Predictably Illiquid: an investigation into UK equity market efficiency

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Abstract

This paper investigates whether the weak-form efficient market hypothesis holds within UK equities. The paper finds strong statistical evidence of negative first order autocorrelation and positive eleventh, twelfth and twenty-fourth order autocorrelation in the monthly returns of UK equities. This implies that the weak-form efficient market hypothesis does not hold when interpreted in its strictest sense. To test whether statistical significance translates to economic significance a contrarian trading strategy is formed to try and exploit the negative first-order autocorrelation. The contrarian strategy generates an average monthly return of 2.3 percent, 1.3 percentage points higher than the average monthly return of the market. The results are robust to seasonality and the inclusion of transaction costs and cannot be explained by systematic or size-based risk taking. Seeking to explain why weak-form inefficiency exists, evidence is found supporting the hypothesis that it is the result of an illiquidity induced reduction in arbitrage activity, particularly in stocks that have recently experienced large value declines.

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I. Introduction

The efficient market hypothesis is one of the most foundational theories in financial economics. It asserts that asset prices reflect all known information at any given time and that when informational innovations do occur prices rapidly adjust to incorporate them. Under the hypothesis market participants should only be able to consistently outperform the market by taking on excess risk and as such an entire sector of the financial industry devoted to generating returns above the market without excess risk is at best ignorant and at worst irresponsible. Moreover, using methods such as technical analysis, which uses past prices, or fundamental analysis, which uses economic and company information, to predict future prices is useless. Yet despite initial wide-spread acceptance, since the late-twentieth century the hypothesis has been consistently challenged (Malkiel, 2003). The degree of success in those challenges is hard to discern, for every strong claim of inefficiency there is an equally strong rebuttal. Despite this though what is not hard to discern is that one should not simply assume efficiency within financial markets and therefore it is a worthwhile endeavour to test financial market efficiency across asset classes and the world.

In this paper I look to do just that, adding to challenges of market efficiency by testing whether the weak-form efficient market hypothesis holds within UK equities. The motivation for such an investigation is two-fold. Firstly, the UK equity market is comparatively under researched compared to its US counterpart and as such it is deserving of attention. Secondly, with many potential inefficiencies uncovered in US equity markets it is of interest as to whether these inefficiencies are geography specific or a universal phenomenon.

From the outset it is then important to define weak-form market efficiency. Under the strictest interpretation weak-form market efficiency can be characterised as the inability of an investor to predict future prices based off past ones (Fama, 1970). A more economically realistic definition however is that in general past prices cannot be used to predict future ones but in cases where predictability does exist it is unexploitable. That is the marginal benefit of acting on the prediction does not exceed the marginal cost (Jensen, 1978). While predicting unexploitable future prices may be of interest to some it is this second, more sensible, definition of weak-form efficiency that is of greater interest and the one I return to throughout this paper.

To test weak-form efficiency in UK equities I begin by testing it in the strictest sense. To do this I follow Jegadeesh 1990 modelling monthly equity returns as the result of a random walk process in prices and using this model to construct an empirical test for the autocorrelation of returns. Secondly, I develop a contrarian trading strategy to test weak-form efficiency under the interpretation any predictability should be economically unexploitable. Thirdly, I adjust the returns to the contrarian trading strategy to their exposure to systematic and size-based risk, looking to test whether any return from the strategy is the result of excess risk taking and hence not at odds with the concept of market efficiency. Fourth and finally, I look to explain the results of the trading strategy through the lens of illiquidity and its inverse relationship with market efficiency (Chordia, Roll, and Subrahmanyam, 2008).

The findings of this paper challenge weak-form market efficiency not only in its strictest sense but in the more economically sensible one too. I first find that not only do individual equity returns exhibit strong autocorrelation between 1994 and 2024, but they do so across multiple orders of lag. There is statistically significant[1] negative first order autocorrelation as well as positive eleventh, twelfth and twenty-fourth order autocorrelation within monthly UK equity returns. Further I find that using a contrarian trading strategy to exploit this perceived inefficiency by buying the fifty stocks that have greatest return decrease the previous month and selling the fifty stocks that have the greatest return increase the previous month yields a statistically significant return of 2.3 percent per month. Once adjusted for transaction costs this falls to 1.3 percent per month, but the return remains statistically different from zero.

Assessing whether the returns to the contrarian strategy are simply the result of excess risk taking and therefore do not challenge market efficiency I adjust the returns to market risk using the Capital Asset Pricing Model (CAPM) and size-based risk following Jegadeesh 1990 to do so. I find that once risk adjusted the contrarian trading strategy still generates statistically significant excess returns. I conclude therefore that the UK equity market exhibits economically exploitable weak-form market inefficiency.

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[1] Throughout this paper “statistically significant” / “significant” will mean statistically significant to the 1 percent level of significance unless otherwise specified.

Seeking to explain the cause of this inefficiency I find evidence supporting the hypothesis that it is the result of the inverse relationship between market efficiency and market illiquidity (Chordia, Roll, and Subrahmanyam, 2008). Under the hypothesis the contrarian trading strategy identifies equities in which there is an illiquidity induced reduction in arbitrage activity leading to sustained and exploitable deviations in price away from fundamental value.

The rest of the paper is structed as follows. Section II evaluates the literature on the efficient market hypothesis. Section III outlines the data and software used in the paper. Section IV develops the empirical model for testing weak-form market efficiency statistically. Section V develops and tests the contrarian trading strategy to see if the observed violation of weak-form market efficiency is economically significant. Section VI investigates if the returns to the contrarian trading strategy are the result of excess risk taking. Section VII explores the cause of weak-form inefficiency through the lens of illiquidity. Section VIII details potential limitations to the findings and areas for further research and Section IX concludes.

II. Literature Review

With lucrative rewards for anyone able to consistently predict future asset prices it is perhaps not surprising that the literature on the efficient market hypothesis is vast and eclectic. As a result, to fully review the literature would require several papers in and of itself. In this section therefore I seek to highlight the most fundamental ideas of the efficient market hypothesis and the statistical and economic significance of any weak-form inefficiencies found.

Eugene Fama's 1970 paper *'Efficient Capital Markets'* is the cornerstone of the efficient market hypothesis. In it he defines an efficient market as one in which prices fully reflect all available information and outlines three different forms of efficiency. *Weak-form* efficiency considers past prices as the information set, *semi-strong form* efficiency considers all publicly available information (e.g. annual earnings) as the information set and *strong form* efficiency considers all information, including information of a proprietary nature, as the information set. Under each form of the hypothesis the use of the respective information set will not allow for the prediction of future price changes or the generation excess returns as it is already incorporated into prices.

Well before the formalisation of the efficient market hypothesis by Fama (1970) however individuals posited of an efficient financial market, with George Gibson reflecting in his 1889 book '*The Stock Markets of London, Paris, and New York'* that as "shares become publicly known in an open market, the value which they acquire may be regarded as the judgment of the best intelligence concerning them" (Gibson, 1889, p.11) and Bachelier in his 1900 doctoral thesis concluding that "the mathematical expectation of the speculator is nil" (Bachelier, 1900, p.10). As research into financial markets progressed throughout the early twentieth century the view of an efficient market became more entrenched too, and asset prices began to be characterised as random walks, whereby price changes are the result of random and unforecastable shocks (Malkiel, 2003). By the time Fama came round to formalising the efficient market hypothesis in his 1970 doctoral thesis then it might seem that an efficient market was a foregone conclusion, however while overall the view of an efficient market prevailed there were those who sought to disagree and, perhaps more importantly, once he published his thesis the consensus of market efficiency became far from ubiquitous (Malkiel, 2003).

