6 concludes the paper.

## 2 Anomalies

U.K. anomaly studies typically focus on a single anomaly or a small set of anomalies. In contrast, we jointly examine nine well-known and robust anomalies. This allows us to conduct a more systematic analysis of anomaly persistence. The U.K. market provides an interesting testing ground as it is both well-developed and liquid. Our work is most closely related to that of Chordia et al. (2014) who report the disappearance of many anomalies in the U.S. stock market.

The nine anomalies we study in this paper are listed in Panel A of Table 1. The accruals anomaly (ACC) refers to the negative relationship between accounting accruals and subsequent stock returns. This anomaly was first documented by Sloan (1996) and has been replicated by Simlai (2016) and many others. Sloan (1996) argues that this anomaly arises because investors do not fully appreciate how firms use accounting accruals to manage reported earnings. Papanastasopoulos and Tsiritakis (2015) and Pincus

et al. (2007) find evidence of the accruals anomaly in the U.K. stock market. However, Leippold and Lohre (2012) provide evidence suggesting that the significance of this anomaly may be weakening over time in the U.K. and various other international stock markets.

The asset growth anomaly (AG) reported by Cooper et al. (2008) is that firm asset growth is negatively related to stock returns. They argue that investors naively extrapolate recent high asset growth into the future which results in predictable underperformance from these firms. Titman et al. (2013) and Watanabe et al. (2013) reports evidence of an asset growth anomaly in other international stock markets including the U.K.

Pontiff and Woodgate (2008) document a new issuance anomaly (ISSUE) whereby firms which issue new equity subsequently experience negative stock return performance. This anomaly suggests that managers may time the market by issuing equity when they believe firm value is too high. McLean et al. (2009) find evidence of a new issuance anomaly in the U.K. stock market.

Book-to-market ratios (B/M) are positively related to U.S. stock returns. Fama and French (1992) suggest that this empirical regularity may compensate investors for bearing risk, but there is no consensus in the literature on this point. Chan and Chui (1996), Clubb and Naffi (2007), and Miles and Timmermann (1996) find similar results in the cross-section of U.K. stocks. More recently, Fama and French (2006) report a positive relationship between firm profitability (PROFIT) and average returns. They link this phenomenon to valuation theories of the firm. Novy-Marx (2013) provides international evidence of a profitability anomaly using pooled cross-sections from different markets, but he does not provide results for the U.K. stock market alone.

Jegadeesh (1990) documents a return reversal anomaly (R1) whereby stock returns in a given month are negatively related to returns in the previous month. Similarly, Antoniou et al. (2006) report a significant short-run reversal effect for U.K. stocks. Another return-based anomaly is “momentum” (R212); Jegadeesh and Titman (1993) find that stock returns in a given month are positively related to performance in the last 3 to 12 months. They argue that over-reaction by investors to past performance may explain this pattern. Liu et al. (1999) and Rouwenhorst (1998) were the first to report evidence of a momentum effect in U.K. stock returns. Agyei-Ampomah (2007) and Hon and Tonks

(2003) provide additional supportive evidence for the U.K. market.

The size anomaly (SIZE) refers to the observation reported by Banz (1981) that small firms tend to earn high average returns. He does not provide a risk-based explanation for this observed pattern. The size effect has also been documented internationally. Andrikopoulos et al. (2008), Bagella et al. (2000), and Dimson and Marsh (1986) all find evidence of a size effect in U.K. stock returns.

Lastly, Datar et al. (1998) find a negative relationship between stock turnover (TURN) and average returns. They interpret this result as evidence of low liquidity stocks earning higher average returns. On the other hand, past research using U.K. stock data shows an anomalous positive relationship between stock turnover and returns (Cotter et al., 2015; Foran et al., 2015).

### 3 Data

We collect monthly returns and firm characteristic data for the cross-section of U.K. stocks in the period January 1990 to December 2013 from Thomson Reuters Datastream. We also collect equity risk factors for the U.K. market from AQR Capital Management. We ensure that dead stocks are included in our sample so as to avoid a survivorship bias. We further require each stock to be a major security (MAJOR=Y), a U.K. firm (GEOGN=United Kingdom), to be listed in London (EXNAME=London), and to be identified as an equity security (TYPE=EQ). Our original sample consists of 2,681 stocks.

We proceed with our data analysis with some caution. Ince and Porter (2006) document particular issues with individual stock information from Datastream. They develop specialised filtering techniques which considerably improve data reliability. Schmidt et al. (2017) build on this contribution and further improve these procedures.

We complete a battery of static and dynamic filters to improve the quality of our dataset. We carefully clean our data using the screens outlined by Schmidt et al. (2017). This is the first paper to use these more refined procedures in a cross-sectional U.K. study. We first remove any securities – such as preference shares – which may have escaped the above filters by searching security extended names for the following terms: “pref”, “prf”, “%”, “dupl”, and “duplicate”.



We retain only stocks that have a return history of at least 24 months. We also require a stock in a given month to have non-missing values for each of the nine anomaly variables we examine. We find that certain stocks consistently have missing values for particular variables and hence we exclude them from our sample. This reduces our sample to 1,533 stocks.

We next consider the potential impact of suspect outliers. We set monthly returns equal to missing if they are greater than 990% or if either price term is greater than £1,000,000. Furthermore, we follow Nagel (2002) in removing stocks with nominal prices of £0.30 or less. This filter ensures that very illiquid – and often very small – stocks are not included in our cross-sectional regressions. This issue may be of particular concern in the U.K. as the London Stock Exchange has historically contained many small firms. Our final sample contains 1,229 stocks.

Panel B of Table 1 presents summary statistics for each of our nine anomaly variables. For instance, the mean annual asset growth for these firms was 0.3% with a relatively large standard deviation of 1.31%. The expected monthly return reversal, R1, is approximately zero, but we do observe a standard deviation across stocks of 0.13%. Our momentum variable, R212, has a mean of 0.3% which is positive as expected. It is possible to observe this zero mean figure even when high (low) returns for individual stocks predict low (high) returns in the subsequent period. Yearly average stock turnover, TURN, is 6.17% while the standard deviation is quite high at 9.21%.

The standard deviation for these variables can be substantial. Similarly to other studies, we note a wide diversity in the size of our firms. While the median firm is valued at £43m, the mean is much higher at £503m. The new issuances variable, ISSUE, also has a wide distribution as different firms often issue very different quantities of new securities in any given month. We also see high levels of skewness and kurtosis for many of our variables. For instance, asset growth kurtosis estimate is 49.12.

Panel C of Table 1 presents a correlation matrix for our anomaly variables. We are interested in understanding the correlations between anomaly variables as we later conduct multivariate Fama-MacBeth regressions. Similarly to Brennan et al. (1998), we find quite low levels of correlation between our anomaly variables. Most coefficients are below 0.1 in absolute value. The highest level of correlation we find is 0.408 between size and turnover – small firms tend to have lower turnover in the stock market.

## 4 Methodology

We conduct two distinct analyses. Our first approach is to consider the returns generated by anomaly-based hedge portfolio strategies. In each month, we sort stocks into portfolios based on the value of a given anomaly variable. We then calculate returns for a portfolio which is long and short in the extreme portfolios. We also consider the robustness of these portfolio results to methodological changes. In particular, we provide results using both quintile and decile sorted portfolios. This analysis provides a tangible measure of the economic magnitude of each anomaly in the form of monthly percentage returns.

The second analysis we conduct is a series of Fama-MacBeth regressions to determine the statistical significance of our set of anomalies. We apply the modified version of the Fama-MacBeth two-step cross-sectional regression methodology proposed by Brennan et al. (1998). We begin with first-pass time series regressions of monthly individual firm returns on the four Fama and French (1993) and Carhart (1997) factors. This generates beta sensitivities for each firm with respect to each factor.

The second-pass of the Fama-MacBeth procedure is to consider the significance of anomaly variables in explaining returns given what we know about the assets' betas. There is a well-known errors-in-variables problem in this procedure as firm betas are prone to estimation error (Miller and Scholes, 1972). Inclusion of mismeasured betas as independent variables in second-pass cross-sectional regressions will result in biased and inconsistent Fama-MacBeth coefficient estimates.

We follow Brennan et al. (1998) by calculating risk-adjusted individual firm returns using first-pass firm betas. This approach addresses the potential errors-in-variables problem by incorporating the betas into the dependent variable. This allows for consistency in our second-pass regression Fama-MacBeth coefficients, but comes at the cost of greater inefficiency (Hausman, 2001). Brennan et al. (1998) implicitly argue this is an acceptable trade-off which prioritises unbiased coefficient estimates.

