Do dividend cuts and omissions signal default risk?

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February 2019

Abstract

Firms that cut or omit their dividends subsequently experience substantial and persistent increases in default risk and have lower survival rates. This increase in default risk is a priced risk factor beyond the Fama-French (1993, 20015) and Carhart (1997) four and five factor models. Larger dividend cuts and more negative market reactions predict larger subsequent increases in financial distress, lower survival rates and lower likelihood to subsequently increase or resume dividends. Using difference-in-differences, Rosenbaum (2002) bounds and instrumental variables to address endogeneity concerns, we establish that dividend cuts and omissions have an information content on future increases in financial distress.

Keywords— Dividend cuts, dividend omissions, information content, financial distress, firm survival

1 Introduction

Dividend changes have been viewed as corporate decisions that convey valuable information to the capital market, with dividend increases and initiations being interpreted by investors as good news and dividend cuts and omissions being interpreted by investors as bad news (e.g.: Michaely, Thaler and Womack, 1995; Grullon, Michaely and Swaminathan, 2002; Jensen, Lundstrum and Miller, 2010; Charitou, Lambertides and Theodoulou, 2011). Traditional signalling models (Bhattacharya, 1979;

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Miller and Rock, 1985; John and Williams 1985) suggest that dividend changes can convey information about future earnings. However, empirical and survey evidence does not lend support to this claim (DeAngelo, DeAngelo and Skinner, 1996; Bernartzi, Michaely and Thaler, 1997; Grullon, Michaely and Swaminathan, 2002; Brav, Graham, Harvey and Michaely, 2005). More recent work suggests that dividends convey information about changes in firm risk. Grullon, Michaely and Swaminathan (GMS) (2002) find that firms that increase (decrease) their dividends experience a significant decline (increase) in their systematic risk exposures. They suggest that firms increase their dividends as transition to a more mature stage in their life cycle, with diminishing investment opportunities and lower levels of risk. Von Eije, Goyal and Muckley (2014) show that dividend initiations and omissions have a causal effect on both systematic and idiosyncratic risk. Charitou, Lambertides and Theodoulou (CLT) (2011) extend the GMS analysis and find a reduction in default risk for firms that initiate or increase their dividends.

In this paper, we extend this literature by examining whether dividend cuts and omissions convey information about an increase in firms' default risk, and whether this increase is priced by the market. We suggest that, due to the extreme managerial reluctance to cut/omit dividends, firms would only do so in the most challenging of circumstances. As a consequence, firms that find themselves having to cut or omit their dividends, may (perhaps unintentionally) convey to the market that it has reached a phase of prolonged financial distress. This suggestion is supported by survey evidence reported by Brav, Graham, Michaely and Harvey (2005):

"Several executives told us that they would try to avoid reducing dividends, if possible, especially if they thought that their own firm would be affected only temporarily by the liquidity crisis. They reason that the market thinks that only firms experiencing long-lasting and severe liquidity crisis cut dividends, and the firm would not want to give the market the misimpression that it expects its own liquidity crisis to be severe".

An alternative channel through which dividend cuts or omissions may convey information about an increase in financial distress is that management might elect to cut/omit dividends as a proactive measure in anticipation of impending liquidity issues faced by to firm (Lei, 2005). This may consequently signal to the market management's private information about the anticipated increase in financial distress.

An alternative to the information-content hypothesis is that dividend cuts and omissions are merely a manifestation of existing levels of financial distress that the market is already already aware of. In this case, the dividend cut/omission event as such would not be an informative event. In our analysis, we attempt to identify whether dividend cuts/omissions signal new information about the announcing firms' financial distress by comparing changes in financial distress for event firms with those of comparable counterfactual firms that are i) equally likely to cut/omit their dividends but do not; and ii) have similar levels of pre-announcement financial distress.

Using a sample of 1,033 dividend cuts and 584 dividend omissions announced between 1972 and 2013, we find that firms that cut/omit their dividends experience a significant increase in their default risk, as measured by Merton's (1974) probability of default. We provide evidence suggesting that this increase in default risk is driven (at least partially) by an information content of dividend cuts and omissions. Our findings are also economically significant - relative to counterfactual firms that are equally likely to cut/omit their dividends, firms that do cut/omit are more than 2.5 times more likely to default on their debt obligations in the three years following the announcement relative to the three-year pre-event period.

We also find that investors recognise the increase in default risk following dividend cuts and omissions and accordingly treat it as a priced risk factor. Following the same methodology as Grullon, Michaely and Swaminathan (2002) and Charitou, Lambertides and Theodoulou (2011), we augment the Fama and French (1993) and Carhart (1997) and the Fama and French (2015) four-factor and five-factor models with a default risk factor. We document a statistically significant increase in default risk factor loadings beyond standard risk factors. Furthermore, the inclusion of the default risk factor subsumes on most of the standard risk factors in our regression, suggesting that the said factors were capturing risks related to financial distress. This finding is robust to matching on firms that are equally likely to cut or omit their dividends. This suggests that the increase in default risk factor loadings can be attributed to the dividend cut/omission event.

We further find that the size of the dividend cut is informative on the increase in default risk - with larger cuts predicting larger increases in default risk. Furthermore, cross-sectional analysis involving announcement-period abnormal returns indicates that the market understands, at least partially, the information content of dividend cut/omission announcements on the subsequent increase in firms' default risk. We find that the more negative is the initial market reaction to the dividend announcement, the greater is the subsequent increase in financial distress.

We then examine whether dividend cuts and omissions convey information about the announcing firms' survival prospects. We find that higher dividend cuts predict a higher probability of involuntary delisting within three years following the announcement, consistent with the size of the dividend cut conveying information about the extent to which a firm is distressed. We also find that more negative announcement-period returns predict higher probability of involuntary delisting within three years, consistent with the initial market reaction reflecting investor pessimism about a firm's survival prospects. Furthermore, we find that firms that cut/omit their dividends are more than 2.3 times more likely to involuntary delist within three-years relative to matched counterfactual firms.

A methodological challenge faced in our study is that dividend cuts and omissions are inherently endogenous events, as their timing and magnitude is decided on by corporate management. This self-selection bias manifests itself as a potential omitted variable that may drive both the dividend cut/omission decision and financial distress, thereby biasing our results. Furthermore, the direction of causality between dividend cuts/omissions and financial distress can go both ways, since firms may decide to cut/omit dividends in response to financial distress. We use two identification strategies to address these concerns and establish that dividend cuts/omissions convey incremental information on future increases in financial distress.

First, we apply a Difference-in-differences regression with propensity score matching (PSM DiD) around the dividend cut/omission event. Following the methodology of von Eije, Goyal and Muckley (2014), we compare the distress risk changes of firms that do cut or omit dividends to a cohort of counterfactual firms that (i) have a similar *ex ante* likelihood to cut or omit dividends; and (ii) have similar levels of financial distress compared to the event firms. Conditional on the treatment and counterfactual firms being indistinguishable in terms of publicly available information, we argue that significant differences in the changes in financial distress between the treatment and counterfactual firms, as measured by difference-in-differences in the probability of default (Merton, 1974; Bharath and Shumway, 2008), can be attributed to an information content of the dividend cut/omission event. We then stratify our sample of event firms by past levels of distress risk and show the individual treatment effects within each group. We confirm that firms that cut/omit dividends experience subsequent increases in financial distress, regardless of where they lie on the distress risk spectrum. Furthermore, we use Rosenbaum (2002) bounds to assess the extent to which hypothetical unobservable bias may influence our results. We find that for an unobservable covariate to reverse our results, it would have to be equivalent to substantial deterioration in the matched firms' operating performance (e.g.; equivalent to control firms being in the bottom 1% of compustat firms in total assets or at the top 10% of leverage). Furthermore, such unobservable covariate would have to be unrelated to the large number of covariates which already control for in estimating our propensity score. Our first identification strategy therefore allows us to alleviate concerns about the endogeneity of the dividend cuts/omission event biasing our results.

Our second identification strategy is to employ two-stage least squares instrumental variables approach (2SLS IV). We use two instrumental variables as plausibly exogenous sources of variation in the magnitude of the dividend cut. Our first instrument is the state propensity to pay dividends, which is measured as the proportion of dividend paying firms (excluding the event firm) in the firm's state of domicile. We argue that the higher the proportion of dividend payers in the event firms' state of domicile, the more reluctant the firm is to cut its dividends or carry out large dividend cuts, suggesting a negative relationship between the state propensity to pay dividends and the magnitude of the dividend cut. Our second instrument is the Dividend Premium of Baker and Wugler (2004a, 2004b), which measures time-varying investor demand for dividends. Following Li and Lie (2005), we argue that during period of high investor demand for dividends, firms would be less likely to cut their dividends or carry out large dividend cuts, therefore suggesting a negative relationship between the dividend premium and the magnitude of the dividend cut. Little evidence, if any, suggests that firms' financial distress would be directly related to our choice of instrumental variables, except through the channel of altering payout policy.

As expected, we find that both our instruments are negatively and significantly related to the magnitude of the dividends cut, with relatively large F-statistics confirming the validity of the instruments. More importantly, our 2SLS results confirm the positive impact of the magnitude of the dividend cut on subsequent increase in the probability of default, default risk factor loadings and the likelihood of involuntary delisting. Our second identification strategy therefore allows us to alleviate concerns about the endogeneity of the magnitude of the dividend cut biasing our results.

Finally, we further extend our analyses by examining the subsequent payout policy of firms that have cut/omitted their dividends. We find that firms that carry out more severe cuts are less likely to make any material dividend increase/resumption in the subsequent three years. We also find that dividend cuts/omissions that had a more severe market reaction are less likely to subsequently increase or resume their dividend within three years, consistent with investor pessimism about the prospects of future dividends following dividend cuts/omissions.

It is important to note that the information content of dividend cuts/omissions on financial distress does not necessarily imply that firms that cut/omit their dividends were not already showing signs of distress prior to the event. Our main findings suggest that that dividend cuts and omissions are an important sign, with new incremental information, that the firm will go through a period of prolonged financial distress, rather than dividend cuts/omissions merely being a manifestation of existing financial distress.

