# PROBABILITIES OF LOSS REVERSALS AND RETURNS IN THE UK

Wei Jiang
(Assistant Professor of Accounting, Warwick Business School)

Nuno Soares
(Assistant Professor, Faculdade de Engenharia, Universidade do Porto and CEF.UP, Faculdade de Economia, Universidade do Porto)

Andrew W. Stark
(Coutts Professor of Accounting and Finance, Manchester Business School)

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## ABSTRACT

In this study, we attempt a number of contributions. Our initial contribution is to develop a loss reversal model which can be applied in the UK. According to the test criteria we establish, our results suggest that the loss reversal model is successful. The second contribution is to examine whether loss reversal probabilities are fully reflected in market prices. We find that, after controlling for other firm characteristics that are known to be, or could be, associated with stock returns in the UK, a hedge portfolio that takes a long position in firms with a high estimated likelihood of loss reversal and a short position in firms with a low estimated likelihood of loss reversal makes an average return of over 20% before trading costs are taken into account. This suggests that the UK stock market does not fully reflect the information in our model concerning loss reversal probabilities. Nonetheless, as a consequence of various trading frictions, it is unlikely that investors can exploit any mispricing opportunity.



Keywords: accounting losses, loss reversal, mispricing, return anomalies

JEL classification: M41 G14

# 1 INTRODUCTION

One of the main objectives of financial accounting is to provide information that enable analyses of aspects of economic performance in a manner useful to financial decisions. To this end, some studies demonstrate that the likelihood of achieving specified levels of earnings performance can be modeled using public available information. For example, in the US, Ou and Penman (1989) show that accounting information is helpful in predicting the likelihood of whether next year's earnings will be higher or lower than the previous growth trend in earnings implies (the difference between next year's earnings and the earnings figure implied by the previous growth trend in earnings being a proxy for unexpected earnings). Further, their work suggests that the market misjudges these likelihoods and, because unexpected earnings are linked to abnormal returns, that a profitable trading strategy can be developed to exploit these misjudgments. The profitability of the trading strategy is challenged in Grieg (1992), however, where the view is expressed that the method of controlling for risk in Ou and Penman (1989) is incomplete. Holthausen and Larcker (1992) develop the basic idea in Ou and Penman (1989) but, instead of developing a model to predict unexpected earnings, they use accounting data to directly predict abnormal returns. They argue that their modeling approach can be used to develop a profitable trading strategy. In the UK, Setiono and Strong (1998) study the approaches of both Ou and Penman (1989) and Holthausen and Larcker (1992). In contrast to the results in the US, Setiono and Strong (1998) find stronger evidence in favour of the approach of Ou and Penman (1989), relative to that of Holthausen and Larcker (1992), in generating profitable trading strategies in the UK.

The studies mentioned above do not separate out profit-making from loss-making firms in their modeling approaches. The lack of separation may be important because, for example, Hayn (1995) and Collins *et al*. (1999) assert that losses are less useful in predicting future earnings than are profits. As a consequence, the prediction of future profitability of loss-making firms might be particularly difficult, over and above the general difficulty of profit forecasting. If this argument holds, focusing on loss-making firms separately from profit-making firms might be useful from the point of view of financial statement analysis generally, and aspects of profit forecasting specifically.[1]

Is it *worthwhile* to focus on loss-making firms – are they a substantial enough set of firms to be worthy of study? In this context, Jiang and Stark (2011) document that the percentage of loss-making firms has increased significantly in recent decades in the UK, which mirrors the US phenomenon (see Hayn, 1995; Collins *et al*., 1999; Joos and Plesko, 2005; Klein and Marquardt, 2006). Although loss-making firms are generally smaller than other listed companies, as a set they can comprise close to 50% of all listed non-financial firms in some years. This suggests that they are a substantial enough part of the UK economy to study.

Focusing on US loss-making firms, Joos and Plesko (2005) develop models of the likelihood of loss reversals and demonstrate that accounting information can help investors forecast the probability of loss reversals in the subsequent year in the US. Further, they demonstrate that the loss reversal probabilities derived from their model can be used to better understand differences in earnings response coefficients across loss-making firms. Li (2011) uses a similar set of accounting determinants to those identified by Joos and Plesko (2005) to forecast future profits for loss-making firms and suggests that the market does not fully

[1] See Li (2011) for arguments in the same vein.

reflect the information in the profit forecasts he develops (misunderstands the persistence in losses). He further argues that a profitable portfolio strategy can be developed to exploit the identified shortfall in informational efficiency. Resutek (2011), however, questions whether the trading strategy is actually profitable.

In this study, we attempt a number of contributions. We start from the position that, the Joos and Plesko (2005) model requires data from not only the loss-making year but also for five years prior to the loss-making year. In a UK context, this imposes such strong data restrictions that very few firms satisfy them. Therefore, their model is not a practical tool for financial statement analysis in the UK. Our initial contribution is to develop a modified version of the Joos and Plesko (2005) loss reversal model which can be applied in the UK. The model is modified in two ways. The first way eliminates the requirement for five years of data prior to the loss-making year, resulting in the loss of some variables from their model. Our modified model only requires data for one prior year. The second way is to develop model by adding in additional variables. We then specifically test the predictive accuracy of our modified loss reversal model using various approaches. According to the test criteria we establish, our results suggest that the loss reversal model is successful. By evaluating the model in the way we do, we document its level of effectiveness as a tool of financial statement analysis.[2]

The second contribution is to examine whether a profitable trading strategy can be generated based upon the model. We find that, after controlling for other firm characteristics that are

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[2] We also evaluate the predictive accuracy of the earnings forecast model in which next year's earnings is regressed on the independent variables that we use in our loss reversal model, following Li (2011). A loss is predicted to be a reversal (non-reversal), when its predicted earnings for the next year are positive (negative). Although the predicted earnings for loss-making firms contain information about loss reversal probabilities, our results suggest that the loss reversal model provides higher overall prediction accuracy, and in particular, the prediction accuracy for reversals than the earnings forecast model.

known to be, or could be, associated with stock returns in the UK, a hedge portfolio that takes a long position in firms with a high estimated likelihood of loss reversal and a short position in firms with a low estimated likelihood of loss reversal makes an average return of over 20%.[3] Nonetheless, the strategy could only be profitable in combination with additional portfolio strategies based upon the firm characteristics that are associated with stock returns. Further, the firms with a low estimated likelihood of loss reversal are predominantly small firms (nearly 50% are in the bottom 30% of all firms by market capitalization) which tend to have high transaction costs and are difficult to sell short. As a consequence, it is unlikely that investors can exploit any mispricing opportunity.[4]

The remainder of the paper is organized as follows. Section 2 presents the prior literature. Section 3 describes data and methodology. The associated empirical results and analysis are provided in Section 4. The paper ends with concluding remarks in Section 5.

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3 Our results differ from Li (2011). He suggests that taking a long position in firms with predicted transitory losses and a short position in firms with predicted persistent losses can produce 10.4% abnormal returns per annum. Li (2011) claims that the abnormal returns are robust to controls for other anomalies and risk factors. Resutek (2011) claims that Li's (2011) results are over-turned when capital contributions are controlled for as a determinant of expected returns. This is not the case for our results, however.

4 Richardson *et al*. (2010) argue that analysis to improve forecasting models of future earnings is invaluable regardless of whether the models can be used to generate profitable trading strategies, since multiple other users of financial statements (e.g., customers, competitors, suppliers, management, *etc*.) would benefit from the information contained by the models.

# 2 PRIOR LITERATURE

## 2.1 THE (MIS)VALUATION OF LOSS-MAKING FIRMS

Accounting earnings are often viewed as the most important item provided in financial statements, because they are widely used as a key performance indicator of business success. Much research shows that earnings are a significant value-determining item of information. However, earnings might lose this role when it is negative. For example, although Klein and Marquardt (2006) demonstrate that the state of the business cycle and macroeconomic productivity are related to the frequency of losses in the US, the growth of the frequency of losses is still observed in economic boom periods for both US and UK (e.g., Joos and Plesko, 2005 for the US; Jiang and Stark, 2011 for the UK). The discrepancy between the existence of an economic boom and the increased prevalence of losses suggests that reported negative earnings might not be a good indicator of a firm's performance.

In this context, understanding the valuation of loss-making firms presents a challenge within the stream of market-based accounting research in which accounting information is used to explain value. Since Modigliani and Miller (1966), researchers have recognized that losses pose a challenge to the value relevance of earnings because not only are they not necessarily a good indicator of a firm's performance but also they reduce reported earnings' forecasting ability for future earnings. Several studies suggest that accounting losses dampen the observed relationship between stock prices and accounting earnings when researchers do not discriminate between profit and loss firms (e.g, Hayn, 1995; Martikainen, 1997a, 1997b).

Further, the fundamental theory underpinning many value relevance studies - Ohlson's linear information dynamics framework (e.g., Ohlson, 1995; Feltham and Ohlson, 1995) and associated empirical linear cross-sectional valuation models which rely on earnings - could be less appropriate for analysing loss-making firms. For example, using a valuation model, Darrough and Ye (2007) report that earnings are not value relevant for loss-making firms in the US. In the UK, Jiang and Stark (2012) suggest that, if anything, earnings have a puzzling negative relationship with market value.

