The Negative Credit Risk-Return Puzzle: A Behavioural Story

Chris Godfrey
ICMA Centre, Henley Business School, University of Reading

Chris Brooks
ICMA Centre, Henley Business School, University of Reading

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Abstract

Prior research has documented that, counter-intuitively, high credit risk stocks earn lower – not higher – returns than low credit risk stocks. In this paper we provide evidence against rational expectations explanations, and argue that behavioural considerations deriving from the disposition effect combine with limits to arbitrage factors to explain this apparent anomaly. In particular, we confirm and advance beyond the rationales suggested by previous studies, and demonstrate that the negative pricing of credit stocks is driven by the underperformance of stocks which have both high credit risk and which have suffered recent relative underperformance, and that their ongoing poor performance can be explained by a small subset of stocks which share three characteristics: they are held disproportionately by investors subject to the disposition effect; they have large unrealised capital losses, which bias these investors towards retaining them in the hope of riding out the loss; and they have high levels of a combination of four limits-to-arbitrage factors – idiosyncratic risk, turnover, illiquidity and bid-ask spreads. Collectively, these impede the arbitrageurs' correction of the mispricing induced by disposition investors, especially on the short leg of the trade, where commonly reported returns are unattainable.

Keywords: behavioural finance, relative distress, credit risk premium puzzle, asset pricing, limits to arbitrage

JEL Classifications: C31, C55, D03, G12

Contact: Chris Godfrey, ICMA Centre, Henley Business School, University of Reading, Whiteknights, Reading RG6 6BA, UK; tel: (+44) 118 378 8239; e-mail: C.Godfrey@icmacentre.ac.uk

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1 Introduction

1.1 Background and motivation

The usual assumption in the fixed income markets is that credit risk is positively priced – that is, investors expect that exposure to credit risk will be compensated by higher returns. Yet a variety of studies have found that it is actually rewarded by lower returns in cross-section among equities: Dichev (1998), Chen et al. (2010) and Chou et al. (2010) find credit risk to be negatively priced for US equities when using accounting-based ratios such as the Altman's (1968) z-score and the Ohlson's (1980) O-Score, as do Campbell et al. (2008) when employing a hazard-rate score, and Avramov et al. (2009) when sorting stocks on the basis of their Standard & Poor's issuer rating.

Broadly, attempts to explain this paradox fall into one of two philosophical paradigms – a rational pricing perspective and an investor behavioural one. Rational pricing arguments have started with the presumption that shareholders are able to endogenously default on the value of the firm's debt, expecting to recover a portion of the firm's value in bankruptcy resolution, and that their default option becomes increasingly important close to the default boundary. Approaches based on rational expectations, notably by George and Hwang (2010) , Garlappi and Yan (2011) and McQuade (2013), have received some prior empirical support but we present evidence against these below. Since the UK features a bankruptcy regime which strongly favours creditors and where shareholders are typically not able to strategically default on the firm's debt, we elect to use UK data to test our hypothesis; isolating the origin of the negative credit risk–return relation is greatly simplified if endogenous default by shareholders can be ruled out as a cause by the nature of the local bankruptcy code.

Turning to behavioural arguments, Avramov et al (2009) find that the negative credit risk-return relation derives primarily from the poor returns of stocks with very low credit ratings as they undergo downgrades, and find that these stocks have severe levels of some factors which hinder arbitrage or otherwise reduce the profitability of the professional undertaking of arbitrage, hereafter termed limits-to-arbitrage factors. They hypothesise that such stocks may be held disproportionately by investors subject to the disposition effect (hereafter, 'disposition investors'), and may simultaneously have high limits to arbitrage factors. However, they uncover no proof for the former, save for demonstrating that these stocks have lower levels of institutional ownership, and also, making the assumption that individual investors are more likely to be subject to the disposition effect.

We contribute to the literature by confirming and advancing upon many of the hypotheses in Avramov et al (2009): we show that the negative credit risk-return relation localises to those stocks with a large unrealised capital loss, where disposition investors would be predicted to retain such stocks in preference to selling, in the hope of riding out the loss and so causing overpricing. We also show that the localisation of the negative credit risk-return relation to stocks undergoing downgrades, noted by Avramov et al (2009), localises yet further to those stocks with the greatest unrealised capital losses, again suggesting a behavioural story. We further localise the origin of the negative credit risk-return relationship to stocks with high credit risk which have suffered low relative returns over the prior six months, that is, in the terminology of the momentum literature, which are 'Losers'. We provide evidence to suggest that these stocks are held disproportionately by disposition investors, and that they tend to have substantial aggregate unrealised capital losses, which the disposition effect predicts will bias such investors to retain them instead of selling them on the market. We suggest that this combination causes such stocks to become overpriced, and hence to suffer persistently low returns.

To explain why these stocks continue to suffer overpricing, we confirm the Avramov et al (2009) finding that these stocks also have high levels of limits-to-arbitrage factors, manifesting high idiosyncratic volatility, high illiquidity, wide bid-ask spreads and low turnover. Together, these hinder the correction of overpricing by arbitrageurs, so that the affected stocks remain overpriced and suffer low returns. If they did not suffer from these limits-to-arbitrage factors, arbitrageurs would be able to short such stocks down to more rational values.

In cross-section, stocks with more severe levels of these four limits-to-arbitrage factors we investigate have lower returns, all else being equal; each factor can be conceived of as creating an "arbitrage channel" surrounding the stock's fundamental price process, within which arbitrageurs are unable to correct a stock's overpricing by shorting it down. We advance on the hypothesis in Avramov et al (2009) that high credit risk stocks remain overpriced owing to limits to arbitrage factors, by showing that the negative pricing of credit risk in cross-section disappears when these four factors are jointly included. In effect, these high credit risk loser stocks lie at the upper end of the arbitrage channel jointly created by these four limits-to-arbitrage factors around the stock's fundamental price process, so that a simple combination of limits-to-arbitrage factors is capable of subsuming the negative pricing of credit risk in cross-section..

In this section of our analysis, an important precursor to our work is the study by Ali et al (2003), discussed in detail below, who provide an incomplete explanation for the book-to-market premium using limits-to-arbitrage factors. The cross-sectional pricing of book-to-market is partially explained in their study by the entry of factors relating to investor sophistication and arbitrage costs – notably, idiosyncratic risk; this is consistent with the Shleifer and Vishny (1997) thesis that risk associated with the volatility of arbitrage returns deters arbitrage activity and constitutes an important reason for the existence of mispricing related to book-to-market. They show that the book-to-market premium is significantly stronger among portfolios with high values of limits-to-arbitrage factors than among stocks with low costs of arbitrage, and that there are significant interactions in cross-section between book-to-market and a range of limits-to-arbitrage factors. The hint there is that the book-to-market premium is perpetuated by the high costs of arbitrage among some stocks.

A key intuition of this paper is that a similar model to that of Ali et al (2003), which explicitly includes a rich variety of limits-to-arbitrage factors, ought to be capable of explaining the negative pricing of credit risk in equities, another outstanding anomaly. Through the results presented in this paper, we argue that this is the case, and as such, it ought to be understood as a consequence of frustrated arbitrage among some stocks.

Finally, we provide additional evidence against the rational expectations explanations for the negative credit risk-return relationship: high credit risk stocks have poor returns not because investors are switching attention to a bankruptcy recovery process, where high distress firms choose low leverage or gain high exposure to innovations in market volatility, but because of a confluence of behavioural and limits-to-arbitrage factors in a small group of overpriced, high credit risk stocks. We thus seek to provide a parsimonious behavioural explanation of the outstanding anomaly of the negative pricing of credit risk among equities.

2 The negative pricing of credit risk in equities

2.1 The negative credit risk–return relation in US data

Whichever way credit risk has been measured, the general finding has been that stocks with greater degrees of financial distress suffer lower realised returns, all else being equal. The initial demonstrations of the negative credit risk–return relation define credit risk by means of accounting ratios, for example, Dichev (1998), using both the Altman's (1968) z-score and Ohlson's (1980) O-Score, Griffin and Lemmon (2002), using the Ohlson's (1980) O-Score, and Chen et al. (2010), who sort stocks based on Altman's (1968) z-score and the Ohlson's (1980) O-Score. Ferguson and Shockley (2003) construct a market value-weighted relative distress factor by double-sorting on Altman's (1968) z-score and market leverage in a similar way to the construction of the Fama-French (1993) factors, while Chou et al. (2010) employ a similarly-constructed market value-weighted Altman's (1968) z-score factor; both find distress risk to be significantly negatively priced in the cross-section for US stocks.

The negative credit risk–return relation persists where credit risk is measured by means of hazard rate measures (Campbell et al., 2008; Chava and Purnanandam, 2010), and when credit risk is measured using credit rating agency ratings (Avramov et al., 2009). One exception comes with the use of Credit Default Swap (hereafter CDS) spreads to infer relative distress: Friewald et al (2014) find a positive relationship between firms' CDS-implied market prices of risk, and realised returns. However, this study only uses CDS spreads for a sample of 675 US-based obligors, covering only a fraction of the sample of the stock universe used by previous studies, and a sample which necessarily consists of the largest, most liquid and least distressed firms, and is heavily reliant upon the assumption that "the market price of risk (the Sharpe ratio) must be the same for all contingent claims written on a firm's assets" (Friewald et al., 2014, p. 2419), an argument disputed by Kapadia and Pu (2012) and Choi and Kim (2015), who find that risk premia in the equity and bond markets are not integrated.

2.2 The negative credit risk–return relation in UK and other international data

The negative credit risk–return relation is also found in UK data, for instance, by Agarwal and Taffler (2008) using the Taffler (1983) z-score, Agarwal and Poshakwale (2010), who construct a z-score factor by a methodology similar to Chen et al. (2010), and by Agarwal and Bauer (2014), who confirm that credit risk is negatively priced in cross-section for the UK, whether measured by the Taffler (1983) z-score, a Shumway (2001) hazard rate model, or a Merton (1974) distance-to-default measure.

These conclusions are confirmed by a number of more recent papers making broad international surveys of the credit spread. Gao et al (2013) sort stocks from a wide range of countries on Moody's-KMV Expected Default Frequencies (hereafter, EDF), and find a significantly negative cross-sectional pricing of credit risk for European stocks in aggregate, and for the UK in particular. Eisdorfer et al (2013) construct Merton (1974) distance-to-default measures for the stocks of a number of countries, and again find a significantly negative pricing of credit risk for developed countries.

2.3 Mispricing and rational expectations explanations for the negative credit risk–return relation

One class of explanations posits that the negative credit risk–return relation is an outcome of investors maximising conventional utility functions under rational expectations; such explanations attempt to show how high credit risk stocks ought to be regarded, paradoxically, as less risky than low credit risk stocks. For example, George and Hwang (2010) argue that firms with high distress costs will choose lower leverage levels, whilst having higher exposure to systematic risk. Firms with low leverage will therefore tend to paradoxically experience lower returns, assuming investors realise the returns predicted by the CAPM.

Alternatively, Garlappi and Yan (2011) employ a model of endogenous default: if shareholders force debtholders to accept a write-down of their debt in bankruptcy resolution, they may be able to recover part of the residual firm value by defaulting strategically on their debt. They propose that high leverage actually reduces the equity beta when financial distress looms, as shareholders switch attention from the volatile value of the distressed company to the more stable value of the payoff they hope to achieve in the event of bankruptcy resolution. In a similar vein, Eisdorfer et al (2012) suggest that investors fail to appreciate the value of this option to default, leading them to strongly undervalue distressed stocks. However, the magnitude of this embedded "option to default" appears unrealistically large in the simulated results to produce the observed negative pricing of credit risk: the mean (median) relative misvaluation between the market and the model is a very surprising 1527% (678%) for the most undervalued tertile. McQuade (2013) proposes a further endogenous default model where excess expected returns are a combination of the risk premia due to its exposure to productivity risk and to its exposure to innovations in market volatility, so that the debt of a firm which is extremely close to default actually benefits from an increase in market volatility and thus hedges market volatility risk. Healthy firms therefore have higher variance risk premia than distressed firms, and a portfolio which is long healthy firms and short distressed firms should earn positive abnormal excess returns, giving rise to the observed negative pricing of credit risk.

Avramov et al (2011) seek to explain the low returns earned by both high credit risk stocks and high idiosyncratic volatility stocks in a rational expectations framework, using the "relative share" concept of Menzly et al. (2004), defined as the ratio of the long-run dividend share of a firm as a proportion of its current dividend share, with dividend share being the fraction of the dividend paid by the firm relative to the aggregate dividend. They propose that firms with low relative share have "low cashflow duration" and are more sensitive to firm-specific dividend shocks but have reduced exposure to shocks to the persistent economic growth rate, and hence low risk premia and low expected returns. If investors regard long-run cash flows as more risky than short-term cash flows, they will apply high risk premia to them, so that firms with low relative share are predicted to have low returns, high idiosyncratic volatility, high default risk and elevated levels of earnings forecast dispersion. However, some of the dividend share modelling in the paper appears unrealistic, with the petroleum industry forecast to yield 38.5% of the total aggregate US corporate dividend in the long term, up from 11.4% at the start of the sample period.

A similar hypothesis is advanced by Radwanski (2010), which relies upon a model economy in which a cointegrating relationship exists between aggregate consumption and dividends. Distressed firms have short expected maturities of cash flows, so that their prices are not as strongly influenced by shocks in the persistent conditional mean of consumption growth; they are therefore hypothesised to be safer, and hence have lower expected returns. In simulations, the model is able to qualitatively match some empirical features of returns of portfolios sorted on credit risk, but is unable to generate a negative pricing of credit risk which matches the observed magnitude.

Another class of explanations posits that investors universally misprice some aspect of risk in high credit risk stocks, and that it is this general failure to properly assess risk which generates the negative credit risk–return relation. For instance, Ozdagli (2013) proposes a model of company default and investor utility which suggests that if default probability is assessed under the risk-neutral measure rather than the real measure, then returns are increasing rather than decreasing with risk-neutral default likelihood. However, as noted previously, Kapadia and Pu (2012) find a lack of integration between the equity and CDS markets, so that risk premia are not integrated between them where limits-to-arbitrage factors are strong.

2.4 Evidence against rational expectations explanations for the negative credit risk–return relation

The rational expectations hypotheses all encounter serious difficulties in explaining the negative credit risk–return relation. In particular, they all assume that the task they must accomplish is to explain why *expected* returns decrease with increasing credit risk, when the evidence is that this is not the case; on the contrary, investors *do,* in fact, expect to be rewarded for bearing exposure to credit risk. Chava and Purnanandam (2010) derive *ex ante* expected returns from implicit costs of capital, and find that there is a significantly positive relationship between default risk and expected returns in cross section. A similar paradox occurs with respect to idiosyncratic volatility: investors *ex ante* expect to be rewarded for bearing exposure to elevated levels of idiosyncratic volatility (Spiegel and Wang, 2005; Fu, 2009). The challenge, then, is not to explain why expected returns for high credit risk stocks should be low, but why investors receive low *ex post* returns when they anticipate high, and this points to an analysis of investor behaviour and market function rather than of expected returns.

Secondly, the Garlappi and Yan (2011), Eisdorfer et al (2012) and McQuade (2013) hypotheses rely upon shareholders being able to recover part of the firm's value in bankruptcy. By the same token, these hypotheses imply that the negative pricing of credit risk ought to disappear in the UK context, where creditors' rights are far stronger (La Porta et al., 1998), since UK shareholders generally recover negligible amounts from a bankruptcy process. Davydenko and Franks (2008) find that the median recovery rate for senior secured debt in bankruptcy is 82% in the UK compared with 61% in Germany and 39% in France, and for unsecured creditors; "recovery rates for junior creditors are negligible" (Davydenko and Franks, 2008, p. 571), confirmed by Blazy et al. (2013). Franks and Sussman (2005) find that while UK banks typically do make efforts to rescue a distressed firm, they tend to be very tough in negotiating with it, so that UK firms do not default strategically in order to extract concessions from banks. If little is left over for junior unsecured creditors, it is surely safe to conclude that UK shareholders' residual claim can be assumed to be negligible once default has occurred.

If the rational expectations hypotheses reliant upon endogenous default were true, these ought to indicate that UK shareholders would tend to expect a negligible recovery in the event of default, and the negative pricing of credit risk ought to disappear in the UK. That it does not hints that the Garlappi and Yan (2011), Eisdorfer et al (2012) and McQuade (2013) explanations do not receive empirical support.

2.5 Behavioural expectations explanations for the negative credit risk–return relation

Avramov et al (2009) investigate the negative credit risk-return relation and suggest, in part, that it may derive from behavioural considerations. Employing a sample of US stocks with S&P credit ratings, they demonstrate that the effect derives principally from the lowest-rated stocks, so that it disappears if stocks rated lower than CCC+ are removed from the sample. They also find that the effect is greatest before and after downgrades in credit rating: the negative credit risk-return relation again disappears if stocks in the lowest decile of credit rating from the sample are deleted, three months before a downgrade to three months after. The shareholding structure of these poorly-rated companies also shifts around downgrades, so that the percentage of institutional holdings decreases from four months before the downgrade to the month of the downgrade, before then increasing for the four months after the downgrade. On this basis, they suggest that the disposition effect (Shefrin and Statman, 1985) causes retail investors to hold on to their high credit risk stocks around downgrades. However, as they point out, this does not explain why retail investors "should buy additional shares of these low-rated, financially-distressed stocks that are sold by institutions around downgrades," (Avramov et al., 2009, p. 497) and that this may be because they mistake such stocks for "good buys", having become "good bargains," a situation which is compounded by these stocks being least covered by analysts.

They further suggest that the mispricing of these stocks is compounded by limits-to-arbitrage factors, since these stocks show a monotonic increase in illiquidity as measured by the Amihud (2002) illiquidity ratio, from 12 months before a downgrade to 12 months afterwards. Following D'Avolio (2002), they use low institutional holdings, low share turnover and low free float as additional indicators of short selling constraints, and show that the negative credit risk-return relationship is only significant for the decile of greatest short selling constraints in each case.

In this paper, we investigate the Avramov et al (2009) hypotheses that the negative credit risk-return relation is caused by behavioural considerations, and provide further evidence that both the disposition effect and limits-to-arbitrage considerations are involved.

The rest of this paper is organised as follows: section 3 introduces the principles of the disposition effect and limits to arbitrage, section 4 describes the data and methodology, section 5 presents the empirical results, and section 6 concludes.

3 Behavioural and limits to arbitrage factors in asset pricing

3.1 The disposition effect

Disposition investors are those subject to the behavioural bias of the disposition effect (Shefrin and Statman, 1985), under which they are assumed to allocate gains and losses on each asset to separate mental accounts (Thaler, 1980, 1985), so that utility is assessed with reference to the position on each asset separately, rather than aggregating gains and losses across their whole portfolio. They are further modelled as possessing an S-shaped utility function, as characterised by the prospect theory of Kahneman and Tversky (1979), being concave-down in the region of gains but concave-up in the region of losses. In the domain of gains, they are modelled as being risk-averse, preferring to sell the asset early to lock in a sure gain, in preference to holding on to the asset with the potential for further appreciation; but in the domain of losses, are modelled as being risk-seeking, prefering to hold on to the asset in the hope of “riding out” the loss. This has been demonstrated in artificial trading simulations (Oehler et al., 2003), in studies of individual investors’ trading through brokerage accounts (Dhar and Ning Zhu, 2006; Goetzmann and Massa, 2008), and in analyses of the behaviour of investors on the entire Finnish and Taiwanese stock exchanges (Grinblatt and Keloharju, 2000; Barber et al., 2007).

