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Business strategy, overvalued equities, and stock price crash risk

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ABSTRACT

This paper examines empirically the effect of firm-level business strategies on future stock price crash risk, and the extent to which equity overvaluation moderates this relation. By exploring the extent to which firms following particular business strategies are more or less likely to experience crash risk, we provide evidence that increases our understanding of the underlying determinants of crash risk. Using a composite strategy score developed by Bentley, Omer and Sharp (2013) and applying two variants of crash risk, we document that firms following innovative business strategies (prospectors) are more prone to future crash risk than defenders. We also find that prospectors are more prone to equity overvaluation which, in turn, increases future crash risk.

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1. Introduction

This paper investigates whether firm-level business strategies affect future stock price crash risk. We also test for whether equity overvaluation moderates the association between the two. By exploring the extent to which firms following particular business strategies are more or less likely to experience crash risk, we provide evidence that increases our understanding of the underlying determinants of crash risk and thus help investors in allocating funds to less risky businesses. Interest in investors' perceptions of crash risk has been increasing, particularly since the 2008 financial crisis. In the advent of the crisis, investors' lack of confidence and fear of further decreases (crash risk) in prices have been identified among the various culprits behind the dramatic price declines. Thus, understanding what affects investors' perceived crash risk warrants our research. Crash risk is a vital element in stock returns to investors because, unlike risks emanating from systematic volatilities, it cannot be diversified away (Sunder, 2010).

The extant literature on the underlying reason for crash risk is dominated by the 'bad news hoarding' theory, which argues that managerial incentives for withholding bad news for an extended period increases the probability of crash risk. When the accumulation of bad news passes a threshold, it is revealed to the market at once, leading to a large negative drop in price for

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the stock (Jin and Myers, 2006).[1] Certain firm-specific characteristics has been examined as increasing crash risk, including opaque financial reporting proxied by accruals and real earnings management (Hutton et al., 2009; Francis et al., 2016); corporate tax avoidance propensity (Kim et al., 2011a), and CEO/CFO equity incentives (Kim et al., 2011b).[2] Interestingly, recent studies (e.g., Bentley et al., 2013; Higgins et al., 2015) show that all of these are determined to a certain extent by the unique business strategies pursued by firms (an antecedent)[3] that remain relatively stable over time (Hambrick, 1983; Snow and Hambrick, 1980). This motivates us to argue that business strategy of the firm has potential to have first order impact on crash risk, a direct economic consequence for investors.

Miles and Snow (2003, 1978) detail three viable business strategies that may exist simultaneously within industries—*Prospectors, Defenders,* and *Analyzers*—because of differences in the magnitude and direction of change regarding their products and markets (Hambrick, 1983). Prospectors, being innovation-oriented, change their product market mix rapidly, while defenders compete on the basis of price, service, or quality focusing more on a narrow product base.

Prior research on organization theory has demonstrated that prospectors are plagued with more information asymmetry due to a high level of outcome uncertainty, (Rajagopalan, 1997; Singh and Agarwal, 2002), and a high degree of information asymmetry can provide opportunities for financial misreporting. But Bentley et al. (2013) document that prospectors experience a greater likelihood of financial reporting irregularities despite the apparent increase in auditor effort, who can mitigate information asymmetry by making financial statements more credible.

Bentley et al. (2015) empirically tests one possible explanations for why prospectors continually experience restatements – i.e., due to higher control risk. Specifically, they find that internal controls over financial reporting (ICFR) mediate the association between strategy and restatements. Hence it is possible that managers and auditors of such firms face greater difficulty in identifying and reporting material weaknesses on a timely basis, allowing the firm to hoard bad news. Furthermore, managers of firms with prospector strategies may be more inclined to hoard bad news, because of (i) executive compensation structure (Rajagopalan, 1997); (ii) a higher propensity for tax avoidance (Higgins et al., 2015); and (iii) exposure to litigation risk. Taken together, we argue that bad news hording propensity associated with prospector strategy makes it more prone to crash risk.

However, extant literature also suggests that prospectors may suffer less from information asymmetry compared to defenders, because of greater analyst coverage and voluntary disclosures that reduces information asymmetry and hence uncertainty about firm value (Bentley et al., 2014; Bushee et al., 2010). Although this perspective suggests that prospectors would be characterized to have a more transparent information environment and hence will be less prone to crash risk. However, as alluded to in the preceding paragraph, the presence of information asymmetry itself is not the dominant reason for more financial misreporting experienced by prospectors. For example, Bentley et al. (2015) suggests that firms following prospector strategy are associated with weaker internal controls.

We then examine whether equity overvaluation mediate the association between business strategy and stock price crash risk. Jensen (2005) argues that overvalued equity creates a form of agency cost that leads managers to engage in value-destroying activities such as managing earnings and committing frauds (Chi and Gupta, 2009; Houmes and Skantz, 2010). Firms following innovator business strategies are more likely to experience equity overvaluation because of (i) overly optimistic expectations about their future growth; (ii) higher outcome uncertainty. Following the arguments that equity overvaluation motivates managers to commit financial misreporting (Jensen, 2005) it follows that crash risk will be higher for prospectors during periods of equity overvaluation.

To examine the association between firm level business strategy and sock price crash risk we employ two measures of crash risk, namely negative conditional skewness (*NSKEW*) and down-up volatility (*DUVOL*) measures as our dependent variable and Bentley et al.'s (2013) composite strategy score as our primary independent variable. Bentley et al. (2013) developed a composite strategy score building on earlier influential works by Miles and Snow (1978, 2003). Bentley et al. (2013) used six accounting variables computed using a rolling average over the prior five years to identify firms with different business strategies. A high (low) score is associated with prospector (defender) strategies. Our results show that firms with prospectors business strategy are associated with future stock price crash risk. We also find this effect to be more pronounced during periods of equity overvaluation.

In order to establish that other determinants of crash risk do not subsume the effects of business strategies, we control for some of the other determinants of crash risk including financial misreporting (Hutton et al., 2009; Francis et al., 2016), growth opportunities, analyst following and institutional ownership (Xu et al., 2013; An and Zhang, 2013), and finally audit quality (Robin and Zhang, 2015). The coefficient on *STRATGEY* with respect to future crash continues to be positive and significant even after controlling for these firm-level internal and external determinants of crash risk.

[1] Chen et al. (2001) test a model in which investor heterogeneity in opinions, coupled with short sale constraints for some investors, leads to stock price crashes. The underlying cause for stock price crashes examined in Chen et al. (2001) is the accumulation of bad news, which is induced by short sale constraints. Extant research, however, considers firm-level incentives for managers to withhold bad news as a likely determinant of crash risk.

[2] See Habib et al. (2016) for a review of the empirical literature on crash risk.

[3] Additionally the differences in organizational structure between prospectors and defenders also have implications for financial misreporting (Dent, 1990; Langfield-Smith, 1997; Chenhall, 2003). For example, prospectors have higher risk of financial reporting irregularities than defenders because of their decentralized operations and the greater instability and complexity in their organizational structure (Bentley et al., 2013).

We contribute to the growing literature on stock price crash risk and business strategy in some important ways. *First*, an understanding of the effect of business strategies on crash risk would assist investors in allocating resources carefully among companies with different business strategies. Our empirical study documents that the business strategy of a firm can greatly influence crash risk: a finding that firms should take into consideration when adapting strategies. *Second*, we contribute to the organization strategy literature by documenting that corporate strategies have the potential to affect a more extreme form of adverse outcome having direct economic consequences for investors, crash risk. Prior research on business strategy consequences examined the effect of strategies (both corporate and business unit) on firm performance, following the structure-conduct-performance paradigm (McNamara et al., 2002; Smith et al., 1997; Nair and Kotha, 2001). However, the effect of strategy on information dissemination that subsequently affects crash risk propensities has not been investigated.

The remainder of the paper proceeds as follows. Section 2 reviews relevant literature and develops testable hypotheses. Section 3 describes the research design issues. Sample selection and descriptive statistics are presented in Section 4. The following Section provides main test results and Section 6 concludes the paper.

2. Literature review and hypotheses development

Stock price crash risk at the firm level refers to the likelihood of observing extreme negative values in the distribution of firm-specific returns after adjusting for the return portions that co-move with common factors (Jin and Myers, 2006; Kim et al., 2011a,b). Understanding the determinants and consequences of crash risk is important because it has direct impact on investors' welfare. Jin and Myers (2006) examine whether information asymmetry between corporate insiders and outsiders could be related to crash risk. Specifically, they predict that opaque stocks are more prone to crash risk because of the managerial tendency to withhold bad news for these stocks. Hutton et al. (2009) test this proposition directly by using absolute accruals as a proxy for opaque financial reporting and find that reporting opaqueness increases crash risk. Francis et al. (2016) extend Hutton et al. (2009) by revealing that real earnings management (REM) also increases crash risk and importantly the effect of REM is more pronounced than accruals earnings management (AEM).