A different strand of research to the linear information dynamics approach to understanding the use of accounting information in valuing firms argues that: (i) accounting losses are a poor signal of future earnings due to the existence of real options; and (ii) real option theories should be incorporated into valuation models. Hayn (1995) proposes the abandonment option hypothesis which suggests that the persistence of losses can be limited because shareholders can liquidate the firm instead of bearing indefinite losses. Building on Hayn (1995), Joos and Plesko (2005) develop a loss reversal model that can be used as a proxy for the probability of exercising the abandonment option. Relating the model to the relationship between returns and earnings, they find that the earnings response coefficient is positive for losses that have high probability to reverse (i.e., transitory losses), whereas it is insignificant for losses that have low probability to reverse (i.e., persistent losses). Although Joos and Plesko (2005) suggest that the causes and nature of the loss are worth exploring because investors do not value losses homogeneously, they do not examine whether profitable trading strategies can be developed based upon the loss reversal model. Li (2011) builds on Joos and Plesko (2005) and develops a quarterly earnings prediction model for loss-making firms.

He suggests that the model can be used to form a trading strategy that produces profitable hedge returns.[5]

Both Joos and Plesko (2005) and Li (2011) use models that require firms to have a considerable history before they can be analysed (in particular, their models require firms to have data for the current period and five prior periods). Certainly, any focus on annual results (Li, 2011, analyses quarterly earnings) in the UK would produce relatively few observations to be analysed if these data requirements are to be maintained. As a consequence, a model directly based upon Joos and Plesko (2005) would be of limited applicability and interest as a tool of financial statement analysis in a UK context, unless it was modified to require less data. Such modification then implies the need to test out the effectiveness of the modified model. Further, given Li's (2011) findings, if on finding that the modified model is effective in analysing loss reversals, the following question naturally arises: can the information contained in this model help investors make better portfolio allocation decisions?

## 2.2 Accounting Anomalies and Fundamental Analysis

Richardson *et al*. (2010) and Lewellen (2010) assess alternative explanations for possible accounting anomalies. In particular, they highlight that any anomalous return patterns might be 'explained away' by potential risks, transactions costs, short sales constraints, firm size, and existing anomalies.

[5] He also argues that using a model of the earnings forecasts not only contains information about the likelihood of loss reversals, but also produces results that can be more easily compared with the findings in prior studies that use levels of earnings to develop portfolio strategies (e.g., Balakrishnan *et al*., 2010).

In this context, researchers often use the Fama and MacBeth (1973) regression framework to estimate the relationship between future stock returns and firm characteristics of interest incremental to that for other firm characteristics associated with future returns. After controlling for an increasing number of return predictors, researchers can claim that the relationship between future returns and the variable of interest suggests that the variable of interest is either mispriced or correlated with systematic risk.

If we adopt the mispricing explanation, however, the existence of a mispricing opportunity does not mean that an implementable portfolio strategy exists which can exploit it. One needs to consider trading restrictions and investor's preferences. For example, smaller, less liquid, securities have higher transaction costs and/or greater idiosyncratic risk, and such features might impede their use in portfolio strategies designed to exploit mispricing opportunities (Fama and French, 2008).

Further, although transaction costs are crucial for understanding why the mispricing opportunity might not be arbitraged away by smart investors, it may be nearly impossible to accurately estimate transaction costs. According to Lewellen (2010), one needs to know an investor's entire portfolio and other trading strategies to assess the incremental cost of an additional predictive variable included in the investor's trading model. In particular, exploring the trading costs of a certain strategy in isolation can be much different than asking whether the strategy can be profitably exploited by an investor who is already trading on other strategies.

As a consequence of the above, in investigating whether the loss reversal probabilities generated by our model are fully reflected in UK market prices and, if not, how a trading strategy could be developed from the probabilities, we attempt to control for risk and/or other firm characteristics that have the potential to explain firm returns as fully as possible. Further, we also attempt to control for the liquidity effects.

# 3 DATA AND METHODOLOGY

## 3.1 THE LOSS REVERSAL MODEL

Logit conditional probability models are used to examine the relationship between the loss-making firms' characteristics and the likelihood of loss reversals in the next period. The general specification of the model is:

$$P(y_{t+1} | X_t) = f(\beta X_t + c)$$

where: (i) $y_{t+1}$ is an indicator variable that is equal to one if the firm makes a loss in year t and becomes profitable in year t+1; and zero if the firm still makes a loss in year t+1; (ii) $X_t$ represents a vector containing a number of categories of information variables; (iii) $f$ is the logistic cumulative density function; (iv) $\beta$ is a vector of parameters; and (v) $c$ is a constant term. Similar to Joos and Plesko (2005), a firm is defined to make a loss if its earnings before extraordinary/exceptional items are less than zero.

Following Joos and Plesko (2005), we initially include four categories of independent variables.[6] They are: (i) a profitability measure – return on assets (*ROA*) defined by earnings before extraordinary/exceptional items divided by last year's total assets (*NI-EI*)/*Lag*(*TA*); (ii) a size measure - *Log*(*MV*) - and the sales growth rate - *SGR*; (iii) a dummy variable *FIRSTLOSS* indicating whether the loss year was preceded by a profit year; and (iv) measures of the dividend-paying behaviour of the firm - two dummies, *DIVDUM* and *DIVSTOP*, where the former variable is one if the firm pays dividends in the loss year, and zero otherwise, and the latter variable is one if the firm stops paying dividends in the loss year, and zero otherwise.

Joos and Plesko (2005) also include variables that: (i) capture the average of five prior ROAs; and (ii) the number of losses in the prior five years. These variables are excluded in our paper on the grounds that including them substantially reduces the number of observations available for study and, hence, the practical applicability of the model. We then have Model 1 to estimate, which represents our closest representation of the model in Joos and Plesko (2005):

<ins>Model 1</ins>:

$$P(y_{t+1}|X_t) = f(a_0 + a_1(NI_t - EI_t)/LagTA + a_2Log(MV)_t + a_3SGR_t + a_4FIRSTLOSS_t + a_5DIVDUM_t + a_6DIVSTOP_t) \qquad (1)$$

[6] In following Joos and Plesko (2005) in developing our models, we ignore any explicit recognition of the possibility that loss-making firms manage earnings to achieve earnings targets (such as making a profit), or to achieve dividend targets. See Gore *et al*. (2007) and Atieh and Hussain (2012) for papers that provide UK evidence on this issue.

In Model 1, the profitability variable is defined as income before extraordinary/exceptional items scaled by lagged total assets. In Model 2, however, we decompose it into two components – earnings before extraordinary/exceptional items *and* RD expenditures (*NI-EI+RD*)/*Lag*(*TA*), and RD expenditures (*RD/Lag*(*TA*)), with both deflated by lagged total assets - and add in extraordinary/exceptional items as a separate variable. In effect, we add two variables into Model 1 - RD expenditures (*RD/Lag*(*TA*)) and extraordinary/exceptional items (*EI/Lag*(*TA*)).[7,8]

Model 2:

$$P(y_{t+1}|X_t) = f(a_0 + a_1^1(NI_t - EI_t + RD_t)/LagTA + a_1^2 RD_t / LagTA + a_1^3 EI_t / LagTA \\ + a_2 Log(MV)_t + a_3 SGR_t + a_4 FIRSTLOSS_t + a_5 DIVDUM_t + a_6 DIVSTOP_t) \quad (2)$$

We conjecture that, *ceteris paribus*, the higher the RD for a loss-making firm, the more likely the loss is going to persist, due to *ex ante* accounting conservatism. Nonetheless, we should emphasise that the expensing of RD reflects a mandated accounting standard which requires most RD to be expensed, and not a discretionary conservative accounting policy chosen by a firm. We have the following hypothesis (expressed in alternative form):

7 We also test the Joos and Plesko (2005) model on sample observation with sufficient data. We find that their model does not result in superior predictions than our more parsimonious models.

8 We also run this model with an additional independent variable - a dummy that equals 1 if a firm is not listed in the official list of the London Stock exchange, and 0 otherwise. The dummy variable is negative and significant at 5% level, whereas log (*MV*) loses significance. As firms that are not listed in the official list of the London Stock exchange are smaller in size, log (*MV*) is associated with the dummy variable, and its predictive power is subsumed by the dummy in the model.

**H1:** The higher the extent of RD for a loss-making firm, the less likely the loss is going to reverse in the next year ($a_1^2 < 0$).

Extraordinary/exceptional items are an example of *ex post* conservatism. Negative extraordinary/exceptional items (representing charges) can effectively increase future earnings. As an example, a firm might have written down assets, effectively recognizing economic bad news about the future in the current period. If those written-down assets continue in use within the firm then, *ceteris paribus*, future profits will be increased. In general, write-offs can lead to smaller depreciation/amortization charges in the subsequent periods and, thus, effectively transfer income between periods. Another possibility is that the firm has recognized restructuring charges related to, for example, discontinued and unprofitable lines of business, the outcome of which is likely to improve its future accounting profitability. In this situation, we argue that, *ceteris paribus*, the higher the negative extraordinary/exceptional items, the more likely the current loss is to reverse. As a consequence, we put forward the following hypothesis (again expressed in alternative form):

**H2:** The more negative are extraordinary/exceptional items for a loss firm, the more likely the loss is going to reverse in the next year ($a_1^3 < 0$).

### 3.2 PREDICTION TESTS

In order to test the predictive ability of the estimated models for loss reversals in the following year, we perform the following process. First, to generate a prediction model to be applied to a given year, we estimate the model on the pooled data from the annual cross-sections for the previous five years. For example, to obtain the prediction model for loss-making firms in 2001, we estimate the loss reversal model on pooled data from 1996 to 2000. Under this methodology, investors are assumed to consider the prior five years of information that is available at the time of analysis as relevant.