One of the most convincing arguments against market efficiency is levied by Grossman and Stiglitz (1980) who show that as information gathering entails cost it is impossible for a market to be perfectly informationally efficient. Instead, there exists an equilibrium degree of inefficiency such that informed traders are compensated for their information gathering.

Moreover, De Bondt and Thaler (1985) show US equities that have experienced large directional returns over the previous three to five years go onto to reverse those returns in the following three to five years, demonstrating strong evidence against weak-form efficiency. This apparent predictability of future prices using previous price information is then furthered by Lo and MacKinlay (1988) who show that weekly stock returns exhibit strong autocorrelation using a simple variance ratio test. In 1990 Jegadeesh goes onto show this pattern of autocorrelation is present at a monthly timeframe. Finding highly significant negative autocorrelation in one-month returns and positive autocorrelation at higher orders of lag. Additionally, he shows that this relationship can be successfully exploited by market participants even after accounting for transaction costs.

Jegadeesh and Titman (1993) then uncover a further form of inefficacy showing that in the medium-term asset prices exhibit momentum. They discovered that equity returns over the past three to twelve months could be used to predict future returns over the following three to twelve months with the returns following in the same direction. This finding and those of Jegadeesh (1990) and De Bondt and Thaler (1985) gave rise to a consensus of weak-form inefficiency and the view that asset prices exhibit short- and long-term reversals and medium-term momentum, with some large market participants such as AQR Capital Management still running funds to exploit these anomalies to this day (AQR Capital Management, 2024).

Despite what seems like a convincing rejection of weak-form market efficiency however there is no shortage of rebuttal. Chan 1988 demonstrates for example that De Bondt and Thaler’s (1985) reversal phenomenon can be explained through systemic risk compensation and Zarowin (1989) finds no evidence of abnormal returns to De Bondt and Thaler’s (1985) strategy once adjusting for size-based risk. In an intriguing tit-for-tat for though De Bondt and Thaler (1987) show their critics explanations to be false and that the reversal phenomenon is not explained by excess risk taking. Further Jegadeesh and Titman (2001) revisit the momentum phenomenon ten-years later and find it robust to the challenges brought against it.

More recently, Chordia, Roll, and Subrahmanyam 2008 find evidence that illiquidity and market efficiency are inversely related, positing that as illiquidity rises prices become more predictable due to a reduction in arbitrage activity. And Hameed, Kang, and Viswanathan 2010 show that as liquidity dries up following large drops in equity prices there are economically significant returns to supplying liquidity following to past loser stocks.

Malkiel 2003 however examines the attacks on the efficient market hypothesis and concludes that, while there is evidence of inefficiency, markets are less predictable and more efficient than research would have you believe. In a nice parallelism with Malkiel (2003) too Wilson and Marashdeh (2007) demonstrate that short-run inefficacy is necessary for long run efficiency.

Ultimately, as Sewell (2011) concluded in his research note '*History of the Efficient Market Hypothesis*' while it is clear markets are not, nor could ever be, perfectly efficient the hypothesis does, on average, hold. And perhaps of more consequence "a hypothesis that is asymptotically true puts the EMH in contention for one of the strongest hypothesis in the whole of social sciences" (Sewell, 2011, p.7).

This paper contributes to the literature above by exploring weak-form market efficiency in the UK equity market: both statistically and economically. Not only is the UK equity market comparatively under researched with most of the papers above focusing on the US, but the use of a more recent data sample also allows for me to provide an up-to-date exploration of market efficiency, with much of the previous research conducted in the 1980s and 1990s. Furthermore, I seek to allow others to add to and update market efficiency research too by contributing a full python code base for statistically and economically testing weak-form market efficiency.

III. Data and Software

Data

Equity return data is gathered from the London Share Price Database (LSPD) monthly file. My sample consists of all London Stock Exchange (LSE) listed equities between January 1994 and January 2024. I exclude all stocks with thirty-six months or less of return data as they are untestable in my specified model.

LSPD reports dividend adjusted log-monthly returns, therefore, to compute the simple monthly return I take the exponential of the log-monthly returns and subtract one. Further to reduce survivorship bias, and as LSPD does not report returns to investors at the point of de-listing, I assume that equities de-listed due to: liquidation, receiver appointed liquidation, administration, cancellation or reasons unknown have a -100 percent return at the point of quote suspension. For all other de-listing returns I assume the return at the point of quote suspension is 0 percent. One final adjustment I make to the data is to set returns greater than zero when price is not recorded equal to 0 percent. This is done to account for when LSPD incorrectly adjusts for dividends and causes data errors that incorrectly show predictability[2].

For the risk-free rate in CAPM regressions I use the monthly yield on a one-month T-Bill gathered from Kenneth French's (2024) website and I compute daily volatility for the link between market efficiency and illiquidity using the FTSE All-share return index including dividends from the LSPD daily index file.

Software

Data analysis and manipulation is conducted using Python (V3.9.18) in a Jupyter Lab (V3.3.2). I use Pandas (V2.2.1), NumPy (V1.26.4) and datetime (V5.4) in data manipulation. For Fama-MacBeth Regressions I use the Bingham Young University Finance Library (V0.2.0) and for Ordinary Least Square (OLS) regressions and one way t-tests I use statsmodels (V0.13.5).

I use and build upon the code 'Momentum' by Drechsler (2023) for my analysis. The full Jupyter Lab and custom functions are shared in a GitHub repository for future researchers[3].

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[2] The results of the paper are consistent with and without this adjustment.
[3] Available at: https://github.com/henry1034/predictably-illiquid.git

IV. Empirical Test

The Model

I start my investigation into the weak-form market efficiency of UK equities by testing the hypothesis in its strictest sense. To do so I begin by following Jegadeesh 1990, and specify an almost identical general cross-sectional regression model of monthly equity returns to the one outlined in his 1990 paper[4]:

$$R_{i,t} - \bar{\mu}_i = \alpha_{0,t} + \sum_{j=1}^{J} \alpha_{j,t} R_{i,t-j} + \varepsilon_{i,t}$$

Where $R_{i,t}$ is the return on equity i at time t, $\bar{\mu}_i$ is the mean return on equity i over its listed period, $\alpha_{0,t}$ is the intercept, $\alpha_{j,t}$ is the co-efficient estimate on $R_{i,t-j}$, and $\varepsilon_{i,t}$ is the error term. I, like Jegadeesh (1990), include time subscripts on the alpha estimates to allow for variation in the estimates over time. A procedure done to reflect changes in the underlying drivers of equity returns.

To understand why this general model is appropriate when assessing weak-form market efficiency consider the following model of equity returns as laid out in Fama, 1970:

$$R_{i,t} = E\left(R_{i,t} \mid \Phi_{\mathrm{t-1}}\right) + z_{i,t}$$

Where $\Phi_{\mathrm{t-1}}$ is the information set containing all previous price information up to $\mathrm{t-1}$, $E\left(R_{i,t} \mid \Phi_{\mathrm{t-1}}\right)$ is the expected return of asset i given the information set $\Phi_{\mathrm{t-1}}$, and $z_{i,t}$ is the difference between the expected return and the observed return at time t known as the residual return.