Miles and Snow (1978, 2003) identify three viable business strategies that may exist simultaneously within industries—prospectors, defenders, and analyzers. Prospectors rapidly change their product market mix to be innovative market leaders, defenders concentrate on a narrow and stable product base to compete on the basis of price, service, or quality, while analyzers have attributes of both prospectors and defenders (Miles and Snow, 1978, 2003). We link the strategy typology with crash risk and argue that prospectors are more prone to crash risk for the following reasons.

2.1. Growth opportunities, outcome uncertainty, project failures, and crash

The rapid growth experienced by prospectors increases the probability of financial reporting irregularities stemming from opaque financial reporting, one of the primary determinants of crash risk (Jin and Myers 2006; Hutton et al., 2009). Growth stocks have underperformed historically relative to other stocks in terms of realized stock returns, since growth firms, in most cases, cannot meet investors' overly optimistic expectations about the prospects of growth stocks. When these expectations are not met subsequently, the stock price of growth stocks takes a dip (Lakonishok et al., 1994). This possibility motivates managers of growth firms to withhold bad news in order to sustain such overvaluation. Skinner and Sloan (2002) find that growth stocks exhibit a much larger negative response to negative earnings surprises, again motivating managers to delay the release of bad news in the market and, consequently, increasing the crash risk.[4] However, it is unlikely that growth prospects per se, explain crash risk phenomenon for prospectors. It's more plausible that high level of outcome uncertainty and associated project failure risk are more likely determinants of crash risk. It is also consistent with SAS 99 observations that indicate that "rapid growth . . .especially compared to that of other companies in the same industry" creates an incentive for companies to misstate their financial results (AU 316.85 [AICPA 2002]). Thus project failure, outcome uncertainty and inability to meet overly optimistic expectations may cause stock price of prospectors to take a dip, stemming the possibility of stock price crash risk.

2.2. Financial misreporting, bad news hoarding, and crash

As has been discussed in the preceding section, extant literature has identified financial misreporting to be an important determinant of crash risk following the arguments proposed by Jin and Myers (2006). Whether prospector firms would be more or less prone to financial misreporting and hence crash risk should be analyzed in terms of the incentives, opportunities, and overall information environment. Bentley et al. (2013) find that prospectors are more likely to misreport (as evidenced

[4] Although managers have incentives to withhold bad news and release good news early (Kothari et al., 2009), litigation risk can motivate managers to reveal bad news quickly (Baginski et al., 2002; Kasznik and Lev, 1995; Skinner, 1994, 1997). However, career concerns can motivate managers to withhold bad news with the expectation that future good performance will negate the withholding decision. Disclosing bad news early could also incur costs for managers in the form of lower bonus payments, reduction in the quantity of stock options awarded, and loss in wealth as a result of the stock price decline following the disclosure of bad news (Kothari et al., 2009).

from their higher likelihood of receiving AAERs) because of the presence of incentives like growth opportunities, equity incentives (discussed below), and financing needs, among other incentives. Bentley et al. (2015) argue and show that firms following prospector business strategy are more likely to have weaker internal controls over financial reporting. This might suggest that managers and auditors of such firms have greater difficulty in detecting and reporting material weaknesses on a timely basis, facilitating prospectors firms to hoard bed news which eventually leads stock price to crash.

2.3. Equity incentives, misreporting, and crash

Differences in the executive compensation structure between prospectors and defenders also contribute to the possibility of crash risk. Prospectors' focus on innovation (heavy investment in R&D among others) produces greater outcome uncertainty and, thus, requires compensation contracts with a longer-term perspective (stock-based compensation incentives), encouraging managerial risk taking (Rajagopalan, 1997; Singh and Agarwal, 2002; Ittner et al., 1997). Balsam et al. (2011) document a decreased emphasis on accounting measures in firms pursuing a differentiation strategy, requiring investment in brand recognition and innovative products for which accounting treatments fail to capture value creation.

Whether innovation-focused compensation scheme will encourage managers to misreport for maximizing personal wealth has not been substantiated. However, extant research, in general has found managers to be guilty of managing earnings to maximize their compensation (e.g., Beneish, 1999; Burns and Kedia, 2006; Efendi et al., 2007). For example, Bartov and Mohanram (2004) find evidence of earnings management leading up to option exercises. Cheng and Warfield (2005) find that stock option exercises and holdings provide incentives for firms to meet or beat earnings targets. Bergstresser and Philippon (2006) find that firms make more aggressive assumptions in their defined benefit pension plans in the period in which they exercise their options. However, we don't draw a causal relation among prospector strategies, equity-based compensation schemes, financial misreporting, and crash risk. Instead we argue for an effect of equity incentives.

Based on the preceding arguments we develop the following hypothesis:

H1. *Ceteris paribus*, firms with a prospector (defender) business strategies are more (less) prone to crash risk.

Our second hypothesis investigates a channel, equity overvaluation, through which the positive association between business strategies and crash risk is likely to manifest. Jensen (2005) theorizes that overvaluation can induce a new type of agency costs: the agency costs of overvalued equity.[5] Jensen (2005, p.7) argues that managers have incentives to prolong misevaluation through earnings manipulation because "... people are paid not for what they do but for what they do relative to some target. And this leads people to game the system by manipulating both the setting of the targets and how they meet their targets. These counterproductive target-based budget and compensation systems provide the fertile foundation for the damaging effects of the earnings management game with the capital markets. And the resulting lack of integrity is the foundation for the release of the value-destroying forces of overvaluation." Equity overvaluation increases investor expectation about the future payoffs of the company although, by definition, overvalued firms do not have sufficient positive-NPV investment opportunities to justify the market valuation.

We argue that prospectors are more prone to equity overvaluation since prior evidence reveals that investors have overly optimistic expectations about the prospects of growth stocks (Lakonishok et al., 1994; Skinner and Sloan, 2002). LaPorta et al. (1997) show that those returns are disproportionately concentrated around earnings announcements. This concentration of returns at earnings announcements suggests that the expectations impounded into price contain systematic errors resulting in predictable surprises when future earnings are announced. Baker and Wurgler (2006) find that sentiment-driven overvaluation is more pronounced for high volatility stocks, un-profitable stocks, and extreme growth stocks: some of the characteristics shared by prospectors. Overvaluation leads to value-destroying opportunistic earnings management and the highly opaque financial reports damage the capital market's ability to incorporate firm-specific information gradually into the stock price.[6] Bergman and Roychowdhury (2008) develop a theoretical model in which managers withhold bad news in periods of overvaluation in an attempt to sustain the overvaluation. However, as the negative firm-specific information continues to accumulate, it will eventually become impossible for the firm's managers to hide it from investors, and a time comes when the accumulated negative information is released to the market all at once causing price crashes in the firm's stocks (Jin and Myers, 2006; Risso, 2008). Since prospectors are more likely to be overvalued than defenders, it follows from the arguments above that these firms will have the incentives to withhold bad news in order to sustain such overvaluation. We develop the following hypothesis to test this proposition.

H2. *Ceteris paribus*, equity overvaluation has a positive impact on crash risk for firms with a prospector business strategy.

[5] In addition to losses in investor wealth, overvaluation can create large welfare losses by eroding investor confidence in the integrity of the capital market and inviting remedial costly action by regulators. Overvalued equity is also likely to result in inefficient outcomes for contracts based on share prices (Beneish et al., 2009)

[6] Such actions could be over-investing through acquisitions or expansions, committing frauds, and managing earnings (Chi and Gupta, 2009). Empirical evidence supports earnings management by firms with overvalued equities. For example, Chi and Gupta (2009) and Houmes and Skantz (2010) find that managers inflate reported earnings by income-increasing accruals in the year following the firms' being overpriced. They also find that overvaluation-induced income-increasing earnings management is related negatively to future abnormal stock returns and operating performance. Badertscher (2011) finds that managers use both accruals and real earnings management strategies before committing financial statement fraud, in order to report the performance demanded by the market.

3. Research design

3.1. Business strategy composite measure

Following Bentley et al. (2013), we use a discrete *STRATEGY* composite score to proxy for an organization's business strategy. Higher *STRATEGY* scores represent companies with prospector strategies and lower scores represent companies with defender strategies. Bentley et al. (2013) adapted some from Ittner et al. (1997) and extended other measures based on the Miles and Snow framework in constructing their composite *STRATEGY* score.

Characteristics included are: (a) the ratio of research and development to sales (measure of a firm's propensity to seek new products); (b) the ratio of employees to sales (firm's ability to produce and distribute its goods and services efficiently); (c) a measure of employee fluctuations (standard deviation of total employees); (d) a historical growth measure (one-year percentage change in total sales) (proxy for a firm's historical growth); (e) the ratio of marketing (SG&A) to sales (a proxy for firms' emphasis on marketing and sales); and (f) a measure of capital intensity (net PPE scaled by total assets) (designed to capture a firms' focus on production).

