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Corporate Tax Avoidance and Stock Price Crash Risk: Firm-Level Analysis

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ABSTRACT

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JEL Classifications: G12; G14; H26; M41

Keywords: Tax avoidance; crash risk; agency theory; governance; extreme outcome

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ABSTRACT

Using a large sample of U.S. firms for the period 1995–2008, we provide strong and robust evidence that corporate tax avoidance is positively associated with firm-specific stock price crash risk. This finding is consistent with the following view: Tax avoidance facilitates managerial rent extraction and bad news hoarding activities for extended periods by providing tools, masks, and justifications for these opportunistic behaviors. The hoarding and accumulation of bad news for extended periods lead to stock price crashes when the accumulated hidden bad news crosses a tipping point, and thus comes out all at once. Moreover, we show that the positive relation between tax avoidance and crash risk is attenuated when firms have strong external monitoring mechanisms such as high institutional ownership, high analyst coverage, and greater takeover threat from corporate control markets.

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1. Introduction

Traditional theory views tax avoidance as a value-maximizing activity that transfers wealth from the state to corporate shareholders. However, this view overlooks an important feature of modern corporations: the separation of ownership and control (Chen and Chu, 2005; Crocker and Slemrod, 2005; Slemrod, 2004). In an agency theory framework, recent research argues that tax avoidance activities can facilitate managerial opportunism, such as earnings manipulation and outright resource diversion (Chen et al., 2010; Desai and Dharmapala, 2006, 2009a). This paper explores the association between the extent of a firm's tax avoidance and its future stock price crash risk.

Our investigation is motivated by the aforementioned agency perspective of tax avoidance, as well as recent academic efforts to forecast extreme outcomes in the capital market. A wide range of incentives, such as compensation contracts, career concerns, and empire building, motivate managers to conceal adverse operating outcomes (Ball, 2009; Kothari et al., 2009). If a firm's manager withholds and accumulates negative information for an extended period, the firm's share price will be severely overvalued, thereby creating a bubble. When the accumulated negative information reaches a tipping point, it will be suddenly released to the stock market, all at once, resulting in the bubble bursting and a stock price crash (Hutton et al., 2009; Jin and Myers, 2006). More importantly, hiding negative information about a firm prevents investors and the board of directors from taking timely corrective actions or liquidating bad projects early. As a result, unprofitable projects are kept alive for too long and their poor performance accumulates over time, until an asset price crash occurs (Bleck and Liu, 2007). Consistent with these conjectures, recent research shows that the lack of information transparency increases future crash risk by enabling managers to hide and accumulate bad news (Hutton et al., 2009; Jin and Myers, 2006; Kim and Zhang, 2010).

Tax avoidance activities can create opportunities for managers to pursue activities that are designed to hide bad news and mislead investors (Desai and Dharmapala, 2006). For example, complex tax shelters, such as Enron's Project Steele, allow managers to manufacture earnings while preventing investors from understanding the sources (Desai and Dharmapala, 2009b). Perhaps more importantly, managers are able to justify the opacity of tax avoidance transactions by claiming that complexity and obfuscation are necessary to minimize the risk of tax avoidance arrangements being detected by the Internal Revenue Service (IRS). To some extent, these avoidance activities are shielded from the investigations of audit committees and external auditors. Simply put, under the ostensible objective of reducing a firm's tax obligations, managers can manipulate earnings and conceal negative firm-specific information using tax planning technologies. Moreover, complex and opaque tax avoidance transactions can also increase the latitude for other means of rent diversion and earnings manipulation. For instance, the complexity created by Tyco's tax avoidance arrangements facilitated the centralization of power by the then-CEO Dennis Kozlowski and CFO Mark Swartz, and enabled them to obscure their rent-diverting activities through means such as unauthorized compensation, abuse of corporate funds for personal purposes, and insider trading for an extended period, from 1997 to 2002 (Desai, 2005).

Building on the above arguments and evidence, we conjecture that tax avoidance activities facilitate managerial rent diversion and bad news hoarding behaviors for an extended period, which increases the probability of future stock price crashes. This conjecture is also supported by anecdotal evidence from Enron's demise, as well as from other high-profile corporate scandals such as Dynegy, Tyco, and Xerox (Desai, 2005; Desai and Dharmapala, 2006; Graham and Tucker, 2006; Slemrod, 2004).[1] For example, the final revelation of the tax shelters employed by Dynegy from September

[1] Desai (2005) and Desai and Dharmapala (2006), among others, provide excellent analyses of these cases in the context of tax sheltering and earnings manipulation.

2000 to April 2002 resulted in a loss of 97% of its market value (Desai and Dharmapala, 2006).[2] This study seeks to provide large-sample evidence on the relation between tax avoidance and crash risk.

To examine the firm-level relation between tax avoidance and future crash risk, we construct multiple measures of firm-specific crash risk and tax avoidance. Following Chen et al. (2001) and Hutton et al. (2009), we measure firm-specific crash risk using two proxies: (i) the likelihood of the occurrence of future negative, extreme firm-specific weekly returns and (ii) the negative skewness of future firm-specific weekly returns. Tax avoidance activities are proxied by (i) the estimated probability of engaging in tax shelters (*SHELTER*) based on Wilson's (2009) tax sheltering prediction model, (ii) the long-run cash effective tax rate (*LRETR*) developed by Dyreng et al. (2008), and (iii) a common factor (*BTDFACTOR*) extracted from three book-tax difference measures.[3] Higher estimated sheltering probabilities, lower long-run cash effective tax rates, and larger book-tax differences are consistent with greater levels of tax avoidance.

Hanlon and Heitzman (2009) state, "If tax avoidance represents a continuum of tax planning strategies where something like municipal bond investments are at one end, then terms such as 'noncompliance,' 'evasion,' 'aggressiveness,' and 'sheltering' would be closer to the other end of the continuum." According to this classification, our story is closer to the aggressiveness and sheltering end of the continuum. Accordingly, we argue that the *SHELTER* measure should be the most suitable measure for our research question. In contrast, the *LRETR* measure can reflect all tax planning activities, which captures the entire spectrum of tax avoidance. Nevertheless, we use this measure for two main reasons. First, a very low level of *LRETR* likely captures extreme cases of tax sheltering activities such as Enron's. As discussed in the next section, Enron paid zero tax during the four-year

[2] Basically, the tax shelters of Dynegy were able to manufacture a large magnitude of operating cash flows, which were essentially disguised loans for the firm.

[3] These three book-tax difference measures are the total book-tax difference, the ETR differential, and the Desai and Dharmapala (2006) residual book-tax difference. Please refer to Appendix C for details on the construction of the common factor.

period of 1996–1999. Second, since rent diversion is likely long run in nature and it is the hoarding of bad news for an extended period that leads to crashes, *LRETR* also should be a necessary measure for our research question. Finally, book-tax differences can be affected by many things besides tax avoidance, and thus it should be the least appropriate measure for our purpose, and we include it simply for completeness and the readers' full information.

Using a large sample of U.S. public firms for the period 1995–2008, we find that firms with higher sheltering probabilities, lower long-run cash effective tax rates, and larger book-tax differences are more likely to experience firm-specific stock price crashes in the future. For instance, we find that the marginal effects of *SHELTER, LRETR*, and *BTDFACTOR* are 3.6%, -4.1%, and 3.1%, respectively, in logistic regressions of crash occurrences in year *t* on tax avoidance measures in year *t - 1* (with the full set of control variables).[4] Moreover, we find that the tax avoidance measures can predict crash risk as far as three years into the future. These results are consistent with our conjecture that tax avoidance activities enable managers to hide and accumulate bad news within the firm, which, in turn, increases future crash risk. The association between tax avoidance and future crash risk is incrementally significant, even after controlling for Hutton et al.'s (2009) measure for accrual manipulation, Chen et al.'s (2001) investor heterogeneity, and many other determinants known to influence the occurrence of negative return outliers.

After establishing a positive relation between tax avoidance and firm-specific crash risk, we further examine whether this relation varies with the quality of external monitoring mechanisms. This additional empirical exercise is motivated by recent studies on the economic consequences of tax avoidance (Desai and Dharmapala, 2009a; Hanlon and Slemrod, 2009). These studies provide evidence suggesting that the impact of tax avoidance activities on investor welfare depends on the strength of a firm's monitoring mechanisms. Using the level of analyst coverage, institutional

[4] The unconditional probability of crash in our sample is 16.1%.

ownership, and shareholder rights as proxies for the strength of external monitoring, we find that the positive relation between tax avoidance and future crash risk is diminished for firms with stronger external monitoring. This evidence adds more credence to the agency theory explanations for the positive relation observed between tax avoidance and crash risk.

Our paper contributes to the literature in at least two ways. First, to our knowledge, this is the first study to document a significant positive relation between tax avoidance and future crash risk, which adds to the recent stream of research on the economic consequences of corporate tax avoidance. Closely related studies include Desai and Dharmapala (2009a) and Hanlon and Slemrod (2009), which provide somewhat mixed evidence on the economic implications of tax avoidance activities.[5] Specifically, Desai and Dharmapala (2009a) find no relation between abnormal book-tax difference and firm value on average, and a positive relation between the two for a subsample of firms with high institutional ownership. On the other hand, Hanlon and Slemrod (2009) find a negative market reaction to news about a firm's involvement in tax shelters, although the negative reaction is less pronounced for well-governed firms.

This paper, instead of relying on investors' current perceptions of tax avoidance activities and exploring the "mean-pricing" effects, investigates the implication of tax avoidance for future extreme returns (i.e., higher-moment effects). Extreme outcomes can have an extraordinary cumulative effect that can provide valuable insights into the true nature of a phenomenon (Taleb, 2007).[6] Therefore, we believe that our empirical evidence is unique and useful to the understanding of the underlying

[5] See Hanlon and Heitzman (2009) for a comprehensive review of the recent literature on tax avoidance.

[6] For example, when corporate insiders withhold bad news, the lack of transparency can have a negative impact on stock returns (mean effect) and an increase in return volatility (variance effect). As noted by Jin and Myers (2006), however, it is the hidden bad news accumulated over time beyond a certain level that increases the frequency of extreme negative returns, crashes, or the left skewness of return distributions (third-moment effect). One can therefore learn more about the economic implications of certain policies or behaviors by examining extreme return outcomes. Furthermore, anecdotal evidence (e.g., the recent financial crisis of 2008–2009) shows that economic actors, though rational on average, have a tendency to take corrective action only after they encounter extreme (negative) outcomes.

motivation and ultimate consequence of corporate tax avoidance activities. However, it is important to note that it is not tax avoidance per se but, rather, the rent diversion and bad news hoarding associated therewith that cause stock price crashes. For example, tax sheltering, that is, the most aggressive and complex form of tax avoidance strategies, provides self-interested managers with means, masks, and justifications to withhold bad news and/or divert corporate resources, which eventually leads to stock price crashes. Our findings reinforce the agency perspective of corporate tax avoidance (Desai and Dharmapala, 2006; Desai and Dharmapala, 2009b; Desai et al., 2007) and identify the significant cost that tax avoidance can impose on firms and their shareholders.

Second, our research extends the emerging literature of forecasting future stock price crash risk. This literature has received much attention from both the investment community and academic researchers since the recent stock market debacles of 2001–2002 and 2008–2009. This paper provides new evidence that several publicly available measures of tax avoidance have an incremental ability to predict future firm-specific crash risk, over and above other predictors identified by previous research. Recent empirical evidence from both the equity and option markets is consistent with occasional observations that extreme outcomes in the stock market significantly impact investor welfare, and that investors are greatly concerned about the probability of these extreme outcomes (Pan, 2002; Yan, 2010). Moreover, Sunder (2010) argues that, unlike the risks stemming from symmetric volatilities, the risk of (extreme) losses cannot be reduced through diversification, but only through screening.[7] In this sense, our study contributes to the literature by providing one potential screening technology. Finally, our findings lend further empirical support to the bad news hoarding theory of stock price crashes (Bleck and Liu, 2007; Jin and Myers, 2006).

[7] In his presentation, Sunder (2010) argues that understanding the differences between these two concepts of risk is one of the "six root accounting issues."

The remainder of the paper is structured as follows. Section 2 reviews the related literature and presents our central predictions. Section 3 describes our sample and research design. Sections 4 and 5 discuss the empirical results. Section 6 presents our conclusions.

2. Related Literature and Hypotheses

Hanlon and Heitzman (2009) broadly define tax avoidance as "the reduction of explicit taxes per dollar of pre-tax accounting earnings or cash flows." The literature has been holding the view that positive book-tax differences (i.e., the differences between incomes reported to the capital market and tax authorities) and low effective tax rates reflect tax avoidance behavior. Accordingly, the growing book-tax differences and declining effective tax rates for U.S. public corporations since the mid-1990s have stimulated researchers to investigate the determinants and consequences of corporate tax avoidance activities (Desai and Dharmapala, 2009b; Graham, 2003; Shackelford and Shevlin, 2001).

Generally, two alternative views underlie empirical research on tax avoidance. One is that managers undertake tax avoidance activities for the sole purpose of reducing corporate tax obligations. Thus, from the investors' perspective, tax avoidance is value enhancing, and managers should be motivated and compensated for engaging in such activities.[8] An example of this view of tax avoidance is Phillips (2003), who finds that compensating business unit managers on an after-tax basis lowers a firm's effective tax rates. Although this view also recognizes the potential costs of tax avoidance, the costs considered mainly include direct costs, such as managers' time and the potential risk of detection by tax authorities.

The other view of tax avoidance incorporates more dimensions of the agency tension between managers and investors. In addition to shirking, this so-called agency perspective of tax

[8] According to this view, the problem that needs to be solved by investors is simply managerial shirking.

avoidance also considers another form of the agency problem: managerial opportunism or resource diversion (Desai and Dharmapala, 2009b). Desai and Dharmapala (2006) argue that complex tax avoidance transactions can provide management with the tools, masks, and justifications for opportunistic managerial behaviors, such as earnings manipulations, related party transactions, and other resource-diverting activities. In other words, tax avoidance and managerial diversion can be complementary. Using a case analysis, Desai (2005) provides detailed evidence on how these opportunistic managerial behaviors can be facilitated by tax avoidance. This agency view of tax avoidance is attracting increasing attention in the literature (Hanlon and Heitzman, 2009). For example, Desai and Dharmapala (2006) show that strengthened equity incentives actually decrease tax avoidance for firms with weaker governance, consistent with the view that tax avoidance facilitates managerial diversion. Chen et al. (2010) find that family firms are less tax aggressive than their non-family counterparts. The authors conclude that family owners appear to forgo tax benefits to avoid the non-tax cost of a potential price discount arising from minority shareholders' concern about family rent seeking masked by tax avoidance activities.

The literature has also begun examining the stock market consequences of tax avoidance activities under the agency perspective. Desai and Dharmapala (2009a) find no relation between tax avoidance and firm value; however, they do find a positive relation between the two for firms with high institutional ownership. Their finding suggests that tax avoidance has a net benefit in an environment in which monitoring and control effectively constrain managerial opportunism afforded by tax avoidance activities. Hanlon and Slemrod (2009) examine the market reaction to news about a firm's involvement in tax shelters. The authors find a negative market reaction to tax shelter disclosure, suggesting that investors are concerned about the possibility that tax shelters are intertwined with managerial diversion and performance manipulation. Furthermore, the authors find that the negative reaction is less pronounced for firms with stronger governance; however, this result seems to be sensitive to how governance is empirically measured.

