Technology Spillovers, Information Externality, and Stock Price Crash Risk*

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Abstract

Technology spillovers are shown to have important implications on firms' market valuation and innovation activities. Building on this literature, we show that value-relevant information from technology spillovers significantly reduces the likelihood of the focal firm experiencing a stock price crash. This result is robust to alternative measures and potential endogeneity. Additional analyses suggest that the underlying channel for our finding is not technology spillovers discouraging managers from hoarding bad news; rather, it is technology spillovers significantly reducing the differences of investor opinion, which in turn leads to a lower crash risk. We demonstrate that the informational role of financial analysts is likely to facilitate the convergence of investor opinion. Finally, we find a stronger crash risk-reducing effect of technology spillovers for opaque firms. Our findings provide novel evidence that the information externality associated with peer firms' technology activities helps to reduce the focal firm's stock price crash risk.

Keywords: Technology spillovers; Stock price crash risk; Differences of opinion; Heterogeneous beliefs; R&D; Product market competition.

JEL classifications: D80, G12, G14, L10, O30

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1. Introduction

The traditional literature on stock price crash risk focuses predominantly on the role of internal information hoarding in determining the downside risk in the equity market. The basic argument is that inside managers with privileged access to internal information of the firm have incentives to withhold bad news or opportunistically manage its disclosure timing (Jin and Myers 2006, Bleck and Liu 2007, Kothari et al. 2009, Hong et al. 2017). When the negative information accumulated for an extended period such that the cost of withholding bad news becomes greater than the associated benefit, managers exercise an abandonment option, triggering an abrupt large-scale decline in the firm's stock price (e.g., Jin and Myers 2006, Hutton et al. 2009, Hong et al. 2017). However, prior research on stock price crash risk pays little attention to the role of *peer* firms' information in shaping a firm's extreme downside risk in the equity market. This study elucidates this under-studied area by examining the impact of technology spillovers from peer firms' research and development (R&D) activities on the focal firm's crash risk.

R&D plays a critical role in a firm's technology advancements, product innovations, and product market competitions. The economics literature has long held the view that R&D has multifaceted effects: while firms face rivalry from industry peers that actively conduct R&D and offer similar products (i.e., the business-stealing effect), they also benefit from knowledge spillovers from technology peers operating in similar technology areas (i.e., the technology spillover effect) (Griliches 1979, Jaffe 1986, Bernstein and Nadiri 1989, Jaffe et al. 1993, Cassiman and Veugelers 2006, Bloom et al. 2013). Bloom et al. (2013) develop two novel empirical proxies that separately quantify the technology spillover effect and the countervailing business-stealing effect. More specifically, they exploit each firm's patent distribution within different technology classes and construct pairwise technology closeness for any two firms. Each firm's technology spillover from peer firms is constructed as the summation of other firms' R&D stocks, weighted by the technology closeness measure. Intuitively, this measure captures the potential knowledge spillover due to technologically-related firms' R&D effort.[1] Their work demonstrates that technology spillovers from peer firms' R&D and innovations boost a firm's market value and productivity, together with the quantity and quality of its innovation output.

This paper examines the crash risk implications of inter-firm technology spillovers. We conjecture that technology spillovers can reduce the differences of opinion among investors as to fundamental value, which in turn leads to low crash risk. In their seminal work, Hong and Stein (2003) argue that in the presence of short-sales constraint, different opinions, formed in the following ways, are a key determinant of stock price crash risk: 1) due to investor specialization in technology areas, some specialized investors (specialists) may receive and comprehend value-relevant information sooner than others, leading to heterogeneous beliefs between specialized investors and other investors (generalists), and 2) investors can have heterogeneous priors about the implication of a firm's R&Ds and innovations, and differently interpret their effect on firm value. We argue that technology spillovers can mitigate these problems. On one hand, in the presence of technology spillovers, even though specific information about a firm is limited, value-relevant information can still be available or accessible from peer firms in a similar technology space, narrowing the information advantage that specialists have over generalists. On the other hand, with an enlarged pool of outside technological knowledge brought by technology spillovers, outside investors can evaluate the focal firm by observing antecedent technology failures and successes of technology peers. This facilitates different investors to form common priors about the

[1] Similarly, the product market rivalry effect on a firm is the summation of the R&D stocks of other firms competing in similar product markets, weighted by a product market closeness measure constructed using firms' segment sales distributions over different SIC industries.

implication of focal firm's R&D activities. Based on the above arguments, we predict technology spillovers to reduce the incidence of stock price crash.

We capture technology spillovers following Bloom et al. (2013) and measure crash risk using negative conditional stock return skewness and down-to-up volatility (e.g., Chen, Hong, and Stein 2001, Jin and Myers 2006, Kim et al. 2011a, 2011b).[2] A higher value of the technology spillover measure means a focal firm has more technology peers working on similar innovation areas or a typical technology peer is conducting more innovation activities in the same area. Using a large sample of U.S. public firms for the period of 1976–2009, we find that higher technology spillover from peer firms' innovation activities is associated with a lower probability of a focal firm's stock price crashing in the future. The effect is economically meaningful: a one standard deviation increase in technology spillovers lowers by 18% of one standard deviation of the negative skewness of stock returns. When we use the likelihood of observing extremely low firm-specific weekly stock returns (Hutton et al. 2009) or the difference between the number of extremely negative and extremely positive returns (Jin and Meyers 2006), we find a consistent crash risk-reducing effect of technology spillover. We further find that the trading volume and abnormal turnover of focal firms' stocks decrease as the level of technology spillovers increases, supporting the idea that technology spillovers reduce the differences of opinion among investors and thus crash risk (Chen et al. 2001).

We conduct additional tests to rule out alternative explanations. First, our results could be due to the fact that technology spillovers intensify external monitoring over firm managers,

[2] Relatedly, we find in some regressions a positive association between the *product rivalry effect* from peer firms' R&D activities and stock price crash risk; however, the results are not consistent across different specifications and the magnitude of this positive association is much smaller than that of the technology spillover effect. This suggests that the first order effect of peer firms' R&D activities on the focal firm is the crash risk-reducing effect of technology spillovers, rather than the crash risk-increasing effects of business stealing or product market rivalry.

reducing the chances for managers to hide bad news, and ultimately reduce stock price crash risk. If this is the case, we should observe a stronger effect of technology spillover among firms that have weaker corporate governance ex ante. However, we find an opposite result: firms with higher CEO pay-performance sensitivity or higher institutional ownership have a stronger spillover-crash risk link. Second, it is possible that a firm with higher technology spillovers attract more financial analysts, which in turn improves the information environment of the focal firm and consequently leads to lower stock price crash risk (Kim, Lu, and Yu, 2019). However, we find no evidence that the number of analysts following the focal firm increases with the level of technology spillover.

Nevertheless, we do find that firms with more financial analysts ex ante exhibit a more negative link between technology spillovers and crash risk. This is consistent with the explanation that financial analysts facilitate the diffusion and comprehension of technological knowledge spilled over from peer firms. A faster diffusion or a better understanding of value-relevant information can reduce the differences of opinion among investors. That is to say, analysts play an information intermediation role.

Finally, whereby technology spillovers enable outside investors to learn the focal firm's intrinsic value from additional information sources (peer firms' technological activities), we expect this effect to be stronger for firms that are more opaque to investors, measured by higher abnormal accrual or information opaqueness (Zhu 2016). Consistent with this argument, we find that the crash risk-reducing effect of technology spillovers is more pronounced for firms with higher financial reporting opacity.

One could be concerned with our results regarding potential endogeneity: some unobserved factors could simultaneously determine firm-specific technology spillovers and stock price crash risk. For example, if a certain technology area is booming due to increasing demand in the product market, then all firms in that area will spend more on R&D. At the same time, increased product market demand could lower the firm's stock price crash risk. We follow Bloom et al. (2013) to address this concern. Specifically, we use changes in the firm-specific tax price of R&D (due to changes in federal and state-specific rules) to construct instrumental variables for R&D expenditures. This provides exogenous variations in R&D spending and allows us to estimate the causal impact of technology spillovers. We find that our results are robust to this instrumental variable approach employing two-stage least squares (2SLS) regressions, suggesting that our baseline results are unlikely to be driven by potential endogeneity.

Our study contributes to the stock price crash risk literature by coming back to the original idea of investor disagreements as the critical determinant of negative skewness of stock returns (Hong and Stein 2003). Up to now, the literature has ample theoretical and empirical studies that focus on managerial hoarding of firm-specific information as the major explanation for stock price crashes (e.g., Jin and Myers 2006, Bleck and Liu 2007, Hutton et al. 2009, He 2014, Zhu 2016, Hong et al. 2017). The role of investor disagreements in inducing stock price crashes has received extremely rare attention and supportive evidence. A recent exception is Chang et al. (2022) that show a reduction in stock price crash risk due to the implementation of the EDGAR system that reduces investor disagreements. Deviating from Chang et al. (2022) that focus on the availability of firm-specific information, our study adds to the same line by documenting the role of *peer firms*' technological information in shaping investor disagreements. Therefore, this study constitutes one of the very few papers that provides supporting evidence for the differences of opinion argument proposed by Hong and Stein (2003).

Second, our study adds to the growing literature examining the consequences of technology spillovers from R&D as well as the information or disclosure effect of patenting.[3] The industrial organization literature calls for more careful examination of the technology spillover effect and the product rivalry effect (e.g., Cassiman and Veugelers 2006, Bloom et al. 2013). Qiu and Wan (2015) show that firms hold cash balances to seize innovation opportunities arising from the knowledge spilled over from peers, confirming the importance of technology spillover effect in corporate finance. Recent accounting studies also emphasize the importance of separating technology spillover and product rivalry. For example, while Cao et al. (2018) find that technological peer pressure induces managers to decrease product disclosures, various recent studies highlight the coexistence of a spillover effect of a firm's technological information on peers' technology disclosure (Ettredge et al. 2019), and stock returns (Tseng 2022), or the informational role of patent disclosure in affecting other firms' innovation (Kim and Valentine 2021; Dyer et al. 2022). Our study shows that in mitigating stock price crash risk, the technology spillover effect plays a distinct role from the product rivalry effect, and that the former is incrementally significant even after controlling for the latter. In this sense, our study is distinguished from prior studies focusing on how product market competition or industry concentration influences crash risk (e.g., Li and Zhan 2019).

