Risk vs. Anomaly: A New Methodology Applied to Accruals

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ABSTRACT: Research suggesting the existence of the accrual anomaly runs into the issue that risk serves as a competing explanation for abnormal returns. This paper proposes a novel approach to distinguish between risk and anomaly explanations for the negative association between accruals and returns. The intuition is that high risk stocks should experience relatively high and low returns more often than low risk stocks. Thus, a variable that has the opposite correlations with high returns than with low returns is unlikely to capture risk, which points toward an anomaly. The paper implements this perspective via two logistic regressions predicting relatively high and low returns. Controlling for standard risk measures, we document that low accruals increase the probability of large positive returns, but reduce the likelihood of large negative returns. This finding is inconsistent with the prediction that accruals reflect risk and supports the hypothesis that the accrual "anomaly" is indeed an anomaly.

Keywords: *the accrual anomaly; risk and anomaly explanations; new research method*

I. INTRODUCTION

Empirical research that purports to have identified a pricing anomaly runs into the standard question: are anomalous returns better explained by risk? No generally accepted methodology has been developed that resolves this question with clarity. Instead authors typically control for various risk-proxies, like Fama and French (1992) measures, to show that abnormal returns remain. But there are two distinct difficulties with this approach: the measurement of risk (the joint hypothesis problem of Fama 1970, 1991) and the sampling errors associated with conditional expected returns.[1] Evaluators of research that identifies a new anomaly therefore tend to worry that the probability that the market efficiency (rational pricing) has been falsely rejected is high because of a perception of tests lacking in robustness.

This paper introduces a new methodology to distinguish between risk and anomaly explanations for apparent abnormal returns generated by some trading rule. We then apply the methodology to examine Sloan's (1996) accrual anomaly. The accrual anomaly suggests that a portfolio long in stocks with low accruals and short in stocks with high accruals can earn excess returns even if one controls for risk.[2] The explanation for why a hedge portfolio generates abnormal returns is that accruals correlate negatively with returns. We take this idea one step further and argue that the existence of an *anomaly* is very plausible if two separate conditions are met: (i) low accruals are *positively* associated with *high* returns and (ii) low accruals are *negatively* associated with *low* returns (high accruals, of course, should *negatively* associate with *high* returns and *positively* associate with *low* returns). Thus, if one agrees with Sloan that the zero-investment portfolio yields on average positive abnormal returns, then it would seem difficult to attribute this positive return to a risk factor if *both* (i) and (ii) are statistically valid. Thus, the correlation structures between accruals and high and low

[1] Fama (1970) was among the first to emphasize that evidence of a market "anomaly" may reflect either that markets are inefficient or a failure of a particular asset pricing model to price stocks. Chan and Lakonishok (1993) and Shevlin (2013) argue that noise in the return data limits the ability of asset pricing models to explain returns.
[2] For a detailed review of the accrual literature see Richardson, Sloan, Soliman, and Tuna 2005; Dechow, Khimich, and Sloan 2011).

returns bear directly on the anomaly vs. risk issue without delving into questions such as what risk controls to include in the expected return model.

To implement the new method we define, using subjective cut-off points, indicator variables for relatively "high" (H) and "low" (L) returns and estimate two separate logistic regressions. In the H regression, the dependent variable is one when the return is higher than a (relatively high) cut-off point and zero otherwise; in the second regression, the dependent variable is one when the return is lower than a (relatively low) cut-off point and zero otherwise. In both regressions, accruals serve as the key independent variable, but the models include controls for standard risk measures to sharpen the analysis. With this experimental setup in place, an anomaly prevails when the coefficient on the accrual is negative in the H regression and positive in the L regression. By contrast, when traditional risk measures, such as market betas and return volatilities are put on the right-hand-side, then the related estimated coefficients should be positive in both regressions, because risky stocks, compared to low risk stocks, have relatively high probabilities to produce extreme returns. Thus one can study the signs of estimated coefficients on accruals in the two regressions to assess whether the driver for claimed "superior returns" is an anomaly or risk.

The next section describes formally the logistic regressions H and L and discusses the advantages of the new methodology. The subsequent section then demonstrates that risk measures such as beta and stock price volatility behave like risk measures, that is, the coefficients on these variables are positive in both the H and L regressions. Following this analysis, the paper introduces the standard measure of an accrual and puts it onto the right-hand side in the logistic regressions. The empirical results show that the coefficient on accruals is negative in the H regression and positive in the L regression. This result suggests an appealing investment opportunity where an investor can increase the likelihood of high returns and reduce the likelihood of low returns. This outcome is central in the evaluation of the accrual anomaly, and we then subject it to various robustness tests. Overall, our results support the original "anomaly" claim by Sloan (1996) in the sense that the negative correlation between returns and accruals is unlikely to be due to some (perhaps unknown) risk factor.

The proposed method has high specificity to reduce the likelihood a candidate predictive variable, like accruals, is a risk proxy. In other words, a variable that has opposite correlations with high than with low returns is unlikely to capture risk. However, the method is less useful to test whether a predictive variable measures risk. We illustrate this qualification by examining how the Francis, LaFond, Olsson, and Schipper (2005) earnings quality measure (their proxy for information risk) behaves in our framework. Francis et al. (2005) argue that information risk is a priced risk factor—a conclusion hotly debated in the accounting literate (e.g. Core, Guay, and Verdi 2008; Clinch 2013; Shevlin 2013). We document that low earnings quality increases the likelihood of both high and low returns, however, these associations do not imply that the earnings quality measure captures risk. This is because, in principle, one cannot rule out the existence of an anomaly variable that correlates positively with extreme returns, e.g. an anomaly variable where the likelihood of a relatively high return is greater than the likelihood of a relatively low return. Hence, the methodology lacks sharpness in the sense that correlations of the same sign with extreme positive and negative returns cannot identify if a variable captures risk or mispricing.

II. THE METHODOLOGY

We propose a simple and intuitive methodology to evaluate whether risk or mispricing are the likely causes for the existence of abnormal returns generated by some "trading attribute", e.g. accruals in Sloan (1996). The method focuses on the signs of correlations between a trading attribute X and high and low returns. Specifically, an anomaly explanation for the relation between X and returns is more likely if X has the opposite correlations with high returns than with low returns. In other words, an investor has the appealing prospect of both increasing the likelihood of high returns and reducing the likelihood of poor returns by investing in stocks with either high or low values of the attribute X.

The new approach builds on the intuition that the anomaly explanation for why X seems to generate abnormal returns in standard tests is more likely if X has the opposite correlations with high returns than with low returns. Any analysis that focuses on high and low returns must address the problem that a few extreme observations may determine statistical conclusions.[3] To avoid this possibility, the methodology uses the simplest possible setup: a binary dependent variable and two independent logistic regressions for "high" (H) and "low" (L) returns. The regressions have the form:

$$P(High\_return) = \alpha_1 + \beta_1 * X + \Gamma_1 * risk\text{-}controls \tag{H}$$

$$P(Low\_return) = \alpha_2 + \beta_2 * X + \Gamma_2 * risk\text{-} controls \tag{L}$$

where *High_return* and *Low_return* are indicator variables if stock returns are respectively higher and lower than specific cut-off points.