As discussed by Joos and Plesko (2005), previous studies (i.e., Hayn, 1995; Klein and Marquardt, 2006; Collins *et al*., 1997; Givoly and Hayn, 2000) illustrate that not only has the occurrence of losses increased but also the properties of earnings have changed in recent years in the USA. The main feature of the research design adopted to generate prediction models is that it allows for the potentially changing nature of earnings (or losses) over the sample period and, thus, attempts to control for its influences on the frequency of losses. As a result, the parameters in the loss reversal prediction model are allowed to vary over time under this methodology.

Second, we conduct a set of tests for the out-of-sample classification accuracy. Initially, each year we rank the predicted reversal probabilities calculated by the prediction model for loss-making firms with next year's earnings in a descending sequence and divide up the numbers into four quartiles. For example, we estimate a logistic regression on pooled data for loss-making firms from 1996 to 2000 and apply the model to the loss-making firms in 2001 to generate probabilities of loss reversals in 2002. Loss-making firms in the first quartile have the highest reversal probabilities; losses in the second quartile have the second highest reversal probabilities, *etc*. To examine the classification accuracy of the loss reversal model, we use the proportion of *ex post* reversals as a benchmark in each quartile. Specifically, we count the numbers of actual reversals and non-reversals in 2002 across these four quartiles. Then, we use a chi-square test with the following null and alternative hypotheses:

**$H3_N$:** The four classifications (the top, the second top, the second bottom and the bottom quartiles) have no association with respect to the proportion of actual, *ex post* loss reversals;

**$H3_A$:** The four classifications (the top, the second top, the second bottom and the bottom quartiles) differ with respect to the proportion of actual, *ex post* loss reversals.

The loss reversal model is then considered to be useful in classifying losses if it satisfies two conditions. One is that the chi-square test provides a significant statistic at the 5% level, which allows us to reject the null hypothesis of no association between classifications and outcomes. The other is that the results for *ex post* classification accuracy provide the same trend as the ordering of the quartiles - that is, the actual *ex post* proportions of the loss reversals decrease across the top, the second top, the second bottom and the bottom quartiles, as do the *ex ante* reversal probabilities. We examine the performance of our loss reversal models in this way annually.

Third, we estimate a cutoff probability on the data used to estimate the prediction model - it is estimated in-sample. As argued by Palepu (1986), the use of the arbitrary cutoff number (such as 0.5, as in Joos and Plesko, 2005, for example) is only acceptable where the sizes of the two groups (reversals and non-reversals) are equal. The majority of firms in our sample do not reverse, however. Thus, we adopt a method of trial and error to find the optimal cutoff probability, as opposed to some preset number. We use trial and error because the approach in Palepu (1986) assumes the existence of a single, unique, cutoff, whereas our analysis sometimes finds multiple optimal cutoffs. Our procedure investigates all feasible cutoff probabilities with two decimal places that start from 0.01 and run through to 0.99. For each feasible cutoff probability, we classify a firm as a non-reversal if the cutoff is higher than the calculated probability based upon the estimated loss reversal model. We classify a firm in a particular sample as a loss reversal if the cutoff probability is lower or equal to the estimated probability. Then, we compare the classification results with the actual outcomes for all firms in the sample and choose the cutoff that provides the highest percent of correct classifications. When two, or more, cutoff probabilities result in the same percentage of correct predictions, we choose the lower one. This process produces a cutoff probability which varies by year.[9]

Fourth, having generated a set of estimated loss reversal models, and associated cutoff probabilities, we apply them out-of-sample. For example, we take the estimated loss reversal model and cutoff probability, based upon data from 1991 to 1995, and apply them to firms incurring losses in 1996, in predicting loss reversals in 1997. If the application of the estimated prediction model to a loss-making firm in 1996 produces an estimate of the loss reversal probability equaling or exceeding the associated cutoff probability, we predict that the loss will reverse. If the application of the estimated prediction model to a loss-making firm in 1996 produces an estimate of the loss reversal probability lower than the associated cutoff probability, we predict that the loss will not reverse. We apply this method of prediction to all 1996 loss-making firms with next year's earnings. We then compare the predictions with actual outcomes and generate estimates of the predictive accuracy of these models. This process is repeated for 1997 loss-making firms through to 2008 loss-making firms.

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9 By picking the cutoff probability to maximize the percentage of correct classifications in-sample, we are implicitly assuming that the costs of mis-classification are equal. As far as we are aware, there are no studies that can provide estimates of such costs in the UK for some particular decision-making context (e.g., valuation, portfolio management, or credit granting).

In order to examine the general effectiveness of the models in predicting loss reversals, benchmarks are required. We first establish a random assignment benchmark in the following fashion. Consistent with the use of five years of data in developing the loss reversal model, we argue that, in the absence of such a model, the prior probability of loss reversals would be the rate of loss reversals over the five years. We denote this rate by $r_{prior}$. We then assume that, in predicting loss reversals, an investor would randomly assign a loss-making firm in the following year into either the loss reversal or non-reversal categories using this rate.[10] If the actual rate of loss reversals in the following year is denoted by $r_{actual}$, the *expected* prediction accuracy rate under the classification strategy identified is equal to:

$$r_{prior}.r_{actual} + (1 - r_{prior}).(1 - r_{actual})$$

We compute this measure for each of the out-of-sample years 1996 to 2008.

Alternatively, we employ a non-random benchmark by using a simple rule which is ‘a loss-making firm is predicted to be a reversal next year if it was profitable in the previous year (i.e., *FIRSTLOSS* =1)’. This benchmark considers part of, but not all of, the information contained in the loss reversal model.[11]

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10 We do not claim that this is the optimal strategy in the absence of the information in the loss reversal models. Another possible strategy is to classify all firms as non-reversals, given that this tends to be the largest category. Nonetheless, in the absence of the costs of mis-classification, an optimal strategy is impossible to identify.

11 Another benchmark could be whether analyst forecasts for loss-making firms predict loss reversals. In the UK, however, the definition for analysts’ predicted earnings is not clear. We do not know how analysts define the forecasting object. The second problem for using such a benchmark is that the number of firms with analysts’ one-year-ahead forecast earnings provided by the IBES database is limited, compared with our sample. As a consequence, we do not test the model against analysts’ forecasts.

### 3.3 FUTURE RETURNS ANALYSIS

Finally, we assess whether it is possible to implement an investment strategy that takes into account the information provided by the proposed loss reversal model. If investors incorporate all the relevant information when determining the price of a loss-making firm, using the information provided by the loss reversal model should not be able to yield high abnormal returns. However, if investors have limited attention (Hirshleifer and Teoh, 2003) and are unable to correctly assess the persistence of losses, firms with higher probabilities of loss reversals may be under-priced and firms with lower probabilities of loss reversals may be over-priced. As a consequence, stock prices may not fully reflect information about loss persistence and this, in turn, may create opportunities for potential mispricing. We put forward the following hypothesis (again expressed in alternative form):

**H4:** Loss reversal probabilities are positively associated with future abnormal returns.

To test this hypothesis, we pool data across years and run regressions of returns on variables that might control for risk, together with experimental variables derived from the loss reversal probabilities using the approach defined above. We also add in a variable to control for the liquidity of shares. First, we define as our dependent variable the annual market-adjusted return (i.e., the return on a firm less the return on the market) with a return accumulation period starting from July 1 of the calendar year following the calendar year in which the financial year of the loss year observation finishes (*MAdjRET*).[12] We use this start date for

[12] To avoid introducing a forward-looking bias, all firms that are eligible for investing at July 1 are considered in the sample, even if they delist during the holding period. If a firm delists and the London Share Price Database assigns a delisting code of 7, 14, 16, 20 or 21, it is assumed that the delisting return is -100%. In all the other cases, it is assumed that the delisting return is the last return provided by Datastream and the delisting proceeds are reinvested at the market rate of return.

the return accumulation period in order to avoid any forward-looking bias because all the information needed to create the reversal probabilities should be available to market participants by July 1 of the calendar year following the loss year.

Second, we control for risk using the following variables: (i) the market value of a firm at the start of the return accumulation period, *SIZE*; (ii) the book-to-market ratio, BM, measured as common shareholders' equity at the end of the loss year, divided by *SIZE*; (iii) the earnings-price ratio, *EP*, measured as operating income in the loss year, divided by *SIZE*; (iv) the dividend yield, *DY*, measured as cash common dividends in the loss year, divided by *SIZE*; (v) research and development expenditures, *RD*, measured as research and development expense in the loss year deflated by *SIZE*; (vi) cash flow, *CF*, measured by the difference between operating income and accruals in the loss year (using the balance-sheet approach, following Soares and Stark, 2009) divided by the average of beginning and end of period total assets for that year; (vii) leverage, *LEV*, measured as total debt at the end of the loss year, divided by *SIZE*; and (viii) momentum, *MOM*, measured as the annual return for the year prior to the return accumulation period. We control for liquidity, following Pincus *et al*. (2007), by using the following variable: (ix) share price, *P*, the price of a common share of the loss-making firm at the start of the return accumulation period.[13] We also control for: (x)

[13] Using portfolio rank methods, univariate size effects in UK returns are identified by, for example, Michou *et al.* (2010), although mainly for the smallest size portfolios. Michou *et al.* (2010) also identify a book-to-market effect. Theoretical justifications for size and book-to-market effects can be found in Berk (1995) and Berk *et al.* (1999). The latter paper, in particular, models the world in a real options framework in which the firm's CAPM $\beta$ evolves over time due to optimal investment decisions. Empirical evidence of UK momentum effects can be found in, for example, Liu *et al*. (1999). Berk *et al*. (1999) develop an optimal investment model from which momentum effects emerge. Earnings-to-price and cash flow-to-price effects in UK stock returns have been identified in single-dimensioned portfolio sorts by, for example, Gregory *et al.* (2001). Soares and Stark (2011) identify both effects operating simultaneously using a regression approach. Both ratios are likely to capture both expected growth and cost of capital effects. Dividend yield effects in UK stock returns are identified in Chan *et al.* (1998). Research and development effects have been identified by Al-Horani *et al.* (2003) and Dedman *et al*. (2009), using both single-dimensioned portfolio sorts and regression approaches. Leverage effects, in which leverage has a *negative* relationship with returns, have been found by Muradoglu and Sivaprasad

capital contributions, *CC*, measured as capital contributions in the loss year, divided by *SIZE*, because of the suggestion of Resultek (2011) that the addition of this variable to the analysis of Li (2011) eliminates any relationship between loss firm persistence and future returns in the USA.