We then obtain Fama-MacBeth coefficients for each anomaly variable in the standard way by calculating the time series average of each variable's estimated premium. These coefficients equal zero under the null hypothesis that the anomaly variable is irrelevant for explaining differences in average returns across stocks. We conduct these regressions

using univariate and various multivariate models.

## 5 Results

In this section, we report our results. We show that most of the nine anomalies we examine have disappeared or are substantially diminished in recent years. This is true of prominent anomalies such as momentum (Jegadeesh and Titman, 1993) and short-run return reversal (Jegadeesh, 1990). We find two main exceptions to this trend – the firm profitability and stock turnover anomalies. Our findings hold for both hedge portfolio return analysis and Fama-MacBeth regressions.

### 5.1 Hedge portfolio returns

Hedge portfolio returns fall substantially in the second half of our sample period for the majority of our anomalies. This is true of even the more robust firm profitability and stock turnover anomalies.

We begin our analysis by estimating the returns of portfolios constructed with stocks sorted by anomaly variables. This analysis allows us to determine the returns investors could have enjoyed had they followed trading strategies based on these anomaly variables. As such, this approach provides a tangible measure of each anomaly’s economic significance.

Each month, we sort our sample of stocks from highest to lowest value of a particular anomaly variable. We calculate the return on an equally-weighted portfolio which is long the quintile with the highest values of the variable and short the quintile with the lowest values of the variable. We then test whether the average monthly return of this portfolio is statistically different from 0%.

Panel A of Table 2 presents the results of our quintile portfolio analysis. The first column of results shows average monthly portfolio returns over the full January 1990 to December 2013 sample period. The second and third columns show average portfolio returns for the first and second halves of the sample period.

In the full sample, we find that five of the average portfolio returns are significantly different from zero. These are the asset growth, book-to-market, profitability, momen-

tum, and turnover portfolios. These significant returns range from 0.836% per month for the book-to-market portfolio to 1.907% per month for the profitability portfolio.

The sub-sample results show that returns to these strategies have fallen for seven of the nine portfolios. The strong statistical significance of the asset growth, book-to-market, and momentum portfolios is sharply diminished in the second sub-sample. In the two cases where portfolio returns rose in absolute terms (the new issuance and size portfolios), neither return is statistically significant in the second sub-sample.

The returns of the profitability and turnover portfolios remain strongly significant in the second sub-sample. Nonetheless, the magnitude of their returns fell in both cases. The return on the profitability portfolio fell from 2.11% to 1.7%. The return on the turnover portfolio sees a more sizeable decline from 2.24% to 1.48%.

A valid concern with this analysis is that the number of portfolios we choose to sort stocks into is somewhat arbitrary. We address this issue by varying the number of portfolios we sort stocks into as a robustness check. We find that our results are broadly insensitive to these changes and we reach the same qualitative conclusions regarding anomaly attenuation.

Panel B of Table 2 presents the results of our hedge portfolio analysis repeated using decile portfolios. The first column of results again shows average monthly portfolio returns over the full January 1990 to December 2013 sample period. The second and third columns show average portfolio returns for the first and second halves of the sample period.

In the full sample, we find that five of the average portfolio returns are significantly different from zero. These are the asset growth, book-to-market, profitability, momentum, and turnover portfolios. These significant returns range from 0.629% per month for the book-to-market portfolio to 2.260% per month for the turnover portfolio.

The sub-sample results show that returns to these strategies have fallen for six of the nine portfolios. The strong statistical significance of the asset growth, book-to-market, and momentum portfolios is sharply diminished in the second sub-sample.

Again, the profitability and turnover portfolios show strongly significant returns in

the second sub-sample. The magnitude of these returns fell in both cases. The return on the profitability portfolio fell from 2.052% to 1.585%. The return on the turnover portfolio fell from 2.589% to 1.931%. The returns for the accruals, new issuance, and size portfolios rose in absolute terms. However, none of these returns are adjudged to be statistically significant.

In summary, our hedge portfolio returns show a clear decline in the statistical significance of anomaly-based trading strategies.

## 5.2 Univariate Fama-MacBeth regressions

We next examine the significance each of our nine anomaly variables using univariate Fama-MacBeth-style regressions. We find evidence of diminished statistical and economic significance for the majority of anomalies we study.

We obtain univariate Fama-MacBeth coefficients for each anomaly in our sample following the regression methodology described in Section 4. We adjust firm returns for risk using the four-factor Fama and French (1993) and Carhart (1997) model in all cases. Tables A.2 and A.3 in the Appendix contains robustness checks where we adjust for risk using the Fama and French (1993) three-factor model and the basic Sharpe-Lintner CAPM.

Table 3 presents the results of our univariate regression analysis. Each regression produces one constant coefficient and one anomaly variable coefficient. We include results for the full January 1990 to December 2013 sample period and for the first and second halves period. The first sub-sample runs from January 1990 to December 2001. The second sub-sample runs from January 2002 to December 2013. This is the same methodological approach as taken by Schwert (2003) and Chordia et al. (2014).

The first column of Table 3 refers to the results from the full sample period. All but one of the nine anomaly variables are statistically significant at a 5% level for this period. Moreover, seven of these variables are significant at a 1% level. The accruals, book-to-market, profitability, return reversal, momentum, size, and turnover effects are all strongly significant. The signs of the Fama-MacBeth coefficients generally correspond closely with the sorted long-short portfolio returns in Table 2, though we find stronger statistical significance for accruals, return reversal, and size in our regression analysis.

The second and third columns of Table 3 show the results of this univariate Fama-MacBeth regression analysis for the first and second halves of our sample. In the first sub-sample, seven anomaly variables are significant at a 5% level in the first sub-sample and five were significant at a 1% level. The coefficients for accruals, profitability, return reversal, momentum, and turnover are all positive and strongly significant.

The results for the second sub-sample shows a marked decline in significance for a number of variables. The Fama-MacBeth coefficients for accruals, book-to-market, return reversal, and momentum are all insignificant at a 5% level. The new issuance anomaly is again insignificant. The asset growth, profitability, and turnover coefficients remain significant, but have all fallen in magnitude. For example, the asset growth coefficient fell from 0.009 to 0.002.

The size anomaly is an exception to the observed trend of anomaly attenuation. It is the only variable we analyse that becomes significant in our second sub-sample. The coefficient for this variable is also positive. This is consistent with the positive (and insignificant) size portfolio return results reported in Table 2. These results are surprising given that most estimates of the size effect in the literature are negative.

In summary, we find that evidence of diminished statistical significance in the second sub-sample using univariate Fama-MacBeth regressions. Two exceptions to this trend are the profitability and turnover anomaly coefficients.

### **5.3 Multivariate Fama-MacBeth regressions**

We next examine the significance of our anomaly variables using multivariate Fama-MacBeth-style regressions. We again follow Brennan et al. (1998), but now regress risk-adjusted individual firm returns on several anomaly variables. We vary the number of anomaly variables from two to the full specification of nine. We find a similar pattern of diminished statistical significance as in our univariate analysis. We also note that the significance of some anomalies is not robust to the inclusion of other anomalies.

Panel A of Table 4 shows the results of our full-sample multivariate Fama-MacBeth regressions of firm returns on anomaly variables. We report a number of different specifications. With the correlation coefficients from Panel C of Table 1 in mind, we explore

the impact of including one or both of the size and turnover variables in our final three specifications.

The book-to-market, profitability, size, and turnover characteristics are all rather robust to alternative specifications. For instance, the largest of the profitability coefficient's p-values is 0.003 and the coefficients rise as we add additional characteristics. The sign of all but size's coefficients match those in the univariate regression results in Table 3.

The size coefficient is negative when we control for many other firm characteristics. This is in keeping with the original findings of Banz (1981), but conflicts with our univariate results in Table 3. The return-reversal coefficient is marginally significant for some specifications, but strongly significant in the final two specifications. The sign on the coefficient is also negative. This is what has been documented in previous studies (Jegadeesh, 1990) and is in contrast with the positive full sample univariate coefficient we report in Table 3.

We see that the coefficients of the other anomaly variables are quite sensitive to specification changes. The new issuances coefficient is significant for two specifications, but insignificant in all others. This is consistent with weak evidence for this effect in our univariate analysis in Table 3. The strong significance of the accruals coefficient disappears with the inclusion of additional anomaly variables. The asset growth coefficient is significant for most specifications, but insignificant at a 5% level in the final specification. The momentum coefficient also disappears with the inclusion of size and turnover.