All variables are computed using a rolling average over the prior five years. Each of the six individual variables is ranked by forming quintiles within each two-digit SIC industry-year. Within each company-year, those observations with variables in the highest quintile are given a score of 5, in the second-highest quintile, a score of 4, and so on, and those observations with variables in the lowest quintile are given a score of 1 (except capital intensity, which is reversed-scored so that observations in the lowest (highest) quintile are given a score of 5 (1)). Then for each company-year, the scores across the six variables are summed such that a company could receive a maximum score of 30 (prospector-type) and a minimum score of 6 (defender-type).[7] In our sample the range between maximum and minimum score is 29 and 6.

3.2. Stock price crash risk

In this study two measures of firm-specific crash risk are used, consistent with Chen et al. (2001). Both measures are based on the firm-specific weekly returns estimated as the residuals from the market model. This ensures that our crash risk measures reflect firm-specific factors rather than broad market movements. Specifically, we estimate the following expanded market model regression:

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

Where $r_{,j,\tau}$ is the return of firm *j* in week τ, and $r_{m,\tau}$ is the return on CRSP value-weighted market return in week τ. The lead and lag terms for the market index return is included, to allow for non-synchronous trading (Dimson, 1979). The firm-specific weekly return for firm *j* in week τ ($W_{j,\tau}$) is calculated as the natural logarithm of one plus the residual return from Eq. (1) above. In estimating Eq. (1), each firm-year is required to have at least 26 weekly stock returns. Our first measure of crash risk is the negative conditional skewness of firm-specific weekly returns over the fiscal year (*NCSKEW*). *NCSKEW* is calculated by taking the negative of the third moment of firm-specific weekly returns for each year and normalizing it by the standard deviation of firm-specific weekly returns raised to the third power. Specifically, for each firm *j* in year τ, *NCSKEW* is calculated as:

$$NCSKEW = -[n(n-1)^{3/2} \sum w^3{}_{j,\tau}] / \left[(n-1)(n-2)\left(\sum \mathrm{w}^2_{\mathrm{j,t}}\right)^{3/2}\right] \tag{2}$$

Our second measure of crash risk is the down-to-up volatility measure (*DUVOL*) of the crash likelihood. For each firm *j* over a fiscal-year period τ, firm-specific weekly returns are separated into two groups: "down" weeks when the returns are below the annual mean, and "up" weeks when the returns are above the annual mean. The standard deviation of firm-specific weekly returns is calculated separately for each of these two groups. *DUVOL* is the natural logarithm of the ratio of the standard deviation in the "down" weeks to the standard deviation in the "up" weeks:

$$DUVOL_{j,\tau} = \log\left\{(n_u - 1)\sum_{Down} w^2{}_{j,\tau} / (n_d - 1)\sum_{Up} w^2{}_{j,\tau}\right\} \tag{3}$$

A higher value of *DUVOL* indicates greater crash risk. As suggested in Chen et al. (2001), *DUVOL* does not involve third moments, and hence is less likely to be overly influenced by extreme weekly returns.

[7] See Appendix 2 in Bentley et al. (2013) for a detailed discussion on the estimation of the *STRATEGY* score.

3.3. Measurement of equity overvaluation

We follow Rhodes et al. (2005) sophisticated technique for decomposing market-to-book (*MTB*) ratios into mis-valuation and growth option components. Rhodes et al. (2005) methodology for decomposing *MTB* into mis-valuation (*MTV*) and growth option (*VTB*) components is as follows:

$$\mathrm{MTB} \equiv \mathrm{MTV} \times \mathrm{VTB}, \tag{4}$$

which, in log form, can be written as

$$m - b \equiv (m - v) + (v - b), \tag{5}$$

where lower case letters indicate logarithms of the respective variables. If markets know the future growth opportunities, discount rates, and cash flows, then the term $(m - v)$ should be zero. If markets make mistakes in estimating discounted future cash flows, or do not have information that managers have, then $(m - v)$ will capture the mis-valuation component of the *MTB* ratio. Decomposing the *MTB* ratio, as depicted in Eq. (4), relies on determining an estimate of firm value, v. For estimation purposes, for each firm i in industry j at time t, v can be expressed as a linear function of observable firm-specific accounting information, θ_{it}, and a vector of corresponding accounting multiples, α. The methodology employs both a vector of contemporaneous time-t accounting multiples, α_{jt}, and a vector of long-run accounting multiples, α_j, such that the *MTB* ratio for firm i at time t can be further decomposed into 3 components as follows:

$$m_{it} - b_{it} = \underbrace{m_{it} - v(\theta_{it};\alpha_{jt})}_{\mathrm{FSE}} + \underbrace{v(\theta_{it};\alpha_{jt}) - v(\theta_{it};\alpha_j)}_{\mathrm{TSSE}} + \underbrace{v(\theta_{it};\alpha_j) - b_{it}}_{\mathrm{LRVTB}} \tag{6}$$

The first term on the right-hand side of Eq. (6), $m_{it} - v(\theta_{it};\alpha_{jt})$, referred to as the firm-specific error (*FSE*), measures the difference between market value and fundamental value, and is estimated using firm-specific accounting data, θ_{it}, and the contemporaneous sector accounting multiples, α_{jt}, and is intended to capture the extent to which the firm is mis-valued relative to its contemporaneous industry peers. The second term, $v(\theta_{it};\alpha_{jt}) - v(\theta_{it};\alpha_j)$, referred to as time-series sector error (*TSSE*), measures the difference in estimated fundamental value when contemporaneous sector accounting multiples at time t, α_{jt}, differ from long-run sector multiples, α_j, and is intended to capture the extent to which the industry (or, possibly, the entire market) may be mis-valued at time t. Total valuation error (*TVE*) is the sum of *FSE* and *TSSE*. The third term, referred to as *LRVTB*, measures the difference between firm value (implied by the vector of long-run sector multiples) and book value. This measure is interpreted as the investment opportunity component of the MTB ratio.

Rhodes et al. (2005) use three different models to estimate $v(\theta_{it};\alpha_{jt})$ and $v(\theta_{it};\alpha_j)$. The models differ only with respect to the accounting items that are included in the accounting information vector, θ_{it}. The 3rd model is the most comprehensive model that includes the book value (b), net income (NI), and market leverage (LEV) ratio in the accounting information vector. Expressing market value as a simple linear model of these variables yields

$$m_{it} = \alpha_{0jt} + \alpha_{1jt} b_{it} + \alpha_{2jt} \ln(NI)^{+}{}_{it} + \alpha_{3jt} I(<0)\ \ln(NI)_{it} + \alpha_{4jt} LEV_{it} + \varepsilon_{it}, \tag{7}$$

where, because NI can sometimes be negative, it is expressed as an absolute value $(\mathrm{NI})^{+}$ along with a dummy variable, $I(<0)$, to indicate when NI is negative.

To calculate the contemporaneous accounting multiples, α_{jt}, each year we group all CRSP/Compustat firms according to the 12 Fama and French industry classifications; run annual, cross-sectional regressions (of Eq. (7)) for each industry; and generate estimated industry accounting multiples for each year $\hat{t}, \alpha_{jt}$. The estimated value of $v(\theta_{it};\alpha_{jt})$ is the fitted value from regression Eq. (7):

$$v(b_{it}, NI_{it}, LEV_{it}; \hat{\alpha}_{0jt}, \hat{\alpha}_{1jt}, \hat{\alpha}_{2jt}, \hat{\alpha}_{3jt}, \hat{\alpha}_{4jt}) = \hat{\alpha}_{0jt} + \hat{\alpha}_{1jt} b_{it} + \hat{\alpha}_{2jt} \ln(NI)^{+}{}_{it} + \hat{\alpha}_{3jt} I(<0) \ln(NI)^{+}{}_{it} + \hat{\alpha}_{4jt} LEV_{it} \tag{8}$$

3.4. Empirical model

To investigate the effect of business strategies on future crash risk, we regress current period crash risk on strategy and other control variables measured using data from the preceding year as follows:

$$\begin{aligned} CRASH_{i,t} &= \gamma_0 + \gamma_1 CRASH_{t-1} + \gamma_2 STRATEGY_{t-1} + \gamma_3 TURN_{t-1} + \gamma_4 RET_{t-1} + \gamma_5 SDRET_{t-1} \\ &+ \gamma_6 SIZE_{t-1} + \gamma_7 MTB_{t-1} + \gamma_8 LEVERAGE_{t-1} + \gamma_9 |DAC_{t-1}| + \gamma_{10} REM_{t-1} + \gamma_{11} FOLLOW_{t-1} \\ &+ \gamma_{12} INSTOW_{t-1} + \gamma_{13} AUD_{t-1} + \varepsilon i, t \end{aligned} \tag{9}$$

where *CRASH* risk is proxied by *NCSKEW* and *DUVOL* measures following Eqs. (2) and (3) above. The independent variables are calculated using data from the preceding year consistent with the crash risk literature. We first control for the lag value of *CRASH* to account for the potential serial correlation of *NCSKEW* or *DUVOL* for the sample firms. *STRATEGY* is the composite

Table 1
Sample Selection Procedure.