2. Hypotheses Development

Hong and Stein (2003) argue that differences of investor opinion is a key driver of stock price crash risk in the presence of short-sales constraint. We conjecture that technology spillovers

[3] Our paper also contributes to a broader literature in management, business and economics that demonstrate the importance of technology spillovers on various outcomes, for example, productivity growth due to IT workers (Tambe and Hitt 2013), cost reduction of health IT investment (Atasoy, Chen, and Ganju 2017), and technology alliance (Li et. al. 2019).

can reduce the differences of opinion among investors as to fundamental value, which in turn contributes to lowering crash risk. Relevant to our context, the following scenarios summarized by Hong and Stein (2007) can lead to heightened differences of opinion among a firms' investors, which in turn could be mitigated by technology spillovers.

First, due to investor specialization in technology areas, specialist investors can receive and comprehend value-relevant information earlier than others, resulting in heterogeneous beliefs between specialist investors and generalist investors. A higher level of technology spillovers could mitigate this problem, because even though specific information about the focal firm might be limited, some value-relevant information is available (or accessible) from peer firms in a similar technology space (Lee et al. 2019), reducing the disadvantage of generalist investors versus specialist investors.

Second, investors can have heterogeneous priors about the implication of a firm's R&Ds and innovations, and differently interpret their effect on firm value. A higher technology spillover means an enlarged pool of outside technological knowledge for the firm's shareholders. In fact, the value-relevant technological knowledge is not confined to innovation or technology itself; it could be related to input or output shocks shared by a firm's technology peers. For example, the demand for certain types of technology or the key inputs used therein could be a common shock facing all technology peers in the same area. Outside investors can evaluate the firm more accurately and promptly by observing antecedent technology failures and successes, which facilitates different investors to form similar beliefs and priors about the focal firm's fundamental value.

Drawing on the above arguments, we predict that technology spillovers can reduce the incidence of stock price crash. We thus propose and test the following hypothesis:

Hypothesis 1: *All else being equal, technology spillovers are negatively associated with future stock price crash risk.*

For the above arguments to work, technology spillovers have to negatively affect differences of opinion among investors. We can validate the underlying channel as divergent investor opinions are associated with higher trading volume and higher abnormal turnovers of the stock (Chen et al. 2001; Hong and Stein, 2007). Therefore, we hypothesize that technology spillovers are negatively associated with the trading volume and abnormal turnover of the focal firm's stock.

Hypothesis 2: *All else being equal, technology spillovers are negatively associated with trading volumes and abnormal turnovers of focal firms' stocks*.

Our finding that higher technology spillover is associated with lower crash risk could be subject to alternative interpretations. It is possible that technology spillovers provide more information sources for external shareholders to better monitor the firm, attenuating managers' incentives to hide bad news. Less hoarding of bad news reduces the chance of abrupt breakout of bad news in the future, thus reducing stock price crash risk. To test this "monitoring" hypothesis, we design subsample tests that rely on the heterogeneity of corporate governance strength across firms. We use firm managers' equity incentives and institutional ownership to proxy for pre-existing level of corporate governance. The rationale for using these measures is that managers whose interests are better aligned with those of shareholders care more about shareholders' value maximization and conduct less bad news hoarding. The marginal effect of technology spillovers on mitigating crash risk should be stronger if the focal firm lacks effective corporate governance mechanisms ex ante. However, if it is the divergent investor opinion, rather than investor monitoring, that is at work, we should not find such a stronger effect. Therefore, we propose and test the following hypothesis:

Hypothesis 3*: The negative association between stock price crash risk and technology spillovers is not stronger for firms with weaker corporate governance mechanisms.*

To outside shareholders, higher technology spillover means that a firm's technology-related information is accessible from an enlarged pool of external information sources such as peer firms in a common technology space. In this sense, technology spillovers are more valuable when the focal firm itself lacks transparency, because an opaque firm's investors can benefit from useful information of peer firms than would a transparent firm's investors. This benefit can ultimately translate into a lower level of differences of investor opinion, which in turn mitigates the firm's stock price crash risk. Therefore, we should find a more negative spillover-crash link for firms whose investors have difficulty obtaining value-relevant information from internal sources (e.g., audited financial statements). For empirical testing, we use the extent of a firm's financial reporting opacity to proxy for firms' information environment. Specifically, we propose and test the following hypothesis, stated in alternative form:

> **Hypothesis 4**: *The negative association between stock price crash risk and technology spillovers is more pronounced for firms with opaque information environment.*

3. Variable Definitions and Empirical Design

This section presents the definitions of our research variables and specifies our empirical model. Appendix A provides more details on the variable definitions.

3.1 Measurement of Perceived Crash Risk

We employ standard measures of crash risk that have been widely used in the literature. Since we are interested in firm-specific factors that contribute to the focal firm's crash risk, we first estimate weekly returns for each focal firm and year. Specifically, we define the firm-specific weekly return, denoted by *W*, as the natural log of 1 plus the residual return from the expanded market model regression:

$$r_{j,t} = \alpha_j + b_{1j} r_{m,t-2} + b_{2j} r_{m,t-1} + b_{3j} r_{m,t} + b_{4j} r_{m,t+1} + b_{5j} r_{m,t+2} + \varepsilon_{j,t}, \quad (1)$$

where r_{jt} is stock j's return during week t; $r_{m,t-2}$, $r_{m,t-1}$, $r_{m,t}$, $r_{m,t+1}$, and $r_{m,t+2}$ are market returns during weeks $t-2$, $t-1$, t, $t+1$, and $t+2$, respectively.

The first measure of crash risk is the negative conditional return skewness (*Ncskew*) measure of Chen et al. (2001), which has been extensively used in subsequent crash risk research, including Jin and Myers (2006) and Kim et al. (2011a, 2011b). Specifically, *Ncskew* for a given firm in a fiscal year is calculated by taking the negative of the third moment of firm-specific weekly returns, W, for each sample year and dividing by the standard deviation of firm-specific weekly returns raised to the third power. That is, for each firm j in year t, we compute *Ncskew* as:

$$Ncskew_{j,t} = -[\mathrm{n}(\mathrm{n}-1)^{3/2} \sum W^3_{j,t}]/[(\mathrm{n}-1)(\mathrm{n}-2)(\sum W^2_{j,t})^{3/2}], \quad (2)$$

where, for firm j and year t, $W_{j,t} = \ln(1 + \varepsilon_{j,t})$; ε is the firm-specific residual return estimated using Equation (1); and n is the number of weeks used to compute *Ncskew*.

Our second crash risk measure is the down-to-up volatility (*Duvol*) measure of crash likelihood from Chen et al. (2001), which is computed as follows. For each firm j over fiscal year t, we separate all the weeks with firm-specific weekly returns below the annual mean (‘‘down’’ weeks) from those with firm-specific returns above the annual mean (‘‘up’’ weeks) and calculate the standard deviation for each of these subsamples separately. The *Duvol* measure is the log of the ratio of the down weeks’ standard deviation to the up weeks’ standard deviation.

3.2 Measurement of Technology Spillovers

Bloom et al. (2013) identify two countervailing R&D spillover effects from peer firms’ R&D on the focal firm’s performance: (i) the positive technology spillover effect; and (ii) the negative product market rivalry effect (or business-stealing effect). We follow Bloom et al. (2013) by separately identifying the technology spillover effect and product market rivalry effect of peer firms' R&D and technological innovations. Bloom et al. (2013) measure firm *i*'s R&D and innovation activity in a technology space using its share of patents in 426 United States Patent and Trademark Office (USPTO) technology classes. Formally, technology spillovers due to peer firms' R&D for focal firm *i* and year *t* are defined as:

$$Lnspilltech_{i,t} = Ln(\sum_{j \neq i} TECH_{i,j} \cdot G_{j,t}), \tag{3}$$

where $G_{j,t}$ is the R&D capital stock of technologically linked firm *j*, calculated using a perpetual inventory method with a 15% depreciation rate. Following Jaffe (1986) and Bloom et al. (2013), $TECH_{i,j}$ is the technology closeness or affinity, defined as the uncentered correlation between any two firms:

$$TECH_{i,j} = \frac{(T_i \cdot T_j')}{(T_i \cdot T_i')^{1/2}(T_j \cdot T_j')^{1/2}} \tag{4}$$

where $T_i = (s_1, s_2, \dots, s_\tau, \dots, s_{426})$ is the vector of firm *i*'s R&D and innovation activity in the technology space of 426 USPTO technology classes, and the τ^{th} element s_τ is the average share of the number of patents in USPTO technology class τ out of firm *i*'s total number of patents from 1976 to 2009. The technology closeness measure, $TECH_{ij}$, is the cosine of the two firms' vectors of patent distributions and has the geometrical interpretation as the similarity of the two vectors. The more similar the two firms' patent distributions, the higher the technology closeness measure. For instance, if two firms file patents in non-overlapping technology classes, then the technology closeness will be 0; if two firms share at least one technology class, then their technology affinity will be positive. Technology closeness ranges between 0 and 1, depending on the degree of technology space overlap, and is symmetric in firm ordering (i.e., $TECH_{i,j} = TECH_{j,i}$). A value of $TECH_{i,j}$ close to 1 means that the two firms are located in close proximity in a technology space and are more likely to benefit from each other's innovation activities.[4]

Similarly, we define the product market rivalry effect by utilizing the product market closeness between firms as follows:

$$Lnspillsic_{i,t} = Ln(\sum_{j \neq i} SIC_{i,j} \cdot G_{j,t}) \tag{5}$$

where $G_{j,t}$ is as defined above, representing the R&D capital stock of technologically linked firm *j*. Following Bloom et al. (2013), $SIC_{i,j}$ is the product market closeness, defined as the uncentered correlation between all pairs:

$$SIC_{i,j} = \frac{(S_i \ \cdot \ S_j')}{(S_i \ \cdot \ S_i')^{1/2}(S_j \ \cdot \ S_j')^{1/2}} \tag{6}$$

where S_i is the vector of firm *i*'s product market activity, with the *k*th element being firm *i*'s average share of sales in SIC four-digit industry segment *k* over the period 1976 to 2009. The product market closeness measure captures the spatial distance in product market space, as revealed by the distribution of sales across industries.