Panels B and C of Table 4 present the sub-sample results for our multivariate Fama-MacBeth regressions. We use the same non-overlapping sub-samples as in the univariate analysis of Table 3. We again find that the significance of a number of anomaly variables has diminished in more recent years. For instance, six variables are significant at a 1% significance level in the final specification of Panel B compared to three in Panel C.

The disappearance of the momentum anomaly is striking. The coefficient is highly significant in the first sub-sample and insignificant in all second sub-sample specifications it appears in. The inclusion of turnover in the regression makes this attenuation even clearer. The coefficient becomes negative in the final specification, but remains insignificant.

The diminishment of the momentum effect in our multivariate analysis is consistent with our univariate results in Table 3. Interestingly, the momentum effect also disappears in the second sub-sample when we adjust for risk without the use of a momentum factor (see Tables A.2 and A.3 in the Appendix). It is not the case that our momentum factor is sapping the statistical significance of the characteristic coefficient.

In summary, we again find evidence of weakening in the significance of anomaly coefficients using multivariate Fama-MacBeth regressions. Similarly to our univariate results, the profitability and turnover coefficients are rather robust over time and in different regression specifications.

## 5.4 Discussion

In this section, we discuss our findings and place them in the context of the extant literature.

Our results show strong evidence of declining strength for most of the anomalies we examine. We find that prominent anomalies such as the momentum (Jegadeesh and Titman, 1993) and short-run return reversal (Jegadeesh, 1990) effects have diminished significantly in recent years. Our findings are also robust to the use of hedge portfolio analyses. Table 2 shows that the results of our quintile and decile portfolio analyses are broadly in line.

Importantly, our results show that anomalies can be very large in an economic sense. For instance, the rather robust firm profitability quintile strategy in Panel A of Table 2 has a full-sample return of 1.819% per month or approximately 22.8% per annum. This figure is higher still – 25.32% per annum – in the first sub-sample. The momentum and turnover quintile portfolio strategy returns in the first sub-sample in Panel B of Table 2 are of a similar magnitude. This is also the case in U.S. data where Chordia et al. (2014) find that anomaly strategies can earn over 20% per annum. Robust and predictable anomalies clearly have the potential to offer sizeable trading returns.

Another interesting point to note is that we find strong evidence of anomaly significance in our univariate Fama-MacBeth regressions. These effects are again primarily evident in the first sub-sample. The most robust anomalies here are the profitability, size, and turnover effects. However, we find that not all anomalies are robust to the in-



clusion of other variables in multivariate Fama-MacBeth specifications. For instance, the accruals coefficient becomes insignificant when we account for a wider set of variables. The asset growth anomaly coefficient is also sensitive to the addition of other anomaly variables. In Panel A of Table 4, it becomes marginally insignificant when we account for firm size. This coefficient is also insignificant for many of the specifications in the second sub-sample in Panel C of Table 4. The most robust anomalies are again the profitability and turnover effects.

The signs on our anomaly effects are predominantly in line with the extant literature. For example, we find a strong positive momentum effect in our first sub-sample. Also, the strong positive relationship we find between firm profitability and returns is consistent with past findings in the U.S. (Fama and French, 2006). However, we do find some results which conflict with findings based on either U.K. or international market data.

The sign of the stock turnover anomaly we document is somewhat puzzling. While the international literature typically anticipates a negative relationship between turnover and returns (Chordia et al., 2014; Datar et al., 1998), we find a large and robust positive relationship. We are not aware of an existing theoretical motivation for this result nor a rationale for why the U.K. may differ from other markets in this respect. Nonetheless, our result is in agreement with the extant U.K. literature which reports a positive turnover effect (Cotter et al., 2015; Foran et al., 2015).

We also find relatively weak evidence of a size anomaly in our sample. Table 3 shows a positive and insignificant relationship between in the first sub-sample, while we find a significant negative relationship in the second sub-sample. However, our portfolio analysis in Table 2 suggests that this size premium is not economically large. This is in contrast to Andrikopoulos et al. (2008) who report a significant negative effect in U.K. data, but they do accept that this relationship is unreliable and difficult to exploit. The general pattern of our results are actually more consistent with recent U.S. evidence. van Dijk (2011) shows that the size anomaly has reversed sign several times and a negative effect has recently returned. Hou and van Dijk (2012) argue that these changes are due to realised returns deviating from expected returns.

The diminished strength of the momentum anomaly is one of the most striking features of our results. It is among the most profitable strategies in the first sub-sample, but is only marginally significant in the second sub-sample in Fama-MacBeth regressions.

Hedge portfolio returns are also greatly reduced. These findings contrast with those of Dimson et al. (2008) who report a robust U.K. momentum effect in the period 1900 to 2007. However, our conclusions are similar to those of other studies such as Agyei-Ampomah (2007) and Li et al. (2009) which find momentum to be unprofitable in the U.K. market.

What economic interpretation can we draw from our results? First, we document out-of-sample persistence for many of the anomalies we examine. This result is inconsistent with the anomalies simply being the product of data mining by researchers. Second, we also find that many of our anomalies are robust to the use of alternative models of risk-adjustment. It is possible that a richer model of expected returns could explain the anomalous variation in returns we report. However, these anomalies have so far proven difficult for theorists to reconcile with risk-based models.

Third, our findings are consistent with improvements in market efficiency. The growth of arbitrage activity in recent years could explain the trends we report. In particular, hedge fund activity has grown substantially (Hanson and Sunderam, 2014; Stein, 2009). We have much anecdotal evidence that these funds target anomalies. Akbas et al. (2015) and McLean and Pontiff (2016) present more formal evidence showing that hedge funds do indeed exploit anomalies. In addition, Boehmer and Kelley (2009) report lower predictability in the returns of stocks with a higher proportions of institutional ownership.

Our evidence is also consistent with the findings of recent studies that have looked at other aspects of pricing efficiency in financial markets. For example, Chaboud et al. (2014) find report a decrease in the number of triangular arbitrage opportunities in foreign exchange markets. Jones and Pomorski (2016) also find that short-run autocorrelations in stock returns have diminished in recent years.

We stress that the decline in anomaly significance we report in this paper may not continue indefinitely. If anomalies arise because of ingrained systematic biases among investors, then there may always be the potential for such biases to influence average returns. Anomalies may emerge and persist in periods of high sentiment if they are not countered by a sufficiently large amount of arbitrage capital.

In summary, our main finding is that many well-known equity market anomalies have diminished in strength over recent years in U.K. data.

## 6 Conclusion

We find strong evidence of anomaly attenuation in the cross-section of U.K. stocks from 1990 to 2013. We confirm the existence of several well-known anomalies in this market, but show that the statistical significance of these anomalies has diminished markedly in recent years. This pattern holds for the momentum (Jegadeesh and Titman, 1993), book-to-market ratio (Fama and French, 1992), accruals (Sloan, 1996), and asset growth (Cooper et al., 2008) effects. Our findings are robust to the use of the use of hedge portfolio strategies, Fama-MacBeth regressions, and various model specifications.

The firm profitability (Fama and French, 2006) and stock turnover (Datar et al., 1998) anomalies remain rather robust throughout our analysis. We do find that portfolio strategy returns based on these anomalies fell over our sample, but these returns remain statistically significant. This also holds for Fama-MacBeth regression coefficients for these two anomalies.

This paper provides insight into how stocks are priced in the U.K. market. It also adds to the body of evidence on the persistence of equity market anomalies over time. Our findings are consistent with improvements in market efficiency over time with respect to well-known anomaly variables.

## References

- Agyei-Ampomah, Sam, 2007, The post-cost profitability of momentum trading strategies: Further evidence from the UK, *European Financial Management* 13, 776–802.
- Akbas, Ferhat, Will J. Armstrong, Sorin Sorescu, and Avanidhar Subrahmanyam, 2015, Smart money, dumb money, and equity return anomalies, *Journal of Financial Economics* 118, 355–382.
- Andrikopoulos, Panagiotis, Arief Daynes, David Latimer, and Paraskevas Pagas, 2008, Size effect, methodological issues and “risk-to-default”: Evidence from the UK stock market, *European Journal of Finance* 14, 299–314.
- Antoniou, Antonios, Emilius C. Galariotis, and Spyros I. Spyrou, 2006, Short-term contrarian strategies in the London Stock Exchange: Are they profitable? Which factors affect them?, *Journal of Business Finance & Accounting* 33, 839–867.
- Bagella, Michele, Leonardo Becchetti, and Andrea Carpentieri, 2000, “the first shall be last”. Size and value strategy premia at the London Stock Exchange, *Journal of Banking & Finance* 24, 893–919.
- Banz, Rolf W., 1981, The relationship between return and market value of common stocks, *Journal of Financial Economics* 9, 3–18.
- Boehmer, Ekkehart, and Eric K. Kelley, 2009, Institutional investors and the informational efficiency of prices, *Review of Financial Studies* 22, 3563–3594.
- Brennan, Michael J., Tarun Chordia, and Avanidhar Subrahmanyam, 1998, Alternative factor specifications, security characteristics, and the cross-section of expected stock returns, *Journal of Financial Economics* 49, 345–373.
- Brogaard, Jonathan, Terrence Hendershott, Stefan Hunt, and Carla Ysusi, 2014, High-frequency trading and the execution costs of institutional investors, *Financial Review* 49, 345–369.
- Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.
- Chaboud, Alain P., Benjamin Chiquoine, Erik Hjalmarsson, and Clara Vega, 2014, Rise of the machines: Algorithmic trading in the foreign exchange market, *Journal of Finance* 69, 2045–2084.