Our study seeks to extend the line of research that examines the consequences of tax avoidance under the agency perspective. Motivated by recent theories that the managerial tendency to conceal bad news engenders stock price crashes (Hutton et al., 2009; Jin and Myers, 2006), we investigate the relation between tax avoidance and crash risk. Kothari et al. (2009) argue that career concerns motivate managers to withhold bad news and overstate financial performance. The authors define career concerns broadly, as including the impact of disclosure on current monetary incentives such as bonus plans and stock/option-based incentives, as well as the long-horizon effects of disclosures on promotion, employment opportunities, and potential termination. In addition, Ball (2001, 2009) argues that nonfinancial motives, such as empire building and maintaining the esteem of one's peers, also provide powerful incentives for managers to conceal bad performance. Empirically, Kothari et al. (2009) find evidence consistent with the tendency of managers to hoard bad news.

The managerial tendency to withhold bad news leads to bad news being stockpiled within the firm. However, there is a certain point at which it becomes too costly or impossible for managers to withhold the bad news (Kothari et al., 2009). When such a tipping point arrives, all the hitherto hidden bad news will come out at once, resulting in a large negative price adjustment, that is, a crash (Hutton et al., 2009; Jin and Myers, 2006). Moreover, Bleck and Liu (2007) argue that the withholding of bad news prevents investors from discerning bad projects from good ones and, therefore, from liquidating bad projects promptly. Thus, bad projects are kept alive and the resulting negative cash flows eventually materialize, triggering asset price crashes. Employing country- and firm-level designs, respectively, Jin and Myers (2006) and Hutton et al.. (2009) provide empirical evidence consistent with the above mechanisms of stock price crashes.

This paper argues that tax avoidance is positively related to crash risk because it can provide masks and tools for managers to withhold bad news and overstate financial performance. This line of reasoning can appear counterintuitive, since tax avoidance requires managers to downplay income reported to tax authorities. However, the different treatments of tax planning transactions under tax and financial reporting, combined with the complexity and obfuscation of those transactions, allow managers to hide bad news from outside investors under the pretense of minimizing corporate tax obligations.

Following Desai (2005) and Desai and Dharmapala (2006), we use the Enron case to illustrate how complex structured transactions originated from tax planning can be used to manipulate financial reporting outcomes because of the book-tax nonconformity.[9] During the second half of the 1990s, Enron's management was motivated to find ways to increase reported earnings and thereby drive up the firm's stock price. The ambition to succeed in the stock market may have stemmed from the large portfolios of stocks and options held by the management and the associated incentives, or, in Ball's (2009) view, from management's desire to be celebrities. As a result of managerial aggressiveness, the reported picture of the company failed to comport with the underlying economic reality, and Enron notoriously collapsed in the end.

The Joint Committee of Taxation (JCT) report of the U.S. Congress (2003) reveals a pattern of behavior showing that Enron deliberately and aggressively engaged in transactions that had little or no business purpose to obtain favorable tax and accounting treatments:

> As Enron's management realized that tax-motivated transactions could generate financial accounting benefits, Enron looked to its tax department to devise transactions that increase financial accounting income. In effect, the tax department was converted into an Enron

[9] Information sources for the Enron case include Palepu and Healy (2003), US. Congress (2003), and Desai (2005).

> business unit, complete with annual revenue targets. The tax department, in consultation with outside experts, then designed transactions to meet or approximate the technical requirements of tax provisions with the primary purpose of manufacturing financial statement income. The slogan "Show Me the Money!" exemplified this effort. (p. 21)

From 1995 until its demise, Enron used tax-planning techniques by engaging in 12 large structured transactions for the primary purpose of achieving financial accounting benefits rather than federal income tax benefits. The design of many of these transactions permitted Enron to immediately report the financial accounting benefits of a transaction, even though the federal income tax benefits would not occur until significantly into the future. Appendix A provides a summary of the 12 structured transactions.

For example, Project Tanya allowed Enron to report a short-term capital loss of \$188.515 million on its 1995 return. It also enabled Enron to deduct a total of \$76.68 million in connection with assumed liabilities in its 1996–2000 tax returns. However, this \$188.515 million loss reported on Enron's tax return did not result in a corresponding loss for financial statement purposes. On the contrary, the tax savings associated with the loss resulted in an increase in financial statement earnings of \$65.8 million, through a reduction in the provision for income tax expenses. Enron booked \$46.5 million of these earnings in 1995 and another \$19.3 million in 1999. The JCT report provides a detailed description for Project Tanya's complicated implementation process.[10] With the help of tax shelters such as Project Tanya, Enron was able to simultaneously maintain a stream of negative taxable incomes and report an amazing growth streak in accounting earnings during the period 1996–1999. As a result, Enron's stock price soared during the same period, until it collapsed in 2001.

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[10] The transaction package involved in Project Tanya was known as the "contingent liability tax shelter."

The case of Enron offers a stylized example of how managers, by engaging in complex tax avoidance activities, manufacture earnings and conceal the true performance of a firm, which creates stock price bubbles and eventually results in stock price crashes. In addition to facilitating bad news hoarding, complex tax avoidance strategies can afford opportunities for managerial straightforward resource diversion, which can also increase stock price crash risk. Tyco is an example of how the complexity and obfuscation of tax avoidance activities provide managers with shields for outright resource diversion for an extended period of time.

In 1997, through a reverse merger with ADT, a Bermuda-based securities service firm, Tyco was able to stop paying U.S. taxes on its non-U.S. income. Tyco then shifted pre-tax profits from countries with high tax rates to its many tax haven subsidiaries, through complex techniques such as transfer pricing. As a result, Tyco was able to cut its effective tax rate from 36% in 1996 to 23% in 2001. During the same period, managerial looting of the firm emerged and accelerated over time. The various types of diversion activities include the expropriation of corporate funds for personal purposes, the abuse of loan programs, unauthorized compensation, related party transactions, and insider trading (Desai, 2005).

Desai (2005) provides a detailed and excellent discussion of how active tax management strategies helped managers diverting funds in Tyco, briefly summarized here.

(i) The complex nature of Tyco's tax avoidance strategies made its operations extremely opaque. The management took advantage of this opaqueness to hide their fund-diverting transactions.

(ii) The ability to manufacture post-tax profits through profit shifting to tax haven subsidiaries obscured true profitability and allowed Tyco's management to divert funds without damaging the reported operating performance.

(iii) The same tax haven subsidiaries that shielded Tyco's profits facilitated managerial concealment of insider trading, because of the bank secrecy policies in these jurisdictions.

The revelation of Tyco managers' extensive resource diversions during 1997–2002 caused its stock price to drop from about \$95 in early 2002 to \$14 in the middle of 2002.

This study intends to provide systematic evidence on the relation between tax avoidance and crash risk. Specifically, it tests the following hypothesis in alternative form.

H1: *All else being equal, tax avoidance is positively associated with future stock price crash risk.*

The prediction of the positive relation between tax avoidance and future crash risk is based on the agency tension between shareholders and managers, which gives rise to managerial opportunism. Thus, the impact of tax avoidance on crash risk should be mitigated for firms with better governance and monitoring. Following Desai and Dharmapala (2009a) and Hanlon and Slemrod (2009), we also examine the moderating role of external monitoring.

H2: *All else being equal, the positive association between tax avoidance and crash risk is attenuated when external monitoring is effective.*

Empirical results consistent with H2 corroborate the agency theory explanation for H1. That is, if the positive relation between tax avoidance and crash risk is not caused by managerial opportunism, we will not observe evidence consistent with H2.

3. Sample and Research Design

3.1. Sample and Data Source

The crash risk measures are constructed using the weekly return data of the Center for Research in Security Prices (CRSP) from 1995 to 2008. Specifically, for each firm-year, we assign weekly returns to the 12-month period ending three months after the firm's fiscal year-end. This definition of the sample year allows us to avoid a "look-ahead" bias by ensuring that the financial data are available to investors when forecasting crash risk. We then obtain *lagged* annual financial statement variables from Compustat. We start our sample period in 1995 (or the collection of tax information in 1994) because two regulatory events in 1993 likely affect the consistent measurement of our tax avoidance variables.[11] First, FAS 109, Accounting for Income Taxes, was enacted, which changed the accounting for income taxes. Also, the statutory corporate income tax rate increased from 34% to 35%.

We further exclude observations with non-positive book values and total assets, observations with fiscal year-end prices of less than $1, and observations with fewer than 26 weeks of stock return data. After applying this minimum data filtering, we are left with a sample of 87,162 firm–year observations for the period 1995–2008. Our crash risk measures are estimated based on this initial sample of firm-years. In our later regression analysis, the sample size varies, depending on the availability of tax avoidance measures and control variables. Table 1 presents the yearly distribution for this initial sample.

[Insert Table 1 Here]

[11] We thank the anonymous referee for suggesting this point.

3.2. Measuring Firm-Specific Crash Risk

To calculate the measures of firm-specific crash risk, we first estimate firm-specific weekly returns for each firm and year. Specifically, the firm-specific weekly return, denoted by *W*, is defined as the natural log of one plus the residual return from the expanded market model regression

$$r_{j,\tau} = \alpha_j + \beta_{1j} r_{m,\tau-2} + \beta_{2j} r_{m,\tau-1} + \beta_{3j} r_{m,\tau} + \beta_{4j} r_{m,\tau+1} + \beta_{5j} r_{m,\tau+2} + \varepsilon_{j\tau}, \tag{1}$$

where $r_{j,\tau}$ is the return on stock *j* in week τ and $r_{m,\tau}$ is the return on the CRSP value-weighted market index in week τ. We include the lead and lag terms for the market index return to allow for nonsynchronous trading (Dimson, 1979). The firm-specific weekly return for firm *j* in week τ, $W_{j,\tau}$, is measured by the natural log of one plus the residual return in Eq. (1), that is, $W_{j,\tau} = \ln(1+\varepsilon_{j.\tau})$.

We define crash weeks in a given fiscal year for a given firm as those weeks during which the firm experiences firm-specific weekly returns 3.2 standard deviations below the mean firm-specific weekly returns over the entire fiscal year, with 3.2 chosen to generate a frequency of 0.1% in the normal distribution. Following Hutton et al. (2009), our first measure of crash likelihood for each firm in each year, denoted by *CRASH*, is an indicator variable that equals one for a firm–year that experiences one or more crash weeks (as defined above) during the fiscal year period, and zero otherwise. As shown in the last column of Table 1, on average, 16.3% of firms in our sample experienced at least one crash event during a given year.[12] Although the percentage of firms with crashes does not exhibit any clear trend over time, we observe that it is highest (27.2%) in 2008, reflecting the recent financial crisis of 2008–2009.

[12] Assuming a normal distribution of firm-specific weekly returns, our definition of crash should lead us to observe about a 5% crash probability during a given year; however, we observe considerably higher probabilities of crashes than this benchmark. This is not surprising, because we do not expect the firm-specific weekly return to be normally distributed. Following Hutton et al. (2009) and others, we merely use the 0.1% cutoff of the normal distribution as a convenient way of obtaining reasonable benchmarks for extreme events.

Our second measure of crash risk is the negative conditional return skewness (*NCSKEW*) measure of Chen et al. (2001). Specifically, we calculate *NCSKEW* for a given firm in a fiscal year by taking the negative of the third moment of firm-specific weekly returns for each sample year and dividing it by the standard deviation of firm-specific weekly returns raised to the third power. Specifically, for each firm *j* in year *t*, we compute *NCSKEW* as

$$NCSKEW_{jt} = -\left[n(n-1)^{3/2}\sum W^{3}{}_{j\tau}\right] \Big/ \left[(n-1)(n-2)\left(\sum W^{2}{}_{j\tau}\right)^{3/2}\right], \tag{2}$$

3.3. Measuring Tax Avoidance

Hanlon and Heitzman (2009) recommend that researchers carefully consider the appropriateness of tax avoidance measures for the research question at hand. Our theory is related to some complicated tax avoidance transactions that are structured specifically to conceal bad news and accomplish rent diversion, or that can help managers camouflage the use of some other means of bad news hoarding and rent diversion. Thus, an ideal measure of tax avoidance for our purpose should be able to capture the most aggressive and complex tax sheltering activities. Bearing this in mind, we choose Wilson's (2009) predicted probability of engaging in tax shelters as our first main measure of tax avoidance. This measure focuses primarily on a firm's tendency of undertaking an extreme form of tax avoidance, which is likely the most suitable measure for our research question.[13] Specially, we define *SHELTER* as the predicted value from the equation

$$\begin{aligned} SHELTER = {} & -4.86 + 5.20 \times BTD + 4.08 \times |DAP| - 1.41 \times LEV + 0.76 \times AT \\ & + 3.51 \times ROE + 1.72 \times FOREIGN\ INCOME + 2.43 \times R\&D, \end{aligned} \tag{3}$$

[13] Hanlon and Heitzman (2009) argue, "Firms that can otherwise avoid taxes may not need to engage in shelters, and firms that for whatever reason cannot otherwise avoid taxes may be the ones that engage in tax shelters." Thus, the use of shelters can be endogenous. However, in this paper, our theory is more about firms that employ complex and opaque tax shelters, but not necessarily firms that avoid the most taxes; therefore this concern should be less important in our setting.

where *BTD* is the total book-tax difference; |*DAP*| is the absolute value of discretionary accruals from the performance-adjusted modified cross-sectional Jones model*;* *LEV* is long-term debt divided by total assets; *AT* is the log of total assets; *ROE* is pre-tax earnings divided by total assets; *FOREIGN INCOME* is an indicator variable set equal to one for firm-years that report foreign income, and zero otherwise; and *R&D* is research and development expenses divided by lagged total assets. According to Wilson (2009), a higher value of *SHELTER* is consistent with a greater level of tax avoidance. The Wilson model predicts the likelihood that a firm is *currently* engaging in tax sheltering activities.

Lisowsky (2010) extends Wilson's (2009) sheltering model by including more predictors. The author also estimates the coefficients of the predictors for both the original and expanded Wilson (2009) models, using confidential tax shelter and tax return data from the IRS. Unfortunately, however, we are not able to estimate the sheltering probability measure using Lisowsky's (2010) expanded model, because we do not have the tax haven information for the firms' subsidiaries, a key input in Lisowsky's model.[14] For robustness tests, we compute an alternative measure of sheltering probability, using Lisowsky's (2010) estimated coefficients for the Wilson (2009) model based on the confidential tax shelter data. Although not tabulated here, all empirical results using this alternative measure are similar to those reported in this paper.