The coefficients on X in the two equations H and L allow us to evaluate the hypothesis of rational pricing. Specifically, the explanation that X captures a market anomaly obtains whenever the product of the β_1 and β_2 parameters is negative or one of the parameters is non-zero while the other one is zero. The former case provides a "strong" version of the irrational pricing; the latter case is "weaker" since the investment opportunity is only in either the upside or the downside, but not both. In other words, in the strong case, there is an opportunity to earn returns from taking both the long and the short position in a stock associated with the signal X. In the weak case, the investment opportunity is either from going long or short in a stock. This weak case is particularly interesting

[3] Fama and French (2008) argue that a few extreme observations can strongly influence the Fama-MacBeth regression analysis that is commonly used in studies that examine the relation between an anomaly variable and returns.

when β_2 is significant while β_1 is not. Much research has suggested this possibility due to transactions costs associated with difficulties of shorting stocks.[4]

As a matter of statistics, there is always the possibility that the estimated parameters β_1 and β_2 are of the opposite sign yet statistically insignificant. In this case, test results are inconclusive and we cannot conclude whether X is more likely to reflect risk or mispricing. Also, the method has low power to discriminate whether X captures risk or mispricing when the product of the β_1 and β_2 coefficients is positive, $\beta_1 * \beta_2 > 0$. Positive product of beta coefficients should be most common among risky stocks because risky stocks, compared to low risk stocks, have relatively high probabilities of extreme returns. In other words, when $\beta_1 * \beta_2 > 0$, implementing a trading strategy that buys stocks with a high value of X and shorts stocks with a low value of X is risky because the potential of relatively high returns is counterbalanced by the potential of relatively low returns. However, we cannot preclude the possibility that significant correlations of the same sign with high and low returns capture mispricing and an investor could engage in risky arbitrage, e.g. when the likelihood of a large upside return is higher than the likelihood of a large downside return. Thus, tests producing coefficients of the same sign do not bear conclusively on the anomaly vs. risk question.

To define relatively high and low returns in models H and L, we compare the return on the stock to the (value-weighted) market return. This approach neutralizes any correlation X may have with the market-return, which leads to greater statistical power. Further, we employ a cut-off point of 50% when defining the dependent variable *High_return* for model H, and −50% when defining the dependent variable *Low_return* for model L. While the cut-offs are necessarily arbitrary,

[4] Lev and Nissim (2006) find that investors gain on average higher returns from shorting high accrual stocks than from a long position in low accrual stocks. Lev and Nissim (2006) attribute this result to lower transaction costs of the long position and, consequently, higher arbitrage intensity of the long position.

robustness tests in section VII show the method is not sensitivity to the magnitudes of the breakpoints.

The vectors Γ_1 and Γ_2 of coefficients on risk controls are of a subordinated importance. Though the set of risk controls could be anything in principle, it should naturally include the most common measures of risk, such as market beta and return volatility. The product of respective coefficients on risk controls $\gamma_1 * \gamma_2$ should be positive and significant to build confidence that the methodology aligns with capital market precepts. From this perspective, it makes sense to first evaluate the two regressions H and L without the X variable. In other words, the analysis should start with the simplest possible question: do standard risk measures such as beta and return variance behave like risk measures in the proposed framework? The CAPM of course does not require such a relation, but, as a matter of intuition, it reassures that the methodology operates as expected.

The proposed methodology has a number of advantages. First, as noted earlier, there is no need to evaluate the (average) returns of specific portfolio strategies, which are likely to be very noisy. In a similar vein, the method does not need to specify how expected returns should be measured.[5] Rather, the method sidesteps the question of the specification of the expected return model to propose a simple approach to distinguish between anomaly and risk interpretation for why a certain strategy generates abnormal return. Second, as the following sections will discuss, the method's conclusions are unlikely to be dependent on precise cut-off points for "high" (H) and "low" (L) returns. In any event, robustness tests can always be evaluated. Third, because the logistic methodology uses a binary dependent variable, results can never be driven by a few extreme return

[5] Studies commonly propose new risk factors to explain anomalies (e.g. Khan 2008 and Wu, Zhang, and Zhang 2009 in the context of the accrual anomaly). Carried to the extreme, one can even entertain "exotic" factors such as the political party of the US president, the weather in Manhattan, global warming, the El Niño phenomenon, sunspots, and the conjunctions of the planets (Novy-Marx 2014). Moreover, Hirshleifer, Hou, and Teoh (2012, 321) emphasize that including additional risk factors to explain an anomaly does not "guarantee that a given proposed factor structure will capture the key economic risks associated with the characteristic that underlies the anomaly" and runs the risk "that model overfitting ("factor fishing") can wrongly identify a mispricing proxy as the loading on some risk factor. A naïve strategy of proposing new factor structures until the anomaly vanishes can "work," even if the anomaly in fact represents market inefficiency rather than a rational risk premium".

outliers, positive or negative. Winsorization of the dependent variable is therefore unnecessary. Fourth, the set up makes it difficult to falsely reject a null hypothesis that risk explains abnormal returns. That is, the anomaly explanation requires that the estimated coefficients in the *two* regressions are of different signs and statistically significant. This outcome should be difficult to accomplish if the null hypothesis is true. Fifth, the methodology permits conceptual evaluation, that is, a researcher can check whether traditional risk measures, like market beta and firm size, have the same signs in the two regressions and if the coefficients are significant. Including traditional risk measures in the regressions also provides further reinforcement preventing a false rejection of the null. Finally, the methodology is intuitive and easy to implement, and holds the potential of allowing researchers to generate easily understood evidence to substantially enhance a researchers' dialogue on how to interpret the existence of certain claimed anomalies.

Of all the above methodological advantages, the most subtle concerns assumptions about correlations between risk measures and realized returns. Our framework does not assume that to qualify a variable as a risk proxy, empirically there should be a positive correlation between the risk measure and stock returns.[6] Rather, the proposed approach emphasizes that an investment opportunity that increases the likelihood of high returns and reduce the likelihood of low returns is unlikely to capture risk. That said, the methodology has two disadvantages. First, there is a possibility that the method will not resolve the "risk vs. anomaly" question—this can happen when the *t*-statistics in both H and L models are insignificant or the product of coefficients from the two logistic models is positive. Second, more subtly, one cannot rule out that there exists some capital market equilibrium where a variable that produces coefficients of different signs in the two logistic

[6] Outliers and the use of noisy realized returns in place of expected returns in empirical tests can explain the puzzling evidence of zero or negative correlations between some risk measures, such as beta and volatility, and realized returns (Fama and French 1992; Ang, Hodrick, Xing, and Zhang 2006), which led some researchers to question if beta and volatility capture risk. At the extreme, one could claim that because expected returns are unobservable, one can never empirically test if risk measures correlate positively with expected returns.

regressions correlates with risk. In other words, one could encounter a risk variable that has a property that intuitively seems anomalous, i.e. investing in a risk factor increases the upside return potential and reduces the likelihood of unfavorable outcomes.

In sum, the proposed methodology finesses the joint problems of dealing with (i) tests where the specification of the expected return model can be questioned (the joint hypothesis problem), (ii) the possibility of results being explained by a few "excessively" influential observations, and (iii) measuring expected returns on the basis of noisy realized returns. Standard empirical methodologies do not address these problems in a satisfactory way, which leaves readers unpersuaded about the conclusions from these methods. Readers need an intuitive approach that poses the question "does risk or an anomaly explain why a trading strategy generates abnormal returns" simply and directly and the proposed method offers such an approach.