In this model $z_{i,t}$ can be thought of as the idiosyncratic shock to $R_{i,t}$ of new information. As new information is, by its nature, random and unforecastable the residual return between periods should be independent, moreover if new information is assumed as likely to be

[4] The difference is in specification of $\bar{\mu}_i$. In his paper Jegadeesh (1990) specifies that an unbiased estimate of the unconditional excess return excluding months $t-j$ is removed from the return at t while I specify the mean return over the entire listing period is removed because I model expected returns as constant for simplicity.

positive as it is negative the residual returns should have an identical distribution. Thus, if markets are perfectly informationally efficient with respect to past prices the residual return in one period cannot be used to predict the residual return in another giving:

$$cov_i\left(z_{i,t}, z_{i,t-j}\right) = 0$$

Under the simplifying assumptions that expected returns are constant (Fama, 1970) and $z_{i,t}$ is independently and identically distributed (i.i.d) prices can then be modelled as a random walk with drift, leading to the return model being specified as:

$$R_{i,t} = \bar{\mu_i} + z_{i,t}$$

Which when combined with the cross-sectional regression model this gives the estimate of $\alpha_{j,t}$ as:

$$\alpha_{j,t} = \frac{cov_i\left(R_{i,t} - \bar{\mu_i},\ R_{i,t-j}\right)}{var_i(R_{i,t-j})} = \frac{cov_i\left(z_{i,t}, z_{i,t-j}\right)}{var_i(z_{i,t-j})}$$

Therefore, only in the case $cov_i\left(z_{i,t}, z_{i,t-j}\right) \neq 0$[5], will the coefficient estimate $\alpha_{j,t}$ on $R_{i,t-j}$ be greater than zero and as a result if $\alpha_{j,t} > 0$ it will imply weak-form market inefficiency[6].

The exact cross-sectional regression used in the empirical tests is, again, almost identical to that of Jegadeesh 1990:

$$R_{i,t} - \bar{\mu_i} = \alpha_{0,t} + \sum_{j=1}^{J=12} \alpha_{j,t} R_{i,t-j} + \alpha_{13,t} R_{i,t-24} + \alpha_{14,t} R_{i,t-36} + \varepsilon_{i,t}$$

I run the model on monthly equity returns and compute coefficient estimates according to Fama and Macbeth, 1973.

[5] Note too the inclusion of i on the estimates on the covariance and variance. By including these as pointed out in Jegadeesh, 1990 it highlights the operation is carried out on the cross section.
[6] For the showing see Appendix A

Results

The results of the Fama MacBeth regressions are presented in Table I. The table clearly shows evidence of predictability in individual UK equity returns with multiple orders of lag showing autocorrelation. The most remarkable of the autocorrelations found is that at lag-1 with a coefficient estimate of -0.0573 statistically significant to the 0.1 percent level. Further, I find statistically significant evidence of positive autocorrelation at lags-eleven, twelve and twenty-four. All other coefficient estimates are statistically indistinguishable from zero at the 10 percent level.

These findings show that the UK equity market, like the US, exhibits predictability at a monthly level. Moreover, the co-efficient estimates are largely consistent with those found by Jegadeesh (1990) in the US. Unlike Jegadeesh (1990) however I do not find most of the coefficient estimates to be statistically significant at the 5 percent level, leading to a potential inference that the UK equity market is less predictable than the US.

The reason for the observed statistical difference between UK and US equities is likely to be nuanced and hard to disentangle. It may, amongst many other things, be caused by variation in return computation, UK and US market structure differences or even simply an increase in overall market efficiency as participants have arbitraged away inefficiencies in the 34 years since Jegadeesh's 1990 paper. Regardless of the differences between the UK and US however what is important is that UK equity returns do exhibit autocorrelation, providing evidence that the weak-from efficient market hypothesis may not hold and that inefficiencies found in the US equity market are applicable outside the geography.

Before claiming that the market is consistently inefficient however it is prudent to account for a well observed seasonal pattern. The January Effect is a seasonal phenomenon whereby US stocks exhibit negative first-order autocorrelation in the month of January (Thaler, 1987). Often attributed to the actions of tax-sensitive investors selling poor performing stocks in December to off-set capital gains tax and buying them back in January this anomalous behaviour, if present in the UK equity market, could lead to spurious results. As seen in Table I however this does not seem to be the case.

Table I
Fama Macbeth Regression Estimates

The table reports the coefficient estimates derived from Fama Macbeth regressions using the model: $R_{i,t} - \overline{\mu_i} = \alpha_{0,t} + \sum_{j=1}^{J=12} \alpha_{j,t} R_{i,t-j} + \alpha_{13t} R_{i,t-24} + \alpha_{14t} R_{i,t-36} + \varepsilon_{i,t}$ where $R_{i,t}$ is the return on equity i at time t and $\overline{\mu_i}$ is the average monthly return of security i over its entire listed period and $\varepsilon_{i,t}$ is the error term. The sample period is between the 1st of January 1994 and 31st of December 2023.

	Coefficient Estimate														
Period	α_0	α_1	α_2	α_3	α_4	α_5	α_6	α_7	α_8	α_9	α_{10}	α_{11}	α_{12}	α_{13}	α_{14}
Jan-Dec	-0.0034	-0.0573	-0.0015	0.0012	0.0072	-0.0011	0.0031	0.0063	0.0030	0.0015	0.0016	0.0119	0.0146	0.0153	0.0050
	(-1.81)	(-10.11)	(-0.29)	(0.25)	(1.35)	(-0.24)	(0.64)	(1.29)	(0.67)	(0.34)	(0.36)	(2.60)	(3.40)	(3.35)	(1.31)
Jan	0.0026	-0.0953	-0.0078	-0.0231	0.0043	-0.0048	-0.0051	-0.0025	0.0151	-0.0038	-0.0039	-0.0120	0.0319	-0.0081	0.0267
	(0.400)	(-6.27)	(-0.39)	(-1.16)	(0.21)	(-0.24)	(-0.35)	(-0.16)	(1.27)	(-0.33)	(-0.25)	(-0.76)	(2.24)	(-0.55)	(1.50)
Feb-Dec	-0.0040	-0.0538	-0.0009	0.0034	0.0074	-0.0008	0.0038	0.071	0.0019	0.0020	0.0021	0.0140	0.0130	0.0175	0.0031
	(-2.01)	(-8.98)	(-0.17)	(0.68)	(1.35)	(-0.17)	(0.75)	(1.38)	(0.40)	(0.41)	(0.46)	(2.96)	(2.90)	(3.63)	(0.79)

The t-statistics are computed under the assumption that the parameter estimates $\alpha_0 - \alpha_{14}$ are equal to zero using the Student's t-distribution and presented in parenthesis.

Excluding the month of January the co-efficient estimate on lag-one remains negative and statistically significant. Interestingly too the co-efficient estimate is close to that of the full sample implying that the negative first-order autocorrelation is not overly biased due to any January Effect. Consistent with the full sample as well lags eleven, twelve and twenty-four remain significant and do not seem to be biased by the inclusion of January in the sample either. I therefore conclude that the autocorrelation found in the full sample is not caused by anomalous return behaviour in the month of January and may truly show consistent weak-from inefficiency in UK equities.