We convert all of our control variables into ranks on an annual basis. The ranks are created with respect to all the UK listed non-manufacturing firms.[14] The superscript $^{qt}$ refers to the scaled-quartile ranking of each individual variable and is determined as (variable of interest quartile-1)/3. The superscript $^{dt}$ refers to the scaled-decile ranking of each individual variable and is determined as (variable of interest decile-1)/9.[15] Using this approach allows the estimated coefficients to be interpreted as the return on a hedge strategy of going long (short) on the high (low) variable of interest quartile (decile), once other effects on returns are controlled for.[16]

We capture loss reversal probabilities in two ways. First, the loss reversal probabilities are annually assigned to deciles and, as with the control variables, a ranking variable ranging from 0 to 1, *LOSSRKG*, is created. Again as with the control variables, the estimated coefficient of *LOSSRKG* captures the abnormal return on an equally-weighted hedge investment strategy based on the loss reversal information. We also use a dummy variable,

(2012) and Soares and Stark (2011), using regression approaches. A negative relationship between price and returns in the UK has been found in Soares and Stark (2011).

[14] We also estimate the return regressions using ranks calculated from our loss sample for the control variables. Our results can be reinforced using this approach, but this approach does not capture the correct benchmark that an investor would face at the time of investment.

[15] For firms that do not report *RD*, *CC* and *DY*, we have replaced the missing values by 0. As there are a high percentage of such firms, using yearly decile rankings for these three variables does not provide enough observations that are non-zeros for each decile. As a consequence, quartile rankings for these variables are used instead, where, for each year, firms with 0 for the relevant variables are assigned to the first portfolio, and the remaining non-zero firms are assigned to three equal-sized portfolios.

[16] See Bernard and Thomas (1990, p. 326) and Pincus *et al*. (2007, p.189) for a discussion on this approach.

*PREDICT*, which takes a value of 1 if, using the appropriate cutoff probability for each year, as defined above, a loss-making firm is predicted to make a profit in the following year.

Thus, the following models are estimated:

Model 3:

$$MAdjRET_{i,t+1} = b_0 + b_1 LOSSRKG^{dt}{}_{i,t} + b_2 SIZE^{dt}{}_{i,t} + b_3 BM^{dt}{}_{i,t} + b_4 EP^{dt}{}_{i,t} + b_5 DY^{qt}{}_{i,t} + b_6 RD^{qt}{}_{i,t} + \\ + b_7 CC^{qt}{}_{i,t} + b_8 CF^{dt}{}_{i,t} + b_9 LEV^{dt}{}_{i,t} + b_{10} MOM^{dt}{}_{i,t} + b_{11} P^{dt}{}_{i,t} + \upsilon_{i,t+1} \tag{3}$$

Model 4:

$$MAdjRET_{i,t+1} = c_0 + c_1 PREDICT_{i,t} + c_2 SIZE^{dt}{}_{i,t} + c_3 BM^{dt}{}_{i,t} + c_4 EP^{dt}{}_{i,t} + c_5 DY^{qt}{}_{i,t} + c_6 RD^{qt}{}_{i,t} + \\ + c_7 CC^{qt}{}_{i,t} + c_8 CF^{dt}{}_{i,t} + c_9 LEV^{dt}{}_{i,t} + c_{10} MOM^{dt}{}_{i,t} + c_{11} P^{dt}{}_{i,t} + \varepsilon_{i,t+1} \tag{4}$$

We follow the Fama and Macbeth (1973) approach and estimate each model separately on annual cross-sections with the mean coefficients across the annual cross sections being tested against the null hypothesis that the true coefficient is zero. Nonetheless, underlying our tests is the alternative hypothesis that, if the loss reversal model is able to capture valuable information on loss reversals in the following year that the market is not be impounding into prices (Li, 2011), then we expect to see $b_1$, $c_1 > 0$.

We adopt this method of estimating the relationship between loss reversal probabilities and future returns for the following reasons. First, a different approach would use portfolio matched returns (e.g., size matched returns). Evidence in Soares and Stark (2011), however, suggests that there are a number of firm characteristics that help explain returns. The number is great enough that to create matched portfolios according to all the relevant firm characteristics both reasonably precisely and simultaneously is impossible, given the number of non-manufacturing firms listed on the UK stock exchange. Our method, therefore, allows us to control for additional risk factors that a traditional portfolio-matched approach cannot.

Another possible approach would be to generate time series of portfolio returns associated with the loss reversal probability rankings, or predictions, and regress these returns on a factor model, with the constant terms in such regressions interpreted as the excess returns on the portfolio. Michou *et al*. (2010) and Gregory *et al*. (2011), however, in combination cast doubt on the ability of any of the CAPM, the Fama-French (1993) three factor model and the Carhart (1997) four factor model to adequately price portfolios in the UK. As a consequence, conventional factor model approaches are unlikely to lead to reliable inferences about any association between loss reversal probabilities and returns, at least in the UK.

### 3.4 DATA COLLECTION AND SAMPLE

The data are obtained from Worldscope, Datastream, and the LSPD databases. Only loss observations that have relevant data available for the financial years ending in the calendar years from 1991 to 2008 are included in the study. 'Dead' firms are included in the sample to mitigate the presence of survivorship bias. Firms are deleted if they are financial firms. For each fiscal year 1996 to 2008, the loss reversal probabilities for the immediate years following, 1997 to 2009, are calculated using Model 2. The predictive ability of the loss reversal model is assessed by comparing the predicted results with the actual outcomes in the next year. Thus, for both the estimations and out-of-sample predictive accuracy tests of loss reversal models, each loss observation needs to have next year's earnings, and other relevant data, to compute variables in the loss reversal models. The specific data needed include bottom line net income (Worldscope Code: WC 01651), research and development expenditures (Worldscope Code: WC 01201), extraordinary items (Worldscope code: WC 01601), exceptional items (Worldscope Code: WC 01253, WC 01254), cash common dividends (Worldscope Code: WC 05376), sales (Worldscope Code: WC 01001), market value (Datastream code: MV) and total assets (Worldscope Code: WC 02999). This yields 4,564 loss observations for the period between 1991 and 2008.[17]

For the future return analysis, the estimated loss reversal models are applied to all loss observations (including those without next year's earnings) from 1996 to 2008. Given that UK listed firms are allowed to publish their financial statements up to six months after their fiscal year end through much of the period studied, the portfolios for, for example, loss year 1996 firms are set up on July 1, 1997, to make sure that all firms have their financial information available by that date. Firms must have return data for at least the first month of the holding period. Other additional data requirement to compute variables in equations (3) and (4) are book value of equity (Worldscope code: WC 03501), operating income (Worldscope Code: WC 03501), accruals (using the balance-sheet approach followed by

[17] This study tests a binary logistic model which identifies only two states (reversals and non-reversals), and ignores the third state (dropped from Datastream in the subsequent year). Therefore, when investigating the predictive accuracy of the loss reversal models, by ignoring loss firms which disappear in the following year, the accuracy and usefulness of the models and methodology is overstated. In general, around 12% of the loss-making firms disappear from Datastream in the following year over the period 1996-2008, with highs of 20% in 2007 and 18% in 2008. The figures in earlier years tend to be lower than the average. This provides an indication of the possible scale of this problem.

Soares and Stark (2009), accruals are defined as the change in total current assets (Worldscope Code: WC 02201) *minus* the change in cash and equivalents (Worldscope Code: WC 02001) *minus* the change in total current liabilities (Worldscope Code: WC 03101) *plus* the change in total short-term debt and current portion of long-term debt (Worldscope Code: WC 03051) *plus* the change in dividends payable (Worldscope Code: WC 03061) *plus* the change in interest payable (Worldscope Code: WC 03062) *plus* the change in income taxes payable (Worldscope Code: WC 3063) *minus* depreciation, depletion and amortization (Worldscope Code: WC 01151)), with cash flow being subsequently defined by operating income *minus* accruals, total debt (Worldscope Code: WC 03255), capital contributions (Worldscope Code: WC 04251), returns (Datastream code: RI), and share price (Datastream code: P). These requirements result in a sample of 4,059 loss observations for years from 1996 to 2008.

Insert Table 1 Here

Details of the resulting samples for the loss reversal probability and return prediction parts of our study are provided in Table 1.

# 4 RESULTS AND DISCUSSION

## 4.1 DETERMINANTS OF LOSS REVERSALS

Panels A and B of Table 2 describe the characteristics of the non-reversals and reversals regarding the independent variables used in Model 2 on the pooled data over the period 1991-2008. There are 3279 (1285) observations in our sample that experience actual non-reversals (reversals) in the next year. Firms in the reversal state tend to have a smaller absolute size of loss, lower RD expenditures, more negative extraordinary/exceptional items, a larger firm size and a higher sales growth rate. Using univariate tests, the associated p-values (two-tailed) reported in Panel C for t tests that are used to compare the means of these continuous variables between the two groups are significant at the 5% level for all variables other than extraordinary/exceptional items. In addition, of firms that reverse, more of them tend to have been profitable in the year prior to the loss, pay dividends in the loss-making year, and stop paying dividends in the loss-making year, than firms that do not reverse. This is confirmed by the associated p-values (two-tailed) for chi-square tests that are used to compare the proportions of the categorical firm characteristics. Further, Wilcoxon tests reveal significant differences in the medians of these variables, except for firm size, between these two groups of loss-making firms.