- Chan, Andrew, and Alice P.L. Chui, 1996, An empirical re-examination of the cross-section of expected returns: UK evidence, *Journal of Business Finance & Accounting* 23, 1435–1452.
- Chordia, Tarun, Avanidhar Subrahmanyam, and Qing Tong, 2014, Have capital market anomalies attenuated in the recent era of high liquidity and trading activity?, *Journal of Accounting and Economics* 58, 41–58.
- Clubb, Colin, and Mounir Naffi, 2007, The usefulness of book-to-market and ROE expectations for explaining UK stock returns, *Journal of Business Finance & Accounting* 34, 1–32.
- Cooper, Michael J., Huseyin Gulen, and Michael J. Schill, 2008, Asset growth and the cross-section of stock returns, *Journal of Finance* 63, 1609–1651.
- Cotter, John, Niall O’Sullivan, and Francesco Rossi, 2015, The conditional pricing of systematic and idiosyncratic risk in the UK equity market, *International Review of Financial Analysis* 37, 184–193.
- Datar, Vinay T., Narayan Y. Naik, and Robert Radcliffe, 1998, Liquidity and stock returns: An alternative test, *Journal of Financial Markets* 1, 203–219.
- De Long, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann, 1990, Noise trader risk in financial markets, *Journal of Political Economy* 98, 703–738.
- Dimson, Elroy, and Paul Marsh, 1986, Event study methodologies and the size effect: The case of UK press recommendations, *Journal of Financial Economics* 17, 113–142.
- Dimson, Elroy, Paul Marsh, and Mike Staunton, 2008, 108 years of momentum profits, Working paper, London Business School.
- Fama, Eugene F., 1991, Efficient capital markets: II, *Journal of Finance* 46, 1575–1617.
- Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.
- Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.
- Fama, Eugene F., and Kenneth R. French, 2006, Profitability, investment and average returns, *Journal of Financial Economics* 82, 491–518.

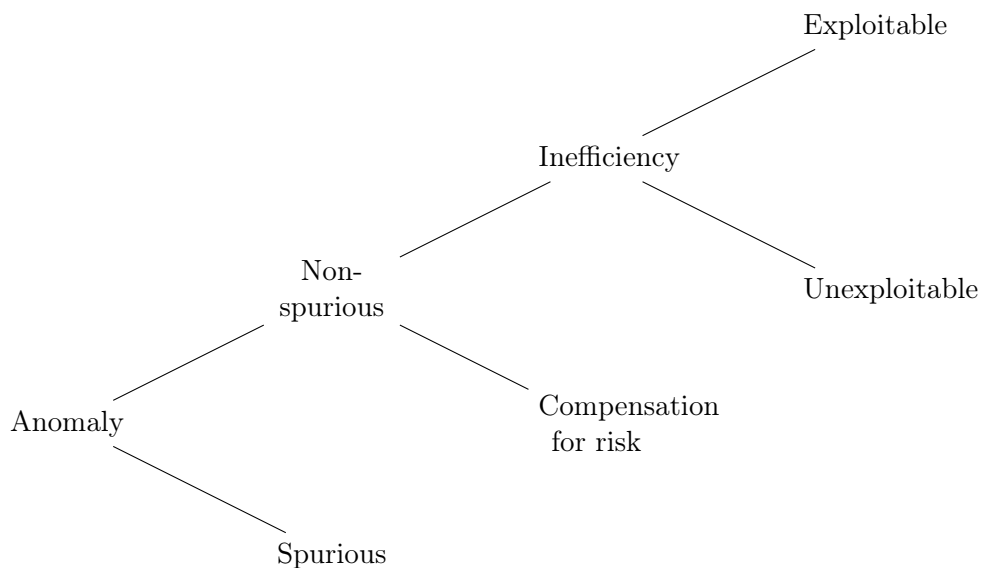
- Foran, Jason, Mark C. Hutchinson, and Niall O’Sullivan, 2015, Liquidity commonality and pricing in UK equities, *Research in International Business and Finance* 34, 281–293.
- Gromb, Denis, and Dimitri Vayanos, 2010, Limits of arbitrage: The state of the theory, *Annual Review of Financial Economics* 2, 251–275.
- Hanson, Samuel G., and Adi Sunderam, 2014, The growth and limits of arbitrage: Evidence from short interest, *Review of Financial Studies* 27, 1238–1286.
- Harvey, Campbell R., Yan Liu, and Heqing Zhu, 2016, ...and the cross-section of expected returns, *Review of Financial Studies* 29, 5–68.
- Hausman, Jerry, 2001, Mismeasured variables in econometric analysis: Problems from the right and problems from the left, *Journal of Economic Perspectives* 15, 57–67.
- Hon, Mark T., and Ian Tonks, 2003, Momentum in the UK stock market, *Journal of Multinational Financial Management* 13, 43–70.
- Hou, Kewei, and Mathijs van Dijk, 2012, Resurrecting the size effect: Firm size, profitability shocks, and expected stock returns, Working paper, The Ohio State University.
- Hou, Kewei, Chen Xue, and Lu Zhang, 2017, Replicating anomalies, Working paper, The Ohio State University.
- Ince, Ozgur S., and R. Burt Porter, 2006, Individual equity return data from thomson datastream: Handle with care!, *Journal of Financial Research* 29, 463–479.
- Jegadeesh, Narasimhan, 1990, Evidence of predictable behavior of security returns, *Journal of Finance* 45, 881–898.
- Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65–91.
- Jones, Christopher S., and Lukasz Pomorski, 2016, Investing in disappearing anomalies, *Review of Finance* 21, 237–267.
- Leippold, Markus, and Harald Lohre, 2012, Data snooping and the global accrual anomaly, *Applied Financial Economics* 22, 509–535.
- Li, Xiafei, Chris Brooks, and Joëlle Miffre, 2009, Low-cost momentum strategies, *Journal of Asset Management* 9, 366–379.

- Liu, Weimin, Norman Strong, and Xinzhong Xu, 1999, The profitability of momentum investing, *Journal of Business Finance & Accounting* 26, 1043–1091.
- McLean, R. David, and Jeffrey Pontiff, 2016, Does academic research destroy stock return predictability?, *Journal of Finance* 71, 5–32.
- McLean, R. David, Jeffrey Pontiff, and Akiko Watanabe, 2009, Share issuance and cross-sectional returns: International evidence, *Journal of Financial Economics* 94, 1–17.
- Miles, David, and Allan Timmermann, 1996, Variation in expected stock returns: Evidence on the pricing of equities from a cross-section of UK companies, *Economica* 63, 369–382.
- Miller, Merton, and Myron Scholes, 1972, Rates of return in relation to risk: A reexamination of some recent findings, in Michael C. Jensen, ed., *Studies in the Theory of Capital Markets* (Praeger, New York).
- Nagel, Stefan, 2002, Is momentum caused by delayed overreaction?, Working paper, London Business School.
- Novy-Marx, Robert, 2013, The other side of value: The gross profitability premium, *Journal of Financial Economics* 108, 1–28.
- Papanastasopoulos, Georgios A., and Emmanuel Tsiritakis, 2015, The accrual anomaly in Europe: The role of accounting distortions, *International Review of Financial Analysis* 41, 176–185.
- Pincus, Morton, Shivaram Rajgopal, and Mohan Venkatachalam, 2007, The accrual anomaly: International evidence, *The Accounting Review* 82, 169–203.
- Pontiff, Jeffrey, and Artemiza Woodgate, 2008, Share issuance and cross-sectional returns, *Journal of Finance* 63, 921–945.
- Rouwenhorst, K. Geert, 1998, International momentum strategies, *Journal of Finance* 53, 267–284.
- Schmidt, Peter S., Urs von Arx, Andreas Schrimpf, Alexander F. Wagner, and Andreas Ziegler, 2017, On the construction of common size, value and momentum factors in international stock markets: A guide with applications, Working paper, Swiss Finance Institute.