Sample filtering	
Total number of firm-year observations from 1969 to 2012 with non-missing variables for calculating two crash risk measures	276,493
Less: Utilities and Financial Industries (SIC 48–49 and 60–69)	(41,733)
Less: Missing 2 digitSICCodes	(29,068)
Less: Observations lost for estimating lagged observations	(16,773)
Less missing values for all other *STRATEGY* component variables	(108,829)
Firm-year observations with non-missing *STRATEGY* scores, crash risk measures, and relevant control variables for testing H1 between 1974 and 2012.	80,090
Missing observations on *TVE* and *LRVTB*	(11,486)
Final sample for equity overvaluation and strategy analysis (H2)	68,604

score (continuous) ranging from a minimum of 6 to a maximum of 30 following the estimation procedure explained in 3.1 above.[8] H1 will be supported if the coefficient on the *STRATEGY* variable is found to be positive and statistically significant.

Inclusion of the control variables follows prior literature on the determinants of crash risk. *TURN* is the average monthly share turnover over the current fiscal year minus the average monthly share turnover over the previous fiscal year, where monthly share turnover is calculated as the monthly trading volume divided by the total number of shares outstanding during the month. Chen et al. (2001) indicate that this variable is used to measure differences of opinion among shareholders and is positively related to crash risk proxies. Chen et al. (2001) show that negative skewness is larger in stocks that have had positive stock returns over the prior 36 months. To control for this possibility, we include past one-year weekly returns (*RET*). *SDRET* is the standard deviation of firm-specific weekly returns over the fiscal year denoting stock volatility as more volatile stocks are likely to be more crash prone. Chen et al. (2001) also demonstrate that negative return skewness is higher for larger firms. To control for the size effect, we add *SIZE* measured as the natural log of total assets. The variable *MTB* is the market value of equity divided by the book value of equity. Both Chen et al. (2001) and Hutton et al. (2009) show that growth stocks are more prone to future crash risk. *LEVERAGE* is the total long-term debt divided by total assets, which is shown to be negatively associated with future crash risk (Kim et al., 2011a,b).

We then include a series of variables that have been found to be related to crash risk. Coefficients on γ_9 and γ_{10} incorporate reporting quality proxies namely, |*DAC*| and *REM* (Hutton et al., 2009; Francis et al., 2016). Coefficients γ_{11} and γ_{12} control for analyst following (*FOLLOW*) and institutional ownership (*INSTOWN*) as the likely determinants of crash risk. *FOLLOW* is the natural log of analyst following; *INSTOWN* is the percentage of outstanding shares owned by top 5 institutional investors. With respect to audit quality effect on mitigating crash risk, Robin and Zhang (2015) find that industry specialist auditors reduce crash risk. They argue that industry specialist auditors have the expertise required to reduce the managerial propensity to hoard bad news and hence subsequent crash. *AUD* is a categorical variable coded 1 if the firms are audited one of the Big 4/5 audit firms. We incorporate these additional variables to mitigate the concern that strategy measure itself does not have incremental explanatory power.

In order to test H_2 we run the following regression for the prospector and defender group separately.

$$CRASH_{i,t} = \gamma_0 + \gamma_1 CRASH_{t-1} + \gamma_2 TVE_{t-1} + \gamma_3 LRVTB_{t-1} + \gamma_4 TURN_{t-1} + \gamma_5 RET_{t-1} + \gamma_6 SDRET_{t-1} + \gamma_7 SIZE_{t-1} + \gamma_8 MTB_{t-1} + \gamma_9 LEVERAGE_{t-1} + \gamma_{10}|DAC_{t-1}| + \gamma_{11} REM_{t-1} + \varepsilon i, t \qquad (10)$$

where *TVE* and *LRVTB* are our proxies for valuation error detailed in 3.3 above. Other variables have been defined as before. Since prospectors are more prone to equity overvaluation, we expect the coefficients on the equity valuation proxies to be positive and significant for prospector group.

4. Sample selection and descriptive statistics

We began with an initial sample of 276,493 firm-year observations from the intersection of COMPUSTAT and CRSP with non-missing crash risk measures during the period 1974–2012. We deleted firm year-observations from the regulated (48–49) and financial institutions industries (SIC 60–69), and observations with missing 2 digit SIC codes. We lost 16,773 firm-year observations because of the requirement for independent variables to be lagged by a year. Finally we deleted observations with missing values for all six *STRATEGY* component variables. Our final usable sample for the regression analyses comprised 80,090 firm-year observations for the period 1974–2012. Our sample size reduced to 68,604 firm-year observations for testing H_2 because of missing values for *TVE* and *LRVTB* measures. However, our final sample size varies due to model specific data requirement. Panel A, Table 1 details the sample selection procedure.

Panel A, Table 2 provides descriptive statistics of the variables used in the regression analyses. The mean values of the crash risk measures, *NCSKEW* and *DUVOL*, are −0.16 and −0.54 respectively. These values are higher than those reported

[8] The composite strategy score remains relatively stable over the sample period. For example, 64% of the sample observations had their *STRATEGY* scores changed within the range of −1 to +1. The proportion increases to 82% when the *STRATEGY* scores take the range from −2 to +2.

Table 2
Descriptive Statistics and Industry Distribution.

Panel A: Descriptive statistics

	Variables		Mean	SD	25%	50%	75%
Crash risk measures	$NCSKEW_t$	80,090	−0.16	1.09	−0.79	−0.16	0.47
	$NCSKEW_{t-1}$	80,090	−0.12	1.01	−0.74	−0.14	0.46
	$DUVOL_t$	80,090	−0.54	0.91	−1.04	−0.47	0.05
	$DUVOL_{t-1}$	80,090	−0.50	0.84	−1.01	−0.46	0.05
Business strategy measures	$STRATEGY_{t-1}$	80,090	17.28	3.80	15.00	17.00	20.00
Equity overvaluation measures	FSE_{t-1}	68,604	0.02	0.66	−0.34	0.02	0.38
	$TSSE_{t-1}$	68,604	0.01	0.24	−0.12	0.04	0.17
	TVE_{t-1}	68,604	0.03	0.66	−0.35	0.03	0.42
	$LRVTB_{t-1}$	68,604	0.43	0.68	−0.03	0.47	0.93
Control variables	$TURN_{t-1}$	80,090	0.0011	0.07	−0.01	0.00	0.02
	RET_{t-1}	80,090	0.0037	0.01	0.00	0.00	0.01
	$STDRET_{t-1}$	80,090	0.07	0.04	0.04	0.06	0.08
	$SIZE_{t-1}$	80,090	5.40	2.08	3.86	5.27	6.82
	MTB_{t-1}	80,090	2.28	3.14	0.93	1.56	2.68
	$LEVERAGE_{t-1}$	80,090	0.17	0.17	0.02	0.15	0.27
	$\|DAC\|_{t-1}$	80,090	0.18	0.39	0.03	0.07	0.15
	REM	80,090	0.51	0.71	0.12	0.28	0.58
	FOLLOW	45,018	1.32	1.22	0.00	1.39	2.40
	INSTOW	45,018	0.42	0.30	0.15	0.40	0.67
	AUD	45,018	0.50	0.50	0.00	1.00	1.00

Panel B: Industry distribution

Code	Industry	Observations	% observations
1–14	Agriculture & mining	4,920	0.06
15–17	Building construction	769	0.01
20–21	Food & Kindred Products	2,868	0.04
22–23	Textile Mill Products & apparels	2,210	0.03
24–27	Lumber, furniture, paper, and printing	4,714	0.06
28–30	Chemical, petroleum, and rubber & Allied Products	8,608	0.11
31–34	Metal	5,252	0.07
35–39	Machinery, electrical, computer equipment	24,856	0.31
40–49	Railroad and other transportation & utilities	3,277	0.04
50–51	Wholesale goods, building materials	4,137	0.05
53–59	Store merchandise, auto dealers, home furniture stores	7,298	0.09
70–79	Business services	8,009	0.10
80–99	Others	3,172	0.04
	Total	80,090	1.00