The remainder of this paper is organised as follows: Section 2 describes the data and our measures of financial distress. Section 3 discusses our empirical results. Section 4 runs robustness tests. We finally conclude in section 5.

2 Data and sample selection

2.1 Sample

Our sample data comprises of cash dividend cuts and omissions of US-based firms listed in NYSE, AMEX and NASDAQ between 1972 and 2013. The sample ends in 2013 to allow for a three-year post-event window to assess distress risk. To be included in the sample, the dividend announcement must meet the following criteria:

a) The firm's financial data are available on CRSP and Compustat;

b) The firm pays either quarterly, semi-annual or annual taxable cash dividends (Distribution codes 1232, 1242 and 1252);

c) The percentage cut in dividends is between 12.5% and 100%. The lower bound of 12.5% parallels Grullon, Michaely and Swaminathan (2002) to ensure that only economically significant dividend cuts are included;

d) The firm has been paying a positive, non-reducing dividend in the three years prior to the announcement;

e) For dividend omissions, we manually collect the announcement dates from the Wall Street Journal (WSJ), Nexis and Factiva;

f) Only ordinary shares domiciled in the US are included (Share codes 10 and 11);

g) The firm does not pertain to regulated utilities (SIC codes 4900-4949) or financial firms (SIC codes 6000-6999).

This leaves us with a sample of 1,033 dividend cuts and 584 dividend omissions for a total of 1,617 dividend events.

2.2 Measuring financial distress

2.2.1 Calculating Default Risk using Merton's option-pricing model

A number of different measures of financial distress have been used in the literature (e.g.; Altman's (1968) Z-score, Merton's (1974) distance to default and Ohlson's (1980) O-score amongst others). We use Merton's (1974) distance-to-default (DD) as a measure of financial distress, from which we accordingly calculate the probability of default[1]. We follow Bharath and Shumway (2008) to calculate Merton's distance-to-default. In Merton's model, the equity of the firm is modeled as a call option on its underlying value with a strike price equal to the face value of its debt. The key advantage of using distance-to-default in lieu of accounting-based measures of financial distress is that its derivation is based on market valuation. This makes Merton's model more forward-looking, in contrast to accounting-based measures of default. Furthermore, since option-based measures are less prone to managerial influence in comparison to accounting measures, we minimize endogeneity concerns arising from using accounting-based measures that are endogenous to firm's management[2].

[1] Nevertheless, we also replicate our findings using Z-score and O-Score. The results, which are available from the authors on request are qualitatively similar.

[2] We acknowledge that management might still be capable of influencing share valuation through certain corporate actions (e.g.; share buybacks, mergers, etc.). However, this influence is contingent on the market's perception of such actions, which is arguably, beyond management's control. We therefore argue that the probability of default is less susceptible to endogeneity problems compared to other accounting-based measures.

2.2.2 The augmented Fama-French and Carhart models

To test whether changes in default risk around dividend cuts and omissions are priced in the cross-section of stock returns, we follow Charitou, Lambertides and Theodoulou's (2011) extension the GMS (2002) approach by augmenting the Fama-French (1993) and Carhart (1997) four-factor model and the Fama-French (2015) five-factor model with a default risk-mimicking portfolio as follows[3]:

$$\begin{aligned} r_{it} - r_{ft} = \alpha_i + \alpha_i D_t + \beta_i(r_{mt} - r_{ft}) + \beta_{\Delta i} D_t(r_{mt} - r_{ft}) + s_i SMB_t + s_{\Delta i} D_t SMB_t \\ + h_i HML_t + h_{\Delta i} D_t HML_t + m_i MOM_t + m_{\Delta i} D_t MOM_t + d_i DF_t + d_{\Delta i} D_i DF_t + \epsilon_t \end{aligned} \tag{1}$$

$$\begin{aligned} r_{it} - r_{ft} = \alpha_i + \alpha_i D_t + \beta_i(r_{mt} - r_{ft}) + \beta_{\Delta i} D_t(r_{mt} - r_{ft}) + s_i SMB_t \\ + s_{\Delta i} D_t SMB_t + h_i HML_t + h_{\Delta i} D_t HML_t + r_i RMW_t \\ + r_{\Delta i} D_t RMW_t + c_i CMA_t + c_{\Delta i} D_t CMA_t + d_i DF_t + d_{\Delta i} D_i DF_t + \epsilon_t \end{aligned} \tag{2}$$

For each firm i, we estimate this model from months $t^* - 36$ to $t^* + 36$, where t^* is the month of the dividend cut or omission; D_t is a dummy variable that is equal to one for $t \geq t^*$, and zero otherwise; r_{it} is the monthly stock return for firm i; r_{mt} is the monthly stock return of the CRSP value-weighted index and r_{ft} is the monthly return on the risk-free rate obtained from CRSP. SMB_t, HML_t, MOM_t, RMW_t and CMA_t are the monthly size, value, momentum, profitability and investment factors respectively. DF_i is the default risk factor. Variables β_i, s_i, h_i, m_i, r_i, c_i and d_i are the factor loadings of firm i on the market, size, value, momentum, profitability, investment and distress risk factors respectively in the 36 months prior to the dividend announcement. Variables $\beta_{\Delta i}$, $s_{\Delta i}$, $h_{\Delta i}$, $m_{\Delta i}$, $r_{\Delta i}$, $c_{\Delta i}$ and $d_{\Delta i}$ are the changes in the factor loadings in the 36 months following the announcement relative to the 36 months prior to the announcement. Variable α_i is the risk-adjusted abnormal return (alpha) in the 36 months prior to the dividend announcement and $\alpha_{\Delta i}$ is the change in alpha after the announcement.

3 Empirical results

3.1 Univariate analysis

Table 1 presents preliminary statistics on the probability of default (PD) and other characteristics of dividend decreasing and omitting firms in the three years before and three years following the announcement (years -3 to +3). $AVE_{(-3,-1)}$ is the three-year average prior to the dividend announcement, $AVE_{(+1,+3)}$ is the three-year average following the dividend announcement and $DIF_{(+3,-3)}$ is

[3]To obtain the default risk-mimicking portfolio, we follow a similar approach to Fama and French (1993) by ranking firms each month into two portfolios, based on their latest value of the probability of default. The default risk-mimicking returns are the differences between the monthly excess returns of the high default risk and low default risk portfolios.

the difference between the average values in the three years following the announcement minus their corresponding averages in the three years prior to the announcement.

The results show that default risk (PD) increases considerably on the announcement year and on the three years following the announcement. Although PD does decrease in years +2 to +3, they do not revert back to pre-announcement levels of default risk. Furthermore, the three-year average PD following the announcement ($AVE_{(+1,+3)} = 9.49\%$) is three times higher than the pre-announcement average ($AVE_{(-3,-1)} = 2.73\%$)[4]. This supports the conjecture that firms that cut and/or omit their dividends experience a long-lived increase in default risk.

In line with GMS (2002), the results in table 1 also indicate that firms that cut or omit their dividends experience lower profitability and undertake less investments, as shown by the declining return on assets (ROA) and capital expenditures ($CAPEX$)[5]. Furthermore, firms that cut or omit their dividends experience a modest increase in cash holdings ($CASH$) and long-term leverage (LEV).

Finally, the results in table 1 also show that firms that cut their dividends struggle to maintain them in the subsequent years. The mean dividend payout ratio increases from 76.54% in year -3 to 118.4% in year 0, and then persistently declines to an average of 45.82% in the three years following the announcement.

[INSERT TABLE 1 HERE]

Overall, the evidence provided in table 1 suggests that firms that cut or omit their dividends continue to experience long-lasting financial difficulties following the dividend cut/omission announcement, with higher default probabilities following the announcement. Furthermore, they experience lower profitability, invest less and struggle to maintain their dividends. The rather modest increase in cash holdings and leverage suggests that the benefit from the cash savings from cutting or omitting dividends is very limited. This suggests that firms that cut/omit their dividends have reached a point beyond which it is very difficult to recover.

Table 2 presents univariate sorts examining whether the probability of default varies with the severity of the dividend event. We use two measures to proxy for the severity of the event: The first measure is the absolute value of the percentage decrease in the dividend on the announcement (CUT) - higher dividend cuts may reflect firms being more distressed. The second measure is the cumulative abnormal returns in the day before to the day after the announcement of the dividend cut/omission event calculated using the market model (CAR), which is a market-based measure of the severity

[4] Further expanding the window to five years following the announcement yields the same conclusion - the probability of default in the five-year period following the announcement does not revert back to pre-announcement levels.

[5] It is worth noting that GMS (2002) examines only dividend decreases, while we examine both. The results for dividend omissions separately are consistent with GMS's (2002) findings for dividend decreases, albeit with larger magnitudes.

of the event. Panel A presents univariate sorts of of PD over quintiles of the absolute percentage dividend cut (CUT). The results in Panel A shows that $DIF_{(+3,-3)}$ is monotone in CUT as it moves from 2.06% for firms in $Q1$ to 10.68% for firms in $Q4$[6]. The difference between $Q4$ and $Q1$ of 8.62% is statistically significant at the 1% level. Furthermore, since dividend omissions represent 91% of $Q4$, we report the differences between $Q3$ and $Q1$ of 3.88%, which are also statistically significant at the 1% level. The results in Panel A are therefore consistent with a positive relationship between the magnitude of the dividend cut and subsequent increases in default risk.

Panel B presents univariate sorts of PD over quintiles of the announcement-period returns (CAR). The results in panel C shows that $DIF_{(+3,-3)}$ is generally decreasing in CAR as it moves from 10.68% for firms in $Q1$ to 7.04% for firms in $Q5$. The difference between $Q1$ and $Q5$ of 3.63% is statistically significant at the 5% level. The results in panel B are therefore consistent with a negative relationship between the market reaction to the announcement of dividend cuts and/or omissions, and subsequent increases in default risk. Firms with lower (more negative) market reactions experience a larger increase in default risk.

