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

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Abstract

We study 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 as it is among the most developed and liquid in the world. We find strong evidence of diminished statistical significance for the return reversal effect, the momentum effect, and a number of other well-documented anomalies. These results hold for both portfolio sorting and Fama-MacBeth regression analyses and are robust to the use of alternative methods of risk adjustment and regression model specifications. 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

Smurfit Graduate School of Business, University College Dublin, Blackrock, Co. Dublin, Ireland. We thank Michael Brennan, Gregory Connor, John J. McConnell, René Stulz, Avanidhar Subrahmanyam, and seminar participants at University College Dublin and Xiamen University for helpful comments and suggestions. We also thank Andrea Frazzini for making risk factor data available. We gratefully acknowledge the support of Science Foundation Ireland under grant number 08/SRC/FMC1389.

1 Introduction

Why do average returns vary across stocks? Standard rational-expectations theories of investor behaviour propose that a stocks risk determines its return. A number of celebrated models have sought to quantify the risk of a stock and relate it its expected return. The Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965), and Black (1972) is perhaps the most widely known of these models. Cochrane (2005) reviews a number of other seminal works including the Intertemporal CAPM of Merton (1973), the Arbitrage Pricing Theory of Ross (1976), and the Consumption CAPM of Lucas (1978) and Breeden (1979).

Anomalies are patterns in historical returns which are not anticipated by established risk-based models. A large body of evidence demonstrates that particular categories of stocks earn average returns which deviate significantly from the expectation of a specified risk-based model. Early contributions to this literature include the observation that firm size is negatively related to returns (Banz, 1981) and that value measures are positively related to returns (Basu, 1977). The documentation of robust anomalies indicates that expected returns vary according to non-risk firm characteristics or that the benchmark model is failing to capture some important aspect of risk.

Fama and French (1992) examine a large set of anomalies and summarise the main empirical failings of the Sharpe-Lintner-Black CAPM. They find that the size and value effects are the most difficult to reconcile with the model. In response, Fama and French (1993) develop size- and value-based risk factors and incorporate them into a model of expected returns. This model has supplanted the CAPM as the standard method for risk adjustment in the empirical asset pricing literature. Indeed, an additional fourth "momentum" factor - due to Carhart (1997) - is often added to this model.

The modern anomalies literature continues to grow. Subrahmanyam (2010) estimates that are at least 50 variables that have been related to the cross-section of expected returns. Establishing the economic significance of these empirical phenomena is an important goal for researchers in asset pricing.

A number of recent papers have made important contributions to the equity market anomalies literature. Harvey et al. (2015) question the statistical significance of many reported anomalies due to concern over data mining by researchers. They argue anomaly discovery rates rise spuriously as researchers investigate the same datasets repeatedly.

Other recent studies have considered the changing behaviour of more robust anomalies over time. McLean and Pontiff (2015) present evidence suggesting that academic publications play a significant role in the disappearance of anomalies. They argue that empirical discoveries in the academic literature prompt investors to the exploit profitable anomalies.

Chordia et al. (2014), on the other hand, provide evidence of anomalies diminishing more gradually over time. They too interpret these results as improvement in the informational efficiency of U.S. stocks with respect to anomalous variables. They argue that this change is driven by improved liquidity and the rise in institutional trading and arbitrage activity. Similarly to McLean and Pontiff (2015), the authors argue that arbitrage activity - such as hedge fund investing - has driven the decline in anomaly strength observed in the U.S. stock market.

Akbas et al. (2015) provide additional evidence on this front by directly linking changes in mutual fund flows ("dumb money") and hedge fund flows ("smart money") to variations in anomaly strength. The improvement of market liquidity and the increased level institutional trading has not been confined to the U.S. An interesting and unexplored question is whether these trends are evident in other developed markets.

In this paper, we examine 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, the most robust anomalies in the literature are also evident in past U.K. returns.

We examine nine anomalies from the literature that have been robust across time and across international markets. The firm characteristic anomalies we consider are accruals (Sloan, 1996), asset growth Cooper et al. (2008), book-to-market ratio (Fama and French, 1992), new issuances of equity (Pontiff and Woodgate, 2008), profitability (Fama and French, 2006), return reversal (Jegadeesh, 1990), momentum (Jegadeesh and Titman, 1993), size (Banz, 1981), and stock turnover (Datar et al., 1998).

We find a general decline in the significance of anomalies in the U.K. market from 1990 to 2013. Many of the anomalies we examine are absent from the data in recent years. Perhaps most notably, the well-known momentum effect is not evident in the cross-section of U.K. stocks from 2002 to 2013. The profitability and turnover effects, however, remain rather robust throughout the sample. We find that the accruals anomaly is also not robust to the inclusion of additional firm characteristics in our Fama-MacBeth regressions. We also find no evidence of a new equity issuance anomaly in our sample.

In addition, we examine the monthly time series of Fama-MacBeth coefficients for each anomaly variable. We find evidence of significant time trends in these series. In most cases, the coefficient series trend towards zero over time. These findings are consistent with declining hedge portfolio strategy returns and summarised in our main Fama-MacBeth regression results; the anomalies in our sample have generally diminished in strength or disappeared.

Our results are consistent with an improvement in market efficiency with respect to well-known anomaly variables. The significance of publicly available anomaly variables to explain differences in returns across stocks has diminished substantially in recent years. The returns on anomaly-based portfolios have in most cases fallen substantially. Our paper makes a clear contribution to the U.K. asset pricing literature, but also provides insight into the issue of anomaly persistence which is relevant to investors more generally.

The remainder of the paper is organised as follows. Section 2 provides a review of the literature on equity market anomalies. Section 3 provides a discussion of the anomalies we examine in this paper. Section 4 presents the details of our data sample. Section 5 reviews our research methodology. Section 6 presents the results of our analysis and provides a discussion of their significance. Section 7 concludes.

2 Interpreting Anomalies

In this section, we review the major contributions to the literature on equity market anomalies. We frame our discussion around the principal question in the literature - what is the economic significance of an observed anomaly? We begin by illustrating the process of interpreting an anomaly in Figure 1. This simple tree structure summarises the vast anomalies literature; all contributions to the literature fit in at one or more stages of the tree.

<Figure 1>

The first stage of the process is to determine the statistical significance of an anomaly. We must consider the possibility that a documented anomaly is a spurious result arrived at by chance or by extensive data mining by researchers.

The second stage of the process is to consider whether an anomaly results from the use of an inappropriate model of expected returns. Put simply, it could be that we are ignoring some important aspect of a stock's risk. "Abnormal returns" may disappear when we use an alternative model of expected returns.

The third stage of the process is to determine the viability of exploiting anomalous returns with a trading strategy. It may not be possible to realize "paper profits" from an anomaly due to transaction costs, trading restrictions, or more complex limits to arbitrage (Gromb and Vayanos, 2010).

We review contributions to the literature for each of these three stages in turn:

2.1 Statistical significance

Are anomalies truly statistically significant? This is the first question we must ask in our analysis of these phenomena. We know that investors and researchers search historical returns for patterns at odds with conventional theories. Does this behaviour make the discovery of spurious anomalies more common?