Panel C: Correlation analysis

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$NCSKEW_t$ (1)	1.00											
$NCSKEW_{t-1}$(2)	0.03	1.00										
DUVOL (3)	***0.78***	***0.03***	1.00									
$DUVOL_{t-1}$(4)	***0.07***	***0.77***	***0.15***	1.00								
$STRATEGY_{t-1}$ (5)	***0.02***	***0.02***	0.007	0.014**	1.00							
$TURN_{t-1}$ (6)	***0.03***	***0.03***	***0.03***	***−0.04***	***−0.02***	1.00						
RET_{t-1} (7)	***0.04***	***0.05***	***0.03***	***−0.31***	***−0.01***	***0.19***	1.00					
$STDRET_{t-1}$ (8)	***−0.05***	***−0.10***	***−0.18***	***−0.42***	***0.09***	***0.12***	***0.17***	1.00				
$SIZE_{t-1}$ (9)	***0.12***	***0.15***	***0.29***	***0.33***	***0.04***	***0.02***	***0.04***	***−0.40***	1.00			
MTB_{t-1} (10)	***0.06***	***0.08***	***0.08***	−0.008	***0.11***	***0.07***	***0.19***	***0.04***	***0.29***	1.00		
$LEVERAGE_{t-1}$(11)	−0.011**	***−0.02***	−0.0033	***0.04***	***−0.09***	***0.03***	***−0.06***	***0.21***	***0.10***	−0.02**	1.00	
$\|DAC\|_{t-1}$ (12)	***0.014***	***0.02***	0.013**	0.016**	0.003	−0.006	−0.003	−0.0016	***0.03***	***0.04***	***−0.03***	1.00

***p < 0.01, ** p < 0.05, * p < 0.10.
Note: See Appendix A for variable definitions. Correlation coefficients significant at better than the 1% level are bold-faced. ** represents statistical significance at the 5% level (two-tailed test).

in studies by Kim et al. (2014); Kim et al. (2011a, 2011b) mainly because of a significantly larger sample size used in this study. The sample firms have an average *STRATEGY* score of 17.28 Average *TVE* and *LRVTB* are 0.03 and 0.43 respectively with a somewhat high standard deviation (0.66 and 0.68 respectively). The average change in monthly trading volume (as a percentage of shares outstanding) is 0.0011. The average firm in our sample has a firm-specific weekly return of 0.37%, total assets of $2005 million, a market-to-book ratio of 2.28, a weekly return volatility of 0.07, and a leverage of 0.17. The average absolute value of abnormal accruals is 0.18 while that on *REM* is 0.51. Moreover, sample firm has average number of analyst

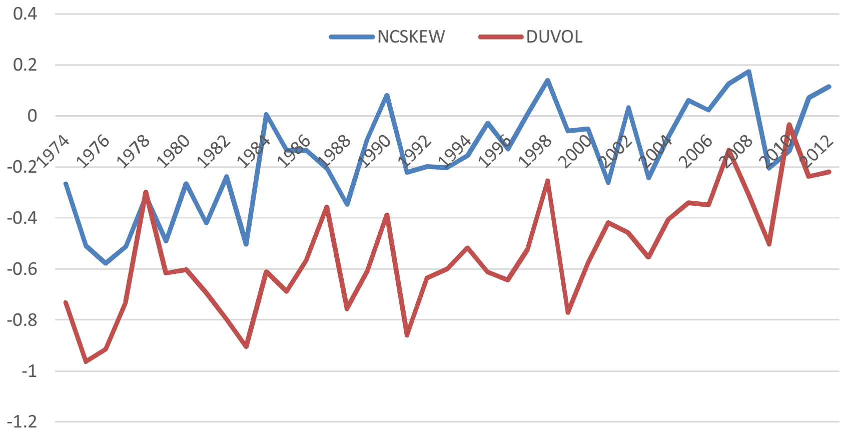

Fig. 1. Time-series distribution of firm-specific crash risk.

coverage of 1.32 and proportion of institutional shareholding of 0.42. Fifty percent of the sample firms are audited by big audit firm while the average *BTD* is 0.0012.

Fig. 1 shows the means of *NCSKEW* and *DUVOL* across the sample years 1974–2012. Both measures of crash risk indicate a considerable variation across years, with a clear increasing pattern in the time-series distribution of crash risk. This figure shows that firm-specific crash risk was highest in 2007–2008, coinciding with the U.S. financial crisis. Moreover, the figure exhibits a relatively lower crash risk in 1976 and 1983, another peak in crash risk in 1990. Overall, time-series distribution of crash risk is consistent with other prior studies (Callen and Fang, 2016, 2013).

Panel B provides the industry distribution of the sample observations. The sample represents a wide variety of industries with a high proportion of firm-year observations coming from SIC codes 35–39. All our regression specifications control for unobserved industry effects. Panel C presents the correlation analysis. Both crash measures are highly correlated (correlation coefficient of 0.78) and are positively and significantly correlated with *STRATEGY* (correlation coefficient of 0.05, significant at better than the 1% level). The positive correlation suggests that prospectors are more prone to crash risk.

5. Main test results

Table 3 reports the results from ordinary least squares (OLS) regression analysis of the relation between business strategies and future firm-specific crash risk, after controlling for other potential determinants of crash risk. All reported t-statistics are based on standard errors adjusted at the firm level (Petersen, 2009). Results with basic controls suggest that firm-level business strategies are positively associated with one-year-ahead crash risk proxied by *NCSKEW* (Column 1) and *DUVOL* (Column 2). The coefficient on *STRATEGY* is 0.005 and 0.006 for the *NCSKEW* and *DUVOL* crash measures respectively, with associated t-statistics of 4.77 and 7.00.[9] The positive and significant coefficients on *STRATEGY* for both crash measures support H1. In terms of economic significance regression results suggests that one standard deviation increases in strategy score leads to 1.74% and 2.50% increase in crash risk for *NCSKEW* and *DUVOL* crash measures respectively. Regression Columns (3) and (4) shows that after incorporating *FOLLOW* and *INSTOW* as additional controls, our regression results remain robust. Our inference relating to strategy and crash risk remains unaffected even when regression Columns (5) and (6) controls for the effect of audit quality (proxied by big audit firms). Finally, in Columns (7) and (8) we control for tax avoidance of the firm and find that the coefficient on *STRATGEY* continues to be positive and significant (coefficient 0.0051, t-stat 2.19, significant at $p < 0.05$) for *NCSKEW* measure but insignificant for *DUVOL* measure.

Among the control variables, the coefficient on average returns is positive and that on return volatility is negative. This suggests that firms with better stock performance and lower volatility are more likely to experience crashes, indicating that crashes are unlikely to be a manifestation of declining business conditions, continuation of poor stock performance (i.e., negative stock momentum), and/or high stock volatility. This is consistent with the notion that crashes occur after a period of illusionary high prices and stability. Larger firms and high growth firms are more prone to crash risk, and so are firms with high discretionary accruals, consistent with Hutton et al.'s (2009) finding that financial reporting opaqueness increases the probability of crash risk. The negative coefficient on *AUD* suggest that audit quality reduces the possibility of crash risk.

Table 4 presents regression results for H_2. Before formally reporting results of H_2, we want to find the relationship between firm-level business strategies and market-level equity overvaluation. In Section 2 we postulated that prospectors will be more prone to equity overvaluation, as investors have overly optimistic expectations about the prospects of these

[9] The coefficients on logged *STRATEGY* become 0.11 (t-stat 6.89) and 0.06 (t-stat 4.64) for *NCSKEW* and *DUVOL* measures respectively if we replace continuous *STRATEGY* score with logged values of *STRATEGY*.

Table 3
Regression Analysis on the Association between Business Strategies and Crash Risk.

$$CRASH_{i,t} = \gamma_0 + \gamma_1 CRASH_{t-1} + \gamma_2 STRATEGY_{t-1} + \gamma_3 TURN_{t-1} + \gamma_4 RET_{t-1} + \gamma_5 SDRET_{t-1} + \gamma_6 SIZE_{t-1} + \gamma_7 MTB_{t-1} + \gamma_8 LEVERAGE_{t-1} + \gamma_9 |DAC_{t-1}| + \gamma_{10} REM_{t-1} + \gamma_{11} FOLLOW_{t-1} + \gamma_{12} INSTOW_{t-1} + \gamma_{13} AUD_{t-1} + \varepsilon i, t \quad (9)$$