Where disposition investors own a stock on which they have an unrealised capital gain (a "Winner" stock hereafter), they will tend to increase selling pressure in the stock, as they attempt to lock in a sure gain; conversely, where they own a stock with an unrealised capital loss (a "Loser" stock hereafter), they will tend to decrease selling pressure in the stock, as they preferentially retain the stock. Where limits-to-arbitrage factors frustrate the actions of arbitrageurs in correcting such overpricing, we should expect that disposition investors will cause Loser stocks to become overpriced, and that this overpricing will increase with the proportion of the stock owned by disposition investors. We here suggest that one reason that high credit risk Loser stocks become overpriced in the first place is that high credit risk stocks are owned disproportionately by disposition investors, and we test this prediction in the empirical results below.

3.2 Measuring the disposition effect

Whereas most studies measure unrealised capital gains or losses by using brokerage data, Grinblatt and Han (2005) calculate a stock-level proxy for the disposition effect which measures the unrealised net gain or loss of the marginal investor in a stock, termed the unrealised capital gains factor. They model demand for a stock in a market composed of rational investors and disposition investors, where the demand of both rational investors and disposition investors is a function of the difference between the currently-observed price and an unobservable, stochastic, fundamental price. Disposition investors will tend to sell stocks on which they have an unrealised capital gain (a "Winner" stock hereafter) too early and to hold on to stocks with an unrealised capital loss (a "Loser" stock hereafter) too long. Where limits-to-arbitrage factors frustrate the actions of arbitrageurs in correcting such overpricing, we should expect that disposition investors will cause Loser stocks to become overpriced, and that this overpricing will increase with the proportion the stock's owned by disposition investors.

The respective demand functions of rational investors and disposition investors are assumed to be:
Rational investors' demand: $D_t^{Rational} = 1 + b_t(F_t - P_t)$ (1)

Disposition investors' demand: $D_t^{Disposition} = 1 + b_t[(F_t - P_t) + \lambda(H_t - P_t)]$ (2)

where P_t is the price of the stock at time t, H_t is the historic or reference price at time t relative to which disposition investors measure their capital gains or losses, F_t is the fundamental value of the asset, following a random walk, which would form the prevailing price of the asset in the absence of disposition trading, λ is a scaling constant which controls the strength of the disposition effect among disposition investors, and the function b_t represents the slope of the rational component of the demand function for the stock.

In the context of the Grinblatt and Han (2005) market model, the limits-to-arbitrage hypothesis accounts for the finite price elasticity of rational investors, so that b_t in the above equations is not infinite, and rational investors do not deploy unlimited funds to eliminate mispricings in the stock. Mispricings due to the presence of disposition investors therefore persist. If disposition investors form a proportion μ of all investors, we can derive a market price by aggregating demand functions and assuming that the market clears, which turns out to be a weighted average of the fundamental value and the reference price:

$$P_t = wF_t + (1-w)H_t \quad (3)$$

where $w = \dfrac{1}{1+\mu\lambda}$. If each disposition investor can be assumed to use a different mental account for each stock, and the reference price at each time point used by disposition investors is their weighted average cost of the stock purchased, the reference price for disposition investors in aggregate turns out to be the weighted average of the previous period's reference price and the current market price:

$$H_{t+1} = V_t P_t + (1 - V_t) H_t \tag{4}$$

where V_t is the stock's volume at t. Grinblatt and Han show that keeping w and turnover V_t constant, the expected return is proportional to the unrealised capital gains factor $\left(\frac{P_t - H_t}{P_t} \right)$.

There is some good evidence that the model possesses explanatory power in the case of momentum. Grinblatt and Han (2005) test their model on a sample of US stocks for July 1967 to December 1996, and find that it is able to explain and subsume medium-term momentum, though it fails to explain short-term momentum.

3.3 The mode of action of limits to arbitrage

The theory of limits to arbitrage, as described by Shleifer and Vishny (1997), holds that arbitrage in financial markets is costly to execute, is risky, and tends to be undertaken by participants operating with limited capital, whose shareholders do not fully appreciate their trades. Professional arbitrageurs therefore stand exposed to fluctuations in asset prices, so that arbitrage trades which would be ultimately profitable in the long-term may show losses in the short-term, and the threat of capital withdrawal by shareholders in such circumstances makes them more cautious in entering into arbitrage trades, and less effective in bringing about market efficiency. Since arbitrageurs are typically not well-diversified, they argue that high volatility arising from noise trader sentiment makes arbitrage unattractive if it does not lead to increased expected profits. In particular, idiosyncratic volatility discourages arbitrage since it cannot be hedged. Financial market anomalies are therefore more likely to persist where market factors make arbitrage more risky or costly to execute.

To this, Miller (1977) adds the insight that arbitrage is more likely to be constrained on the trade leg requiring a short sale, since this requires that a stock be first borrowed from a willing counterparty, and the facility for stock lending in sufficient size may be limited; additionally, a short seller does not receive the cash equivalent of the share upon the sale, as the Black-Scholes (1973) model assumes, as this is normally retained as collateral by the stock lending agent. Although many proposed limits-to-arbitrage factors ought in theory to result in overpricing and underpricing with equal regularity, the additional difficulty of shorting means that the net effect will be that overpricing is more prevalent. We should therefore expect anomalies to derive their apparent profits from the short leg of the arbitrage transaction which would have to be effected in order to exploit them, as Finn et al (1999) find for the value and size premia. We should also expect to find that stocks with high levels of limits-to-arbitrage factors will tend to suffer low returns, owing to their persistent overpricing.

We may distinguish between three categories of limits-to-arbitrage factors:[1]

Firstly, factors which impede the adoption of short positions but not long positions, and so hinder the correction of overpricing but not underpricing: these include short selling costs, as modelled in Gromb and Vayanos (2010); whether collateral is classed as "general collateral" or "special collateral," as investigated by Ali and Trombley (2006); and low institutional ownership, which may limit the number of shares available to borrow, as studied by Duan et al (2010) and Ali and Trombley (2006).

Secondly, factors which impede the adoption of long positions but not short positions, and hinder the correction of underpricing. The factors in this category may include concentration limits by asset managers, but these are not likely to be significant.

Thirdly, limits-to-arbitrage factors which are symmetrical in impeding arbitrage positions in either direction. These include high leverage costs as modelled in Gromb and Vayanos (2010); wide bid-ask spreads; high illiquidity; low turnover; and high idiosyncratic volatility. In practice, though these ought to have bi-directional action, we expect to find that the additional constraints imposed by the difficulty of taking short positions will lead to these factors resulting in more overpricing than underpricing, that is, stocks with more severe levels of these factors will on average manifest lower returns and display stronger momentum effects.

Ordinarily, under classical asset pricing theory, we would expect that sources of risk which are systematic should earn positive risk premia – that is, investors will receive higher returns for accepting exposure to them. Limits to arbitrage factors, however, are frequently found to be *negatively* priced in cross-section, that is, stocks with higher exposure to the limits-to-arbitrage factor suffer *lower*, rather than higher, ex-post returns. While this may at first seem paradoxical, it arises as a necessary consequence of the tendency of such limits-to-arbitrage factors to impede arbitrage by frustrating the shorting of the stock. All else being equal, stocks with higher exposure to such factors therefore tend to remain overvalued, and suffer lower realised returns as a result.

If a limits-to-arbitrage factor impedes both the taking of long and short positions, then we should expect that it would contribute to both the elevated returns of prior Winners, as ranked by prior returns, and the depressed returns of prior Losers. Absent these factors, good (bad) news would be reflected immediately in the price of these stocks, but in their presence, the inability of arbitrageurs to force up (down) the price to the new fundamental value by taking sizeable long (short) positions is hindered, so that stock prices take longer to drift upwards (downwards) to the new fundamental value,

[1] We are grateful to Kim Kaivanto for suggesting this taxonomy.

and so exhibiting multi-period price momentum. We should therefore expect that momentum profits will tend to be stronger among stocks where limits-to-arbitrage factors are stronger. Additionally, if limits-to-arbitrage factors tend to induce abnormally low returns by frustrating the shorting of a stock, then we might expect that this would exacerbate the poor returns of Losers in cross-sectional momentum strategies, so that momentum profits will tend to derive predominantly from the underperformance of Losers rather than the superior performance of Winners among stocks experiencing higher limits to arbitrage.

In this paper, we consider four direct limits-to-arbitrage factors, namely, idiosyncratic volatility, illiquidity, the bid-ask spread and turnover. Idiosyncratic volatility and illiquidity have been established as forming limits-to-arbitrage factors in US data by Duan et al. (2010), and the bid-ask spread is an obvious addition. Further, low turnover makes arbitrage more difficult by increasing the time taken for an arbitrageur to enter or exit a position in size. This apparent *negative* pricing of limits-to-arbitrage factors in cross-section is a different phenomenon from the *positive* pricing of innovations in the aggregate level of these factors in time series. For example, Pástor and Stambaugh (2003) argue that aggregate market-wide illiquidity forms a non-diversifiable, systemic risk factor, and they posit that investors are compensated for bearing exposure to unexpected innovations in its level. However, the pricing of a stock's time-series weighting on the unexpected innovations in aggregate market-wide illiquidity may be very different from the pricing effects induced by the limits to arbitrage arising from its own illiquidity.

3.4 Turnover as a limit to arbitrage

If a stock has low turnover, it is likely to be more difficult to enter and exit positions in a timely manner, and hence the arbitrageur is likely to be more exposed to adverse stock movements in an arbitrage transaction. We would expect momentum profits to be greater among stocks with higher turnover, as arbitrageurs are hindered from correcting the underpricing of Winners and the overpricing of Losers. We would also expect turnover to be overall positively priced in cross-section, since for an increase in turnover, short selling to correct overvaluation would become easier to effect, overvaluation would decrease, and ex-post returns would increase. There is some evidence that turnover functions in this manner in the limits-to-arbitrage literature: Ali and Trombley (2006) find prior month turnover to be positively priced in cross-section, predominantly driven by the underperformance of low turnover Losers. Additional evidence for the positive pricing of turnover in cross-section comes from Ali et al. (2003), and Duan et al. (2010).

3.5 Illiquidity as a limit to arbitrage

If we define liquidity as the facility for an investor to enter or exit a position without adversely causing price impact in the process of trading, then illiquidity is an obvious candidate for a limits-to-arbitrage factor. If illiquidity operates as a limit-to-arbitrage factor, then we ought to observe that momentum will be stronger among more illiquid stocks, and that stocks with higher illiquidity are more likely to be overpriced since arbitrageurs will face greater costs in using short selling to force them down to fair value. Thus in aggregate, stocks with higher illiquidity will tend to exhibit lower realised returns and illiquidity will tend to be negatively priced in cross-section.

Prima facie evidence exists that this is so: the direction of causation appears to be that high levels of illiquidity lead to lower levels of short interest by making shorting more expensive. For instance, Au et al. (2009) find that increases in the Amihud (2002) illiquidity ratio for both low and high short interest portfolios significantly predict decreases in short interest, and Duan et al. (2010) find that the illiquidity ratio is significantly higher among high short interest stocks than among low short interest stocks.

Spiegel and Wang (2005) find the contemporaneous year Amihud (2002) illiquidity factor to be significantly negatively priced in cross-section. Likewise, Chua et al. (2010) find that the illiquidity ratio has a significantly negative pricing in stock level cross-sectional regression; moreover, other measures of illiquidity, including the Hasbrouck (2009) Gibbs sampler and the Pastor and Stambaugh (2003) reversal gamma are also negatively priced in cross-section.

3.6 The bid-ask spread as a limit to arbitrage

The bid-ask spread forms an obvious potential deterrent to arbitrage, for the activity of arbitrage is critically dependent on round-trip cost, and even where liquidity is high and positions can be entered with minimal price impact, the bid-ask spread places a lower bound on round-trip costs. Whereas rational asset pricing would suggest that investors would require to be compensated by higher expected returns in order to accept an increased bid-ask spread, some studies suggest that the bid-ask spread is actually negatively priced. If, in fact, the bid-ask spread does act as a limit-to-arbitrage factor, as before, we would expect momentum profits to be stronger among stocks with wider bid-ask spreads, and since the correction of overpricing would be more constrained than the correction of underpricing, again, we would expect assets with higher bid-ask spreads on average to exhibit a greater potential for overpricing and lower ex-post returns. A negative pricing of the bid-ask spread in cross-section would therefore be consistent with this role.

Eleswarapu and Reinganum (1993) investigate the seasonality of the proportional bid-ask spread premium for NYSE stocks, finding that for 1981-90, it is significantly *negatively* priced for non-

Januaries but significantly *positively* priced for Januaries; overall, it is negatively but non-significantly priced. Confirming, Brennan and Subrahmanyam (1996) find the bid-ask spread to be significantly negatively priced in cross-sectional, even when the Glosten and Harris (1988) fixed and variable costs of price impact of a trade are also included, while Chua et al. (2010) show that the proportional effective spread, the proportional quoted spread and increases in the bid-ask spread over the prior month are all significantly negatively priced in cross-section. The bid-ask spread has also been proxied by the proportion of days with zero returns (Lesmond et al., 1999). This proxy correlates with other cost-of-shorting measures: (Duan et al., 2010), and has been found to be negatively priced in cross-section (Ang et al., 2009). One contrary finding is that of Amihud and Mendelson (1986), who find that returns increase with bid-ask spread; however, their measure of bid-ask spread for each stock is only extracted on a yearly basis, and then applied to all months of the previous year in cross-sectional regressions.

3.7 Idiosyncratic volatility as a limit to arbitrage

There have been two opposing approaches to the impact of idiosyncratic volatility on stock returns: the first theory, set out by Merton (1987), argues that where investors only have knowledge of a subset of the total number of stocks, then among firms with the same level of market risk, firms with higher idiosyncratic volatility will have larger CAPM alphas. Accordingly, studies in this vein look to calculate *expected* idiosyncratic volatility, and expect to find it *positively* priced in cross-section, since many investors will hold portfolios with incomplete diversification. However, as Shleifer and Vishny (1997) point out, this model has no place for noise traders, and so does not consider the possibility that noise traders may push prices further away from fundamental values.

The other approach considers idiosyncratic volatility as a potential limit to arbitrage, by reducing the amount of capital that an arbitrageur would rationally to an arbitrage trade in a stock, as suggested by Duan et al. (2010) and Pontiff (2006), making use of the Treynor and Black (1973) model of portfolio construction. Another basis is suggested by Shleifer and Vishny (1997): arbitrageurs in the financial markets are specialised, and hence cannot be assumed to diversify away all idiosyncratic volatility.

There is evidence to confirm that idiosyncratic volatility does act to hinder the correction of overpricing and underpricing, so that Winner – Loser momentum profits are stronger among stocks with high idiosyncratic volatility; additionally, since the correction of overpricing is more constrained than the correction of underpricing, stocks with high realised idiosyncratic risk in aggregate suffer more overpricing and have lower ex-post returns. For instance, Arena et al (2008) and Duan et al (2010) find that stocks with higher idiosyncratic volatility tend to exhibit stronger momentum effects, and realised, historic idiosyncratic volatility is usually found to predict negative month-ahead returns (Ang et al., 2009, 2006; Chen et al., 2010). The study by Bali and Cakici (2008) is sometimes quoted as contradicting the general finding of a negative pricing of idiosyncratic volatility, but where portfolio returns are value-weighted and idiosyncratic volatility is calculated using daily returns, they find the idiosyncratic volatility arbitrage return to be significantly negative.

4 Data and Methodology

4.1 Universe construction

The stock universe is defined as all UK-domiciled stocks, active and dead, whose primary listing is or was on the London Stock Exchange Main Market or the Alternative Investment Market from 30 June 1987 to 30 April 2012. Daily price data are taken from Datastream and accounting data from Worldscope. Secondary classes of shares, non-voting shares, ADRs, Investment Trusts, Real Estate Investment Trusts and partly-paid classes of shares were removed by hand, while taking care to keep listings which represent re-flotations or simple replacement of the same company under a different name or ISIN number. Special care was also taken to reconcile accounts data under one company identifier with return data under another identifier representing a subsequent listing of the same company; this is especially important where a company has been delisted and then relisted, or in the case of reverse takeovers. The approaches we use to filter and clean the data, to deal with delisted stocks and timing measurement are all detailed in the Appendix.

4.2 Calculation of market betas

We follow Fama and French (1996, 1992) in estimating market betas on a rolling basis by regressing monthly excess stock returns above the risk-free rate against excess monthly market returns, using a minimum of 24 and a maximum of 60 prior monthly returns, ending with month t-1. For the market return, we use the proportional monthly increase in the Total Return Index of the FTSE All-Share Index, obtained from Thomson Reuters Datastream, and calculate excess returns over the pro-rated three-month UK Treasury Bill Tender Rate.

4.3 Size and Book to market

We calculate Log (Size) as the natural logarithm of the market value of each stock in millions at the start of month t. Log (book to market) is calculated as ln(((Common Equity + Deferred Taxes) / Market Value) +3.5), where accounting information is taken from the last set of accounts with a financial year end at least six months prior to month t and Market Value is taken at the last trading day prior to that financial year end. Negative book-to-market values are not excluded.

4.4 Credit risk measures

Whereas options-based measures of distance-to-default, such as those by using the methodologies of Vassalou and Xing (2004) or Hillegeist et al. (2004), can be used to produce relative rankings of financial distress without reference to local data, models which rely upon accounting ratios to predict default must first be calibrated to local data, so that default measures whose coefficients have been calibrated on US data cannot be directly applied to those based on UK data. In the present study, we prefer to remain with the Taffler (1983) z-score, which has been used in the Agarwal and Taffler (2008) study of financial distress and momentum and the Agarwal and Poshakwale (2010) application of the Ferguson and Shockley (2003) three-factor model to the UK. Further, Agarwal and Bauer (2014) demonstrate in the UK context that the Taffler (1983) z-score subsumes the pricing information of a Shumway (2001) hazard rate model and a Merton (1974) distance-to-default measure.

The z-score is calculated as:

$$z= 3.20 + 12.18\, x_1 + 2.50\, x_2 - 10.68\, x_3 + 0.029\, x_4 \quad (1)$$

where x_1 = profit before tax / current liabilities, x_2 = current assets / total liabilities, x_3 = current liabilities / total assets and x_4 = 365 × (quick assets - current liabilities / (sales - profit before tax - depreciation).

In the cross-sectional regressions, we multiply the z-score by (-1), so that an increased z-score represents increasing credit risk, as with the Ohlson (1980) O-Score and the Altman (1968) version of the z-score. This ensures that premia on the z-score are comparable in sign to previous studies on the pricing of credit risk in equities.

4.5 Calculation of idiosyncratic volatility

Idiosyncratic volatility is calculated following Ang et al. (2006, 2009) as the standard deviation of residuals of each stock, derived by regressing the daily excess returns of each stocks against the Fama-French (1993) factors, over the month immediately prior to the start of the holding period. We require a stock to have a minimum of ten valid daily returns in a month in order to calculate the idiosyncratic volatility for that month.