Data mining is the practice of repeatedly using the same dataset to test many different hypotheses. The likelihood of identifying a spurious anomaly - one with no economic significance - increases with the number of new variables we investigate. This is a first-order concern in anomalies research as almost all empirical work in this literature is non-experimental. This issue should weigh on the minds of researchers visiting and revisiting historical databases.

The distortionary impact of data mining on the analysis of anomalies has been stressed repeatedly in the literature. Some researchers have tried to directly analyse the influence the practice has on reported results. Harvey et al. (2015) 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. Similarly, Sullivan et al. (1999) find that data mining by researchers has generated many spuriously significant results in the calendar anomalies literature.

This data mining problem may be aggravated by the incentives academic researchers typically face. Novel results may lead to acceptance to conference programmes, journal publications, and promotion. This may bias the focus of academic discussion towards spurious results that challenge existing theory and away from unexciting results in line with expectations. This is sometimes termed the "file drawer" or "publication bias" problem in academia. Novel results are given prominence in discussion while uninteresting results are more likely to be consigned to an academic's "file drawer".

An important aspect of research on anomalies is the replication of results across different samples. Economically meaningful cross-sectional anomalies should not be confined to a particular sample period in a particular market. Fama (1991) makes this point clearly. He states that anomalies "warrant out-of-sample tests before being accepted as regularities that are likely to be present in future returns."

Out-of-sample replication is our main tool in establishing whether or not a result is truly statistically significant. This involves testing for the presence of an anomaly in other time periods and in alternative markets. Indeed, most robust anomalies in the literature - including those we consider in our analysis - were first documented in the U.S. equity market and then investigated further in international data.

2.2 Compensation for risk or inefficiency?

Anomalies are relative phenomena; to identify a deviation from the norm, we require a definition of the norm. Thus, robust anomalies may be evidence of abnormally high or low returns or simply evidence that we have not fully accounted for the given asset's risk. This "dual hypothesis" problem is one of the enduring messages from Fama (1970).

Still, the type of risk anomalies may reflect is generally not clear. Theorists have struggled to provide ex-post risk-based explanations for many well-known anomalies. Fama and French (1993) famously incorporate size- and value-based factors into a risk-based model of expected returns, but concede that these two variables have "no special standing in asset-pricing theory." This approach has drawn some sharp criticism. For instance, Shleifer (2000) cites the loose theoretical foundation for these factors as a major problem for the model. Researchers have faced the same difficulty with other well-known anomalies such as momentum (Jegadeesh and Titman, 1993) and the short-run return reversal effect (Jegadeesh, 1990).

The alternative explanation is that robust anomalies are evidence of market inefficiency. A market price is said to be "efficient" in the most general sense if, on average, no information can help us improve upon its estimate of an asset's value. Many behavioural financial economists argue that anomalies arise due to irrational trading on the part of investors. Traders may neglect relevant information and place too much emphasis on other signals. Importantly, anomaly variables can typically be observed easily by the public. Behavioural researchers generally argue that investor sentiment pushes prices (and expected returns) away the levels justified by firm fundamentals. Shiller (2000) provides a famous account of this position.

The existence and persistence of market inefficiencies depend on the two influences - investor sentiment and rational arbitrage (smart money"). We discuss these two issues below.

2.2.1 Investor Sentiment

The traditional approach of microeconomics and its application in finance has been to develop models of rational decision-making under resource constraints. Homo economicus is given a utility function to maximise and a set of resources with which to do so. An alternative literature has developed over the last few decades. Researchers in behavioural economics have drawn inspiration from the psychology literature and analysed real-world economic decision-making of individuals.

Behavioural economists have documented a large number of decision-making biases that are difficult to reconcile with traditional models of individual utility. Examples include loss aversion (Kahneman and Tversky, 1979) and money illusion (Shafir et al., 1997). The message from this literature is clear; people are not always dispassionate utility maximisers. The implications of this for individual outcomes and market dynamics is now central to the debate in most fields of economics including finance.

Importantly, broad studies of economic behaviour may not lead to appropriate conclusions about the behaviour of investors. Direct participants in the stock market make up a relatively small subset of society. Wealth is a major factor in determining participation rates (Mankiw and Zeldes, 1991). Other important factors that researchers have highlighted include financial literacy (van Rooij et al., 2011), IQ (Grinblatt et al., 2011), and sociability (Hong et al., 2004). These findings highlight the importance of developing an understanding of the economic behaviour of investors as distinct from individuals in general.

Researchers in behavioural finance have found that investors suffer from many behavioural biases. Barberis and Thaler (2003) provide an excellent survey of these findings. For instance, investors are often over-confident about their ability to predict future market trends. Investors also attribute successful investments to their skill and attribute failures to bad luck.

Importantly, Kumar and Lee (2006) demonstrate that these biases have the potential to influence market prices. They show that the trading decisions of individual investors are systematically correlated. That is, individual investors consistently behave like other individual investors. The implication of this result is that investor sentiment must be counterbalanced by the actions of rational arbitrageurs. In the absence of such action, investor sentiment will support the persistence of market anomalies.

2.2.2 Smart money

The claim that anomalies are the result of psychological biases among investors is a contentious issue in finance. Proponents of market efficiency typically argue that competition for information in capital markets will result in irrational traders losing money. They argue that sophisticated investors - "smart money"- will eliminate market anomalies generated by investor sentiment among irrational traders. Friedman (1953) was perhaps the first to lay out this argument. Shleifer (2000) states that "the theoretical case for efficient markets rests on the effectiveness of such arbitrage."

A common argument in the literature is that the discovery of a profitable anomaly - an inefficiency - will lead to its destruction. Smart investors should, it is argued, exploit the abnormal returns on offer by constructing portfolios which capture these returns. Anecdotal evidence abounds of academic discoveries informing investor trading. More formally, McLean and Pontiff (2015) argue that the publication of academic papers directly leads to the elimination of anomalies.

Chordia et al. (2014), on the other hand, provide evidence of anomalies gradually diminishing over time. They link this to dramatic improvements in market liquidity and the growth in arbitrage activity in recent years. Akbas et al. (2015) go further and present evidence suggesting that aggregate fund flows are related to variations in the magnitude of anomalies. Mutual fund flows (a proxy for "dumb money") often result in anomalies becoming more pronounced and hedge fund flows (a proxy for "smart money") lead to anomaly attenuation.

The Adaptive Markets Hypothesis (Lo, 2004) presents an alternative perspective on these results which is rooted in evolutionary biology. The efficiency of a market in this context will depend on the intensity of competition among investors for exploitable anomalies. Intense competition will lead to the elimination of profitable opportunities and a decline in the population of traders. The theory anticipates cycles in the level of profitability anomalies offer in response to changing market conditions and the number of competing investors. Roll (1994) and Stambaugh (2014) explore similar ideas.

2.3 Exploitability

Can savvy investors profit from market anomalies? This is the subject of a growing literature on the limits to arbitrage. Theoretical contributions to this literature have demonstrated that arbitrageurs may be unable or unwilling to exploit anomalies for a variety of reasons.