III. DEFINITIONS OF THE DEPENDENT AND INDEPENDENT VARIABLES

This section defines the dependent and independent variables in the two logistic models from Section II.

A two-step procedure defines the H and L dependent variables in the two logistic regressions. First, for each firm-year we calculate the 12-month cumulative market-adjusted return, *CAR*. The normal return benchmark is the monthly value-weighted (VW) CRSP market index. To avoid hindsight bias, *CAR* starts four months after the fiscal year-end. In the second step, cut-off points of ±50% identify stocks with relatively high and low returns. Specifically, the dependent variable *High_return* in model H equals one if the annual *CAR* is higher than 50%, and zero otherwise.

Low_return equals one if the annual *CAR* is lower than −50%, and zero otherwise.[7] Robustness tests in Section VI also consider other ways to define the dependent variables for models H and L.

Accruals definition closely follows Sloan (1996) and includes three components. The first is the difference in changes in current assets and in cash and cash equivalents. The second term is the difference in changes in current liabilities, and changes in short-term debt, and in income taxes payable. The third term is depreciation and amortization expense.

$$\begin{aligned} \textit{Accruals} = &(\Delta\text{Current assets} - \Delta\text{Cash and cash equivalents}) \\ &-(\Delta\text{Current liabilities} - \Delta\text{Debt included in current liabilities} - \Delta\text{Income taxes payable}) \\ &-\text{Depreciation and amortization expense.} \end{aligned}$$

We calculate changes between two consecutive fiscal years. *Accruals* are scaled by average of the beginning and end-of-year book value of total assets to ensure comparability across firms.

The logistic regressions H and L control for three standard risk proxies. The firm's market beta (*Beta*) captures the stock's systematic risk. *Beta* is estimated from the market model over 3-years ending three months after the fiscal year-end. The stock's monthly return volatility (*Vol*) controls for total firm risk. *Vol* is estimated over the same period as market beta. Firm market capitalization (*MV*) captures firm size. Small stocks have high distress risk (Chan and Chen 1991; Perez-Quiros and Timmermann 2000) and low information quality leading to higher information asymmetries (Gertler and Gilchrist 1994; Barry and Brown 1984). Firm market capitalization is measured three months after the fiscal year-end. The product of coefficients on the risk controls from the two logistic models should be significant and positive.[8] Industry dummies (*Industry effect*) control for

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[7] The ±50% cut-off points are four times higher than the annual equally-weighted return on the CRSP index, which is 12.5% over 1941–1991 (Kothari and Shanken 1997). Thus, the breakpoints should be successful in identifying stocks with unexpectedly good and bad returns. To avoid a delisting bias, we follow Shumway (1997) and include delisting returns. When a delisting return is missing, we assume a return of −1 for delisting due to liquidation (CRSP codes 400–490), −0.33 for performance related delisting (CRSP codes 500 and 520–584), and zero otherwise.

[8] Significant coefficients on return volatility and beta are consistent with Fu (2009), who build on the evidence that investors do not hold well diversified portfolios and predict that under-diversified investors may require a premium for

industry variation in abnormal returns.[9]

Main tests for models H and L use pooled cross-sectional samples and we adjust for cross-sectional and time-series dependence among observations using dual-clustered standard errors on firm and fiscal year (Petersen 2009). As is standard in the literature, the regressions include a set of year dummies (*Year effect*) to control for temporal variation in abnormal returns. For robustness and to show comparability with previous studies, we also use the Fama-MacBeth method.[10] All explanatory variables are winsorized at the 1st and 99th percentiles.

IV. DATA AND DESCRIPTIVE STATISTICS

This section describes the data sources, the pooled sample descriptive statistics, and descriptives for stocks that earn annual market-adjusted returns higher than 50% and lower than −50%.

The sample includes all firms with ordinary common stock listed on NYSE/AMEX and Nasdaq that are available on the intersection of CRSP and CRSP/Compustat merged databases over fiscal years 1970 to 2009. Selecting stocks with non-missing return and accounting information produces a sample of 103,034 firm-year observations.

Panel A of Table 1 reports the pooled sample descriptive statistics for the dependent variables in models H and L, and for the explanatory variables. The ±50% cut-off points allocate 14.6% of stocks into the high return portfolio and 10.6% of stocks into the low return group. The mean

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bearing both systematic and idiosyncratic risk. Controlling for return volatility also eliminates the possibility that the correlation between accruals and high and low returns exists because accruals correlate with volatility.

9 Our main tests do not control for the book-to-market ratio, B/M, as the risk explanation for the B/M ratio is tenuous (see Dichev 1998; Griffin and Lammon 2002; Lakonishok, Shleifer, and Vishny 1994 and Campbell, Hilscher, and Szilagyi 2008). Sensitivity tests discuss the association between the B/M ratio and returns.

10 The Fama-MacBeth approach controls for the cross-sectional correlations among stocks, but ignores the time-series dependence among observations. Gow, Ormazabal, and Taylor (2010) criticize the use of the Fama-MacBeth method in accounting research pointing out that the method fails to adjust for both the time-series and cross-sectional dependence of observations. Our pooled regressions control for both cross-sectional and time-series dependence.

assets-scaled accruals are −0.032. Average return volatility is 14.4%, mean beta is 1.175, and average firm capitalization is over $1bn.

[Insert Table 1 around here]

Panel A1 compares means of the explanatory variables for stocks that earn annual market-adjusted returns in excess of 50% and below this level. The methodology predicts that stocks in the right tail of the return distribution should be more risky compared to the remaining stocks. Consistent with this proposition, stocks with relatively high returns have higher return volatility and betas, and have smaller market capitalizations compared to the remaining stocks. The absolute magnitudes of differences in risk characteristics across the two groups are substantial: 38.7% for return volatility, 11.8% for market beta, and 67% for firm size. These results confirm that more risky stocks cluster in the right tail of the return distribution. Accruals at stocks with relatively high returns are on average 84.4% smaller compared to the remaining stocks.

Panel A2 reports means of the explanatory variables for stocks earning annual market-adjusted return of less than −50% and above that level. Here, the prediction is that stocks in the left tail of the return distribution should be more risky compared to the remaining stocks. Stocks that experience relatively low returns are indeed more risky as characterized by their smaller size and higher return volatility and betas. The absolute magnitudes of differences in risk characteristics between the two groups are also significant: 31.4% for return volatility, 15.5% for market beta, and 59.5% for firm size. This result confirms that more risky stocks are more likely to experience relatively poor future performance. Accruals are on average higher among stocks that experience relatively low returns.

To sum up, Table 1 results document that simple univariate tests that focus on relatively high and low returns provide valuable insights on whether risk or stock mispricing are the likely causes for the existence of abnormal returns. We document that (i) high risk stocks cluster in the tails of the cross-sectional return distribution and (ii) high accrual stocks concentrate in the left-tail of the cross-sectional return distribution. The latter evidence is inconsistent with the risk explanation for the accrual anomaly. These findings anticipate next section results that examine the logistic regressions H and L that predict relatively low and high returns from accruals.

V. LOGISTIC REGRESSIONS: MAIN FINDINGS

This section presents main regression results for the two logistic regressions H and L that predict relatively high and low returns. First, we report results for models H and L where risk controls are the only explanatory variables. Regression results show that standard risk measures behave like risk proxies in the proposed framework. Second, we present regression results where accruals is the main explanatory variable. This test confirms Table 1 findings that accruals capture stock mispricing. Third, we present results for models H and L where accruals are included with risk controls in the two predictive models. This test documents that the conclusion that accruals capture an anomaly persists when risk controls are included in the model.