[INSERT TABLE 2 HERE]

Taken together, the evidence provided in table 2 suggests that more severe dividend cuts/omissions are associated with a larger subsequent increase in financial distress. This increase is higher for firms that have announced larger dividend cuts and for announcements that were more heavily penalised by the market. This evidence is indicative of a potential information content of dividend cuts/omissions on an increase in default risk.

3.2 Dividend cuts and omissions and increases in default risk

In this section, we test whether dividend cuts and omissions convey information about future distress risk, as measured by PD. We do this using a difference-in-differences (DiD) methodology with propensity-score matching (PSM). The identification strategy consists of comparing changes in the probability of default of firms that have cut or omitted their dividend payout with a matched set of counterfactual firms that have a similar *ex ante* likelihood to cut or omit their dividends as the firms which actually do.

Following von Eije, Goyal and Muckley (2014), we select the counterfactual firms by matching on the propensity to cut or omit a dividend, based on publicly available information to the capital market. Therefore, in line with the argument by von Eije, Goyal and Muckley (2014), our matched counterfactual firms have a similar *ex ante* likelihood to cut or omit their dividends as the firms which

[6] We can only sort into four groups rather than five since dividend omissions represent over 35% of the total sample of events.

actually do. Conditional on the treatment and counterfactual firms being indistinguishable in terms of publicly available information, we argue that significant differences in the changes in financial distress between the treatment and counterfactual firms, as measured by difference-in-differences in PD, can be attributed to an information content of the treatment effect (i.e., dividend cuts/omissions).

Table A1 in the appendix presents the logistic model estimates used in estimating the propensity score. We match each firm that has cut or omitted its dividend in a given year with a dividend payer that has not reduced or omitted its dividend using a one-to-one nearest neighbor matching with replacement. To verify the reliability of our matching, we re-run the same logit model on the post-match sample. As shown in the second column of Table A1, the Pseudo-R^2 is reduced from 0.1245 in the pre-match sample to 0.008 in the post-match sample. Furthermore, the coefficients on all the variables have lost their statistical significance at the 5% level. Table A2 reports the mean differences and the standardised bias (Rosenbaum and Rubin, 1985) for the treated and control group. The results show that the differences in the means between all the variables are statistically indistinguishable at the 5% level, and that all the standardised biases are smaller than 20% in absolute value, following the rule of thumb of Rosenbaum and Rubin (1985).

Having obtained the set of matched counterfactual firms, we use the pooled sample of matched pairs from years -3 to +3 relative to the announcement (matched) year for event (counterfactual) firms to run a DiD regression. More specifically, we run the following model:

$$\begin{aligned} PD_{it} = \beta_0 + \beta_1 * TREATED_{it} + \beta_2 * AFTER_{it} + \beta_3 \\ * (TREATED_{it} * AFTER_{it}) + \beta_k * CONTROLS_{it} + \epsilon_t \end{aligned} \tag{3}$$

The dependent variable PD_{it} is the probability of default of firm i at year t. $TREATED_{it}$ is a dummy variable that takes the value of one for event firms and zero for the counterfactual firms, $AFTER_{it}$ is a dummy variable that takes the value of one if $t = (+1, +3)$ and zero for $t = (-3, -1)$, $(TREATED_{it} * AFTER_{it})$ is an interaction term and $CONTROLS$ is a set of control variables. Our coefficient of interest, β_3, is the differences-in-differences in PD_{it} between the event firms and the matched counterfactual firms. All specifications include industry-year fixed effects to control for common industry shocks that affects all firms in a given year.

We use annual changes in total assets (ΔTA), capital expenditures ($\Delta CAPEX$), return on assets (ΔROA), probability of default (ΔPD), leverage (ΔLEV), cash holdings ($\Delta CASH$), stock price volatility (ΔVOL) and 12-month buy-and-hold abnormal returns ($BHAR$) as control variables in our tests. This allows us to control for any observable changes in firm characteristics that may influence its distress risk in the post-event window[7]. The change in the probability of default is of

[7]We control for changes rather than levels in the variables since our event and control firms have been matched on most of the said variables. We therefore believe that the controlling for changes in these variables following the event matter more than controlling for the levels. Nevertheless, we repeat the regression with levels instead of changes. The results, which have not been tabulated for brevity, are not appreciably different from those of our baseline regression.

particular importance, since it explicitly controls for any potential path-dependence in default risk (i.e., to ensure that increases in default risk in year t are not driven by increases in year $t-1$).

Table 3 presents the estimation results of the difference-in-differences regression. Column 1 presents the results including only $TREATED$, $AFTER$ and their interaction term (DiD), controlling for industry-year fixed effects. The DiD term, which is statistically significant at the 1% level, shows that firms that cut or omit their dividends experience an increase of 5.6% in their probability of default in the three years following the announcement, relative to counterfactual firms that are equally likely to cut/omit their dividends but do not. This is the central result of our paper, and it suggests that there is a significant information content of dividend cuts/omissions on firms' financial distress. In economic terms, an increase of 5.6% in the probability of default translates into event firms being more than three times more likely to default on their debt obligations relative to their pre-event levels of the probability of default. Column 2 presents an augmented specification which controls for past changes in financial distress, which may potentially influence the direction and the magnitude of subsequent changes in distress. The DiD estimate only marginally changes relative to that in column 1. The coefficient on the interaction term implies that firms that cut/omit their dividends experience an increase of 5.2% in their probability of default in the three-year post-event period relative to pre-event levels. Column 3 includes past stock return volatility and buy-and-hold abnormal returns in the regression specification, following Shumway (2001) who shows that market variables are strongly related to bankruptcy. The DiD estimate remains qualitatively similar at 4.5%[8]. Finally, column 4 presents the results after controlling for an array of accounting-based variables related to financial distress. Consistent with the findings in columns 1 to 4, the DiD estimate holds at 4.1%, which is statistically significant at the 1% level and is in economic terms equivalent to firms being more than 2.5 times more likely to default after a dividend cut/omission[9].

[INSERT TABLE 3 HERE]

Overall, the results above provide evidence of an information content of dividend cuts and omissions on distress risk. Relative to a counterfactual that is equally likely to cut/omit dividends but

[8] von Eije, Goyal and Muckley (2014) show that firms that omit dividends experience significant increases in systematic and idiosyncratic risk. We rerun our model with the individual risk components rather than the measure of total risk (ΔVOL). The results, which are untabulated for brevity, are qualitatively similar and suggest that idiosyncratic risk matters more than systematic risk (which is only marginally significant at the 10% level) in explaining distress risk of firms that cut/omit their dividends. This suggests that the increase in distress risk for firms that cut/omit dividends is more likely to be driven by firm-specific rather than systematic factors.

[9] Jensen, Lundstrum and Miller (2010) show that firms which cut/omit dividends subsequently allow their growth options to expire, by reducing capital expenditures, R&D expenditures and number of employees. In an untabulated analysis, we augment the regression in column 4 with changes in R&D to total assets and the number of employees, which drops our sample size to 4,963 firm-years. Despite the substantial loss in sample size, the DiD estimate still holds at 3.2%, which is statistically significant at the 1% level. Furthermore, the coefficients on both the changes in R&D and number employees are statistically insignificant, suggesting that the drop in the DiD estimate is due to sample attrition rather than the inclusion of the said variables in the regression.

does not, firms that do cut/omit their dividends are more than 2.5 times more likely to default on their debt obligations in the three years following the announcement relative to the three-year pre-event levels. It is also worth noting that this increase is above the 90th percentile of the full-sample distribution of the three-year increase in PD, suggesting that these increases are particularly large.

3.3 Changes in the pricing of default risk around dividend cuts and omissions

In the previous section, we have provided evidence in favour of an information content of dividend cuts and omissions on default risk. We proceed to examine whether investors recognize the increase in default risk and accordingly treat it as a priced risk factor beyond standard risk factors. To the extent that investors interpret a dividend cut/omission as a signal of an increase in default risk, we would expect higher factor loadings on the distress risk factor in the post-event period relative to that of the pre-event period. We do this by augmenting the Fama-French (1993) and Carhart (1997) four-factor model and the Fama-French (2015) five-factor model with the default risk-mimicking portfolio, following Charitou, Lambertides and Theodolou's (2011) extension of the GMS (2002) approach.

Table 4 presents the results for the estimated factor loadings and their respective changes in the three years following the announcement relative to the corresponding years prior to the announcement. As a benchmark, column (1) presents the estimated factor loadings of the four-factor model without the default risk factor. Consistent with GMS (2002), we find that dividend cuts and omissions are associated with statistically significant increases in the loadings on the Fama-French three factors. Column (2) augments the four-factor model with the default risk factor (d_i) and it's respective post-announcement change ($d_{\Delta i}$). Our evidence shows that the change in the default risk factor loading is significantly positive ($d_{\Delta i} = 0.173$) at the 1% level. To be more precise, the distress risk factor loadings increase from a statistically significant 0.392 in the pre-event window (d_i) to 0.565 in the post-event window ($d_i + d_{\Delta i}$), which is an increase of over 44%. This is consistent with our prediction that investors recognise the increase in financial distress for firms that cut/omit their dividends, and accordingly price this increase following the announcement. Furthermore, we find that the inclusion of the default risk factor in column (2) attenuates the magnitude and statistical significance of the changes in the loadings on the Fama-French three factors, with none of them being statistically significant at the 5% level or lower. This suggests that the changes in the loadings on the default risk factor subsume on the respective changes in the Fama-French three factors and that the previously reported findings of GMS (2002) with respect to dividend cuts were capturing changes in default risk. Our results continue to hold when using an augmented Fama-French five factor model (2015) in column (3), with an increase in the default risk factor loading of 0.228 that is statistically significant at the 1% level. This translates into an increase of 62% in the loadings on the default risk factor in the three-year post-event period.