Our ability to make inferences based on the first tax avoidance measure is, of course, limited by the extent to which the sheltering models capture the profile of tax sheltering participants. Therefore, we also employ a second measure, the long-run cash effective tax rate (*LRETR*), developed by Dyreng et al. (2008)[15]:

[14] Subsidiary tax haven information for a firm's subsidiaries needs to be manually collected from the 10-K Schedule 21, which is a nontrivial task given our large sample size.
[15] The results are qualitatively the same if we do not adjust for special items.

$$LRETR_{it} = \frac{\sum_{t=t-4}^{t} CashTaxPaid_{it}}{\sum_{t=t-4}^{t} (PretaxIncome_{it} - SpecialItems_{it})}. \quad (4)$$

According to Dyreng et al., measuring effective taxes using cash taxes paid rather than GAAP tax expenses has at least two advantages. First, cash effective tax rates take into account the tax benefits of employee stock options, whereas GAAP effective tax rates do not. Second, cash effective tax rates are not affected by changes in accounting estimates such as the valuation allowance or tax contingency reserve. In addition, measuring cash effective tax rates over long horizons achieves better matching between taxes paid and the income to which these taxes relate.

Hanlon and Heitzman (2009) argue that an additional benefit of the *LRETR* measure is that it has the potential to identify firms successful at avoiding taxes in the long run. This feature is useful for our study because rent diversion is likely long run in nature and it is the hoarding of bad news for an extended period that leads to crashes. Moreover, because we cannot identify all firms that engage in tax shelters per se, *LRETR* also is a necessary measure for our purpose. Nonetheless, we acknowledge that this measure can capture all tax planning transactions (including municipal bond investments), whereas our story is more consistent with the more aggressive end of the tax avoidance spectrum (e.g., tax sheltering).

We use a measurement period of five years to alleviate concern about potential survivorship bias associated with the use of horizons longer than five years.[16] In addition, we require at least three consecutive years of non-missing data for the *LRETR* measure. Thus, the *LRETR* sample includes three-, four-, and five-year long-term cash effective tax rates.[17] Note that a *lower LRETR* is consistent

[16] Dyreng et al. (2008) use measurement windows of one, five, and 10 years.
[17] The empirical results are all very similar if we require five years of non-missing data for the *LRETR* measure.

with *higher* tax avoidance. For example, as discussed in our case analysis, Enron paid zero tax during 1996–1999, reflecting its engagement in extremely aggressive tax avoidance activities.

Many prior studies also use a variety of book-tax difference measures for tax avoidance, where book-tax difference is defined as the difference between income reported to the capital market and that reported to the tax authorities. Mills (1998) finds that firms with large book-tax differences are more likely to have IRS audits and larger proposed audit adjustments, which can suggest that book-tax differences capture some element of tax avoidance. However, large book-tax differences can also be indicative of accrual manipulation (or a combination of tax avoidance and accrual manipulation), or be a simple reflection of differences in financial and tax accounting rules. Thus, book-tax difference measures are likely to be less appropriate for our research question. Nonetheless, we include them for completeness as well as the robustness of our results.

Instead of examining each individual book-tax difference measure, we use factor analysis to extract one common factor (*BTDFACTOR*) from the following three book-tax difference measures commonly used in the literature[18]:

(i) The total book-tax difference, which equals pre-tax book income less estimated taxable income. Wilson (2009) finds that total book-tax differences are larger for firms accused of engaging in tax shelters than for a matched sample of non-accused firms.

(ii) The ETR differential, which equals the total book-tax difference less the temporary book-tax difference. This measure is intended to pick up the permanent component of book-tax

[18] Other papers that use factor analysis to measure tax aggressiveness include Chen et al. (2010) and Lennox et al. (2010). The common factor extracted from factor analysis provides a concise measure of book-tax difference and also captures a firm's "underlying" tendency of avoiding taxes. In addition, the book-tax difference factor extracts information from multiple book-tax difference measures and therefore could be advantageous over any individual such measure. Appendix C provides more detailed descriptions of the three book-tax difference measures used in the factor analysis. The eigenvalue of this factor is 1.961, whereas the other factors have eigenvalues of less than 0.355. The correlations between the book-tax difference factor and the three variables are 0.822 (total book-tax difference), 0.027 (ETR differential), and 0.147 (Desai and Dharmapala's 2006 residual book-tax difference).

difference, even though it captures more than permanent book-tax difference (Hanlon and Heitzman, 2009). Some prior research claims that permanent differences reflect aggressive tax sheltering. However, this claim is not well supported by empirical data (Hanlon and Heitzman, 2009). We include this measure mainly because it is less likely to be affected by pre-tax accrual management.

(iii) Desai and Dharmapala's (2006) residual book-tax difference, which equals the residual from a firm fixed-effect regression of the total book-tax difference on total accruals measured using the cash flow statement method (Hribar and Collins, 2002). Since the total book-tax difference can reflect tax avoidance and accrual management, this measure intends to isolate the component of the estimated book-tax difference that is not explained by accruals or abnormal accruals. Appendixes B and C offer more detailed definitions for these measures.

Two other popular book-tax difference measures in the literature are Manzon and Plesko's (2002) book-tax differences and Frank et al.'s (2009) so-called discretionary permanent book-tax difference (DTAX). We exclude Manzon and Plesko's (2002) measure because it is based on U.S. numbers only and is not the focus of our paper. We do not use the DTAX measure because it is potentially problematic, given the lack of good structural models of book-tax differences (Hanlon and Heitzman, 2009).[19] Moreover, using a large sample of tax shelters from the IRS during the period 2000–2004, Lisowsky (2010) and Lisowsky et al. (2009) do not find a reliably positive relation between the DTAX measure and incidence of tax shelters.[20]

[19] See Hanlon and Heitzman (2009) for more detailed discussions on the problems inherent in the DTAX measure. Though not reported, we find similar results when we include the DTAX measure in constructing *BTDFACTOR*.

[20] Frank et al. (2009) find a significantly positive association between the DTAX measure and their measure of earnings management. However, in this study, we are unable to find a similar positive correlation between DTAX and our three measures of earnings management.

3.4. Research Design

To test H1, we estimate the following two regressions that link our measures of crash risk in year *t* to our proxies for tax avoidance in year *t - 1* and to a set of control variables in year *t - 1*:

$$CRASH_t = \alpha_0 + \alpha_1 TAXVAR_{t-1} + \sum_{q=2}^{m} \alpha_q (q^{th} ControlVariables_{t-1}) + \varepsilon_t, \quad (5)$$

$$NCSKEW_t = \alpha_0 + \alpha_1 TAXVAR_{t-1} + \sum_{q=2}^{m} \alpha_q (q^{th} ControlVariables_{t-1}) + \varepsilon_t, \quad (6)$$

where $CRASH_t$ is an indicator variable that equals one if a firm experiences one or more crash events in year *t*, and zero otherwise; $NCSKEW_t$ is the negative skewness of firm-specific weekly returns; and $TAXVAR_{t-1}$ is one of the three tax avoidance metrics discussed in Section 3.3, measured in year *t - 1*. Equation (5) is estimated using logistic regressions, while Eq. (6) is estimated using ordinary least squares (OLS) regressions. Hypothesis H1 predicts a positive coefficient for $SHELTER_{t-1,}$ a negative coefficient for $LRETR_{t-1}$, and a positive coefficient for$BTDFACTOR_{t-1}$.

The set of control variables includes $DTURN_{t-1}$, $NCSKEW_{t-1}$,$SIGMA_{t-1}$, RET_{t-1}, $SIZE_{t-1}$,MB_{t-1}, LEV_{t-1}, ROA_{t-1}, and $ACCM_{t-1}$,which are taken from Chen et al. (2001) and Hutton et al. (2009). The variable $DTURN_{t-1}$ is the detrended average monthly stock turnover in year *t - 1*. This is Chen et al.'s (2001) key variable of interest, a proxy for differences of opinion among investors. The authors find this detrended turnover variable to be positively related to future crash risk. The variable $NCSKEW_{t-1}$ is the negative skewness of firm-specific weekly returns in year *t - 1*. They find that firms with high return skewness in year *t - 1* are likely to have high return skewness in year *t* as well. The variable $SIGMA_{t-1}$ is the standard deviation of firm-specific weekly returns over the fiscal year period *t - 1*. More volatile stocks are more likely to experience stock price crashes in the future (Chen et al., 2001). The variable RET_{t-1} is defined as the arithmetic average of firm-specific weekly returns in year *t - 1*. The authors also document that stocks with high past returns are more likely to crash. The variable $SIZE_{t-1}$ is defined as the log of the market value of equity in year t - 1. Both Chen et al. (2001) and Hutton et al. (2009) report a positive relation between size and crash risk. The variable MB_{t-1} is the market value of equity divided by the book value of equity in year t - 1. Both groups of authors show that growth stocks are more likely to experience future price crashes. The variable LEV_{t-1} is the total long-term debt divided by total assets. The variable ROA_{t-1} is defined as income before extraordinary items divided by lagged total assets. Hutton et al. (2009) show that financial leverage and operating performance are both negatively related to crash risk.

The variable $ACCM_{t-1}$ is Hutton et al.'s (2009) measure of accrual manipulation, which is measured by a three-year moving sum of absolute discretionary accruals. This is the key variable of interest for these authors, who find a positive relation between *ACCM* and crash risk. This variable is also the most important control variable in our analysis, especially in the regressions with the book-tax difference measure as the tax avoidance proxy. This is because book-tax differences are likely to be affected by both pre-tax accrual management and tax avoidance activities. Some previous studies even employ book-tax differences as an indicator of accrual quality (Hanlon, 2005; Lev and Nissim, 2004).[21] Note, however, that accrual manipulation is also part of our story: Tax avoidance activities can facilitate accrual management, which increases crash risk. Thus, we conservatively control for *ACCM* in an effort to isolate the direct effect of tax avoidance from the indirect effect through its impact on accrual manipulation. In our later discussion of empirical results and robustness tests, we elaborate on the relations between tax avoidance, earnings management, and crash risk. Finally, year dummies are included in both Eqs. (5) and (6) to control for year fixed effects. Appendix B provides more detailed definitions for these control variables.

To test H2, we augment Eqs. (5) and (6) with external monitoring variables and their interactions with tax avoidance variables as follows:

[21] These authors use taxable income as a benchmark of "true earnings."

$$CRASH_t = \alpha_0 + \alpha_1 TAXVAR_{t-1} + \alpha_2 MON_{t-1} + \alpha_3 TAXVAR_{t-1} \times MON_{t-1} + \sum_{q=4}^{m} \alpha_q (q^{th} ControlVariables_{t-1}) + \varepsilon_t, \tag{7}$$

$$NCSKEW_t = \alpha_0 + \alpha_1 TAXVAR_{t-1} + \alpha_2 MON_{t-1} + \alpha_3 TAXVAR_{t-1} \times MON_{t-1} + \sum_{q=4}^{m} \alpha_q (q^{th} ControlVariables_{t-1}) + \varepsilon_t, \tag{8}$$

where MON_{t-1} refers to a proxy for the effectiveness of external monitoring. We consider three proxies for external monitoring mechanisms: $ANAL_{t-1}$, $INST_{t-1}$, and HIG_{t-1}. The variable $ANAL_{t-1}$ is the log of one plus the number of analysts following.[22] Previous research suggests that financial analysts play an external monitoring role. For example, Yu (2008) finds that firms with high analyst coverage engage less in opportunistic earnings management, a finding consistent with the monitoring role of analysts. The variable $INST_{t-1}$ is the level of institutional ownership. Institutional investors are more sophisticated than individual investors and act as external monitors of the firm. Desai and Dharmapala (2009a) find tax avoidance to be positively related to firm value for firms with higher institutional ownership, consistent with the view that institutional owners play an important governance role. Finally, the variable HIG_{t-1} is an indicator variable that takes on the value of one if a firm has an above-median *GINDEX*, and zero otherwise, where *GINDEX* is the number of anti-takeover provisions for a firm. More anti-takeover provisions insulate a firm's management from takeover threats from the corporate control market, indicating lower shareholder rights and thus weaker monitoring (Gompers et al., 2003). Desai and Dharmapala (2006) find that a better alignment of interest between shareholders and managers leads to less tax sheltering, but only for firms with *HIG* = 1 (weaker external monitoring).

Hypothesis H2 predicts that the positive association between tax avoidance and crash risk is attenuated for firms with strong external monitoring. Thus, H2 should translate into (i) *negative*

[22] We assign zero to analyst following if analyst following data are missing from I/B/E/S.

coefficients for *TAXVAR* × *ANAL* and *TAXVAR* × *INST* and *positive* coefficients for *TAXVAR* × *HIG,* when tax avoidance is proxied by *SHELTER (or BTDFACTOR)* and (ii) *positive* coefficients for *TAXVAR* × *ANAL* and *TAXVAR* × *INST* and *negative* coefficients for *TAXVAR* × *HIG,* when tax avoidance is measured by *LRETR.*

4. Empirical Results

4.1. Descriptive Statistics

Table 2 presents the descriptive statistics and correlations for all the variables used in the regression analyses, based on the sample of firm-years with non-missing control variables. As seen in Panel A of Table 2, the mean value of *CRASH* is 0.161, suggesting that 16.1% of firm–years experience at least one crash event.[23] The average value of *NCSKEW* is -0.079, which is much larger than that reported by Chen et al. (2001), suggesting that the sample of firm-years in our study is more crash-prone than that of Chen et al.[24] The mean and median *LRETR* are 36.5% and 30.1%, respectively. More interestingly, the 25th percentile of *LRETR* is 19.1%, suggesting that approximately one-fourth of our sample firms are able to maintain a long-run cash effective tax rate below 20%. This result is similar to that of Dyreng et al. (2008), who employ a smaller sample than ours.[25] The distributions of other variables are largely consistent with those reported in prior studies.

Panel B of Table 2 shows that the two crash risk measures (i.e., $CRASH_t$ and $NCSKEW_t$) are highly correlated, with a ratio of 0.585. In addition, the correlations between the three tax avoidance

[23] The percentage is slightly lower than the mean of the full sample, without restrictions from tax avoidance and control variables.
[24] The sample period of Chen et al. (2001) is 1962–1998.
[25] The mean and median five-year *LRETR* values in Dyreng et al. (2008) are 29.1% and 27.7%, respectively. The difference between the mean *LRETR* in our study and that in Dyreng et al.'s can be caused by different sample selection criteria. Dyreng et al. require their sample firms to have 10 consecutive years of non-missing data for #317, #16, and #170. Our study does not impose such restrictive requirements, requiring only three consecutive years of non-missing data for these items. In addition, their sample covers 1995–2004, whereas our sample period of tax variables covers 1994–2007.

proxies are as expected: *SHELTER* is negatively correlated with *LRETR* (-0.330) and positively correlated with *BTDFACTOR* (0.439), and *LRETR* is negatively correlated with *BTDFACTOR* (-0.245). More importantly, both measures of future crash risk are positively correlated with *SHELTER* and *BTDFACTO*R and negatively correlated with *LRETR*, which is consistent with our predictions that firms with high tax avoidance levels have higher future crash risk. Finally, we observe negative correlations between accrual earnings management (*ACCM*) and tax avoidance measures, which is inconsistent with the finding of Frank et al. (2009).[26] Although this result could be caused by the different empirical proxies employed, another possibility is that tax avoidance and accrual management are substitutes in inflating earnings and hiding bad news.[27] Note also that this negative correlation works against our predictions, since Hutton et al. find that *ACCM* is *positively* related to future crash risk. This is actually good news for our study, in the sense that a positive relation between tax avoidance and future crash risk, once observed, would be unlikely to be simply picking up the positive effects of *ACCM* on crash risk documented by Hutton et al. (2009).