To summarize, for firm *i*, $Lnspilltech_{i,t}$ measures its rivals' R&D stock aggregated by pairwise relatedness in patent application filings, which can proxy for informational externalities from technology peers' innovations. Similarly, $Lnspillsic_{it}$ quantifies its rivals' R&D stock aggregated by spatial distance in segment sales, which can be interpreted as technology-induced competition in the product market. Therefore, the key difference between the two measures lies in potentially different relevant peer firms and the weighting schemes, i.e., the proximity measures that quantify relatedness among firms in technology space (Equation (4)) and in product market space (Equation (6)).

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[4] Since we use firms' average share of patents in each technology class to calculate technology closeness, firms that have no patent granted are dropped.

3.3 Empirical Model

To examine the effects of peer firms' R&D spending on the focal firm's crash risk, we employ the following baseline model, consistent with prior studies (Chen et al. 2001, Kim et al. 2011a, 2011b):

$$\begin{aligned} CrashRisk_{i,t} = {} & \alpha_0 + \alpha_1 Lnspilltec_{i,t-1} + \alpha_2 Lnspillsic_{i,t-1} + \alpha_3 Dturn_{i,t-1} + \alpha_4 Ncskew_{i,t-1} \\ & + \alpha_5 Sigma_{i,t-1} + \alpha_6 Wret_{i,t-1} + \alpha_7 Size_{i,t-1} + \alpha_8 MB_{i,t-1} + \alpha_9 Lev_{i,t-1} + \alpha_{10} ROA_{i,t-1} + \varepsilon_{i,t}, \end{aligned} \tag{7}$$

where, for firm i, $CrashRisk_{i,t}$ is the crash risk in year t. $Lnspilltec_{i,t-1}$ and $Lnspillsic_{i,t-1}$ respectively measure the positive technology spillover effect of peer firms' R&D stock in year $t-1$ and the associated negative business-stealing effect from product market rivals. In addition, we include a similar set of control variables used in prior crash risk research (Chen et al. 2001, Kim et al. 2011a, 2011b) to isolate the two countervailing R&D spillover effects on crash risk from the effect of those control variables. For firm i in year $t-1$: $Dturn_{i,t-1}$ is the detrended share turnover; $Ncskew_{i,t-1}$ is the negative firm-specific weekly return skewness; $Sigma_{i,t-1}$ is the firm-specific weekly return volatility; and $Wret_{i,t-1}$ is the average firm-specific weekly return. For firm i at the end of year $t-1$: $Size_{i,t-1}$ is the logarithmic transformation of a firm's total assets; $MB_{i,t-1}$ is the market-to-book ratio; $Lev_{i,t-1}$ is the ratio of total liabilities to total assets; and $ROA_{i,t-1}$ is the ratio of net income to total assets. We include year and firm indicators to control for year and firm fixed effects.

3.4 Sample and Descriptive Statistics

We identify a firm's technology space position using a patent dataset from Google generously provided by Kogan et al. (2017). They use optical character recognition technology and a number of textual analysis algorithms to extract relevant information from patent documents, and then map the identified assignees to the Center for Research in Security Prices (CRSP) unique identifiers (PERMNO). This dataset has complete annual coverage of over 1.9 million CRSP-matched patents granted by the USPTO from 1926 to 2009.[5] By construction, we drop firms without any patent in calculating the technology spillover measure. To identify a firm's position in the product market space, we use Compustat segment data, for which reporting started in 1976. We extract firm-level accounting information from the Compustat annual files and merge it with the above two datasets to calculate firm-level technology spillovers effects and product market rivalry effects (*Lnspilltec* and *Lnspillsic*, respectively), and then construct our sample. We exclude firms in the financial service industry (SIC codes 6000–6999) and the utilities industry (SIC codes 4900–4999). The sample period covers the 24 years from 1976 to 2009. Appendix A provides the detailed definitions of all the variables used in this study. After requiring non-missing information for all the study's variables, our sample includes 38,418 firm-year observations.

[INSERT TABLE 1 NEAR HERE]

Table 1 presents descriptive statistics of all variables used in this study. The average value of *Ncskew* is −0.033 and that of *Duvol* is −0.024. The mean value of *Crash* is 0.142, suggesting that 14.2% of firm-years experience at least one crash event. The mean value of *Jump* is 0.155, suggesting that 15.5% of firm-years experience at least one jump event. The average firm size of all observations is around USD 296 million. An average firm-year observation has a 2.700 *MB*, an 18.4% leverage, and a 3.2% ROA.

[5] The Google patent data is more extensive than the National Bureau of Economic Research (NBER) patent data developed by Hall et al. (2001). For example, during the same period covered by the NBER patent data (1976-2006), an average of 2,187 additional patents per year are found in the Google patent dataset, which also corrects some errors in the NBER patent data.

4 Main Results

4.1 Baseline Results

To examine the effects of technology spillovers on crash risk, we estimate Equation (7) using OLS regressions that control for year and firm fixed effects. Results are reported in Table 2. In the first two columns, we *only* use $Lnspilltec_{i,t-1}$ as the independent variable and control for year and firm fixed effects. We further add a common set of control variables used in crash risk regressions in columns (3) and (4). We additionally control for $Lnspillsic_{i,t-1}$ in columns (5) and (6). Following Bloom et al. (2013) and Qiu and Wan (2015), we control for year and firm fixed effects in all regressions.[6] All reported t-values are on an adjusted basis using robust standard errors corrected for firm-level clustering (Petersen 2009) and heteroskedasticity (White 1980). Across all specifications, the coefficient on $Lnspilltec_{i,t-1}$ is negative and significant, demonstrating a statistically significant negative correlation between technology spillover and crash risk. More specifically, it is −0.116 ($t = -3.44$) when we use $Ncskew_t$ as the dependent variable (column (5)) and −0.057 ($t = -3.60$) when we use $Duvol_t$ as the dependent variable (column (6)). As explained below, the estimated coefficients on both *Lnspilltech* and *Lnspillsic* are also economically significant.

Interestingly, when we control for $Lnspillsic_{i,t-1}$ in columns (5) and (6), the magnitude of the coefficients on $Lnspilltec_{i,t-1}$ increases, demonstrating the importance of separately identifying the technology spillover effect and the product market rivalry effect (Bloom et al. 2013). The

[6] If we only control for year fixed effects, the coefficients on $Lnspilltec_{i,t-1}$ have an opposite sign. The same pattern was documented by Bloom et al. (2013), where their dependent variable is Tobin's Q. We further test that the fixed effects are highly jointly significant, with a p-value < 0.001; the Hausman test rejects the null of random effects versus fixed effects (p-value < 0.001).

coefficients on $Lnspillsic_{i,t-1}$ are positive and significant, consistent with higher product market competition leading to higher crash risk (Li and Zhan 2019). However, the magnitudes are much smaller than those of $Lnspilltec_{i,t-1}$ and the coefficients are only significant at the 5% level. Coefficients for other control variables are largely consistent with those reported in prior research on crash risk.

To assess the economic magnitude, we consider the regression results in column (5). Multiplying one standard deviation of *Lnspilltec* (1.2) by the estimated *Linspilltec* coefficient of −0.116 gives −0.139. As one standard deviation of *Ncskew* is 0.72, this means that a one standard deviation change in *Lnspilltec* explains around 19% of a one standard deviation change in *Ncskew*. Similarly, based on the regression result in column (6), we calculate that a one standard deviation change in *Lnspilltec* explains around 20% of a one standard deviation change in *Duvol*. Our results in Table 2 collectively demonstrate that peer firms' technology spillovers contain economically sizable information that can greatly alleviate a firm's crash risk, even after controlling for the associated business-stealing effect.

[INSERT TABLE 2 NEAR HERE]

4.2 Results Using Alternative Crash Risk Proxies

The main analysis in Table 2 uses a one-year window to estimate future firm-specific stock price crash risk. Following Kim et al. (2011b) and Kim and Zhang (2016), we also calculate the crash risk measures – *Ncskew* and *Duvol* – using firm-specific weekly returns over the future two- and three-year periods. As reported in in Table 3, the relation between technology spillover and future crash risk continues to be negative and significant. The economic magnitudes of the spillover effects are slightly larger, though not significantly different from the main results in Table

2. These findings demonstrate that the crash risk-reducing effects of technology spillovers persist across various lengths of time.

[INSERT TABLE 3 NEAR HERE]

4.3 Dealing with Potential Endogeneity

In our main specifications, we lag the technology spillovers variable by one year to mitigate concern about potential endogeneity. By nature, technology spillovers emanate from peer firms, rather than the focal firm itself. Nevertheless, our results might still be subject to potential endogeneity. Some unobserved factors could simultaneously affect firm-specific technology spillovers and stock price crash risk. For example, if a certain technology area is booming due to increasing product market demand, then all firms in that technology area will spend more on R&D. Increasing product demand could also reduce the focal firm's stock price crash risk.

We formally address this concern using changes in the firm-specific tax price of R&D (due to changes in federal and state-specific rules regarding R&D tax credits). To this end, we follow Bloom et al. (2013) by constructing instrumental variables for R&D expenditures. In recent decades, the proliferation of R&D tax incentives among U.S. states have been quite effective in increasing in-state R&D (Wilson 2009). Current literature also suggests a large degree of randomness regarding the timing and level of R&D tax credits, and Bloom et al. (2013) find no statistical evidence that changes in economic conditions (such as lagged changes in state R&D or GDP) predict the R&D policy. Therefore, these exogenous variations in R&D spending due to state-level R&D tax credits help to alleviate the concern that technology spillovers' observed impact is driven by potential endogeneity.