Gromb and Vayanos (2010) describe this literature as having two branches. The first branch deals with fundamental limits to arbitrage. Trading costs are perhaps the most basic difficulty that investors face when trading on an anomaly. Though an anomaly may be persistent and may not be explained by variation in risk across stocks, investors may choose not to trade on it if it is overly costly to do so.

Another issue for arbitrageurs is that short selling may be restricted by government or stock exchange policy. In addition, position limits may prevent fund managers from constructing portfolios they see as optimal for capturing anomaly profits.

The second branch of this literature deals with non-fundamental limits to arbitrage. De Long et al. (1990) develop a model in which arbitrageurs face "noise trader risk". That is, the risk arbitrageurs face of irrational traders sustaining or intensifying anomalies after the arbitrageur has taken a position. Alternatively, Shleifer and Vishny (1997) develop a model in which an arbitrageur is concerned about their clients withdrawing funds in the event of temporarily negative performance. This incentivises the arbitrageur not to trade on anomalies.

Coordination failure among arbitrageurs is another potential problem for investors seeking to exploit anomalies. Abreu and Brunnermeier (2002) and Stein (2009) develop models in which arbitrageurs are unaware of the behaviour of other arbitrageurs. Trades can become "crowded" as many institutional traders try to exploit an anomaly. Rather than eliminating anomalies and driving prices closer to their fundamental value, arbitrageurs in this setting may generate substantial instability (at least in the short run).

The main implication of this literature is that well-known market anomalies may persist over time. These models suggests that cross-sectional equity market anomalies - the subject of our study - may persist even in the presence of knowledgeable arbitrageurs.

3 Anomalies

In our study, we examine a set of well-known cross-sectional anomalies which have generated much discussion in the literature. These anomalies have shown to be robust across different samples and have proven difficult for theorists to incorporate into risk-based models of expected return. Table 1 lists the variables.

<Table 1>

Sloan (1996) shows that high levels of accounting accruals are associated with low average returns. He posits that investors do not fully appreciate the information that is contained in the components of firms' earnings. Cooper et al. (2008) find a negative relationship between the rate of firm asset growth and average stock returns. These authors argue that biased decision-making among investors is the best explanation for this anomaly. Specifically, investors may be naively extrapolating asset growth rates of firms.

Pontiff and Woodgate (2008) report a negative relationship between firm equity issuance and average returns. This result suggests that firm managers conduct equity issuances and share repurchases opportunistically. Again, these authors argue that their results are difficult to reconcile with risk-based models.

Fama and French (1992) present evidence that firm book equity to market equity ratios are positively related to average returns. The authors hypothesise that distress risk for firms might drive this relationship. Cochrane (2005) notes that this interpretation is not fully consistent with the current evidence.

Jegadeesh (1990) documents a short-run reversal effect in stock returns. That is, stock returns in a given month are negatively related to returns in the previous month. None of the risk-based models he considers can account for this predictability. Fama and French (2006) report a positive relationship between firm profitability and expected returns. They link this phenomenon to valuation theories of the firm.

Jegadeesh and Titman (1993) report a "momentum" effect in stock returns whereby returns in a given month are positively related to performance in the last 3 to 12 months. They argue that over-reaction of investors to past performance may explain the pattern. Banz (1981) identifies a negative relationship between firm market capitalisation and average returns. He is unable to attribute this effect to a risk-based model of expected returns. Lastly, Datar et al. (1998) find a negative relationship between stock turnover and average returns. They interpret this result as evidence of low liquidity stocks earning higher average returns.

4 Data

In this section, we discuss the data we use in our analysis. We place particular emphasis on the process of enhancing the quality of the data through a careful screening process.

Our data sample consists of individual equity returns and firm characteristics for the cross-section of U.K. stocks from January 1990 to December 2013. We source these data from Thomson Reuters Datastream. We ensure that dead stocks are included to avoid a survivorship bias in our sample. In addition, we obtain market, size, value, and momentum risk factors published by AQR Capital Management.

Data quality is an important consideration for researchers studying asset pricing in international markets. Ince and Porter (2006) identify a number of systematic errors in individual equity databases. Thus, we proceed with caution. To counter these issues, Ince and Porter (2006) devise a set of screens which improve equity data reliability. Schmidt et al. (2014) build on this contribution and further improve these screening procedures.

We carefully clean our data using the static and dynamic screens outlined by Schmidt et al. (2014). This is the first paper to use these more refined procedures with U.K. data. We retain stocks that have a price history and a return history of at least 24 months, are identified by Datastream as "equity" securities, are the major security of the given firm, are listed in London, and are identified as U.K. companies.

We also remove 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 next conduct an exploratory analysis of the data to identify suspect outliers. More formally, we set a firm's market value equal to missing if the difference between it and unadjusted price times number of shares outstanding is larger than 0.5 in absolute value. We also set monthly returns equal to missing if they are greater than 990% or if either price term is greater than £1,000,000.

The London Stock Exchange has historically contained many small firms. Researchers analysing this market have typically filtered out firms with very low stock prices. We follow Nagel (2002) and filter out stocks with nominal prices below £0.30. In addition, we remove securities which have unadjusted prices below the 5th percentile of the price distribution for the full sample as a "penny stock"-style filter.

Our final sample is comprised of 1,229 stocks. We believe our battery of static and dynamic screens improved the quality of our dataset.

5 Methodology

In this section, we discuss our methodological approach. We conduct two distinct analyses. First, we consider the returns generated by trading strategies designed around anomaly variables. In each month, we sort stocks into quintile portfolios based on the value of a given anomaly variable. We then calculate returns for a strategy which is long the portfolio with the highest values of the anomaly variable and short the portfolio with the lowest values of the anomaly variable. This provides a tangible measure of the economic magnitude of each anomaly in the form of monthly percentage trading returns.

We also consider the robustness of our hedge portfolio results to methodological changes. In particular, we vary the number of portfolios we sort stocks into each month and report results generated from monthly decile sorts.

Second, we use regression analysis to determine the statistical significance of our set of anomalies. We apply the modified version of the Fama and MacBeth (1973) two-step cross-sectional regression methodology proposed by Brennan et al. (1998).

We begin with a first-pass time series regression described by equation (1) to estimate sensitivies of individual firm returns to a set of L specified factors. We choose these factors from established models of expected return. This first pass regression gives us estimated betas with respect to L factors for each firm j. We generate the results in the main body of the paper using the four-factor Fama and French (1993) and Carhart (1997) model.

$$\tilde{R}_{jt} = R_{Ft} + \sum_{k=1}^{L} \hat{\beta}_{jk} \tilde{f}_{kt} \tag{1}$$

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. An important point to note is that measurement error is a well-known problem in firm betas (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.