[Insert Table 2 Here]

4.2. Portfolio Analysis

To obtain a preview of the relation between crash risk and tax avoidance and detect potential nonlinear relations, this section conducts portfolio analyses on the relation between tax avoidance and stock price crash risk. For this purpose, we first identify break points that sort our sample firms into three accrual management groups and three tax avoidance groups, based on the values of *ACCM* and one of the three tax avoidance measures in year *t - 1*. These two-way sorts result in a 3 × 3 grid of firms for each of the three tax avoidance measures. Then, for each cell of firms in each 3 × 3 grid

[26] Blaylock et al. (2010) and Lennox et al. (2010) are also unable to replicate the positive relation between tax avoidance and earnings management documented by Frank et al. (2009).

[27] Note that the negative correlation between tax avoidance and accrual management is observed for all three tax avoidance proxies.

for each tax avoidance measure, we calculate the average value of crash risk in year *t*. We condition our groupings of tax avoidance on *ACCM,* because prior research suggests that tax avoidance and accrual earnings manipulation are correlated (Frank et al., 2009) and *ACCM* is the key variable that forecasts future crash risk in Hutton et al. (2009).

Table 3 reports the results. Panel A of Table 3 shows that future crash probability increases monotonically as we move from groups with the least amount of tax avoidance to those with the most for all *ACCM* groups and for all measures of tax avoidance. This finding is consistent with our first hypothesis, that the bad news hoarding and resource diversion associated with tax avoidance activities increase future crash risk. In addition, the relation between tax avoidance and crash risk is robust to controlling for accrual earnings management, suggesting that our tax avoidance measures are not simply picking up the effect of accrual manipulation.

Panel B of Table 3 reports the results of using *NCSKEW* as the crash risk measure, which generally tells the same story as Panel A. Note also that both Panels A and B of Table 3, overall, reveal a positive relation between *ACCM* and crash risk across different tax avoidance groups, with a few exceptions, although some nonlinear relations appear in a few tax avoidance groups. This result is largely consistent with that reported by Hutton et al. (2009).

In short, our results in Table 3 reveal a positive relation between tax avoidance and crash risk, with no obvious pattern of nonlinearity between the two, which is consistent with the prediction of H1. Moreover, the results also suggest that our tax avoidance measures are picking up substantially different aspects than those captured by earnings management in their relation to future crash risk. Put differently, the positive relation observed between tax avoidance and crash risk is unlikely to be driven by the positive impact of *ACCM* on crash risk.

[Insert Table 3 Here]

4.3. Multivariate Test of H1

Hypothesis H1 predicts that tax avoidance is positively related to future stock price crash risk, because it facilitates rent diversion and bad news hoarding. Table 4 presents the multivariate regression analyses for testing H1, with the full set of control variables. To alleviate concern about potential cross-sectional and time-series dependence in the data, we report t-values (z-values) on an adjusted basis, using robust standard errors corrected for double (firm and year) clustering (Cameron et al., 2009; Gow et al., 2010; Petersen, 2009).[28,29]

Panel A of Table 4 presents the coefficient estimates for Eq. (5), using logistic regressions with $CRASH_t$ as the dependent variable. In Panel A, each of the three columns presents the regression results with each of three proxies for tax avoidance as our test variable. As shown in column 1, when *SHELTER*, that is, the predicted probability of tax sheltering computed using the Wilson (2009) model, is used as our test variable, the coefficient of *SHELTER* is highly significant with an expected positive sign (0.270 with t = 4.59). This significantly positive relation between the probability of engaging in complex tax shelters and future crash risk is consistent with H1, suggesting that complex tax shelters provide self-interested managers with opportunities, means, and masks to conceal negative information or divert company resources for extended periods, which in turn leads to an increase in future crash risk.

In column 2 of Panel A of Table 4, where *LRETR* is used as a proxy for tax avoidance, the coefficient of *LRETR* is highly significant with an expected negative sign (-0.305 with t = -4.58), which is also consistent with H1. This finding suggests that firms with lower long-run effective cash tax rates have higher future crash risk. In other words, the likelihood of future stock price crashes is

[28] The double-clustering programs for logistic models are obtained from Mitchell A. Petersen's website: http://www.kellogg.northwestern.edu/faculty/petersen/htm/papers/se/se_programming.htm.See Cameron et al. (2009) for detailed procedures.

[29] We also include year fixed effects in the regressions. Even though we use market-adjusted (firm-specific) returns to construct the crash risk measures, it still seems necessary to control for year fixed effects. Table 1 shows that the *firm-specific* crash risks are significantly higher in 2001 and 2008 than in other periods.

significantly higher for firms with the ability to pay a low amount of cash taxes per dollar of pre-tax earnings over an extended period. The above result raises an alarm to the investment community about using effective tax rates to gauge a firm's operating efficiency. Under the guise of lowering corporate taxes and saving money for investors, managers could in fact engage in opportunistic behaviors such as concealing bad operating performance to minimize attention and scrutiny from outside investors or to maximize private gains. These personal gains can take the form of receiving undeserved bonuses, retaining their current positions and reputations, and even hiding direct asset diversion or stealing. Of course, outside investors eventually bear the costs associated with such managerial opportunism when the stock price crashes.

Column 3 of Panel A of Table 4 presents the results of the logistic regression with *BTDFACTOR* as our proxy for tax avoidance. As shown, we find that the coefficient of *BTDFACTOR* is significantly positive (0.233 with t = 3.59), which is in line with H1. Since the results in column 3 are similar to those reported in columns 1 and 2, for brevity, we do not repeat our interpretation here.

To assess the economic significance of the results, we estimate the marginal effect of each tax avoidance variable on crash risk, which is the expected increase in the probability of a crash as a function of the given tax avoidance variable, holding all other variables at their sample mean. The marginal effect is 3.6% for *SHELTER*, -4.1% for *LRETR*, and 3.1% for *BTDFACTOR*.[30] Given that the unconditional probability of a crash in our sample is 16.1%, these results suggest that the association between tax avoidance and crash risk is economically significant as well.

The coefficients of the control variables are generally consistent with the findings of prior studies. First, consistent with Chen et al. (2001), we find that the coefficient of *DTURN* is significantly positive, suggesting that differences of opinion among investors increase future crash

[30] By comparison, the marginal effects of *ACCM* are 3.7%, 4.4%, and 4.2%, respectively, in the models with *SHELTER*, *LRETR,* and *BTDFACTOR* as the dependent variable.

risk. We also find that past negative return skewness, past return, firm size, and market-to-book ratio are all positively related to crash risk, consistent with the findings of Chen et al. (2001). Second, consistent with Hutton et al. (2009), we find negative coefficients for both *LEV* and *ROA*. Finally, the coefficient of *ACCM* is significantly positive, suggesting that firms with more accrual manipulation as proxied by a three-year moving sum of absolute discretionary accruals are more likely to crash in the future.

[Insert Table 4 Here]

To obtain a clearer picture on the relation between tax avoidance and crash risk, Figure 1 presents the predicted crash probabilities that are computed using the mean values of *SHELTER* (*LRETR, BTDFACTOR*) for each of the *SHELTER* (*LRETR, BTDFACTOR*) decile portfolios, with all other control variables set to their sample means. In so doing, we use the estimated coefficients reported in Panel A of Table 4. As illustrated in Panel A of Figure 1, the predicted crash risk in year *t* increases monotonically as we move from the lowest *SHELTER* decile to the highest, suggesting a positive and linear relation between tax avoidance and future crash risk. The crash likelihood of firms in the lowest *SHELTER* decile is about 4.5% higher than for firms in the highest *SHELTER* decile. Given that the unconditional crash likelihood in our sample is 16.1%, this is a meaningful difference that accounts for about 28% variation in crash risk. Panels B and C of Figure 1 present the predicted crash risk for the *LRETR* and *BTDFACTOR* decile portfolios, respectively. Again, we see that the relations of the predicted crash likelihood with these two proxies for tax avoidance are monotonically increasing, and that the relations are economically significant.

Panel B of Table 4 reports the results of OLS regressions for Eq. (6), where *NCSKEW* is used as the dependent variable. As shown, firm-specific negative return skewness in year *t* is negatively related to *LRETR* in year *t - 1* and positively related to *SHELTER* and *BTDFACTOR* in year *t - 1*, which is in line with the results reported in Panel A of Table 4. These findings lend further support to hypothesis H1, indicating that firms with lower cash effective tax rates, a higher likelihood of using tax shelters, and larger book–tax differences are more crash prone in that their firm-specific return distributions are more negatively skewed.

Overall, the results in Table 4 strongly support our hypothesis H1, that tax avoidance activities are positively associated with future crash risk. These results are robust to the use of three alternative proxies for tax avoidance and two alternative measures of crash risk. Furthermore, our results hold even after controlling for the accrual manipulation measure of Hutton et al. (2009), the investor heterogeneity of Chen et al. (2001), and other potential determinants of crash risk.

[Insert Figure 1 Here]

4.4. Test of H2

If the positive relation between tax avoidance and future crash risk is due to tax avoidance facilitating opportunistic managerial behaviors, such as bad news hoarding and resource diversion, one can expect the strength of the relation to be attenuated for firms with effective external monitoring, as hypothesized in H2. To test H2, we estimate Eqs. (7) and (8), in which our tax avoidance proxies are interacted with our proxies for external monitoring. Table 5 presents the estimated results, using analyst coverage and institutional shareholding as the proxies for the efficacy of external monitoring.

Panel A of Table 5 presents the logistic regression results with *CRASH* as the dependent variable. As noted by Ai and Norton (2003), the estimated coefficients of the interaction terms in a logit regression can be biased when estimated using routine estimation methods. To address this concern, we estimate the coefficients and z-statistics of the interaction terms by applying the methodology of Norton et al. (2004).[31] As shown in column 1 of Panel A of Table 5, when tax avoidance is proxied by *SHELTER*, the coefficient of the main effect variable (*TAXVAR* = *SHELTER*)

[31] The STATA command (inteff.ado) is available at http://www.unc.edu/~enorton. Note that the coefficients generated by the *inteff* command represent *marginal* effects of the interaction terms.

is significantly positive, which is consistent with H1. We find that the coefficients of the interaction terms, that is, *ANAL* × *SHELTER* and *INST* × *SHELTER*, are both significant and negative, which is consistent with H2, that the positive association between tax avoidance and crash risk is less pronounced for firms with stronger external monitoring.

As reported in columns 2 and 3 of Table 5, when tax avoidance is proxied by *LRETR* and *BTDFACTOR*, respectively, the coefficients of the main effect variables (*TAXVAR* = *BTDFACTOR or SHELTER*) are highly significant with an expected sign in both cases, which is again consistent with H1. The coefficients of both interaction terms, that is, *ANAL* × *TAXVAR* and *INST* × *TAXVAR*, are significant with an expected negative sign in all cases, except that *INST* × *BTDFACTOR* is not significant. The above results are, overall, consistent with H2.

Panel B of Table 5 presents the regression results when crash risk is proxied by *NCSKEW*. We find that all the coefficients of both the main effect terms and the interaction effect terms are highly significant with expected signs in all cases, except that only in one out of six cases is the coefficient of the interaction term (*INST* ×*BTDFACTOR*) insignificant.

In short, the results reported in Panels A and B of Table 5 lend strong support to H2, especially when tax avoidance is proxied by our two main measures, that is, *SHELTER* and *LRETR*. These results suggest that the positive association between tax avoidance and crash risk is attenuated when external monitoring is effective, which could be viewed as evidence corroborating the agency theory explanation for the association.

[Insert Table 5 Here]

In Table 6, using a smaller sample of firms with available shareholder rights data, we examine the role of shareholder rights in moderating the relation between tax avoidance and crash risk. As shown in both Panels A and B of Table 6, we find that the coefficients of the main effect terms are highly significant with expected signs across all six cases, which further corroborates the prediction of H1. We find, however, that only three out of six specifications load significant coefficients for the interactions between shareholder rights and tax avoidance, that is, *HIG* × *TAXVAR*, with expected signs, suggesting that the moderating role of shareholder rights in determining the relation between tax avoidance and crash risk is less pronounced than that played by analyst coverage and institutional shareholding.

In short, the results presented in both Tables 5 and 6, taken together, are consistent with the agency theory explanation for tax avoidance advocated by Desai and Dharmapala (2006). Our results are also in line with the empirical results of Desai and Dharmapala (2009a) and Hanlon and Slemrod (2009), in the sense that the impact of tax avoidance on investor welfare depends on the efficacy of governance or external monitoring.

[Insert Table 6 Here]

5. Additional Tests and Robustness Checks

5.1. Tax Avoidance, Earnings Management, and Crash Risk

One reason tax avoidance is positively related to crash risk is that it can help managers conceal negative information for an extended period.[32] The role of tax avoidance in bad news hoarding can take at least two forms. First, tax avoidance activities themselves, for example, via transactions with special-purpose vehicles or related party transactions, can manufacture (unsustainable or fake) earnings or operating cash flows that offset adverse operating performance, as in the case of Enron, Dynegy, and others. In this sense, tax avoidance is similar in spirit to earnings

[32] Note that tax avoidance can also be related to crash risk by facilitating managers' engagement in more direct resource diversion activities (e.g., direct theft), as discussed in Sections 1 and 2, although bad news hoarding is also a type of rent diversion in a broader sense.

manipulations through restructuring real activities, as discussed in Roychowdhury (2006), even though tax avoidance transactions can be more opaque than real earnings management activities such as overproduction. Second, complex tax sheltering arrangements can decrease corporate transparency and provide managers with masks for earnings manipulation via discretionary accrual choices. For example, in the case of Tyco, the complexity of the firm's operations (achieved by tax avoidance strategies) prevented investors from detecting accrual earnings manipulation.

In our main tests, we explicitly control for earnings manipulation to examine the direct effect of tax avoidance on bad news hoarding (and thus crash risk) beyond and above its indirect effect through facilitating accrual manipulation. In other words, we want to examine whether the bad news hoarding and resource diversion associated with complicated tax avoidance arrangements can incrementally increase crash risk, holding the firm's earnings management level constant. However, the challenge is that we cannot perfectly control for earnings manipulation because of the potential limitations inherent in the available empirical measures of earnings manipulation. This section tries to at least partially address this issue by using two alternative measures of earnings management (in addition to Hutton et al.'s (2009) measure denoted by *ACCM*). Specially, we use Dechow and Dichev's (2002) accrual quality measure and Dechow et al.'s (2010) *F-SCORE* to control for the effect of earnings manipulation on crash risk.