	(1) NCSKEW	(2) DUVOL	(3) NCSKEW	(4) DUVOL	(5) NCSKEW	(6) DUVOL
Variables	Coefficient [t-statistic]	Coefficient [t-statistic]	Coefficient [t-statistic]	Coefficient [t-statistic]	Coefficient [t-statistic]	Coefficient [t- statistic]
Constant	−0.529***	−1.37***	−0.767***	−1.022***	0.023	0.221
	[−4.43]	[−15.63]	[−3.83]	[−10.08]	[0.07]	[0.87]
NCSKEW $_{t-1}$	0.051***	–	0.042***	–	0.041***	–
	[9.80]		[5.76]		[5.53]	
DUVOL $_{t-1}$	–	0.04***	–	0.055***	–	0.052***
		[9.76]		[8.14]		[7.63]
STRATEGY $_{t-1}$	**0.005*** **	**0.006** **	**0.004*** **	**0.002* **	**0.004*** **	**0.0025** **
	[4.77]	**[7.00]**	**[2.86]**	**[1.88]**	**[2.85]**	**[2.05]**
TURN $_{t-1}$	0.169***	0.31***	0.074	0.115**	0.069	0.073
	[3.16]	[7.11]	[1.07]	[2.18]	[0.98]	[1.39]
RET $_{t-1}$	8.604***	6.26***	10.127***	13.894***	10.400***	11.626***
	[16.36]	[18.86]	[13.44]	[28.10]	[13.55]	[22.43]
STDRET $_{t-1}$	−0.552***	−3.10***	−0.825***	−3.780***	−0.875***	−3.153***
	[−3.92]	[−29.04]	[−3.95]	[−21.15]	[−4.08]	[−17.15]
SIZE $_{t-1}$	0.065***	0.10***	0.039***	0.047***	0.038***	0.071***
	[27.71]	[50.05]	[9.40]	[14.96]	[9.12]	[20.82]
MTB $_{t-1}$	0.007***	0.007***	0.008***	0.007***	0.009***	0.001
	[5.05]	[6.89]	[4.51]	[4.55]	[4.54]	[0.69]
LEVERAGE$_{t-1}$	−0.007	−0.17***	−0.040	−0.106***	−0.047	−0.050*
	[−0.28]	[−8.45]	[−1.14]	[−3.53]	[−1.29]	[−1.71]
|DAC| $_{t-1}$	0.014	0.04***	0.001	−0.014	0.004	−0.015
	[1.29]	[4.94]	[0.06]	[−1.32]	[0.30]	[−1.35]
REM $_{t-1}$	0.018***	−0.001	0.017***	0.002	0.017***	0.005
	[3.97]	[−0.30]	[3.06]	[0.47]	[3.01]	[1.16]
FOLLOW $_{t-1}$	–	–	0.026***	0.070***	0.028***	0.038***
			[3.72]	[13.22]	[3.94]	[6.88]
INSTOW $_{t-1}$	–	–	0.15***	0.174***	0.143***	0.158***
			[5.79]	[8.60]	[5.64]	[7.93]
AUD $_{t-1}$	–	–	–	–	−0.028***	−0.005
					[−2.68]	[−0.62]
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Firm Cluster	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.05	0.14	0.04	0.15	0.04	0.11
Observations	80,090	80,090	45,018	44,382	45,018	44,382

Note: See Appendix A for variable definitions. ***p < 0.01, **p < 0.05, *p < 0.10.

Table 4
Overvalued Equity, Business strategy, and Crash risk.

$$CRASH_{i,t} = \gamma_0 + \gamma_1 CRASH_{t-1} + \gamma_2 TVE_{t-1} + \gamma_3 LRVTB_{t-1} + \gamma_4 TURN_{t-1} + \gamma_5 RET_{t-1} + \gamma_6 SDRET_{t-1} + \gamma_7 SIZE_{t-1} + \gamma_8 MTB_{t-1} + \gamma_9 LEVERAGE_{t-1} + \gamma_{10}|DAC_{t-1}| + \gamma_{11} REM_{t-1} + \varepsilon i, t \quad (10)$$

	Business strategy and equity overvaluation		Prospector = 1		Defender = 1	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	TVE Coefficient [t-statistic]	LRVTB Coefficient [t-statistic]	NCSKEW Coefficient [t-statistic]	DUVOL Coefficient [t-statistic]	NCSKEW Coefficient [t-statistic]	DUVOL Coefficient [t-statistic]
Constant	−0.838***	−0.093	−0.832**	−1.349***	−0.655**	−1.147***
	[−4.42]	[−0.66]	[−2.37]	[−4.89]	[−2.09]	[−3.57]
NCSKEW $_{t-1}$	–	–	0.099***	–	0.049***	–
			[4.29]		[2.78]	
DUVOL $_{t-1}$	–	–	–	0.083***	–	0.052***
				[4.12]		[3.21]
STRATEGY$_{t-1}$	**0.004*** **	**0.013*** **	–	–	–	–
	[3.27]	[9.18]				
TVE $_{t-1}$	–	–	−**0.037**	**0.026**	−**0.051***	−**0.045***
			[−1.07]	[0.92]	[−1.83]	[−1.78]
LRVTB $_{t-1}$	–	–	**0.076****	**0.067****	**0.031**	−**0.003**
			[2.19]	[2.38]	[1.12]	[−0.13]
TURN $_{t-1}$	–	–	0.056	0.131	0.392*	0.215
			[0.27]	[0.90]	[1.88]	[1.33]
RET $_{t-1}$	–	–	12.513***	13.133***	9.779***	9.674***
			[5.77]	[9.46]	[4.98]	[7.29]
STDRET $_{t-1}$	1.437***	1.403***	−1.577**	−4.010***	−1.302***	−2.925***
	[10.56]	[10.40]	[−2.56]	[−7.87]	[−2.97]	[−7.21]
SIZE $_{t-1}$	0.081***	0.001	0.055***	0.084***	0.066***	0.113***
	[16.89]	[0.29]	[4.98]	[8.77]	[6.82]	[14.46]
MTB $_{t-1}$	0.012**	0.026***	0.015***	0.000	0.033***	0.007
	[1.99]	[4.06]	[2.62]	[0.00]	[4.13]	[1.21]
LEVERAGE$_{t-1}$	1.661***	−1.542***	0.069	−0.077	0.034	0.163*
	[53.71]	[−43.29]	[0.51]	[−0.74]	[0.32]	[1.90]
|DAC| $_{t-1}$	0.006	0.007	−0.042	−0.086**	−0.009	−0.014
	[0.66]	[0.78]	[−0.85]	[−2.18]	[−0.30]	[−0.61]
REM	0.038***	0.044***	−0.000	−0.026*	0.036**	0.013
	[8.44]	[9.36]	[−0.01]	[−1.77]	[2.13]	[1.07]
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Firm Cluster	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.24	0.26	0.05	0.18	0.06	0.17
Observations	68,604	68,604	4397	4397	7337	7337

Note: We did not include *FOLLOW*, *OWN*, and *AUDIT* because sample size will shrink significantly as the total number of observations in prospector and defender category is rather small. See Appendix A for variable definitions. Robust t-statistics in brackets; ***p < 0.01, **p < 0.05, *p < 0.10.

companies (Lakonishok et al., 1994; Skinner and Sloan, 2002). Columns (1) and (2) in Table 4 reveals that the coefficient on lagged *STRATEGY* is positive and statistically significant for both the overvaluation proxies (coefficients of 0.004 and 0.013 for *TVE* and *LRVTB* measures respectively, and $p<0.01$). Regression results also suggest that equity overvaluation is more likely to occur for larger firms and for firms with high stock return volatility, high growth opportunities and high leverage.

We then proceed to our crash risk regression. We run Eq. (10) for the prospector and defender groups separately. Columns (3) and (4) report the results for the former whilst Columns (5) and (6) report the results for the defender group. We find that the coefficient on *LRVTB* is positive and significant for then prospector group for both the crash proxies (coefficients of 0.076 and 0.067, with associated t-statistic of 2.19 and 2.38 respectively). The coefficient on *TVE*, however is insignificant. For the defender group, the coefficient on *TVE* is negative and marginally significant (coefficient −0.051 and −0.045, with associated t-statistic of −1.83 and −1.78 respectively). The coefficient on *LRVTB*, however is insignificant. Taken together, we conclude that firms with prospector business strategies are more to equity overvaluation and hence future crash risk.

Taken together, our regression results are consistent with both the hypotheses, highlighting the importance of considering fundamental business strategies as potential determinants of future stock price crash risk.

6. Sensitivity tests

6.1. Firm fixed effects analysis

In our main analysis, we used OLS regression, and included industry and year dummies to control for industry and year effects, respectively. However, one may be concerned that the use of industry dummies in regression models is not an effective way of controlling for unobserved heterogeneity. Therefore, we examine the robustness of the results by estimating a firm fixed-effects version of the regression estimates, where every firm and every year in the sample is assigned a dummy variable. Un-tabulated regression results suggest that the results in the main analysis are robust to the use of firm fixed effect model, implying that the results are not driven by the omitted unknown time invariant firm characteristics.