The defining feature of our regression approach is the incorporation of the mismeasured first-pass betas into the dependent variable of the second-pass cross-sectional regression. We construct risk-adjusted firm returns $\tilde{R}^*_{jt}$ for each firm j in equation (2).

$$\tilde{R}^*_{jt} = \tilde{R}_{jt} - R_{Ft} - \sum_{k=1}^{L} \hat{\beta}_{jk} \tilde{F}_{kt} \tag{2}$$

We next regress these returns on a set of specified anomaly variables in month-by-month cross-sectional regressions. We vary the set of anomalies to produce univariate and multivariate estimates c_m in equation (3).

$$\tilde{R}^*_{jt} = c_0 + \sum_{m=1}^{M} c_m Z_{mjt} + \tilde{e}'_{jt} \tag{3}$$

The use of risk-adjusted returns returns as the dependent variable in equation (3) allows for consistency in the anomaly variable coefficient estimates, but comes at the cost of greater inefficiency of these coefficient estimates (Hausman, 2001). Brennan et al. (1998) argue that this is, on balance, a good tradeoff and is an appropriate method for addressing this well-known errors-in-variables problem.

We then calculate Fama and MacBeth (1973) coefficients for each anomaly variable. These are the time series means of each variable's estimated premium. These coefficients equal zero under the null hypothesis that firm returns are determined by the set of L specified factors.

Finally, we look closer at the month-by-month Fama-MacBeth coefficient estimates for each anomaly variable. We examine the dynamics of these series over our sample period and conduct a trend analysis on them using simple t-tests.

6 Results

6.1 Hedge portfolio returns

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%.

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.

<Table 2>

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 0.836% 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. Why analyse quintiles and not sextiles or deciles? We seek to 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.

Table 3 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.

<Table 3>

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. This holds even for the portfolios for which returns remain statistically significant in the second sub-sample.

6.2 Univariate Fama-MacBeth regressions

In this section, we examine the significance each of our nine anomaly variables using univariate Fama and MacBeth (1973)-style regressions. We regress risk-adjusted individual firm returns on each anomaly variable in turn following Brennan et al. (1998). This provides us with univariate Fama-MacBeth coefficients for each anomaly in each month of our sample. We adjust firm returns for risk using the four-factor Fama and French (1993) and Carhart (1997) model in all cases.

Table 4 presents the results of our univariate regression analysis. Each regression produces a 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 a common method in the literature to examine the persistence over time of anomalies. See, for example, Schwert (2003).

<Table 4>

The first column of Table 4 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 Tables 2 and 3, though we find stronger statistical significance for accruals, return reversal, and size in our regression analysis.

The second and third columns of Table 4 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 Tables 2 and 3. These results are surprising given that most estimates of the size effect in the literature are negative. We discuss this disparity further in Section 6.5.

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.

6.3 Multivariate Fama-MacBeth regressions

We next examine the significance of our anomaly variables using multivariate Fama and MacBeth (1973)-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.

Table 5 presents the correlation matrix of our set of anomaly variables. We find that the correlations among the variables are quite low. Most are below 0.1 in absolute value. These are similar to the findings of Brennan et al. (1998). The highest correlation in our sample is 0.408 between size and turnover.

<Table 5>

Table 6 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 results of Table 5 in mind, we explore the impact of including one or both of the size and turnover variables in our final three specifications.

<Table 6>

The book-to-market, profitability, size, and turnover characteristics are all rather robust to alternative specifications. For instance, the largest of the profitability coefficients p-values is 0.003 and the coefficients rise as we add additional characteristics. The sign of all but sizes coefficients match those in the univariate regression results in Table 4.

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 4. 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 4.

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 4. 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.

Tables 7 and 8 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 4. 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 Table 7 compared to three in Table 8.

<Table 7>

<Table 8>

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 4. 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 14 and 17 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.

6.4 Fama-MacBeth coefficient time trends

In this section, we examine the time series of multivariate Fama-MacBeth regression coefficients for each anomaly. The series correspond to a regression specification where we include all nine anomalies as independent variables. We use the four-factor Fama and French (1993) and Carhart (1997) model to risk-adjust individual firm returns.

We construct 60-month moving averages for the regression coefficients. The moving average calculation shortens the sample period by five years. This truncated sample runs from January 1995 to December 2013.

Figure 2 presents the time of Fama-MacBeth coefficient moving averages for each of the nine anomaly variables. Casual inspection shows that most series trend towards zero. There are two main exceptions. The series corresponding to the size and turnover variables appear to trend away from zero.

<Figure 2>

We conduct time-trend t-tests to produce more formal results. We present these results in Table 9. We find that most of the time trend coefficient have statistically significant time trends towards zero. Size and turnover are, as expected, the two exceptions. Both of these series have significant time trends away from zero. The Fama-MacBeth coefficients for size become more negative over time and the coefficients for turnover become more positive.

<Table 9>

Our results in Table 9 match closely the trends we see between the subsamples shown in Tables 7 and 8. The correspondence is unsurprising given that the statistics in these tables are drawn from the raw Fama-MacBeth coefficient time series.

6.5 Discussion

In this section, we provide a discussion of our results and place them in the context of the 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 results provide other important insights. For instance, the economic magnitudes of the anomalies we investigate can be substantial. For instance, the quintile portfolio profitability strategy in Table 2 has a full-sample return of 1.819% per month or approximately 22.8% per annum. This figure is even higher - 25.32% per annum - in the first sub-sample. Similarly, the momentum and turnover quintile portfolio strategy returns in the first sub-sample of Table 2 are of a similar magnitude. Chordia et al. (2014) find similar results using U.S. stocks. For example, they find that momentum portfolios earn between 17.27% and 22.58% per annum.

Our findings are robust to the use of alternative portfolio construction methods. The decile portfolio strategy returns in Table 3 are broadly similar to the quintile strategy returns in Table 2. The largest difference is for the turnover portfolio returns. This portfolio performs even better - 27.12% per annum - when constructed using decile portfolios. This improved performance is driven by the use stocks with more extreme characteristics.

The positive relationship we find between size and returns in Table 4 is perhaps puzzling in light of the historical evidence of a negative relationship between these variables. van Dijk (2011) shows that though the negative relationship between size and average returns has persisted in U.S. data, it has reversed several times. Indeed, many of these reversals have lasted a number of years. A potential explanation our result is a deviation of realised returns from expected returns (Elton, 1999). That is, the ex ante expectation of a negative relationship was not observed in our sample period by chance. It may be this ex ante expectation is still appropriate in future. Hou and van Dijk (2012) present evidence supporting this explanation. In any case, our analysis suggests that size continues to be related to average risk-adjusted stock returns.

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. Another result of note is the significance of the asset growth anomaly in the second sub-sample.

We find that not all anomalies are robust to the inclusion 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 Table 6, 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 Table 8. The most robust anomalies are again the profitability, size, and turnover effects.

The results of our time trend analysis in Table 9 provide another perspective on the data. We find significant time trends toward zero for most of the anomaly variable coefficient series we examine. These findings are consistent with the conclusions we draw from the sub-sample Fama-MacBeth regression results in Tables 7 and 8.

What economic interpretation can we draw from our results? Firstly, 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. They appear to be robust in the sense of statistical significance.

Secondly, 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 proven difficult for theorists to reconcile with risk-based theoretical models.

Thirdly, 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 (2015) present more formal evidence showing that hedge funds do exploit anomalies. Boehmer and Kelley (2009) also report lower predictability in the returns of stocks with a higher proportion of institutional investors.

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. Also, Jones and Pomorski (2013) find that short-run autocorrelations in stock returns have diminished in recent years.