As shown in columns 1 to 4 of Table 7, the coefficients of our test variables (*TAXVAR*) are highly significant with expected signs, indicating that our main results are robust to the inclusion of various proxies for earnings manipulation. The results for earnings management are generally consistent with those of Hutton et al. (2009). For example, we find that firms with greater accrual manipulation (higher *ACCM*), lower accrual quality (lower *DD_AQ*), and higher tendencies to manipulate earnings (higher *F-SCORE*) are more crash prone. In column 5 of Table 7, we regress crash risk on one of three proxies for tax avoidance without controlling for earnings manipulation. In doing so, we want to capture the total effect (both direct and indirect) of tax avoidance, as discussed above. Again, we observe no significant changes in the coefficients of the tax avoidance variables.

Overall, the results in Table 7 suggest that the "indirect" effect of tax avoidance on bad news hoarding (and, in turn, crash risk) through earnings management may not be the dominating force that drives our main empirical results. This is not surprising, because we cannot replicate Frank et al.'s (2009) finding on the positive association between tax avoidance and financial reporting aggressiveness using our sample and empirical measures. Also, we are aware of at least two other studies that show no significant positive relation between tax avoidance and earnings manipulation (Blaylock et al., 2010; Lennox et al., 2010). Thus, we argue that the relation between tax avoidance and earnings management is far from obvious and warrants further investigation. Finally, the results in this subsection also help to differentiate our study from that of Hutton et al. (2009), which shows a significant positive relation between earnings management and crash risk. Overall, our results in Table 7 suggest that tax shelters can help managers conceal bad news, even if earnings manipulation is absent.[33]

[Insert Table 7 Here]

5.2. Longer Forecast Windows

In our logit and OLS regressions thus far, we examine the predictive ability of our tax avoidance proxies with respect to future crash risk. In measuring crash risk, we consider future crash occurrences in the one-year-ahead forecast window. This section further examines how far out the three tax avoidance proxies can predict future crash risk. For this purpose, we now expand the measurement interval of future crash risk into two- and three-year-ahead windows. Specifically, we estimate *CRASH* and *NCSKEW* using firm-specific weekly returns during the two- and three-year

[33] Note that this interpretation can be problematic because of the imperfect measures of earnings management.

periods, starting three months after the current fiscal year-end. In so doing, we require at least 100 and 150 weekly returns for each firm for the two- and three-year window tests, respectively. Using these longer-interval crash risk measures as our dependent variable, we re-estimate all the regressions in Table 4 and report the new results in Table 8.

Panel A of Table 8 displays the regression results of forecasting future crash risk in the two-year-ahead window. As shown, all three proxies of tax avoidance are significantly and positively related to the longer-interval crash risk measured for the two-year-ahead window, except that the relation between *BTDFACTOR* and *CRASH* is positive but insignificant. As shown in Panel B of Table 8, when future crash risk is measured using the three-year-ahead window, we find that the predictive abilities of both *SHELTER* and *LRETR* remain highly significant, although that of *BTDFACTOR* becomes insignificant. These results hold, irrespective of whether future crash risk is measured by *CRASH* or *NCSKEW*. In short, the results presented in Table 8 lend further support to the predictive ability of our tax avoidance proxies with respect to future crash risk up to three years ahead.[34]

[Insert Table 8 Here]

5.3. Hazard Model Tests

Jin and Myers (2006) suggest that past crash history affects future crash likelihood. For instance, they argue that the likelihood of another crash immediately after a crash is zero. Kim and Zhang (2010) point out that a proportional hazard model approach is more appropriate in examining the determinants of crash risk, because it naturally controls for the past history of crashes. Following their suggestion, we test the robustness of our main results using the Cox proportional hazard model.

[34] A limitation of longer forecast window tests is that they can suffer from the survivorship bias. For example, those firms that crashed in the first year could be dropped from CRSP (delisted) during the second or third year, and thus excluded from the two or three-year window samples. However, it is not clear how this effect can bias for or against our finding of a significant positive relation between crash risk and tax avoidance (although it can reduce the power of tests).

Untabulated results from the hazard model approach are generally consistent with the logistic regression results, except that the coefficient of the book-tax difference proxy is not always significant, although it carries an expected positive sign.[35] It should be pointed out, however, that estimation of the hazard model necessarily leads to a substantial reduction in sample size, because it requires that only firms that experienced at least one crash event be included in the sample. In short, the use of the hazard model has an advantage in incorporating past crash history into the crash prediction, while it can reduce the power of our statistical tests because non-crash firms are excluded from the sample.

5.4. Firm Fixed Effects Regressions

Since the empirical literature on forecasting crash risk is relatively new, it is possible that our analysis omits from the regressions some crash determinants that are correlated with other included variables. To mitigate potential problems that can arise from correlated omitted variables, we re-estimate the logit model in Table 4 using a conditional logistic regression technique that allows us to control for firm fixed effects (Allison, 2005). Table 9 presents the results of this exercise. As shown in Table 9, the relation between tax avoidance and future crash risk remains highly significant with an expected negative (positive) sign in column 2 (columns 1 and 3), suggesting that our results reported in Table 4 are unlikely to be driven by omitted correlated time-invariant variables.

[Insert Table 9 Here]

5.5. Alternative Measures of Crash Risk

As another proxy for future crash risk, Chen et al. (2001) use the "down-to-up volatility" measure (*DUVOL*), which captures asymmetric volatilities between negative and positive firm-specific weekly returns. We re-estimate all the regressions reported in Table 4, using *DUVOL* as the

[35] The estimated results of the Cox proportional hazard model are available upon request.

dependent variable. Though not tabulated for brevity, the results using this alternate measure are qualitatively similar to those reported in Table 4.

6. Conclusions

This study documents strong evidence that tax avoidance is positively associated with the future crash risk of firm-specific returns. Our results are robust to the use of three alternative proxies for tax avoidance: a measure of the probability of tax sheltering, a long-run cash effective tax rate measure, and a common factor extracted from three book-tax difference measures. The results are also robust to the use of alternative measures of future crash risk and a variety of sensitivity checks.

Our results are, overall, consistent with the agency perspective on tax avoidance: Tax avoidance activities facilitate managerial opportunistic behavior (Desai and Dharmapala 2006). Specifically, complex tax shelters create tools and masks for managers to manufacture earnings and conceal negative operating outcomes for an extended period. Accordingly, negative information and bad performance are likely to stockpile within the firm, until an asset price crash occurs when a threshold is crossed. To the best of our knowledge, our paper is the first systematic study to identify an adverse consequence of corporate tax avoidance activities in the context of stock price crashes. Moreover, we find that the relation between tax avoidance and crash risk is less pronounced for firms with effective external monitoring, a finding consistent with the agency perspective of tax avoidance.

Our results are also consistent with the bad news hoarding theory of stock price crashes, as developed by Jin and Myers (2006) and Bleck and Liu (2007). In view of the recent stock market debacle, academic researchers, regulators, and the investment community have paid increasing attention to the causes and consequences of extreme negative return outcomes or crashes. Given the scarcity of systematic evidence on these issues, our study can be seen as a joint test that aggressive and complex tax avoidance strategies facilitate managerial rent diversion and bad news hoarding, and that rent diversion and bad news hoarding increase future crash risk. Admittedly, however, the evidence on our maintained assumption that tax avoidance facilitates bad news hoarding is largely anecdotal (e.g., in the cases of Enron and Dynegy). We therefore recommend further research on the association between tax avoidance and bad news hoarding.[36]

In the context of the crash risk literature, our study is distinguished from a related study by Hutton et al. (2009) in the following ways. First, Hutton et al. (2009) focus on accrual-based earnings management as an important cause of stock price crashes. It is well known, however, that accruals reverse over time, and thus it is unlikely that managers can conceal negative information for an extended period by relying only on discretionary accrual choices. In contrast, we argue that complex tax shelters and tax planning tools allow managers to manufacture earnings via restructuring real transactions, which provides a powerful means for hiding unfavorable information for an extended period. Second, accrual manipulation cannot create operating cash flows. Boosting earnings without increasing operating cash flows will attract investors' suspicions about the quality of the firm's earnings. In fact, this was a particular concern faced by Dynegy and many other energy companies in 2000 (Desai and Dharmapala, 2006). To mitigate this disconnect between earnings and cash flows, Dynegy turned to a tax sheltering arrangement, which created $300 million in operating cash flows for fiscal year 2001. In this sense, tax sheltering can be viewed as a more effective vehicle for concealing unfavorable information from outside stakeholders. Third, tax shelters can provide shields that can facilitate accrual management: Without the masks provided by tax shelters, accrual management could be more easily detected.

[36] If one is convinced by prior research that crashes are caused by bad news hoarding, our empirical tests can then be seen as a test of the relation between tax avoidance and bad news hoarding. Note that Kothari et al. (2009) infer bad news hoarding from large negative market reactions to voluntary disclosures. However, we argue that our method may be better in detecting bad news hoarding, since not all hoarded bad news is released during a firm's voluntary disclosure.

One potential empirical challenge of our study is that our measures of tax avoidance may be simply picking up the effect of earnings management. This concern is more relevant for book-tax difference measures. We mitigate this concern by using multiple proxies for tax avoidance, especially our two main measures besides book-tax differences. In addition, we explicitly control for earnings manipulation and show that the predictive power of tax avoidance with respect to crash risk is incrementally significant beyond and above that of earnings management.

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Appendix A. Benefits of Enron's Structured Transactions, 1995–2001
(Millions of Dollars)

Project Name	Financial Accounting Income through 2001	Total Projected Financial Accounting Income	Federal Tax Savings through 2001	Total Projected Federal Tax Savings
Tanya (1995)	66	66	66	66
Valor (1996)	–	82	82	82
Steele (1997)	65	83	39	78
Teresa (1997)	226	257	-76	263
Cochise (1998)	101	143	–	141
Apache (1998)	51	167	51	167
Tomas (1998)	37	113	95	109
Renegade (1998)	1	1	0	0
Condor (1999)	88	328	0	332
Valhalla (2000)	16	64	0	0
Tammy I (2000)	–	406	0	414
Tammy II (2001)	–	369	0	370
Totals	**651**	**2,079**	**257**	**2,022**

This table partly reproduces Table 1 of the JCT report (U.S. Congress, 2003, p. 107). It summarizes certain tax and accounting information regarding 12 of Enron's structured transactions. Federal tax savings are computed using a 35% tax rate.

Appendix B. Variable Definitions

Dependent Variables: Crash Risk Measures

CRASH is an indicator variable that takes the value one for a firm–year that experiences one or more firm-specific weekly returns falling 3.2 standard deviations below the mean firm-specific weekly returns over the fiscal year, with 3.2 chosen to generate frequencies of 0.1% in the normal distribution during the fiscal year period, and zero otherwise.

The firm-specific weekly return (W) is equal to ln(1 + residual), where the residual is from the following expanded market model regression:

$$r_{j,\tau} = \alpha_j + \beta_{1j} r_{m,\tau-2} + \beta_{2j} r_{m,\tau-1} + \beta_{3j} r_{m,\tau} + \beta_{4j} r_{m,\tau+1} + \beta_{5j} r_{m,\tau+2} + \varepsilon_{j\tau} .$$

NCSKEW is the negative skewness of firm-specific weekly returns over the fiscal year period.

Measures of Tax Avoidance

SHELTER is the firm's estimated sheltering probability, based on Wilson's (2009) tax sheltering model: *SHELTER* = -4.86 + 5.20 × *BTD* + 4.08 × |*DAP*| - 1.41 × *LEV* + 0.76 × *AT* + 3.51 × *ROE* + 1.72 × *FOREIGN INCOME* + 2.43 × *R&D*, where *BTD* is defined in Appendix C; |*DAP*| is the absolute value of discretionary accruals from the performance-adjusted modified cross-sectional Jones model*; LEV* is long-term debt (#9) divided by total assets (#6); *AT* is the log of total assets (#6); *ROE* is pre-tax earnings (#170) divided by total assets; *FOREIGN INCOME* is an indicator variable set equal to one for firm observations reporting foreign income (#273), and zero otherwise; and *R&D* is R&D expense (#46) divided by lagged total assets.

LRETR is the long-run cash effective tax rate, computed as the sum of income tax paid (#317) over the previous five years divided by the sum of a firm's pre-tax income (#170) less special items (#17). We winsorize the values at zero and one.

BTDFACTOR is a common factor extracted from three different book-tax difference measures: *BTD*, *ETR Differential*, and *DD_BTD*. These individual measures are defined in Appendix C.

Control Variables

DTURN is the average monthly share turnover over the current fiscal year period minus the average monthly share turnover over the previous fiscal year period, where monthly share turnover is calculated as the monthly trading volume divided by the total number of shares outstanding during the month.

SIGMA is the standard deviation of firm-specific weekly returns over the fiscal year period.

RET is the mean of firm-specific weekly returns over the fiscal year period, times 100.

SIZE is the log of the market value of equity.

MB is the market value of equity divided by the book value of equity.

LEV is total long-term debts divided by total assets.

ROA is income before extraordinary items divided by lagged total assets.

ACCM is the prior three years' moving sum of the absolute value of discretionary accruals, where discretionary accruals are estimated from the modified Jones model (denoted *OPAQUE* in Hutton et al., 2009). See Appendix D for more details.

INST is the percentage of shares held by institutional owners, obtained from the Thomson 13F database.

ANAL is the log of 1 + (number of estimates), where the number of estimates is the number of analysts following from I/B/E/S.

HIG is an indicator variable that takes the value of one if the governance index of Gompers et al. (2003) is greater than the sample median, and zero otherwise.

DD_AQ is Dechow and Dichev's (2002) accrual quality measure. See Appendix D for more details.

F-SCORE is Dechow et al.'s (2010) measure of the likelihood of accounting misstatements. See Appendix D for more details.

Appendix C. Construction of *BTDFACTOR*

The *BTDFACTOR* is extracted using factor analysis from the following three book–tax difference measures.

BTD	The total book-tax difference, which equals book income less taxable income scaled by lagged assets (#6). Book income is pre-tax income (#170) in year *t*. Taxable income is calculated by summing the current federal tax expense (#63) and current foreign tax expense (#64) and dividing by the statutory tax rate (*STR*) and then subtracting the change in NOL carryforwards (#52) in year *t*. If current the federal tax expense is missing, the total current tax expense is calculated by subtracting deferred taxes (#50), state income taxes (#173), and other income taxes (#211) from the total income taxes (#16) in year *t.*
ETR Differential	The ETR differential based on Frank et al. (2009), which equals *(BI - ((CFTE + CFOR)/STR)) – (DTE / STR),* scaled by lagged assets (#6); *BI* is pre-tax book income (#170); *CFTE* is the current federal tax expense (#63); and *CFOR* is the current foreign tax expense (#64).
DD_BTD	The Desai–Dharmapala (2006) residual book-tax difference, which equals the residual from the following firm fixed effects regression: $BT_{i,t} = \beta_1 TA_{i,t} + \mu_i + \varepsilon_{i,t}$, where *BT* is the total book-tax difference and *TA* is total accruals measured using the cash flow method of Hribar and Collins (2002). Both variables are scaled by lagged total assets and are winsorized at the 1% and 99% levels for regression purposes.