One concern with the results reported thus far in Table 4 is that the increases in the factor loadings may be driven by factors other than the event. To alleviate this concern, we rely on our sample of matched firms from the previous section. Since the counterfactual firms by definition do not have an event date, we assign a random month of the year as the pseudo-event date and set it as $t = t^*$. We then estimate and collect the factor loadings similar to what we did for the event firms. Since our matched firms are indistinguishable based on publicly available information, we again use the argument of von Eije, Goyal and Muckley (2014), and argue that the information content of the dividend cut/omission can yield an exogenous shock to the expectations of investors in the capital market. Investors then accordingly price in the new information about the firms default risk, based on their interpretation of the dividend event. Accordingly, we obtain the adjusted factor loadings and their respective changes as the differences between the factor loadings of the event firms and their respective counterfactual firms.

Columns (4) to (6) of Table 4 show the adjusted factor loadings of the PSM-matched pairs. Consistent with the findings in the full (unadjusted) sample, the adjusted distress risk factor loadings are still significantly positive (at the 5% level) using both the four-factor model ($d_{\Delta i}$=0.290) in column (5) and the five-factor model ($d_{\Delta i}$=0.246) in column (6). Using the four-factor (five-factor) model, adjusted the default risk factor loadings increase from 0.063 (0.165) in the pre-event period to $0.063 + 0.290 = 0.353$ ($0.165 + 0.246 = 0.411$), which is 5.5 (2.5) times the pre-event level, which is considerably larger than the effect reported for the unadjusted results. One potential explaination for the more pronounced adjusted effect is that the counterfactual (ie: maintaining the dividend level when the firm is predicted to cut/omit) would prompt investors to price default risk downwards, which would exacerbate the adjusted increase in the default risk factor loadings.

It is also worth noting that the adjusted pre-event default risk factor loadings (d_i) is statistically indistinguishable from zero when using the four-factor model and only marginally significant at the 10% level using the five-factor model. This suggests that *ex ante*, investors do not perceive the default risk of the counterfactual firms to be any different from that of the event firms, which gives even more assurance on the quality of our matching procedure.

[INSERT TABLE 4 HERE]

Taken together, our findings so far suggest that investors recognise the information content of dividend cuts/omissions on default risk, and accordingly price in the increase in default risk following the announcement, which is reflected as increases in the loadings on the default risk factor. Furthermore, the robustness of our findings to propensity-score matching allows us to attribute the increase in the default risk factor loadings to the dividend cut/omission event.

3.4 The information content of the magnitude of the dividend cut

The evidence provided thus far supports the hypothesis that dividend cuts/omissions convey information about a firm's default risk. Another important follow-on question is whether the magnitude of these events conveys information about the magnitude of the increase in default risk. The univariate sorts which were presented in Table 2 were indicative of such a relationship. We examine this more formally in a multivariate setting using the following regression models:

$$\Delta DISTRESS_{i(+3,-3)} = \beta_0 + \beta_1 * CUT_i + \beta_k * CONTROLS_i + \epsilon_t \quad (4)$$

$$\Delta DISTRESS_{i(+3,-3)} = \beta_0 + \beta_1 * CAR_i + \beta_k * CONTROLS_{it} + \epsilon_t \quad (5)$$

Where $\Delta DISTRESS_{i(+3,-3)}$ is the change in default risk for firm i in the three years following the dividend event relative to the corresponding three years prior to the event. We use two measures of default risk - the first measure is the probability of default, and the second measure is the loadings on the default risk factor using the Fama-French five-factor model[10]. Equation (3) uses the absolute value of the percentage decrease in the firms announced dividend (CUT_i) as an independent variable and Equation (4) uses the announcement period abnormal returns (CAR_i) as an independent variable. $CONTROLS_i$ are a set of control variables related to default risk and are the same in both regression models.

Table 5 presents the results of the cross-sectional regressions of the changes in distress risk on our variables of interest - CUT and CAR. Columns 1 to 4 show the results with the changes in the probability of default ($\Delta PD_{(+3,-3)}$) as the dependent variable. Column 1 reports the results for a univariate regression of $\Delta PD_{(+3,-3)}$ on CUT_i. We find that the coefficient of CUT_i is positive and statistically significant at the 1% level. Therefore, a larger announced percentage decrease in a firm's dividend predicts a higher increase in the firm's probability of default. Column 2 reports the results for a univariate regression of $\Delta PD_{(+3,-3)}$ on CAR_i. The coefficient of CAR_i is negative and statistically significant at the 1% level. Therefore, smaller (more negative) market reaction predicts larger increases in the probability of default. These results hold up well with the inclusion of control variables in columns 3 and 4. As shown in column 3, all else equal, a 1% increase in CUT_i increases the change in default risk by 0.092%. The coefficient on CAR in column 5 implies that all else equal, a 1% drop in CAR_i increases the change in default risk by 0.128%.

Columns 5 to 8 show the results with the changes in the default risk factor loadings ($d_{\Delta i}$) as the dependent variable. Columns 5 and 6 show a significantly positive (negative) relationship between CUT_i (CAR_i) and changes in factor loadings. These findings continue to hold with the inclusion of control variables in columns 7 and 8. The coefficient estimate on CUT_i in column 7 imply that all

[10] In an untabulated analysis, we also re-run the regressions using the factor loadings from the Fama-French (1993) and Carhart (1997) four-factor model. The results are almost identical to those obtained using the five-factor model.

else equal, a 1% increase in CUT_i increases the change in default risk factor loadings by 4.10%. The coefficient estimate on CAR_i in column 8 imply that all else equal, a 1% drop in CAR_i increases the change in factor loadings by 12.30%.

[INSERT TABLE 5 HERE]

Taken together, the results above confirm that the magnitude of the event, both in terms of the size of the dividend decrease and the market reaction to the announcement, convey information about the magnitude of the increase in default risk. Higher dividend cuts predict higher increases in default risk, and lower announcement-returns predict higher increases in default risk.

3.5 Dividend cuts and omissions and firm survival

We now move to the question of whether dividend cuts and omissions convey information about announcing firms' survival prospects. Unlike our previous measures of distress, which are by definition *ex ante*, a firm ceasing to survive is an observable event in its life cycle. If dividend cuts and omissions do indeed convey information about an increase in announcing firms' financial distress, then we would also expect them to have an information content on their actual survival prospects.

In order to examine a firm's survival in relation to dividend cuts/omissions, we follow the definition of Bhattacharya, Borisov and Yue (2015) to identify firms that have involuntarily delisted in the three years following the announcement of a dividend cut/omission. We then carry out a logistic analysis to determine the effect of dividend cuts/omissions on survival probabilities. More formally, the model takes the following form:

$$Pr(Delisting_i) = f(CUT_i, Controls_i) \tag{6}$$

$$Pr(Delisting_i) = f(CAR_i, Controls_i) \tag{7}$$

Where $Delisting_i$ is a dummy variable that takes the value of 1 if the firm i has involuntarily delisted in the three years following the dividend announcement, and zero otherwise. Our variables of interest are CUT_i and CAR_i. The controls are common across both specifications and mimic those in the previous analysis.

Table 6 present the results of the logistic regression. Columns 1 and 2 present the results of a univariate regression on CUT and CAR respectively. Column 1 suggests that CUT is positively related to the log-odds of involuntary delisting within three years. This effect is statistically significant at the 1% level. Turning to column 2, we find that CAR is negatively related to the log-odds of involuntary delisting within three years, with a coefficient that is statistically significant at the 5% level. The significance of the univariate evidence holds up with the inclusion of control variables in columns 3 and 4, albeit with the coefficient on CAR being only significant at the 10% level. The results in column 3 show that a 1% increase in CUT increases the log-odds of involuntary delisting by 0.023. Therefore, a larger dividend cut predicts a higher probability of involuntary delisting within three years. For column 4, a 1% drop in CAR increases the log-odds of involuntary delisting by 0.026. Therefore, a lower (more negative) market reaction, at least partially reflects investor pessimism about a firms' survival prospects.

To alleviate potential selection bias, we use our propensity-score matched sample in a pooled logistic regression in column 5. Similar to the sample of event firms, we identify the counterfactual firms that have involuntarily delisted in the three years following the matched year. Our independent variable of interest, $TREATED$, is a dummy variable that takes the value of one for the event firms, and zero for the counterfactual firms. The positive coefficient on $TREATED$, which is statistically significant at the 1% level can be interpreted as event firms being 2.3 ($e^{0.833}$) times more likely to involuntarily delist within three years, compared to counterfactual firms that are equally likely to cut/omit their dividends.

[INSERT TABLE 6 HERE]

Overall, our results suggest that dividend cuts/omissions convey useful information about a firms survival prospects, thereby corroborating our central finding that dividend cuts/omissions convey information about an increase in announcing firms' financial distress.

3.6 Instrumental variables approach

To further address the endogeneity concerns arising from the relationship between the magnitude of the dividend cut and subsequent changes in financial distress, we employ instrumental variables to isolate the exogenous component of the magnitude of the dividend cut and use it to explain subsequent changes in financial distress. We use two instrumental variables that are related to firms'payout policy, but are not directly correlated with firms' financial distress. The predicted value of the dividend cut from the first stage regression is then used to explain the three-year change in the probability of default, the three-year change in the default risk factor loadings and the likelihood to involuntarily delist.

Our first instrument is the propensity to pay dividends for firms domiciled in the same state as the event firm, which is calculated as the proportion of dividend-paying firms (excluding the event firm) in the state of domicile. On one hand, firms' payout policy is influenced by their geographic location (John, Knyazeva and Knyazeva, 2011; Ucar, 2016), and local shareholder clienteles (Becker, Ivković and Weisbenner, 2011). On the other hand, there is no convincing economic rationale as to why the dividend-paying status of firms domiciled in the same state would be directly related to the event firms' financial distress, except through the channel of influencing dividend policy. We therefore expect a negative relationship between the state propensity to pay dividends and the magnitude of the dividend cut, since firms domiciled in states with a higher proportion of dividend payers might be more reluctant to carry out a dividend cut/omission.