While I conclude that the January Effect does not drive the autocorrelation, running a Fama MacBeth regression within the month of January does still reveal some interesting insights. Table I shows that the January Effect is likely present within UK equities with the negative co-efficient estimate on lag-one in the January only sample close to double that of the full sample and the sample excluding January. Further, there is no statistical significance at lags eleven and twenty-four in the January only sample while the co-efficient on lag twelve does remain significant but only to the 5 percent level. This twelfth order autocorrelation does imply though that stocks that rose the previous January do so the following year and moreover that if the anomalous returns in January are the effect of tax sensitive investors selling loser stocks in December it implies those stocks continue to lose the following year, potentially demonstrating the momentum effect documented by Jegadeesh and Titman (1993, 2001). Again, these findings add to the evidence inefficiencies found in the US stock market are not country specific and are present elsewhere.

It seems therefore that monthly individual equity returns exhibit predictability across seasons and over a sufficiently long period for that predictability to characterised as a general phenomenon. This poses a strong challenge to the concept of weak-form market efficiency in the UK.

V. Contrarian Trading

As Jegadeesh (1990) notes however the size of the sample means that regression estimates are highly precise and small changes could lead erroneously to statistical rejection of the null hypothesis and ultimately to an incorrect conclusion of market inefficiency. Further, if we return to the more realistic definition of market efficiency: that one must be able to capitalise on an observed inefficiency (Jensen, 1978), it is economic significance not statistical significance that should be of interest. To that end, as in Jegadeesh 1990, I develop a trading strategy to attempt to economically exploit the autocorrelation found in section IV.

Developing A Trading Strategy

The observed autocorrelation is statistically strongest, most consistent, and of the greatest magnitude at lag-one, and I therefore develop a contrarian trading strategy to exploit the negative first-order autocorrelation. The strategy is a modification of De Bondt and Thaler's 1985 contrarian strategy for exploiting the long term mean reverting tendency of US stocks.

Under the strategy all tradeable LSE listed securities at the start month of the sample are ranked in ascending order according to their simple return in the previous month[7]. From this ranking the fifty stocks with the largest negative returns in the previous month are assigned to a loser portfolio and the fifty stocks with the largest positive returns in the previous month are assigned to a winner portfolio. To exploit the negative autocorrelation the strategy then buys all stocks in the loser portfolio and sells all stocks in the winner portfolio to form a zero-net investment long-short portfolio of stocks[8]. This process is then repeated for each month in the sample period to re-balance the portfolio.

Strategy Performance

Table II shows the performance of the strategy over the sample period. On average the strategy generates 2.3 percent per month, over double the average monthly return of the equally weighted market index, and the performance is statistical distinguishable from zero.

[7] As in Jegadeesh 1990 to avoid using ex-post data in the portfolio formation I use the simple return rather than the estimated residual from the original model.

[8] The zero net investment refers to the fact the strategy finances the buying of the loser portfolio through the short sale of the winner portfolio.

Yet despite the strategy profits, and in contrast to the implications of the observed statistical relationship in Section IV, it is not the case that both portfolios show negative first order autocorrelation. In fact, it is only the loser portfolio that shows this relationship, generating a statistically significant average return of 2.6 percent per month, while the winner portfolio generates a return that is statistically indistinguishable from zero. It could then be argued that the creation of a winner portfolio is frivolous, it does generate no return after-all, but as will be seen later there are unexpected benefits to having a long-short versus directional portfolio to exploit inefficiency.

Table II

The table reports the average monthly returns for portfolios formed based on the past month's returns over the sample period 1st January 1994 to 31st December 2023 in percent. 'Winner' is the portfolio containing the stocks with the 50 largest return increases the previous month, 'Loser' is the portfolio containing stocks with the 50 largest return decreases the previous month and 'Loser – Winner' is the returns to the 'Loser' portfolio minus the 'Winner' portfolio. 'EWI' is the average monthly return on the equal-weighted index of all LSE listed stocks throughout the sample period. Notation is consistent with earlier tables.

	Sample Months		
Portfolio	Jan. – Dec.	Jan.	Feb. – Dec.
Winner	0.33 (0.98)	1.06 (1.09)	0.27 (0.74)
Loser	2.61 (5.73)	5.84 (3.65)	2.32 (4.90)
Loser - Winner	2.23 (6.36)	4.79 (3.93)	2.05 (5.50)
EWI	0.96 (3.88)	1.83 (2.39)	0.088 (3.38

T-statistics are presented in parenthesis are calculated under the assumption the returns are equal to zero using the Student's t-distribution.

As in Section IV it is prudent to investigate whether anomalous behaviour in January drives the returns. It can be seen in Table II however that the strategy's performance is statistically different from zero both inside and outside of January. As would be expected after observing the January Effect in Section IV the returns to the strategy are highest in the month of

January with the returns in January roughly 2.7 percentage points higher on average than other months. T-statistics are lower for the January only sample and while this could indicate greater variation in returns during January it could also be attributable to a lower power of the tests due to fewer observations (30 vs 330).

To truly estimate the economic significance of the strategy transaction costs should be accounted for. As the strategy uses monthly returns to form portfolios it is highly likely that the portfolio turnover is close to 100 percent each month. Using this upper bound for turnover and using a round-trip transaction cost of 0.5 percent (Jegadeesh, 1990) the upper bound of the zero net investment portfolio transaction cost is 1 percent of the total value of the long or short portfolio (Jegadeesh, 1990). Accounting for this the average monthly return of the strategy falls to 1.3 percent but remains statistically different from zero[9]. It therefore seems reasonable to conclude that the returns to the contrarian trading strategy are both statistically and economically different from zero.

[9] The associated t-statistic is 3.57.

VI. Risk Adjustments

Abnormal Returns and Risk Premium

So far in the contrarian trading strategy analysis very little has been said about risk and as a result it is entirely possible that the results up to this point do not challenge market efficiency. While there is negative autocorrelation in the loser portfolio and the potential for profitable trading the returns may still simply be the result of risk compensation. If this is the case, then the contrarian trading strategy selects a loser portfolio of stocks that are on average risker than the winner portfolio of stocks. This too would help to explain why the loser portfolio is the only one seen to exhibit negative autocorrelation and generate return, it is simply that previous loser stocks contain risk, and resultingly investors demand a return for holding them.

To test the hypothesis that the returns are the result of risk I draw from De Bondt and Thaler (1987) using the CAPM to define risk in terms of the market and risk-free rate. To do this I regress using OLS the monthly returns of the contrarian strategy $R_{C,t}$[10] on the market risk premium: $(R_{M,t} - R_{f,t})$. $R_{M,t}$ is the return on the equal weighted LSE market index portfolio at time t and $R_{f,t}$ is the risk-free rate at time t, specified as the yield on a 1-month T-Bill. The model is thus:

$$R_{C,t} = \alpha_C + \beta_C\left(R_{M,t} - R_{f,t}\right) + \epsilon_{C,t}$$

Where α_C is the abnormal return to the trading strategy unexplained by systemic market risk and β_C is the difference between the risk of the loser and winner portfolios. The equation, as in De Bondt and Thaler (1987), is also estimated separately for the winner and loser portfolios with $R_{w,t} - R_{f,t}$ and $R_{L,t} - R_{f,t}$ as dependent variables where $R_{w,t}$ is the return to the winner portfolio at time t and $R_{L,t}$ is the return to the loser portfolio at time t.