The table below presents the summary statistics on the three individual tax aggressive measures by ranking firm-years into deciles of the *BTDACTOR*.

BTDFACTOR (Decile)	*BTD*	*ETR Differential*	*DD_BTD*
-1.978	-0.998	-0.882	-0.690
-0.177	-0.161	-0.191	-0.067
0.050	-0.050	-0.066	-0.016
0.123	-0.017	-0.030	0.010
0.155	-0.002	-0.015	0.025
0.179	0.006	-0.012	0.046
0.207	0.018	-0.005	0.063
0.244	0.034	-0.005	0.085
0.315	0.064	-0.006	0.124
0.883	0.318	-0.134	0.419

Appendix D. Procedures for Estimating *ACCM, DD_AQ,* and *F-SCORE*

1. ACCM

Following Hutton et al. (2009), we employ the modified Jones model (Dechow et al., 1995) to estimate discretionary accruals. Specifically, we first estimate the following cross-sectional regressions for each Fama and French 48-industry for each fiscal year from 1991 to 2008:

$$\frac{TACC_{jt}}{TA_{jt-1}} = \alpha \frac{1}{TA_{jt-1}} + \beta_1 \frac{\Delta SALE_{jt}}{TA_{jt-1}} + \beta_2 \frac{PPE_{jt}}{TA_{jt-1}} + \varepsilon_{jt}, \qquad \text{D-(1)}$$

where TA_{jt-1} is the total assets for firm *j* at the beginning of year *t*; $TACC_{jt}$ is total accruals from firm *j* during year *t*, which is calculated as income before extraordinary items minus cash flow from operating activities adjusted for extraordinary items and discontinued operations; $\Delta SALE_{jt}$ is the change in sales for firm *j* in year *t*, and PPE_{jt} is property, plant, and equipment for firm *j* at the end of year *t*.

The estimated coefficients from Eq. D-(1) are then used to compute discretionary accruals ($DISACC_{jt}$):

$$DISACC_{jt} = \frac{TACC_{jt}}{TA_{jt-1}} - \hat{\alpha} \frac{1}{TA_{jt-1}} - \hat{\beta}_1 \frac{\Delta SALE_{jt} - \Delta REC_{jt}}{TA_{jt-1}} + \hat{\beta}_2 \frac{PPE_{jt}}{TA_{jt-1}}, \qquad \text{D-(2)}$$

where ΔREC_{jt} is the change in accounts receivable and $\hat{\alpha}$, $\hat{\beta}_1$, and $\hat{\beta}_2$ are the estimated coefficients from Eq. D-(1). The variable $ACCM_{t-1}$ (denoted by *OPAQUE* in Hutton et al., 2009) is the moving sum of the absolute value of discretionary accruals over the last three years (years *t* - 1, *t* - 2, and *t* - 3).

2. DD_AQ

Following Dechow and Dichev (2002), we first estimate the following cross-sectional regressions for each industry with at least 20 observations in a given year based on the Fama and French 48-industry classification:

$$ACC_{jt} = \alpha_0 + \alpha_1 \frac{CFO_{jt-1}}{TA_{jt}} + \alpha_1 \frac{CFO_{jt}}{TA_{jt}} + \alpha_1 \frac{CFO_{jt+1}}{TA_{jt}} + \varepsilon_{jt}, \qquad \text{D-(3)}$$

where *ACC* is total accruals scaled by total assets and *CFO* is operating cash flow scaled by total assets.

Then *DD_AQ* is computed as the standard deviation of the firm-level residuals from the Dechow and Dichev model during the previous five years and multiplied by negative one.

3. F-SCORE

We first calculate the predicted value for model 1 of Panel A of Table 7 in Dechow et al. (2010):

$$\begin{aligned} P_{jt} &= (-7.893) + 0.790 \times RSST\_ACC_{jt} + 2.518 \times \Delta REC_{jt} + 1.191 \times \Delta INV_{jt} + 1.979 \times SOFT_{jt} \\ &+ 0.171 \times \Delta CSALE_{jt} + (-0.932) \times \Delta ROA_{jt} + 1.029 \times ISSUE_{jt}, \end{aligned} \qquad \text{D-(4)}$$

where $RSST\_ACC_{jt}$ is Richardson et al.'s (2005) measure of accruals for firm j in year t, which is the sum of the change in non-cash working capital, the change in net non-current operating assets, and the change in net financial assets, scaled by average total assets; ΔREC_{jt} is the change in receivables for firm j in year t, scaled by average total assets; ΔINV_{jt} is the change in inventory for firm j in year t, scaled by average total assets; $SOFT_{jt}$ is total assets minus property, plant, and equipment and cash for firm j in year t, scaled by total assets; $\Delta CSALE_{jt}$ is the percentage change in cash sales for firm j in year t; ΔROA_{jt} is the change in return on assets for firm j in year t; and $ISSUE_{jt}$ is an indicator variable that takes the value of one if the firm has issued new debt or equity during the year, and zero otherwise.

The probability of misstatement is then calculated as

$$\Pr_{jt} = e^{p_{jt}} \Big/ (1+e^{p_{jt}}) \; ,$$

Finally,

F-SCORE = Pr /0.0037.

Table 1. Sample distribution and descriptive statistics for stock price crashes.

This table presents the yearly distribution of observations and the descriptive statistics for annual stock price crashes. The sample period is from 1995 to 2008. Stock price crash is defined in Appendix B.

Fiscal Year	Number of Firms	Number of Firms with Stock Price Crash	Percentage of Firms with Stock Price Crash
1995	6,698	864	0.129
1996	6,942	847	0.122
1997	7,405	948	0.128
1998	7,436	1,331	0.179
1999	6,888	895	0.130
2000	6,746	1,012	0.150
2001	6,498	1,443	0.222
2002	6,091	993	0.163
2003	5,709	788	0.138
2004	5,553	944	0.170
2005	5,503	980	0.178
2006	5,414	812	0.150
2007	5,228	941	0.180
2008	5,051	1,374	0.272
Total	87,162	14,171	0.163

Table 2. Descriptive statistics and correlations.

This table presents descriptive statistics and correlations for stock price crash risk, corporate tax avoidance, and control variables. The sample contains firm–years from 1995 to 2008 with non-missing values for all the control variables. The *p*-values are reported under the correlation coefficients in Panel B. Variables are defined in Appendix B.

Panel A: Descriptive Statistics

Variable	N	Mean	Std	5%	25%	Median	75%	95%
Crash Risk Measures								
$CRASH_t$	48,245	0.161	0.368	0	0	0	0	1
$NCSKEW_t$	48,245	-0.079	0.739	-2.242	-0.485	-0.077	0.319	1.178
Tax Avoidance Measures								
$SHELTER_{t-1}$	43,339	0.476	0.294	0.001	0.213	0.473	0.733	0.932
$LRETR_{t-1}$	38,370	0.365	0.283	0.000	0.191	0.301	0.407	1.000
$BTDFACTOR_{t-1}$	43,172	0.163	0.298	-1.257	0.122	0.185	0.254	0.503
Control Variables								
$DTURN_{t-1}$	48,245	0.006	0.074	-0.207	-0.018	0.002	0.026	0.145
$NCSKEW_{t-1}$	48,245	-0.096	0.713	-2.105	-0.499	-0.102	0.285	1.127
$SIGMA_{t-1}$	48,245	0.060	0.030	0.017	0.038	0.054	0.077	0.122
RET_{t-1}	48,245	-0.223	0.225	-1.070	-0.290	-0.144	-0.071	-0.027
$SIZE_{t-1}$	48,245	5.547	2.061	0.114	4.119	5.562	7.003	9.008
MB_{t-1}	48,245	2.761	2.469	0.425	1.277	1.977	3.258	7.829
LEV_{t-1}	48,245	0.202	0.182	0.000	0.026	0.174	0.331	0.542
ROA_{t-1}	48,245	0.019	0.135	-0.540	-0.004	0.038	0.084	0.185
$ACCM_{t-1}$	48,245	0.210	0.173	0.014	0.094	0.162	0.270	0.554
$ANAL_{t-1}$	48,214	1.217	1.041	0.000	0.000	1.099	2.079	2.944
$INST_{t-1}$	48,191	0.436	0.289	0.000	0.176	0.422	0.675	0.920
$GINDEX_{t-1}$	14,580	9.102	2.735	4.000	7.000	9.000	11.000	14.000

Panel B: Correlations

		A	B	C	D	E	F	G	H	I	J	K	L	M	N
$CRASH_{t}$	A	1.000													
$NCSKEW_{t}$	B	0.585	1.000												
		(0.000)													
$SHELTER_{t-1}$	C	0.059	0.203	1.000											
		(0.000)	(0.000)												
$LRETR_{t-1}$	D	-0.033	-0.099	-0.330	1.000										
		(0.000)	(0.000)	(0.000)											
$BTDFACTOR_{t-1}$	E	0.028	0.057	0.439	-0.245	1.000									
		(0.000)	(0.000)	(0.000)	(0.000)										
$DTURN_{t-1}$	F	0.024	0.062	0.111	-0.044	0.028	1.000								
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)									
$NCSKEW_{t-1}$	G	0.034	0.075	0.171	-0.083	0.035	0.028	1.000							
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)								
$SIGMA_{t-1}$	H	-0.015	-0.085	-0.414	0.288	-0.193	0.099	-0.047	1.000						
		(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)							
RET_{t-1}	I	0.023	0.090	0.378	-0.288	0.197	-0.105	0.080	-0.968	1.000					
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)						
$SIZE_{t-1}$	J	0.044	0.180	0.761	-0.253	0.194	0.047	0.181	-0.438	0.411	1.000				
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
MB_{t-1}	K	0.029	0.069	0.077	0.006	-0.093	0.138	0.003	0.130	-0.128	-0.073	1.000			
		(0.000)	(0.000)	(0.000)	(0.211)	(0.000)	(0.000)	(0.460)	(0.000)	(0.000)	(0.000)				
LEV_{t-1}	L	-0.006	-0.004	0.011	-0.049	0.044	0.013	0.007	-0.125	0.113	0.256	-0.061	1.000		
		(0.203)	(0.335)	(0.019)	(0.000)	(0.000)	(0.003)	(0.121)	(0.000)	(0.000)	(0.000)	(0.000)			
ROA_{t-1}	M	0.000	0.055	0.331	-0.286	0.337	0.046	0.032	-0.311	0.314	0.322	-0.004	0.009	1.000	
		(0.935)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.392)	(0.038)		
$ACCM_{t-1}$	N	0.003	-0.048	-0.208	0.207	-0.153	-0.026	-0.046	0.405	-0.374	-0.315	0.173	-0.115	-0.180	1.000
		(0.483)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Table 3. Portfolio analysis of stock price crash risk.

This table presents the average stock price crash risk in various portfolios sorted by corporate tax avoidance and accrual manipulation. The sample contains firm–years from 1995 to 2008 with non-missing values for all the control variables in the price crash models. Variables are defined in Appendix B.

Panel A: *CRASH*

	ACCM		
Tax Avoidance	1 (Lowest)	2	3 (Highest)
SHELTER			
1 (Least Aggressive)	0.138	0.132	0.130
2	0.161	0.160	0.183
3 (Most Aggressive)	0.159	0.173	0.191
LRETR			
1 (Most Aggressive)	0.166	0.167	0.180
2	0.153	0.160	0.191
3 (Least Aggressive)	0.152	0.144	0.144
BTDFACTOR			
1 (Least Aggressive)	0.158	0.143	0.151
2	0.150	0.155	0.169
3 (Most Aggressive)	0.163	0.167	0.171

Panel B: *NCSKEW*

	ACCM		
Tax Avoidance	1 (Lowest)	2	3 (Highest)
SHELTER			
1 (Least Aggressive)	-0.346	-0.354	-0.322
2	-0.059	-0.063	-0.040
3 (Most Aggressive)	0.043	0.101	0.080
LRETR			
1 (Most Aggressive)	-0.020	-0.024	-0.036
2	-0.028	-0.039	-0.028
3 (Least Aggressive)	-0.105	-0.162	-0.194
BTDFACTOR			
1 (Least Aggressive)	-0.092	-0.142	-0.165
2	-0.060	-0.092	-0.109
3 (Most Aggressive)	-0.016	-0.028	-0.079

Table 4. The impact of tax avoidance on stock price crash risk (H1).

This table presents the results of the impact of corporate tax aggressiveness on stock price crash risk. The sample contains firm–year observations from 1995 to 2008 with non-missing values for all the control variables. The *z*-values (*t*-values) reported in parentheses in Panel A (Panel B) are based on standard errors clustered by both firm and time. Year fixed effects are included in all regressions. Here *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Variables are defined in Appendix B.

Panel A. Logistic Regression of *CRASH* on Tax Avoidance:

$$CRASH_t = \alpha_0 + \alpha_1 TAXVAR_{t-1} + \sum_{q=2}^{m} \alpha_q (q^{th} ControlVariables_{t-1}) + \varepsilon_t$$

Tax Avoidance	(1)	(2)	(3)
SHELTER $_{t-1}$	0.270***		
	(4.59)		
LRETR $_{t-1}$		-0.305***	
		(-4.58)	
BTDFACTOR $_{t-1}$			0.233***
			(3.59)
Control Variables			
DTURN $_{t-1}$	0.550*	0.515*	0.542**
	(1.91)	(1.67)	(1.99)
NCSKEW $_{t-1}$	0.049**	0.056**	0.053**
	(2.03)	(2.08)	(2.19)
SIGMA $_{t-1}$	11.958**	12.327*	10.722*
	(1.98)	(1.82)	(1.77)
RET $_{t-1}$	1.855**	1.913**	1.724**
	(2.32)	(2.09)	(2.15)
SIZE $_{t-1}$	0.033**	0.045**	0.060***
	(2.50)	(2.55)	(3.67)
MB $_{t-1}$	0.026***	0.045***	0.033***
	(3.04)	(3.77)	(3.83)
LEV $_{t-1}$	-0.150	-0.226*	-0.227*
	(-1.16)	(-1.94)	(-1.73)
ROA $_{t-1}$	-0.219*	-0.737***	-0.330***
	(-1.71)	(-3.05)	(-2.63)
ACCM $_{t-1}$	0.279***	0.327***	0.317***
	(3.44)	(3.32)	(3.66)
Intercept	-2.641***	-2.487***	-2.662***
	(-11.72)	(-10.52)	(-11.72)
Year Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	No	No	No
No. of Observations	43,339	38,370	43,172
Pseudo-R^2	0.020	0.021	0.020

Panel B. OLS Regression of *NCSKEW* on Tax Avoidance:

$$NCSKEW_t = \alpha_0 + \alpha_1 TAXVAR_{t-1} + \sum_{q=2}^{m} \alpha_q (q^{th} ControlVariables_{t-1}) + \varepsilon_t$$

Tax Avoidance	(1)	(2)	(3)
SHELTER $_{t-1}$	0.253***		
	(10.53)		
LRETR $_{t-1}$		-0.148***	
		(-7.60)	
BTDFACTOR $_{t-1}$			0.070***
			(3.60)
Control Variables			
DTURN $_{t-1}$	0.330***	0.334***	0.379***
	(5.05)	(4.38)	(6.07)
NCSKEW $_{t-1}$	0.024***	0.026***	0.028***
	(4.20)	(3.91)	(4.73)
SIGMA $_{t-1}$	4.399***	3.686***	3.274**
	(3.34)	(2.66)	(2.44)
RET $_{t-1}$	0.633***	0.568***	0.526***
	(4.16)	(3.42)	(3.39)
SIZE $_{t-1}$	0.035***	0.059***	0.062***
	(7.88)	(8.84)	(9.91)
MB $_{t-1}$	0.018***	0.026***	0.023***
	(6.94)	(7.79)	(8.36)
LEV $_{t-1}$	-0.102***	-0.163***	-0.174***
	(-3.66)	(-5.59)	(-6.13)
ROA $_{t-1}$	-0.030	-0.134*	-0.040
	(-0.63)	(-1.91)	(-0.80)
ACCM $_{t-1}$	0.001	0.062***	0.031
	(0.07)	(2.71)	(1.55)
Intercept	-0.659***	-0.593***	-0.659***
	(-9.79)	(-7.81)	(-9.20)
Year Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	No	No	No
No. of Observations	43,339	38,370	43,172
Adjusted R^2	0.074	0.072	0.072

Table 5. Tax avoidance on stock price crash risk: The effects of external monitoring (H2).