Table 2 examines how standard risk measures, such as market beta, firm return volatility and firm size behave in our framework. The new method offers a simple specification test to build confidence that the framework aligns with capital market perceptions of what a risky stock is. This happens if coefficients on a risk proxy from the H and L regressions are significant and of the same sign. The empirical results in Table 2 confirm that the coefficients on return volatility, market beta and firm size conform to these expectations. This result is evident whether firm size and firm return volatility are the only controls (*Model* 1) or are included jointly with market beta (*Model* 2). These tests verify that standard risk measures behave as expected in the proposed framework.

The conclusion that risk proxies behave as expected is unchanged when we estimate the logistic models H and L separately for each fiscal year and then calculate average coefficients on the risk proxies and the associated *t*-statistics.[11] These results are reported in the column *Fama MacBeth* in Table 2. The Fama MacBeth regression results are noteworthy as they show that the conclusions from the proposed method are not dependent on the sample size used in the pooled regression analysis, i.e. the coefficients in the pooled regressions can be significant simply because of a large sample size. This suggests that our framework has similar power when using pooled regressions and the more demanding Fama MacBeth method.

[Insert Table 2 around here]

Although the magnitudes of coefficient estimates are not of direct importance, it is noteworthy that the magnitudes are fairly close across the two logistic regressions H and L. To illustrate, the coefficient on market beta in *Model* 2 is 0.153 when predicting relatively high returns and 0.146 when predicting relatively low returns.

Table 3 examines how accruals behave in our logistic models. If, consistent with Sloan (1996), accruals capture stock mispricing, the accrual coefficient should be negative in the H model and positive in the L model. The first columns of Table 3 report results for the models H and L when accruals are included without risk controls. The coefficients on *Accruals* in the two models are significant, but of the opposite sign. Thus, the test confirms that accruals are more likely to capture stock mispricing than risk.

[Insert Table 3 around here]

To examine if the conclusion that accruals capture a pricing anomaly changes controlling for standard risk measures, we include risk controls together with accruals in the two logistic models. Column *Model* 2 of Table 3 reports pooled regression results when accruals are included with risk controls. The coefficient on *Accruals* is negative and significant in the model predicting high returns and positive and significant in the model predicting low returns. Further, the more demanding Fama

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[11] The Fama MacBeth *t*-statistics are adjusted for the time-series dependence of observations.

MacBeth framework produces corroborating results, which shows that our inferences are not sensitive to the way the logistic regressions are estimated. These results confirm that the anomaly interpretation of accruals persists controlling for risk.

To complete the analysis of the results in Table 3, we assess the materiality of the effects accruals have on the likelihood of relatively high and low returns. We follow standard procedures and multiply the coefficient estimates on accruals from *Model* 2 by the accruals standard deviation. A one standard deviation increase in accruals reduces the likelihood of relatively high future returns by 7.8%, and increases the likelihood of relatively low returns by 9.2%. For comparison, a one standard deviation increase in market beta increases the likelihood of relatively high returns by 13.1% and of relatively low returns by 12.2%. Presumably, beta should be more important in explaining variation in stocks returns than accruals, yet the economic significance of accruals is not too far from that of beta. This result suggests non-trivial economic effect accruals have on returns.

Like our conclusion, prior research has been largely supportive of the anomaly explanation for the negative relation between accruals and returns (Xie 2001; Pincus, Rajgopal, and Venkatachalam 2007; Shi and Zhang 2012; Hirshleifer et al. 2012), but past evidence is not without controversies. Specifically, one important issue relates to the role of outliers. Kraft, Leone, and Wasley (2006) attribute the accrual anomaly to data errors and emphasize that outliers may affect the inferences drawn from trading strategies based on accruals. They suggest that eliminating the extreme 1% of observations questions the anomaly interpretation of the accruals result (the word "questions" is appropriate because the ambiguity of risk-adjusting returns does not go away). However, Teoh and Zhang (2011) challenge the findings of Kraft et al. because their trimming of outliers builds in a bias. A correction of this bias restores the accrual anomaly. Zhu (2013) takes yet another approach by suggesting that outliers are indeed a driving force for the accrual anomaly, but now due to the idea of price crashes and the possibility of material price jumps. Because prior research on the accrual anomaly has been controversial, our research contributes by showing how some of the difficult methodological issues (e.g. the effect of outliers) can be circumvented to reach more clear-cut resolutions.

VI. LOGISTIC REGRESSIONS: EARNINGS QUALITY

As highlighted earlier, our approach has low power to test whether a variable *X* that shows positive associations with high and low returns captures risk. This section illustrates this point by examining how the earnings quality measure from Francis, LaFond, Olsson, and Schipper (2005) behaves in the new framework.

Francis et al. (2005, 296) show that controlling for standard risk measures, there is a positive association between returns and low accrual quality stocks and conclude that "[T]his result is consistent with the view that information risk (as proxied by accrual quality) is a priced risk factor.". However, there is an ongoing debate in the accounting literature on whether earnings quality captures a priced information risk factor (Core et al. 2008; Clinch 2013; Shevlin 2013). To examine how the earnings quality measure from Francis et al. (2005) behaves in our framework, we construct their *AQ* measure and include it in the two logistic regressions. *AQ* is the variation in discretionary current earnings accruals from the Dechow and Dichev (2002) model, and higher values indicate lower earnings quality. Table 4 reports results for models H and L when *AQ* is included (i) on its own, (ii) with risk controls, and (iii) with risk controls and accruals. Firms with low earnings quality are more likely to experience relatively high and low returns, however, as described in Section II, this result is insufficient to conclude that *AQ* captures risk. We believe more work is needed to examine if *AQ* measures information risk. These tests are necessary since Dechow and Dichev (2002) and Francis et al. (2005) show that *AQ* strongly correlates with measures of operating risk, such as firm size, cash flow and sales volatility, operating cycle, and negative earnings. Thus, *AQ* may not necessarily capture information risk as argued by Francis et al. (2005). Importantly, controlling for *AQ* leaves intact our conclusion that accruals behave like an anomaly variable in our framework.

[Insert Table 4 around here]

VII. LOGISTIC REGRESSIONS: ROBUSTNESS EVALUATION

This section presents results of the robustness analysis. First, we document that the conclusions from Section V are not sensitive to (i) alternative cut-off points used to define the dependent variables in models H and L, and (ii) to calculating abnormal returns relative to size and book-to-market benchmark portfolios. Then, we show that Section V conclusions persist (i) when we use the cash flow statement to calculate accruals, and (ii) when we split accruals into discretionary and non-discretionary components. Finally, robustness tests document that the negative relation between returns and accruals remains (i) after controlling for the book-to-market ratio and a measure of earnings quality, (ii) when we split the sample into sub-periods, (iii) after excluding the recent financial crises from the sample period, (iv) when using a bivariate probit model to jointly estimate models H and L, and (v) when using only stocks with a December 31st fiscal year-end as in Fama and French (1992). All robustness tests strongly corroborate our main conclusions.