[10] A reader may question why I do not subtract the risk-free rate from $R_{C,t}$. As $R_{C,t} = R_{L,t} - R_{W,t}$ the return in excess of the risk free rate for the contrarian strategy is $\left(R_{L,t} - R_{f,t}\right) - \left(R_{W,t} - R_{f.t}\right) = R_{L,t} - R_{W,t} = R_{c,t}$

Table III

Market Risk Adjusted Returns to The Contrarian Trading Strategy

The table reports the results of the OLS regression model: $R_{P,t} = \alpha_P + \beta_p(R_{M,t} - R_{f,t}) + \epsilon_{P,t}$ where $R_{P,t}$ is the return on the specified dependent variable portfolio at month t, α_P is the abnormal return on the specified dependent variable portfolio when adjusting for market risk, $(R_{M,t} - R_{f,t})$ is the market risk premium, $R_{M,t}$ is the return on the equal-weighted index of all LSE listed stocks in month t and $R_{f,t}$ is the risk free rate at month t defined as the 1-month yield on a T-bill. Remaining notation is consistent with earlier tables.

	Independent Variables	
Dependent Variables	α_P	$(R_m - R_f)$
$R_W - R_f$	-0.002 (-0.88)	1.023 (90.78)
$R_L - R_f$	0.019 (4.29)	1.016 (56.50)
$R_{C,t}$	0.021 (4.17)	-0.008 (-0.35)

T-statistics are presented in parenthesis and are heteroskedasticity robust using HC3 as outlined by Holigan and Welsch (1973). They are computed under the assumption the co-efficient estimates are equal to zero.

Table III shows the results of the OLS regressions. The regression with $R_{C,t}$ as the dependent variable shows that the contrarian trading strategy generates a statistically significant abnormal return of 2.1 percent per month once accounting for market risk. Moreover, the estimate of β_C is equal to -0.008 and not significantly different from zero, implying that both the winner and loser portfolios have roughly the same risk level. This leads to the conclusion that the returns of the strategy are not generated by the loser portfolio holding inherently risker stocks than those in the winner portfolio. This can be seen clearer in the regressions with $R_{w,t} - R_{f,t}$ and $R_{L,t} - R_{f,t}$ as the dependent variables, with both the winner and loser portfolios having Beta estimates close to one. Interestingly not only do the Beta estimates show the winner and loser stocks have the same risk but they also show that the individual portfolios are, on average, no risker than the market. Hence the hypothesis that the returns to the contrarian trading strategy are the result of excess risk appears incorrect and the Beta estimate of zero shows the trading strategy is market neutral, hedging any systemic market risk away through its short position in the winner portfolio: a rather large benefit of not simply going long the previous loser stocks.

De Bondt and Thaler (1987) go one step further though before concluding returns are not the result of excess risk and hence so do I. Chan 1988 notes that risk relative to the market is not a constant but instead varies with both the market direction and time. The argument, as laid out by De Bondt and Thaler (1987), is that the Beta values vary in response to common state variables and thus one cannot assume them a constant. To investigate the impact of varying Betas I follow De Bondt and Thaler (1987) to calculate two Beta values, one for when the market return is positive and one for when the market return is negative. To investigate the impact of varying Betas I regress the returns of the contrarian strategy using OLS under the following model (De Bondt and Thaler, 1987):

$$R_{C,t} = \alpha_C + \beta_{CU}(R_{M,t} - R_{f,t})D + \beta_{CD}(R_{M,t} - R_{f,t})(1 - D) + \epsilon_{C,t}$$

Where D denotes a dummy variable equal to one if $R_{M,t} > 0$ and zero if $R_{M,t} < 0$. Again, I run the model separately for the winner and loser portfolios individually with $R_{w,t} - R_{f,t}$ and $R_{L,t} - R_{f,t}$ as the dependent variables.

Table IV shows that once the Betas vary according to the market direction the estimate α_C reduces to become statistically indifferent from zero. These results confirm that Beta values are not constant and vary with the market as posited by Chan (1988). Despite the reduction of the abnormal profit though the Beta estimates do not show the return as the result of excess risk. Instead, the positive Beta when the markets rises and negative Beta when the market falls shows that the strategy consistently generates return regardless of the market's underlying movement. Not only does this confirm the market neutrality of the contrarian trading strategy but highlights the possibility the strategy exploits a true mispricing that is unrelated to market movements. The regressions with $R_{w,t} - R_{f,t}$ and $R_{L,t} - R_{f,t}$ as the dependent variables too show how the market neutrality in the non-varying Beta model is maintained with the winner portfolio losing more than the loser portfolio in down markets and the loser portfolio gaining more than the winner portfolio in up markets.

Table IV

Market Risk Adjusted Returns to The Contrarian Trading Strategy with Varying Betas

The table reports the results of the OLS regression model:

$R_{P,t} = \alpha_C + \beta_{PU}(R_{M,t} - R_{f,t})D + \beta_{PD}(R_{M,t} - R_{f,t})(1 - D) + \epsilon_{P,t}$ where D is a dummy variable equal to one when $R_{M,t} > 0$ and equal to zero when $R_{M,t} < 0$. Remaining notation is consistent with earlier tables.

	Independent Variables		
Dependent Variables	α_P	$(R_M - R_f) \cdot D$	$(R_M - R_f) \cdot (1 - D)$
$R_W - R_f$	-0.004 (-1.32)	1.111 (9.31)	1.018 (81.14)
$R_L - R_f$	0.003 (0.76)	1.870 (11.51)	0.964 (56.79)
$R_{C,t}$	0.007 (1.30)	0.769 (3.37)	-0.054 (-2.40)

T-statistics are presented in parenthesis and are heteroskedasticity robust using HC3 as outlined by Holigan and Welsch (1973). They are computed under the assumption the co-efficient estimates are equal to zero.

It seems illogical to conclude that a trading strategy that generates return in both up and down markets does so through market related systemic risk and thus I conclude the same as De Bondt and Thaler (1987): systemic market risk compensation is not the driver of returns to the contrarian trading strategy.

Size Based Risk Factors

Having concluded that systemic risk is insufficient to explain returns to the contrarian trading strategy I now turn to another potential source of risk: firm size.

Size-based risk was noted by Fama and French (1993) in their influential paper 'Common risk factors in the returns on stocks and bonds'. The argument for size risk is that small companies operate with less market diversification and power in addition to having to contend with a more volatile business environment (Hayes, 2023). As a result, small firms pose a greater risk of bankruptcy than their larger counterparts and because of this, risk averse investors demand a higher return for holding stock in small companies. If it is the case that size-based risk drives the return of the contrarian trading strategy the loser portfolio must then hold stocks with more size-based risk exposure than the winner portfolio. Under such a situation the returns to the trading strategy will be the result of investors demanding return for taking on excess size-based risk in the loser portfolio and hence not at odds with an efficient market.

Table V

Average Market Capitalisation of an Equity in Each Portfolio

The table reports the average market capitalisation of an equity in each portfolio throughout the entire sample period. 'All Stocks' is the average market capitalisation of a stock in the data sample across the sample period. Remaining notation is consistent with earlier tables.

Portfolio	Mean Market Capitalisation (million)
Winner	£1,137
Loser	£857
All Stocks	£1,575

Table V shows the average market capitalisation of equities in the respective portfolios. Equities in the winner and loser portfolios both have an average market capitalisation below that of the average LSE stock and further, giving initial credibility to size-based risk driving returns, the average market capitalisation of an equity in the loser portfolio is over £300 million less than that of an equity in the winner portfolio.