- Schwert, G. William, 2003, Anomalies and market efficiency, in George M. Constantinides, Milton Harris, and René M. Stulz, eds., *Handbook of the Economics of Finance* (Elsevier, Amsterdam).
- Shleifer, Andrei, and Robert W. Vishny, 1997, The limits of arbitrage, *Journal of Finance* 52, 35–55.
- Simlai, Prodosh E., 2016, Time-varying risk, mispricing attributes, and the accrual premium, *International Review of Financial Analysis* 48, 150–161.
- Sloan, Richard G., 1996, Do stock prices fully reflect information in accruals and cash flows about future earnings?, *The Accounting Review* 71, 289–315.
- Stein, Jeremy C., 2009, Presidential address: Sophisticated investors and market efficiency, *Journal of Finance* 64, 1517–1548.
- Titman, Sheridan, K.C. Wei, and Feixue Xie, 2013, Market development and the asset growth effect: International evidence, *Journal of Financial & Quantitative Analysis* 48, 1405–1432.
- van Dijk, Mathijs A., 2011, Is size dead? A review of the size effect in equity returns, *Journal of Banking and Finance* 35, 3263–3274.
- Watanabe, Akiko, Yan Xu, Tong Yao, and Tong Yu, 2013, The asset growth effect: Insights from international equity markets, *Journal of Financial Economics* 108, 529–563.



Figure 1: The process of interpreting anomalies



This figure illustrates the process of investigating an anomaly's economic significance. There are three stages. First, the anomaly may be a spurious result produced by data mining. Second, a non-spurious anomaly may compensate investors for bearing risk or it may indicate informational inefficiency. Third, an inefficiency may be exploitable and could generate abnormal returns or it could be unexploitable due to trading costs and more complex restrictions on investor behaviour.

Table 1: Anomaly definitions and summary statistics

Panel A: Definitions					
Variable	Definition	Publication			
ACC	Accruals: the change in non-cash current assets minus the change in current liabilities all divided by total assets	Sloan (1996)			
AG	Asset growth: yearly percentage change in total assets	Cooper et al. (2008)			
B/M	Book-to-market ratio: book equity over lagged market equity	Fama and French (1992)			
ISSUE	Share issuance: change in number of shares outstanding from 11 months ago	Pontiff and Woodgate (2008)			
PROFIT	Profitability: earnings over book equity	Fama and French (2006)			
R1	Return reversal: lagged 1 month return	Jegadeesh (1990)			
R212	Momentum: 11 month cumulative return to the start of previous month	Jegadeesh and Titman (1993)			
SIZE	Firm size: market value of firm's equity	Banz (1981)			
TURN	Stock turnover: trading volume over number of shares outstanding	Datar et al. (1998)			

Panel B: Summary statistics					
	Mean	Median	Std. Dev.	Skew.	Kurt.
ACC	-0.04	-0.04	0.05	-2.19	14.87
AG	0.30	0.07	1.31	5.80	49.12
B/M	0.89	0.65	0.89	3.35	20.14
ISSUE	6.87	0.02	45.31	5.12	60.60
PROFIT	-0.05	0.08	0.76	-5.91	51.71
R1	-0.00	-0.00	0.13	-0.17	7.33
R212	0.30	0.24	0.26	1.64	6.61
SIZE	503.48	43.29	2001.63	7.07	59.95
TURN	6.17	3.36	9.21	3.92	23.54

Panel C: Correlation matrix									
	ACC	AG	B/M	ISSUE	PROFIT	R1	R212	SIZE	TURN
ACC	1.000								
AG	0.066	1.000							
B/M	0.068	0.080	1.000						
ISSUE	0.010	0.096	0.025	1.000					
PROFIT	0.070	0.031	-0.021	-0.009	1.000				
R1	0.018	0.028	0.027	-0.004	0.055	1.000			
R212	-0.020	0.117	0.051	0.038	-0.029	0.199	1.000		
SIZE	0.018	-0.007	-0.245	0.061	0.101	0.018	-0.099	1.000	
TURN	0.015	-0.012	-0.093	-0.016	0.065	0.040	0.071	0.410	1.000

Panel A lists nine anomaly variables we examine in this study along with a definition of each variable and a seminal study with which the anomaly is associated. Panel B provides mean, median, standard deviation, skewness, and kurtosis statistics for each of the nine anomaly variables. Panel C provides time series averages of monthly cross-sectional correlations between each anomaly variable.

Table 2: Hedge portfolio returns

Panel A: Quintile portfolio returns			
	Full sample 1990–2013	Sub-sample I 1990–2001	Sub-sample II 2002–2013
ACC	0.208 (0.680)	0.355 (0.550)	0.060 (0.869)
AG	1.158** (0.004)	1.467* (0.016)	0.849 (0.203)
B/M	0.836* (0.015)	1.179** (0.008)	0.494 (0.271)
ISSUE	-0.222 (0.768)	-0.124 (0.658)	-0.300 (0.343)
PROFIT	1.907** (0.000)	2.110** (0.000)	1.704** (0.000)
R1	-0.209 (0.418)	-0.450 (0.268)	0.032 (0.902)
R212	1.488** (0.000)	2.296** (0.000)	0.680 (0.061)
SIZE	-0.112 (0.675)	0.070 (0.866)	-0.252 (0.573)
TURN	1.857** (0.000)	2.237** (0.000)	1.478** (0.009)
Panel B: Decile portfolio returns			
	Full sample 1990–2013	Sub-sample I 1990–2001	Sub-sample II 2002–2013
ACC	0.266 (0.517)	0.182 (0.697)	0.661 (0.344)
AG	0.964** (0.001)	1.483* (0.020)	0.445 (0.309)
B/M	0.629** (0.003)	0.782* (0.022)	0.477 (0.096)
ISSUE	-0.707 (0.263)	-0.343 (0.644)	-1.071 (0.120)
PROFIT	1.819** (0.000)	2.052** (0.000)	1.585** (0.000)
R1	-0.296 (0.444)	-0.810 (0.076)	0.218 (0.681)
R212	1.473** (0.000)	2.069** (0.000)	0.877* (0.050)
SIZE	0.191 (0.494)	0.050 (0.895)	0.332 (0.421)
TURN	2.260** (0.000)	2.589** (0.000)	1.931** (0.000)

Panel A shows average monthly returns of hedge portfolios which are long and short extreme quintiles of stocks sorted by a given anomaly variable. The first column of results refers to the full sample period. The second and third results columns refer to the first and second non-overlapping sub-samples. P-values are stated in parentheses below each coefficient. \*\* and \* indicate significance at a 1% and 5% level, respectively. Panel B shows equivalent returns for decile portfolio sorts.

Table 3: Univariate Fama-MacBeth regression coefficients

	Full sample 1990–2013		Sub-sample I 1990–2001		Sub-sample II 2002–2013	
	Constant	FM Coef.	Constant	FM Coef.	Constant	FM Coef.
ACC	-0.001 (0.420)	0.043** (0.000)	0.001 (0.432)	0.054** (0.000)	0.003 (0.385)	0.027 (0.065)
AG	-0.004 (0.190)	0.005* (0.013)	-0.003 (0.279)	0.009* (0.022)	0.000 (0.483)	0.002** (0.008)
B/M	-0.006 (0.118)	0.002** (0.004)	-0.003 (0.262)	0.002* (0.018)	-0.003 (0.380)	0.002 (0.079)
ISSUE	-0.004 (0.200)	0.000 (0.285)	-0.002 (0.353)	0.000 (0.189)	-0.001 (0.449)	0.000 (0.104)
PROFIT	-0.003 (0.246)	0.007** (0.000)	-0.002 (0.335)	0.010** (0.001)	0.001 (0.451)	0.004** (0.000)
R1	-0.004 (0.229)	-0.017** (0.005)	-0.001 (0.392)	-0.029** (0.002)	0.000 (0.479)	-0.007 (0.162)
R212	0.000 (0.445)	0.011** (0.008)	-0.001 (0.347)	0.023** (0.000)	0.005 (0.215)	0.006 (0.110)
SIZE	-0.017* (0.024)	0.001** (0.005)	-0.007 (0.294)	0.000 (0.271)	-0.018* (0.041)	0.001** (0.000)
TURN	-0.012** (0.004)	0.009** (0.000)	-0.012** (0.003)	0.010** (0.000)	-0.007 (0.195)	0.008** (0.000)

This table shows univariate Fama-MacBeth regression coefficients from risk-adjusted individual firm returns on firm characteristics. We follow the procedure set out by Brennan et al. (1998) and risk-adjust the individual firm returns using the four-factor Fama and French (1993) and Carhart (1997) model. The table shows results for the full sample (January 1990 to December 2013), the first half of the sample (January 1990 to December 2001), and the second half of the sample (January 2002 to December 2013). Newey-West p-values are stated in parentheses below each coefficient. \*\* and \* indicate significance at a 1% and 5% level, respectively.