Alternative specifications of the dependent variables in models H and L

This section shows that the conclusion that accruals reflect a pricing anomaly does not change when we consider using more extreme cut-off points to isolate stocks with relatively high and low returns, and when using size and book-to-market adjusted returns to form the dependent variables.

First, we show that Section V conclusions are not sensitive to the magnitudes of the cut-off points used to define the dependent variables in models H and L. For this purpose, two tests are performed. First, we use new cut-off points of 100% for model H and −75% for model L. These cut-off points allocate 4.6% of stocks to the *High_return* portfolio and 4.7% of stocks to the *Low_return* portfolio. Second, each year we split stocks into deciles based on their 12-month CARs. The dependent variable for model H takes a value of one for stocks in the top CAR decile, and zero otherwise. For model L, the dependent variable is one for stocks in the bottom CAR decile, and zero otherwise.

Columns *+100%/−75% cut-off points* and *Top and bottom CAR deciles* of Table 5 report regression results for the two tests described above. Using alternative definitions of the cut-off points for the dependent variables in models H and L, we continue to find that high accruals lower the likelihood of large positive abnormal returns and increase the probability of large negative abnormal returns. These results confirm that the earlier conclusions in Section V are not sensitive to the magnitude of the cut-off points used to isolate stocks with relatively high and low returns.

[Insert Table 5 around here]

Next, we report that calculating abnormal returns relative to size and book-to-market (B/M) benchmark portfolios does not affect the conclusions from the two logistic regressions. We use 25 size and book-to-market portfolios from Kenneth French's website and match stocks with these benchmarks based on the B/M ratio measured at the end of the previous fiscal year, and the firm's market capitalization measured three-months after the fiscal year-end. Mean 12-month size- and B/M adjusted returns are 1.04% compared to 5.6% for the market-adjusted returns, with the Pearson correlation coefficient between the two measures equal to 0.91. As before, we use the ±50% cut-off points to define the dependent variables *High_return* and *Low_return*. Columns *Size and B/M adjusted returns* in Table 5 show that the conclusion about the negative association between accruals and returns remains unchanged when using size and B/M benchmarks to calculate abnormal returns. Specifically, the accruals coefficient is negative in the H regression and positive in the L regression. These results confirm that our approach is insensitive to the specification of the normal return benchmark used to define relatively high and relatively low returns.[12] Summing up, the results in this section show that the proposed method is insensitive to alternative definitions of the cut-off points used to define the dependent variables in models H and L, and to alternative measures of abnormal returns.

Alternative measures of accruals

Hribar and Collins (2002) argue that the balance sheet approach to calculating accruals can lead to measurement error. They propose that researchers use cash flow statements to calculate accruals. Cash flow statements are available on Compustat from 1998. We re-calculate accruals using the cash flow statement method where accruals, *HC ACC*, equal earnings before extraordinary items and discontinued operations less net cash flows from operating activities. We then re-estimate models H and L when we include *HC ACC* instead of *Accruals*. Columns *Hribar and Collins accruals* in Table 5 show that accruals estimated from consecutive cash flow statements behave in a similar way to accruals estimated from consecutive balance sheets in Table 3, which strengthens the conclusion that accruals are more likely to capture stock mispricing than risk.[13]

Previous research documents that the accrual anomaly seems to be more pronounced for stocks with large discretionary accrual components (Xie 2001 and Kothari, Loutskina, and Nikolaev 2009). To test if this evidence is present in our framework, we use the Jones model (Jones 1991) to

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[12] In unreported results, we also use raw returns to define dependent variables for models H and L. Using raw returns avoids the need to specify the normal return benchmark and excludes the possibility that results from the predictive regressions are due to the choice of the normal return measure. In this setting, *High_return* is one if log(1+12-month buy-and-hold return) is higher than 100%. *Low_return* is one if log(1+12-month buy-and-hold return) is lower than −%75. Using raw returns produces a negative association between accruals and high returns, and a positive association between accruals and low returns, consistent with the earlier findings.

[13] The cash flow accrual results in Table 5 are directly comparable to the balance sheet accrual results in Table 3, since the logistic models have the same dependent variables. We favor Sloan's balance sheet accrual calculation over the Hribar and Collins (2002) cash flow accrual measure as the statement of cash flows does not include accruals that relate to noncash activities (e.g. reclassifications between two non-cash accounts), which can reduce the power of tests examining the relation between accruals and returns (Richardson et al. 2005; Dechow et al. 2011). Further, using balance sheet accruals aligns us with Sloan's (1996) tests and one can always replicate the analysis using alternative accrual measures.

decompose accruals into discretionary and non-discretionary components. The Jones model takes the form:

$$Accruals = \alpha_0 \frac{1}{\overline{Assets}} + \alpha_1 \Delta REV + \alpha_2 PPE + \varepsilon$$

where $\overline{Assets}$ is the average of the beginning and end-of-year book value of total assets, *PPE* is the gross value of property plant and equipment, and ΔREV is the change in firm sales. *PPE* and ΔREV are scaled by $\overline{Assets}$. The model residuals capture discretionary accruals and the predicted values reflect non-discretionary accruals. We estimate the Jones model annually for each 2-digit SIC industry with a minimum of 20 firms. Columns *Discretionary accruals* in Table 5 report results for models H and L where we split accruals into discretionary, *disc Accruals,* and non-discretionary components, *ndisc Accruals*. The accrual anomaly seems stronger for the discretionary component, which correlates negatively with high returns and positively with low returns. Non-discretionary accruals only correlate with low returns. As the non-discretionary component of accruals may be easier to identify, investors may be more successful in arbitraging the accrual anomaly among these stocks.[14] This result is consistent with the weak case of an anomaly we described in Section II.

Subsample tests and expanding the set of risk controls

This section presents results from additional robustness tests. Specifically, we show that our conclusion that accruals capture stock mispricing persists when we estimate the two logistic regressions for subsamples, when we use a bivariate probit model to estimate the two predictive regressions, and when we control for the book-to-market ratio.

[14] It is unlikely that an insignificant coefficient on *ndisc Accruals*, but a significant coefficient on *disc Accruals* in the model predicting relatively high returns is due to a lower variation in non-discretionary accruals than in discretionary accruals. This explanation would have been likely if the *t*-statistic for *ndisc Accruals* was lower than the *t*-statistic for *disc Accruals* in the model predicting relatively low returns, however, this is not the case.

To examine if our conclusions are sensitive to the choice of the sample period, we split the sample period into two subsamples, 1970–1993 and 1994–2009. Columns *1970–1993* and *1994–2009* in Table 6 reports results for models H and L estimated for these two sub-periods. Accruals reduce the likelihood of relatively high returns and increase the probability of relatively low returns for both subsamples.[15] Thus, the results suggest that our conclusions are not sensitive to the choice of the sample period.

[Insert Table 6 around here]

Next, we re-estimate models H and L after we exclude the financial crisis period from the sample. We perform this test because high accrual stocks may have been particularly negatively affected by stock price declines during this period.[16] Columns *Without financial crisis* in Table 6 report results when we estimate models H and L for the sample without fiscal years 2007–2009. Excluding the financial crisis leaves the conclusions from Section V unaffected. Together, the sub-sample results confirm the conclusion that the accrual anomaly is indeed an anomaly.[17]

Columns *Bivariate probit* in Table 6 report results for models H and L when we estimate the two predictive regressions using a bivariate probit model that allows for correlations in error terms between the two regressions. The efficiency of standard error estimates can improve if the error terms in models H and L are correlated. Jointly estimating the two predictive models H and L leaves our conclusions intact. This result confirms that the simple setup with two independent logistic models produces valid conclusions.