4.6 Illiquidity measures

Since the log of the standard version of the Amihud (2002) illiquidity measure contains an embedded log (size) factor, we use the log of the turnover version of the measure, following Brennan et al. (2013), which we calculate over the month immediately prior to the start of the holding period for each stock. We require a minimum of ten trading days with valid returns, nonzero volumes and unadjusted prices each month in order to calculate the statistic, and additionally, the stock price must not have been static over the month. We calculate:

$$AMIHUD_{i,t} = \ln(TO\_AMIHUD_{i,t}) = \ln\left[\frac{1}{D_{i,t}}\sum_{t=1}^{D_{i,t}}\frac{|R_{i,t,d}|}{TO_{i,t,d}}\times 10^{7}\right] \tag{2}$$

where $R_{i,t,d}$ is the log return of stock *i* on day *d* in month *t*, $TO_{i,t,d}$ is the proportionate turnover of stock *i* traded on day *d*, and $D_{i,t,d}$ is the number of days in month *t* for stock *i* with valid $R_{i,t,d}$ and $TO_{i,t,d}$. Additionally, following Brennan et al. (2013), we calculate Up and Down versions of the turnover illiquidity measure, denoted *AMIHUD_UP* and *AMIHUD_DOWN* respectively, calculated only using days of the month when the stock return is positive and negative respectively.

4.7 Bid-ask spread measure

The bid-ask spread is calculated as the average of the proportional spread at the end of each trading day over the month immediately prior to the start of the holding period of each stock. Days when the spread is negative are ignored and the stock price must not have been static over the month. It is calculated as:

$$SPREAD_{i,t} = \frac{1}{D_{i,t}}\sum_{t=1}^{D_{i,t}}\frac{PA_{i,t,d} - PB_{i,t,d}}{0.5\times(PA_{i,t,d} + PB_{i,t,d})} \tag{3}$$

where $PA_{i,t,d}$ and $PB_{i,t}$ are the end-of-day adjusted Ask and Bid prices of stock *i* on day *d* in month *t*, and $D_{i,t}$ is the number of days in month *t* for stock *i* with valid $PA_{i,t,d}$ and $PB_{i,t}$.

While it could be argued that close-of-day spreads are likely to be wider than those during the middle of the trading day, many well-published studies have derived important results from close-of-day spreads: Stoll (1989) calculates a daily proportional spread from closing bid and ask prices for NASDAQ stocks, Stoll and Whaley (1983), Jegadeesh (1990) and Eleswarapu and Reinganum (1993) use *year-end* closing spreads for NYSE stocks. Jegadeesh and Subrahmanyam (1993) use close-of-day spreads on a monthly rather than a daily basis, as here.

4.8 Turnover measures

Log (Turnover) is calculated as the natural logarithm of the average proportionate turnover for each day over the month immediately prior to the start of the holding period for each stock:

$$LOGTO_{i,t} = \ln(TO_{i,t}) = \ln\left[\frac{1}{D_{i,t}}\sum_{t=1}^{D_{i,t}}\frac{VOLUME_{i,t,d}}{NOSH_{i,t,d}}\right] \quad (4)$$

where $VOLUME_{i,t,d}$ is the number of shares of stock i traded on day d in month t, and $NOSH_{t,d}$ is the number of shares in issue of stock i on day d in month t. Days in which a null volume is recorded are counted as having had zero volume, rather than being ignored.

4.9 Measuring the unrealised capital gains factor

To test whether the disposition effect is a driving force in the negative pricing of credit risk and momentum phenomena, we calculate the Grinblatt and Han (2005) unrealised capital gains factor. For each holding period for each stock, we first calculate the average cost basis approximation over the preceding m days:

$$RP_{m,i,t-1} = \frac{1}{k}\sum_{n=1}^{m}\left(V_{i,t-1-n}\prod_{\tau=1}^{n-1}[1-V_{i,t-1-n+\tau}]\right)P_{i,t-1-n} \quad (9)$$

where $V_{i,t}$ is the proportion of stock i's total number of shares in issue traded on day t, $P_{i,t}$ is the price of stock i on day t, and k is a constant which makes the weights on past prices sum to unity. In order for $RP_{m,i,t-1}$ to be calculated, the stock must have a price history dating back m days. We then calculate the unrealised capital gains for each stock as:

$$GH_{m,i,t} = \frac{P_{i,t-1} - RP_{m,i,t-1}}{P_{i,t-1}} \quad (10)$$

We find rankings on the Grinblatt and Han (2005) unrealised capital gains factor vary according to the lookback period, as a larger value for m prevents the calculation of the unrealised capital gains factor during the first m days of a stock's price history, but allows a longer history of accumulated gains (or losses) to be taken into account. We calculate the unrealised capital gains factor for lookback periods of 12, 24, 36, 48 and 60 months, with associated coefficients denoted *GH_12*, *GH_24* .. *GH_60*, respectively in the regressions. We vary slightly from Grinblatt and Han (2005) in the calculation of this factor, since they use average weekly turnover figures and weekly prices in place of our daily calculations, and employ $P_{i,t-2}$ in place of $P_{i,t-1}$ in the second stage of the calculation. We feel the accuracy gained in using daily data over weekly data for the unrealised capital gains factor and the avoidance of artefacts through using stale prices in the second stage outweigh the microstructure concerns which motivated the authors' choices in the original paper.

4.10 Winner / Loser Indicator variables

$I_{[Winner]}$is a dummy variable which take the value 1 when a stock's prior returns from *t*-7 months to *t*-1 months is above the 30th percentile of prior returns. $I_{[Middle]}$is a dummy variable which take the value 1 when a stock's prior returns from *t*-7 months to *t*-1 months is between 70th and 30th percentiles of prior returns, respectively, and 0 otherwise.

4.11 Cross-sectional regression methodology

For each month *t* from June 1989 to April 2012, we run a cross-sectional OLS regression of the excess returns of each individual stock against a set of independent variables, over all stocks having sufficient data, and save the coefficients of the independent variables from each regression. Time-series averages of each coefficient are then taken across all 274 months, and the averages and t-ratios of these time-series averages are reported in the tables.

The dependent variable in each case is the excess return for each stock over each month-long holding period, defined here as the proportional increase in the Datastream Return Index over the month, minus the pro-rated 3-month Sterling Treasury Bill rate for that month. The Datastream Return Index includes the cumulative effect of dividends. We apply the method suggested by Shanken (1992) to correct the standard errors for the intercepts and the coefficients of firm market beta.

5 Empirical results

Table 1 presents summary statistics. All the variables exhibit the properties that would be expected, although perhaps a comment on the reported bid-ask spread figures may be in order. At first blush, these appear to be very wide, but in fact they are comfortably within the range found in the literature. For instance, Stoll (1989, p. 128) examines average percentage spreads for NASDAQ stocks sorted on dollar volume, and finds that the most liquid decile has an bid-ask spread of 1.16%, and the least liquid decile an bid-ask spread of 6.87%. Eleswarapu and Reinganum (1993) compute bid-ask spreads for decile portfolios of NYSE firms sorted on bid-ask spread for 1961-90, with 0.45% and 3.53% representing the lowest and highest bid-ask spreads recorded; their requirement for stocks to have been listed for 10 years may however bias their sample towards more stable firms.

Figure 1 and Figure 2 present the average, 10th percentile and 90th percentile values through time for the Grinblatt & Han (2005) unrealised capital gains factor, for lookback periods of 12 and 36 months respectively. There are large troughs at September 1992, October 1998 and October 2001, corresponding to Black Wednesday (the UK exit from the Exchange rate Mechanism), the Russian default and the 9/11 attacks, respectively.

Figure 3 presents the average, 10^{th} percentile and 90^{th} percentile values through time for the log turnover Amihud (2002) illiquidity ratio; this, again, shows spikes in aggregate illiquidity at the same events.

5.1 The cross-sectional pricing of credit risk

We first conduct an elementary exploration of how returns vary with credit risk. Since Avramov et al. (2007) and Agarwal and Taffler (2008) find that returns vary with both prior returns and credit rating, we double-sort on 6–month prior return and credit risk and then construct a Jegedeesh and Titman (1993) momentum strategy with a skipped period of 1 month and a holding period of 6 months on the 50 portfolios so formed. For each of these, we calculate equal-weighted returns; we also calculate the (Winner – Loser) momentum return for each quintile of credit risk, and the (high credit risk – low credit risk) credit spread for each momentum quintile, in Table 2.

We further regress the return of each momentum portfolio *i* is regressed against the Fama-French (1993) factors using the equation:

$$R_{i,t} - R_{f,t} = \beta_{0,i} + \beta_{RmRf,i}(R_{m,t} - R_{f,t}) + \beta_{SMB,i} SMB_t + \beta_{HML,i} HML_t + \varepsilon_{t,i}, \quad (5)$$

and the credit spread and momentum returns against the Fama-French (1993) factors using the equation:

$$R_{j,t} = \beta_{0,i} + \beta_{RmRf,i}(R_{m,t} - R_{f,t}) + \beta_{SMB,i} SMB_t + \beta_{HML,i} HML_t + \varepsilon_{t,i}, \quad (6)$$

where $R_{i,t}(R_{j,t})$ represents the portfolio (credit spread / Winner – Loser momentum profit) time-series in question. Coefficient estimates for equal-weighted portfolios are presented in Table 3.

The present findings confirm and expand upon those already noted in the literature. For UK stocks, Agarwal and Taffler (2008) show that low credit risk – high credit risk arbitrage returns are significantly negative only for the lowest Loser quintile and that credit spreads decline monotonically from Winners to Losers, finding the same pattern also with Fama-French (1993) abnormal excess returns. These results also show that the underperformance of high credit risk, extreme Loser stocks is the element which drives the presence of the negative credit risk–return relation among Loser stocks. If these stocks experienced higher returns and higher abnormal excess returns than they do, then this anomaly would disappear: the negative credit risk-return relation among Loser stocks would be smaller in magnitude, not greater, than among Winner stocks. The negative credit risk–return relation therefore turns out to be a story about the apparently unexplained underperformance of high credit risk, extreme Loser stocks.

This also builds upon the findings of Avramov et al. (2007), who perform a two-way sort on S&P credit rating and prior 6-month returns and find that the raw returns of Loser tertiles exhibit a pattern of lower returns with declining credit rating not followed by the raw returns of Winner tertiles, although they do not calculate risk-adjusted returns or credit spreads for these. Consequently, they miss the presence of a significant negative credit risk-return relation from AA-rated portfolios to B-rated portfolios among the loser tertiles, and the absence of any comparable significant credit spread among winner tertiles. In this analysis, we contribute to the literature in demonstrating a smooth increase in the significance of the negative credit risk-return relationship from the highest Winner decile to the lowest Loser quintile in terms of risk-adjusted returns. This also builds upon the results of Avramov et al. (2009): we show that the negative credit risk-return relationship derives from the underperformance specifically of high credit risk stocks with very low relative returns over the prior 6 months.

We also present evidence against the Garlappi and Yan (2011) hypothesis: Table 3 shows that high credit risk stocks have significantly *higher*, not lower, market betas compared to low credit risk stocks, contrary to their prediction that the equity beta of a distressed stock should fall as investors shift attention to the sure value they hope to recover in bankruptcy resolution; high credit risk Loser stocks have the highest market betas of all. This also represents an implicit proof against the George and Hwang (2010) hypothesis that firms with high distress costs will choose lower leverage levels, whilst having higher exposure to systematic risk, which is argued to dominate the amplification effect of leverage on equity risk. Though their model concerns the systematic risk of the firm's assets, rather than the systematic risk of firm's equity, the implicit link made to equity returns implies that these firms with high distress costs have high expected returns on their equity because they have high equity betas. However, Table 3 reveals the opposite pattern – that the low credit risk stocks with high returns have significantly lower, not higher, betas than the high credit risk stocks.

5.2 The negative pricing of credit risk in cross-sectional regressions

We verify the above results obtained by double-sorts in cross-sectional regressions. Table 4 presents the results of the regression

$$r_{i,t,t+1} = a_0 + a_1 BETA_{i,t} + a_2 MV_{i,t} + a_3 B/M_{i,t} + a_4 Z_{i,t} + a_5 (Z_{i,t} \cdot \mathrm{I}_{[\text{Winner}]_{i,t}}) + a_6 (Z_{i,t} \cdot \mathrm{I}_{[\text{Middle}]_{i,t}}) + a_7 \mathrm{I}_{[\text{Winner}]_{i,t}} + a_8 \mathrm{I}_{[\text{Middle}]_{i,t}} + \varepsilon_{i,t} \quad (7)$$

In this model, the significantly negative z-score coefficient confirms that credit risk is significantly *negatively* priced among Loser stocks. The z-score coefficient, by construction, represents the pricing of credit amongst the lowest 30th percentiles of prior returns between months *t*-7 and *t*-1, and shows that the negative pricing of credit risk is most significant for Loser stocks, and is significantly different amongst winner and middle deciles to loser deciles. These confirm the previous results that the negative pricing of credit risk is strongest among Loser stocks, and diminishes with increasing momentum decile.

5.3 The effect of removing stocks with unrealised capital losses from the sample

As previously noted, Avramov et al (2009) analyse the effect of removing stocks with low credit ratings from their sample, and observe that the negative credit risk-return relation becomes non-significant if stocks with a rating of CCC+ or worse are excluded. In a similar spirit, in Table 5, we experiment with the effect of removing stocks with large unrealised capital losses from the sample, beginning with stocks with a Grinblatt and Han (2005) unrealised capital gains factor of -200% or less. For a lookback period of 12 (36) [60] months, we find that the negative pricing of credit risk becomes non-significant at the 5% level when stocks with an unrealised capital gains factor of -50% (-70%) [-70%] are excluded, which account for 4.83% (6.52%) [7.67%] of stocks with a valid unrealised capital gain statistic, but which account for only 0.63% (0.55%) [0.60%] of stocks by market capitalisation.

In this way, we demonstrate that the negative credit risk-return relationship derives from a narrow group of small stocks which have large accumulated capital losses, and that the magnitude of the negative credit risk-return relationship decreases as stocks with greater unrealised capital losses are removed. We therefore build on the results of Avramov et al. (2009) by providing evidence for their hypothesis that the negative credit risk-return relationship arises in part from the disposition effect, since the stocks which are responsible for the effect are precisely those which the disposition effect would predict would be most retained by disposition investors, and hence, those which have the greatest tendency to remain overpriced.

We confirm this by examining returns around shifts from a less distressed credit quintile to a more distressed credit risk quintile. On the face of it, this differs from the technique in Avramov et al (2009), since the use of credit risk quintiles reflects a more relative measure of distress than the S&P credit ratings they utilise, and the downward shift in credit quintile reflects the release of accounting information rather than rating agency news, and so may be may regarded as being less timely. However, the fact that similar declines in returns are seen in response to downward shifts in credit rating quintiles in the present study, as appear in response to rating agency downgrades in Avramov et al (2009), suggests that a similar process is at work in both studies. Additionally, it is highly likely that a majority of the companies in this sample will not have credit ratings issued by one of the major rating agencies, and the release of accounting information which indicates firm distress will be the first public indication of worsened company conditions. As detailed in the methodology section, credit risk quintiles reflect the most recent accounting information released at last six months prior on a rolling basis, so the date of the shift in credit quintile will closely parallel the point at which the market would have become aware of the new information; even if the news relates to operational conditions which are "old", publication of the accounting information will still reflect the first point at which the deteriorating finances would have been made public. Figure 4 shows the cumulative returns before and after shifts from a less distressed credit quintile to a more distressed credit risk quintile, for stocks which have unrealised capital gains / losses in the upper 8 deciles in the month of downgrade. Figure 5 shows the cumulative returns before and after downward shifts only for stocks which have unrealised capital losses below the 8th decile in the month of the downward shifts, that is, which have large unrealised capital losses by comparison with all other stocks in that month . Comparing the two, it is evident that the sample with unrealised capital gains or small losses shows little decline, either before or after the downward shift. However, the subsample with large unrealised capital losses shows a steady decline in value before the downward shift in credit risk quintile, and a steep decline in value after the downward shift in credit risk quintile. We therefore confirm the finding by Avramov et al (2009) that the negative credit risk-return relation derives principally from the performance of stocks around declines in creditworthiness, and moreover show that this phenomenon is a feature only of stocks with very sizeable unrealised capital losses; this provides further evidence that it is the disposition effect which drives the overpricing of high credit risk stocks, and hence which contributes to the negative pricing of credit risk.

5.4 The limits to arbitrage characteristics of portfolios sorted on prior returns and credit risk

We first move to investigate whether the proposed limits-to-arbitrage factors function as predicted. As a preliminary investigation, we double-sort stocks on prior return between months *t*-7 and *t*-1, and on credit risk, and then measure the average value of each suggested limits-to-arbitrage factor for each of these double-sorted portfolios; results are presented in Table 6 and Table 7. This also serves as a test of whether these limits–to-arbitrage factors can explain the anomalously low returns of the high credit risk Loser stocks which have been noted as being responsible for the negative credit risk-return relationship and the increased strength of stock momentum among high credit risk stocks. If this is the case, we would expect high credit Loser stocks to have higher idiosyncratic volatility, to be more illiquid, to have lower turnover and to have wider bid-ask spreads than all other stocks.

In line with predictions, high credit risk stocks have significantly higher levels of idiosyncratic risk than low credit risk stocks, Loser stocks have significantly higher idiosyncratic risk than Winner stocks for all quintiles of credit risk, and idiosyncratic risk manifests a U-shaped profile with respect to momentum decile, being higher among extreme Winner and Loser portfolios than among mid-ranking stocks. Again, as predicted, high credit risk stocks have higher levels of illiquidity than low credit risk stocks, as measured by the log turnover Amihud (2002) measure, and this difference is significant for extreme Winner and Loser deciles. Loser stocks are significantly more illiquid than Winner stocks for all quintiles of credit risk, and illiquidity manifests a U-shaped profile with respect to momentum decile, being higher among extreme Winner and Loser portfolios than among mid-ranking stocks. One explanation of this is that illiquidity makes it more difficult for arbitrageurs to correct the underpricing and overpricing generated by this disagreement; high credit risk Loser stocks are the most illiquid of all, and illiquidity in its action as a limit to arbitrage is another strong potential candidate to explain their anomalously low returns.

Further reasons for the greater illiquidity of Loser stocks are suggested by Brennan et al. (2013), who note that trading volume and price changes are positively correlated; besides the models proposed by Karpoff (1987) relating trading volume and price changes, the disposition effect should also predict the same relationship. Since disposition investors sell Winners and retain Losers preferentially, they increase the trading volume of Winners compared to Losers. As volume forms part of the denominator of the Amihud illiquidity ratio, its value in positive return periods, likely to be accompanied by higher volume, should be lower than its value in negative return periods, more likely to be accompanied by lower volume. If negative returns are in any way persistent, as momentum suggests they should be, it is therefore more likely that past Losers should have low current returns in the present month, with accompanying low volume and high illiquidity, and conversely, that past Winner portfolios should have higher present returns, higher volume and hence lower illiquidity. Therefore, the result that Winners have significantly lower turnover illiquidity than Losers is in line with the predicted effect of disposition investors.