6.2. Two-step system generalized method of moments (GMM)

Our analysis so far suggests that firms following prospector business strategies are more likely to experience future crash risk. However, the sign, magnitude and statistical significance of these estimates may be biased if firm-level business strategy is correlated with the error term (ε). Therefore, we use the two-step system GMM approach adopted by Arellano and Bover (1995) and Blundell and Bond (1998) to validate our interpretation of the results documented in Table 3. This should also alleviate any concerns with unobserved heterogeneity and omitted variable bias. We obtained system GMM estimates using Roodman's (2009) 'xtabond2' module in Stata.

Table 5 reports diagnostics results for serial correlation tests, Hansen test of over-identifying restrictions, and a Difference Hansen test. Given that errors in levels are serially uncorrelated, we expect significant first-order serial correlation, but insignificant second-order correlation in the first-differenced residuals. Test results reported Table 5 show the desirable statistically significant AR(1) and statistically insignificant AR(2). Moreover, statistically insignificant Hansen test of over-identifying restrictions tests indicate that the instruments are valid in the two-step system GMM estimation.

Results in Table 5 suggest that the relationship between business strategy and stock price crash risk remains robust after accounting for the endogenous relationship between strategy and crash risk. For example, the estimated coefficients (and p value) is 0.059 ($p<0.01$) for *NCSKEW* and 0.068 ($p<0.01$) for the *DUVOL* measures of crash risk. Overall, Two-step system GMM estimate provides strong evidence that the prospector business strategy is associated with firm level stock price crash risk, and the diagnostic tests, including the first-order and second-order serial correlation tests and Hansen test of over-identifying restrictions are supportive.

6.3. Investor sentiment, business strategies, and crash risk

Recent works in finance have studied the impact of investor sentiment on corporate actions, such as equity issues (Baker et al., 2003; Saade, 2015), stock mispricing (Miwa, 2016), dividend pay outs (Baker and Wurgler, 2004; Li and Lie, 2006), investment (Gilchrist et al., 2005; Polk and Sapienza, 2009) and acquisitions (Dong et al., 2006). In the financial reporting context, investor sentiment has been found to have influenced management forecast disclosures (Bergman and Roychowdhury, 2008); disclosure of pro-forma earnings metrics (Brown et al., 2012); and earnings management (Simpson, 2013). As discussed earlier, investors have overly optimistic expectations about the prospects of stocks for firms following innovator strategies which push the stock price upwards. It is, therefore, reasonable to argue that these firms will be under increasing pressure to cater to investor expectations. Managing earnings to fulfil investor expectations during high sentiment periods is one such mechanism (Simpson, 2013) which increases financial reporting opaqueness and, consequently, future crash risk.

Table 5
GMM Model – strategy and crash risk.

	(1)	(2)
Variables	NCSKEW	DUVOL
Constant	16.678	8.248
	[1.19]	[0.99]
NCSKEW $_{t-1}$	0.144***	–
	[7.58]	
DUVOL $_{t-1}$	–	0.043***
		[2.60]
STRATEGY $_{t-1}$	**0.059*** **	**0.068*** **
	[2.65]	**[3.84]**
TURN $_{t-1}$	0.160	0.139
	[0.98]	[1.08]
RET $_{t-1}$	30.011***	18.124***
	[10.65]	[11.60]
STDRET $_{t-1}$	−3.656**	−4.305***
	[−2.44]	[−3.30]
SIZE $_{t-1}$	0.238***	0.173**
	[2.92]	[2.44]
MTB $_{t-1}$	−0.009	0.006
	[−0.69]	[0.46]
LEVERAGE$_{t-1}$	−0.542	−0.490
	[−0.86]	[−1.11]
|DAC| $_{t-1}$	0.113	0.105
	[1.18]	[1.35]
REM $_{t-1}$	0.036	0.011
	[1.18]	[0.49]
FOLLOW $_{t-1}$	−0.025***	−0.013**
	[−3.02]	[−2.04]
INSTOW $_{t-1}$	0.0303	0.014
	[0.75]	[0.05]
AUD $_{t-1}$	0.022	0.005
	[1.55]	[0.49]
AR(1) (*p*-value)	0.000	0.000
AR(2) (*p*-value)	0.263	0.749
Hansen (*p*-value)	0.212	0.392
Diff-Hansen (*p*-value)	0.584	0.910
Industry FE	Yes	Yes
Year FE	Yes	Yes
Observations	45,018	44,382

We use the Baker and Wurgler (2006) investor sentiment index[10] and create an interactive variable *STRATEGY*SENT*. We find that the interactive variable is positive and statistically significant for both the crash measures (coefficients of 0.0081 and 0.0027 respectively) suggesting that crash risk increases for prospectors after a period of high investor sentiment. The coefficient on lagged sentiment index is positive and statistically significant at better than the 1% level implying that crash risk is more likely to follow a period of high investor sentiment.

6.4. Alternative crash risk measure

Following prior literature on crash risk, we construct measures of the likelihood of crashes or positive jumps based on the number of the *Firm-Specific Weekly Returns* exceeding 3.09 standard deviations below or above its mean value, respectively (Hutton et al., 2009). An indicator variable, *CRASH*, is set equal to one for a firm year if the firm experiences one or more *Firm-Specific Weekly Returns* falling 3.09 standard deviations below the mean weekly firm-specific return for that fiscal year; otherwise, *CRASH* is set equal to zero. Untabulated probit regression result reveals a positive and significant coefficient on *STRATEGY* in our baseline regression (coefficient 0.0031, t-stat 1.92, significant at better than the 10% level).

6.5. Control for managerial compensations

We also argued that firms with prospector strategies are more likely to experience future crashes, because of managerial incentives to hoard bad news emanating from stock-based incentive compensations. However, Bentley et al. (2013) argue

[10] Investor sentiment is based on the common variation in six underlying proxies for sentiment: the closed-end fund discount, NYSE share turnover, the number and average of first-day returns on IPOs, the equity share in new issues, and the dividend premium (Baker and Wurgler, 2006). As each sentiment proxy is likely to include a sentiment component as well as idiosyncratic components, the authors use principal components analysis to isolate the common component. Investor sentiment, SENT, is an indicator variable coded 1 for a high sentiment period (SENT index greater than zero) and zero otherwise.

that defenders, too, may have similar incentives. We, therefore, rerun our analysis after incorporating the natural log of option awards (*COMP*), and interacting this with a dummy variable coded 1 for prospectors and zero otherwise (*COMP*PROS*). We find the coefficient on the interactive variable to be positive and marginally significant for the prospectors (untabulated). This suggests that compensation-induced bad news hoarding is greater, and crash risk is higher, for prospectors as compared to defenders.

6.6. Alternative strategy score

We also replaced lagged *STRATEGY* with two indicator variables for prospectors and defenders, where analyzers are used as the benchmark for analysis, and find the coefficients on prospectors (defenders) to be significantly positive (negative) for the *NCSKEW* as well as *DUVOL* crash measures. For both models, the intercept, which captures the effect of analyzer-type strategy on the probability of crash risk, is negative and highly significant, implying that analyzers will encounter fewer future crashes. Finally we also ran a constrained-model regression using the prospectors and defenders sample only, with prospectors taking a value of 1 for firm-year observations having a high strategy score (*PROSPECT* = 1), and zero otherwise. Again we find positive and significant coefficients on *PROSPECT* for both crash risk measures.

6.7. Alternative sample period

We rerun our baseline model using data from 1988 and onwards. The rationale for doing this stems from the fact that historical SIC codes using the Compustat Annual file are mostly missing prior to 1988. The use of historical SIC code results in a more reliable *STRATEGY* measure since current SIC codes are updated according to current year industry classification. Untabulated result reveals the coefficient on *STRATGEY* to be 0.004 (t-stat 2.98, $p < 0.01$) for the sample period 1988 and onwards for the baseline model using *NCSKEW* as the crash measure. The corresponding coefficient is 0.005 (t-stat 4.86, $p < 0.001$) for *DUVOL* crash measure. Our sample period begins from 1988 when we start including other determinants of crash risk, e.g., analyst following, institutional ownership, audit quality, and tax avoidance.

7. Conclusion

Stock price crash risk is a vital element in stock returns to investors because of its undiversifiable nature. Given the importance of crash risk, it is not surprising to find a growing body of literature exploring the likely determinants of crash risk. Financial reporting opaqueness, proxied both by accruals and real earnings management, managerial propensity to engage in tax avoidance activities, and equity incentives, have all been found to explain the variation in crash risk. However, these outcomes are very much a product of the firm-level business strategies pursued by individual firms. By exploring the extent to which firms that follow particular business strategies are more or less likely to experience crash risk, we provide evidence that increases our understanding of the underlying determinants of crash risk.

We use the Miles and Snow (1978, 2003) strategy typology that focuses on the organization's rate of change regarding its products and markets. We argue that the asymmetric market response to negative earnings surprises reported by firms following prospector business strategies, and the long-term incentive-based compensation design for these firms, induce managers to withhold bad news which increases future crash risk. Our empirical findings show that firms with high (low) strategy scores are more (less) prone to crash risk. We also find that firms following innovator business strategies are more prone to equity overvaluation and the combination of these two further increases future crash risk.