Table 4: Multivariate Fama-MacBeth regression coefficients

## Panel A: Full sample (1990–2013)

Constant	ACC	AG	B/M	ISSUE	PROFIT	R1	R212	SIZE	TURN
-0.002 (0.342)	0.036** (0.002)	0.006* (0.012)							
-0.004 (0.186)	0.033** (0.006)	0.006** (0.006)	0.003** (0.001)						
-0.004 (0.199)	0.034** (0.005)	0.007** (0.003)	0.002** (0.001)	0.000 (0.057)					
-0.005 (0.157)	0.020* (0.041)	0.006** (0.002)	0.003** (0.000)	0.000 (0.124)	0.008** (0.000)				
-0.005 (0.173)	0.021* (0.032)	0.006** (0.001)	0.003** (0.000)	0.000 (0.138)	0.008** (0.000)	-0.001 (0.427)			
-0.004 (0.125)	-0.002 (0.452)	0.004** (0.005)	0.003** (0.003)	0.000** (0.002)	0.018** (0.000)	-0.009 (0.090)	0.013** (0.002)		
0.005 (0.226)	-0.001 (0.455)	0.004** (0.006)	0.002* (0.015)	0.000** (0.008)	0.019** (0.000)	-0.011 (0.066)	0.013** (0.002)	-0.001* (0.032)	
-0.015** (0.000)	0.003 (0.420)	0.004** (0.009)	0.007** (0.000)	0.000 (0.066)	0.024** (0.003)	-0.027** (0.002)	0.006 (0.065)		0.009** (0.000)
0.033** (0.001)	0.011 (0.238)	0.003 (0.061)	0.005** (0.000)	0.000 (0.124)	0.024** (0.001)	-0.038** (0.000)	0.005 (0.137)	-0.004** (0.000)	0.011** (0.000)

## Panel B: Sub-sample I (1990–2001)

Constant	ACC	AG	B/M	ISSUE	PROFIT	R1	R212	SIZE	TURN
-0.001 (0.421)	0.045** (0.004)	0.010* (0.022)							
-0.003 (0.285)	0.038* (0.021)	0.011* (0.011)	0.002* (0.013)						
-0.003 (0.288)	0.038* (0.023)	0.011** (0.007)	0.002* (0.015)	0.000 (0.439)					
-0.004 (0.200)	0.023 (0.096)	0.010** (0.004)	0.003** (0.003)	0.000 (0.431)	0.010** (0.000)				
-0.004 (0.215)	0.024 (0.073)	0.010** (0.003)	0.002** (0.004)	0.000 (0.392)	0.010** (0.000)	-0.014 (0.110)			
-0.008* (0.030)	-0.006 (0.370)	0.007** (0.002)	0.003* (0.020)	0.000* (0.036)	0.021** (0.000)	-0.004 (0.360)	0.023** (0.000)		
0.005 (0.316)	-0.005 (0.380)	0.007** (0.002)	0.002 (0.102)	0.000 (0.077)	0.022** (0.000)	-0.007 (0.256)	0.023** (0.000)	-0.001 (0.052)	
-0.021** (0.000)	0.009 (0.355)	0.007* (0.015)	0.007** (0.000)	0.000 (0.168)	0.028* (0.013)	-0.042** (0.002)	0.017** (0.005)		0.008** (0.000)
0.024 (0.069)	0.017 (0.266)	0.005 (0.062)	0.006** (0.005)	0.000 (0.238)	0.031** (0.010)	-0.049** (0.001)	0.019** (0.005)	-0.004** (0.000)	0.010** (0.000)

Table 4: Multivariate Fama-MacBeth regression coefficients (continued)

Panel C: Sub-sample II (2002–2013)

Constant	ACC	AG	B/M	ISSUE	PROFIT	R1	R212	SIZE	TURN
0.002	0.020	0.003*							
(0.416)	(0.118)	(0.010)							
-0.001	0.020	0.002*	0.002*						
(0.467)	(0.117)	(0.013)	(0.020)						
0.000	0.021	0.003**	0.002*	0.000*					
(0.479)	(0.104)	(0.005)	(0.034)	(0.036)					
0.000	0.009	0.003**	0.002*	0.000	0.006**				
(0.477)	(0.275)	(0.006)	(0.029)	(0.085)	(0.000)				
0.000	0.010	0.003**	0.002*	0.000	0.006**	-0.014**			
(0.482)	(0.255)	(0.005)	(0.030)	(0.078)	(0.000)	(0.008)			
0.002	-0.009	0.001	0.002	0.000*	0.015**	-0.007	0.006		
(0.390)	(0.274)	(0.165)	(0.081)	(0.028)	(0.000)	(0.228)	(0.080)		
0.008	-0.009	0.001	0.002	0.000*	0.016**	-0.007	0.006	0.000	
(0.191)	(0.281)	(0.193)	(0.054)	(0.036)	(0.000)	(0.237)	(0.104)	(0.154)	
-0.006	-0.009	0.002	0.005**	0.000	0.013**	-0.013	0.002		0.008**
(0.140)	(0.254)	(0.151)	(0.001)	(0.223)	(0.006)	(0.081)	(0.295)		(0.000)
0.046**	-0.006	0.001	0.003*	0.000	0.016**	-0.019*	-0.003	-0.004**	0.011**
(0.000)	(0.340)	(0.188)	(0.019)	(0.273)	(0.003)	(0.029)	(0.156)	(0.000)	(0.000)

This table shows multivariate Fama-MacBeth regression coefficients from risk-adjusted individual firm returns on firm characteristics. We follow the procedure set out by Brennan et al. (1998) and risk-adjust the individual firm returns using the four-factor Fama and French (1993) and Carhart (1997) model. Panel A shows results for the full sample (January 1990 to December 2013), Panel B shows results for the first half of the sample (January 1990 to December 2001), and Panel C shows results for the second half of the sample (January 2002 to December 2013). Newey-West p-values are stated in parentheses below each coefficient. \*\* and \* indicate significance at a 1% and 5% level, respectively.

## Appendix

In this section, we re-examine the significance of our nine anomaly variables using alternative methods of risk-adjustment. In the main body of the paper, we risk-adjust individual firm returns using the four-factor Fama and French (1993) and Carhart (1997) model. Here we repeat the univariate and multivariate Fama-MacBeth regressions from Tables 3 and 4 using the three-factor Fama and French (1993) model and the basic Sharpe-Lintner CAPM.

### A.1 Univariate Fama-MacBeth regressions

We first repeat our univariate Fama-MacBeth analysis from Section 5.2 using the three-factor Fama and French (1993) model and the Sharpe-Lintner CAPM to adjust for risk.

Panel A of Table 5 presents these results based on returns adjusted using the three-factor Fama and French (1993) model. Panel B presents these same results, but using the one-factor CAPM to adjust firm returns for risk. In each case, risk-adjusted returns are regressed on a constant and one specified anomaly variable. Thus, each regression produces a constant coefficient and one anomaly variable coefficient.

We follow the approach of our early work and analyse the data over three time periods. The full sample period of January 1990 to December 2013. The first sub-sample runs from January 1990 to December 2001. The second sub-sample runs from January 2002 to December 2013.

Our results are remarkably similar to those in Panel A of Table 2. We see that omitting the Carhart (1997) “momentum” factor has little impact on our results and we draw the same conclusions regarding anomaly attenuation. The first column in both Panel A and Panel B of Table A.1 refer to the results for the full sample period. We see that univariate Fama-MacBeth coefficients are strongly significant for the full sample period. In both cases, seven of the nine coefficients are significant at a 1% level and eight of the coefficients are significant at a 5% level.

The second and third columns of Panels A and B of Table A.1 show our results for the first and second sub-samples, respectively. We find that the significance of these anomaly coefficients is most pronounced in the first sub-sample. The signs of these coefficients

also correspond closely to our earlier results. Similarly to Table 3, we find that the asset growth, profitability, size, and turnover coefficients remain significant in this more recent time period.

## **A.2 Multivariate Fama-MacBeth regressions**

Finally, we repeat our multivariate Fama-MacBeth regression analysis using the three-factor Fama and French (1993) model and the Sharpe-Lintner CAPM. Our results are again very similar to those in the main body of the paper.