When the Up- and Down-Amihud measures of illiquidity are considered, the situation is more complex: extreme Losers are still significantly more illiquid than extreme Winners by both metrics. Interestingly, for each momentum / credit risk category, the Down-Amihud measure indicates greater illiquidity than the Up-Amihud measure. Since disposition investors sell Winners and retain Losers preferentially, they increase the trading volume of stock on up-days compared to down-days. As volume forms part of the denominator of the Amihud illiquidity ratio, its value in positive return periods, likely to be accompanied by higher volume as disposition investors sell, should be lower than in negative return periods, which are more likely to be accompanied by lower volume as disposition investors hold on to their losing stocks. If negative returns are in any way persistent, as momentum suggests they should be, it is therefore likely that this effect will carry over into the following month too.

By the Down-Amihud measure, high credit risk stocks are still significantly more illiquid than low credit risk stocks for all momentum deciles. When the Up-Amihud measure is employed, however, high credit risk stocks are only significantly more illiquid than low credit risk stocks among extreme

Losers. Brennan et al (2013) argue that the greater illiquidity of the Down-Amihud measure compared to the Up-Amihud measure is driven by disposition investors: if they trade less on negative return days, they will increase the Down-Amihud illiquidity measure for these stocks on down-days. By the same logic, these disposition investors will tend to trade more on positive return days, reducing the Up-Amihud illiquidity measure for these high credit risk stocks on up-days. In this way, the divergence between Up-Amihud and Down-Amihud measures for the quintile of highest credit risk provides evidence for disposition investors creating measurable effects on daily illiquidity, and also for high credit risk stocks being held disproportionately by disposition investors. A similar conclusion is reached by applying the finding by Da and Gao (2010) that institutional investors tend to sell, and individual investors tend to buy, stocks which undergo declines in creditworthiness. If, as Barber and Odean (2000) show, such individual investors are more prone to exhibit the disposition effect, high credit risk stocks will be held disproportionately by disposition investors.

Proportional turnover displays a similar pattern to the turnover Amihud (2002) measure: high credit risk stocks have significantly lower turnover than low credit risk stocks for extreme Winners and Losers, and Winners have significantly higher turnover than Losers for three out of the five quintiles of credit risk. There is a U-shaped variation of turnover with momentum decile for the least distressed two quintiles of credit risk, but turnover decreases monotonically from Winners to Losers for the three most distressed quintiles of credit risk. One potential explanation for this is that the comparatively high turnover enjoyed by high credit risk Winners is caused by these stocks being sold by disposition investors after a string of positive returns, so that disposition investors now hold an unrealised capital gain in them, and hence are motivated to sell them early in order to lock in a sure gain. This, in turn, provides further evidence that high credit risk stocks are held predominantly by disposition investors.

Bid-ask spread again displays the patterns previously predicted for limits-to-arbitrage factors: Loser stocks have significantly wider spreads than Winner stocks for all quintiles of credit risk; high credit risk stocks have significantly wider bid-ask spreads than low credit risk stocks for all momentum deciles, and the bid-ask spread again has a U-shaped profile with respect to momentum decile, being wider among extreme Winner and Loser portfolios than among mid-ranking stocks.

Average market capitalisation displays some, but not all of these characteristics; Winners are significantly larger than Losers for four out of five quintiles of credit risk, and size displays an inverted U-shaped profile with regard to momentum decile, so that both Winners and Losers are smaller than mid-ranking stocks. However, high credit risk stocks are not significantly smaller than low credit stocks, showing that firms do not have high credit risk simply because they are small.

In summary, idiosyncratic volatility, illiquidity, turnover and average spread behave as a limits-to-arbitrage explanation would predict, and size shows some limits-to-arbitrage characteristics.

5.5 The unrealised capital gains factor characteristics of portfolios sorted on prior returns and credit risk

We next consider the variation in unrealised capital gains factor in Table 8, which shows the variation in this statistic over portfolios double-sorted on prior returns and credit risk. As expected, the unrealised capital gains factor for extreme Winners is significantly more positive than for extreme Losers, Winners tend to have unrealised capital gains whereas Losers tend to have unrealised capital losses, and unrealised capital gains / losses are greater in absolute magnitude when these are assessed over long lookback periods (e.g. 60 months) than over shorter lookback periods (e.g. 12 months). Interestingly, high credit risk stocks have significantly greater unrealised capital losses than low credit risk stocks. While this is to be expected if high credit risk stocks have significantly lower returns than low credit risk stocks, all else being equal, it may also indicate that high credit risk stocks are held disproportionately by disposition investors, who tend to retain Losers, and will therefore tend to accumulate high credit risk stocks to the extent that these suffer lower returns. These two patterns combine in the case of high credit extreme Loser stocks, which have very large unrealised capital losses.

5.6 The pricing of the limits-to-arbitrage measures in cross-section

We next move to examine the pricing of the limits-to-arbitrage factors in stock-level cross-sectional regressions, which are added to the Fama-French factors individually in Table 9. The equation estimated is:

$$r_{i,t,t+1} = a_0 + a_1 BETA_{i,t} + a_2 MV_{i,t} + a_3 B/M_{i,t} + a_4 IDIO\_VOL_{i,t} + a_5 AMIHUD_{i,t} + a_6 AMIHUD\_UP_{i,t} \\ + a_7 AMIHUD\_DOWN_{i,t} + a_8 SPREAD_{i,t} + a_9 LOGTO_{i,t} + \varepsilon_{i,t} \qquad (8)$$

In the first column of Table 9, idiosyncratic volatility has a significantly negative coefficient, so that stocks with high levels of idiosyncratic volatility earn lower returns than stocks with lower levels of idiosyncratic volatility. This, again, is in line with the studies of realised, prior month historic idiosyncratic volatility previously mentioned, specifically, Ang et al. (2006) and Bali and Cakici (2008) for US stocks, and Ang et al. (2009) for international stocks. This also confirms in cross-section the result from Table 6 that Losers have significantly higher idiosyncratic volatility than Winners.

In the second column of Table 9, the Turnover Amihud illiquidity measure is significantly negatively priced in cross-section, that is, less illiquid stocks earn higher ex-post returns than more illiquid stocks. This is in line with what would be expected if it were acting as a limit to arbitrage, preventing overvalued, illiquid stocks from being shorted down to fair value. It is also in line with the negative pricing of the Amihud illiquidity measure for US stocks in Spiegel and Wang (2005) and Chua et al.

(2010), as previously noted. The Up and Down versions of the Turnover Amihud illiquidity measure are also negatively priced, both singly and in combination. This again confirms the results from Table 6 that Losers are significantly more illiquid than Winners.

In the sixth column of Table 9, the bid-ask spread has a significantly negative price, so that stocks with wider spreads have lower returns in cross-section than stocks with narrower spreads. This is in line with three studies on US data previously noted, namely, Eleswarapu and Reinganum (1993), Brennan and Subrahmanyam (1996), and Chua et al (2010). This result is, however, novel for the UK context, and confirms the findings in Table 7 that Losers have significantly wider spreads than Winners. In the seventh column, turnover has a significantly positive price, so that high proportional turnover stocks earn higher returns than low turnover stocks, similar to the results in Ali and Trombley (2006) and Ali et al. (2003) previously detailed. Again, this confirms the results from Table 7 that Losers have significantly lower turnover than Winners. Finally, when all four limits-to-arbitrage factors are included together in results presented in the final column of Table 9, idiosyncratic volatility and turnover remain significant but bid-ask spread and the turnover Amihud factor factors become non-significant: this may indicate that the action of low turnover and high idiosyncratic volatility subsume all other factors in frustrating arbitrage.

5.7 The variation of the negative pricing of credit risk with limits-to-arbitrage factors

In Table 10 we further probe the relationship by performing an analysis of the negative credit risk-return relation similar to that performed on the book-to-market premium by Ali et al. (2003), in which we double-sort stocks simultaneously into quintiles on credit risk and deciles on each limits-to-arbitrage factor, and record the (highest credit risk quintile – lowest credit risk quintile) credit spread, for each decile of the limits-to-arbitrage factor. In a similar fashion to the findings in Ali et al. (2003) that the book-to-market premium is most significant where limits-to-arbitrage factors are more severe, we find that the negative pricing of credit risk is likewise only significant where arbitrage is most constrained. Specifically, Table 10 demonstrates the negative pricing of credit risk is only significant for the decile of widest credit risk, lowest turnover, highest turnover Amihud (2002) illiquidity, Up-Amihud and Down-Amihud illiquidity and smallest size. We include Unadjusted Price for comparison with Ali et al. (2003), where we find that the magnitude of the credit spread becomes more negative with declining adjusted price, but that it is insignificant at the 5% level for the decile of smallest unadjusted price, implying that unadjusted price does not hinder arbitrage to the same extent as the other factors surveyed. Within Table 10, the result for idiosyncratic risk apparently defies this trend: the negative pricing of credit risk is not significant for the most volatile deciles, but is significant for deciles 5, 8 and 9. One potential explanation for this is that this table ignores the confounding effect of momentum, and that the (high credit risk, high idiosyncratic risk) portfolio will end up containing both high credit risk, extreme Winners, and high credit risk, extreme Losers which will tend to cancel each other out. By contrast, the (high credit risk, low idiosyncratic risk) portfolio will end up containing high credit risk, mid-ranking stocks; the difference in return between these two will therefore tend to be insignificant.

5.8 Do the limits-to-arbitrage factors explain the negative credit risk–return relation in cross-section?

Ali et al. (2003) test whether their proposed limits-to-arbitrage factors subsume the book-to-market premium by including them and their interactions with book-to-market in Fama-French (1993) three-factor stock-level cross-sectional regressions. In a similar fashion, in Table 11, we add the four limits-to-arbitrage to Model 3, Table 4, to test whether their entry subsumes the significance of credit risk; the model is:

$$\begin{aligned} r_{i,t,t+1} = {} & a_0 + a_1 BETA_{i,t} + a_2 MV_{i,t} + a_3 B/M_{i,t} + a_4 Z_{i,t} + a_5 (IDIO\_VOL_{i,t} \cdot Z_{i,t}) \\ & + a_6 (Z_{i,t} \times AMIHUD_{i,t}) + a_7 (AMIHUD\_UP_{i,t} \times Z_{i,t}) + a_8 (AMIHUD\_DOWN_{i,t} \times Z_{i,t}) \\ & + a_9 IDIO\_VOL_{i,t} + a_{10} AMIHUD_{i,t} + a_{11} AMIHUD\_UP_{i,t} + a_{12} AMIHUD\_DOWN_{i,t} + \varepsilon_{i,t} \end{aligned} \quad (9)$$

We find that the coefficient of credit risk remains negative and significant when the respective limits to arbitrage are included singly, that is, those in Table 11 do not explain credit risk on their own. The interactions between credit risk and the turnover Amihud (2002) illiquidity factor, and between credit risk and the Up- and Down-Amihud illiquidity factors are negative and significant, confirming in cross-section the evidence in Table 6 that returns, on average, decrease for a joint increase in illiquidity and credit risk; this is effectively tracking the underperformance of high credit risk, highly illiquid stocks, which Table 6 shows to be high credit risk Losers.

In Table 12, we add the remaining limits-to-arbitrage factors to Model 3, Table 4, to test whether their entry subsumes the significance of credit risk. The model is:

$$\begin{aligned} r_{i,t,t+1} = {} & a_0 + a_1 BETA_{i,t} + a_2 MV_{i,t} + a_3 B/M_{i,t} + a_4 Z_{i,t} + a_5 (SPREAD_{i,t} \cdot Z_{i,}) + a_6 (LOGTO_{i,t} \cdot Z_{i,t}) \\ & + a_7 SPREAD_{i,t} + a_8 LOGTO_{i,t} + \varepsilon_{i,t} \end{aligned} \quad (10)$$

Again, we find that the coefficient of credit risk remains negative and significant when the respective limits to arbitrage are included singly, that is, average spread and turnover do not explain the negative credit risk-return relation, singly considered. The interaction between credit risk and turnover is positive and significant, confirming in cross-section the evidence in Table 7 that returns, on average, decrease for a joint decrease in turnover and an increase in credit risk; this is effectively tracking the underperformance of high credit risk, low turnover stocks, which Table 7 shows to be high credit risk Losers.

Finally, in Table 12, we include all four limits-to-arbitrage factors simultaneously, with the models being:

$$r_{i,t,t+1} = a_0 + a_1 BETA_{i,t} + a_2 MV_{i,t} + a_3 B/M_{i,t} + a_4 Z_{i,t} + a_5 IDIO\_VOL_{i,t} + a_6 AMIHUD\_UP_{i,t} + a_7 AMIHUD\_DOWN_{i,t} + a_8 SPREAD_{i,t} + a_9 LOGTO_{i,t} + \varepsilon_{i,t} \qquad (11)$$

and:

$$r_{i,t,t+1} = a_0 + a_1 BETA_{i,t} + a_2 MV_{i,t} + a_3 B/M_{i,t} + a_4 Z_{i,t} + a_5 IDIO\_VOL_{i,t} + a_6 AMIHUD_{i,t} + a_7 SPREAD_{i,t} + a_8 LOGTO_{i,t} + \varepsilon_{i,t} \qquad (12)$$

In both Model 29, featuring the Up- and Down-Amihud illiquidity measures, and Model 30, featuring the turnover Amihud (2002) illiquidity ratio, the combination of idiosyncratic risk, illiquidity, average spread and turnover subsumes the significance of the credit risk coefficient. This suggests that the negative pricing of credit risk in cross-section can be explained by the action of these limits-to-arbitrage factors, so that high credit risk stocks possess abnormally low returns because they have high idiosyncratic risk, high illiquidity, wide bid-ask spreads and low levels of turnover. We also test different combinations of limits-to-arbitrage factors: in Model 31, Table 12 only idiosyncratic risk and turnover are included, since these are the only two which retain their significance in Model 30, and the coefficient of credit risk becomes significant only at the 10% level. Model 32 includes idiosyncratic risk, illiquidity and turnover; the illiquidity coefficient is insignificant, but this specification has a higher adjusted R-squared than Model 31. Again, this combination subsumes the significant of credit risk in cross-section. Finally, Model 33 includes idiosyncratic risk, average spread and turnover; this has an even higher adjusted R-squared, even though the average spread coefficient is insignificant. Again, this combination subsumes the significance of credit risk, so that it becomes significant only at the 10% level.

In summary, a combination of idiosyncratic risk, the turnover Amihud (2002) illiquidity ratio and turnover is sufficient to subsume credit risk in cross-section, reducing it to insignificance even at the 10% level. This implies that high credit risk stocks do not suffer abnormally low returns because they have wide bid-ask spreads, and that the limits to arbitrage posed by thin trading, high illiquidity and high idiosyncratic volatility are sufficient to explain why they remain overpriced.

6 Conclusions

The negative cross-sectional pricing of credit risk in equities has been a persistent “anomaly” of the asset pricing literature, manifesting reliably when credit risk is measured using accounting ratios, hazard rate scores, distance-to-default measures and credit rating agency issuer ratings. A number of rational expectations theories have been proposed to explain why high credit stocks might, paradoxically, be predicted to have low expected returns, most of which rely upon a process of endogenous default, in which shareholders hope to make a non-negligible recovery of their investment in the bankruptcy resolution process, by strategically defaulting on their debt.

In order to more clearly understand the origins of the negative pricing of credit risk in equities, we here elect to employ a dataset of UK stocks in our analysis, on the grounds that the UK bankruptcy regime is much more favourable to creditors than the US system, such that equity shareholders typically expect to make a negligible recovery in bankruptcy resolution processes. If the aforementioned rational expectations theories are correct, shareholders in UK firms will be unable to default strategically on their debt, and the negative credit risk-return relation should disappear in our sample. We argue that the persistence of the negative credit risk–return relation in the present study shows that these rational expectations approaches cannot be the principal driver of the phenomenon, and that we must look elsewhere for its origin.

Our analysis of the characteristics of high credit risk stocks also supplies further evidence against rational expectations approaches: against the Garlappi and Yan (2011) hypothesis, we find that high credit risk stocks have significantly *higher*, not lower, market betas compared to low credit risk stocks, contrary to their prediction that the equity beta of a distressed stock should fall as investors shift attention to the sure value they hope to recover in bankruptcy resolution. The same evidence weighs against the George and Hwang (2010) hypothesis, that firms with high distress costs will choose lower leverage levels whilst having higher exposure to systematic risk and hence higher expected returns, so that low credit risk stocks will have low leverage, high market betas and high expected returns.

Avramov et al (2009) hypothesise that the negative credit risk-return relationship derives in part from the disposition effect, though they do not present empirical support for this. We make use of the Grinblatt and Han (2005) unrealised capital gain / loss statistic to identify those stocks which are most liable to overpricing, driven by disposition investors' preference to hold on to assets in which they have recorded a large unrealised loss, and contribute to the literature by providing proof for this Avramov et al (2009) hypothesis. Avramov et al (2009) demonstrate that the negative credit risk-return relationship disappears if stocks rated lower than CCC+ are removed from the sample. Building on this, we show that the negative credit risk-return relationship likewise disappears when stocks with large unrealised capital losses are removed from the sample, demonstrating that the negative credit risk return relationship clusters principally in stocks with large unrealised capital losses.

We also advance on their findings that the effect is greatest before and after downgrades in credit rating, and that the negative credit risk-return relation disappears if stocks in the lowest decile of credit rating from the sample are deleted, three months before a downgrade to three months afterwards. We first replicate their results, confirming that stocks tend to experience sharp declines around the time that they move from a less distressed credit risk quintile to a more distressed credit risk quintile. However, we also find that this effect clusters in stocks with large unrealised capital losses: when stocks with unrealised capital gains in the top 80% are considered, the returns around the downward shift in credit quintile are mostly flat. By contrast, when stocks with unrealised capital losses in the lower 20% are considered, stocks suffer gradual declines before and heavy declines after moving from a less distressed credit risk quintile to a more distressed credit risk quintile. The downgrade effect noticed by Avramov et al (2009) therefore clusters only in stocks with large unrealised capital losses, as would be expected if these stocks suffered overpricing arising from the disposition effect.

Taken together, these advance the results in Avramov et al (2009) by providing evidence that it is the disposition effect which drives the negative relationship between credit risk and return, specifically, that disposition investors are driving overpricing in high credit risk stocks with large unrealised capital gains, preferring to retain them in the hope of riding out the losses.

Avramov et al (2009) also hypothesise that the negative credit risk-return relationship derives in part from the influence of limits-to-arbitrage factors, though they investigate a limited range of these factors. We test a wider range of limits-to-arbitrage factors, and provide empirical support for their hypothesis: in cross-section, a combination of limits-to-arbitrage factors is capable of subsuming the negative pricing of credit risk. One visualisation of this is that each of these limits-to-arbitrage factors creates an arbitrage channel around the fundamental process, inside which the correction of mispricing is unprofitable. High credit risk stocks remain inside the upper bound of this arbitrage channel, which permits their overpricing to persist.

Additionally, in novel results, we trace the negative credit risk–return relation back to the underperformance of high credit risk Losers: this subgroup of stocks has, on average, very substantial unrealised capital losses and severe levels of limits-to-arbitrage factors. We argue that the former will cause them to become overpriced through the action of disposition investors, and the latter will perpetuate their overpricing. We further suggest that the uncertainty surrounding the future of high credit risk firms is likely to drive increased uncertainty and divergence of opinion among investors concerning their equities, and, following Miller (1977), that this is likely to create overpricing where a stock's ownership can be absorbed by only the most optimistic investors.