Table 4 reports the results of two-stage least squares (2SLS) regressions. Columns (1) and (2) show the first-stage regression results on the two endogenous variables. We first predict R&D flow by regressing the current year R&D expenditure on the user cost of R&D capital, accounting for federal and state-level R&D tax credit following Wilson (2009). Then we use the predicted R&D flow to generate predicted R&D stock using a perpetual inventory method with a 15% depreciation rate. We then weight these predicted values of R&D stock by technology and sales distance to generate the instruments. As shown in columns (1) and (2), our instrumental variables *Lntectax* and *Lnsictax,* using federal and state-level R&D tax credits as the predictors, represent predicted R&D stock weighted by technology closeness and product market closeness, respectively. These instrumental variables are positively correlated with the endogenous variables *Lnspilltec* and *Lnspillsic*. On testing the joint significance of the instrumental variables, the F-statistics are well above 10, which confirms that the instrumental variables are not weak. Columns (3) and (4) report the second-stage regression results in our 2SLS regressions: the estimated coefficients for technology spillovers are all negative and significant at the 1% level, and their magnitudes are almost identical to those of our main results in columns (5) and (6) of Table 2. We, therefore, conclude that our results are robust to controlling for potential endogeneity through the instrumental variable approach.

[INSERT TABLE 4 NEAR HERE]

4.4 Controlling for Firms' Own Innovations

In previous works such as Bloom et al. (2013), technology spillovers from peer firms' R&D have been found to significantly boost the focal firm's own performance in terms of Tobin's Q and innovation activities output. While we control for firm performance, our results might be driven by the confounding effect of focal firms' own innovative activities. *A priori*, how focal firms' own innovation affects their crash risk is unclear. As innovative activity is an inherently risky investment with uncertain outcomes, a higher level of such activity could increase the crash risk. Relatedly, as firms are reluctant to disclose details of their R&D projects, firms that more actively pursue R&D are perceived to have higher information asymmetry or lower transparency, leading to a higher crash risk (Kim and Zhang 2014, Hong et al. 2017). Conversely, innovation is critical to a firm's success in the product market, and more innovation by a firm could increase its product market competitiveness and reduce the likelihood of a stock price crash.

To see if a firm's own innovation does confound our analysis, we control for focal firms' own innovative input or output in our main regressions, and present our analysis in Table 5. In columns (1) and (2) where we control for the log of 1 plus the focal firm's own R&D capital stock, denoted by $Ln(1{+}grd)_{t-1}$, we find that the R&D capital stock is positively associated with stock price crash risk, significant at less than the 1% level. In terms of economic magnitude, a one standard deviation change in $Ln(1{+}grd)_{t-1}$ leads to a 4.1% of one standard deviation change in $Ncskew_t$.

More importantly, the coefficients on our main variable of interest, *Lnspilltec,* remain almost identical from our main results even after controlling for the R&D capital stock. We alternatively control for R&D expenditure, captured by $Ln(1{+}xrd)_{t-1}$ (columns (3) and (4)), and the quantity and quality of innovation output, in terms of both the number of new patents, captured by $Ln(1{+}npat)_{t-1}$ (columns (5) and (6)), and the average number of new patent citations, $Ln(1{+}ncite)_{t-1}$ (columns (7) and (8)). As shown in columns (3) to (8), we consistently find that the estimated results, i.e., the sign, significance, and magnitude of the estimated coefficients on *Lnspilltec* and *Lnspillsic*, are similar to those of our baseline tests in Table 2.

Overall, our results in Table 5 demonstrate that a firm's own innovation activities could affect its stock price crash risk, though its economic magnitude is relatively small. Moreover, our technology spillover effect remains significant and almost identical in magnitude even after controlling for the focal firm's own innovation activities.

[INSERT TABLE 5 NEAR HERE]

5. Underlying Mechanisms

We demonstrate above that technology spillovers from peer firms' R&D alleviate focal firms' stock price crash risk. To further shed light on the specific channels underlying these findings, we examine whether focal firms with a higher level of technology spillovers experience lower differences of opinion among investors. We also examine the role played by financial analysts in intermediating the technological information between firms and investors.

5.1 Differences of Investor Opinion

Our main argument relies on reduced differences of opinion due to technology spillovers. We need to validate this link to pin down the underlying channel. To this end, we estimate the following model:

$$\begin{aligned} Diff\_Opinion_{i,t} = {} & \beta_0 + \beta_1 Lnspilltec_{i,t-1} + \beta_2 Lnspillsic_{i,t-1} + \beta_3 Dturn_{i,t-1} + \beta_4 Ncskew_{i,t-1} \\ & + \beta_5 Sigma_{i,t-1} + \beta_6 Wret_{i,t-1} + \beta_7 Size_{i,t-1} + \beta_8 MB_{i,t-1} + \beta_9 Lev_{i,t-1} + \beta_{10} ROA_{i,t-1} + \varepsilon_{i,t}, \end{aligned} \tag{8}$$

where we use two proxies, *Log(Volume)* and *Dturn*, for the dependent variable *Diff_Opinion*. We include year and firm indicators to control for year and firm fixed effects. If the differences of opinion regarding the focal firm can be reduced by technology spillovers, we expect β_1 to be significantly negative.

The results are presented in Table 6, in which the dependent variable is *Log(Volume)* in columns (1) and (2) and *Dturn* in columns (3) and (4). Columns (1) and (3) exclude *Lnspillsic* and columns (2) and (4) include it. For *Log(Volume)*, the coefficients on *Lnspilltec* are negative and significant (t = −4.92 and −4.15, respectively). In terms of economic magnitude, a one standard deviation increase in technology spillover will leads to about 6.4% standard deviation decrease in the log of trading volume. Similarly, when *Dturn* is the dependent variable, both coefficients on *Lnspilltec* are significantly negative (t = −3.43 and −2.47, respectively), or about 13% of a standard deviation decrease in the abnormal turnover, when the technology spillover increases by one standard deviation. These results suggest that technology spillovers significantly reduce trading volume and abnormal turnover of the focal firm's stock. To the extent that trading volume and turnover gauge the level of differences of investor opinion, we establish a negative association between technology spillovers and a critical determinant of stock price crash risk.

[INSERT TABLE 6 NEAR HERE]

Overall, the results presented in Table 6 are in line with the prediction in Hypothesis 2, thus providing a validation for our economic story – the reduced stock price crash risk by technology spillovers is indeed due to the reduced differences of opinion among investors.

5.2 The Role of Financial Analysts

Financial analysts are an important information intermediary in the capital market and can have an interesting interaction with our setting. First, a higher level of technology spillovers may trigger higher analyst coverage. More analysts following a firm can better monitor firm managers, discourage them from hoarding bad news, and thus reduce future stock price crash risk. This constitutes an alternative explanation for our main finding.

This can be easily tested though. We use the natural logarithm of the number of analysts following a firm as the dependent variable, and examine whether a higher level of technology spillovers increases the number of analysts. The set of control variables is the same as that in Equation (7). The estimation results are presented in columns (1) and (2) of Table 7. With or without controlling for *Lnspillsic*, the coefficient on *Lnspilltec* is insignificant both economically and statistically, suggesting that a higher level of technology spillovers does not necessarily trigger more analysts to follow the focal firm. Therefore, our main finding could not be explained by the alternative story of analysts deterring bad news hoarding.

[INSERT TABLE 7 NEAR HERE]

However, no change in the number of financial analysts does not preclude the possibility that pre-existing analysts can play an important role in dissecting and communicating technological information to the general investors, facilitating the formation of common opinion about the firm's fundamental value and thus reducing crash risk. In this sense, analyst coverage serves as an additional channel for our main results. To test this idea, we separate the sample into two groups, one with a higher level of analyst coverage and the other with a lower level, according to the median level of analyst coverage. We then estimate our baseline model in both subsamples and expect to find a more pronounced result in the subsample with a higher level of analyst coverage.

The results are presented in columns (3) to (6) of Table 7. When *Ncskew* is the dependent variable, the coefficient on *Lnspilltec* is -0.~~046~~ 037 and not significant for low analyst coverage group. However, the coefficient is -0.~~206~~ 235 and highly significant for high analyst coverage group, and the difference in coefficients of the two groups is statistically significant (p = 0.~~059~~080), as shown in the third row from the bottom of Table 7. Similarly, when *Duvol* is the dependent variable, the coefficient on *Lnspilltec* for the low analyst coverage group is -0.~~029~~ 015 while that for the high analyst coverage group is -0.~~094~~104. The difference in coefficients is again statistically significant (p = 0.~~099~~088). This evidence is consistent with our conjecture, supporting the idea that financial analysts play an information intermediation role.

6. Cross-sectional Analyses

In this section, we conduct additional cross-sectional analyses for two purposes. First, we try to rule out the monitoring hypothesis (Hypothesis 3) that technology spillovers intensify external monitoring, discipline managers, and subsequently reduce stock price crash risk. Second, we examine how firms' ex ante information environment affects the association between technology spillovers and crash risk (Hypothesis 4), which has the potential to further buttress the main inference of our study.

6.1 Monitoring Hypothesis

We use two measures to quantify the effectiveness of pre-existing corporate governance. The first measure is the CEO pay-performance sensitivity or Delta, which measures the sensitivity of CEO equity wealth, including both the stock and option compensation, to stock price changes. A higher Delta can mean that managers work harder or more effectively because they share gains and losses with shareholders; it is, thus, seen as a better alignment of managerial incentives with shareholders' interests (Coles et al. 2006). Our second measure is the percentage of total shares held by institutional investors (or simply institutional shareholdings), as institutional investors play important roles in shaping corporate governance and serve as external monitors (Aghion et al. 2013, Giannetti and Laeven 2009). We then conduct subsample analyses to examine how the crash risk-reducing effect of technology spillovers varies with the effectiveness of firms' corporate governance mechanisms.