Our second instrument is the Dividend Premium of Baker and Wurgler (2004a, 2004b), which measures time-varying investor demand for dividends. This variable has been shown to explain the decision to pay dividends (Baker and Wurgler, 2004a, 2004b) and the decision to change dividends, the magnitude of the dividend changes and their corresponding market reaction (Li and Lie, 2005). On the other hand, there is no convincing economic rationale as to why time-varying investor demand for dividends might influence event firms' financial distress, except through the channel of influencing dividend policy. Therefore, in line with Li and Lie (2005), we expect a negative relationship between the dividend premium and the magnitude of the dividend cut, since firms might be more reluctant to cut dividends during periods of high investor demand for dividends.

Table 7 reports the estimates of the two-stage least squares instrumental variables (2SLS IV) method. Regressions (1) to (3), (4) to (6) and (7) to (9) report the regression output with the three-year change in the probability of default ($\Delta PD_{+3,-3}$), the three-year change in the distress-risk factor loadings ($d_{\Delta i}$) and the probability of involuntary delisting within three years ($DELIST$) respectively as the dependent variables. For brevity, we only report the coefficient estimates on the main variables of interest, namely the above-mentioned instruments for the first-stage regression and the predicted value of the dividend cut for the second-stage regression. The control variables used are identical to those used in tables 5 and 6. Panel A reports the first-stage regressions where the dependent variable is the magnitude of the dividend cut, along with diagnostic tests on the instruments. Regressions (1), (4) and (7) uses the state propensity to pay dividends as an instrument, regressions (2), (5) and (8) uses the Dividend Premium of Baker and Wurgler (2004) as an instrument. Finally, regressions (3), (6) and (9) uses both instruments. Consistent with our expectations, both our instruments are negatively related to the magnitude of the dividend cut, with coefficient estimates that are negative and statistically significant at the 1% in all our regressions. The reported F-statistics of the first-stage regression are all higher than their corresponding Stock and Yogo (2005) critical values, therefore rejecting the null hypothesis that the instruments are weak. Finally, the Hansen (1992) J-stats for overidentification indicates that both instruments are valid, as shown by their corresponding p-values that cannot reject the null that the instruments are uncorrelated with the error term.

[INSERT TABLE 7 HERE]

Panel B of table 7 reports the second-stage regression. The variable of interest is the predicted value of the dividend cut ($PCUT$), obtained from the first-stage regression. All the nine regressions confirm the positive relationship between the size of the dividend cut and subsequent increases in financial distress, with coefficients that are statistically significant at the 1% level for $\Delta PD_{(+3,-3)}$, 10% or better level for $d_{\Delta i}$ and at the 5% level for $DELIST$ as dependent variables[11]. This confirms our conjecture that larger dividend cuts predict larger subsequent increases in financial distress, and that these findings are not driven by the endogeneity of the magnitude of the dividend cut.

3.7 Dividend cuts and omissions and subsequent dividend increases and resumptions

Finally, we take a look at subsequent dividend resumptions and re-increases carried out by firms that cut/omit their dividends. This complements our main analysis since Charitou, Lambertides and Theodoulou (2011) show that firms that increase or initiate their dividends experience a decline in their financial distress. We therefore use subsequent dividend resumptions and increases as signs of firm recovery and carry out an analysis similar to that of the previous subsection. To be more specific, we argue that to the extent that dividend cuts/omissions convey information about increase in financial distress, the larger the magnitude of the dividend event, the less likely the firm is to recover and therefore resume/re-increase its dividend payout following the cut/omission.

To do this, we track the dividend policy of firms that have announced a dividend cut or omission for three years subsequent to the initial dividend cut/omission announcement. For firms that have cut dividends, we look for any subsequent dividend increases in the three-year period. For dividend omissions, we look for any subsequent dividend resumptions in the same three-year period. We then carry out a logistic analysis to determine the effect of the magnitude of dividend cuts/omissions on dividend resumption/re-increase probabilities. The model takes the following form:

$$Pr(Recovery_i) = f(CUT_i, Controls_i) \tag{8}$$

$$Pr(Recovery_i) = f(CAR_i, Controls_i) \tag{9}$$

Where $Recovery_i$ is a dummy variable that takes the value of one if the firm i has resumed a dividend payment in three years following an omission or re-increased it's dividend by at least 12.5% in the three years following a dividend cut. Similar to the previous analysis, our variables of interest are CUT and CAR. Since we are looking at payout policy of these firms, our choice of the control variables mimics those that have been used to estimate the propensity score.

Table 8 presents the results of the logistic regression. The univariate regression in column 1 implies that the higher the percentage decrease in dividends, the less likely a firm is to make any dividend increase or resumption within three years. This relationship, which is statistically significant

[11] Ideally, we would like to use a logistic regression in the second stage where $DELIST$ is an independent variable. However, due to the absence of diagnostic tests where logistic models are in the second-stage, we run a 2SLS. In an untabulated analysis, we use an instrumental variable probit model using *ivprobit* on Stata and find that the coefficient on $PCUT$ is positive and statistically significant at the 1% level.

at the 1% level holds with the inclusion of control variables in column 3. Interpreting the coefficient, a 1% cut in the dividend decreases the odds of any increase within three years by 1.6%. This effect is not trivial, considering that the average firm in our sample has cut its dividend by 68%.

The results with CAR as an independent variable in columns 2 and 4 are also consistent with our conjecture. We find that CAR is positively related to the odds of a subsequent dividend increase. In other words, a more negative market reaction to the announcement of a dividend cut/omission partially reflects investors' pessimism about future dividends.

[INSERT TABLE 8 HERE]

All in all, the results in this subsection suggest that the more severe the dividend cuts/omission event is, the lower the likelihood of any subsequent dividend increase/resumption within three years. This complements and corroborates our earlier findings on higher dividend cuts and more negative market reactions predicting higher future financial distress.

4 Robustness tests

4.1 The role of past financial distress

One concern that may arise about our findings is that the increase in default risk might be due to firms being already in financial distress in the first place, rather than an information content of dividend cuts/omissions. Although we have already addressed this issue to a large extent by controlling for past changes in default risk in our DiD regressions, we nevertheless revisit this concern by stratifying our event firms into quintiles of PD and examining the increases in default risk within each quintile. The results, which are presented in Table A3 in the appendix examine the difference-in-differences in the probability of default (DiD_{PD}) and the difference-in-differences in the default risk factor loadings using the Fama-French and Carhart (1997) four-factor model (DiD_{4F}) and the Fama-French (2015) five-factor model (DiD_{5F}).

Our results for DiD_{PD} show that our DiD estimates are positive and statistically significant across all quintiles of default risk, although the DiD estimates are increasing in past default risk. We obtain similar, albeit weaker results for DiD_{4F} and DiD_{5F}. Nevertheless, our central finding of dividend cuts and omissions signalling an increase in financial distress holds across the distress risk spectrum, and is not driven by highly distressed firms' persistence in financial distress.

4.2 Selection bias

Another concern that may arise with our findings is that they might be driven by selection bias. While our propensity-score matching is one way to control for the same, there may be unobservable variables that affect the propensity to cut/omit dividends which may lead to a bias in our results. While we cannot totally rule out the possibility of our results being driven by unobservable selection bias in our sample, we can assess the extent to which our results are sensitive to potential selection bias (if it exists), by employing the Rosenbaum bounds (Rosenbaum, 2002), which are denoted by Γ. As DiPrete and Gangl (2004) point out, the Rosenbaum bound is a "worst-case scenario". It does not tell the observer whether or not hidden bias exists, but how large the influence of unobservables should be to overturn the treatment effects obtained from matching on observables.

The results of the Rosenbaum bounds are presented in Table A4 in the appendix. The second column of Table A4 reports the Γ values of the Rosenbaum bounds at the 90% confidence level. Larger values of Γ indicates that the treatment effect is less-sensitive to unobservable bias. For example, a Γ value of 2 indicates that the matched control firms have to be twice as likely to receive treatment (i.e.: cut or omit their dividends) due to unobservables to render our findings insignificant. The third column reports the hidden-bias equivalent, which is calculated following DiPrete and Gangl (2004). This allows us to translate the Γ value to it's equivalent in terms of the observable covariates that have a significant effect on the propensity to cut/omit dividends, which in this case are the statistically significant variables used to estimate our propensity-score. The final column reports the hidden-bias equivalent relative to the the non-event firms (i.e.: the equivalent percentage change in the observable covariate required to reverse our findings).

Panel A presents the results for the difference-in-differences in the probability of default DiD_{PD}. The reported Γ value of 2.07 suggests that the unobserved covariate (if it exists) should be large enough to make control firms 2.07 times more likely to cut/omit their dividend payout to make DiD_{PD} statistically insignificant. To illustrate its economic significance in terms of observable variables, the last column shows that this, for example, is equivalent to total assets ($LNTA$) being 73% lower, market-to-book ratios (MB) being 69% lower and leverage (LEV) being 74% higher for control firms. These effects are substantial in that they require a very large deterioration in the control firms' operating performance[12].

Panels B and C presents the results for the difference-in-differences in the default risk factor loadings using the four-factor model (DiD_{4F}) and five-factor model (DiD_{5F}) respectively. The reported Γ value of 1.41 (1.37) for the four-factor (five-factor) model suggests that the unobserved covariate should be large enough to make control firms 41% (37%) more likely to cut/omit their dividend payout to make DiD_{4F} (DiD_{5F}) statistically insignificant. The unobserved covariate must have an impact that is comparable in magnitude to, for example, a 34% drop in $LNTA$ and MB and a 35% increase in LEV for DiD_{4F}. While the sensitivity of DiD_{4F} and DiD_{5F} to hidden bias is considerably higher in comparison to DiD_{PD}, it still requires an effect that is equivalent to economically

[12] For example, relative to the full sample of firms used to estimate the propensity score, this would require the control firms to be in the bottom 1% of $LNTA$ and MB and in the top 10% of LEV.

large deterioration in firm characteristics.