Avramov et al (2009) suggest that high credit risk stocks may be held disproportionately by disposition investors, but in support of this show only that institutional ownership first declines and then increases for the decile of highest distress around a downgrade. We are able to supply firmer evidence for this: in novel results, we demonstrate a clear divergence between the Amihud illiquidity measures for highest credit risk Winner stocks on up- versus down-days, and argue that this is most easily explained if high credit risk stocks are held disproportionately by disposition investors, who retain them on down-days, so increasing down-day illiquidity, but sell preferentially on up-days, decreasing up-day illiquidity. Further, we find that portfolios double-sorted on prior returns and credit risk have greater illiquidity on down-days compared to up-days for each double-sorted category, which again suggests that disposition investors have measurable impacts on daily liquidity measures. Further proof comes from our results on the variation of turnover with momentum decile: for the two least distressed quintiles of credit risk, turnover manifests a U-shaped variation with respect to momentum decile, as would be predicted if it were acting a limits-to-arbitrage factor. For the three most distressed quintiles of credit risk, however, turnover decreases monotonically from Winners to Losers, so that Winner stocks exhibit higher turnover than both mid-ranking stocks and Loser stocks, as would be expected if such stocks were held predominantly by disposition investors.

Based on these results, we argue a joint behavioural and limits-to-arbitrage story for the negative credit risk–return relation: that high credit risk stocks are disproportionately held by disposition investors, who will tend to increase selling pressure on high credit risk stocks which are also Winners, hoping to lock in a sure gain, and reduce selling pressure on high credit risk stocks which are also Losers, hoping to ride out their losses. We therefore argue that high credit risk Loser stocks will tend to become overpriced under the action of disposition investors.

We explain why such overpricing persists by making use of the Shleifer and Vishny (1997) theory of restricted arbitrage, in which the cost, risk or difficulty of executing arbitrage trades explains why arbitrageurs can be unable or unwilling to arbitrage away the price distortions introduced by other investors. It therefore ought to be expected that pricing anomalies will be most severe in stocks which have high levels of limits to arbitrage factors. In this vein, Ali et al. (2003) demonstrate that the book-to-market anomaly clusters in stocks which have high levels of limits-to-arbitrage. In similar fashion, we find that the negative pricing of credit risk likewise clusters in such stocks, specifically, those with high average spread, high illiquidity and small size. Moreover, we show that high credit risk Loser stocks have the highest levels of limits-to-arbitrage factors of all stocks: they have the highest levels of idiosyncratic volatility, are the most illiquid, have the widest bid-ask spreads and the lowest proportional turnover.

Ali et al. (2003) examine the case that their limits-to-arbitrage factors are capable of subsuming the book-to-market premium in cross-section, by testing whether the entry of these factors renders the pricing of book-to-market insignificant. In a similar manner, we test whether our limits-to-arbitrage factors are capable of subsuming the negative pricing of credit risk in cross-section. Firstly, we show that the limits-to-arbitrage factors we consider have the expected pricing in cross-section, that is, stocks with higher levels of limits-to-arbitrage factors suffer greater overpricing and lower returns than stocks with low levels. Credit risk is significantly negatively priced in cross-section when included on its own or with the size and book-to-market, but the joint entry of these limits-to-arbitrage factors reduces credit risk to insignificance.

We also contribute to the limits-to-arbitrage literature by showing that each of the factors we examine has a characteristic U-shaped pattern with respect to prior return deciles. Theory would predict that arbitrageurs will be inhibited from correcting both overpricing and underpricing where the barriers to arbitrage are high, and accordingly, we find that both Winners and Losers have higher levels of each limits-to-arbitrage factor than mid-ranking stocks. Further, as Miller (1977) argues, the arbitrage of a short leg of a trade is usually inhibited to a greater extent than the long leg of a trade, owing to the greater practical difficulty of shorting a stock. On this basis, we should expect overpricing to be more prevalent among Loser stocks than Winner stocks, so that Losers should be expected to have higher levels of limits-to-arbitrage factors than Winners.

As these two effects would predict, we find that Winner and Loser stocks, as ranked on prior returns, have higher levels of each factor than mid-ranking stocks, and that Losers have significantly higher levels than Winners. Specifically, this pattern holds for illiquidity as measured by the log turnover Amihud (2002) measure, the Down-Amihud measure and the Up-Amihud measure; for idiosyncratic risk, for bid-ask spread, and for turnover among the least distressed stocks. A portfolio of stocks with very *high* levels of each limits-to-arbitrage factor will contain more Losers than Winners, that is, will have low returns, whereas a portfolio of stocks with very *low* levels of each factor will contain predominantly mid-ranking stocks. The overall effect is that the limits-to-arbitrage factors have a net negative pricing in cross-section. Though a U-shaped relationship between momentum decile and idiosyncratic risk has been noted by Arena et al (2008), our findings of similar profiles for illiquidity, bid-ask spread and proportional turnover are novel and support the hypothesis that these are driven by limits-to-arbitrage processes.

Table 1: Summary statistics for tax data and other key variables

Statistic	Mean	Median	Standard Deviation	10th Percentile	90th Percentile
Market Beta	0.88	0.83	0.56	1.56	0.24
log (Size)	4.75	4.45	1.72	7.24	2.76
log (Book to market)	0.62	0.51	0.44	1.31	0.15
z-score	-3.95	-3.48	6.91	4.51	-13.34
Idiosyncratic Risk	1.6%	1.3%	1.3%	3.0%	0.5%
Average Spread	3.6%	2.7%	3.2%	7.2%	0.9%
Average log (Turnover)	-6.36	-6.14	1.39	-4.98	-8.03
Illiquidity Factor)	2.28	2.14	1.35	3.92	0.81
Illiquidity Factor) Up	1.69	1.61	1.40	3.35	0.13
Illiquidity Factor) Down	2.74	2.60	1.58	4.70	0.95

Notes: Statistics defined as in Section 4.

Figure 1: Average values of the Grinblatt & Han (2005) unrealised capital gains factor through time, with lookback period of 12 months

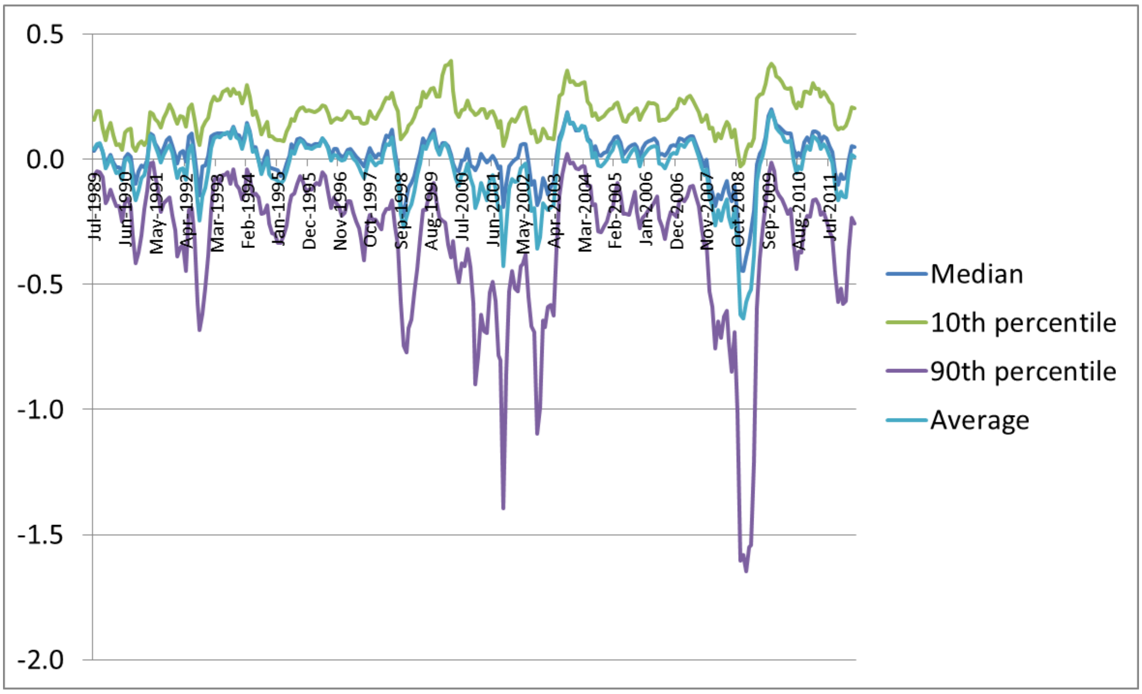

Figure 2: Average values of the Grinblatt & Han (2005) unrealised capital gains factor through time, with lookback period of 36 months

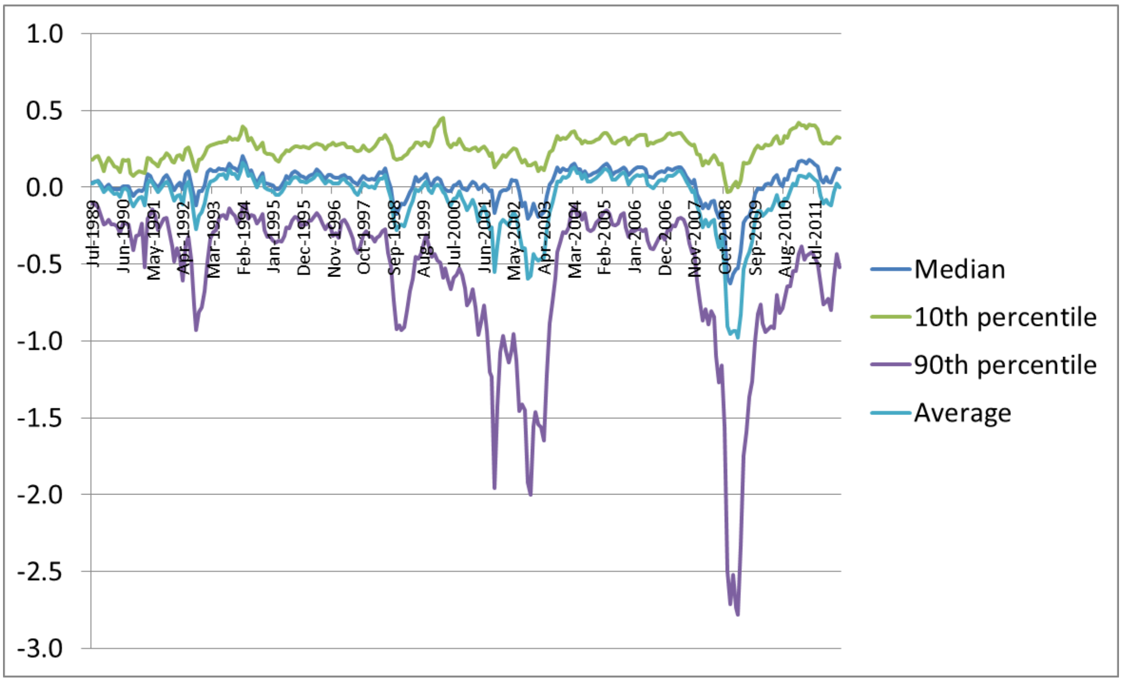

Figure 3: Average values of the log turnover Amihud (2002) illiquidity factor through time

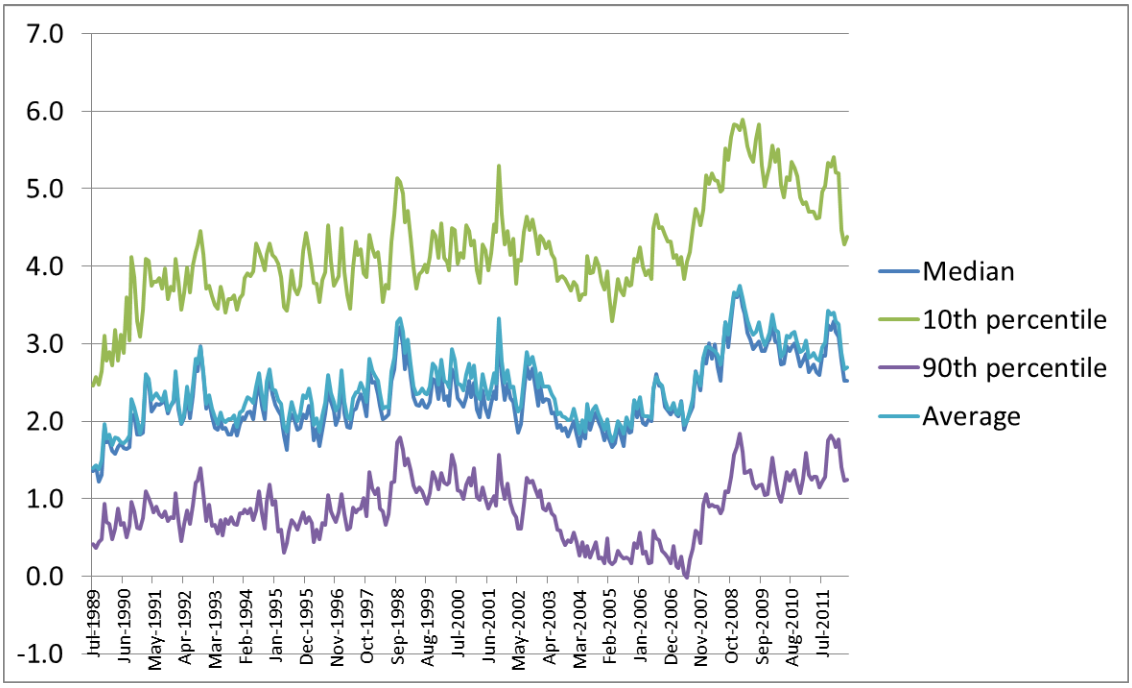

Table 2: Raw equal-weighted time-series momentum returns

Intercept (β_1)

		Momentum quintile					Momentum
		Winners				Losers	1 - 5
		1	2	3	4	5	return
High credit risk	1	0.11%	0.25%	0.18%	-0.57%***	-1.50%***	1.62%***
	2	-0.19%	-0.02%	0.08%	-0.37%**	-0.89%***	0.70%*
Z-Score	3	-0.16%	0.21%	0.02%	-0.27%	-0.84%***	0.69%*
	4	-0.09%	-0.01%	0.02%	-0.13%	-0.44%*	0.34%
Low credit risk	5	0.17%	-0.03%	0.20%	-0.26%	-0.67%**	0.84%**
Z-Score 1 - Z-Score 5 return		-0.06%	0.27%	-0.02%	-0.31%	-0.83%**	
Z-Score 2 - Z-Score 5 return		-0.36%	0.01%	-0.12%	-0.11%	-0.22%	

Table 3: Fama-French regressions of equal-weighted time-series momentum returns

Intercept (β_1)

		Momentum quintile					Momentum
		Winners				Losers	1 - 5
		1	2	3	4	5	return
High credit risk	1	0.03%	-0.26%	-0.49%***	-0.94%***	-1.83%***	1.86%***
	2	0.20%	-0.27%**	-0.37%***	-0.59%***	-1.34%***	1.55%***
Z-Score	3	0.02%	-0.07%	-0.18%	-0.54%***	-1.33%***	1.35%***
	4	0.13%	-0.06%	-0.14%	-0.34%**	-0.71%***	0.85%***
Low credit risk	5	0.47%**	0.13%	-0.02%	-0.37%**	-0.92%***	1.39%***
Z-Score 1 - Z-Score 5 return		-0.43%**	-0.39%***	-0.47%***	-0.58%***	-0.91%***	
Z-Score 2 - Z-Score 5 return		-0.26%*	-0.40%***	-0.35%***	-0.22%	-0.42%*	

β_{RmRf}

		Momentum quintile					Momentum
		Winners				Losers	1 - 5
		1	2	3	4	5	return
High credit risk	1	1.00***	0.92***	0.96***	1.04***	1.24***	-0.24***
	2	0.86***	0.85***	0.87***	0.98***	1.20***	-0.34***
Z-Score	3	0.86***	0.79***	0.85***	0.93***	1.14***	-0.29***
	4	0.84***	0.84***	0.87***	0.94***	1.11***	-0.26***
Low credit risk	5	0.81***	0.78***	0.77***	0.90***	1.18***	-0.37***
Z-Score 1 - Z-Score 5 return		0.20***	0.14***	0.19***	0.14***	0.06	
Z-Score 2 - Z-Score 5 return		0.05	0.07***	0.10***	0.08**	0.02	

Notes: Statistics in Table 2 represent raw returns to an equal-weighted (6,1,6) Jegadeesh and Titman (1993) momentum strategy, and statistics in Table 3 represent the regression intercepts and market betas from the time-series regression $R_{i,t} - R_{f,t} = \beta_{0,i} + \beta_{RmRf,i}(R_{m,t} - R_{f,t}) + \beta_{SMB,i} SMB_t + \beta_{HML,i} HML_t + \varepsilon_{t,i}$, for the momentum portfolio returns, and the regression $R_{i,t} = \beta_{0,i} + \beta_{RmRf,i}(R_{m,t} - R_{f,t}) + \beta_{SMB,i} SMB_t + \beta_{HML,i} HML_t + \varepsilon_{t,i}$, for the arbitrage returns (Momentum 1 - 5 return, z-score 1/2 – z-score 5 return), where $R_{i,t}$ represents the time-series return to an equal-weighted (6,1,6) Jegadeesh and Titman (1993) momentum strategy. In each case, stocks are sorted independently each month on Taffler (1983) z-score based on the most recent financial information having a year-end six months prior to the month of sorting, and aggregate return over the formation period. Holding periods are overlapping and portfolios are equally-weighted at the start of the holding period. $R_{f,t}$ represents the pro-rated 3-month Sterling Treasury Bill Rate in month t, $R_{m,t}$ represents the proportional return to the FTSE All-Share Return Index in month t, SMB_t and HML_t represent the SMB and HML factors for each month, calculated as in Gregory (2013). *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

Table 4: The cross sectional pricing of credit risk

	Model 3	Model 4
Intercept	-3.76***	-3.69***
	(-3.59)	(-3.93)
Market Beta	-0.09	-0.09
	(-0.55)	(-0.62)
log (Size) †	11.96**	8.16*
	(2.40)	(1.72)
log (Book to market)	2.39***	1.95***
	(3.97)	(3.60)
z-score †	-2.12***	-4.62***
	(-3.74)	(-4.67)
z-score x I [Winner mom decile] †		4.25***
		(3.49)
z-score x I [Middle mom decile] †		3.52***
		(3.46)
I [Winner mom decile]		1.47***
		(6.36)
I [Middle mom decile]		0.77***
		(4.89)
Average no. of observations	815	815
Adjusted R-squared (%)	2.90	3.93

Notes: t-ratios in parentheses; All coefficients are multiplied by 100 except for those marked †, which are multiplied by 10,000. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Fama–MacBeth (1973) cross-sectional regressions conducted across 274 months. Shanken (1992) corrections are applied to the t-ratios for the intercept and slope estimate on the market beta.