An important point to note is that the decline in anomaly significance we observe may not continue indefinitely. Models in the limits to arbitrage literature predict that anomalies will emerge and persist if investor sentiment influences expected returns and a sufficiently large supply of arbitrage capital does not seek to correct this influence.

Long-Term Capital Management (LTCM) is an excellent example of the dangers facing hedge funds targeting market anomalies. Though the fund was initially very successful, Lowenstein (2000) documents how deteriorating market conditions led to the collapse of the fund. The experience of LTCM highlights the potential sensitivity of anomaly-based investment strategies to swings in the investor sentiment.

In summary, our results show a clear trend of diminishing significance for most of the anomalies we examine.

7 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 profitability (Fama and French, 2006) and 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 true for Fama-MacBeth regression coefficients for these two anomalies. Furthermore, we document statistically significant time trends in Fama-MacBeth coefficient series for many of our anomaly variables. We find that most coefficient series trend towards zero over the sample period.

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.

Further work on this topic might consider a direct link between institutional investment behaviour, measures of investor sentiment, and the strength of anomalies in the U.K. equity market.

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Table 1: Firm characteristic definitions

Variable	Definition
ACC	Accounting 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 equity over market equity from previous December (Fama and French, 1992)
ISSUE	New issues - 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 lagged by 1 month (Jegadeesh, 1990)
R212	11 month cumulative return to the start of previous month (Jegadeesh and Titman, 1993)
SIZE	Market value of firm's equity (Banz, 1981)
TURN	Stock turnover - trading volume over number of shares outstanding (Datar et al., 1998)

This table provides definitions for the anomalous firm characteristic variables we analyse in this paper.

Table 2: Long-short quintile portfolio returns

	Jan 1990 - Dec 2013	Jan 1990 - Dec 2001	Jan 2002 - Dec 2013
	Return (%)	Return (%)	Return (%)
ACC	0.208	0.355	0.060
	(0.680)	(0.550)	(0.869)
AG	1.158**	1.467*	0.849
	(0.004)	(0.016)	(0.203)
B/M	0.836*	1.179**	0.494
	(0.015)	(0.008)	(0.271)
ISSUE	-0.222	-0.124	-0.300
	(0.768)	(0.658)	(0.343)
PROFIT	1.907**	2.110**	1.704**
	(0.000)	(0.000)	(0.000)
R1	-0.209	-0.450	0.032
	(0.418)	(0.268)	(0.902)
R212	1.488**	2.296**	0.680
	(0.000)	(0.000)	(0.061)
SIZE	-0.112	0.070	-0.252
	(0.675)	(0.866)	(0.573)
TURN	1.857**	2.237**	1.4775**
	(0.000)	(0.000)	(0.009)

The table shows average monthly returns of sorted portfolios long the quintile of stocks with the highest values of a given characteristic and short the quintile with the lowest values of the characteristic. 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. ACC is the change in accounting accruals measured as the change in non-cash current assets minus the change in current liabilities all divided by total assets. AG is asset growth measured as percentage change in total assets. B/M is the book to market ratio. ISSUE is the change in number of shares outstanding from 11 months ago. PROFIT is profitability measured as earnings over book equity. R1 is one-month lagged return. R212 is the cumulative return in the 11 months prior to the previous month. SIZE is firm size measured as the market value of the firm's equity. TURN is stock turnover measured as trading volume over number of shares outstanding.

Table 3: Long-short decile portfolio returns

	Jan 1990 - Dec 2013	Jan 1990 - Dec 2001	Jan 2002 - Dec 2013
	Return (%)	Return (%)	Return (%)
ACC	0.266	0.182	0.661
	(0.517)	(0.697)	(0.344)
AG	0.964**	1.483*	0.445
	(0.001)	(0.020)	(0.309)
B/M	0.629**	0.782*	0.477
	(0.003)	(0.022)	(0.096)
ISSUE	-0.707	-0.343	-1.071
	(0.263)	(0.644)	(0.120)
PROFIT	1.819**	2.052**	1.585**
	(0.000)	(0.000)	(0.000)
R1	-0.296	-0.810	0.218
	(0.444)	(0.076)	(0.681)
R212	1.473**	2.069**	0.877
	(0.000)	(0.000)	(0.502)
SIZE	0.191	0.050	0.332
	(0.494)	(0.895)	(0.421)
TURN	2.260**	2.589**	1.931**
	(0.000)	(0.000)	(0.000)

The table shows average monthly returns of sorted portfolios long the decile of stocks with the highest values of a given characteristic and short the decile with the lowest values of the characteristic. 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. ACC is the change in accounting accruals measured as the change in non-cash current assets minus the change in current liabilities all divided by total assets. AG is asset growth measured as percentage change in total assets. B/M is the book to market ratio. ISSUE is the change in number of shares outstanding from 11 months ago. PROFIT is profitability measured as earnings over book equity. R1 is one-month lagged return. R212 is the cumulative return in the 11 months prior to the previous month. SIZE is firm size measured as the market value of the firm's equity. TURN is stock turnover measured as trading volume over number of shares outstanding.

Table 4: Univariate Fama-MacBeth regression coefficients

	Jan 1990 - Dec 2013		Jan 1990 - Dec 2001		Jan 2002 - Dec 2013	
	Constant	FM Coef.	Constant	FM Coef.	Constant	FM Coef.
ACC	-0.001	0.043**	0.001	0.054**	0.003	0.027
	(0.420)	(0.000)	(0.432)	(0.000)	(0.385)	(0.065)
AG	-0.004	0.005*	-0.003	0.009*	0.000	0.002**
	(0.190)	(0.013)	(0.279)	(0.022)	(0.483)	(0.008)
B/M	-0.006	0.002**	-0.003	0.002*	-0.003	0.002
	(0.118)	(0.004)	(0.262)	(0.018)	(0.380)	(0.079)
ISSUE	-0.004	0.000	-0.002	0.000	-0.001	0.000
	(0.200)	(0.285)	(0.353)	(0.189)	(0.449)	(0.104)
PROFIT	-0.003	0.007**	-0.002	0.010**	0.001	0.004**
	(0.246)	(0.000)	(0.335)	(0.001)	(0.451)	(0.000)
R1	-0.004	-0.017**	-0.001	-0.029**	0.000	-0.007
	(0.229)	(0.005)	(0.392)	(0.002)	(0.479)	(0.162)
R212	0.000	0.011**	-0.001	0.023**	0.005	0.006
	(0.445)	(0.008)	(0.347)	(0.000)	(0.215)	(0.110)
SIZE	-0.017*	0.001**	-0.007	0.000	-0.018*	0.001**
	(0.024)	(0.005)	(0.294)	(0.271)	(0.041)	(0.000)
TURN	-0.012**	0.009**	-0.012**	0.010**	-0.007	0.008**
	(0.004)	(0.000)	(0.003)	(0.000)	(0.195)	(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. ACC is the change in accounting accruals measured as the change in non-cash current assets minus the change in current liabilities all divided by total assets. AG is asset growth measured as percentage change in total assets. B/M is the book to market ratio. ISSUE is the change in number of shares outstanding from 11 months ago. PROFIT is profitability measured as earnings over book equity. R1 is one-month lagged return. R212 is the cumulative return in the 11 months prior to the previous month. SIZE is firm size measured as the market value of the firm's equity. TURN is stock turnover measured as trading volume over number of shares outstanding.