This table presents the results of the effects of institutional monitoring and analyst coverage on the association between corporate tax avoidance and stock price crash risk. The sample contains firm–years from 1995 to 2008 with non-missing values for all the control variables. The *z*-values (*t*-values) reported in parentheses in Panel A (Panel B) are based on standard errors clustered by both firm and time. In Panel A, for the interaction terms in the logistic model, the coefficients and the z-statistics are calculated according to Norton et al. (2004). Year fixed effects are included. Here *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Variables are defined in Appendix B.

Panel A. Logistic Regression of *CRASH* on Tax Avoidance

Tax Avoidance Measure	*SHELTER*	*LRETR*	*BTDFACTOR*
$TAXVAR_{t-1}$	1.261***	-1.044***	0.609***
	(8.16)	(-7.61)	(6.89)
$ANAL_{t-1}$	0.304***	-0.032	0.093***
	(3.95)	(-1.07)	(4.29)
$ANAL_{t-1} \times TAXVAR_{t-1}$	-0.052***	0.020**	-0.038***
	(-6.25)	(2.21)	(-4.53)
$INST_{t-1}$	0.777***	0.045	0.331*
	(4.67)	(0.26)	(1.85)
$INST_{t-1} \times TAXVAR_{t-1}$	-0.116***	0.107***	0.040
	(-3.66)	(3.06)	(1.43)
Control Variables:			
$DTURN_{t-1}$	0.530*	0.429	0.507*
	(1.66)	(1.23)	(1.64)
$NCSKEW_{t-1}$	0.051*	0.061*	0.061**
	(1.77)	(1.87)	(2.22)
$SIGMA_{t-1}$	15.456**	18.091**	16.567**
	(2.38)	(2.42)	(2.41)
RET_{t-1}	2.588***	2.969***	2.797***
	(2.98)	(2.95)	(3.08)
$SIZE_{t-1}$	0.045***	0.024	0.037**
	(2.88)	(1.15)	(2.34)
MB_{t-1}	0.034***	0.051***	0.034***
	(3.23)	(3.84)	(3.86)
LEV_{t-1}	-0.225	-0.245**	-0.232*
	(-1.54)	(-2.12)	(-1.74)
ROA_{t-1}	-0.317**	-1.014***	-0.450***
	(-2.08)	(-3.20)	(-2.87)
$ACCM_{t-1}$	0.414***	0.451***	0.439***
	(4.49)	(4.13)	(4.63)
Intercept	-3.480***	-2.502***	-3.005***
	(-11.42)	(-11.21)	(-11.21)
Year Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	No	No	No
No. of Observations	42,934	38,098	42,865
Pseudo-R^2	0.038	0.033	0.032

Panel B. OLS Regression of *NCSKEW* on Tax Avoidance

Tax Avoidance Measure	*SHELTER*	*LRETR*	*BTDFACTOR*
$TAXVAR_{t-1}$	0.416***	-0.271***	0.095***
	(11.44)	(-12.00)	(5.16)
$ANAL_{t-1}$	0.131***	0.043***	0.072***
	(6.96)	(5.07)	(7.43)
$ANAL_{t-1} \times TAXVAR_{t-1}$	-0.135***	0.041***	-0.051***
	(-6.01)	(3.03)	(-3.93)
$INST_{t-1}$	0.242***	0.075*	0.167***
	(4.81)	(1.94)	(4.71)
$INST_{t-1} \times TAXVAR_{t-1}$	-0.212**	0.261***	0.071
	(-2.46)	(3.79)	(1.36)
Control Variables			
$DTURN_{t-1}$	0.331***	0.327***	0.370***
	(5.42)	(4.18)	(5.67)
$NCSKEW_{t-1}$	0.011*	0.015**	0.017***
	(1.95)	(2.21)	(3.03)
$SIGMA_{t-1}$	2.183*	2.043*	1.828
	(1.88)	(1.66)	(1.49)
RET_{t-1}	0.363***	0.368**	0.357**
	(2.65)	(2.41)	(2.51)
$SIZE_{t-1}$	0.014***	0.023***	0.023***
	(3.84)	(4.72)	(6.28)
MB_{t-1}	0.014***	0.021***	0.016***
	(5.83)	(6.62)	(6.94)
LEV_{t-1}	-0.053**	-0.093***	-0.091***
	(-2.16)	(-3.61)	(-3.67)
ROA_{t-1}	0.038	-0.112	0.022
	(0.81)	(-1.56)	(0.44)
$ACCM_{t-1}$	0.010	0.064***	0.036*
	(0.48)	(2.63)	(1.71)
Intercept	-0.665***	-0.444***	-0.572***
	(-11.38)	(-6.48)	(-8.94)
Year Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	No	No	No
No. of Observations	42,830	37,887	42,622
Adjusted R^2	0.099	0.093	0.094

Table 6. Tax avoidance on stock price crash risk: The effect of takeover threat (H2).

This table presents the results of the effects of internal corporate governance (inversely measured by anti-takeover provisions) on the association between corporate tax aggressiveness and stock price crash risk. The sample contains firm–years from 1995 to 2008 with non-missing values for all the control variables. The variable *HIG* is a dummy that equals 1 if *GINDEX* is above the median, and 0 otherwise. The *z*-values (*t*-values) reported in parentheses in Panel A (Panel B) are based on standard errors clustered by both firm and time. In Panel A, for the interaction terms, the coefficients and the z-statistics are calculated according to Norton et al. (2004). Year fixed effects are included. Here *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Variables are defined in Appendix B.

Panel A. Logistic Regression of *CRASH* on Tax Avoidance			
Tax Avoidance Measure	*SHELTER*	*LRETR*	*BTDFACTOR*
$TAXVAR_{t-1}$	2.265***	-1.599***	1.199***
	(3.96)	(-4.21)	(2.61)
HIG_{t-1}	0.168	0.164**	-0.039
	(0.97)	(2.24)	(-0.42)
$HIG_{t-1} \times TAXVAR_{t-1}$	-0.014	-0.066**	0.041
	(-0.34)	(-1.93)	(1.12)
$ANAL_{t-1}$	0.250*	-0.213***	0.002
	(1.89)	(-4.55)	(0.06)
$ANAL_{t-1} \times TAXVAR_{t-1}$	-0.064***	0.063***	-0.043***
	(-3.77)	(3.96)	(-2.74)
$INST_{t-1}$	2.015***	0.423*	0.802***
	(4.22)	(1.73)	(2.93)
$INST_{t-1} \times TAXVAR_{t-1}$	-0.207**	0.059	-0.046
	(-2.28)	(0.63)	(-0.50)
Control Variables			
$DTURN_{t-1}$	0.088	0.206	0.111
	(0.19)	(0.41)	(0.24)
$NCSKEW_{t-1}$	0.111***	0.127***	0.123***
	(4.07)	(5.17)	(4.29)
$SIGMA_{t-1}$	33.776***	36.458***	34.163***
	(6.59)	(6.57)	(6.84)
RET_{t-1}	5.225***	5.812***	5.291***
	(6.57)	(6.77)	(7.01)
$SIZE_{t-1}$	0.052	0.038	0.061**
	(1.24)	(1.23)	(2.04)
MB_{t-1}	0.033**	0.044***	0.034**
	(2.30)	(2.81)	(2.23)
LEV_{t-1}	-0.556**	-0.587**	-0.510*
	(-2.19)	(-2.30)	(-1.95)
ROA_{t-1}	-1.639***	-2.074***	-1.667***
	(-4.09)	(-4.53)	(-4.07)
$ACCM_{t-1}$	-0.059	-0.079	-0.069
	(-0.24)	(-0.30)	(-0.29)
Intercept	-4.905***	-2.893***	-3.732***
	(-8.78)	(-11.07)	(-12.04)
Year Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	No	No	No
No. of Observations	14,412	13,840	14,406
Pseudo-R^2	0.039	0.042	0.037

Panel B. OLS Regression of *NCSKEW* on Tax Avoidance

Tax Avoidance Measure	*SHELTER*	*LRETR*	*BTDFACTOR*
$TAXVAR_{t-1}$	0.408***	-0.122**	0.307***
	(5.19)	(-2.09)	(2.89)
HIG_{t-1}	-0.077**	0.060***	-0.023
	(-2.23)	(2.83)	(-0.99)
$HIG_{t-1} \times TAXVAR_{t-1}$	0.111***	-0.192***	0.108
	(2.94)	(-4.21)	(1.14)
$ANAL_{t-1}$	0.105***	0.010	0.057***
	(4.05)	(1.10)	(5.58)
$ANAL_{t-1} \times TAXVAR_{t-1}$	-0.108***	0.071***	-0.097***
	(-3.18)	(5.78)	(-3.40)
$INST_{t-1}$	0.332***	0.133***	0.189***
	(3.43)	(3.53)	(2.97)
$INST_{t-1} \times TAXVAR_{t-1}$	-0.296***	-0.006	-0.195
	(-2.67)	(-0.06)	(-1.11)
Control Variables			
$DTURN_{t-1}$	0.082	0.118	0.111
	(1.02)	(1.27)	(1.36)
$NCSKEW_{t-1}$	0.015**	0.018***	0.019***
	(2.09)	(3.02)	(2.75)
$SIGMA_{t-1}$	3.396***	3.503***	2.774**
	(3.67)	(3.01)	(2.53)
RET_{t-1}	0.605***	0.643***	0.544***
	(4.88)	(3.68)	(3.79)
$SIZE_{t-1}$	0.014*	0.017***	0.018***
	(1.67)	(2.92)	(3.34)
MB_{t-1}	0.012***	0.015***	0.013***
	(3.03)	(3.90)	(3.29)
LEV_{t-1}	-0.075**	-0.075*	-0.077**
	(-2.42)	(-1.83)	(-2.01)
ROA_{t-1}	-0.130	-0.210***	-0.125
	(-1.53)	(-2.61)	(-1.46)
$ACCM_{t-1}$	0.077	0.102	0.077
	(1.21)	(1.53)	(1.22)
Intercept	-0.724***	-0.443***	-0.561***
	(-7.50)	(-6.02)	(-8.86)
Year Fixed Effects	Yes	Yes	Yes
Firm Fixed Effects	No	No	No
No. of Observations	14,309	13,743	14,293
Adjusted R^2	0.059	0.059	0.059

Table 7. Tax avoidance, earnings management, and stock price crash risk.

This table presents the results of the impact of corporate tax avoidance and earnings management on stock price crash risk. The sample contains firm–years from 1995 to 2008 with non-missing values for all the control variables. The *z*-values (*t*-values) reported in parentheses in Panel A (Panel B) are based on standard errors clustered by both firm and time. The same set of control variables as in Table 4 is included, but their coefficients are not reported for conciseness. Here *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Variables are defined in Appendix B.

Panel A. Logistic Regression of *CRASH*					
Model	(1)	(3)	(3)	(4)	(5)
		SHELTER			
$TAXVAR_{t-1}$	0.270***	0.301***	0.316***	0.311***	0.231***
	(4.59)	(4.60)	(4.24)	(4.24)	(3.23)
Earnings Management					
$ACCM_{t-1}$	0.279***			0.170	
	(3.44)			(1.39)	
DD_AQ_{t-1}		-0.308**		-0.439**	
		(-2.06)		(-1.97)	
$F\text{-}SCORE_{t-1}$			0.002	0.002	
			(1.06)	(1.44)	
No. of Observations	43,339	40,227	36,169	33,349	45,263
Pseudo-R^2	0.020	0.020	0.020	0.021	0.019
		LRETR			
$TAXVAR_{t-1}$	-0.305***	-0.327***	-0.291***	-0.299***	-0.324***
	(-4.58)	(-4.65)	(-3.69)	(-3.48)	(-4.94)
Earnings Management					
$ACCM_{t-1}$	0.327***			0.213	
	(3.32)			(1.41)	
DD_AQ_{t-1}		-0.429**		-0.532**	
		(-2.04)		(-2.09)	
$F\text{-}SCORE_{t-1}$			0.002	0.005*	
			(0.89)	(1.74)	
No. of Observations	38,370	37,189	31,806	29,420	40,919
Pseudo-R^2	0.021	0.022	0.020	0.021	0.021
		BTDFACTOR			
$TAXVAR_{t-1}$	0.233***	0.256***	0.236***	0.234***	0.250***
	(3.59)	(4.50)	(3.81)	(3.41)	(4.24)
Earnings Management					
$ACCM_{t-1}$	0.317***			0.238*	
	(3.66)			(1.83)	
DD_AQ_{t-1}		-0.320**		-0.390*	
		(-2.29)		(-1.80)	
$F\text{-}SCORE_{t-1}$			0.002	0.003**	
			(1.58)	(2.33)	
No. of Observations	43,172	41,812	36,217	33,209	47,242
Pseudo-R^2	0.020	0.021	0.020	0.021	0.020
Control Variables	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	No	No	No	No

Panel B. OLS Regression of *NCSKEW*					
Model	(1)	(3)	(3)	(4)	(5)
			SHELTER		
TAXVAR $_{t-1}$	0.253***	0.255***	0.257***	0.273***	0.245***
	(10.53)	(11.00)	(10.60)	(10.69)	(10.57)
Earnings Management					
ACCM $_{t-1}$	0.001			-0.052*	
	(0.07)			(-1.87)	
DD_AQ $_{t-1}$		-0.043		-0.179**	
		(-0.70)		(-2.25)	
F-SCORE $_{t-1}$			0.001**	0.001*	
			(2.00)	(1.73)	
No. of Observations	43,339	40,227	36,169	33,349	45,263
Adjusted R^2	0.074	0.075	0.078	0.078	0.073
			LRETR		
TAXVAR $_{t-1}$	-0.148***	-0.174***	-0.139***	-0.153***	-0.165***
	(-7.60)	(-9.04)	(-7.09)	(-7.61)	(-8.90)
Earnings Management					
ACCM $_{t-1}$	0.062***			0.003	
	(2.71)			(0.12)	
DD_AQ $_{t-1}$		-0.196***		-0.289***	
		(-3.23)		(-3.22)	
F-SCORE $_{t-1}$			0.001*	0.003**	
			(1.74)	(2.32)	
No. of Observations	38,370	37,189	31,806	29,420	40,919
Adjusted R^2	0.072	0.073	0.076	0.077	0.071
			BTDFACTOR		
TAXVAR $_{t-1}$	0.070***	0.076***	0.070***	0.067***	0.076***
	(3.60)	(3.98)	(3.63)	(3.26)	(4.24)
Earnings Management					
ACCM $_{t-1}$	0.031			-0.009	
	(1.55)			(-0.29)	
DD_AQ $_{t-1}$		-0.033		-0.162**	
		(-0.60)		(-2.03)	
F-SCORE $_{t-1}$			0.001***	0.001**	
			(2.62)	(2.10)	
No. of Observations	43,172	41,812	36,217	33,209	47,241
Adjusted R^2	0.072	0.072	0.075	0.075	0.070
Control Variables	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	No	No	No	No

Table 8. Impact of tax avoidance on stock price crash risk: Longer forecasting windows.