Table A.2 presents Fama-MacBeth results for which individual firms are adjusted using the three-factor Fama and French (1993) model. This corresponds to Table 4 of the main body of the paper. Table A.3 present Fama-MacBeth results for which individual firms are adjusted using the one-factor CAPM. This again corresponds to Table 4 in the main body of the paper.

We find that the profitability and turnover effects are the most robust of our set of anomalies to specification changes and the use of alternate sub-samples. This is consistent with our earlier findings. We find less reliable significance for the book-to-market and size effects.

Interestingly, we find that momentum effect is insignificant in our second sub-sample for all three models of expected returns we consider. We also find that the accruals and asset growth anomalies are quite sensitive to our choice of regression specification.

In summary, our Fama-MacBeth regression findings are robust to the use of the four-factor Fama and French (1993) and Carhart (1997) model, the three-factor Fama and French (1993) model, and the Sharpe-Lintner CAPM.



Table A.1: Univariate Fama-MacBeth regression coefficients

Panel A: Fama and French (1993) three-factor risk adjustment

	Full sample 1990–2013		Sub-sample I 1990–2001		Sub-sample II 2002–2013	
	Constant	FM Coef.	Constant	FM Coef.	Constant	FM Coef.
ACC	-0.001 (0.400)	0.043** (0.000)	0.000 (0.470)	0.055** (0.000)	0.000 (0.479)	0.027 (0.065)
AG	-0.005 (0.179)	0.005* (0.012)	-0.003 (0.259)	0.008* (0.024)	-0.003 (0.348)	0.002* (0.014)
B/M	-0.006 (0.107)	0.002** (0.003)	-0.004 (0.219)	0.003** (0.005)	-0.006 (0.253)	0.002 (0.074)
ISSUE	-0.005 (0.186)	0.000 (0.236)	-0.002 (0.325)	0.000 (0.209)	-0.004 (0.317)	0.000 (0.055)
PROFIT	-0.004 (0.234)	0.008** (0.000)	-0.003 (0.302)	0.010** (0.001)	-0.002 (0.404)	0.004** (0.000)
R1	-0.004 (0.218)	0.020** (0.001)	-0.002 (0.370)	0.031** (0.001)	-0.004 (0.342)	0.009 (0.099)
R212	0.000 (0.460)	0.011** (0.009)	-0.001 (0.353)	0.021** (0.000)	0.003 (0.342)	0.004 (0.241)
SIZE	-0.017* (0.023)	0.001** (0.005)	-0.006 (0.325)	0.000 (0.340)	-0.024* (0.015)	0.002** (0.000)
TURN	-0.013** (0.003)	0.009** (0.000)	-0.012** (0.003)	0.009** (0.000)	-0.010 (0.110)	0.008** (0.000)

Panel B: Sharpe-Lintner CAPM risk adjustment

	Full sample 1990–2013		Sub-sample I 1990–2001		Sub-sample II 2002–2013	
	Constant	FM Coef.	Constant	FM Coef.	Constant	FM Coef.
ACC	-0.001 (0.440)	0.044** (0.000)	0.000 (0.488)	0.060** (0.000)	-0.001 (0.466)	0.030 (0.059)
AG	-0.004 (0.207)	0.005* (0.012)	-0.004 (0.222)	0.009* (0.022)	-0.004 (0.329)	0.002* (0.015)
B/M	-0.006 (0.127)	0.003** (0.003)	-0.005 (0.182)	0.003** (0.005)	-0.006 (0.232)	0.002* (0.044)
ISSUE	-0.004 (0.216)	0.000 (0.287)	-0.003 (0.285)	0.000 (0.199)	-0.005 (0.300)	0.000 (0.058)
PROFIT	-0.003 (0.266)	0.008** (0.000)	-0.003 (0.265)	0.011** (0.000)	-0.003 (0.386)	0.004** (0.000)
R1	-0.004 (0.248)	0.024** (0.000)	-0.002 (0.329)	0.035** (0.000)	-0.004 (0.329)	0.012 (0.065)
R212	0.001 (0.404)	0.012** (0.007)	-0.001 (0.353)	0.020** (0.001)	0.003 (0.333)	0.004 (0.236)
SIZE	-0.017* (0.030)	0.001** (0.006)	-0.006 (0.324)	0.000 (0.363)	-0.024* (0.017)	0.002** (0.000)
TURN	-0.012** (0.005)	0.009** (0.000)	-0.014** (0.002)	0.010** (0.000)	-0.011 (0.104)	0.008** (0.000)

This table shows univariate Fama-MacBeth regression coefficients from risk-adjusted individual firm returns on firm characteristics. Panel A shows results using the procedure set out by Brennan et al. (1998) and risk-adjust the individual firm returns using the three-factor Fama and French (1993) model. Panel B shows results using the procedure set out by Brennan et al. (1998) and risk-adjust the individual firm returns using the Sharpe-Lintner CAPM. Each panel shows results for the full sample (January 1990 to December 2013), the first half of the sample (January 1990 to December 2001), and the second half of the sample (January 2002 to December 2013). Newey-West p-values are stated in parentheses below each coefficient. \*\* and \* indicate significance at a 1% and 5% level, respectively.

Table A.2: Multivariate Fama-MacBeth regression coefficients

Fama and French (1993) three-factor risk adjustment

Panel A: Full sample (1990–2013)

Constant	ACC	AG	B/M	ISSUE	PROFIT	R1	R212	SIZE	TURN
-0.002 (0.325)	0.035** (0.004)	0.006* (0.013)							
-0.005 (0.169)	0.032** (0.009)	0.006** (0.007)	0.003** (0.000)						
-0.005 (0.179)	0.033** (0.008)	0.007** (0.003)	0.003** (0.001)	0.000 (0.057)					
-0.005 (0.139)	0.018 (0.066)	0.006** (0.002)	0.003** (0.000)	0.000 (0.127)	0.008** (0.000)				
-0.005 (0.155)	0.018 (0.054)	0.006** (0.002)	0.003** (0.000)	0.000 (0.146)	0.008** (0.000)	0.000 (0.478)			
-0.005 (0.108)	-0.003 (0.397)	0.004** (0.006)	0.003** (0.002)	0.000** (0.001)	0.019** (0.000)	-0.008 (0.120)	0.012** (0.002)		
0.004 (0.270)	-0.003 (0.391)	0.004** (0.007)	0.002* (0.009)	0.000** (0.005)	0.020** (0.000)	-0.009 (0.092)	0.012** (0.002)	-0.001* (0.042)	
-0.015** (0.000)	0.003 (0.422)	0.004* (0.015)	0.007** (0.000)	0.000* (0.038)	0.021** (0.000)	-0.029** (0.001)	0.006 (0.075)		0.008** (0.000)
0.032** (0.001)	0.009 (0.289)	0.003 (0.066)	0.005** (0.000)	0.000 (0.116)	0.024** (0.000)	-0.036** (0.000)	0.005 (0.148)	-0.004** (0.000)	0.011** (0.000)

Panel B: Sub-sample I (1990–2001)

Constant	ACC	AG	B/M	ISSUE	PROFIT	R1	R212	SIZE	TURN
-0.001 (0.399)	0.045** (0.005)	0.009* (0.028)							
-0.004 (0.241)	0.038* (0.027)	0.010* (0.015)	0.003** (0.004)						
-0.004 (0.244)	0.036* (0.031)	0.010** (0.009)	0.003** (0.004)	0.000 (0.449)					
-0.005 (0.163)	0.021* (0.120)	0.009** (0.006)	0.003** (0.001)	0.000 (0.443)	0.010** (0.000)				
-0.005 (0.186)	0.021 (0.095)	0.009** (0.005)	0.003** (0.001)	0.000 (0.383)	0.010** (0.000)	0.015 (0.087)			
-0.008* (0.021)	-0.007 (0.335)	0.007** (0.004)	0.003** (0.006)	0.000* (0.044)	0.022** (0.000)	-0.003 (0.392)	0.021** (0.000)		
0.005 (0.345)	-0.007 (0.333)	0.006** (0.004)	0.003* (0.047)	0.000 (0.094)	0.023** (0.000)	-0.006 (0.282)	0.022** (0.000)	-0.001 (0.061)	
-0.021** (0.000)	0.004 (0.426)	0.006* (0.024)	0.008** (0.000)	0.000 (0.186)	0.029** (0.006)	-0.040** (0.004)	0.016* (0.011)		0.008** (0.000)
0.022 (0.075)	0.011 (0.332)	0.005 (0.086)	0.007** (0.001)	0.000 (0.261)	0.032** (0.006)	-0.048** (0.001)	0.018* (0.011)	-0.004** (0.001)	0.010** (0.000)