To test if size-based risk can explain the returns to the contrarian trading strategy I emulate Jegadeesh (1990) and construct a specialised three factor model:

$$R_{C,t} = \alpha_C + \beta_{CS} R_{S,t} + \beta_{CM} R_{M,t} + \beta_{CL} R_{L,t} + \varepsilon_{C,t}$$

Where $R_{S,t}$, $R_{M,t}$ and $R_{L,t}$ are the returns of small-, medium-, and large-firm size-tercile portfolios at time t[11]. I use OLS for parameter estimation and as with market-based risk I run the model on the winner and loser portfolios separately too, this time using $R_{L,t}$ and $R_{W,t}$ as dependent variables (Jegadeesh, 1990).

Table VI

Size-based Risk Adjusted Returns to the Contrarian Trading Strategy

The table reports the results of the OLS regression model: $R_{P,t} = \alpha_P + \beta_{PS}R_{S,t} + \beta_{PM}R_{M,t} + \beta_{PL}R_{L,t} + \varepsilon_{P,t}$ where $R_{S,t}$, $R_{M,t}$, and $R_{L,t}$ are the returns of small-, medium-, and large-firm size-tercile portfolios at time t formed using market capitalisation. Remaining notation is consistent with earlier tables.

	Independent Variables			
Dependent Variables	α_P	R_S	R_M	R_L
R_W	-0.007 (-3.47)	0.470 (4.15)	0.296 (1.31)	0.358 (1.54)
R_L	0.016 (5.77)	1.055 (7.46)	0.188 (0.89)	0.348 (2.11)
R_C	0.022 (6.04)	0.586 (2.81)	-0.109 (-0.33)	-0.009 (-0.03)

T-statistics are presented in parenthesis and are heteroskedasticity robust using HC3 as outlined by Holigan and Welsch (1973). They are computed under the assumption the co-efficient estimates are equal to zero.

Table VI shows the results of the regressions. The positive and significant coefficient estimate on $R_{S,t}$ for the contrarian strategy returns shows that the loser portfolio does have greater exposure to size-based risk than the winner portfolio. Despite this though, the estimate of α_C is still positive at 2.2 percent and significant, implying that the difference in size-based risk between portfolios is unable to fully explain the returns to the contrarian trading strategy. Interestingly the regressions with $R_{L,t}$ and $R_{W,t}$ as dependent variables show that when accounting for size-based risk both portfolios, not just the loser portfolio, generate abnormal returns. What is even more striking is that once adjusted for size risk the winner portfolio has an abnormal return of -0.7 percent per month. Demonstrating that once adjusted

[11] The terciles are formed using market capitalisation.

for size-based risk compensation the winner portfolio may exhibit some level of negative autocorrelation.

The contrarian trading strategy does then have some exposure to size-based risk. The loser portfolio holds equities with an average market capitalisation nearly £300 million less than the winner portfolio and part of the contrarian strategy returns can be explained by compensation for the risk of this. Yet the risk exposure is insufficient to explain the returns in full and as a result it appears ultimately that the returns to the contrarian trading strategy are robust to systemic and size-based risk adjustments.

The implication of this robustness is severe: the UK equity market is not weak-form efficient. There exists not only a level of predictability in UK equity returns but one that may be exploited by financial market participants for economic return without taking on excess risk. The onus now falls to explaining why such an inefficiency might exist.

VII. Market Efficiency and Illiquidity

Chordia, Roll, and Subrahmanyam (2008) demonstrate that market efficiency is inversely related to illiquidity. They hypothesize that in illiquid markets fewer arbitragers operate and as a result mispricing can remain. Building on this Hameed, Kang, and Viswanathan (2010) find evidence supporting the hypothesis that capital constraints cause liquidity reductions in equities that undergo large price declines. Furthering their research, Hameed, Kang, and Viswanathan (2010) then illustrate that because of this illiquidity one can generate economically significant returns by buying stocks with large prices declines in the previous period. Their research confirms not only the predictability of returns in past loser stocks, as found in this paper, but further evidences the inverse relationship between market efficiency and illiquidity uncovered by Chordia, Roll, and Subrahmanyam (2008).

As a result of those papers' findings, and the observation that it is the loser portfolio that generates much of the contrarian trading strategy return, I hypothesise that the predictability of individual equity returns is the result of a rise in illiquidity in stocks that have experienced price declines causing a reduction in arbitrage activity.

To understand the mechanism behind this hypothesis and why illiquidity leads to inefficiency, consider an inventory or funding constrained market maker who operates as the sole liquidity provider for an equity. Under balanced order-flow the market maker quotes bids and asks around the fair price without hitting their constraint. If, however, order-flow becomes strongly directional the market maker reaches their constraint and can no longer quote one side of the bid-ask spread, causing prices to begin to deviate from their fair value. In a highly efficient market arbitragers would identify this mispricing instantaneously and enter the market to profit from the price deviation, simultaneously allowing the market maker to off-load their inventory and begin quoting again. When a market is illiquid however fewer arbitrage actors operate (Chordia, Roll, and Subrahmanyam, 2008) due to higher transaction costs and lower expected profits[12] and if sufficiently few arbitragers operate this can lead the mispricing remaining, resulting in market inefficiency (Chordia, Roll, and Subrahmanyam, 2008). This effect would be compounded in cases of price decreases as collateral values also decrease (Hameed, Kang, and Viswanathan, 2010), preventing market participants from being

[12] In an illiquid market trading volumes lower and as a result arbitragers might not be able to enter the market in sufficient size to make the marginal benefit of exploiting a price deviation worth the marginal cost of finding it.

able to take on new positions to return the asset to fair-value, with some market participants even forced into liquidating existing positions to avoid a margin call: increasing the directional order-flow, illiquidity, and reduction in arbitrage activity.

If the mechanism of the hypothesis above is correct it would then be expected that returns to the contrarian trading strategy, and loser portfolio in particular, rise when overall market liquidity falls and it is this I seek to test.

Without orderbook data market liquidity is hard to measure directly, however taking inspiration from Nagel (2010) I look to test the impact of illiquidity on the trading strategy's profits by using market volatility as an instrumental variable for market illiquidity[13]. The abnormal returns to the contrarian trading strategy once adjusted of for illiquidity are estimated using OLS under the model:

$$R_{c,t} = \alpha_C + \lambda_c \sigma_{M,t} + \beta_{cs} R_{s,t} + \varepsilon_{c,t}$$

Where $\sigma_{M,t}$ is the daily standard deviation of the FTSE All-Share index from its daily month t mean. I include $R_{s.t}$ as a control for the size-based risk compensation found in Section VI. Again, I also run the analysis on the winner and loser portfolios independently with $R_{L,t}$ and $R_{W,t}$ as dependent vairables.