Table 5: Correlation matrix of firm characteristics

	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

This table shows the time series averages of monthly cross-sectional correlations between the transformed firm characteristics. The sample period is January 1990 to December 2013. ACC is the change in accounting accruals measured as the change in non-cash current assets minus the change in current liabilities all divided by total assets. AG is asset growth measured as percentage change in total assets. B/M is the book to market ratio. ISSUE is the change in number of shares outstanding from 11 months ago. PROFIT is profitability measured as earnings over book equity. R1 is one-month lagged return. R212 is the cumulative return in the 11 months prior to the previous month. SIZE is firm size measured as the market value of the firm's equity. TURN is stock turnover measured as trading volume over number of shares outstanding.

Table 6: Multivariate Fama-MacBeth regression coefficients

Full sample: Jan 1990 - Dec 2013

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

This table shows Fama-MacBeth regression coefficients from 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 sample period is January 1990 to December 2013. Newey-West p-values are stated in parentheses below each coefficient. ** and * indicate significance at a 1% and 5% level, respectively. ACC is the change in accounting accruals measured as the change in non-cash current assets minus the change in current liabilities all divided by total assets. AG is asset growth measured as percentage change in total assets. B/M is the book to market ratio. ISSUE is the change in number of shares outstanding from 11 months ago. PROFIT is profitability measured as earnings over book equity. R1 is one-month lagged return. R212 is the cumulative return in the 11 months prior to the previous month. SIZE is firm size measured as the market value of the firm's equity. TURN is stock turnover measured as trading volume over number of shares outstanding.

Table 7: Multivariate Fama-MacBeth regression coefficients

Sub-sample I: Jan 1990 - Dec 2001

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

This table shows Fama-MacBeth regression coefficients from 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 sample period is January 1990 to December 2001. Newey-West p-values are stated in parentheses below each coefficient. ** and * indicate significance at a 1% and 5% level, respectively. ACC is the change in accounting accruals measured as the change in non-cash current assets minus the change in current liabilities all divided by total assets. AG is asset growth measured as percentage change in total assets. B/M is the book to market ratio. ISSUE is the change in number of shares outstanding from 11 months ago. PROFIT is profitability measured as earnings over book equity. R1 is one-month lagged return. R212 is the cumulative return in the 11 months prior to the previous month. SIZE is firm size measured as the market value of the firm's equity. TURN is stock turnover measured as trading volume over number of shares outstanding.

Table 8: Multivariate Fama-MacBeth regression coefficients

Sub-sample II: Jan 2002 - Dec 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)

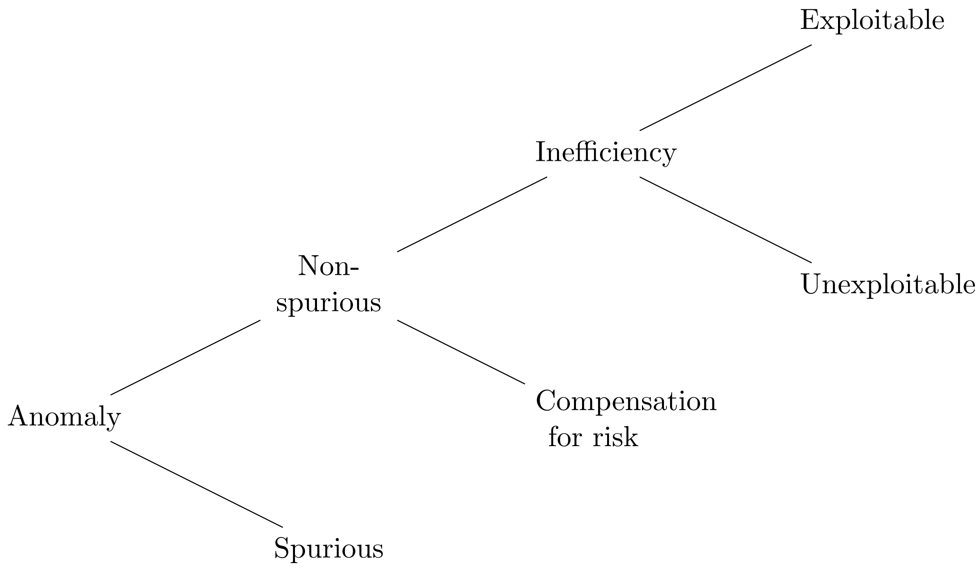
This table shows Fama-MacBeth regression coefficients from firm returns on firm characteristics. We follow the procedure set out by Brennan et al. (1998) and risk-adjust the individual firm returns using the four-factor Fama and French (1993) and Carhart (1997) model. The sample period is January 2002 to December 2013. Newey-West p-values are stated in parentheses below each coefficient. ** and * indicate significance at a 1% and 5% level, respectively. ACC is the change in accounting accruals measured as the change in non-cash current assets minus the change in current liabilities all divided by total assets. AG is asset growth measured as percentage change in total assets. B/M is the book to market ratio. ISSUE is the change in number of shares outstanding from 11 months ago. PROFIT is profitability measured as earnings over book equity. R1 is one-month lagged return. R212 is the cumulative return in the 11 months prior to the previous month. SIZE is firm size measured as the market value of the firm's equity. TURN is stock turnover measured as trading volume over number of shares outstanding.

Table 9: Time trend t-statistics of Fama-MacBeth coefficients

Variable	ACC	AG	B/M	ISSUE	PROFIT	R1	R212	SIZE	TURN
Trend coef.	0.475	-0.0778**	-0.095**	-0.000**	-0.635**	3.242**	-2.092**	-0.046**	0.068**
t-stat	1.430	-2.605	-5.109	-3.124	-3.970	15.752	-32.142	-3.931	4.140