Table 5 Effect of removing stocks with unrealised capital losses from the sample

Lookback period for unrealised capital gain	12 Months			36 Months			60 Months		
Stock sample excludes stocks with an aggregate unrealised capital gain of less than: (relative to current share price)	z-score coefficient	% of firms	% of Market Cap	z-score coefficient	% of firms	% of Market Cap	z-score coefficient	% of firms	% of Market Cap
All firms with valid capital unrealised capital gain statistic	-1.90*** (-2.69)	100%	100%	-2.05*** (-2.96)	100%	100%	-2.25*** (-3.23)	100%	100%
-200%	-1.96*** (-2.77)	99.86%	99.99%	-2.06*** (-2.97)	99.13%	99.96%	-2.22*** (-3.16)	98.91%	99.96%
-150%	-1.97*** (-2.80)	99.62%	99.98%	-1.91*** (-2.75)	98.38%	99.93%	-2.04*** (-2.92)	97.74%	99.91%
-100%	-1.93*** (-2.76)	98.93%	99.92%	-1.70** (-2.45)	96.28%	99.77%	-1.93*** (-2.81)	95.59%	99.76%
-90%	-1.85*** (-2.63)	98.52%	99.88%	-1.58** (-2.28)	95.55%	99.71%	-1.87*** (-2.75)	94.77%	99.68%
-80%	-1.85*** (-2.61)	97.91%	99.82%	-1.56** (-2.25)	94.71%	99.62%	-1.67** (-2.50)	93.84%	99.60%
-70%	-1.74** (-2.48)	97.33%	99.74%	-1.38** (-2.02)	93.48%	99.45%	-1.37** (-2.08)	92.33%	99.40%
-60%	-1.50** (-2.15)	96.51%	99.63%	-1.14* (-1.67)	92.03%	99.14%	-1.13* (-1.72)	90.56%	99.07%
-50%	-1.42** (-2.06)	95.17%	99.37%	-0.35 (-0.52)	89.75%	98.65%	-0.67 (-1.00)	88.37%	98.59%
-40%	-0.52 (-0.77)	93.10%	98.93%	-0.52 (-0.77)	86.76%	97.88%	-0.77 (-1.19)	85.85%	97.87%
-30%	-1.06 (-1.55)	89.43%	97.84%	-0.35 (-0.52)	83.27%	96.72%	-0.67 (-1.00)	82.53%	96.77%
-20%	-0.52 (-0.77)	84.00%	95.20%	0.06 (0.09)	78.46%	94.12%	-0.38 (-0.58)	77.89%	94.40%
-10%	0.15 (0.22)	74.78%	88.73%	0.49 (0.72)	71.03%	88.73%	0.25 (0.38)	70.79%	89.44%
0%	0.49 (0.64)	56.30%	69.31%	0.55 (0.75)	57.03%	74.99%	0.30 (0.43)	57.26%	76.65%
All stocks inc. those without valid aggregate capital gain factors	-2.13*** (-3.75)	144.62%	102.93%	-2.13*** (-3.75)	137.80%	104.63%	-2.13*** (-3.75)	152.68%	109.69%

Figure 4: Returns around increases in credit risk : all stocks with a Grinblatt & Han (2005) unrealised capital gains factor in the upper 8 deciles at the month of downward shift in credit quintile (12 month lookback period)

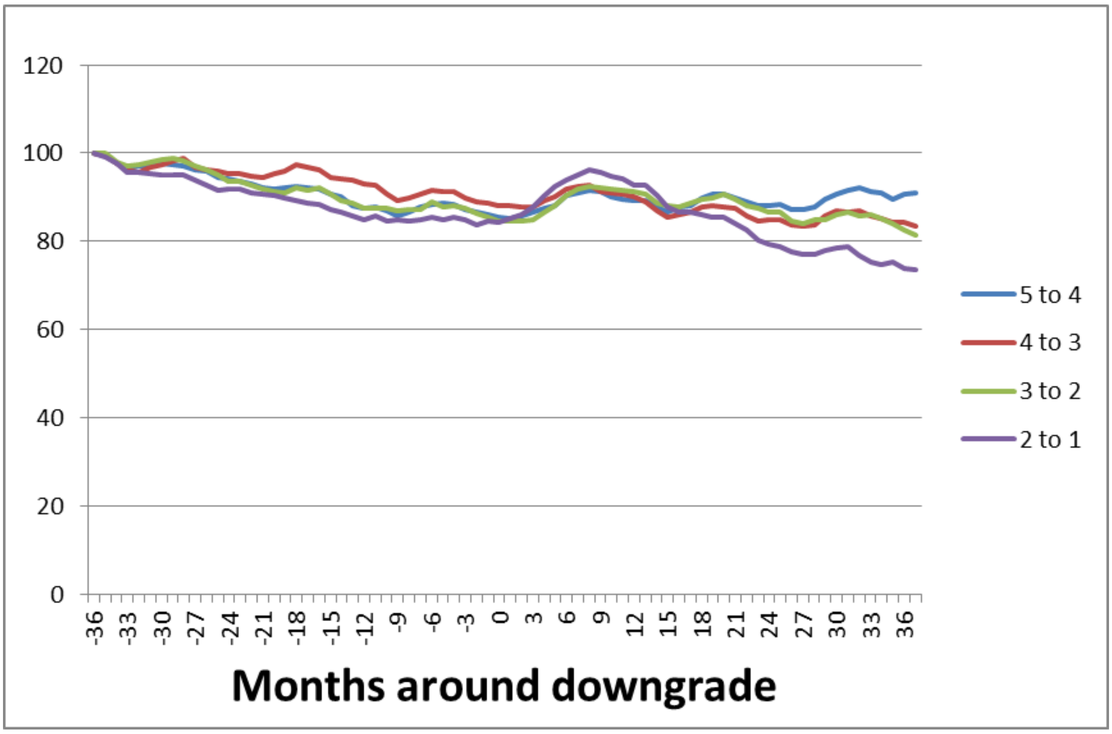

Figure 5: Returns around increases in credit risk: all stocks with a Grinblatt & Han (2005) unrealised capital gains factor in the lower 2 deciles at the month of downward shift in credit quintile (12 month lookback period)

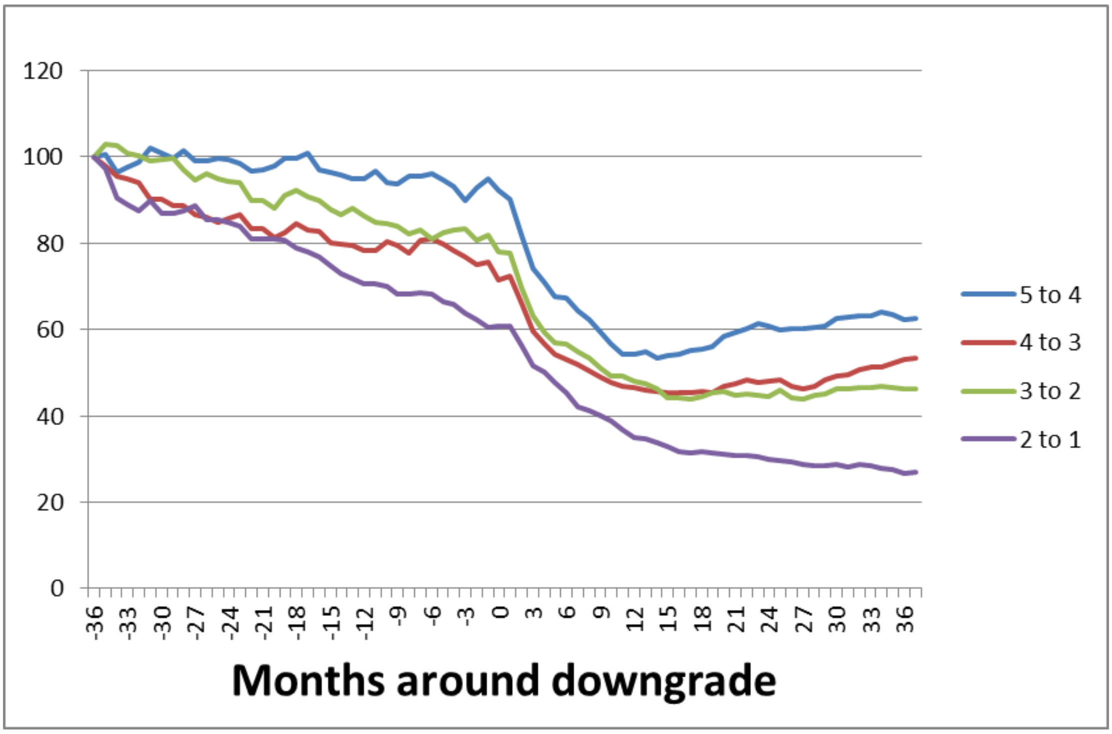

Table 6: The variation of limits-to-arbitrage factors with credit risk and prior returns

		Winners 1	2	Momentum decile 5	6	9	Losers 10	Difference 1 - 10	t	p
Idiosyncratic volatility										
High credit risk	1	2.21%	1.75%	1.59%	1.68%	2.25%	3.25%	-1.04%***	(-10.13)	0.000
	2	1.69%	1.38%	1.30%	1.36%	1.80%	2.67%	-0.98%***	(-10.39)	0.000
z-Score quintiles	3	1.54%	1.31%	1.21%	1.24%	1.71%	2.48%	-0.93%***	(-10.88)	0.000
	4	1.59%	1.27%	1.19%	1.23%	1.65%	2.31%	-0.72%***	(-8.70)	0.000
Low credit risk	5	1.68%	1.28%	1.19%	1.21%	1.71%	2.40%	-0.72%***	(-8.02)	0.000
Dfference (Quintile 5 - Quintile 1)		-0.53%***	-0.47%***	-0.40%***	-0.47%***	-0.53%***	-0.85%***			
	t	(-5.69)	(-7.09)	(-7.44)	(-8.54)	(-6.61)	(-8.52)			
	p	0.000	0.000	0.000	0.000	0.000	0.000			
Average Amihud (2002) factor										
High credit risk	1	2.29	2.27	2.35	2.47	2.90	3.07	-0.78***	(-13.28)	0.000
	2	2.09	2.02	2.13	2.19	2.55	2.74	-0.65***	(-11.48)	0.000
z-Score quintiles	3	2.01	2.00	2.12	2.14	2.45	2.68	-0.67***	(-10.63)	0.000
	4	1.98	1.95	2.06	2.11	2.42	2.51	-0.54***	(-9.00)	0.000
Low credit risk	5	2.08	2.11	2.29	2.36	2.66	2.75	-0.66***	(-10.14)	0.000
Dfference (Quintile 5 - Quintile 1)		-0.21***	-0.15***	-0.06	-0.10	-0.24***	-0.33***			
	t	(-3.33)	(-2.59)	(-0.96)	(-1.57)	(-4.10)	(-5.29)			
	p	0.001	0.010	0.339	0.118	0.000	0.000			
Average Amihud Up (2002) factor										
High credit risk	1	1.69	1.68	1.67	1.78	2.16	2.27	-0.59***	(-10.12)	0.000
	2	1.61	1.49	1.56	1.59	1.87	1.98	-0.38***	(-6.17)	0.000
z-Score quintiles	3	1.49	1.52	1.62	1.57	1.80	1.91	-0.42***	(-6.24)	0.000
	4	1.45	1.45	1.58	1.56	1.75	1.74	-0.29***	(-4.65)	0.000
Low credit risk	5	1.64	1.58	1.70	1.79	1.94	1.96	-0.32***	(-4.61)	0.000
Dfference (Quintile 5 - Quintile 1)		-0.05	-0.10	0.04	0.02	-0.22***	-0.32***			
	t	(-0.78)	(-1.61)	(0.60)	(0.27)	(-3.46)	(-4.94)			
	p	0.436	0.109	0.550	0.790	0.001	0.000			
Average Amihud Down (2002) factor										
High credit risk	1	2.85	2.80	2.92	3.06	3.60	3.82	-0.97***	(-14.13)	0.000
	2	2.52	2.45	2.54	2.62	3.10	3.39	-0.87***	(-13.46)	0.000
z-Score quintiles	3	2.43	2.38	2.47	2.54	2.93	3.28	-0.85***	(-11.15)	0.000
	4	2.40	2.31	2.41	2.50	2.86	3.10	-0.70***	(-9.34)	0.000
Low credit risk	5	2.45	2.49	2.67	2.77	3.18	3.33	-0.88***	(-12.05)	0.000
Dfference (Quintile 5 - Quintile 1)		-0.40***	-0.31***	-0.25***	-0.29***	-0.42***	-0.48***			
	t	(-5.45)	(-4.47)	(-3.15)	(-3.53)	(-6.07)	(-7.05)			
	p	0.000	0.000	0.002	0.000	0.000	0.000			

Notes: Stocks are sorted independently at the start of each month on past return from *t*-7 to *t*-1 and z-score quintile as at the start of the month. Accounting figures are taken from the most recent set of accounts having a financial year end finishing at least 6 months prior to the start of the month in which returns are measured. Averages of each metric are then calculated for each momentum / z-Score category for each month, and values represent equal-weighted time-series averages of these averages across all months, in each category. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Each month, Idiosyncratic Volatility and each of the illiquidity measures are winsorized each month at the 0.05% and 99.5% fractiles in order to minimise the effect of outliers.

Table 7:The variation of limits-to-arbitrage factors with credit risk and prior returns

		Winners		Momentum decile			Losers	Difference		
		1	2	5	6	9	10	1 - 10	t	p
Average log (Turnover)										
High credit risk	1	-6.33	-6.41	-6.48	-6.64	-6.81	-6.72	0.39***	(6.97)	0.000
	2	-6.19	-6.21	-6.29	-6.28	-6.43	-6.39	0.20***	(3.58)	0.000
z-Score quintiles	3	-6.20	-6.22	-6.28	-6.27	-6.33	-6.30	0.10	(1.56)	0.120
	4	-6.21	-6.15	-6.28	-6.28	-6.29	-6.21	0.00	(-0.04)	0.969
Low credit risk	5	-6.20	-6.32	-6.50	-6.50	-6.64	-6.44	0.24***	(3.66)	0.000
Dfference (Quintile 5 - Quintile 1)		0.14**	0.09	-0.02	0.14**	0.18***	0.29***			
	t	(2.24)	(1.64)	(-0.24)	(2.23)	(3.22)	(4.71)			
	p	0.025	0.101	0.808	0.026	0.001	0.000			
Average Spread										
High credit risk	1	4.33%	4.10%	4.14%	4.28%	6.02%	7.93%	-3.60%***	(-25.00)	0.000
	2	3.13%	2.86%	2.93%	3.01%	4.23%	5.83%	-2.70%***	(-25.34)	0.000
z-Score quintiles	3	2.99%	2.61%	2.62%	2.69%	4.06%	5.40%	-2.41%***	(-18.84)	0.000
	4	2.88%	2.49%	2.48%	2.67%	3.66%	5.27%	-2.39%***	(-18.27)	0.000
Low credit risk	5	2.97%	2.71%	2.94%	2.99%	4.17%	5.51%	-2.54%***	(-17.22)	0.000
Dfference (Quintile 5 - Quintile 1)		-1.36%***	-1.39%***	-1.20%***	-1.29%***	-1.86%***	-2.42%***			
	t	(-12.51)	(-12.89)	(-10.74)	(-11.13)	(-11.82)	(-13.83)			
	p	0.000	0.000	0.000	0.000	0.000	0.000			
Average market capitalisation (£m)										
High credit risk	1	432.00	712.81	975.45	863.35	508.79	258.36	173.6***	(2.64)	0.009
	2	508.68	791.57	1,070.90	997.23	800.06	366.14	142.5*	(1.93)	0.055
z-Score quintiles	3	596.96	1,070.30	1,500.08	1,345.29	615.15	321.85	275.1***	(2.94)	0.004
	4	631.13	1,106.14	1,559.79	1,323.70	960.73	330.29	300.8***	(3.47)	0.001
Low credit risk	5	438.60	646.20	665.09	705.34	425.53	271.78	166.8***	(3.95)	0.000
Dfference (Quintile 5 - Quintile 1)		6.6	-66.6	-310.4***	-158.0	-83.3	13.4			
	t	(0.11)	(-0.83)	(-2.63)	(-1.40)	(-0.96)	(0.26)			
	p	0.909	0.409	0.009	0.163	0.340	0.799			

Notes: Stocks are sorted independently at the start of each month on past return from *t*-7 to *t*-1 and z-score quintile as at the start of the month. Accounting figures are taken from the most recent set of accounts having a financial year end finishing at least 6 months prior to the start of the month in which returns are measured. Averages of each metric are then calculated for each momentum / z-Score category for each month, and values represent equal-weighted time-series averages of these averages across all months, in each category. *, ** and *** denotes significance at the 10%, 5% and 1% levels. Each month, Average Spread is winsorized each month at the 0.05% and 99.5% fractiles in order to minimise the effect of outliers.

Table 8: The variation of unrealised capital gains factor with credit risk and prior returns

Grinblatt & Han (2005) capital overhang factor - lookback period of 12 months x 100:

		Winners		Momentum decile			Losers	Difference		
		1	2	5	6	9	10	1 - 10	t	p
High credit risk	1	15.55***	10.04***	1.61**	-1.56*	-20.53***	-68.64***	84.20***	(15.89)	0.000
	2	15.97***	11.28***	2.90***	0.47	-15.19***	-41.99***	57.96***	(22.95)	0.000
z-Score quintiles	3	16.07***	11.97***	3.83***	0.43	-15.28***	-44.39***	60.46***	(19.59)	0.000
	4	15.72***	11.58***	3.70***	0.52	-14.62***	-40.93***	56.65***	(19.35)	0.000
Low credit risk	5	15.15***	11.34***	3.26***	0.55	-18.14***	-47.05***	62.20***	(15.38)	0.000
Dfference (Quintile 5 - Quintile 1)		-0.41	1.30	1.65*	2.11**	2.39	21.59***			
2-sample t-test		(-0.42)	(1.58)	(1.82)	(2.12)	(1.07)	(3.27)			
p		0.676	0.115	0.070	0.035	0.286	0.001			

Grinblatt & Han (2005) capital overhang factor - lookback period of 36 months x 100:

		1	2	5	6	9	10	1 - 10	t	p
High credit risk	1	3.09	1.08	-17.97*	-14.09***	-83.17***	-183.34***	186.42***	(9.60)	0.000
	2	17.23***	11.72***	4.05***	0.77	-22.57***	-66.66***	83.88***	(18.63)	0.000
z-Score quintiles	3	16.61***	14.92***	6.18***	1.77**	-20.73***	-85.73***	102.35***	(9.68)	0.000
	4	16.80***	13.90***	6.37***	2.63***	-17.76***	-59.30***	76.10***	(14.20)	0.000
Low credit risk	5	16.57***	13.21***	5.09***	2.04**	-25.43***	-75.64***	92.21***	(10.04)	0.000
Dfference (Quintile 5 - Quintile 1)		13.48***	12.14***	23.06**	16.13***	57.74***	107.69***			
2-sample t-test		(4.58)	(6.23)	(2.27)	(6.13)	(2.82)	(5.06)			
p		0.0	0.0	0.0	0.0	0.0	0.0			

Grinblatt & Han (2005) capital overhang factor - lookback period of 60 months x 100:

		1	2	5	6	9	10	1 - 10	t	p
High credit risk	1	-4.52	-5.90**	-9.13***	-42.80***	-69.91***	-266.21***	261.69***	(8.55)	0.0%
	2	16.37***	11.32***	3.66***	0.30	-31.90***	-76.75***	93.12***	(18.23)	0.0%
z-Score quintiles	3	16.51***	15.32***	6.86***	2.50***	-21.09***	-76.36***	92.86***	(10.28)	0.0%
	4	15.19***	13.83***	6.45***	3.27***	-17.89***	-63.04***	78.24***	(13.57)	0.0%
Low credit risk	5	15.63***	12.00***	6.39***	2.31**	-28.53***	-87.86***	103.49***	(10.20)	0.0%
Dfference (Quintile 5 - Quintile 1)		20.15***	17.89***	15.53***	45.11***	41.38***	178.35***			
2-sample t-test		(4.09)	(7.03)	(8.44)	(3.86)	(5.11)	(5.60)			
p		0.0%	0.0%	0.0%	0.0%	0.0%	0.0%			

Notes: Stocks are sorted independently at the start of each month on past return from *t*-7 to *t*-1 and z-score quintile as at the start of the month. Accounting figures are taken from the most recent set of accounts having a financial year end finishing at least 6 months prior to the start of the month in which returns are measured. Averages of each metric are then calculated for each momentum / z-Score category for each month, and values represent equal-weighted time-series averages of these averages across all months, in each category. *, ** and *** denotes significance at the 10%, 5% and 1% levels. Each month, Average Spread is winsorized each month at the 0.05% and 99.5% fractiles in order to minimise the effect of outliers.