This table presents the results of the impact of corporate tax avoidance on stock price crash risk during the next two-year and three-year window. The sample contains firm–years from 1995 to 2008 with non-missing values for all the control variables. The *z*-values (*t*-values) reported in parentheses in Panel A (Panel B) are based on standard errors clustered by both firm and time. Year fixed effects are included. Here *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Variables are defined in Appendix B.

Panel A: Two-Year Window

Dependent Variable:	**CRASH** $_{[t, t+1]}$			**NCSKEW** $_{[t, t+1]}$		
Tax Avoidance						
$SHELTER_{t-1}$	0.166*			0.356***		
	(1.69)			(10.40)		
$LRETR_{t-1}$		-0.263***			-0.158***	
		(-4.18)			(-5.33)	
$BTDFACTOR_{t-1}$			0.060			0.033*
			(1.18)			(1.94)
Control Variables						
$DTURN_{t-1}$	0.472**	0.389*	0.492**	0.327***	0.307***	0.406***
	(2.06)	(1.65)	(2.18)	(2.95)	(2.70)	(3.53)
$NCSKEW_{t-1}$	0.024	0.024	0.027	0.028***	0.028***	0.034***
	(1.33)	(1.21)	(1.55)	(3.41)	(2.93)	(3.96)
$SIGMA_{t-1}$	13.874***	15.955***	13.278***	7.864***	7.032***	6.529***
	(4.07)	(4.40)	(4.00)	(7.63)	(5.96)	(6.35)
RET_{t-1}	1.924***	2.217***	1.873***	0.949***	0.869***	0.833***
	(4.31)	(4.48)	(4.21)	(6.93)	(5.34)	(6.21)
$SIZE_{t-1}$	0.038**	0.045**	0.055***	0.049***	0.088***	0.088***
	(2.56)	(2.56)	(3.43)	(10.37)	(15.60)	(16.75)
MB_{t-1}	0.034***	0.043***	0.037***	0.027***	0.036***	0.033***
	(4.68)	(4.90)	(4.92)	(8.13)	(9.27)	(9.84)
LEV_{t-1}	-0.194**	-0.217**	-0.238***	-0.070*	-0.137***	-0.166***
	(-1.99)	(-2.29)	(-2.60)	(-1.82)	(-3.82)	(-4.63)
ROA_{t-1}	0.113	-0.008	0.096	0.056	0.125	0.091
	(0.82)	(-0.04)	(0.70)	(0.75)	(1.42)	(1.22)
$ACCM_{t-1}$	0.164**	0.222**	0.199***	0.026	0.127***	0.075***
	(2.27)	(2.14)	(2.58)	(0.84)	(4.28)	(2.60)
Intercept	-1.691***	-1.620***	-1.701***	-0.971***	-0.953***	-0.979***
	(-11.39)	(-10.01)	(-11.52)	(-21.32)	(-17.59)	(-21.06)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	No	No	No	No	No	No
No. of Observations	37,886	33,585	37,751	37,886	33,585	37,751
Pseudo-/Adjusted R^2	0.019	0.021	0.019	0.084	0.083	0.079

Panel B: Three-Year Window

Dependent Variable:		CRASH $_{[t, t+2]}$			NCSKEW $_{[t, t+2]}$	
Tax Avoidance						
SHELTER $_{t-1}$	0.146*			0.371***		
	(1.85)			(8.99)		
LRETR $_{t-1}$		-0.168**				
		(-2.32)			-0.165***	
BTDFACTOR $_{t-1}$			0.025		(-5.49)	0.020
			(0.49)			(1.19)
Control Variables						
DTURN $_{t-1}$	0.557***	0.530*	0.570***	0.302***	0.277**	0.387***
	(2.79)	(1.88)	(2.87)	(2.96)	(2.56)	(3.64)
NCSKEW $_{t-1}$	0.055**	0.047**	0.058***	0.044***	0.040***	0.049***
	(2.56)	(1.98)	(2.78)	(5.11)	(3.54)	(5.55)
SIGMA $_{t-1}$	13.775***	16.342***	13.275***	8.402***	7.760***	7.129***
	(4.16)	(4.42)	(4.03)	(11.90)	(9.39)	(10.46)
RET $_{t-1}$	1.810***	2.137***	1.767***	1.030***	0.959***	0.924***
	(4.55)	(4.81)	(4.47)	(10.57)	(8.61)	(9.91)
SIZE $_{t-1}$	0.050***	0.063***	0.065***	0.058***	0.100***	0.098***
	(3.37)	(4.03)	(4.68)	(9.52)	(16.01)	(16.47)
MB $_{t-1}$	0.030***	0.034***	0.034***	0.030***	0.037***	0.036***
	(3.73)	(3.65)	(4.41)	(8.23)	(9.28)	(10.26)
LEV $_{t-1}$	-0.151	-0.227**	-0.186**	-0.034	-0.104**	-0.137***
	(-1.61)	(-2.38)	(-2.09)	(-0.71)	(-2.30)	(-3.09)
ROA $_{t-1}$	0.249*	0.330**	0.265*	0.134*	0.289***	0.185***
	(1.71)	(1.97)	(1.74)	(1.92)	(3.34)	(2.80)
ACCM $_{t-1}$	0.042	0.105	0.053	-0.006	0.082**	0.042
	(0.47)	(1.01)	(0.58)	(-0.15)	(2.38)	(1.05)
Intercept	-1.055***	-1.089***	-1.059***	-1.019***	-1.028***	-1.030***
	(-8.91)	(-8.12)	(-8.95)	(-22.86)	(-19.02)	(-22.15)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	No	No	No	No	No	No
No. of Observations	30,467	27,098	30,368	30,467	27,098	30,368
Pseudo-/Adjusted R^2	0.017	0.018	0.017	0.106	0.107	0.101

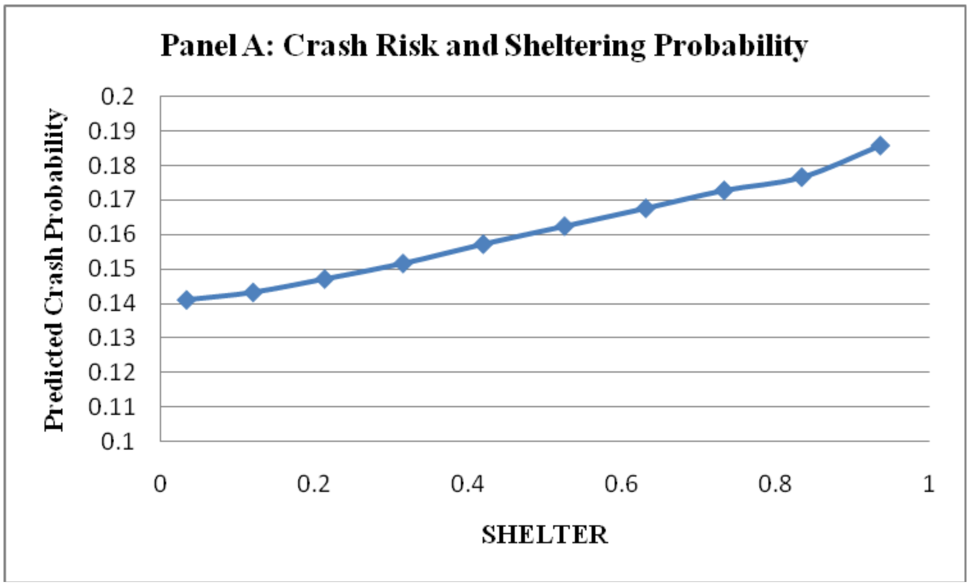
Table 9. Impact of tax avoidance on stock price crash risk: Controlling for firm fixed effect.

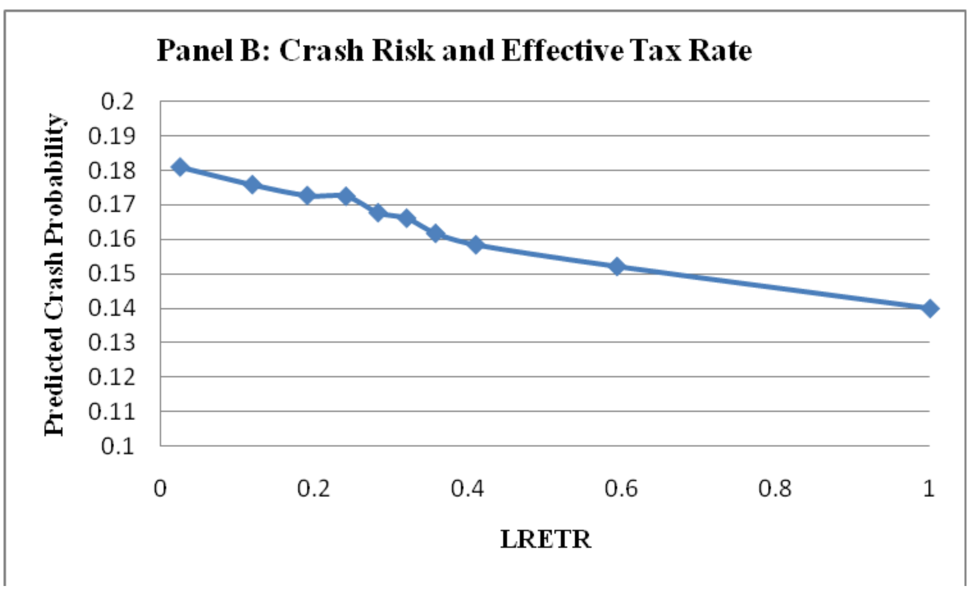
This table presents the results of the impact of corporate tax avoidance on stock price crash risk, using conditional (firm fixed effects) logistic regressions. The sample contains firm–years from 1995 to 2008 with non-missing values for all the control variables. The *z*-statistics reported in parentheses are based on standard errors clustered by both firm and time. Year fixed effects are included. Here *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Variables are defined in Appendix B.

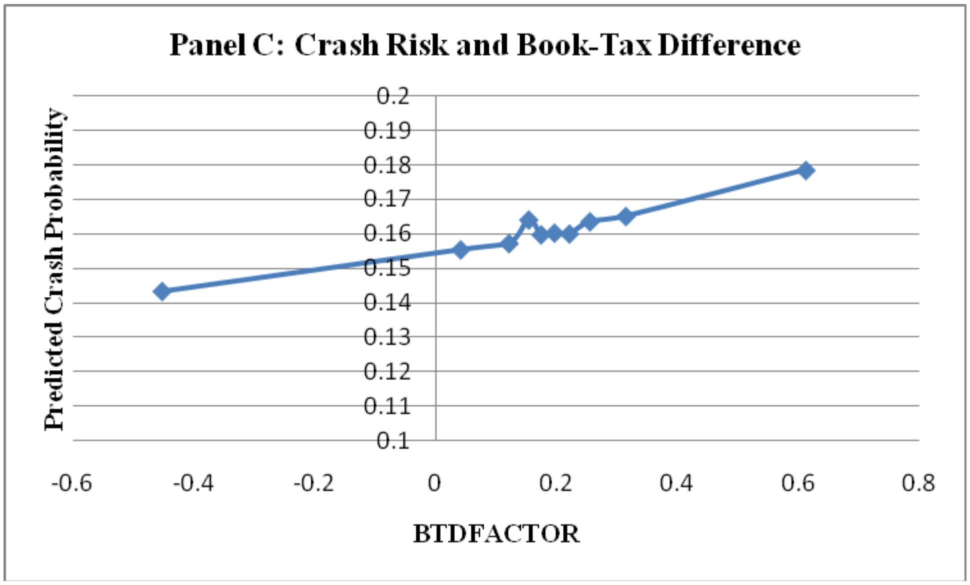
Dependent Variable: *CRASH* $_t$			
Tax Avoidance			
SHELTER $_{t-1}$	0.625***		
	(5.76)		
LRETR $_{t-1}$		-0.185**	
		(-2.17)	
BTDFACTOR $_{t-1}$			0.208***
			(3.38)
Control Variables			
DTURN $_{t-1}$	0.947***	1.061***	1.022***
	(4.56)	(4.66)	(4.91)
NCSKEW $_{t-1}$	-0.256***	-0.257***	-0.255***
	(-12.47)	(-11.75)	(-12.39)
SIGMA $_{t-1}$	0.449	2.720	0.378
	(0.16)	(0.91)	(0.13)
RET $_{t-1}$	0.927***	1.205***	0.976***
	(2.77)	(3.27)	(2.90)
SIZE $_{t-1}$	0.205***	0.296***	0.269***
	(5.45)	(6.92)	(7.43)
MB $_{t-1}$	0.057***	0.078***	0.062***
	(6.41)	(7.65)	(7.02)
LEV $_{t-1}$	-0.286*	-0.559***	-0.505***
	(-1.70)	(-3.17)	(-3.10)
ROA $_{t-1}$	-0.619***	-0.883***	-0.566***
	(-3.76)	(-4.51)	(-3.41)
ACCM $_{t-1}$	0.067	0.194	0.158
	(0.52)	(1.33)	(1.23)
Year Fixed Effect	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes
No. of Observations	30,885	27,477	30,753
Adjusted R^2	0.038	0.038	0.038

Figure 1. Tax avoidance and crash risk.

This figure presents the estimated crash probability in decile portfolios of tax avoidance levels. For each tax avoidance measure, we plot the predicted crash probability against the portfolio mean of the tax avoidance measure, based on the estimated coefficients from the corresponding model in Panel A of Table 4, holding all the control variables at their sample mean. The sample contains firm–years from 1995 to 2008 with non-missing values for all the control variables. Variables are defined in Appendix B.







Panel C: Crash Risk and Book-Tax Difference
Predicted Crash Probability
0.2
0.19
0.18
0.17
0.16
0.15
0.14
0.13
0.12
0.11
0.1
-0.6
-0.4
-0.2
0
0.2
0.4
0.6
0.8
BTDFACTOR