Our study contributes to the growing literature on both stock crash risk and corporate strategy. We extend the crash risk literature by showing that firm strategy is one important determinant of stock crash risk. an understanding of the association between business strategies and crash risk would assist investors in allocating resources carefully among companies with different business strategies. We also contribute to the strategy literature by showing that business strategies have wider implications as they can affect the probability of firm-level crash risk by altering the timing of information disclosure.

Appendix A.

Variable definitions

Variable	Explanation
RD_5	Ratio of research and development expenditures [XRD] to sales [SALE] computed over a rolling prior 5 year average
EMPLOYEE_5	Ratio of the number of employees [EMP] to sales [SALE] computed over a rolling prior 5 year average.
REV_5	One-year percentage change in total sales computed over a rolling prior five-year average
SG&A_5	Ratio of selling, general and administrative (SG&A) expenses to sales computed over a rolling prior five-year average.
S.D.EMPLOYEE_5	Standard deviation of the total number of employees computed over a rolling prior five-year period
CAP_5	Capital intensity measured as net property, plant, and equipment scaled by total assets and computed over a rolling prior five-year average

STRATEGY	Each of the above six individual variables is ranked by forming quintiles within each two-digitSICindustry-year. Within each company-year, those observations with variables in the highest quintile are given a score of 5, in the second-highest quintile are given a score of 4, and so on ((except capital intensity which is reversed-scored so that observations in the lowest (highest) quintile are given a score of 5 (1)). Then for each company-year, the scores across the six variables are summed such that a company could receive a maximum score of 30 (prospector-type) and a minimum score of 6 (defender-type).
NCSKEW	Negative conditional skewness of firm-specific weekly returns over the fiscal year. NCSKEW is calculated by taking the negative of the third moment of firm-specific weekly returns for each year and normalizing it by the standard deviation of firm-specific weekly returns raised to the third power [See text for the detailed formula].
DUVOL	Down-to-up volatility measure of the crash likelihood. For each firm j over a fiscal-year period t, firm-specific weekly returns are separated into two groups: "down" weeks when the returns are below the annual mean, and "up" weeks when the returns are above the annual mean. Standard deviation of firm-specific weekly returns is calculated separately for each of these two groups, and *DUVOL* is the natural logarithm of the ratio of the standard deviation in the "down" weeks to the standard deviation in the "up" weeks. For both crash risk measures the firm-specific weekly return for firm *j* in week τ ($W_{j,\tau}$) is calculated as the natural logarithm of one plus the residual return from the following expanded market model regression: $r_{j,\tau} = \alpha_j + \beta_{1,j} r_{m,\tau-2} + \beta_{2,j} r_{m,\tau-1} + \beta_{3,j} r_{m,\tau} + \beta_{4,j} r_{m,\tau+1} + \beta_{5,j} r_{m,\tau+2} + \varepsilon_{j,\tau}$ (1) Where $r_{j,\tau}$ is the return of firm *j* in week τ, and $r_{m,\tau}$ is the return on CRSP value-weighted market return in week τ. The lead and lag terms for the market index return is included to allow for nonsynchronous trading (Dimson, 1979). above. In estimating Eq. (1), each firm-year is required to have at least 26 weekly stock returns.
OVERVALUATION	Rhodes et al. (2005) technique for decomposing market-to-book (MTB) ratios into misevaluation (MTV) and growth option (VTB) as follows: $MTB = MTV \times VTB$ (4), which, in log form, can be written as $m - b = (m - v) + (v - b)$ (5), where lower case letters indicate logarithms of the respective variables. Decomposing the MTB ratio, relies on determining an estimate of firm value, v. For estimation purposes, for each firm *i* in industry *j* at time *t*, v can be expressed as a linear function of observable firm-specific accounting information, θ_{it}, and a vector of corresponding accounting multiples, α. The methodology employs both a vector of contemporaneous time-*t* accounting multiples, α_{jt}, and a vector of long-run accounting multiples, α_j, such that the *MTB* ratio for firm *i* at time *t* can be further decomposed into 3 components as follows: $m_{it} - b_{it} = m_{it} - v(\theta_{it};\alpha_{jt}) + v(\theta_{it};\alpha_{jt}) - v(\theta_{it};\alpha_j) + v(\theta_{it};\alpha_j) - b_{it}$ (6) FSE TSSE LRVTB The first term on the right-hand side of Eq. (6), $m_{it} - v(\theta_{it};\alpha_{jt})$, referred to as the firm-specific error (*FSE*), measures the difference between market value and fundamental value, and is estimated using firm-specific accounting data, θ_{it}, and the contemporaneous sector accounting multiples, α_{jt}, and is intended to capture the extent to which the firm is mis-valued relative to its contemporaneous industry peers. The second term, $v(\theta_{it};\alpha_{jt}) - v(\theta_{it};\alpha_j)$, referred to as time-series sector error (*TSSE*), measures the difference in estimated fundamental value when contemporaneous sector accounting multiples at time *t*, α_{jt}, differ from long-run sector multiples, α_j, and is intended to capture the extent to which the industry (or, possibly, the entire market) may be mis-valued at time *t*. Total valuation error (*TVE*) is the sum of *FSE* and *TSSE*. The third term, referred to as *LRVTB*, measures the difference between firm value (implied by the vector of long-run sector multiples) and book value. This measure is interpreted as the investment opportunity component of the MTB ratio.
SENT	An indicator variable coded 1 for high sentiment period and zero otherwise. High sentiment periods are 1987-88, 1996-97, 1999-01, 2004, and 2006–07. Investor sentiment is based on the common variation in six underlying proxies for sentiment: the closed-end fund discount, NYSE share turnover, the number and average of first-day returns on IPOs, the equity share in new issues, and the dividend premium (Baker and Wurgler, 2006). Since each sentiment proxy is likely to include a sentiment component as well as idiosyncratic components, the authors use principal components analysis to isolate the common component.
TURN	$TURN_{t-1}$ is the average monthly share turnover over the current fiscal year minus the average monthly share turnover over the previous fiscal year, where monthly share turnover is calculated as the monthly trading volume divided by the total number of shares outstanding during the month.
SDRET	Standard deviation of firm-specific weekly returns over the fiscal year.
SIZE	Natural log of total assets.
SGROW	Growth in sales from t-1 to t divided by sales (t-1).
LEVERAGE	Total long-term debt divided by total assets.
DAC	Absolute discretionary accruals calculated using the performance-adjusted Modified Jones model (Kothari et al., 2005). We estimate the following model for all firms in the same industry (using theSICtwo-digit industry code) with at least 8 observations in an industry in a particular year, to get industry-specific parameters for calculating the non-discretionary component of total accruals (*NDAC*). *DAC* is then the residual from model (1), i.e., *DAC* = *ACC* – *NDAC*. Where *ACC* = Net income – operating cash flows (*OCF*)/Lagged total assets. $ACC_t/TA_{t-1} = \gamma_0(1/TA_{t-1}) + \gamma_1[(\Delta SALES_t - \Delta RECEIVABLE_t)/TA_{t-1}] + \gamma_2(PPE_t/TA_{t-1}) + \gamma_3(ROA_{t-1}) + \varepsilon_t$ (11) where *ACC* is total accruals calculated as earnings before extraordinary items and discontinued operations minus operating cash flows; *TA* is total assets in year t-1; $\Delta SALES$ is change in sales from year t-1 to year t; $\Delta RECEIVABLE$ is change in accounts receivable from year t-1 to year t; *PPE* is gross property plant & equipment; *ROA* is return on assets measured as earnings before extraordinary items and discontinued operations for the preceding year divided by total assets for the same year.
REM	Real earnings management is the sum of *ACFO* – *APROD* + *ADISX*; where *ACFO* is the level of abnormal cash flows from operations, *APROD* is the level of abnormal production costs, and *ADISX* is the level of abnormal discretionary expenses (Roychowdhury, 2006).
ACFO	Abnormal cash flows from operations, measured as the difference between actual and predicted cash flow from operations. We multiply the residuals by −1 so that higher values indicate income-increasing REM.

APROD	Abnormal production cost, measured as the difference between actual and predicted production cost, where production costs are measured as the sum of cost of goods sold and change in inventory.
ADISX	Abnormal discretionary expenses, measured as the difference between actual and predicted discretionary expenses. We multiply the residuals by −1 so that higher values indicate income-increasing REM.
FOLLOW	Natural log of number of analysts following a firm.
INSTOW	The percentage of the firm's shares owned by institutional owners.
AUD	Indicator variable equal to 1 if the company is audited by a Big 4 audit firm

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