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Insert Table 2 Here

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To give insight into multivariate effects, we estimate Models 1 and 2 on the pooled sample from 1991 to 2008. The coefficient estimates of the two models, and their associated Wald chi-square statistics, are presented in Table 3. To compare the incremental improvement from Model 1 to Model 2, a likelihood-ratio test is used and its associated p-value is reported in the table. Pseudo R-squared values for each model are also presented. Model 1 is the simplified Joos and Plesko (2005) model in which variables capturing the loss sequence and the five-year past average return on assets are removed from their original model. Model 2 differs from Model 1 by adding two variables *RD*/*LagTA* and *EI*/*LagTA*. Also, instead of using (*NI-EI*)/*LagTA*, Model 2 uses (*NI+RD-EI*)/*LagTA* to measure profitability.

Insert Table 3 Here

All the independent variables inherited from Joos and Plesko (2005) have the coefficients with the signs consistent with their results except for *DIVSTOP*. We find that both *DIVDUM* and *DIVSTOP* are positively associated with the probability of loss reversals, the latter result being in contrast with that for the US. Our conjecture is that the positive sign of *DIVDUM* captures the good signalling effect of dividends (when paying dividends is economically justified), whereas the positive sign for *DIVSTOP* captures the bad signalling effect of dividends. In other words, paying dividends in the current loss year signals that the firm does not need the cash, as it has sufficient resources to realize its growth opportunities. Stopping paying dividends in the current loss year suggests that paying dividends is bad, as the firm has better uses for the funds. In this latter case, the firm has more chance to reverse if managers keep dividends in the company for its improvement, instead of sending money out of the company.[18] The two new variables - *RD*/*LagTA* and *EI*/*LagTA* - added to the Joos and Plesko (2005) have significant coefficients in the predicted direction, which is consistent with our hypotheses that they capture accounting conservatism effects. The explanatory power of our loss reversal models improves significantly as we move from Model 1 to Model 2, as indicated by a log likelihood ratio test comparing the two models, because the p-value for the test is less than .05. As a consequence, we use Model 2 in our assessments of prediction accuracy.[19, 20, 21]

### 4.2 PREDICTION ACCURACY

The first test for annual out-of-sample classification accuracy is reported in Table 4. The chi-square statistics testing whether there is an association between quartile assignment and the likelihood of loss reversals are always significant at the 5% level. Therefore, we can reject the null hypothesis of no association between loss reversal classifications and outcomes.

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18 When replicating the Joos and Plesko's (2005) model that includes variables capturing loss sequence and the past five-year average return on assets, the coefficient for *DIVSTOP* is still positive but insignificant. Further, replicating their model on restricted data reveals that the variables requiring data over the past five years add nothing to the explanatory power of the model.

19 In untabulated estimations, it is clear that there is instability in models estimated on only one year of data, and there is relatively little consistency in these models, in terms of the significance of variables, over time. Altman and Eisenbeis (1978) and Martikainen and Ankelo (1991) suggest that, when the estimates for a model are not stable across time, the model's in-sample classification ability will not equal its out-of-sample classification ability. Also, Barnes (1999) argues that model coefficients for accounting variables are not likely to be stable over time, due to the changing nature of accounting variables across time. The above provides a justification for the practice, following Joos and Plesko (2005), of pooling information across the prior five years to generate the prediction model for a given year as an attempt to overcome this problem. As discussed above, this research design allows for the potentially changing nature of earnings (or losses) over the sample period and controls for its influence on the frequency of losses as well.

20 We also follow Joos and Plesko (2005) by averaging coefficients estimated from applying the model to the prior five annual cross-sections to obtain the model to be used to predict loss reversals. In essence, the two methodologies for developing prediction models are different ways of pooling information in data from the prior five years in terms of the impact of the variables in the model on the likelihood of loss reversals. Which approach is superior is not clear from a theoretical perspective. Comparison of the prediction accuracy between the two approaches to estimating the prediction model suggests that both approaches provide generally similar results.

21 The results for the prediction models are not reported in the interests of brevity but are available from the authors on request.

Further, the proportions of *ex post* reversals always decrease across the top, the second top, the second bottom and the bottom quartiles. Overall, these observations suggest that the four quartile classifications from the loss reversal model do differ from each other with respect to the proportion of actual, *ex post* loss reversals in the way expected, and that the loss reversal model is useful in predicting loss reversals.

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Insert Table 4 Here

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Second, we evaluate the models out-of-sample based upon the use of optimal cutoffs, and compare their prediction accuracies with our two benchmarks in Tables 5 and 6. Again, for estimates of prediction accuracy, if the calculated probability based on the estimation model is equal or higher than the optimal cutoff, we predict the firm to reverse its loss in the following year. Otherwise, the firm is predicted not to reverse its loss.

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Insert Table 5 Here

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Table 5 suggests that the loss reversal models (using the optimal cutoffs) provide superior predictions in all years relative to the two benchmarks examined. Between these two benchmarks, the simple rule of ‘predict a reversal if the firm was profitable in the previous year’ produces significantly higher prediction accuracy rates than the random assignment approach.

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Insert Table 6 Here

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We further compare between the prediction models (with the optimal cutoffs) and the simple rule with regard to their prediction accuracy for reversals and non-reversals. Table 6 provides the aggregated classification results over the whole out-of-sample period studied. In Panel A, in which the prediction model is estimated on five years of pooled data, and the optimal cutoff is derived by using the trial and error approach, the exercise results in predicting 12.48% of loss-making firms (476) as reversals and 87.52% of firms (3339) as non-reversals. Of the 476 firms predicted to be reversals, 251 are in fact reversals in the following year. Of the 3339 firms predicted to be non-reversals, 2629 are actually non-reversals in the following year. In terms of the precision of the signals emerging from the model, the loss reversal signal is accurate 52.73% (= 251/476) of the time and the non-reversal signal is accurate 78.74% (= 2629/3339) of the time. The overall signal accuracy rate is 75.49%.[22, 23]

Moreover, the prediction models with optimal cutoffs provide much higher accuracy in predicting reversals, compared with Panel B in which the results of adopting the simple rule of 'predict a reversal if the firm was profitable in the previous year' are reported. The loss reversal signal is only accurate 42.87% of the time when using the simple rule. The simple

[22] We also use the annual models together with optimal cutoffs and test for their predictive accuracy. Their overall accuracy is worse than using the models estimated from five years' worth of data, although not substantially so. Also, they are substantially worse at predicting loss reversals.

[23] We find similar prediction accuracy when using the loss observations over the period 1991-2005 to estimate the prediction model and apply the model together with optimal cutoff to loss observations in 2006 to test the model out-of-sample.

rule provides a higher accuracy in predicting non-reversals (80.94% accuracy), and a lower overall accuracy (71.14%). As a consequence, it can be argued that the models reported upon above are, at least to some degree, effective in providing the basis for predicting loss reversals, over and above the simple benchmark rule.

### 4.3 THE ASSOCIATION BETWEEN THE PROBABILITY OF LOSS REVERSAL AND FUTURE STOCK RETURNS

We now turn our attention to the implementation of an investment strategy based on the loss reversal probability estimated using Model 2. As explained in Section 2.3, future abnormal returns are regressed on either the loss reversal probability ranking (*LOSSRKG*) or the loss reversal prediction (*PREDICT*), as well as other variables that control for other possible correlates of future returns. This is done by running Models 3 and 4, using the Fama and MacBeth (1973) procedure. The estimated coefficients are shown in table 7.[24]

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Insert Table 7 Here

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In Table 7, column 1, we report the results of running the regressions without controlling for any loss reversal information. This allows us to see how the risk controls chosen behave in our sample. Results suggest that, mainly consistent with prior literature, *SIZE*, *BM*, *EP*, *CC*,

[24] Following Petersen (2009) and Gow *et al*. (2010), as a robustness test, we run Models 3 and 4 using firm- and time-clustered standard errors. Furthermore, we also estimate the models using the GMM procedure with the Newey and West (1987) correction for autocorrelation with one lag year. Finally, we also investigate if using quintiles instead of deciles has an impact on the results. In all these robustness tests the main conclusions remained unchanged, despite some differences in the magnitude of the estimated coefficients. Results are available from the authors on request.

*LEV* and *P* have a negative relationship, and, *DY*, *RD*, *CF* and *MOM* are positively related, with future market-adjusted abnormal returns. However, only the relationships for *CC*, *RD*, and *P* are statistically significant at the 5% level of significance. Despite some difference in the magnitude of the estimated coefficients, these results remain stable in the different models estimated in columns (2) and (3).

Of interest to our hypotheses are the estimated coefficients of *LOSSRKG* and *PREDICT*. Results of including *LOSSRKG* together with the control variables (Model 3) are shown in Table 7, column 2. The estimated *LOSSRKG* coefficient of 0.196 is statistically significant at the 5% level of significance. This implies that, after controlling for other firm characteristics that can be correlated with firm returns, a trading strategy that goes long on firms with high probability of loss reversals and short on firms with low probability of loss reversals, is able to yield an abnormal annual return of 0.196. The use of *PREDICT* together with control variables (Model 4) also suggests a positive relationship between the variable and future returns, although it is only significant at a 10% level of significance.[25,26]

It is worth noting that the significantly positive coefficients of *LOSSRKG* and *PREDICT* hold even with the inclusion of *CC*. Although Li (2011) demonstrates the existence of a profitable portfolio strategy based upon the forecasted earnings for loss-making firms, Resutek (2011) suggests that the profitability of the strategy disappears after controlling for new equity

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25 One possible explanation for the difference in significance between *PREDICT* and *LOSSRKG* is that the latter variable can capture firms with the highest/lowest probabilities of reversals which are assigned to the extreme decile portfolios. The results also indicate that the abnormal returns are mainly generated by trading the extreme portfolios.