Table VII shows the results of the model. The most striking finding is that once we account for market volatility[14] and size-based risk exposure the abnormal returns of the strategy fall to become statistically indistinguishable from zero. Further the coefficient estimate on market volatility is highly positive and significant. The results indicate that for a 1 percent increase in daily volatility, and a corresponding increase in illiquidity, the returns to the contrarian trading strategy rise by 2.3 percentage points, as would be expected under the hypothesis. Looking at the individual portfolio regressions there are also some deeply interesting findings. Firstly, once market volatility (and hence liquidity) is accounted for the abnormal returns to the loser portfolio become statistically insignificant. As hypothesised too the effect

[13] See Adrian and Shin (2010); Ang, Gorovy and Van Inwegen (2011); and Ben-David, Franzoni and Moussawi (2011) for links between volatility, leverage and liquidity. I conform to Nagel, 2010 in using a measure volatility as an instrumental variable as I am unable to test relevance directly.
[14] And by proxy illiquidity.

of illiquidity is higher for the loser portfolio than the overall strategy with a 1 percent increase in volatility leading to a 2.7 percent increase in loser portfolio returns. Moreover, the results show that the winner portfolio returns are the result of size-based risk exposure with the coefficient estimate on market volatility not discernibly different from zero. Additionally, the abnormal return to the winner portfolio is statistically insignificant, a change from the size-based risk model. This change is most likely the result of the variance in returns due to market volatility and illiquidity being attributed to the intercept in the size-based risk model but being controlled for in the liquidity one.

Table VII

Abnormal Returns to the Contrarian Trading Strategy Adjusting for Market Illiquidity and Size Based Risk

The table results of the OLS regression model: $R_{P,t} = \alpha_P + \lambda_P \sigma_{M,t} + \beta_{Ps} R_{s.t} + \varepsilon_{P,t}$ where $\sigma_{M,t}$ is the daily standard deviation of returns to the FTSE-all Share Index including dividends from its month t mean. Remaining notation is consistent with earlier tables.

	Independent Variables		
Dependent Variables	α_P	σ_M	R_S
R_W	-0.004 (-0.65)	0.419 (0.62)	1.055 (11.91)
R_L	-0.004 (-0.76)	2.709 (4.59)	1.639 (29.65)
R_C	0.000 (-0.02)	2.290 (2.63)	0.585 (5.74)

T-statistics are presented in parenthesis and are heteroskedasticity robust using HC3 as outlined by Holigan and Welsch (1973). They are computed under the assumption the co-efficient estimates are equal to zero.

The results of the liquidity model provide strong evidence for the hypothesis that it is an illiquidity driven reduction in arbitrage activity in past loser stocks that causes the weak-form inefficiency within UK equities. The implication of this evidence is that the informational content of past prices is not fully reflected in current prices with past prices containing information about future arbitrage activity in the market for an equity. As a result, I conclude that the observed first-order negative autocorrelation and abnormal returns to the contrarian trading strategy are the result of a true market inefficiency.

VIII. Limitations and Robustness

Bid-Ask Bounce

One of the biggest potential limitations to this paper is the fact LSPD uses transaction rather than quote prices in return calculation. Transactions on exchanges are executed at the respective bid or ask price and as a result, in a situation where the mid-price quote remains constant, the observed negative first order autocorrelation and profits to the contrarian trading strategy could simply be the result of the last transacted price oscillating between the bid and ask (Scholes and Williams, 1977): the so-called bid-ask bounce.

While I am unable to test the impact of this effect directly due to data constraints there are several reasons to believe, at least partially, that the results are not purely driven by bid-ask bounce. Firstly, the interval of a month between portfolio formation and re-balancing makes it highly unlikely that the price of each equity has not evolved in some capacity. And while the average market capitalisation of an equity in the contrarian trading strategy is below the average market capitalisation of an LSE equity it seems very difficult to argue that equities with an average market cap of £800 Million in the loser portfolio and £1.1 Billion in winner portfolio see no price evolution in a month. Secondly, Nagel (2011) uses both transaction and quote data to investigate a daily short-term reversal (contrarian) trading strategy in US equities and finds that while there is a reduction in return when using quoted prices, it remains significantly positive. By extrapolation if profits remain significant at a daily level, they should do at the monthly one too[15].

Moreover, a re-interpretation of the contrarian trading strategy may mean the use of transaction prices does not matter at all. The observed hedging of market risk through the winner portfolio in the trading strategy allows for the interpretation of the strategy as one belonging to a de-facto delta neutral market maker. And as Nagel 2011 points out the return derived from transaction prices represents the hypothetical profits of a market maker who sees their limit orders executed at quoted prices earning the non-adverse selection component

[15] There are, of course, arguments around UK-US equity market differences and methodical differences that should mean this extrapolation is taken with some sense of caution.

of the bid ask spread. Thus, if we accept the strategy as belonging to a market maker one can interpret all the results of this paper, even with bid-ask bounce, as is.

That said, I do not claim bid-ask bounce may not influence these findings and therefore I leave open for future research the impact of bid-ask bounce.

Subperiod Analysis

Blitz, Frient and Honarvar (2023) find that a contrarian trading strategy like the one proposed in this paper has seen weakening profits over the past 30 years. Therefore, to test whether returns to the contrarian trading strategy have decreased over time I split my data sample into three equal 10-year subperiods and run the contrarian trading strategy.

Table VIII

Returns to The Contrarian Trading Strategy in Three Equal Subperiods

The table shows the average monthly percentage returns to the contrarian trading strategy over three ten-year subperiods: 1994-2003, 2004-2013 and 2014-2023 where subperiods begin on the 1st of January and end on 31st of December of the specified year. Notation is consistent with earlier tables.

	Subperiod		
Portfolio	1994 - 2003	2004 - 2013	2014 - 2023
Winner	0.00 (-0.03)	0.71 (1.29)	0.32 (0.67)
Loser	4.17 (5.10)	1.88 (2.37)	1.80 (2.41)
Loser - Winner	4.19 (5.69)	1.17 (2.24)	1.48 (2.69)

T-statistics are presented in parenthesis are calculated under the assumption the returns are equal to zero using the Student's t-distribution.

Table VIII shows the results of the subperiod analysis. While there is some level of variation in the statistical significance of the returns to the strategy the subsamples show that returns have remained consistently significant at the 5 percent level throughout. The returns to the contrarian trading strategy are strongest in the first sub- period with the strategy generating a mean return of 4.2 percent per month, potentially suggesting there has been an increase in market efficiency in the past 20 years. The returns then decrease towards 1% for the remaining two subsamples but remain statistically robust at the 5 percent and 1 percent levels respectively.

An astute reader may, at this point, recall from Section IV that 1 percent was equal to the transaction cost of the contrarian trading strategy and therefore while agreeing the results are statistically robust would conclude the results may no longer be economically. To the astute reader I highlight two key points. Firstly, the portfolio turnover of 100 percent used to calculate the monthly transaction cost was an upper bound. It is in fact unlikely there would be 100 percent turn over with Jegadeesh (1990) finding that turnover is closer to 90 percent in his paper's strategy. Secondly, and more importantly, I used 0.5 percent as the round-trip transaction cost for consistency with Jegadeesh (1990) but even in 1990 this was considered an upper bound (Berkowitz et al., 1988). In fact, with modern brokers (e.g. Alpaca Markets, Interactive Brokers) there exists some commission-free trading and so transaction cost analysis may become largely redundant or at the very least have a much more minimal impact on strategy profit than I first proposed.

Like the impact of bid-ask bounce though I leave open for future research the impact of more realistic transaction costs on the contrarian trading strategy returns.