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[15] Our results for subsamples are consistent with the findings in Lev and Nissim (2006), Collins et al. (2003) and Bushee and Raedy (2006) that the accrual anomaly has persisted over time. Lev and Nissim (2006, 201) also note that "[S]urprisingly, some of the returns in the late 1990s and in 2003 […], a period during which the accruals anomaly was widely discussed in academic and practitioners' circles, are larger than previous years' returns".

[16] Dechow et al. (2011) exemplify that in the lead-up to the recent financial crisis, many banks reported strong earnings by issuing loans that were unlikely to be repaid. Banks capitalized the promised future payments resulting in high accruals and earnings. The banking sector was most negatively affected by declining valuations during the financial crisis.

[17] In unreported results, we estimate the two predictive regressions only for stocks with a December 31st fiscal year-end. This is because studies commonly use fixed starting dates for calculating abnormal returns (e.g. Lev and Nissim 2006; Hirshleifer et al. 2012). High accruals reduce the likelihood of large positive returns and increase the probability of large negative returns for stocks with December 31st fiscal year-ends. This result confirms that our conclusions are not sensitive to the specification of the trading rule that generates abnormal returns.

Next, we examine whether our conclusions change when we estimate models H and L after including the B/M ratio as a control. Fama and French (1992) propose that the B/M ratio proxies for distress risk and consider high B/M stocks as more risky. However, they also acknowledge that the cross-sectional variation in the B/M ratio can be driven by "irrational market whims about the prospects of firms" (Fama and French 1992, 429). Even if the B/M ratio captures another anomaly, it is important to examine if the "accrual" anomaly is distinct from the "value" anomaly. Columns *Controlling for the B/M ratio* in Table 6 show that controlling for the B/M ratio, accruals continue to exhibit negative association with high returns, but positive association with low returns. Further, the insignificant coefficient on the B/M ratio in model H, but the significant negative coefficient on the B/M ratio in model L, suggest that the B/M ratio behaves like an anomaly variable. This result is consistent with the conclusions of the "value anomaly" literature that the B/M ratio captures stock mispricing (e.g. Lakonishok et al. 1994; Barberis, Shleifer, and Vishny 1998; Hirshleifer, 2001).

To sum up, the tests presented in this section indicate that the approach promoted in the paper is insensitive to alternative specifications of the dependent and independent variables, to the choice of the sample period, or to the set of control variables included in the model. These results reinforce our conclusion that the simplicity and robustness of the method we propose make it an appealing alternative to standard testing frameworks in the anomaly literature.

VIII. CONCLUSIONS

An increasing number of studies identify trading strategies that seem to generate abnormal returns. However, no generally accepted method has been proposed to address the question: does risk or anomaly better explain why the claimed abnormal returns exist? Assuming some investment strategy generates abnormal returns, this study proposes a simple method to distinguish between these two competing explanations.

The framework we propose uses a set of logistic regressions predicting high and low returns to distinguish between risk and anomaly interpretations. The method has a number of virtues: it is intuitive, easy to implement and our empirical tests show that it is hard to falsely reject the null hypothesis that risk, rather than an anomaly, explains why abnormal returns exist. Further, the method offers a simple specification test that builds confidence that the method aligns with capital market perceptions of what a risky investment is. Specifically, we show that standard risk measures do behave as risk measures in the estimations. Finally, the analysis is not sensitive to the way we estimate the logistic regression and even demanding methods, such as Fama-McBeth techniques, produce consistent results.

To illustrate how the method operates in practice, we apply it in the context of the accrual anomaly. Test results using the new framework show that accruals increase the likelihood of low returns and reduce the probability of high returns. In light of this evidence, we feel confident in asserting that an anomaly explanation for the negative relation between accruals and returns is more plausible than the risk explanation.

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TABLE 1

Descriptive statistics

	Mean	Median	STD
Panel A: Descriptive statistics			
High_return	0.146	0.000	0.354
Low_return	0.106	0.000	0.308
Accruals	−0.032	−0.034	0.127
Vol	0.144	0.123	0.088
Beta	1.175	1.090	0.851
MV	1068.430	91.783	3412.220
N 103034			

Panel A1: Averages for explanatory variables split by the High_return dummy

	High_return=1	*High_return=0*	*Difference*	*% Difference*	*t-test*
Accruals	−0.052	−0.028	−0.024	84.4%	−19.090
Vol	0.189	0.136	0.053	38.7%	61.020
Beta	1.292	1.155	0.136	11.8%	16.360
MV	391.046	1184.650	−793.604	−67.0%	−42.350

Panel A2: Averages for explanatory variables split by the Low_return dummy

	Low_return=1	*Low_return=0*	*Difference*	*% Difference*	*t-test*
Accruals	−0.028	−0.032	0.004	−12.7%	−2.580
Vol	0.183	0.140	0.044	31.4%	−44.220
Beta	1.336	1.156	0.180	15.5%	−17.990
MV	462.149	1140.650	−678.501	−59.5%	31.730

Panel A reports descriptive statistics for the dependent and independent variables in the two logistic regressions H and L predicting relatively high and low returns. *High_return* is an indicator variable that takes a value of one if the firm's 12-month cumulative abnormal returns are higher than 50%, and zero otherwise. The normal return benchmark is the return on the value-weighted CRSP market index and the cumulation starts four months after the fiscal year-end. *Low_return* is an indicator variable that takes a value of one if the firm's 12-month cumulative abnormal returns are lower than −50%, and is zero otherwise. *Accruals* are accounting accruals, *Vol* is the stock's return volatility, *Beta* is the market beta, and *MV* is the market capitalization. Panel A1 reports means of the explanatory variables split by the *High_return* dummy. Panel A2 reports means of the explanatory variables split by the *Low_return* dummy.

TABLE 2

Predicting relatively high and low returns: risk controls

	***Model* 1**		***Model* 2**		***Fama MacBeth***	
	Estimate	*z-test*	*Estimate*	*z-test*	*Estimate*	*t-test*
Panel A: Predicting relatively high future returns						
Intercept	−1.290	−8.440	−1.282	−8.370	−3.065	−4.290
Vol	2.901	5.280	2.338	4.920	2.585	7.080
Beta			0.153	3.920	0.172	2.830
ln *MV*	−0.288	−11.520	−0.305	−11.990	−0.338	−13.700
Industry effects	Yes		Yes		Yes	
Year effects	Yes		Yes		NA	
N	103034		103034		40	
Wald X^2	8557.81		8622.64			
$p(X^2)$	0.000		0.000			
Pseudo R^2	11.29%		11.51%			

Panel B: Predicting relatively low future returns

	***Model* 1**		***Model* 2**		***Fama MacBeth***	
	Estimate	*z-test*	*Estimate*	*z-test*	*Estimate*	*t-test*
Intercept	−2.860	−16.440	−2.865	−16.580	−3.723	−3.830
Vol	4.455	10.830	3.949	11.390	4.936	10.510
Beta			0.146	4.910	0.129	2.650
ln *MV*	−0.099	−5.060	−0.114	−5.980	−0.110	−4.450
Industry effects	Yes		Yes		Yes	
Year effects	Yes		Yes		NA	
N	103034		103034		40	
Wald X^2	6129.88		6240.21			
$p(X^2)$	0.000		0.000			
Pseudo R^2	9.48%		9.69%			