26 In the spirit of Li (2011), we also test whether the existence of analyst forecasts results in a market price that appropriately reflects the likelihood of loss reversal. Given that the number of firms being followed by analysts in our sample is limited, we do not run separate regressions for firms that have analyst forecast and firms that do not. Instead, we add a dummy variable (that equals 1 for firms with analyst forecast, and 0 otherwise) into Models 3 and 4. The estimated coefficient for this variable is insignificant for both models. Also, our conclusions remain unchanged relative to the evidence presented in Table 7. Results are available from the authors on request.

issuances in the return regression.[27] This is not the case for our results. Our results suggest that the market does not fully incorporate the loss reversal probability information when setting prices, possibly leaving some room for a degree of exploitability of this information.

Nonetheless, there are two possible alternative explanations for our results. First, the results could be interpreted as the loss reversal probability capturing some additional risk factor. Although we believe that we have included all the relevant sources of risk that have been studied in the UK (Soares and Stark, 2011), the bad-model problem of expected returns (Fama, 1998; Richardson *et al*. 2010) and omitted risk sources in the return regression could still explain the results.

Second, although investors might misunderstand the differences in the persistence of losses, trading on these shares might be extremely difficult or expensive as a consequence of various trading frictions. For example, the firms with the lowest probability of loss reversals are predominantly small firms (nearly 50% of them are in the bottom 30% of all firms by market capitalization). Also, many of our loss-making firms are listed on the AIM. Such firms tend to have high transaction costs and are difficult to sell short. Further, the investment strategy could only be profitable in combination with additional portfolio strategies based upon the firm characteristics that are associated with future returns.[28] Taken together, the true return of investing in loss-making firms could be substantially lower than the one being reported. It is likely that investors cannot exploit any mispricing opportunity.

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[27] Resutek (2011) adds two other firm characteristics in the return regression considered by Li (2011) - firm age and new equity issuance. Firm age explains very little future return (the coefficient is not significant) in the regression, but new equity issuances explains a significant amount of the future return.

[28] In untabulated univariate regressions, neither *LOSSRKG* nor *PREDICT* are significant in explaining future returns, suggesting that a hedge portfolio strategy based purely on these variables is not profitable before trading costs are taken into account.

## 5 CONCLUSIONS

This study first investigates the estimation and predictive ability of a modified loss reversal model in the UK, based upon Joos and Plesko (2005). For most variables that are common to the two analyses, their signs and significance are similar. Nonetheless, one variable that captures whether a firm initiates a dividend stop in the year of the loss has the opposite effect than that found in the USA, suggesting that the use of dividends to signal future profitability might be different in the UK, over the period studied, than in the USA. For the two new variables added to the model of Joos and Plesko (2005), we find evidence supporting both an *ex ante* conservatism accounting effect from RD expensing and an *ex post* conservatism accounting effect from extraordinary/exceptional items.

Second, our prediction accuracy tests indicate that the model is successful in predicting the likelihood of loss reversals. Further, our prediction model provides superior forecasts of loss reversals relative to a random assignment benchmark model that ignores the information content of the independent variables for predicting loss reversals and a simple rule benchmark such as ‘predict a loss reversal if a loss-making firm was profitable in the prior year’.

Third, we test whether a profitable portfolio strategy can be generated based upon the information contained by the loss reversal model. In particular, we examine whether, ignoring costs of trading, taking a long position in firms that are predicted to return to the profit status in the next year and taking a short position in firms that are predicted to continue making a loss in the next year is, in principle, profitable once other factors that affect the cross-section of returns are controlled for. When combined with other firm characteristics that are known to be associated with future returns, such a strategy is able to yield positive abnormal returns. Nonetheless, other evidence we present suggests that it might be difficult, if not impossible, to realize the estimated hedge return.

Although we believe that our results of the effectiveness of loss reversal models can have important practical implications for multiple users of financial accounting, we would also like to stress that there is plenty room to improve the predictive models. First, they might not be the optimal models in their use of available information. For example, given the time-varying nature of loss firms and temporal instability of the annual models, arguably it is unknown how many previous years of information investors should take into account in developing an understanding of the probability of loss reversal. Thus, the period of five years used in both approaches is arbitrary. Further, other independent variables could be investigated and possibly incorporated into the analysis, perhaps reflecting the possibility of using earnings management to achieve a return to profit status.

## REFERENCES


Al-Horani, A., Pope, P. F. and Stark, A. W., 2003. Research and development activity and expected returns in the United Kingdom. *European Finance Review*, 7 (1), 161-181.

Altman, E.I. and Robert, A. Eisenbeis., 1978. Financial applications of discriminant analysis: a clarification. *Journal of Finance and Quantitative Analysis*, 13 (1), 185-195.

Atieh, A. and Hussain, S., 2012. Do UK firms manage earnings to meet dividend thresholds? *Accounting and Business Research*, 42 (1), 77-94.

Balakrishnan, K., Bartov, E. and Faurel, L., 2010. Post loss/profit announcement drift. *Journal of Accounting and Economics*, 50 (1), 20-41.

Barnes, P., 1999. Predicting UK takeover targets: some methodological issues and an empirical study. *Review of Quantitative Finance and Accounting*, 12 (3), 283-301.

Berk, J.,1995. A critique of size-related anomalies. *Review of Financial Studies*, 8(2), 275-286.

Berk, J. B., Green, R.C. and Naik V., 1999. Optimal investment, growth options, and security returns. *Journal of Finance*, 54(5), 1553-1607.

Bernard, V. L. and Thomas, J.K., 1990. Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. *Journal of Accounting and Economics*, 13 (4), 305-340.

Carhart, M. M., 1997. On persistence in mutual fund performance. *Journal of Finance*, 52 (1), 57-82.

Chan, L.K.C., Karceski, J. and Lakonishok, J., 1998. The risk and returns from factors. *Journal of Financial and Quantitative Analysis*, 33(2), 159-188.

Collins, D. W., Maydew, E. L. and Weiss, I. S., 1997. Changes in the value relevance of earnings and book values over the past forty years. *Journal of Accounting and Economics*, 24 (1), 39-67.

Collins, D. W., Pincus, M. and Xie, H., 1999. Equity valuation and negative earnings: the role of book value of equity. *The Accounting Review*, 74 (1), 29-61.

Darrough, M. and Ye, J., 2007. Valuation of loss firms in a knowledge-based economy. *Review of Accounting Studies*, 12 (1), 61-93.

Dedman, E., Mouselli, S., Shen, Y. and Stark, A.W., 2009. Accounting, intangible assets, stock market activity, and measurement and disclosure policy - views from the U.K. *Abacus*, 45 (3), 312-341.

Fama, E. F., 1998. Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics*, 49 (3), 283-306.

Fama, E. F., and French, K. R., 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1), 3-56.

Fama, E. and French, K., 2008. Dissecting anomalies. *Journal of Finance*, 63 (4), 1653-1678.

Fama, E. F. and MacBeth J. D., 1973. Risk, return, and equilibrium: empirical tests. *Journal of Political Economy*, 81 (3), 607-636.

Feltham, G. A. and Ohlson, J. A., 1995. Valuation and clean surplus accounting for operating and financial activities. *Contemporary Accounting Research*, 11 (2), 689-731.

Givoly, D. and Hayn, C., 2000. The changing time-series properties of earnings, cash flows and accruals: has financial reporting become more conservative? *Journal of Accounting and Economics*, 29 (3), 287-320.

Gow, I. D., Ormazabal, G. and Taylor, D., 2010. Correcting for cross-sectional and time-series dependence in accounting research. *The Accounting Review*, 85 (2), 483-512.

Gore, P., Pope, P.F. and Singh, A.K., 2007. Earnings management and the distribution of earnings relative to targets: UK evidence. *Accounting and Business Research*, 37 (2), 123–150.

Gregory, A., R., Harris, D.F. and Michou, M., 2001. An analysis of contrarian investment strategies in the UK. *Journal of Business Finance & Accounting*, 28(9&10), 1192-1228.

Gregory, A., Tharyan, R. and Christidis, A.C., 2011. Constructing and testing alternative versions of the Fama-French and Carhart models in the UK. Available at SSRN: http://ssrn.com/abstract=1951831 or http://dx.doi.org/10.2139/ssrn.1951831.

Greig, A., 1992. Fundamental analysis and subsequent stock returns. *Journal of Accounting and Economics*, 15 (2-3), 413-422.

Hayn, C., 1995. The information content of losses. *Journal of Accounting and Economics*, 20, 125-153.

Hirshleifer, D. and Teoh, S. H., 2003, Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics*, 36(1-3), 337-386.

Holthausen, R. and Larcker, D., 1992. The prediction of stock returns using financial statement information. *Journal of Accounting and Economics,* 15 (2-3), 373-411.

Jiang, W. and Stark, A.W., 2011. Accounting and economic determinants of loss reversals. Available at SSRN: http://ssrn.com/abstract=1619173.

Jiang, W. and Stark, A.W., 2012. Dividends, research and development expenditures, and the value relevance of book value for UK loss-making firms. *British Accounting Review,* forthcoming.