IX. Conclusion

This paper investigates whether the weak-form efficient market hypothesis holds within the UK equity market between 1994 and 2024. I first test weak-form efficiency under its strictest interpretation following Jegadeesh 1990 to do so. I find that monthly equity returns exhibit statistically significant negative autocorrelation at the first order and positive autocorrelation at the eleventh, twelfth and twenty-fourth order. From this I conclude that the UK equity market exhibits statistically robust weak-form inefficiency and that UK equity prices do not follow a random walk. Further I show that inefficiencies found in the US equity market are present in the UK.

Taking a more realistic approach to the definition of market efficiency as in Jensen 1978 I then seek to test whether this statistical relationship can be exploited by market participants. To do this I develop a contrarian trading strategy based off De Bondt and Thaler 1985 whereby I select the fifty equities with the highest return in the previous month to form a winner portfolio and the fifty equities with the lowest return in the previous month to form a loser portfolio, selling the winner portfolio and buying the loser portfolio and holding each for a month. I find the contrarian trading strategy generates a statistically significant average monthly return of 2.3 percent throughout the sample period. When adjusted for an upper bound of transaction costs the strategy still generates a statistically significant monthly return of 1.3 percent.

To explore whether the returns to this strategy are the result of excess risk taking and therefore not at odds with the efficient market hypothesis I adjust the returns to the contrarian trading strategy for both market based and size-based risk. I find that once adjusted for market-based risk and size-based risk the contrarian trading strategy still generates returns of 2.1 percent and 2.2 percent respectively. I therefore conclude that the UK equity market exhibits weak-form inefficiency when defined in both the strictest and economically exploitable sense.

Eager to understand what drives this inefficiency I hypothesise that it is the result of an illiquidity induced reduction in arbitrage activity (Chordia, Roll, and Subrahmanyam, 2008) in past loser stocks. To test whether this is the case I draw from Nagel 2011 and regress the returns of the contrarian trading strategy on market volatility, using it as an instrumental variable for illiquidity. I hypothesise that if the observed market inefficiency results from illiquidity induced reductions arbitrage activity the profits to the contrarian trading strategy should increase when market illiquidity does. I find this is the case and moreover I find that once illiquidity and risk compensation are considered the abnormal returns to the contrarian trading strategy fall to zero. As a result, I conclude there is strong evidence supporting the hypothesis that the weak-form market inefficiency in UK equities found in this paper stems from an illiquidity induced reduction in arbitrage activity in past loser stocks.

Potential areas for future research include looking to assess the impact of bid-ask bounce and more realistic transaction costs on the economic exploitability of the inefficiency. And additionally, while I find evidence weak-form inefficiency is a result of reduction in arbitrage activity I do so indirectly, creating a lucrative area for future research in investigating the relationship using order-book and high frequency data.

For now, though I leave these areas to future research.

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Appendix

Appendix A: Derivation of covariance estimate for the empirical test in Section IV

To show that $\frac{cov_i(R_{i,t}-\overline{\mu_\iota},R_{i,t-j})}{var_i(R_{i,t-j})}=\frac{cov_i(z_{i,t},z_{i,t-j})}{var_i(R_{i,t-j})}$ consider the numerator and denominator in turn:

Numerator:

First consider the random walk return model derived in Section IV:

$$R_{i,t}=\overline{\mu_\iota}+z_{i,t}$$

Which can be rearranged to:

$$R_{i,t}-\overline{\mu_\iota}=z_{i,t}$$

Substituting in:

$$cov_i\left(R_{i,t}-\overline{\mu_\iota},R_{i,t-j}\right)=cov_i\left(z_{i,t},\overline{\mu_\iota}+z_{i,t-j}\right)=cov_i\left(z_{i,t},\overline{\mu_\iota}\right)+cov_i\left(z_{i,t},z_{i,t-j}\right)$$

As $\overline{\mu_\iota}$ is a constant then:

$$cov_i\left(R_{i,t}-\overline{\mu_\iota},R_{i,t-j}\right)=cov_i\left(z_{i,t},\overline{\mu_\iota}+z_{i,tj}\right)=0+cov_i\left(z_{i,t},z_{i,t-j}\right)=cov_i\left(z_{i,t},z_{i,t-j}\right)$$

Denominator:

For $var_i\left(R_{i,t-j}\right)=\ var_i(z_{i,t-j})$ substituting the return model in again:

$$var_i\left(R_{i,t-j}\right)=\ var_i\left(\overline{\mu_\iota}+z_{i,t-j}\right)=var_i(\overline{\mu_\iota})+var_i\left(z_{i,t-j}\right)+2cov_i(\overline{\mu_\iota},z_{i,t-j})$$

Again as $\bar{\mu_i}$ is a constant:

$$var_i(\bar{\mu_i} + z_{i,t-j}) = 0 + var_i(z_{i,t-j}) + 0 = var_i(z_{i,t-j})$$

Combining:

$$\frac{cov_i(R_{i,t} - \bar{\mu_i},\ R_{i,t-j})}{var_i(R_{i,t-j})} = \frac{cov_i(\ z_{i,t}, z_{i,t-j})}{var_i(z_{i,t-j})}$$

And therefore if $cov_i(\ z_{i,t}, z_{i,t-j}) \neq 0$ the covariance of returns are not independent and past residual returns can be used to predict future returns, violating weak-form market efficiency.

Appendix B: OLS regression robustness tests

Durbin-Watson Test: this test assesses the autocorrelation of residuals. The test value falls between 0 and 2. Values between 1.5 and 2.5 are considered to indicate no autocorrelation in residuals is present.

White's Heteroskedasticity Test: this test asses the heteroskedasticity. T-statistics are presented along with P-value for homoscedasticity in parenthesis.

Robustness Test for the model: $R_{P,t} = \alpha_P + \beta_P(R_{m,t} - R_{f,t}) + \epsilon_{P,t}$

	Durbin-Watson Test Value	White's Test T-Statistic	Adjusted R^2
$R_W - R_f$	1.584	1.924 (0.382)	0.960
$R_L - R_f$	1.647	24.439 (0.000)	0.925
R_C	1.688	6.731 (0.035)	-0.002

Robustness Test for the model: $R_{P,t} = \alpha_P + \beta_{PU}(R_{m,t} - R_{f,t})D + \beta_{PD}(R_{m,t} - R_{f,t})(1 - D) + \epsilon_{P,t}$

	Durbin-Watson Test Value	White's Test T-Statistic	Adjusted R^2
$R_w - R_f$	1.587	2.783 (0.595)	0.960
$R_L - R_f$	1.726	2.878 (0.578)	0.934
R_C	1.723	5.087 (0.279)	0.054

Robustness Test for the model: $R_{P,t} = \alpha_P + \beta_{PS}R_{S,t} + \beta_{PM}R_{M,t} + \beta_{PL}R_{L,t} + \varepsilon_{P,t}$

	Durbin-Watson Test Value	White's Test T-Statistic	Adjusted R^2
R_w	1.601	75.324 (0.000)	0.647
R_L	1.487	12.164 (0.204)	0.727
R_C	1.546	61.609 (0.000)	0.106

Robustness Test for the model: $R_{P,t} = \alpha_P + \lambda_{c\sigma,t}\sigma_{M,t} + \beta_{cs.t}R_{s.t} + \varepsilon_{P,t}$

	Durbin-Watson Test Value	White's Test T-Statistic	Adjusted R^2
R_w	1.727	7.205 (0.206)	0.590
R_L	1.580	31.869 (0.000)	0.726
R_C	1.556	10.220 (0.069)	0.133