Panel A of Table 8 reports our subsample analysis for these proxies. In columns (1) to (4), we divide the sample based on the median CEO Delta; and in columns (5) to (8), the samples are divided based on the median institutional ownership. As shown, the impact of technology spillovers on crash risk is generally more pronounced for firms that with better corporate governance. Specifically, as shown in columns (1) to (4), the coefficients on *Lnspilltec* are much greater, in their absolute magnitude, for the subsample of firms with high CEO Delta than for firms with low CEO Delta. We also test if the coefficients on *Lnspilltec* for the two subsamples are significantly different, and find that the *p*-values for the null hypothesis range from 0.~~015~~ 042 to 0.0~~20~~82. In addition, as shown in columns (5) to (8), we find that the crash risk-reducing effect of technology spillovers is greater when institutional ownership is higher and managerial incentives are, thus, better aligned with shareholders' incentives. The *p*-values on testing the difference in regression coefficients between the two subsamples are highly significant~~, ranging from 0.002 to~~ at 0.003.

6.2 Firms' Information Environment

As discussed in the Hypothesis Development section, investors could learn about a focal firm's R&D and innovative activities from those of its technology peers, therefore reducing the differences of investor opinion. Hypothesis 4 predicts that this investor learning effect is stronger when investors are faced with opacity (or lack of transparency) in the focal firm's financial reporting. To test this hypothesis, we use the absolute abnormal accruals measure of Dechow and Dichev (2002) and the information opaqueness measure of Hutton et al. (2009), i.e., a three-year moving sum of absolute discretionary accruals, to proxy for the level of a firm's financial reporting opacity. A higher value in these proxies indicates a higher level of reporting opacity.

Panel B of Table 8 reports our subsample analysis for these proxies. In columns (1) to (4), we divide the sample based on abnormal accruals, while in columns (5) to (8), we divide the sample based on information opaqueness. Consistent with our prediction, the impact of technology spillovers on crash risk is generally more pronounced for firms with higher reporting opacity. The coefficients on *Lnspilltec* in the low-opacity subsample are not significantly different from 0, and are only from 1/3 to 1/10 of the magnitude of those in the high-opacity subsample. We also test if the coefficients on *Lnspilltec* are significantly different for the two subsamples, and find that the *p*-values for the null hypothesis range from 0.010 to 0.~~018~~ 020 (as shown in the third row from the bottom of Table 8). These results are consistent with Hypothesis 4, suggesting that technology spillovers, as an external information source, has a larger marginal effect when investors have difficulty digesting a firm's internal information due to financial reporting opacity.

[INSERT TABLE 8 NEAR HERE]

7. Conclusion

It is well-established that firms benefit from technological knowledge that spills over from peers. This study argues that such technology spillovers improve the focal firm's external information environment, reduce differences of opinion among investors, and consequently reduce its stock price crash risk. Our findings are consistent with this argument. We find that technology spillovers are negatively associated with the focal firm's stock price crash risk. The result still holds when we use an instrumental variable approach to address potential endogeneity and are robust to alternative measures of stock price crash risk. We also find that technology spillovers indeed lead to lower level of differences of investor opinion. Overall, our paper provides supporting evidence for the argument of Hong and Stein (2003) that differences of opinion among investors are a key determinant of stock price crash risk.

Further tests show that the presence of more analysts strengthens the negative association between technology spillovers and crash risk, consistent with the role of financial analysts in intermediating technological information between the firm and general investors. Further cross-sectional analysis suggests that opaque firms benefit more from the crash risk-mitigating role of technology spillovers. Overall, as the literature on stock price crash risk predominantly focuses on the role of internal information, our findings are not driven by internal bad news hoarding and thus provide novel evidence on the role of external information source (i.e., peer firms' R&D) in reducing stock price crashes.

References

Aghion P, Van Reenen J, Zingales L (2013) Innovation and Institutional Ownership. *American Economic Review* 103:277–304.

Aboody D, Lev B (2000) Information Asymmetry, R&D, and Insider Gains. *Journal of Finance* 55:2747–2766.

Atasoy H, Chen P, Ganju K (2017) The Spillover Effects of Health IT Investments on Regional Healthcare Costs. *Management Science.* 64(6): 2515-2534.

Baker M, Wurgler J (2006) Investor Sentiment and the Cross-Section of Stock Returns. *Journal of Finance* 61:1645–1680.

Bernstein JI, Nadiri MI (1989) Research and Development and Intra-industry Spillovers: An Empirical Application of Dynamic Duality. *Review of Economic Studies* 56:249–267.

Bleck A, Liu X (2007) Market Transparency and the Accounting Regime. *Journal of Accounting Research* 45:229–256.

Bloom N, Schankerman M, Van Reenen J (2013) Identifying Technology Spillovers and Product Market Rivalry. *Econometrica* 81:1347–1393.

Bond P, Edmans A, Goldstein I (2012) The Real Effects of Financial Markets. *Annual Review of Financial Economics* 4:339–360.

Cassiman B, Veugelers R (2006) In Search of Complementarity in Innovation Strategy: Internal R&D and External Knowledge Acquisition. *Management Science* 52:68–82.

Cao S, Ma G, Tucker JW, Wan C (2018) Technological Peer Pressure and Product Disclosure. *Accounting Review* 93:95–126.

Chang X, Chen Y, Zolotoy L (2017) Stock Liquidity and Stock Price Crash Risk. *Journal of Financial Quantitative Analysis* 52:1605–1637.

Chang YC, Hsiao PJ, Ljungqvist A, Tseng K (2022) Testing Disagreement Models. *Journal of Finance* 77: 2239–2285.

Chen J, Hong H, Stein JC (2001) Forecasting Crashes: Trading Volume, Past Returns, and Conditional Skewness in Stock Prices. *Journal of Financial Economics* 61:345–381.

Chen Q, Goldstein I, Jiang W (2006) Price Informativeness and Investment Sensitivity to Stock Price. *Review of Financial Studies* 20:619–650.

Cohen L, Diether K, Malloy C (2013) Misvaluing Innovation. *Review of Financial Studies* 26, 635–666.

Coles J, Daniel ND, Naveen L (2006) Managerial Incentives and Risk-Taking. *Journal of Financial Economics* 79:431–468.

Dechow PM, Dichev ID (2002) The Quality of Accruals and Earnings: The role of accrual estimation errors. *Accounting Review* 77:35–59.

DeFond ML, Hung M, Li S, Li Y (2015) Does Mandatory IFRS Adoption Affect Crash Risk? *Accounting Review* 90:265–299.

Dyer T, Glaeser S, Lang MH, Sprecher C (2022) The Effect of Patent Disclosure Quality on Innovation. *Working paper*.

Edmans A, Jayaraman S, Schneemeier J (2017) The Source of Information in Prices and Investment-Price Sensitivity. *Journal of Financial Economics* 126:74–96.

Ettredge M, Guo F, Lisic LL, Tseng K (2019) Technology Spillover and Corporate Technology Disclosures. *Working paper*.

Foucault T, Fresard L (2014) Learning from Peers' Stock Prices and Corporate Investment. *Journal of Financial Economics* 111:554–577.

Giannetti M, Laeven L (2009) Pension Reform, Ownership Structure, and Corporate Governance: Evidence from a Natural Experiment. *Review of Financial Studies* 22:4091–4127.

Griliches Z (1979) Issues in Assessing the Contribution of Research and Development to Productivity Growth. *Bell Journal of Economics* 10:92–116.

Hall BH, Jaffe AB, Trajtenberg M (2001) The NBER patent citation data file: Lessons, insights and methodological tools, No. w8498. *National Bureau of Economic Research*.

He G (2014) The Effect of CEO Inside Debt Holdings on Financial Reporting Quality. *Review of Accounting Studies* 21:349–399.

Hirshleifer D, Hsu P-H, Li D (2013) Innovative Efficiency and Stock Returns. *Journal of Financial Economics* 107:632–654.

Hirshleifer D, Hsu P-H, Li D (2017) Innovative Originality, Profitability, and Stock Returns. *Review of Financial Studies* 31:2553–2605.

Hong HA, Kim J-B, Welker M (2017) Divergence of Cash Flow and Voting Rights, Opacity, and Stock Price Crash Risk: International Evidence. *Journal of Accounting Research* 55:1167–1212.

Hutton AP, Marcus AJ, Tehranian H (2009) Opaque Financial Reports, R^2, and Crash Risk. *Journal of Financial Economics* 94:67–86.

Jaffe AB (1986) Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits, and Market Value. *American Economic Review* 76:984–1001.

Jaffe AB, Trajtenberg M, Henderson R (1993) Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations. *Quarterly Journal of Economics* 108:577–598.

Jin L, Myers SC (2006) R^2 Around the World: New Theory and New Tests. *Journal of Financial Economics* 79:257–292.

Kim J-B, Li Y, Zhang L (2011a) Corporate Tax Avoidance and Stock Price Crash Risk: Firm-Level Analysis. *Journal of Financial Economics.* 100:639–662.

Kim J-B, Li Y, Zhang L (2011b) CFOs versus CEOs: Equity Incentives and Crashes. *Journal of Financial Economics* 101:713–730.

Kim J-B, Lu L Y, Yu Y (2019). Analyst Coverage and Expected Crash Risk: Evidence from Exogenous Changes in Analyst Coverage. *Accounting Review* 94: 345-364.

Kim J, Valentine K (2021). The Innovation Consequences of Mandatory Patent Disclosures. *Journal of Accounting and Economics* 71:101381.

Kim J-B, Zhang L (2014) Financial Reporting Opacity and Expected Crash Risk: Evidence from Implied Volatility Smirks. *Contemporary Accounting Research* 31:851–875.

Kim J-B, Zhang L (2016) Accounting Conservatism and Stock Price Crash Risk: Firm-level Evidence. *Contemporary Accounting Research* 33:412–441.

Kogan L, Papanikolaou D, Seru A, Stoffman N (2017) Technological Innovation, Resource Allocation, and Growth. *Quarterly Journal of Economics* 132:665–712.