Joos, P. and Plesko, G. A., 2005. Valuing loss firms. *The Accounting Review*, 80 (3), 847-870.

Klein, A. and Marquardt, C. A., 2006. Fundamentals of accounting losses. *The Accounting Review,* 81 (1), 179-206.

Lewellen, J., 2010. Accounting anomalies and fundamental analysis: an alternative view. *Journal of Accounting and Economics*, 50 (2&3), 455-466.

Li, K., 2011. How well do investors understand loss persistence? *Review of Accounting Studies*, 16 (3), 630-667.

Liu, W., Strong, N. and Xu, X., 1999. The profitability of momentum investing. *Journal of Business Finance & Accounting*, 26(9&10), 1043-1091.

Martikainen, M., 1997(a). Accounting losses and earnings response coefficients: the impact of leverage and growth opportunities. *Journal of Business Finance and Accounting*, 24 (2), 277-291.

Martikainen, M., 1997(b). Accounting losses and investors' growth expectations. *International Review of Financial Analysis,* 6 (2), 97-105.

Martikainen, T. and Ankelo, T., 1991. On the instability of financial patterns of failed firms and the predictability of corporate failure. *Economics Letters*, 35 (2), 209-214.

Michou, M., Mouselli, S. and Stark, A., 2010. Fundamental analysis and the modelling of normal returns in the UK. Available at SSRN: http://ssrn.com/paper=1607759.

Modigliani, F. and Miller, M.H., 1966. Some estimates of the cost of capital to the electric utility industry, 1954-57. *The American Economic Review*, 56 (3), 333-391.

Muradoglu, Y. G. and Sivaprasad, S., 2012. Capital structure and abnormal returns. *International Business Review*, forthcoming.

Newey, W. K. and West, K. D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, 703-708, *Econometrica*, 55(3), 703-308.

Ohlson, J.A., 1995, Earnings, book values and dividends in equity valuation. *Contemporary Accounting Research*, 11 (2), 661-87.

Ou, J. and Penman, S., 1989. Financial statement analysis and the prediction of stock returns. *Journal of Accounting and Economics*, 11 (4), 295-329.

Palepu, K. G., 1986. Predicting takeover targets – a methodological and empirical analysis. *Journal of Accounting and Economics*, 8 (1), 3-35.

Petersen, M., 2009. Estimating standard errors in finance panel data sets: comparing approaches. *Review of Financial Studies*, 22(1), 435-480.

Pincus, M., Rajgopal, S. and Venkatachal, M., 2007. The accrual anomaly: international evidence. *The Accounting Review*, 82 (1), 169-203.

Resutek, R., 2011. Discussion of "How well do investors understand loss persistence?". *Review of Accounting Studies*, 16 (3), 668 – 678.

Richardson, S., Tuna, I. and Wysocki, P., 2010. Accounting anomalies and fundamental analysis: a review of recent research advances. *Journal of Accounting and Economics*, 50 (2-3), 410-454.

Setiono, B. and Strong, N., 1998. Predicting stock returns using financial statement information. *Journal of Business Finance and Accounting*, 25 (5-6), 631-657.

Soares, N. and Stark, A.W., 2009. The accruals anomaly - can implementable portfolio strategies be developed that are profitable net of transactions costs in the UK? *Accounting and Business Research*, 39 (4), 1-25.

Soares, N. and Stark, A.W., 2011. Is there an accruals or a cash flow anomaly in UK stock returns? Available at SSRN: http://ssrn.com/paper=1734507.

# TABLE 1

## SAMPLE DETAILS

| Year | Panel A: Loss Reversal Model Next year's earnings | | | Panel B: Return Analysis Next year's earnings | | | |
|---|---|---|---|---|---|---|---|
| | >= 0 | < 0 | Total | >=0 | <0 | Delist | Total |
| **1991** | 56 | 99 | 155 | | | | |
| **1992** | 66 | 111 | 177 | | | | |
| **1993** | 88 | 88 | 176 | | | | |
| **1994** | 63 | 62 | 125 | | | | |
| **1995** | 51 | 65 | 116 | | | | |
| **1996** | 43 | 73 | 116 | 42 | 70 | 13 | 125 |
| **1997** | 56 | 118 | 174 | 56 | 114 | 14 | 184 |
| **1998** | 70 | 135 | 205 | 70 | 131 | 25 | 226 |
| **1999** | 57 | 153 | 210 | 55 | 150 | 22 | 227 |
| **2000** | 74 | 207 | 281 | 70 | 198 | 21 | 289 |
| **2001** | 80 | 301 | 381 | 80 | 294 | 39 | 413 |
| **2002** | 102 | 325 | 427 | 101 | 319 | 27 | 447 |
| **2003** | 107 | 277 | 384 | 107 | 268 | 28 | 403 |
| **2004** | 75 | 255 | 330 | 70 | 235 | 26 | 331 |
| **2005** | 80 | 274 | 354 | 77 | 254 | 23 | 354 |
| **2006** | 89 | 261 | 350 | 89 | 251 | 28 | 368 |
| **2007** | 77 | 242 | 319 | 76 | 239 | 58 | 373 |
| **2008** | 51 | 233 | 284 | 50 | 231 | 38 | 319 |
| **Total** | 1,285 | 3,279 | 4,564 | 943 | 2,754 | 362 | 4,059 |

***Note***: The table provides details of sample sizes for each year. Panel A gives information covering the estimation and test periods for loss reversal models. The estimation of the loss reversal model requires each loss firm observation having three successive years of relevant data to compute variables in the loss reversal models, including next year's earnings. To generate a prediction model for a given year *t*, we generate a single regression estimated on the pooled data from the annual cross-sections for the previous five years. The out-of-sample predictive accuracy tests for the model require the observations for year *t* having next year's earnings. Panel B gives information for the future return analysis. We apply the estimated loss reversal models on all loss-making firms (including those without next year's earnings) each year to avoid forward-looking bias. Loss year observations need to have at least one month's return data starting on July 1 of the following calendar year to be included in the analysis.

# TABLE 2

## DESCRIPTION OF THE SAMPLE FOR LOSS REVERSAL MODEL FROM 1991 TO 2008

| | *(NI-EI+RD)/LAG(TA)* | *RD/LAG(TA)* | *EI/LAG(TA)* | *LOG(MV)* | *SGR* | *FIRSTLOSS* | *DIVDUM* | *DIVSTOP* | *No. of Obs* |
|---|---|---|---|---|---|---|---|---|---|
| **Panel A: Characteristics for Non-Reversals** | | | | | | | | | |
| *MEAN* | -0.357 | 0.091 | -0.068 | 9.426 | 2.014 | 0.222 | 0.150 | 0.071 | 3279 |
| *MEDIAN* | -0.116 | 0.000 | 0.000 | 9.255 | 0.033 | 0.000 | 0.000 | 0.000 | |
| *MIN* | -94.318 | 0.000 | -16.319 | 0.693 | -1.000 | 0.000 | 0.000 | 0.000 | |
| *MAX* | 0.773 | 12.698 | 8.884 | 18.648 | 936.600 | 1.000 | 1.000 | 1.000 | |
| *STD* | 1.970 | 0.322 | 0.453 | 1.681 | 23.695 | 0.416 | 0.357 | 0.257 | |
| **Panel B: Characteristics for Reversals** | | | | | | | | | |
| *MEAN* | -0.129 | 0.028 | -0.168 | 9.652 | 8.292 | 0.449 | 0.403 | 0.096 | 1285 |
| *MEDIAN* | -0.033 | 0.000 | -0.007 | 9.341 | -0.026 | 0.000 | 0.000 | 0.000 | |
| *MIN* | -47.804 | 0.000 | -152.839 | 2.303 | -1.000 | 0.000 | 0.000 | 0.000 | |
| *MAX* | 1.030 | 1.675 | 2.050 | 18.324 | 6620.000 | 1.000 | 1.000 | 1.000 | |
| *STD* | 1.358 | 0.097 | 4.266 | 1.829 | 209.966 | 0.498 | 0.491 | 0.294 | |
| **Panel C: The Comparison of Means/Medians between Non-Reversals and Reversals** | | | | | | | | | |
| *P value(Mean)* | 0.000 | 0.000 | 0.185 | 0.000 | 0.092 | 0.000 | 0.000 | 0.007 | |
| *P value (Median)* | 0.000 | 0.000 | 0.000 | 0.139 | 0.000 | 0.000 | 0.000 | 0.006 | |

***Note***: Loss firm-year observations in the sample have prior year data such as sales, earnings and dividends; current year data such as market values, sales, earnings, RD and dividends; and subsequent year data such as earnings. The number of current losses that return to profitability in the next year (reversals) over the sample period 1991-2008 is 1285, and that do not return to profitability in the next year (non-reversals) is 3279. T tests (Chi-square tests) are used to compare the means of continuous (category) variables between reversals and non-reversals. Wilcoxon tests are used to compare the medians of these variables between reversals and non-reversals. The associated P-values (two tailed) are reported in Panel C.