The table shows results from logistic regressions predicting relatively high and low returns. The dependent variable in Panel A is an indicator variable that takes a value of one if the firm's 12-month cumulative abnormal returns are higher than 50%, and zero otherwise. The dependent variable in Panel B is an indicator variable that takes a value of one if the firm's 12-month cumulative abnormal returns are lower than −50%, and zero otherwise. *Model* 1 and *Model* 2 are pooled cross-sectional models with standard errors clustered on firm and fiscal-year. *Fama MacBeth* are annual Fama-MacBeth regressions with standard errors corrected for time-series dependence. *Vol* is the stock's return volatility, *Beta* is the market beta, and *MV* is the market capitalization. *Industry effects* and *Year effects* capture industry- and year-fixed effects. NA stands for non-applicable. ln denotes a logarithm and *N* is the number of observations. *Wald* X^2 is the Wald X^2–test for model specification and $p(X^2)$ is the corresponding p-value. *Pseudo* R^2 is the pseudo R-squared.

TABLE 3

Predicting relatively high and low returns: accruals

	***Model* 1**		***Model* 2**		***Fama MacBeth***	
	Estimate	*z-test*	*Estimate*	*z-test*	*Estimate*	*t-test*
Panel A: Predicting relatively high future returns						
Intercept	−1.860	−20.190	−1.349	−8.850	−3.094	−4.350
Accruals	−1.347	−10.560	−0.613	−6.650	−0.589	−4.560
Vol			2.281	4.820	2.522	6.810
Beta			0.154	4.000	0.175	2.840
ln *MV*			−0.300	−11.800	−0.334	−13.500
Industry effects	Yes		Yes		Yes	
Year effects	Yes		Yes		NA	
N	103034		103034		40	
Wald X^2	4318.74		8697.97			
$p(X^2)$	0.000		0.000			
Pseudo R^2	5.46%		11.60%			

Panel B: Predicting relatively low future returns

	***Model* 1**		***Model* 2**		***Fama MacBeth***	
	Estimate	*z-test*	*Estimate*	*z-test*	*Estimate*	*t-test*
Intercept	−2.036	−18.980	−2.786	−16.510	−3.716	−3.860
Accruals	0.386	2.890	0.723	6.600	1.047	4.330
Vol			4.010	11.830	5.039	10.490
Beta			0.143	4.860	0.122	2.470
ln *MV*			−0.119	−6.330	−0.116	−4.800
Industry effects	Yes		Yes		Yes	
Year effects	Yes		Yes		NA	
N	103034		103034		40	
Wald X^2	3299.14		6339.41			
$p(X^2)$	0.000		0.000			
Pseudo R^2	5.93%		9.82%			

The table shows results from logistic regressions predicting relatively high and low returns. The dependent variable in Panel A is an indicator variable that takes a value of one if the firm's 12-month cumulative abnormal returns are higher than 50%, and zero otherwise. The dependent variable in Panel B is an indicator variable that takes a value of one if the firm's abnormal returns are lower than −50%, and zero otherwise. *Model* 1 and *Model* 2 are pooled cross-sectional models with standard errors clustered on firm and fiscal-year. *Fama MacBeth* are annual Fama-MacBeth regressions with standard errors corrected for time-series dependence. *Accruals* are accounting accruals, *Vol* is the stock's return volatility, *Beta* is the market beta, and *MV* is the market capitalization. *Industry effects* and *Year effects* capture industry- and year-fixed effects. NA stands for non-applicable. ln denotes a logarithm and *N* is the number of observations. *Wald* X^2 is the Wald X^2–test for model specification and $p(X^2)$ is the corresponding *p*-value. *Pseudo* R^2 is the pseudo R-squared.

TABLE 4

Predicting relatively high and low returns: earnings quality

	Model 1		*Model* 2		*Model* 3		*Fama MacBeth*	
	Estimate	*z−test*	*Estimate*	*z−test*	*Estimate*	*z−test*	*Estimate*	*z−test*
Panel A: Predicting relatively high future returns								
Intercept	−1.430	−14.190	−0.549	−2.840	−0.611	−3.170	−2.150	− 4.650
Accruals					−0.637	−5.930	−0.634	−4.280
Vol			2.047	4.300	2.016	4.250	2.578	8.880
Beta			0.144	3.900	0.145	3.960	0.138	4.270
ln *MV*			−0.305	−11.190	−0.301	−11.010	−0.333	−14.790
AQ	4.461	6.700	1.074	2.010	1.010	1.910	1.027	2.160
Industry effects	Yes		Yes		Yes		Yes	
Year effects	Yes		Yes		Yes		No	
N	79610		79610		79610		36	
Wald X^2	3865.6		6805.53		6868.45			
$p(X^2)$	0.000		0.000		0.000			
Pseudo R^2	5.95%		11.47%		11.57%			

Panel B: Predicting relatively low future returns

	Model 1		*Model* 2		*Model* 3		*Fama MacBeth*	
	Estimate	*z−test*	*Estimate*	*z−test*	*Estimate*	*z−test*	*Estimate*	*z−test*
Intercept	−2.905	−24.38	−3.361	−17.250	−3.287	−17.030	−3.858	−5.280
Accruals					0.694	5.410	1.046	4.500
Vol			3.600	10.580	3.635	10.920	4.678	9.270
Beta			0.118	3.880	0.117	3.840	0.108	2.720
ln *MV*			−0.094	−4.730	−0.099	−5.080	−0.088	−3.510
AQ	5.450	8.950	2.733	5.670	2.731	5.640	4.034	5.590
Industry effects	Yes		Yes		Yes		Yes	
Year effects	Yes		Yes		Yes		No	
N	79610		79610		79610		36	
Wald X^2	3642.78		5131.07		5202.40			
$p(X^2)$	0.000		0.000		0.000			
Pseudo R^2	7.77%		10.29%		10.42%			

The table reports results from logistic regressions predicting relatively high and low returns. *Model* 1 to *Model* 3 are pooled cross-sectional models with standard errors clustered on firm and fiscal-year. *Fama MacBeth* are annual Fama-MacBeth regressions with standard errors corrected for time-series dependence. *Accruals* are accounting accruals, *Vol* is the stock's return volatility, *Beta* is the market beta, *MV* is the market capitalization, and *AQ* is the variation in discretionary current earnings accruals from the Dechow and Dichev (2002) current accruals model calculated as in Francis et al. (2005). *Industry effects* and *Year effects* capture industry- and year-fixed effects. NA stands for non-applicable. ln denotes a logarithm and *N* is the number of observations. *Wald* X^2 is the Wald X^2–test for model specification and $p(X^2)$ is the corresponding *p*-value. *Pseudo* R^2 is the pseudo R-squared.