Table A.2: Multivariate Fama-MacBeth regression coefficients (continued)

Panel C: Sub-sample II (2002–2013)

Constant	ACC	AG	B/M	ISSUE	PROFIT	R1	R212	SIZE	TURN
-0.001	0.021	0.003**							
(0.451)	(0.108)	(0.015)							
-0.004	0.021	0.002*	0.002*						
(0.339)	(0.103)	(0.019)	(0.019)						
-0.003	0.023*	0.003**	0.002*	0.000*					
(0.350)	(0.088)	(0.007)	(0.033)	(0.024)					
-0.003	0.011	0.003**	0.002*	0.000	0.006**				
(0.346)	(0.245)	(0.008)	(0.029)	(0.054)	(0.001)				
-0.003	0.012	0.003**	0.002*	0.000*	0.006**	-0.012*			
(0.355)	(0.225)	(0.007)	(0.030)	(0.049)	(0.001)	(0.016)			
0.000	-0.003	0.001	0.002	0.000*	0.016**	-0.006	0.005		
(0.497)	(0.415)	(0.224)	(0.105)	(0.017)	(0.000)	(0.254)	(0.171)		
0.005	-0.004	0.001	0.002	0.000*	0.017**	-0.005	0.004	0.000	
(0.275)	(0.413)	(0.252)	(0.068)	(0.024)	(0.000)	(0.271)	(0.205)	(0.190)	
-0.008	-0.003	0.001	0.004**	0.000	0.014**	-0.012	0.000		0.008**
(0.082)	(0.422)	(0.215)	(0.001)	(0.148)	(0.003)	(0.090)	(0.455)		(0.000)
0.043**	0.000	0.001	0.003*	0.000	0.017**	-0.018*	-0.005	-0.004**	0.011**
(0.001)	(0.497)	(0.261)	(0.025)	(0.206)	(0.002)	(0.033)	(0.101)	(0.000)	(0.000)

This table shows multivariate Fama-MacBeth regression coefficients from risk-adjusted individual firm returns on firm characteristics. We follow the procedure set out by Brennan et al. (1998) and risk-adjust the individual firm returns using the Fama and French (1993) three-factor model. Panel A shows results for the full sample (January 1990 to December 2013), Panel B shows results for the first half of the sample (January 1990 to December 2001), and Panel C shows results for the second half of the sample (January 2002 to December 2013). Newey-West p-values are stated in parentheses below each coefficient. \*\* and \* indicate significance at a 1% and 5% level, respectively.

Table A.3: Multivariate Fama-MacBeth regression coefficients

Sharpe-Lintner CAPM risk adjustment

Panel A: Full sample (1990–2013)

Constant	ACC	AG	B/M	ISSUE	PROFIT	R1	R212	SIZE	TURN
-0.002 (0.365)	0.038** (0.003)	0.006* (0.012)							
-0.004 (0.197)	0.034** (0.007)	0.006** (0.008)	0.003** (0.000)						
-0.004 (0.208)	0.034** (0.007)	0.007** (0.003)	0.003** (0.003)	0.000 (0.082)					
-0.005 (0.163)	0.020 (0.056)	0.006** (0.002)	0.003** (0.000)	0.000 (0.161)	0.008** (0.000)				
-0.005 (0.179)	0.020* (0.046)	0.006** (0.002)	0.003** (0.000)	0.000 (0.182)	0.008** (0.000)	0.004 (0.274)			
-0.004 (0.132)	-0.004 (0.384)	0.004** (0.007)	0.003** (0.002)	0.000** (0.001)	0.019** (0.000)	-0.004 (0.272)	0.012** (0.001)		
0.005 (0.236)	-0.004 (0.382)	0.004** (0.009)	0.002* (0.009)	0.000** (0.006)	0.020** (0.000)	-0.005 (0.209)	0.012** (0.001)	-0.001* (0.035)	
-0.015** (0.000)	0.000 (0.485)	0.004** (0.009)	0.007** (0.000)	0.000 (0.058)	0.022** (0.000)	-0.025** (0.003)	0.005 (0.109)		0.009** (0.000)
0.033** (0.001)	0.005 (0.352)	0.003* (0.050)	0.005** (0.000)	0.000 (0.131)	0.025** (0.001)	-0.032** (0.000)	0.004 (0.173)	-0.004** (0.000)	0.011** (0.000)

Panel B: Sub-sample I (1990–2001)

Constant	ACC	AG	B/M	ISSUE	PROFIT	R1	R212	SIZE	TURN
-0.002 (0.361)	0.050** (0.005)	0.009* (0.027)							
-0.004 (0.202)	0.042* (0.026)	0.010* (0.015)	0.003** (0.003)						
-0.004 (0.205)	0.040* (0.030)	0.010** (0.009)	0.003** (0.003)	0.000 (0.385)					
-0.006 (0.132)	0.023 (0.114)	0.009** (0.006)	0.003** (0.001)	0.000 (0.380)	0.011** (0.000)				
-0.006 (0.151)	0.022 (0.095)	0.009** (0.005)	0.003** (0.000)	0.000 (0.315)	0.011** (0.000)	0.019* (0.042)			
-0.009* (0.016)	-0.010 (0.259)	0.007** (0.003)	0.004** (0.003)	0.000* (0.047)	0.023** (0.000)	0.002 (0.418)	0.020** (0.000)		
0.005 (0.349)	-0.010 (0.249)	0.007** (0.003)	0.003* (0.042)	0.000 (0.103)	0.024** (0.000)	-0.001 (0.444)	0.021** (0.000)	-0.001 (0.057)	
-0.023** (0.000)	0.000 (0.497)	0.007** (0.009)	0.009** (0.000)	0.000 (0.191)	0.031** (0.005)	-0.036* (0.012)	0.012* (0.045)		0.008** (0.000)
0.021 (0.091)	0.007 (0.380)	0.005 (0.057)	0.007** (0.001)	0.000 (0.261)	0.034** (0.006)	-0.044** (0.003)	0.014* (0.024)	-0.004** (0.001)	0.010** (0.000)

Table A.3: Multivariate Fama-MacBeth regression coefficients (continued)

Panel C: Sub-sample II (2002–2013)

Constant	ACC	AG	B/M	ISSUE	PROFIT	R1	R212	SIZE	TURN
-0.001	0.023	0.003*							
(0.436)	(0.095)	(0.019)							
-0.004	0.024	0.002*	0.003**						
(0.319)	(0.089)	(0.020)	(0.009)						
-0.004	0.026	0.003**	0.003*	0.000*					
(0.330)	(0.076)	(0.007)	(0.014)	(0.025)					
-0.004	0.013	0.003**	0.003*	0.000	0.006**				
(0.326)	(0.210)	(0.008)	(0.011)	(0.052)	(0.001)				
-0.004	0.014	0.003**	0.003*	0.000*	0.006**	-0.010*			
(0.337)	(0.192)	(0.007)	(0.013)	(0.047)	(0.001)	(0.041)			
0.000	0.000	0.001	0.002*	0.000*	0.016**	-0.008	0.005		
(0.497)	(0.500)	(0.187)	(0.049)	(0.026)	(0.000)	(0.175)	(0.144)		
0.006	0.000	0.001	0.002*	0.000*	0.017**	-0.008	0.005	0.000	
(0.233)	(0.499)	(0.211)	(0.037)	(0.034)	(0.000)	(0.192)	(0.176)	(0.145)	
-0.008	0.000	0.001	0.005**	0.000	0.014**	-0.015*	0.001		0.009**
(0.076)	(0.499)	(0.192)	(0.000)	(0.186)	(0.004)	(0.044)	(0.423)		(0.000)
0.045**	0.003	0.001	0.003*	0.000	0.017**	-0.021*	-0.005	-0.005**	0.012**
(0.000)	(0.429)	(0.226)	(0.014)	(0.246)	(0.002)	(0.014)	(0.101)	(0.000)	(0.000)

This table shows multivariate Fama-MacBeth regression coefficients from risk-adjusted individual firm returns on firm characteristics. We follow the procedure set out by Brennan et al. (1998) and risk-adjust the individual firm returns using the Sharpe-Lintner CAPM. Panel A shows results for the full sample (January 1990 to December 2013), Panel B shows results for the first half of the sample (January 1990 to December 2001), and Panel C shows results for the second half of the sample (January 2002 to December 2013). Newey-West p-values are stated in parentheses below each coefficient. \*\* and \* indicate significance at a 1% and 5% level, respectively.