# TABLE 3

## ESTIMATES OF THE LOSS REVERSAL MODEL ON POOLED DATA

| | Predicted Sign | (1) | (2) |
|---|---|---|---|
| ***CONSTANT*** | | -1.229*** | -1.282*** |
| | | (37.349) | (40.203) |
| **(*NI-EI*)/*LagTA*** | + | 1.419*** | |
| | | (74.286) | |
| **(*NI-EI+RD*)/*LagTA*** | + | | 1.610*** |
| | | | (71.444) |
| ***RD*/*LagTA*** | – | | -2.954*** |
| | | | (54.836) |
| ***EI*/*LagTA*** | – | | -0.459*** |
| | | | (35.689) |
| ***Log(MV)*** | + | 0.018 | 0.036* |
| | | (0.808) | (3.013) |
| ***SGR*** | ? | 0.010*** | 0.001 |
| | | (73.851) | (1.277) |
| ***FIRSTLOSS*** | + | 0.356*** | 0.304*** |
| | | (16.701) | (12.130) |
| ***DIVDUM*** | + | 0.915*** | 0.837*** |
| | | (92.569) | (76.707) |
| ***DIVSTOP*** | – | 0.494*** | 0.405*** |
| | | (16.150) | (10.758) |
| **Pseudo R squared** | | 0.096 | 0.105 |
| **No. of Obs. for Loss Reversals** | | 1285 | |
| **No. of Obs. for Non-Loss Reversals** | | 3279 | |
| **Likelihood-Ratio Test (p > $\chi$2)** | | 0.000 | |

***Note***: The table presents the result of the estimation of the logistic loss reversal regression on the pooled data over 1991 to 2008. The dependent variable $P(y_{t+1}|x_t)$ is a dummy variable that equals to 1 if a firm makes a loss in year *t* and becomes profitable in year *t*+1, and 0 otherwise. Reported in parentheses are Wald chi-square statistics. The Pseudo R squared indicate the overall explanatory power of these models. *** p<0.01, ** p<0.05, * p<0.1.

# TABLE 4

## OUT-OF-SAMPLE CLASSIFICATION ACCURACY RESULTS AND CHI-SQUARE STATISTICS

| | | **Models Obtained Using Five Years of Pooled Data** | | | | |
|---|---|---|---|---|---|---|
| | | Top Quartile | Second Top Quartile | Second Bottom Quartile | Bottom Quartile | P Value (Chi-Square test) |
| **1996** | Non-Reversals | 13 | 17 | 18 | 25 | 0.011 |
| | Reversals | 16 | 12 | 11 | 4 | |
| **1997** | Non-Reversals | 23 | 27 | 29 | 39 | 0.003 |
| | Reversals | 20 | 17 | 14 | 5 | |
| **1998** | Non-Reversals | 21 | 30 | 38 | 46 | 0.000 |
| | Reversals | 31 | 21 | 12 | 6 | |
| **1999** | Non-Reversals | 24 | 36 | 44 | 49 | 0.000 |
| | Reversals | 29 | 16 | 9 | 3 | |
| **2000** | Non-Reversals | 33 | 45 | 64 | 65 | 0.000 |
| | Reversals | 38 | 24 | 7 | 5 | |
| **2001** | Non-Reversals | 59 | 73 | 85 | 84 | 0.000 |
| | Reversals | 37 | 21 | 11 | 11 | |
| **2002** | Non-Reversals | 53 | 80 | 93 | 99 | 0.000 |
| | Reversals | 53 | 28 | 13 | 8 | |
| **2003** | Non-Reversals | 46 | 62 | 79 | 90 | 0.000 |
| | Reversals | 50 | 34 | 17 | 6 | |
| **2004** | Non-Reversals | 48 | 65 | 67 | 75 | 0.000 |
| | Reversals | 35 | 17 | 15 | 8 | |
| **2005** | Non-Reversals | 52 | 64 | 77 | 81 | 0.000 |
| | Reversals | 36 | 25 | 12 | 7 | |
| **2006** | Non-Reversals | 36 | 61 | 79 | 85 | 0.000 |
| | Reversals | 52 | 26 | 8 | 3 | |
| **2007** | Non-Reversals | 47 | 51 | 69 | 75 | 0.000 |
| | Reversals | 32 | 29 | 12 | 4 | |
| **2008** | Non-Reversals | 49 | 57 | 63 | 64 | 0.003 |
| | Reversals | 22 | 14 | 8 | 7 | |

***Note:*** The table reports the classification results and their associated chi-square statistics over our out-of-sample period of 1996-2008 for losses which have next year's earnings. The prediction models are estimated on the pooled prior five years data. We rank the out-of-sample predicted probabilities in a descending sequence and then divide the numbers into four quartiles. The four quartiles are referred as top quartile, second top quartile, second bottom quartile, and bottom quartile. Then, we count the actual *ex-post* reversals and non-reversals in each quartile. We further report the p-values for chi-square tests for each year's classification result.

# TABLE 5

## % PREDICTIVE ACCURACY COMPARISONS OUT-OF-SAMPLE FOR LOSS REVERSALS

| | **Benchmark I (Random Assignment)** | **Benchmark II (Simple Rule)** | **Prediction Models with Optimal Cutoff** |
|---|---|---|---|
| **1996** | 51.56% | 58.62% | 64.66% |
| **1997** | 53.38% | 64.37% | 67.82% |
| **1998** | 54.14% | 69.27% | 70.24% |
| **1999** | 56.40% | 70.00% | 70.95% |
| **2000** | 57.70% | 69.04% | 77.22% |
| **2001** | 61.35% | 69.29% | 76.64% |
| **2002** | 62.04% | 73.30% | 77.05% |
| **2003** | 60.86% | 74.48% | 75.78% |
| **2004** | 63.66% | 76.06% | 78.18% |
| **2005** | 64.09% | 72.60% | 78.53% |
| **2006** | 62.94% | 72.86% | 74.86% |
| **2007** | 63.16% | 70.53% | 74.61% |
| **2008** | 66.25% | 70.42% | 80.63% |

***Note***: Table 5 compares the annual out-of-sample predictive accuracies amongst the use of prediction models with optimal cutoffs, and two benchmarks. Benchmark I is the predictions using a method of random assignment of firms to a prediction of reversal or non-reversal. Benchmark II is the predictions using a simple rule of ‘predict a reversal if *FIRSTLOSS* = 1’.

# TABLE 6

## OVERALL CLASSIFICATION RESULTS FOR THE PREDICTION OF LOSS REVERSALS

**Panel A – Optimal Cutoff**

| | | *Actual Outcome* | | |
|---|---|---|---|---|
| | | **Non-Reversal** | **Reversal** | **Total** |
| ***Prediction*** | **Non-Reversal** | 2629 | 710 | 3339 |
| | **Reversal** | 225 | 251 | 476 |
| | **Total** | 2854 | 961 | 3815 |

**Panel B – Simple Rule**

| | | *Actual Outcome* | | |
|---|---|---|---|---|
| | | **Non-Reversal** | **Reversal** | **Total** |
| ***Prediction*** | **Non-Reversal** | 2293 | 540 | 2833 |
| | **Reversal** | 561 | 421 | 982 |
| | **Total** | 2854 | 961 | 3815 |

***Note***: The table presents the aggregated classification results which are in the form of 2 rows x 2 columns over the period 1996-2008. Panel A reports the results for the use of the prediction models and the associated optimal cutoffs. Panel B reports the results for the use of a simple rule of ‘predict a reversal if FIRSTLOSS = 1’.

## TABLE 7

### REGRESSION RESULTS ON FUTURE ABNORMAL RETURNS

| | (1) | (2) | (3) |
|---|---|---|---|
| ***CONSTANT*** | 0.109 | 0.079 | 0.114 |
| | (0.456) | (0.333) | (0.476) |
| ***$LOSSRKG^{dt}$*** | | 0.196** | |
| | | (2.646) | |
| ***PREDICT*** | | | 0.110* |
| | | | (1.790) |
| ***$SIZE^{dt}$*** | -0.069 | -0.112 | -0.088 |
| | (-0.981) | (-1.650) | (-1.171) |
| ***$BM^{dt}$*** | -0.049 | -0.095 | -0.059 |
| | (-0.327) | (-0.631) | (-0.396) |
| ***$EP^{dt}$*** | -0.011 | -0.021 | -0.011 |
| | (-0.277) | (-0.457) | (-0.312) |
| ***$DY^{qt}$*** | 0.050 | -0.001 | -0.013 |
| | (1.474) | (-0.045) | (-0.287) |
| ***$RD^{qt}$*** | 0.111** | 0.136** | 0.115** |
| | (2.549) | (2.983) | (2.532) |
| ***$CC^{qt}$*** | -0.069*** | -0.061** | -0.066*** |
| | (-3.329) | (-2.502) | (-3.215) |
| ***$CF^{dt}$*** | 0.019 | -0.024 | 0.011 |
| | (0.265) | (-0.324) | (0.149) |
| ***$LEV^{dt}$*** | -0.142* | -0.166** | -0.147* |
| | (-2.133) | (-2.410) | (-2.168) |
| ***$MOM^{dt}$*** | 0.136 | 0.120 | 0.131 |
| | (1.358) | (1.188) | (1.302) |
| ***$P^{dt}$*** | -0.230*** | -0.226*** | -0.228*** |
| | (-5.281) | (-4.977) | (-5.204) |
| ***Observations*** | 4,059 | 4,059 | 4,059 |
| ***Average $R^2$*** | 0.072 | 0.079 | 0.077 |

***Note***: The table presents the results of estimating future market-adjusted abnormal returns (*ABRET*) on loss reversal probability ranking (*LOSSRKG*), loss reversal prediction (*PREDICT*), market value (*SIZE*), book-to-market (*BM*), earnings-price (*EP*), dividend-yeld (*DY*), research and development expenses deflated by SIZE (*RDMV*), cash flow deflated by average total assets (*CF*), total debt deflated by SIZE (*LEV*), past 12 months cumulative returns (*MOM*), and price (*P*). All variables are calculated as of July 1, t+1, and the *qt* superscript indicates that the variables are defined as (variable ranking - 1)/(number of rankings – 1), where rankings are 4 for *qt* superscript variables and 10 for *dt* superscript variables. Fama and MacBeth (1973) estimates reported. *t*-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1.