Kothari SP, Shu S, Wysocki PD (2009) Do Managers Withhold Bad News? *Journal of Accounting Research* 47:241–276.

Lambert R, Leuz C, Verrecchia RE (2007) Accounting Information, Disclosure, and the Cost of Capital. *Journal of Accounting Research* 45:385–420.

Lee CMC., Sun ST, Wang R, Zhang R (2019) Technological Links and Predictable Returns. *Journal of Financial Economics* 132:76-96.

Lerner J, Wulf J (2007) Innovation and Incentives: Evidence from Corporate R&D. *Review of Economic Statistics* 89:634–644.

Li, K, Qiu, J, Wang, J (2019) Technology Conglomeration, Strategic Alliances, and Corporate Innovation. *Management Science* 65: 4951-5448.

Li S, Zhan X (2019) Product Market Threats and Stock Crash Risk. *Management Science* 65: 3949-4450.

Ma M (2017) Economic Links and the Spillover Effect of Earnings Quality on Market Risk. *Accounting Review* 92:213–245.

Maskell P, Malmberg A (1999) Localized Learning and Industrial Competitiveness. *Cambridge Journal of Economics* 23:167–185.

Petersen M (2009) Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. *Review of Financial Studies* 22:435–480.

Qiu J, Wan C (2015) Technology Spillovers and Corporate Cash Holdings, *Journal of Financial Economics* 115:558–573.

Storper M (1995) The Resurgence of Regional Economies, Ten Years Later: The Region as a Nexus of Untraded Interdependencies. *European Urban and Regional Studies* 2:191–221.

Tseng K (2022) Learning from the Joneses: Technology Spillover, Innovation Externality, and Stock Returns. *Journal of Accounting and Economics* 73:101478.

Tambe P, Hitt, L (2013) Job Hopping, Information Technology Spillovers, and Productivity Growth. *Management Science* 60: 338-355.

White H (1980) A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. *Econometrica* 48:817–838.

Wilson DJ (2009) Beggar Thy Neighbor? The In-State, Out-of-State, and Aggregate Effects of R&D Tax Credits. *Review of Economics and Statistics* 91:431–436.

Zhu W (2016) Accruals and Price Crashes. *Review of Accounting Studies* 21:349–399.

Table 1. Descriptive Statistics

	N	Mean	Std	Lower Quartile	Median	Upper Quartile
$Ncskew_t$	38,418	−0.033	0.718	−0.422	−0.060	0.307
$Duvol_t$	38,418	−0.024	0.338	−0.245	−0.035	0.183
$Lnspilltec_{t-1}$	38,418	9.787	1.227	9.115	9.925	10.658
$Lnspillsic_{t-1}$	38,418	7.899	2.303	6.688	8.226	9.487
$Dturn_{t-1}$	38,418	0.004	0.068	−0.014	0.001	0.018
$Ncskew_{t-1}$	38,418	−0.018	0.647	−0.403	−0.054	0.311
$Sigma_{t-1}$	38,418	0.141	0.139	0.063	0.100	0.163
$Wret_{t-1}$	38,418	−1.519	3.154	−1.293	−0.482	−0.191
$Size_{t-1}$	38,418	5.692	1.956	4.237	5.543	7.048
MB_{t-1}	38,418	2.700	2.681	1.170	1.866	3.138
Lev_{t-1}	38,418	0.184	0.155	0.039	0.169	0.287
ROA_{t-1}	38,418	0.032	0.142	0.008	0.056	0.100
$Ln(1+grd)_{t-1}$	38,418	1.709	2.063	0.031	0.652	3.038
$Ln(1+xrd)_{t-1}$	38,418	0.984	1.515	0.000	0.145	1.530
$Ln(1+npat)_{t-1}$	38,418	1.197	1.477	0.000	0.693	1.946
$Ln(1+ncite)_{t-1}$	38,418	1.247	1.351	0.000	0.693	2.464
$Log(Volume)_t$	34,755	14.066	2.131	12.463	14.040	15.594
$Ln(analysts)_t$	34,755	14.066	2.131	12.463	14.040	15.594

This table reports the descriptive statistics for crash risk, technology spillover and control variables. The main measures for crash risk are *Ncskew* and *Duvol*. The main measure for technology spillover is *Lnspilltec* developed by Bloom et al. (2013). The sample contains 38,418 unique firm-years for 3,073 publicly traded U.S. firms over the period from 1976 to 2009. Variable definitions are in Appendix Table A. All variables are winsorized at 1% and 99%.

Table 2. Technology Spillovers and Crash Risk

Variables	(1) *Ncskew*$_t$	(2) *Duvol*$_t$	(3) *Ncskew*$_t$	(4) *Duvol*$_t$	(5) *Ncskew*$_t$	(6) *Duvol*$_t$
Lnspilltec$_{t-1}$	−0.060*	−0.031**	−0.097***	−0.048***	−0.116***	−0.057***
	[−1.90]	[−2.06]	[−2.97]	[−3.16]	[−3.44]	[−3.60]
Lnspillsic$_{t-1}$					0.024**	0.011**
					[2.39]	[2.30]
Dturn$_{t-1}$			0.236***	0.092***	0.239***	0.094***
			[3.97]	[3.43]	[4.02]	[3.48]
Ncskew$_{t-1}$			−0.060***	−0.025***	−0.060***	−0.025***
			[−9.22]	[−8.54]	[−9.26]	[−8.57]
Sigma$_{t-1}$			0.425***	0.238***	0.426***	0.239***
			[4.21]	[4.70]	[4.22]	[4.72]
Wret$_{t-1}$			−0.002	−0.000	−0.002	−0.000
			[−0.68]	[−0.17]	[−0.68]	[−0.17]
Size$_{t-1}$			0.059***	0.029***	0.058***	0.028***
			[6.56]	[6.80]	[6.50]	[6.74]
MB$_{t-1}$			0.020***	0.010***	0.020***	0.010***
			[9.47]	[9.79]	[9.45]	[9.76]
Lev$_{t-1}$			−0.056	−0.029	−0.054	−0.029
			[−1.32]	[−1.48]	[−1.28]	[−1.44]
ROA$_{t-1}$			0.347***	0.173***	0.348***	0.174***
			[7.60]	[8.33]	[7.63]	[8.36]
Constant	0.395	0.187	0.367	0.169	0.371	0.171
	[1.42]	[1.42]	[1.30]	[1.27]	[1.31]	[1.28]
Year Indicators	Yes	Yes	Yes	Yes	Yes	Yes
Firm Indicators	Yes	Yes	Yes	Yes	Yes	Yes
Observations	38,418	38,418	38,418	38,418	38,418	38,418
R-sq	0.013	0.017	0.026	0.029	0.026	0.030

This table reports the regression results on the effect of technology spillover on crash risk. The odd columns use *Ncskew* and the even columns use *Duvol* for our main proxies of crash risk, and we measure technology spillover using *Lnspilltec* developed by Bloom et al. (2013). In Columns (1) and (2) we do not include any control variables, and we include all control variables in Columns (3) and (4). We further control for business stealing effect in Columns (5) and (6). Variable definitions are in Appendix Table A. Reported t-values are on an adjusted basis using robust standard errors corrected for firm-level clustering (Petersen 2009) and heteroskedasticity (White 1980). ***, ** and * respectively represent 1%, 5%, and 10% significance levels.

Table 3. Technology Spillovers and Crash Risk in Longer Forecasting Windows

Variables	(1)	(2)	(3)	(4)
	Two-year Window		*Three-year Window*	
	Ncskew $_{[t,t+1]}$	*Duvol* $_{[t,t+1]}$	*Ncskew* $_{[t,t+2]}$	*Duvol* $_{[t,t+2]}$
$Lnspilltec_{t-1}$	−0.151***	−0.065***	−0.146**	−0.063***
	[−3.10]	[−3.49]	[−2.46]	[−3.06]
$Lnspillsic_{t-1}$	0.025*	0.008	0.024	0.007
	[1.89]	[1.58]	[1.55]	[1.14]
$Dturn_{t-1}$	0.311***	0.117***	0.285***	0.099***
	[4.76]	[4.91]	[4.34]	[4.69]
$Ncskew_{t-1}$	−0.068***	−0.025***	−0.067***	−0.023***
	[−9.62]	[−9.55]	[−9.07]	[−9.78]
$Sigma_{t-1}$	0.249**	0.130***	0.161	0.093**
	[2.18]	[3.07]	[1.40]	[2.22]
$Wret_{t-1}$	−0.004	−0.001	−0.005	−0.000
	[−1.00]	[−0.57]	[−1.20]	[−0.13]
$Size_{t-1}$	0.082***	0.035***	0.068***	0.027***
	[6.44]	[7.35]	[4.71]	[5.49]
MB_{t-1}	0.021***	0.009***	0.019***	0.008***
	[7.03]	[8.42]	[5.85]	[7.06]
Lev_{t-1}	−0.080	−0.044**	−0.057	−0.040*
	[−1.43]	[−2.09]	[−0.94]	[−1.86]
ROA_{t-1}	0.406***	0.167***	0.468***	0.170***
	[6.94]	[7.95]	[7.37]	[8.25]
Constant	0.485	0.196	0.480	0.217
	[1.16]	[1.23]	[0.94]	[1.24]
Year Indicators	Yes	Yes	Yes	Yes
Firm Indicators	Yes	Yes	Yes	Yes
Observations	33,996	33,996	31,409	31,409
R-sq	0.036	0.049	0.040	0.058

This table reports the regression results on the effect of technology spillover on crash risk, using crash risk calculated from longer forecasting windows. The first two columns calculate crash risk using 2-year window and the last two columns use 3-year window instead. Variable definitions are in Appendix Table A. Reported t-values are on an adjusted basis using robust standard errors corrected for firm-level clustering (Petersen 2009) and heteroskedasticity (White 1980). ***, ** and * respectively represent 1%, 5%, and 10% significance levels.