5 Conclusion

This paper examines the information content of dividend cuts/omissions on financial distress. We show that firms that cut or omit their dividends experience economically large and long-lived increases in default risk and that the increase in default risk is a priced risk factor beyond Fama-French (1993, 2015) and Carhart (1997) four and five factor models. Firms that cut/omit dividends also have lower survival rates and are less-likely to subsequently increase or resume their dividend payouts. We find that larger dividend cuts and more negative initial market reactions predict larger subsequent default risk. Using difference-in-differences, Rosenbaum (2002) bounds and instrumental variables to address endogeneity concerns, we establish that dividend cuts and omissions have an information content on future increases in financial distress.

As suggested by Brav, Graham, Michaely and Harvey (2005), managerial reluctance to cut/omit dividends stems from management not wanting to give the misimpression that the firm is expecting a severe liquidity crisis, and would therefore avoid cutting/omitting dividends if they believe that the firm would only be temporarily affected. Our evidence lends empirical support to this claim by showing that dividend cuts and omissions are an important sign that the firm will go through a prolonged period of financial distress.

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Table 1: Changes in firm characteristics around Dividend cuts and Omissions

This table reports the means of key firm characteristics in the seven years centered around the announcements of dividend cuts and omissions. PD is the probability of default, which is constructed following Bharath and Shumway's (2008) approximation of Merton's (1974) model. ROA is the return on assets. $CAPEX$ is the ratio of capital expenditures to total assets, $CASH$ is the ratio of cash hodlings to total assets. LEV is the ratio of long-term debt to total assets, $PAYOUT$ is the dividend payout ratio, which is calculated only for firms with non-zero and non-negative earnings. $AVE_{(-3,-1)}$ is the average in the three years prior to the dividend change, $AVE_{(+1,+3)}$ is the average in the three years following the dividend change, $DIF_{(+3,-3)}$ is the difference between the average in the three years after the dividend change and the respective average for the three years prior to the dividend change. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels respectively.

	Year									
	-3	-2	-1	0	+1	+2	+3	$AVE_{(-3,-1)}$	$AVE_{(+1,+3)}$	$DIF_{(+3,-3)}$
PD	1.47%	1.95%	4.74%	11.49%	12.19%	7.53%	6.26%	2.73%	9.49%	6.82%***
N	1,395	1,453	1,497	1,484	1,399	1,295	1,178	1,522	1,432	1,389
ROA	6.34%	5.21%	1.20%	-2.37%	0.05%	0.09%	1.58%	4.50%	0.41%	-4.16%***
N	1,598	1,608	1,613	1,614	1,513	1,405	1,302	1,613	1,516	1,512
$CAPEX$	7.10%	7.12%	6.76%	5.39%	4.78%	5.14%	5.37%	6.97%	5.02%	-1.89%***
N	1,581	1,595	1,598	1,601	1,502	1,395	1,292	1,603	1,510	1,502
$CASH$	9.73%	8.86%	7.90%	8.44%	9.16%	9.70%	9.89%	8.82%	9.52%	0.71%***
N	1,598	1,609	1,613	1,613	1,514	1,405	1,304	1,613	1,517	1,513
LEV	18.22%	19.26%	21.09%	22.15%	21.79%	21.03%	20.77%	19.59%	21.26%	1.68%***
N	1,598	1,609	1,613	1,610	1,512	1,405	1,302	1,613	1,516	1,512
$PAYOUT$	76.54%	103.71%	178.32%	118.40%	49.79%	45.08%	43.28%	116.06%	45.82%	-61.33%***
N	1,480	1,462	1,172	829	983	977	961	1,590	1,281	1,266

Table 2: Changes in Default Risk around Dividend cuts and Omissions

This table reports univariate sorts of the probability of default in the seven years centered around the announcements of dividend cuts and omissions. The probability of default is constructed following Bharath and Shumway's (2008) approximation of Merton's (1974) model. $AVE_{(-3,-1)}$ is the average probability of default in the three years prior to the dividend change, $AVE_{(+1,+3)}$ is the average probability of default in the three years following the dividend change, $DIF_{(+3,-3)}$ is the difference between the average probability of default in the three years after the dividend change and the respective average for the three years prior to the dividend change. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels respectively.

	Year									
	-3	-2	-1	0	+1	+2	+3	$AVE_{(-3,-1)}$	$AVE_{(+1,+3)}$	$DIF_{(+3,-3)}$
Panel A: Sorted by CUT										
(1)	1.37%	1.18%	2.02%	1.48%	4.05%	3.14%	3.99%	1.46%	3.50%	2.06%
N	263	288	298	296	274	259	238	301	279	271
(2)	0.87%	0.75%	2.71%	6.89%	7.18%	5.64%	4.44%	1.42%	6.50%	4.86%
N	277	285	289	285	284	268	245	298	293	281
(3)	1.30%	2.08%	4.12%	10.19%	10.32%	7.96%	5.30%	2.48%	8.47%	5.94%
N	286	297	308	305	291	268	241	314	296	292
(4)	1.89%	2.84%	7.39%	19.39%	19.82%	10.60%	8.94%	4.14%	14.54%	10.68%
N	569	583	602	598	550	500	454	609	564	545
(4) - (1)	0.51%	1.67%**	5.37%***	17.91%***	15.77%***	7.46%***	4.95%***	2.67%***	11.04%***	8.62%***
(3) - (1)	-0.07%	0.90%	2.10%**	8.54%***	6.27%***	4.82%***	1.31%	1.01%**	4.97%***	3.88%***
Panel B: Sorted by CAR										
(1)	1.72%	2.67%	6.90%	18.27%	19.89%	10.61%	8.03%	3.87%	14.30%	10.68%
N	284	295	308	304	286	256	235	310	296	288
(2)	1.89%	2.16%	5.34%	12.56%	12.76%	8.64%	5.41%	3.09%	9.67%	6.56%
N	287	294	303	300	279	270	243	306	288	281
(3)	0.89%	1.59%	3.98%	8.54%	8.84%	6.51%	6.57%	2.16%	7.66%	5.62%
N	279	290	298	303	283	263	239	303	288	279
(4)	1.15%	1.35%	2.49%	4.87%	6.20%	5.40%	4.48%	1.74%	5.46%	3.84%
N	259	284	289	281	262	244	214	296	265	256
(5)	1.65%	1.95%	4.86%	12.75%	12.74%	6.40%	6.63%	2.76%	9.89%	7.04%
N	286	290	299	296	289	262	247	307	295	285
(1) - (5)	0.01%	0.72%	2.04%*	5.52%***	7.14%***	4.21%**	1.40%	1.10%*	4.41%***	3.63%**

Table 3: Difference-in-Differences (DiD) estimations of the probability of default

This table reports the results of the baseline difference-in-differences (DiD) estimations of the probability of default. The pooled sample consists of firms that have cut and/or omitted their dividends and their matched counterfactual firms from the years -3 to +3 relative to the dividend announcement year for the treated firms and matched year for the counterfactual firms. The dependent variable is the probability of default PD, which is calculated following Bharath and Shumway (2008). $TREATED$ is a dummy variable that takes the value of one for firms that have cut or omitted their dividends and zero for the matched counterfactual firms. $AFTER$ is a dummy variable that takes the value of one for years +1 to +3 and zero for the years -3 to -1. $TREATED * AFTER$ is the DiD interaction term. ΔPD is the change in the probability of default. ΔVOL is the change in the volatility of monthly returns. $BHAR$ is the 12-month buy-and-hold abnormal returns. ΔTA is the change in total assets. $\Delta CAPEX$ is the change in the ratio of capital expenditures to total assets. ΔROA is the change in the return on assets. $\Delta CASH$ is the change in the ratio of cash holdings to total assets. ΔLEV is the change in the ratio of long-term debt to total assets. $Industry * YearFE$ are industry-year fixed effects, where industry is defined using the two-digit SIC code. All control variables are annual and calculated as of the fiscal year $t-1$. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels respectively.

	(1)	(2)	(3)	(4)
$TREATED$	-0.002	0.000	-0.002	-0.002
	(0.444)	(0.847)	(0.337)	(0.480)
$AFTER$	0.005*	0.003	0.004	0.004
	(0.060)	(0.223)	(0.128)	(0.100)
$\boldsymbol{TREATED * AFTER}$	**0.056***	**0.052***	**0.045***	**0.041***
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**
ΔPD		0.296***	0.212***	0.203***
		(0.000)	(0.000)	(0.000)
ΔVOL			2.409***	2.475***
			(0.000)	(0.000)
$BHAR$			-0.059***	-0.052***
			(0.000)	(0.000)
ΔTA				-0.017
				(0.102)
$\Delta CAPEX$				-0.063**
				(0.022)
ΔROA				-0.085***
				(0.004)
$\Delta CASH$				0.031
				(0.115)
ΔLEV				0.076***
				(0.010)
$CONS$	-0.017	-0.011	-0.000	-0.003
	(0.178)	(0.372)	(0.989)	(0.805)
$Industry * YearFE$	Yes	Yes	Yes	Yes
N	12,732	11,920	11,758	11,318
R^2	0.118	0.205	0.267	0.273

Table 4: Factor loadings surrounding dividend cuts and omissions

This table reports the cross-sectional mean values of the estimated coefficients using the Fama-French (1993) and Carhart (1997) four-factor model and the Fama-French (2015) five-factor model augmented to include the default risk factor. The model is estimated as a time-series regression from the months -36 to +36 centered around the event month for the event firms and pseudo-event month for the PSM-matched firms. The Unadjusted results presents the mean estimates for the full sample of the event firms. The PSM-adjusted results presents the differences in the estimates between the event firm and their correspondent counterfactual firms, which are obtained using propensity-score matching. The pseudo-event month for each counterfactual firm is determined using a random number generator. The variables β_i, s_i, h_i, m_i, r_i , $c_i$and d_i are the factor loadings of firm i corresponding to the market, size, book-to-market, momentum, profitability, investment and default-risk factors respectively during the 36 months prior to the announcement month. The variables $\beta_{\Delta i}$, $s_{\Delta i}$, $h_{\Delta i}$, $m_{\Delta i}$, $r_{\Delta i}$, $c_{\Delta i}$ and $d_{\Delta i}$ are the changes in the corresponding factor loadings in the 36 months after the announcement month relative to the 36 months prior to the announcement month. α_i is the abnormal return of firm i prior to the announcement month and $\alpha_{\Delta i}$ is the change in abnormal return after the announcement month. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels respectively.