Table 9: The cross-sectional pricing of limits-to-arbitrage factors

	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15
Intercept	-3.13*** (-3.25)	-2.57** (-2.13)	-3.39*** (-2.71)	-2.37* (-1.90)	-2.58** (-1.99)	-2.73*** (-2.64)	-0.69 (-0.52)	1.65 (1.43)
Market Beta	-0.02 (-0.15)	0.01 (0.08)	0.03 (0.19)	-0.03 (-0.17)	0.00 (0.00)	-0.07 (-0.47)	-0.14 (-0.91)	-0.04 (-0.26)
log (Size) †	9.11* (1.83)	2.92 (0.48)	9.08 (1.49)	-1.67 (-0.27)	0.80 (0.12)	0.90 (0.18)	2.71 (0.44)	-11.10* (-1.83)
log (Book to market)	2.32*** (4.10)	2.53*** (3.52)	2.62*** (3.53)	2.63*** (3.60)	2.67*** (3.58)	2.37*** (3.86)	2.86*** (4.06)	2.46*** (3.75)
Idiosyncratic risk	-20.86*** (-3.81)							-33.07*** (-4.95)
Turnover Amihud Illiquidity factor †		-42.00*** (-11.37)						-4.57 (-0.88)
Turnover Amihud Up Illiquidity factor †			-34.81*** (-10.37)		-21.17*** (-4.72)			
Turnover Amihud Down Illiquidity factor †				-37.46*** (-10.78)	-23.66*** (-5.02)			
Average Spread						-9.98*** (-4.85)		-5.12 (-1.05)
Turnover †							50.28*** (11.17)	56.16*** (8.75)
Average no. of observations	799.40	608.17	586.89	593.53	572.25	779.56	643.73	607.71
Adjusted R-squared (%)	3.52	3.34	3.36	3.34	3.59	3.09	3.41	5.01

Notes: t-ratios in parentheses; All coefficients are multiplied by 100 except for those marked †, which are multiplied by 10,000. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Fama–MacBeth (1973) cross-sectional regressions conducted across 274 months. Shanken (1992) corrections are applied to the t-ratios for the intercept and slope estimate on the market beta.

Table 10: Variation of the pricing of credit risk with limits-to-arbitrage factors

Variable	Idiosyncratic Volatility	Average Spread	Unadjusted Price	Turnover	Turnover Amihud Illiquidity Factor	Up Turnover Amihud Illiquidity Factor	Down Turnover Amihud Illiquidity Factor	Size
LTA1	-0.68%	-1.31%***	0.09%	0.06%	-1.20%**	-0.85%*	-1.25%**	0.05%
(High)	(-1.38)	(-3.26)	(0.29)	(0.11)	(-2.37)	(-1.76)	(-2.44)	(0.18)
LTA2	-0.36%	-0.37%	-0.10%	0.28%	-0.88%*	-1.09%**	-0.82%	-0.32%
	(-0.92)	(-0.88)	(-0.35)	(0.52)	(-1.88)	(-2.46)	(-1.56)	(-0.94)
LTA3	-0.36%	-0.45%	-0.21%	-0.34%	-0.26%	-1.07%**	0.27%	-0.13%
	(-1.03)	(-1.17)	(-0.65)	(-0.75)	(-0.55)	(-2.16)	(0.54)	(-0.39)
LTA4	-0.38%	-0.39%	-0.26%	-0.21%	-0.77%	-0.83%	-0.49%	-0.53%
	(-1.09)	(-1.17)	(-0.82)	(-0.49)	(-1.56)	(-1.46)	(-1.14)	(-1.45)
LTA5	-0.66%**	-0.44%	-0.35%	-0.38%	-0.31%	-1.19%**	-0.33%	-0.46%
	(-2.18)	(-1.17)	(-1.02)	(-0.80)	(-0.61)	(-2.37)	(-0.76)	(-1.34)
LTA6	-0.37%	-0.65%*	-0.89%***	-0.68%	-0.34%	0.27%	-0.30%	-0.63%*
	(-1.20)	(-1.94)	(-2.71)	(-1.58)	(-0.79)	(0.53)	(-0.61)	(-1.77)
LTA7	-0.43%	-0.27%	-0.12%	-0.42%	-0.55%	-0.60%	0.20%	-1.07%***
	(-1.41)	(-0.78)	(-0.33)	(-0.96)	(-1.05)	(-1.30)	(0.37)	(-2.75)
LTA8	-0.62%**	0.16%	0.18%	-0.55%	0.14%	-0.08%	0.13%	-1.10%***
	(-2.04)	(0.44)	(0.50)	(-1.16)	(0.35)	(-0.20)	(0.28)	(-2.95)
LTA9	-0.79%**	-0.21%	-0.46%	-1.34%***	-0.24%	0.83%*	-0.10%	-0.22%
	(-2.37)	(-0.55)	(-1.30)	(-2.92)	(-0.60)	(1.94)	(-0.24)	(-0.59)
LTA10	-0.58%*	0.07%	-0.99%*	-1.23%***	0.48%	-0.45%	0.43%	-1.04%***
(Low)	(-1.95)	(0.23)	(-1.79)	(-2.75)	(1.07)	(-0.94)	(1.12)	(-2.71)
LTA1 - LTA10	-0.10%	-1.38%***	1.07%*	1.13%*	-1.53%**	-0.21%	-1.46%**	1.09%**
(High - Low)	(-0.20)	(-2.75)	(1.70)	(1.96)	(-2.35)	(-0.32)	(-2.53)	(2.35)

Notes: Risk-adjusted credit-risk return relation, by deciles of limits-to-arbitrage factors, after Ali et al (2003). Each month, stocks are sorted simultaneously into quintiles of credit risk and deciles of each limits-to-arbitrage factor, with Q1 (Q5) representing the quintile of highest (lowest) credit risk, and LTA1 (LTA10) representing the decile of highest (lowest) limits-to-arbitrage factor, i.e. highest (lowest) idiosyncratic volatility, widest (narrowest) average spread, highest (lowest) unadjusted share price, highest (lowest) turnover, most illiquid (most liquid), and highest market value (smallest market value) stocks, respectively. Reported statistics for each LTA decile *x* represent the month-ahead return for the trading strategy which is long the Q1, LTA*x* portfolio and short the Q5, LTA*x* portfolio. LTA1 – LTA10 statistics represent the month-ahead trading strategy which is long (short) the Q1, LTA1 and Q5, LTA10 (Q1, LTA5 and Q5, LTA1) portfolios. t-statistics are in brackets. Accounting figures are taken from the most recent set of accounts having a financial year end finishing at least 6 months prior to the start of the month in which returns are measured. Portfolios are equal-weighted, in each category. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

Table 11: The interaction of multiple limits to arbitrage factors and credit risk

	Model 16	Model 17	Model 18	Model 19	Model 20	Model 21	Model 22	Model 23	Model 24
Intercept	-3.02***	-2.93***	-2.26*	-1.95	-3.12**	-2.94**	-2.07*	-1.65	-1.86
	(-3.14)	(-3.06)	(-1.89)	(-1.64)	(-2.53)	(-2.40)	(-1.68)	(-1.34)	(-1.45)
Market Beta	-0.00	-0.00	0.01	0.02	0.03	0.03	-0.03	-0.03	-0.01
	(-0.05)	(-0.01)	(0.07)	(0.12)	(0.16)	(0.19)	(-0.19)	(-0.19)	(-0.06)
log (Size) †	7.94	7.74	0.28	0.08	6.75	6.49	-4.05	-4.35	-2.33
	(1.61)	(1.58)	(0.04)	(0.01)	(1.16)	(1.12)	(-0.69)	(-0.75)	(-0.38)
log (Book to market)	2.20***	2.16***	2.37***	2.27***	2.47***	2.44***	2.47***	2.34***	2.40***
	(3.88)	(3.82)	(3.32)	(3.20)	(3.37)	(3.32)	(3.40)	(3.21)	(3.24)
z-score †	-1.67***	-0.98	-1.85**	2.50*	-1.65**	1.03	-1.60**	3.71***	2.94**
	(-3.10)	(-1.26)	(-2.57)	(1.85)	(-2.28)	(0.89)	(-2.17)	(2.82)	(2.25)
z-score x Idiosyncratic Risk		-0.45							
		(-0.96)							
z-score x log Turnover Amihud factor †				-1.85***					
				(-3.33)					
z-score x log Turnover Amihud Up factor †						-1.42***			0.72
						(-2.72)			(0.85)
z-score x log Turnover Amihud Down factor †								-1.96***	-2.37***
								(-3.93)	(-2.90)
Idiosyncratic risk	-19.70***	-21.51***							
	(-3.63)	(-3.78)							
Turnover Amihud Illiquidity factor †			-42.83***	-49.43***					
			(-11.64)	(-10.76)					
Turnover Amihud Up Illiquidity factor †					-35.56***	-40.94***			-17.89***
					(-10.61)	(-9.65)			(-2.85)
Turnover Amihud Down Illiquidity factor †							-38.02***	-44.48***	-33.65***
							(-10.91)	(-10.62)	(-4.96)
Average no. of observations	799	799	608	608	587	587	594	594	572
Adjusted R-squared (%)	3.70	3.98	3.56	3.77	3.59	3.76	3.57	3.79	4.20

Notes: t-ratios in parentheses; All coefficients are multiplied by 100 except for those marked †, which are multiplied by 10,000. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Fama–MacBeth (1973) cross-sectional regressions conducted across 274 months. Shanken (1992) corrections are applied to the t-ratios for the intercept and slope estimate on the market beta.

Table 12: The interaction of multiple limits to arbitrage factors and credit risk

	Model 25	Model 26	Model 27	Model 28	Model 29	Model 30	Model 31	Model 32	Model 33
Intercept	-2.61**	-2.49**	-0.34	-0.02	1.88	1.85	2.13*	2.44**	2.17*
	(-2.54)	(-2.41)	(-0.26)	(-0.01)	(1.55)	(1.61)	(1.84)	(2.10)	(1.87)
Market Beta	-0.06	-0.06	-0.14	-0.13	-0.03	-0.04	-0.05	-0.06	-0.05
	(-0.40)	(-0.42)	(-0.90)	(-0.85)	(-0.20)	(-0.28)	(-0.41)	(-0.47)	(-0.41)
log (Size) †	-0.12	-0.31	0.19	0.46	-12.31**	-12.47**	-14.52***	-16.32***	-14.67***
	(-0.02)	(-0.06)	(0.03)	(0.07)	(-2.04)	(-2.07)	(-2.74)	(-3.08)	(-2.62)
log (Book to market)	2.26***	2.20***	2.67***	2.59***	2.40***	2.34***	2.37***	2.26***	2.38***
	(3.70)	(3.58)	(3.81)	(3.70)	(3.47)	(3.54)	(3.55)	(3.37)	(3.58)
z-score †	-1.46**	-0.86	-2.08***	5.71**	-1.04	-1.23*	-1.04*	-0.82	-1.02*
	(-2.53)	(-1.13)	(-2.96)	(2.11)	(-1.52)	(-1.87)	(-1.67)	(-1.28)	(-1.67)
z-score x Average Spread		-0.16							
		(-0.84)							
z-score x log Turnover †				1.18***					
				(2.81)					
Idiosyncratic risk					-34.20***	-32.65***	-32.24***	-32.70***	-32.04***
					(-5.02)	(-4.91)	(-5.51)	(-5.29)	(-5.32)
Turnover Amihud Illiquidity factor †						-5.40		-2.78	
						(-1.04)		(-0.56)	
Turnover Amihud Up Illiquidity factor †					-2.69				
					(-0.64)				
Turnover Amihud Down Illiquidity factor					1.16				
					(0.22)				
Average Spread	-9.63***	-10.33***			-4.54	-4.32			-2.79
	(-4.77)	(-4.66)			(-0.85)	(-0.88)			(-0.01)
Turnover †			50.91***	54.31***	59.31***	56.24***	59.38***	59.44***	59.91***
			(11.38)	(11.36)	(8.55)	(8.78)	(14.39)	(9.73)	(14.87)
Average no. of observations	780	780	644	644	572	608	676	647	675
Adjusted R-squared (%)	3.29	3.51	3.62	3.72	5.38	5.18	4.23	4.44	4.50

Notes: t-ratios in parentheses; All coefficients are multiplied by 100 except for those marked †, which are multiplied by 10,000. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Fama–MacBeth (1973) cross-sectional regressions conducted across 274 months. Shanken (1992) corrections are applied to the t-ratios for the intercept and slope estimate on the market beta.

Appendix: Data Handling Approach

Filtering methodology

The analyses in this paper are principally either double-sorts, in which one axis of the sort is a ranking on prior returns over a holding period, or else are cross-sectional regressions. In order to be included in the dataset at the start of the holding period, in the case of double-sorts, or at the start of the month in which returns are measured, in the case of cross-sectional regression, a company must have:

- A market capitalisation of at least £10m, in order to select only those stocks in which a realistic degree of liquidity is present;

- Been listed for at least 24 months, in order to enable 24-month pre-ranking market betas to be calculated for each stock;

- An actively-quoted mid-price available for at least 10 days in the previous month before the start of the respective period;

- Valid PI (price index), RI (return index) and MV (market cap) information in Datastream at the start of the respective period;

- An industry code other than finance stocks, real estate investment trusts or real estate holding companies, or an indeterminate industry classification (Datastream industry level 2 codes FINAN or NA);

- Valid accounting information at the start of the respective period to calculate the Taffler z-score (defined in the following section), namely, Profit before Tax, Total Liabilities, Current Liabilities, Total Assets, Current Assets, Cash, Sales and Depreciation. In order to guarantee non-infinite values of the z-score, Current Liabilities, Total Liabilities, Total Assets and (Sales - Profit before Tax - Depreciation) must be all nonzero. Additionally, in order to exclude Cash Shells, equities representing investment vehicles and dormant companies, the value of Sales must be present and nonzero;

- Valid accounting information at the start of the respective period to calculate Book-to-Market values, namely, Common Equity and a nonzero Market Value on the latest trading date immediately prior to the financial year end.

Delisting methodology

Delisting information is taken from the London Share Price Database (LSPD), or where information is unavailable, from Regulatory News Service news searches collated by hand. Where a stock is delisted through failure, it is assigned a -100% return upon delisting, otherwise we assume that the investor receives its full value, as at the date of delisting. Although the LSPD records the month from which a stock is no longer quoted, we prefer to use the last active date of trading as the date on which a stock exits the sample. There is normally is a delay of some weeks between the last day of active trading for practical purposes and the point at which a stock is formally delisted, and this is caused sometimes by the issuer or a bidder announcing the possibility of delisting, and at others by unilateral suspension of the shares by the Financial Conduct Authority.

Sorting methodology

Studies involving US data generally presume a December 31 financial year-end for the vast majority of companies, and allow six months for the publication of accounts, and so match monthly returns from July of year t to June of year t+1 with accounts whose financial year ends are in December of year t–1. As regards UK studies, Dimson et al. (2003) follow the standard US practice, while Agarwal and Taffler (2008), Agarwal and Poshakwale (2010) and Gregory et al. (2013) sort stocks from 1 October each year on the basis of accounts filings having financial year end dates of 31 March in the same year, at the latest.

However, the distribution of year ends in the present sample is spread over the year, so that this latter sorting methodology would be three months late in using accounts information relating to the 41% of stocks with December financial year ends; the conventional method for US stocks would not be any more timely in using accounts information, as it would be nine months late in using accounts information relating to the 20% of stocks with March financial year ends. Since both yearly sorting methods employed in the literature have drawbacks, we sort stocks on a rolling monthly basis, taking at each month the most recent accounts with a financial year end at least six months prior to the month in which sorting is taking place. A firm that has a financial year end of December will then have the monthly returns of July of year t to June of year t+1 matched with the accounts data for the financial year ending December of year t–1, while a firm having a financial year end in March will have the monthly returns of October of year t to September of year t+1 matched with the accounts data for the financial year ending March of year t.

Data cleaning and winsorization methodology

Comparison of Datastream with other datasets has given rise to warnings that care ought to be taken when calculating returns from Datastream to avoid spurious results arising from data errors, and to avoid incorrect sample inferences being drawn from a handful of extreme returns. The general practice in cleaning Datastream data is therefore to exclude small stocks by some criterion (Hong et al., 2003), and to winsorize returns to avoid spurious inferences being drawn from data errors (Chui et al., 2010; Ince and Porter, 2006; Sudarsanam and Mahate, 2003). For the present sample, we elect not to exclude stocks on the basis of falling below a certain percentile of market capitalisation, since this introduces the risk that more small, illiquid stocks will be admitted to the sample simply because there were more small stocks listed at that point in time. Instead, for the present paper, we exclude all stocks from the dataset which have a market capitalisation of less than £10m at the start of the month over which dependent variable returns are taken – this is a more severe criterion than in Hong et al. (2003), since it excludes on average 22.6% of the sample which would have otherwise been admitted had this rule not been applied.

Regarding winsorization on the downside, our delisting procedure generates monthly returns of -100% when a stock delists due to bankruptcy or distress, and these cases have either been designated from LSPD delisting data or coded by hand using news searches, so we treat these as reliable. Though Ince and Porter (2006) find examples of monthly returns of 300% or more which are reversed within the month, we find only three examples of monthly returns over 100% which are reversed the next month, and each of these is explicable by relation to extant company news rather than data errors. The remaining very small proportion of returns (0.08% of sample firm-months) which have monthly returns over 100% reflect real permanent changes in company value, and so we elect instead to winsorize each month on the upside at 200%, to avoid undue influence being exerted on the results by the handful of cases (20 firm-months, representing 0.008% of sample firm-months) which have monthly returns in excess of that limit.