Table 4. Technology Spillover and Crash Risk: Instrumental Variables Approach

Variables	(1)	(2)	(3)	(4)
	First stage		*Second stage*	
	$Lnspilltec_{t-1}$	$Lnspillsic_{t-1}$	$Ncskew_t$	$Duvol_t$
$Lnspilltec_{t-1}$			−0.121***	−0.062***
			[−2.87]	[−3.08]
$Lnspillsic_{t-1}$			0.033**	0.014**
			[2.37]	[2.11]
$Lntectax_{t-1}$	1.118***	0.187***		
	[33.77]	[2.82]		
$Lnsictax_{t-1}$	0.007	1.136***		
	[0.92]	[27.09]		
$Dturn_{t-1}$	−0.019***	−0.066***	0.239***	0.095***
	[−2.70]	[−4.05]	[3.99]	[3.50]
$Ncskew_{t-1}$	−0.001	0.002	−0.059***	−0.025***
	[−1.48]	[0.64]	[−9.07]	[−8.35]
$Sigma_{t-1}$	−0.040**	−0.052	0.422***	0.240***
	[−2.10]	[−1.47]	[4.12]	[4.66]
$Wret_{t-1}$	−0.000	0.001	−0.003	−0.000
	[−0.70]	[0.81]	[−0.80]	[−0.20]
$Size_{t-1}$	0.022***	0.011	0.058***	0.029***
	[6.13]	[1.06]	[6.31]	[6.60]
MB_{t-1}	−0.000	0.001	0.020***	0.010***
	[−0.44]	[0.42]	[9.35]	[9.70]
Lev_{t-1}	0.059***	0.066*	−0.057	−0.030
	[4.63]	[1.78]	[−1.32]	[−1.48]
ROA_{t-1}	0.034***	−0.014	0.349***	0.171***
	[3.08]	[−0.67]	[7.76]	[8.25]
Year Indicators	Yes	Yes	Yes	Yes
Firm Indicators	Yes	Yes	Yes	Yes
Observations	37,298	37,298	37,298	37,298
R-sq			0.026	0.030

This table presents the first and second-stage regression results on the relation between technology spillover and a firm's crash risk, using the instrumental variable approach. Columns (1) and (2) show the first stage and the dependent variables are *Lnspilltec* and *Lnspillsic.* Columns (3) and (4) show the second stage and the dependent variables are *Ncskew* and *Duvol*. Variable definitions are in Appendix Table A. Reported t-values are on an adjusted basis using robust standard errors corrected for firm-level clustering (Petersen 2009) and heteroskedasticity (White 1980). ***, ** and * respectively represent 1%, 5%, and 10% significance levels.

Table 5. Technology Spillover and Crash Risk: Controlling for Own Innovation

Variables	(1) $Ncskew_t$	(2) $Duvol_t$	(3) $Ncskew_t$	(4) $Duvol_t$	(5) $Ncskew_t$	(6) $Duvol_t$	(7) $Ncskew_t$	(8) $Duvol_t$
$Lnspilltec_{t-1}$	−0.112***	−0.056***	−0.109***	−0.054***	−0.114***	−0.057***	−0.115***	−0.057***
	[−3.37]	[−3.52]	[−3.27]	[−3.41]	[−3.38]	[−3.56]	[−3.44]	[−3.60]
$Lnspillsic_{t-1}$	0.025**	0.012**	0.025**	0.012**	0.024**	0.011**	0.024**	0.011**
	[2.55]	[2.48]	[2.55]	[2.48]	[2.43]	[2.32]	[2.40]	[2.32]
$Ln(1+grd)_{t-1}$	0.013***	0.007***						
	[2.97]	[3.46]						
$Ln(1+xrd)_{t-1}$			0.018***	0.010***				
			[3.41]	[4.02]				
$Ln(1+npat)_{t-1}$					−0.009	−0.003		
					[−1.48]	[−0.98]		
$Ln(1+ncite)_{t-1}$							0.003	0.003
							[0.86]	[1.44]
$Dturn_{t-1}$	0.235***	0.091***	0.235***	0.092***	0.237***	0.093***	0.239***	0.094***
	[3.95]	[3.39]	[3.96]	[3.40]	[3.99]	[3.46]	[4.02]	[3.47]
$Ncskew_{t-1}$	−0.060***	−0.026***	−0.060***	−0.026***	−0.060***	−0.026***	−0.060***	−0.025***
	[−9.27]	[−8.59]	[−9.30]	[−8.63]	[−9.28]	[−8.59]	[−9.25]	[−8.56]
$Sigma_{t-1}$	0.427***	0.239***	0.428***	0.240***	0.428***	0.239***	0.426***	0.239***
	[4.23]	[4.73]	[4.24]	[4.74]	[4.24]	[4.73]	[4.22]	[4.71]
$Wret_{t-1}$	−0.002	−0.000	−0.002	−0.000	−0.002	−0.000	−0.002	−0.000
	[−0.68]	[−0.17]	[−0.68]	[−0.18]	[−0.67]	[−0.16]	[−0.68]	[−0.17]
$Size_{t-1}$	0.056***	0.027***	0.055***	0.027***	0.061***	0.029***	0.058***	0.028***
	[6.24]	[6.46]	[6.07]	[6.24]	[6.67]	[6.81]	[6.45]	[6.66]
MB_{t-1}	0.021***	0.010***	0.021***	0.010***	0.020***	0.010***	0.020***	0.010***
	[9.64]	[10.03]	[9.63]	[10.03]	[9.50]	[9.80]	[9.44]	[9.76]
Lev_{t-1}	−0.047	−0.024	−0.047	−0.024	−0.057	−0.029	−0.053	−0.028
	[−1.10]	[−1.23]	[−1.11]	[−1.23]	[−1.34]	[−1.48]	[−1.26]	[−1.40]
ROA_{t-1}	0.354***	0.177***	0.353***	0.176***	0.346***	0.173***	0.349***	0.174***
	[7.74]	[8.51]	[7.73]	[8.50]	[7.55]	[8.31]	[7.63]	[8.38]
Constant	0.305	0.134	0.295	0.127	0.350	0.164	0.364	0.166
	[1.08]	[1.01]	[1.05]	[0.96]	[1.23]	[1.23]	[1.29]	[1.24]
Year Indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	38,418	38,418	38,418	38,418	38,418	38,418	38,418	38,418
R-sq	0.026	0.030	0.027	0.030	0.026	0.030	0.026	0.030

This table reports the regression results on the effect of technology spillover on crash risk, controlling for own innovation input or output. The odd columns use *Ncskew* and the even columns use *Duvol* for our main proxies of crash risk, and we measure technology spillover using *Lnspilltec* developed by Bloom et al. (2013). Variable definitions are in Appendix Table A. Reported t-values are on an adjusted basis using robust standard errors corrected for firm-level clustering (Petersen 2009) and heteroskedasticity (White 1980). ***, ** and * respectively represent 1%, 5%, and 10% significance levels.

Table 6. Technology Spillovers, Trading Volume and Stock Turnover

	(1)	(2)	(3)	(4)
	Log(Volume)$_t$		*Dturn$_t$*	
Lnspilltec$_{t-1}$	-0.129***	-0.110***	-0.012***	-0.009**
	[-4.92]	[-4.15]	[-3.43]	[-2.47]
Lnspillsic$_{t-1}$		-0.024***		-0.004***
		[-3.41]		[-3.76]
Dturn$_{t-1}$	3.140***	3.136***	-0.178***	-0.179***
	[45.60]	[45.56]	[-17.28]	[-17.32]
Ncskew$_{t-1}$	0.020***	0.020***	-0.008***	-0.007***
	[5.21]	[5.27]	[-11.06]	[-11.02]
Sigma$_{t-1}$	1.361***	1.360***	-0.090***	-0.090***
	[13.73]	[13.69]	[-6.10]	[-6.11]
Wret$_{t-1}$	0.019***	0.019***	-0.003***	-0.003***
	[5.70]	[5.70]	[-4.89]	[-4.88]
Size$_{t-1}$	0.255***	0.256***	-0.017***	-0.017***
	[31.54]	[31.81]	[-16.11]	[-16.05]
MB$_{t-1}$	0.040***	0.040***	0.001***	0.001***
	[23.35]	[23.44]	[3.38]	[3.40]
Lev$_{t-1}$	-0.300***	-0.302***	0.016***	0.016***
	[-10.31]	[-10.37]	[3.44]	[3.38]
ROA$_{t-1}$	0.374***	0.372***	-0.014**	-0.015**
	[10.91]	[10.87]	[-2.27]	[-2.31]
Constant	3.471***	3.477***	0.221***	0.221***
	[13.27]	[13.51]	[6.47]	[6.51]
Year Indicators	Yes	Yes	Yes	Yes
Firm Indicators	Yes	Yes	Yes	Yes
Observations	34,755	34,755	34,758	34,758
R-sq	0.968	0.968	0.138	0.139

This table reports the regression results on the effect of technology spillover on trading volume and stock abnormal turnover. Variable definitions are in Appendix Table A. Reported t-values are on an adjusted basis using robust standard errors corrected for firm-level clustering (Petersen 2009) and heteroskedasticity (White 1980). ***, ** and * respectively represent 1%, 5%, and 10% significance levels.