Variable	**Unadjusted**			**PSM-adjusted**		
	(1)	(2)	(3)	(4)	(5)	(6)
Alpha						
α_i	-0.008***	-0.007***	-0.008***	-0.008***	-0.007***	-0.008***
$\alpha_{\Delta i}$	0.006***	0.006***	0.007***	0.002	0.001	0.003*
Market factor						
β_i	0.946***	0.917***	0.916***	-0.009	-0.015	-0.017
$\beta_{\Delta i}$	0.063**	0.046*	0.049**	0.064*	0.043	0.031
Size factor						
s_i	0.810***	0.751***	0.795***	0.037	0.048	0.051
$s_{\Delta i}$	0.169***	0.003	-0.039	0.239***	0.094	0.063
Book-to-market factor						
h_i	0.298***	0 .184***	0.256***	0.147***	0.143***	0.207***
$h_{\Delta i}$	0.189***	0.092*	0.012	0.050	-0.067	-0.142
Momentum factor						
m_i	-0.198***	-0.179***		-0.100***	-0.116***	
$m_{\Delta i}$	-0.072**	-0.045		-0.070	-0.043	
Profitability factor						
r_i			0.047			0.049
$r_{\Delta i}$			-0.163**			-0.378***
Investment factor						
c_i			-0.108**			-0.144
$c_{\Delta i}$			0.101			0.116
Default risk factor						
d_i		0.392***	0.368***		0.063	0.165*
$\boldsymbol{d_{\Delta i}}$		**0.173*** **	**0.228*** **		**0.290** **	**0.246** **
N	1,358	1,358	1,358	1,262	1,262	1,262

Table 5: Cross-sectional regressions of changes in default risk around dividend cuts and omissions

This table reports results of regressions examining whether dividend cuts and omissions can influence firms' default risk. Columns (1) to (4) use the change in the average probability of default in the three years after the announcement relative to the corresponding three years prior to the announcement as the dependent variable. Columns (5) to (8) use the change in the default risk factor loadings in the three years after the announcement relative to the corresponding three years prior to the announcement as the dependent variable. CUT is the magnitude of the dividend cut in absolute value, which ranges between 0.125 and 1. CAR is the announcement period abnormal return in the three-days centered around the announcement of the dividend event. ROA is the return on assets. $LNTA$ is the natural log of the firm's total assets. $BHAR$ is the 12-month buy-and-hold abnormal returns. LEV is the ratio of long-term debt to total assets. $CASH$ is the ratio of cash holdings to total assets. $CAPEX$ is the ratio of capital expenditures to total assets. VOL is the 12-month standard deviation of a firm's monthly stock returns. All variables (with the exception of CUT) are winsorized at the top and bottom 1% and measured as of the fiscal year $t-1$. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels respectively.

	Dependent variable: $\Delta PD_{(+3,-3)}$				Dependent variable: $d_{\Delta i}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\boldsymbol{CUT}$	**0.106*** **		**0.092*** **		**0.952*** **		**0.756*** **	
	(0.000)		**(0.000)**		**(0.001)**		**(0.008)**	
$\boldsymbol{CAR}$		**-0.156*** **		**-0.128** **		**-2.418** **		**-1.959** **
		(0.002)		**(0.012)**		**(0.012)**		**(0.043)**
ROA			0.064	0.012			-1.843*	-2.198**
			(0.239)	(0.819)			(0.083)	(0.036)
$LNTA$			-0.008***	-0.007***			-0.073	-0.063
			(0.002)	(0.008)			(0.136)	(0.199)
$BHAR$			-0.053***	-0.059***			-0.443**	-0.505**
			(0.000)	(0.000)			(0.045)	(0.021)
LEV			0.186***	0.207***			-0.487	-0.333
			(0.000)	(0.000)			(0.429)	(0.585)
$CASH$			-0.074	-0.056			-0.308	-0.079
			(0.214)	(0.347)			(0.726)	(0.928)
$CAPEX$			-0.091	-0.107			0.093	-0.102
			(0.252)	(0.182)			(0.949)	(0.944)
VOL			-1.123**	-0.622			0.141	4.129
			(0.010)	(0.148)			(0.986)	(0.590)
$Constant$	-0.008	0.058***	0.043*	0.077***	-0.459**	0.086	0.223	0.465
	(0.507)	(0.000)	(0.063)	(0.000)	(0.032)	(0.349)	(0.603)	(0.251)
N	1,389	1,389	1,348	1,348	1,358	1,358	1,335	1,335
R^2	0.031	0.007	0.079	0.064	0.008	0.005	0.017	0.016

Table 6: Logistic regressions of involuntary delisting on dividend cuts and omission variables

This table reports results of logit regressions examining whether dividend cuts and omissions are associated with a higher likelihood of involuntary delisting within three years following the announcement. The dependent variable, $DELIST$ is a dummy variable that equals one if the firm has involuntarily delisted within three years following the announcement and zero otherwise. Following Bhattacharya, Borisov and Yu (2015), we define an involuntary delisting as either a liquidation (CRSP delisting codes 400-490) or forced delisting (CRSP delisting codes 500-591). CUT is the magnitude of the dividend cut in absolute value, which ranges between 0.125 and 1. CAR is the announcement period abnormal return in the three-days centered around the announcement of the dividend event. $TREATED$ is a dummy variable that equals one for firms that have cut or omitted their dividends and zero for the matched counterfactual firms. PD is the probability of default, which is measured following Bharath and Shumway (2008). ROA is the return on assets. $LNTA$ is the natural log of the firm's total assets. $BHAR$ is the 12-month buy-and-hold abnormal returns. VOL is the 12-month standard deviation of a firm's monthly stock returns. LEV is the ratio of long-term debt to total assets. $CASH$ is the ratio of cash holdings to total assets. $CAPEX$ is the ratio of capital expenditures to total assets. All variables (with the exception of CUT) are winsorized at the top and bottom 1% and measured at the year of the dividend announcement. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels respectively.

	(1)	(2)	(3)	(4)	(5)
CUT	**2.663***** **(0.000)**		**2.257***** **(0.000)**		
CAR		**-3.499**** **(0.010)**		**-2.624*** **(0.056)**	
TREATED					**0.833***** **(0.000)**
ROA			-2.569** (0.027)	-3.068*** (0.008)	-3.746*** (0.000)
$LNTA$			-0.145* (0.069)	-0.115 (0.144)	-0.188*** (0.002)
$BHAR$			-0.770* (0.052)	-0.851** (0.034)	-0.582* (0.057)
VOL			3.069 (0.784)	14.340 (0.187)	24.716*** (0.000)
LEV			1.055 (0.238)	1.314 (0.138)	2.273*** (0.001)
$CASH$			0.995 (0.373)	1.257 (0.262)	0.120 (0.893)
$CAPEX$			-5.495** (0.038)	-5.893** (0.027)	-7.514*** (0.001)
$Constant$	-4.823*** (0.000)	-2.988*** (0.000)	-3.762*** (0.000)	-2.687*** (0.000)	-3.293*** (0.000)
N	1,563	1,563	1,549	1,549	2,510
$Pseudo-R^2$	0.0472	0.0114	0.0884	0.0586	0.1466

Table 7: Two-stage Least Squares Instrumental Variables (2SLS IV) estimator

This table reports the estimates of the two-stage least squares instrumental variables method. Panel A presents the first-stage regression results where the dependent variable is the percentage cut in the dividend in absolute value (CUT). The instrumental variables are as follows: *State Propensity*, which is the proportion of dividend paying firms that are domiciled in a given state in the fiscal year-end $t-1$ and *Dividend Premium* which is the Baker and Wurgler (2004) measure of time-varying investor demand for dividends for the calendar year-end $t-1$. Panel B presents the second-stage regression results where the dependent variables are as follows: $\Delta PD_{(+3,-3)}$ is the change in the probability of default in the three-years following the announcement relative to the three years prior to the announcement. $d_{\Delta i}$ is the three-year change in the default-risk factor loadings using the Fama-French (2015) five-factor model augmented with the default risk factor. *Delist* is a dummy variable that equals 1 if the company has involuntarily delisted in the three-years following the announcement and zero otherwise. The independent variable of interest is the predicted value of the dividend cut $PCUT$ obtained from the first-stage regression. The control variables mimic those of the previous baseline analysis carried out without the instrumental variables, but have not been reported for brevity. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels respectively.