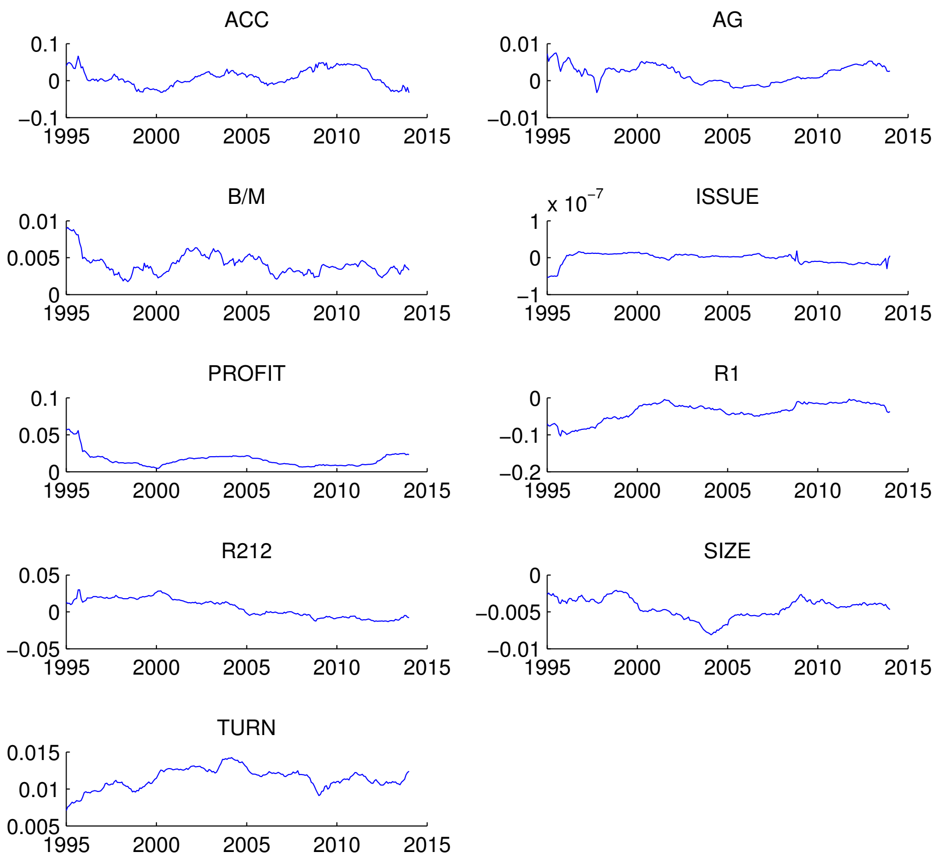
This table provides the time trend t-statistic from regressions of 60-month moving average Fama-MacBeth multiple regression (returns on all nine anomaly variables) coefficients on time. The we adjust for risk in the regressions using the four-factor Fama and French (1993) and Carhart (1997) model. ** and * indicate significance at a 1% and 5% level, respectively. ACC is the change in accounting accruals measured as the change in non-cash current assets minus the change in current liabilities all divided by total assets. AG is asset growth measured as percentage change in total assets. B/M is the book to market ratio. ISSUE is the change in number of shares outstanding from 11 months ago. PROFIT is profitability measured as earnings over book equity. R1 is one-month lagged return. R212 is the cumulative return in the 11 months prior to the previous month. SIZE is firm size measured as the market value of the firm's equity. TURN is stock turnover measured as trading volume over number of shares outstanding.

Figure 1: Interpreting an anomaly



This figure illustrates the process of investigating an anomaly's economic significance. 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.

Figure 2: 60-month moving averages of simple Fama-MacBeth coefficients



This figure shows 60-month moving averages of Fama-MacBeth coefficients from multiple regressions of risk-adjusted returns on all nine firm characteristic over the full sample period using the Fama and French (1993) and Carhart (1997) factors to adjust for risk. ACC is the change in accounting accruals measured as the change in non-cash current assets minus the change in current liabilities all divided by total assets. AG is asset growth measured as percentage change in total assets. B/M is the book to market ratio. ISSUE is the change in number of shares outstanding from 11 months ago. PROFIT is profitability measured as earnings over book equity. R1 is one-month lagged return. R212 is the cumulative return in the 11 months prior to the previous month. SIZE is firm size measured as the market value of the firm's equity. TURN is stock turnover measured as trading volume over number of shares outstanding.

Appendix

A.1 Alternative Fama-MacBeth risk-adjustment

In this section, we re-examine the significance of our nine anomaly variables using alternative methods of risk-adjustment for individual firm returns. 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 4, 6, 7, and 8 using the three-factor Fama and French (1993) model and the CAPM.

A.2 Univariate Fama-MacBeth regressions

We first repeat our univariate Fama-MacBeth analysis from Section 6.2 using the three-factor Fama and French (1993) model and the one-factor CAPM to adjust for risk.

Table 10 presents these results based on returns adjusted using the three-factor Fama and French (1993) model. Table 11 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.

<Table 10>

<Table 11>

Our results are remarkably similar to those in Table 4. 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 of Table 10 and Table 11 both 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 Tables 10 and 11 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 4, we find that the asset growth, profitability, size, and turnover coefficients remain significant in this more recent time period.

A.2.2 Multivariate Fama-MacBeth regressions

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

Tables 12, 13, and 14 present Fama-MacBeth results for which individual firms are adjusted using the three-factor Fama and French (1993) model. They correspond to Tables 6, 7, and 8 of the main body of the paper. Tables 15, 16, and 17 present Fama-MacBeth results for which individual firms are adjusted using the one-factor CAPM. They again correspond to Tables 6, 7, and 8 of 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 one-factor CAPM.

<Table 12>

<Table 13>

<Table 14>

<Table 15>

<Table 16>

<Table 17>

Table 10: Univariate Fama-MacBeth regression coefficients

	Jan 1990 - Dec 2013		Jan 1990 - Dec 2001		Jan 2002 - Dec 2013	
	Constant	FM Coef.	Constant	FM Coef.	Constant	FM Coef.
ACC	-0.001	0.043**	0.000	0.055**	0.000	0.027
	(0.400)	(0.000)	(0.470)	(0.000)	(0.479)	(0.065)
AG	-0.005	0.005*	-0.003	0.008*	-0.003	0.002*
	(0.179)	(0.012)	(0.259)	(0.024)	(0.348)	(0.014)
B/M	-0.006	0.002**	-0.004	0.003**	-0.006	0.002
	(0.107)	(0.003)	(0.219)	(0.005)	(0.253)	(0.074)
ISSUE	-0.005	0.000	-0.002	0.000	-0.004	0.000
	(0.186)	(0.236)	(0.325)	(0.209)	(0.317)	(0.055)
PROFIT	-0.004	0.008**	-0.003	0.010**	-0.002	0.004**
	(0.234)	(0.000)	(0.302)	(0.001)	(0.404)	(0.000)
R1	-0.004	0.020**	-0.002	0.031**	-0.004	0.009
	(0.218)	(0.001)	(0.370)	(0.001)	(0.342)	(0.099)
R212	0.000	0.011**	-0.001	0.021**	0.003	(0.004)
	(0.460)	(0.009)	(0.353)	(0.000)	(0.342)	(0.241)
SIZE	-0.017*	0.001**	-0.006	0.000	-0.024*	0.002**
	(0.023)	(0.005)	(0.325)	(0.340)	(0.015)	(0.000)
TURN	-0.013**	0.009**	-0.012**	0.009**	-0.010	0.008**
	(0.003)	(0.000)	(0.003)	(0.000)	(0.110)	(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 three-factor Fama and French (1993) 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. ACC is the change in accounting accruals measured as the change in non-cash current assets minus the change in current liabilities all divided by total assets. AG is asset growth measured as percentage change in total assets. B/M is the book to market ratio. ISSUE is the change in number of shares outstanding from 11 months ago. PROFIT is profitability measured as earnings over book equity. R1 is one-month lagged return. R212 is the cumulative return in the 11 months prior to the previous month. SIZE is firm size measured as the market value of the firm's equity. TURN is stock turnover measured as trading volume over number of shares outstanding.