TABLE 5

Sensitivity analysis

	+100%/−75% cut-off points		*Top and bottom CAR deciles*		*Size and B/M adjusted returns*		*Hribar and Collins accruals*		*Discretionary accruals*	
	Estimate	*z−test*	*Estimate*	*z−test*	*Estimate*	*z−test*	*Estimate*	*z−test*	*Estimate*	*z−test*
Panel A: Predicting relatively high future returns										
Intercept	−2.344	−9.35	−2.850	−19.08	−1.827	−13.64	−1.448	−8.97	−1.263	−8.66
Accruals	−1.056	−7.25	−0.666	−6.40	−0.602	−6.74				
Vol	3.236	9.32	2.679	11.26	3.036	12.55	2.116	3.70	2.234	4.71
Beta	0.178	3.54	0.126	4.02	0.128	4.30	0.152	3.28	0.156	4.02
ln *MV*	−0.492	−9.85	−0.341	−12.78	−0.266	−11.90	−0.280	−9.21	−0.305	−11.63
HC ACC							−0.935	−7.94		
disc Accruals									−0.672	−7.27
ndisc Accruals									−0.428	−1.49
Industry effects	Yes		Yes		Yes		Yes		Yes	
Year effects	Yes		Yes		Yes		Yes		Yes	
N	103034		103034		103034		68109		96124	
Wald X^2	6833.06		5440.84		6758.53		6245.93		8231.72	
$p(X^2)$	0.000		0.000		0.000		0.000		0.000	
Pseudo R^2	19.37%		8.48%		8.87%		11.53%		11.73%	

Panel B: Predicting relatively low future returns

	+100%/−75% cut-off points		*Top and bottom CAR deciles*		*Size and B/M adjusted returns*		*Hribar and Collins accruals*		*Discretionary accruals*	
	Estimate	*z−test*	*Estimate*	*z−test*	*Estimate*	*z−test*	*Estimate*	*z−test*	*Estimate*	*z−test*
Intercept	−3.939	−25.70	−2.069	−13.00	−1.864	−12.35	−2.720	−13.26	−2.838	−16.53
Accruals	0.489	3.23	0.704	6.54	0.678	6.66				
Vol	4.685	15.81	4.102	15.07	2.844	9.43	3.749	9.85	4.032	11.97
Beta	0.133	3.95	0.126	4.06	0.101	3.13	0.118	3.84	0.139	4.47
ln *MV*	−0.120	−5.01	−0.094	−4.80	−0.168	−11.59	−0.104	−4.49	−0.123	−6.62
HC ACC							0.470	2.34		
disc Accruals									0.491	4.15
ndisc Accruals									1.830	5.76
Industry effects	Yes		Yes		Yes		Yes		Yes	
Year effects	Yes		Yes		Yes		Yes		Yes	
N	103034		103034		103034		68109		96124	
Wald X^2	4407.98		3623.07		4922.13		3844.97		5990.22	
$p(X^2)$	0.000		0.000		0.000		0.000		0.000	
Pseudo R^2	10.85%		4.43%		5.76%		7.64%		9.90%	

The table reports results from logistic regressions predicting relatively high and low returns. Columns *+100%/−75% cut-off points* report regression results where we use a 100% breakpoint to define the dependent variable for model H and a −75% breakpoint to define the dependent variable for model L. *Accruals* are accounting accruals, *Vol* is the stock's return volatility, *Beta* is the market beta, and *MV* is the market capitalization. *Industry effects* and *Year effects* capture industry- and year-fixed effects. Columns *Top and bottom CAR deciles* report results where we use the top and the bottom abnormal return deciles to construct the dependent variables for models H and L. Columns *Size and B/M adjusted returns* show results for the two logit models when we use the size and B/M benchmark portfolios to calculate abnormal returns. Columns *Hribar and Collins accruals* report results for the logit regressions where we recalculate accruals using the cash flow statement information, *HC ACC*. Columns *Discretionary accruals* report results for models H and L where we split accruals into discretionary accruals, *disc Accruals,* and non-discretionary accruals, *ndisc Accrual* using the Jones model (Jones 1991). ln denotes a logarithm and *N* is the number of observations. *Wald* X^2 is the Wald X^2–test for model specification and $p(X^2)$ is the corresponding *p*-value. *Pseudo* R^2 is the pseudo R-squared.

TABLE 6

Subsample analysis and further tests

	1970–1993		*1994–2009*		*Without financial crisis*		*Bivariate probit*		*Controlling for the B/M ratio*	
	Estimate	*z–test*	*Estimate*	*z–test*	*Estimate*	*z–test*	*Estimate*	*z–test*	*Estimate*	*z–test*
Panel A: Predicting relatively high future returns										
Intercept	−1.514	−9.06	−1.532	−9.64	−1.409	−9.38	−0.830	−7.13	−1.356	−9.49
Accruals	−0.437	−3.46	−0.725	−6.59	−0.613	−6.26	−0.363	−8.96	−0.617	−6.58
Vol	2.580	8.53	1.974	2.69	2.139	4.49	1.141	17.56	2.312	5.09
Beta	0.143	4.47	0.175	3.31	0.146	3.65	0.079	12.38	0.159	4.01
ln *MV*	−0.362	−18.08	−0.259	−7.07	−0.301	−10.94	−0.155	−47.72	−0.296	−11.80
ln *B/M*									0.011	0.31
Industry effects	Yes		Yes		Yes		Yes		Yes	
Year effects	Yes		Yes		Yes		Yes		Yes	
N	53266		49768		97349		103034		100148	
Wald X^2	3616.82		4644.04		8059.83		13467.22		8280.64	
$p(X^2)$	0.000		0.000		0.000		0.000		0.000	
Pseudo R^2	10.97%		11.47%		11.54%				11.51%	

Panel B: Predicting relatively low future returns

	1970–1993		*1994–2009*		*Without financial crisis*		*Bivariate probit*		*Controlling for the B/M ratio*	
	Estimate	*z–test*	*Estimate*	*z–test*	*Estimate*	*z–test*	*Estimate*	*z–test*	*Estimate*	*z–test*
Intercept	−1.748	−9.14	−2.906	−12.49	−1.138	−6.86	−1.538	−10.91	−2.610	−15.76
Accruals	0.832	4.16	0.645	5.53	0.740	6.62	0.391	9.12	0.705	6.46
Vol	4.171	8.91	3.847	7.84	4.083	11.67	2.056	30.33	3.303	10.37
Beta	0.207	4.66	0.120	3.42	0.148	4.84	0.072	10.37	0.131	4.51
ln *MV*	−0.152	−9.24	−0.094	−3.37	−0.113	−6.04	−0.061	−17.85	−0.168	−8.95
ln *B/M*									−0.279	−8.83
Industry effects	Yes		Yes		Yes		Yes		Yes	
Year effects	Yes		Yes		Yes		Yes		Yes	
N	53266		49768		97349		103034		100148	
Wald X^2	3149.71		3041.21		6114.89		13467.22		6603.91	
$p(X^2)$	0.000		0.000		0.000		0.000		0.000	
Pseudo R^2	10.76%		8.51%		9.90%				10.64%	

The table reports results from logistic regressions predicting relatively high and low returns. Columns *1970–1993* and *1994–2009* show results for models H and L estimated for periods 1970–1993 and 1994–2009, respectively. Columns *Without financial crisis* report results where we estimate models H and L for the sample without fiscal years 2007–2009. Columns *Bivariate probit* report results where we estimate the two predictive regressions using a bivariate probit model that allows for correlations in error terms between the two regressions. Columns *Controlling for the B/M ratio* show results for models H and L when we control for the B/M ratio. ln denotes a logarithm and *N* is the number of observations. *Wald* X^2 is the Wald X^2–test for model specification and $p(X^2)$ is the corresponding *p*-value. *Pseudo* R^2 is the pseudo R-squared.