We also winsorize some independent variables: we follow Fama and French (1992), Chordia and Shivakumar (2006), Fu (2009), Chordia et al. (2009), Chou et al. (2010) and Brennan et al. (2013) in winsorizing the log (book to market) variable to avoid placing undue emphasis on outliers. We follow the example of Dichev (1998), who winsorizes the Ohlson (1980) O-Score and the Altman (1968) Z-Score measures of relative distress, in winsorizing values of the Taffler (1983) z-score; both are winsorized each month at the 2.5% and 97.5% fractiles. Following Brennan et al. (2013), we winsorize the bid-ask spread, and following Fu (2009), we winsorize idiosyncratic volatility each month at the 0.5% and 99.5% fractiles. The Turnover Amihud statistics and bid-ask spread are winsorized each month at the 0.5% and 99.5% fractiles.

Calculation of Fama-French factors

SMB and HML factors for each day are calculated by using the methodology and breakpoints as in Gregory et al. (2013).

Pairwise correlation statistics are calculated using the analytics in RExcel (Baier and Neuwirth, 2007).

References

Agarwal, V., Bauer, J., 2014. Distress Risk and Stock Returns: The neglected Profitability Effect? Paper presented at the 2014 FMA Annual Meeting, Nashville, TN, October 15 - 18 [WWW Document]. URL http://www.fma.org/Nashville/Papers/Distress_and_Returns_Full.pdf (accessed 5.16.14).

Agarwal, V., Poshakwale, S., 2010. Size and book-to-market anomalies and omitted leverage risk. European Journal of Finance 16, 263–279. doi:10.1080/13518470903314402

Agarwal, V., Taffler, R., 2008. Does Financial Distress Risk Drive the Momentum Anomaly? Financial Management 37, 461–484.

Ali, A., Hwang, L.-S., Trombley, M.A., 2003. Arbitrage risk and the book-to-market anomaly. Journal of Financial Economics 69, 355–373. doi:10.1016/S0304-405X(03)00116-8

Ali, A., Trombley, M.A., 2006. Short Sales Constraints and Momentum in Stock Returns. Journal of Business Finance & Accounting 33, 587–615. doi:10.1111/j.1468-5957.2006.00616.x

Altman, E.I., 1968. Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. Journal of Finance 23, 589–609. doi:10.2307/2978933

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets 5, 31–56. doi:10.1016/S1386-4181(01)00024-6

Amihud, Y., Mendelson, H., 1986. Asset pricing and the bid-ask spread. Journal of Financial Economics 17, 223–249. doi:10.1016/0304-405X(86)90065-6

Ang, A., Hodrick, R.J., Xing, Y., Zhang, X., 2009. High idiosyncratic volatility and low returns: International and further U.S. evidence. Journal of Financial Economics 91, 1–23. doi:10.1016/j.jfineco.2007.12.005

Ang, A., Hodrick, R.J., Xing, Y., Zhang, X., 2006. The Cross-Section of Volatility and Expected Returns. Journal of Finance 61, 259–299.

Arena, M.P., Haggard, K.S., Yan, X. (Sterling), 2008. Price Momentum and Idiosyncratic Volatility. Financial Review 43, 159–190. doi:10.1111/j.1540-6288.2008.00190.x

Au, A.S., Doukas, J.A., Onayev, Z., 2009. Daily short interest, idiosyncratic risk, and stock returns. Journal of Financial Markets 12, 290–316. doi:10.1016/j.finmar.2008.09.001

Avramov, D., Cederburg, S., Hore, S., 2011. Cross-Sectional Asset Pricing Puzzles: A Long-Run Perspective [WWW Document]. URL http://papers.ssrn.com/abstract=1314869 (accessed 8.14.14).

Avramov, D., Chordia, T., Jostova, G., Philipov, A., 2009. Credit ratings and the cross-section of stock returns. Journal of Financial Markets 12, 469–499. doi:10.1016/j.finmar.2009.01.005

Avramov, D., Chordia, T., Jostova, G., Philipov, A., 2007. Momentum and Credit Rating. Journal of Finance 62, 2503–2520. doi:10.1111/j.1540-6261.2007.01282.x

Baier, T., Neuwirth, E., 2007. Excel :: COM :: R. Computational Statistics 22, 91–108. doi:10.1007/s00180-007-0023-6

Bali, T.G., Cakici, N., 2008. Idiosyncratic Volatility and the Cross Section of Expected Returns. Journal of Financial & Quantitative Analysis 43, 29–58.

Barber, B.M., Odean, T., 2000. Trading Is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors. Journal of Finance 55, 773–806.

Barber, B.M., Yi-Tsung Lee, Yu-Jane Liu, Odean, T., 2007. Is the Aggregate Investor Reluctant to Realise Losses? Evidence from Taiwan. European Financial Management 13, 423–447. doi:10.1111/j.1468-036X.2007.00367.x

Blazy, R., Chopard, B., Nigam, N., 2013. Building legal indexes to explain recovery rates: An analysis of the French and English bankruptcy codes. Journal of Banking & Finance 37, 1936–1959. doi:10.1016/j.jbankfin.2012.10.024

Brennan, M., Huh, S.-W., Subrahmanyam, A., 2013. An Analysis of the Amihud Illiquidity Premium. Review of Asset Pricing Studies 3, 133–176. doi:10.1093/rapstu/ras017

Brennan, M.J., Subrahmanyam, A., 1996. Market microstructure and asset pricing: On the compensation for illiquidity in stock returns. Journal of Financial Economics 41, 441–464. doi:10.1016/0304-405X(95)00870-K

Campbell, J.Y., Hilscher, J., Szilagyi, J., 2008. In Search of Distress Risk. Journal of Finance 63, 2899–2939. doi:10.1111/j.1540-6261.2008.01416.x

Chava, S., Purnanandam, A., 2010. Is Default Risk Negatively Related to Stock Returns? Review of Financial Studies 23, 2523–2559. doi:10.1093/rfs/hhp107

Chen, J., Chollete, L., Ray, R., 2010. Financial distress and idiosyncratic volatility: An empirical investigation. Journal of Financial Markets 13, 249–267. doi:10.1016/j.finmar.2009.10.003

Choi, J., Kim, Y., 2015. Anomalies and Market (Dis)Integration [WWW Document]. URL http://papers.ssrn.com/abstract=2412086 (accessed 5.25.15).

Chordia, T., Huh, S.-W., Subrahmanyam, A., 2009. Theory-Based Illiquidity and Asset Pricing. Review of Financial Studies 22, 3629–3668. doi:10.1093/rfs/hhn121

Chordia, T., Shivakumar, L., 2006. Earnings and price momentum. Journal of Financial Economics 80, 627–656. doi:10.1016/j.jfineco.2005.05.005

Chou, P.-H., Ko, K.-C., Lin, S.-J., 2010. Do relative leverage and relative distress really explain size and book-to-market anomalies? Journal of Financial Markets 13, 77–100. doi:10.1016/j.finmar.2009.07.007

Chua, C.T., Goh, J., Zhang, Z., 2010. Expected Volatility, Unexpected Volatility, and the Cross-Section of Stock Returns. Journal of Financial Research 33, 103–123. doi:10.1111/j.1475-6803.2010.01264.x

Chui, A.C. w, Titman, S., Wei, K. c. J., 2010. Individualism and Momentum around the World. Journal of Finance 65, 361–392. doi:10.1111/j.1540-6261.2009.01532.x

Da, Z., Gao, P., 2010. Clientele Change, Liquidity Shock, and the Return on Financially Distressed Stocks. Journal of Financial & Quantitative Analysis 45, 27–48.

D’Avolio, G., 2002. The market for borrowing stock. Journal of Financial Economics, Limits on Arbitrage 66, 271–306. doi:10.1016/S0304-405X(02)00206-4

Davydenko, S.A., Franks, J.R., 2008. Do Bankruptcy Codes Matter? A Study of Defaults in France, Germany, and the U.K. Journal of Finance 63, 565–608.

Dhar, R., Ning Zhu, 2006. Up Close and Personal: Investor Sophistication and the Disposition Effect. Management Science 52, 726–740. doi:10.1287/mnsc.1040.0473

Dichev, I.D., 1998. Is the Risk of Bankruptcy a Systematic Risk? Journal of Finance 53, 1131–1147.

Dimson, E., Nagel, S., Quigley, G., 2003. Capturing the Value Premium in the United Kingdom. Financial Analysts Journal 59, 35–45.

Duan, Y., Hu, G., McLean, R.D., 2010. Costly arbitrage and idiosyncratic risk: Evidence from short sellers. Journal of Financial Intermediation 19, 564–579. doi:10.1016/j.jfi.2009.06.003

Eisdorfer, A., Goyal, A., Zhdanov, A., 2013. Distress Anomaly and Shareholder Risk: International Evidence [WWW Document]. URL http://papers.ssrn.com/abstract=2267611 (accessed 5.25.15).

Eisdorfer, A., Goyal, A., Zhdanov, A., 2012. Misvaluation and Return Anomalies in Distress Stocks [WWW Document]. URL http://papers.ssrn.com/abstract=2023778 (accessed 3.20.13).

Eleswarapu, V.R., Reinganum, M.R., 1993. The seasonal behavior of the liquidity premium in asset pricing. Journal of Financial Economics 34, 373–386. doi:10.1016/0304-405X(93)90032-7

Fama, E.F., French, K.R., 1996. The CAPM is Wanted, Dead or Alive. Journal of Finance 51, 1947–1958. doi:10.2307/2329545

Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56. doi:10.1016/0304-405X(93)90023-5

Fama, E.F., French, K.R., 1992. The Cross-Section of Expected Stock Returns. Journal of Finance 47, 427–465. doi:10.2307/2329112

Fama, E.F., MacBeth, J.D., 1973. Risk, return, and equilibrium: Empirical tests. Journal of Political Economy 607–636.

Ferguson, M.F., Shockley, R.L., 2003. Equilibrium "Anomalies." Journal of Finance 58, 2549–2580. doi:10.1046/j.1540-6261.2003.00615.x

Finn, M.T., Fuller, R.J., King, J.L., 1999. Equity Mispricing: It's Mostly on the Short Side. Financial Analysts Journal 55, 117.

Franks, J., Sussman, O., 2005. Financial Distress and Bank Restructuring of Small to Medium Size UK Companies. Review of Finance 9, 65–96. doi:10.1007/s10679-005-2988-8

Friewald, N., Wagner, C., Zechner, J., 2014. The Cross-Section of Credit Risk Premia and Equity Returns. The Journal of Finance 69, 2419–2469. doi:10.1111/jofi.12143

Fu, F., 2009. Idiosyncratic risk and the cross-section of expected stock returns. Journal of Financial Economics 91, 24–37. doi:10.1016/j.jfineco.2008.02.003

Gao, P., Parsons, C.A., Shen, J., 2013. The Global Relation between Financial Distress and Equity Returns [WWW Document]. URL http://papers.ssrn.com/abstract=2086475 (accessed 5.25.15).

Garlappi, L., Yan, H., 2011. Financial Distress and the Cross Section of Equity Returns. Journal of Finance 66, 789–822. doi:10.1111/j.1540-6261.2011.01652.x

George, T.J., Hwang, C.-Y., 2010. A resolution of the distress risk and leverage puzzles in the cross section of stock returns. Journal of Financial Economics 96, 56–79. doi:10.1016/j.jfineco.2009.11.003

Glosten, L.R., Harris, L.E., 1988. Estimating the components of the bid/ask spread. Journal of Financial Economics 21, 123–142. doi:10.1016/0304-405X(88)90034-7

Goetzmann, W.N., Massa, M., 2008. Disposition Matters: Volume, Volatility, and Price Impact of a Behavioral Bias. Journal of Portfolio Management 34, 103–125.

Gregory, A., Tharyan, R., Christidis, A., 2013. Constructing and Testing Alternative Versions of the Fama–French and Carhart Models in the UK. Journal of Business Finance & Accounting 40, 172–214. doi:10.1111/jbfa.12006

Griffin, J.M., Lemmon, M.L., 2002. Book–to–Market Equity, Distress Risk, and Stock Returns. Journal of Finance 57, 2317–2336. doi:10.1111/1540-6261.00497

Grinblatt, M., Han, B., 2005. Prospect theory, mental accounting, and momentum. Journal of Financial Economics 78, 311–339. doi:10.1016/j.jfineco.2004.10.006

Grinblatt, M., Keloharju, M., 2000. The investment behavior and performance of various investor types: a study of Finland's unique data set. Journal of Financial Economics 55, 43–67. doi:10.1016/S0304-405X(99)00044-6

Gromb, D., Vayanos, D., 2010. Limits of Arbitrage: The State of the Theory, INSEAD Working Paper Series 2010/23/FIN [WWW Document]. URL https://flora.insead.edu/fichiersti_wp/inseadwp2010/2010-23.pdf (accessed 6.18.15).

Hasbrouck, J., 2009. Trading Costs and Returns for U.S. Equities: Estimating Effective Costs from Daily Data. Journal of Finance 64, 1445–1477.

Hillegeist, S.A., Keating, E.K., Cram, D.P., Lundstedt, K.G., 2004. Assessing the Probability of Bankruptcy. Review of Accounting Studies 9, 5–34. doi:10.1023/B:RAST.0000013627.90884.b7

Hong, D., Lee, C.M.C., Swaminathan, B., 2003. Earnings Momentum in International Markets [WWW Document]. URL http://papers.ssrn.com/abstract=390107 (accessed 8.20.14).

Ince, O.S., Porter, R.B., 2006. Individual Equity Return Data from Thomson Datastream: Handle with Care! Journal of Financial Research 29, 463–479. doi:10.1111/j.1475-6803.2006.00189.x

Jegadeesh, N., 1990. Evidence of Predictable Behavior of Security Returns. Journal of Finance 45, 881–898. doi:10.2307/2328797

Jegadeesh, N., Subrahmanyam, A., 1993. Liquidity Effects of the Introduction of the S&P 500 Index Futures Contract on the Underlying Stocks. Journal of Business 66, 171–187.

Jegadeesh, N., Titman, S., 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. Journal of Finance 48, 65–91. doi:10.2307/2328882

Kahneman, D., Tversky, A., 1979. Prospect Theory: An Analysis of Decision under Risk. Econometrica 47, 263–291. doi:10.2307/1914185

Kapadia, N., Pu, X., 2012. Limited arbitrage between equity and credit markets. Journal of Financial Economics 105, 542–564. doi:10.1016/j.jfineco.2011.10.014

Karpoff, J.M., 1987. The Relation between Price Changes and Trading Volume: A Survey. Journal of Financial & Quantitative Analysis 22, 109–126.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., Vishny, R.W., 1998. Law and Finance. Journal of Political Economy 106, 1113. doi:10.1086/250042

Lesmond, D., Ogden, J., Trzcinka, C., 1999. A new estimate of transaction costs. Review of Financial Studies 12, 1113–1141. doi:10.1093/rfs/12.5.1113

McQuade, T.J., 2013. Stochastic Volatility and Asset Pricing Puzzles, Working Paper. [WWW Document]. URL http://web.stanford.edu/~tmcquade/StochVol.pdf (accessed 5.25.15).

Menzly, L., Santos, T., Veronesi, P., 2004. Understanding Predictability. Journal of Political Economy 112, 1–47. doi:10.1086/379934

Merton, R.C., 1987. A Simple Model of Capital Market Equilibrium with Incomplete Information. Journal of Finance 42, 483–510. doi:10.2307/2328367

Merton, R.C., 1974. On the Pricing of Corporate Debt: The Risk Structure of Interest Rates. Journal of Finance 29, 449–470. doi:10.2307/2978814

Miller, E.M., 1977. Risk, Uncertainty, and Divergence of Opinion. Journal of Finance 32, 1151–1168. doi:10.2307/2326520

Oehler, A., Heilmann, K., Läger, V., Oberländer, M., 2003. Coexistence of disposition investors and momentum traders in stock markets: experimental evidence. Journal of International Financial Markets, Institutions and Money 13, 503–524. doi:10.1016/S1042-4431(03)00020-9

Ohlson, J.A., 1980. Financial Ratios and the Probabilistic Prediction of Bankruptcy. Journal of Accounting Research 18, 109–131. doi:10.2307/2490395

Ozdagli, A.K., 2013. Distressed, but not risky: Reconciling the empirical relationship between financial distress, market-based risk indicators, and stock returns (and more). University of Connecticut Finance Seminars. [WWW Document]. URL http://www.business.uconn.edu/finance/seminars/papers/Distress_Ozdagli.pdf (accessed 8.18.14).

Pástor, Ľ., Stambaugh, R.F., 2003. Liquidity Risk and Expected Stock Returns. Journal of Political Economy 111, 642–685.

Pontiff, J., 2006. Costly arbitrage and the myth of idiosyncratic risk. Journal of Accounting and Economics 42, 35–52. doi:10.1016/j.jacceco.2006.04.002

Radwanski, J.F., 2010. Can Long-Run Risks Explain the Distress Puzzle? [WWW Document]. URL http://papers.ssrn.com/abstract=1701275 (accessed 8.18.14).

Shanken, J., 1992. On the estimation of beta-pricing models. Review of Financial Studies 5, 1–55. doi:10.1093/rfs/5.1.1

Shefrin, H., Statman, M., 1985. The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence. Journal of Finance 40, 777–790. doi:10.2307/2327802

Shleifer, A., Vishny, R.W., 1997. The Limits of Arbitrage. Journal of Finance 52, 35–55. doi:10.2307/2329555

Shumway, T., 2001. Forecasting Bankruptcy More Accurately: A Simple Hazard Model. The Journal of Business 74, 101–124. doi:10.1086/209665

Spiegel, M.I., Wang, X., 2005. Cross-sectional Variation in Stock Returns: Liquidity and Idiosyncratic Risk, Yale ICF Working Paper No. 05-13 [WWW Document]. URL http://papers.ssrn.com/abstract=709781 (accessed 2.26.14).

Stoll, H.R., 1989. Inferring the Components of the Bid-Ask Spread: Theory and Empirical Tests. Journal of Finance 44, 115–134. doi:10.2307/2328278

Stoll, H.R., Whaley, R.E., 1983. Transaction costs and the small firm effect. Journal of Financial Economics 12, 57–79. doi:10.1016/0304-405X(83)90027-2

Sudarsanam, S., Mahate, A.A., 2003. Glamour Acquirers, Method of Payment and Post-acquisition Performance: The UK Evidence. Journal of Business Finance & Accounting 30, 299–342. doi:10.1111/1468-5957.00494

Taffler, R.J., 1983. The Assessment of Company Solvency and Performance Using a Statistical Model. Accounting and Business Research 13, 295–308. doi:10.1080/00014788.1983.9729767

Thaler, R., 1985. Mental Accounting and Consumer Choice. Marketing Science 4, 199.

Thaler, R., 1980. Toward a positive theory of consumer choice. Journal of Economic Behavior & Organization 1, 39–60. doi:10.1016/0167-2681(80)90051-7

Treynor, J.L., Black, F., 1973. How to Use Security Analysis to Improve Portfolio Selection. Journal of Business 46, 66–86.

Vassalou, M., Xing, Y., 2004. Default Risk in Equity Returns. Journal of Finance 59, 831–868. doi:10.1111/j.1540-6261.2004.00650.x