Table 11: Univariate Fama-MacBeth regression coefficients

	Jan 1990 - Dec 2013		Jan 1990 - Dec 2001		Jan 2002 - Dec 2013	
	Constant	FM Coef.	Constant	FM Coef.	Constant	FM Coef.
ACC	-0.001	0.044**	0.000	0.060**	-0.001	0.030
	(0.440)	(0.000)	(0.488)	(0.000)	(0.466)	(0.059)
AG	-0.004	0.005*	-0.004	0.009*	-0.004	0.002*
	(0.207)	(0.012)	(0.222)	(0.022)	(0.329)	(0.015)
B/M	-0.006	0.003**	-0.005	0.003**	-0.006	0.002*
	(0.127)	(0.003)	(0.182)	(0.005)	(0.232)	(0.044)
ISSUE	-0.004	0.000	-0.003	0.000	-0.005	0.000
	(0.216)	(0.287)	(0.285)	(0.199)	(0.300)	(0.058)
PROFIT	-0.003	0.008**	-0.003	0.011**	-0.003	0.004**
	(0.266)	(0.000)	(0.265)	(0.000)	(0.386)	(0.000)
R1	-0.004	0.024**	-0.002	0.035**	-0.004	0.012
	(0.248)	(0.000)	(0.329)	(0.000)	(0.329)	(0.065)
R212	0.001	0.012**	-0.001	0.020**	0.003	0.004
	(0.404)	(0.007)	(0.353)	(0.001)	(0.333)	(0.236)
SIZE	-0.017*	0.001**	-0.006	0.000	-0.024*	0.002**
	(0.030)	(0.006)	(0.324)	(0.363)	(0.017)	(0.000)
TURN	-0.012**	0.009**	-0.014**	0.010**	-0.011	0.008**
	(0.005)	(0.000)	(0.002)	(0.000)	(0.104)	(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 one-factor CAPM. 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. ACC is the change in accounting accruals measured as the change in non-cash current assets minus the change in current liabilities all divided by total assets. AG is asset growth measured as percentage change in total assets. B/M is the book to market ratio. ISSUE is the change in number of shares outstanding from 11 months ago. PROFIT is profitability measured as earnings over book equity. R1 is one-month lagged return. R212 is the cumulative return in the 11 months prior to the previous month. SIZE is firm size measured as the market value of the firm's equity. TURN is stock turnover measured as trading volume over number of shares outstanding.

Table 12: Multivariate Fama-MacBeth regression coefficients

Full sample: Jan 1990 - Dec 2013

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

This table shows Fama-MacBeth regression coefficients from 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 three-factor Fama and French (1993) model. The sample period is January 1990 to December 2013. Newey-West p-values are stated in parentheses below each coefficient. ** and * indicate significance at a 1% and 5% level, respectively. ACC is the change in accounting accruals measured as the change in non-cash current assets minus the change in current liabilities all divided by total assets. AG is asset growth measured as percentage change in total assets. B/M is the book to market ratio. ISSUE is the change in number of shares outstanding from 11 months ago. PROFIT is profitability measured as earnings over book equity. R1 is one-month lagged return. R212 is the cumulative return in the 11 months prior to the previous month. SIZE is firm size measured as the market value of the firm's equity. TURN is stock turnover measured as trading volume over number of shares outstanding.

Table 13: Multivariate Fama-MacBeth regression coefficients

Sub-sample I: Jan 1990 - Dec 2001

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

This table shows Fama-MacBeth regression coefficients from 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 three-factor Fama and French (1993) model. The sample period is January 1990 to December 2001. Newey-West p-values are stated in parentheses below each coefficient. ** and * indicate significance at a 1% and 5% level, respectively. ACC is the change in accounting accruals measured as the change in non-cash current assets minus the change in current liabilities all divided by total assets. AG is asset growth measured as percentage change in total assets. B/M is the book to market ratio. ISSUE is the change in number of shares outstanding from 11 months ago. PROFIT is profitability measured as earnings over book equity. R1 is one-month lagged return. R212 is the cumulative return in the 11 months prior to the previous month. SIZE is firm size measured as the market value of the firm's equity. TURN is stock turnover measured as trading volume over number of shares outstanding.

Table 14: Multivariate Fama-MacBeth regression coefficients

Sub-sample II: Jan 2002 - Dec 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 Fama-MacBeth regression coefficients from 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 three-factor Fama and French (1993) model. The sample period is 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. ACC is the change in accounting accruals measured as the change in non-cash current assets minus the change in current liabilities all divided by total assets. AG is asset growth measured as percentage change in total assets. B/M is the book to market ratio. ISSUE is the change in number of shares outstanding from 11 months ago. PROFIT is profitability measured as earnings over book equity. R1 is one-month lagged return. R212 is the cumulative return in the 11 months prior to the previous month. SIZE is firm size measured as the market value of the firm's equity. TURN is stock turnover measured as trading volume over number of shares outstanding.

Table 15: Multivariate Fama-MacBeth regression coefficients

Full sample: Jan 1990 - Dec 2013

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

This table shows Fama-MacBeth regression coefficients from CAPM-adjusted individual firm returns on firm characteristics. The sample period is January 1990 to December 2013. Newey-West p-values are stated in parentheses below each coefficient. ** and * indicate significance at a 1% and 5% level, respectively. ACC is the change in accounting accruals measured as the change in non-cash current assets minus the change in current liabilities all divided by total assets. AG is asset growth measured as percentage change in total assets. B/M is the book to market ratio. ISSUE is the change in number of shares outstanding from 11 months ago. PROFIT is profitability measured as earnings over book equity. R1 is one-month lagged return. R212 is the cumulative return in the 11 months prior to the previous month. SIZE is firm size measured as the market value of the firm's equity. TURN is stock turnover measured as trading volume over number of shares outstanding.

Table 16: Multivariate Fama-MacBeth regression coefficients

Sub-sample I: Jan 1990 - Dec 2001

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

This table shows Fama-MacBeth regression coefficients from CAPM-adjusted individual firm returns on firm characteristics. The sample period is January 1990 to December 2001. Newey-West p-values are stated in parentheses below each coefficient. ** and * indicate significance at a 1% and 5% level, respectively. ACC is the change in accounting accruals measured as the change in non-cash current assets minus the change in current liabilities all divided by total assets. AG is asset growth measured as percentage change in total assets. B/M is the book to market ratio. ISSUE is the change in number of shares outstanding from 11 months ago. PROFIT is profitability measured as earnings over book equity. R1 is one-month lagged return. R212 is the cumulative return in the 11 months prior to the previous month. SIZE is firm size measured as the market value of the firm's equity. TURN is stock turnover measured as trading volume over number of shares outstanding.

Table 17: Multivariate Fama-MacBeth regression coefficients

Sub-sample II: Jan 2002 - Dec 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 Fama-MacBeth regression coefficients from CAPM-adjusted individual firm returns on firm characteristics. The sample period is 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. ACC is the change in accounting accruals measured as the change in non-cash current assets minus the change in current liabilities all divided by total assets. AG is asset growth measured as percentage change in total assets. B/M is the book to market ratio. ISSUE is the change in number of shares outstanding from 11 months ago. PROFIT is profitability measured as earnings over book equity. R1 is one-month lagged return. R212 is the cumulative return in the 11 months prior to the previous month. SIZE is firm size measured as the market value of the firm's equity. TURN is stock turnover measured as trading volume over number of shares outstanding.