	Dependent variable : $\Delta PD_{(+3,-3)}$			Dependent variable: $d_{\Delta i}$			Dependent variable: $DELIST$		
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: First-stage regressions									
State Propensity	-0.211***		-0.196***	-0.193***		-0.181***	-0.202***		-0.189***
	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)
Dividend Premium		-0.002***	-0.002***		-0.002***	-0.002***		-0.002***	-0.002***
		(0.000)	(0.000)		(0.000)	(0.001)		(0.000)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,348	1,348	1,348	1,335	1,335	1,335	1,560	1,560	1,560
F-statistics	33.70	32.55	31.54	35.45	35.52	32.90	39.52	37.32	36.63
Stock-Yogo (2005) weak ID critical values	16.38	16.38	19.93	16.38	16.38	19.93	16.38	16.38	19.93
J-stats for overidentification	-	-	2.678	-	-	0.013	-	-	0.118
			(0.101)			(0.911)			(0.731)
Panel B: Second-stage regressions									
PCUT	**0.315*** **	**0.507*** **	**0.420*** **	**0.184***	**0.147** **	**0.045***	**0.383** **	**0.280** **	**0.356** **
	(0.007)	**(0.006)**	**(0.000)**	**(0.094)**	**(0.046)**	**(0.081)**	**(0.018)**	**(0.022)**	**(0.011)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,348	1,348	1,348	1,335	1,335	1,335	1,560	1,560	1,560

Table 8: Logistic regressions of dividend resumptions and (re)-increases on dividend cuts and omission variables

This table reports results of logit regressions examining whether the magnitude of dividend cuts and omissions are associated with a lower probability to re-increase or resume a dividend payment within three years following the announcement. The dependent variable, $RECOVERY$ is a dummy variable that takes the value of one if the firm has resumed a dividend payment within three years following an omission or increased its dividend payment by 12.5% or more within three years following a dividend cut, and zero otherwise. CUT is the magnitude of the dividend cut in absolute value, which ranges between 0.125 and 1. CAR is the announcement period abnormal return in the three-days centered around the announcement of the dividend event. $LNTA$ is the natural log of the firm's total assets. $BHAR$ is the 12-month buy-and-hold abnormal returns. $RETE$ is the ratio of retained earnings to total equity. ROA is the return on assets. MB is the market-to-book ratio. LEV is the ratio of long-term debt to total assets. $CASH$ is the ratio of cash holdings to total assets. ΔTA is the fiscal-year change in total assets. $SDROA$ is the three-year standard deviation of the return on asets. AGE is the number of years since the firm appeared on CRSP. $IRISK$ and $SRISK$ are the fiscal-year idiosyncratic and systematic risk measures respectively. All variables (with the exception of CUT) are winsorized at the top and bottom 1% and measured at the year of the dividend cut/omission announcement. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels respectively.

	(1)	(2)	(3)	(4)
CUT	**-1.736*** **		**-1.642*** **	
	(0.000)		**(0.000)**	
CAR		**2.186*** **		**2.405*** **
		(0.001)		**(0.001)**
TA			-0.092**	-0.101**
			(0.042)	(0.024)
$BHAR$			0.332**	0.440***
			(0.032)	(0.004)
$RETE$			0.026	0.034
			(0.621)	(0.507)
ROA			0.130	1.718
			(0.913)	(0.140)
MB			0.024	-0.061
			(0.802)	(0.531)
LEV			0.391	0.054
			(0.382)	(0.901)
$CASH$			0.027	-0.289
			(0.968)	(0.662)
ΔTA			-0.144	-0.239
			(0.609)	(0.392)
$SDROA$			-5.277**	-5.636***
			(0.017)	(0.010)
AGE			-0.002	-0.002
			(0.575)	(0.607)
$IRISK$			-7.920	-15.322**
			(0.248)	(0.024)
$SRISK$			53.282***	49.951***
			(0.000)	(0.000)
$Constant$	0.451***	-0.619***	0.815**	0.238
	(0.002)	(0.000)	(0.012)	(0.443)
N	1,482	1,482	1,430	1,430
$Pseudo-R^2$	0.041	0.0063	0.0657	0.0431

Table A1: Logit regressions for dividend cuts and omissions

This table presents the ouput for the logit model used to estimate the propensity score and the corresponding estimate on the matched sample. $LNTA$ is the natural log of total assets. $BHAR$ is the past year's buy-and-holder returns. $RETE$ is retained earnings to total equity. ROA is return on assets. MB is the market-to-book ratio. LEV is long-term debt to total assets. $DISTRESS$ is an ordinal variable that is obtained by sorting the universe of compustat firms by their probability of default for each fiscal year, and takes values between 1 for firms in the bottom decile and 10 for firms in the top decile of the probability of default. $CASH$ is cash holdings to total assets. ΔTA is the relative change in total assets in year t relative to t-1. $SDROA$ is the past three-years standard deviation in return on assets. AGE is the firm's age in years. $IRISK$ is idiosyncratic risk. $SRISK$ is systematic risk. All variables are lagged at one year, with continuous variables winsorized at the top and bottom 1%. Year dummies and Industry dummies (based on one-digit SIC code) are included but have been suppressed to conserve space.

	(1) *Before matching*	(2) *After matching*
$LNTA$	-0.114***	0.035
	(0.000)	(0.291)
$BHAR$	-0.858***	-0.184*
	(0.000)	(0.087)
$RETE$	0.033	0.019
	(0.166)	(0.529)
ROA	-1.803***	-1.651*
	(0.000)	(0.052)
MB	-0.860***	-0.179*
	(0.000)	(0.069)
LEV	0.604***	-0.205
	(0.006)	(0.500)
$DISTRESS$	0.116***	-0.062
	(0.000)	(0.462)
$CASH$	-0.362**	0.019
	(0.026)	(0.970)
ΔTA	-0.748***	0.134
	(0.000)	(0.475)
$SDROA$	2.768	1.259
	(0.113)	(0.209)
AGE	0.009***	0.001
	(0.000)	(0.627)
$IRISK$	-2.595	0.473
	(0.418)	(0.919)
$SRISK$	-7.432	3.098
	(0.253)	(0.738)
$Constant$	-0.861**	-0.276
	(0.015)	(0.557)
N	32,074	2,524
$Pseudo-R^2$	0.1245	0.008

Table A2: Tests on common mean characteristics of treated and counterfactual firms for variables used in the logit analysis

This table reports the differences in the (lagged) matching covariates used in the propensity score matching for dividend cutting and omitting firms (Treated) and their nearest neighbours in the common support region (Controls). $DISTRESS$ is an ordinal variable that is obtained by sorting the universe of compustat firms by their probability of default for each fiscal year, and takes values between 1 for firms in the bottom decile and 10 for firms in the top decile of the probability of default. ROA is return on assets, $SDROA$ is the standard deviation of the return on assets. $LNTA$ is the natural log of total assets. ΔTA is the relative change in total assets. $RETE$ is retained earnings to total equity. LEV is long-term debt to total assets. $CASH$ is cash holdings to total assets. MB is the market-to-book value. $IRISK$ is idiosyncratic risk. $SRISK$ is systematic risk. $BHAR$ is the 12-month buy-and-hold returns. AGE is the firm's age in years. Differences is the difference in the matching covariates and %bias is the standardised bias.

Variable	Treated	Controls	Differences	%bias	T-stat	P-value
$DISTRESS$	5.291	5.385	-0.094	-2.4	-0.86	0.391
ROA	0.02	0.022	-0.002	-8.7	-1.480	0.140
$SDROA$	0.039	0.038	0.001	2.9	0.710	0.476
$LNTA$	5.697	5.571	0.126	6.6	1.840	0.066*
ΔTA	0.068	0.065	0.003	1.2	0.320	0.747
$RETE$	0.605	0.518	0.087	6.2	1.480	0.140
LEV	0.222	0.222	0.000	0.2	0.050	0.962
$CASH$	0.07	0.073	-0.003	-3.2	-0.840	0.398
MB	1.117	1.157	-0.04	-7.5	-1.500	0.134
$IRISK$	0.026	0.026	0.000	-0.1	-0.03	0.980
$SRISK$	0.008	0.007	0.001	3.5	0.980	0.325
$BHAR$	0.021	0.028	-0.007	-6.0	-1.690	0.092*
AGE	22.385	21.337	1.048	5.9	1.650	0.100
N	2,524					

Table A3: Robustness of treatment effects to past default risk

This table presents results examining whether the impact of dividend cuts and omissions on future default risk is robust to past levels of default risk. DiD_{PD} is the difference-in-differences in the probability of default between the event firm and the matched counterfactual firms. DiD_{4F} is the difference-in-differences in the loadings on the default risk factor between the event firms and the matched counterfactual firms using the Fama-French and Carhart (1997) four-factor model. DiD_{5F} is the difference-in-differences in the loadings on the default risk factor between the event firms and the matched counterfactual firms using the Fama-French (2015) five-factor model. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels respectively.

Quintile	DiD_{PD}	DiD_{4F}	DiD_{5F}
(1)	0.0113**	0.170*	0.095*
(2)	0.0283***	0.431**	0.324**
(3)	0.0432***	-0.134	-0.016
(4)	0.0893***	0.491**	0.507*
(5)	0.0439***	0.707*	0.562**

Table A4: Rosenbaum bounds and hidden-bias equivalents

This table presents the Rosenbaum bounds (2002) and hidden-bias equivalents for the outcome variables. The second column shows the Γ estimates, which are level of hidden bias required to overturn the treatment effects. The third column, Hidden-bias equivalent is the equivalent change in terms of the variables that are statistically significant in predicting the treatment, following DiPrete and Gangl (2004). The fourth column present the hidden-bias equivalent in percentage terms relative to the non-event firms. $LNTA$ is the natural log of total assets. $BHAR$ is the 12-month the Buy-and-hold abnormal returns. ROA is the return on assets. MB is the market-to-book ratio. LEV is the ratio of long-term debt to total assets. $CASH$ is the ratio of cash holdings to total assets. ΔTA is the change in total assets. All variables are measured as of the fiscal year $t-1$.

Variable	Γ	Hidden-bias equivalent	Hidden-bias equivalent relative to non-event firms (%)
Panel A - Outcome variable: DiD_{PD}			
LNTA	2.07	-4.213	-73%
BHAR	2.07	-0.150	-69%
ROA	2.07	-0.049	-70%
MB	2.07	-1.131	-72%
LEV	2.07	0.122	74%
CASH	2.07	-0.076	-72%
ΔTA	2.07	-0.097	-71%
Panel B - Outcome variable: DiD_{4F}			
LNTA	1.41	-1.990	-34%
BHAR	1.41	-0.071	-33%
ROA	1.41	-0.023	-33%
MB	1.41	-0.534	-34%
LEV	1.41	0.058	35%
CASH	1.41	-0.036	-34%
ΔTA	1.41	-0.046	-33%
Panel C - Outcome variable: DiD_{5F}			
LNTA	1.37	-1.823	-31%
BHAR	1.37	-0.065	-30%
ROA	1.37	-0.021	-30%
MB	1.37	-0.489	-31%
LEV	1.37	0.053	32%
CASH	1.37	-0.033	-31%
ΔTA	1.37	-0.042	-31%