Table 7. Technology Spillovers and Crash Risk: The Role of Financial Analysts

	(1)	(2)	(3)	(4)	(5)	(6)
			Number of analysts			
			Low	*High*	*Low*	*High*
	Ln(analysts)$_t$		*Ncskew$_t$*		*Duvol$_t$*	
Lnspilltec$_{t-1}$	-0.000	-0.005	-0.037	-0.235***	-0.015	-0.104***
	[-0.02]	[-0.29]	[-0.43]	[-2.94]	[-0.37]	[-2.80]
Lnspillsic$_{t-1}$		0.006	0.034	0.066**	0.015	0.027**
		[1.08]	[1.34]	[2.54]	[1.30]	[2.19]
Dturn$_{t-1}$	0.158***	0.158***	0.311***	0.258***	0.128***	0.099***
	[4.99]	[5.01]	[4.37]	[3.60]	[3.88]	[2.96]
Ncskew$_{t-1}$	0.030***	0.030***	-0.125***	-0.153***	-0.057***	-0.065***
	[9.50]	[9.49]	[-10.11]	[-13.03]	[-10.00]	[-11.81]
Sigma$_{t-1}$	0.021	0.021	0.068	0.582***	0.083	0.270***
	[0.48]	[0.49]	[0.55]	[3.58]	[1.45]	[3.56]
Wret$_{t-1}$	0.005***	0.005***	-0.005***	0.003	-0.002**	0.001
	[3.56]	[3.55]	[-2.69]	[0.95]	[-2.35]	[0.93]
Size$_{t-1}$	0.146***	0.146***	0.132***	0.097***	0.057***	0.045***
	[24.20]	[24.18]	[5.87]	[4.62]	[5.44]	[4.61]
MB$_{t-1}$	0.013***	0.013***	0.000	0.000	0.000	0.000
	[11.51]	[11.50]	[0.27]	[0.57]	[0.00]	[0.22]
Lev$_{t-1}$	-0.205***	-0.204***	-0.238***	-0.199**	-0.105**	-0.101**
	[-9.02]	[-9.01]	[-2.62]	[-2.21]	[-2.51]	[-2.41]
ROA$_{t-1}$	0.214***	0.215***	0.175***	0.119***	0.084***	0.075***
	[9.53]	[9.55]	[3.56]	[2.67]	[3.68]	[3.58]
Constant	-0.443**	-0.446**	0.006	1.129	-0.035	0.505
	[-2.46]	[-2.47]	[0.01]	[1.49]	[-0.09]	[1.42]
Year Indicators	Yes	Yes	Yes	Yes	Yes	Yes
Firm Indicators	Yes	Yes	Yes	Yes	Yes	Yes
p-value for test of diff (High−Low)			[0.080]*		[0.088]*	
Observations	34,893	34,893	9,441	9,464	9,441	9,464
R-sq	0.708	0.708	0.273	0.243	0.281	0.233

This table reports the regression results on the effect of technology spillover on the number of analysts as well as the heterogenous effect of crash risk depending on the level of analysts following. Column (1) and (2) examine *Ln(analysts)*, column (3) and (4) examine *Ncskew* and column (5) and (6) examine *Duvol*, and we measure technology spillover using *Lnspilltec* developed by Bloom et al. (2013). Column (3) and (5) restrict to sample with number of analysts below median while Column (4) and (6) restrict to sample with number of analysts above median. Variable definitions are in Appendix Table A. Reported t-values are on an adjusted basis using robust standard errors corrected for firm-level clustering (Petersen 2009) and heteroskedasticity (White 1980). ***, ** and * respectively represent 1%, 5%, and 10% significance levels.

Table 8. Heterogeneous Effects of Technology Spillovers on Crash Risk

Panel A. Corporate governance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CEO Delta				Institutional Ownership			
	Low	High	Low	High	Low	High	Low	High
	$Ncskew_t$		$Duvol_t$		$Ncskew_t$		$Duvol_t$	
$Lnspilltec_{t-1}$	-0.215**	-0.471***	-0.085*	-0.218***	0.042	-0.199***	0.015	-0.099***
	[-2.20]	[-4.54]	[-1.83]	[-4.59]	[0.74]	[-3.31]	[0.57]	[-3.55]
$Lnspillsic_{t-1}$	0.061*	0.054*	0.029*	0.023*	-0.018	0.035*	-0.008	0.015*
	[1.76]	[1.94]	[1.76]	[1.82]	[-0.96]	[1.90]	[-0.88]	[1.69]
$Dturn_{t-1}$	-0.065	0.317***	-0.033	0.141***	0.213***	0.299***	0.097***	0.112***
	[-0.52]	[3.73]	[-0.56]	[3.62]	[3.61]	[4.53]	[3.48]	[3.64]
$Ncskew_{t-1}$	-0.101***	-0.150***	-0.042***	-0.065***	-0.084***	-0.121***	-0.038***	-0.052***
	[-7.01]	[-10.19]	[-6.11]	[-9.65]	[-9.01]	[-13.08]	[-8.64]	[-12.12]
$Sigma_{t-1}$	0.575***	0.427**	0.284***	0.227**	0.149*	0.369***	0.080**	0.175***
	[4.12]	[1.97]	[4.30]	[2.28]	[1.92]	[3.06]	[2.17]	[3.11]
$Wret_{t-1}$	-0.002	0.008	-0.001	0.003	-0.002*	0.000	-0.001	0.000
	[-1.09]	[1.19]	[-0.79]	[1.08]	[-1.83]	[0.18]	[-1.55]	[0.12]
$Size_{t-1}$	0.082***	0.149***	0.035***	0.065***	0.074***	0.094***	0.037***	0.045***
	[2.96]	[5.62]	[2.69]	[5.39]	[4.95]	[5.98]	[5.29]	[6.12]
MB_{t-1}	0.002*	0.000	0.001*	-0.000	0.000	0.000	0.000	0.000
	[1.67]	[0.11]	[1.83]	[-0.08]	[0.30]	[0.78]	[0.19]	[0.36]
Lev_{t-1}	-0.113	0.108	-0.052	0.034	-0.026	-0.151**	-0.014	-0.072**
	[-0.99]	[0.95]	[-0.96]	[0.66]	[-0.40]	[-2.21]	[-0.46]	[-2.26]
ROA_{t-1}	0.412***	0.169***	0.224***	0.086***	0.084***	0.128***	0.036***	0.083***
	[3.37]	[3.00]	[3.87]	[3.34]	[3.03]	[3.21]	[2.75]	[4.45]
Constant	0.892	2.737***	0.322	1.281***	-0.741	0.956*	-0.293	0.534**
	[0.98]	[2.61]	[0.74]	[2.66]	[-1.24]	[1.85]	[0.49]	[−3.11]
Year Indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p-value for test of diff (High−Low)	[0.082]*		[0.042]**		[0.003]***		[0.003]***	
Observations	5,945	5,921	5,945	5,921	14,935	15,050	14,935	15,050
R-sq	0.175	0.222	0.176	0.228	0.232	0.205	0.235	0.197

Panel B. Firm opacity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Abnormal Accruals				Information Opaqueness			
	Low	High	Low	High	Low	High	Low	High
	Ncskew$_t$		*Duvol*$_t$		*Ncskew*$_t$		*Duvol*$_t$	
Lnspilltec$_{t-1}$	-0.051	-0.242***	-0.028	-0.112***	-0.047	-0.275***	-0.016	-0.130***
	[-0.87]	[-4.39]	[-1.02]	[-4.44]	[-0.67]	[-4.19]	[-0.48]	[-4.35]
Lnspillsic$_{t-1}$	0.032*	0.028	0.015*	0.011	0.042*	0.032	0.023**	0.010
	[1.66]	[1.38]	[1.71]	[1.21]	[1.93]	[1.24]	[2.22]	[0.88]
Dturn$_{t-1}$	0.084	0.260***	0.029	0.110***	0.142	0.232***	0.070	0.098***
	[1.07]	[5.01]	[0.81]	[4.64]	[1.53]	[4.37]	[1.60]	[4.05]
Ncskew$_{t-1}$	-0.074***	-0.089***	-0.032***	-0.037***	-0.104***	-0.129***	-0.047***	-0.055***
	[-7.54]	[-9.06]	[-6.97]	[-8.13]	[-9.84]	[-11.81]	[-9.38]	[-11.05]
Sigma$_{t-1}$	0.455***	0.244***	0.219***	0.124***	0.761***	0.234***	0.346***	0.123***
	[5.15]	[3.37]	[5.27]	[3.74]	[4.09]	[2.97]	[3.94]	[3.43]
Wret$_{t-1}$	-0.002	-0.002***	-0.001	-0.001**	0.009	-0.002**	0.004	-0.001**
	[-1.42]	[-2.96]	[-1.21]	[-2.58]	[1.40]	[-2.22]	[1.35]	[-2.04]
Size$_{t-1}$	0.056***	0.063***	0.023***	0.029***	0.059***	0.085***	0.028***	0.038***
	[3.57]	[4.78]	[3.06]	[4.91]	[2.98]	[5.46]	[2.98]	[5.32]
MB$_{t-1}$	0.004**	0.000	0.002**	0.000	0.006**	0.000	0.002**	0.000
	[2.18]	[1.10]	[2.23]	[0.80]	[2.44]	[0.77]	[2.26]	[0.37]
Lev$_{t-1}$	-0.111	-0.088	-0.044	-0.031	-0.265***	-0.090	-0.113***	-0.025
	[-1.57]	[-1.31]	[-1.32]	[-1.02]	[-3.16]	[-1.19]	[-2.86]	[-0.73]
ROA$_{t-1}$	0.520***	0.096***	0.248***	0.046***	0.644***	0.079***	0.328***	0.037***
	[6.12]	[4.12]	[6.23]	[4.35]	[5.62]	[3.10]	[6.06]	[3.18]
Constant	-0.401	1.663***	-0.156	0.827***	-0.405	1.584**	-0.270	0.830**
	[-0.73]	[3.01]	[-0.60]	[3.28]	[−0.35]	[2.78]	[-0.85]	[2.53]
Year Indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p-value for test of diff (High−Low)	[0.016]**		[0.020]**		[0.018]***		[0.010]***	
Observations	13,997	13,974	13,997	13,974	11,765	11,743	11,765	11,743
R-sq	0.265	0.267	0.259	0.278	0.242	0.268	0.242	0.279

Panel A examines how the effect of technology spillover on crash risk varies with different levels of managerial agency cost: Columns (1)-(4) use CEO's pay-performance sensitivity or Delta, and Columns (5)-(8) use the share of institutional stock ownership. Panel B examines how the effect of technology spillover on crash risk varies with different levels of firm opacity: Columns (1)-(4) use the abnormal accruals from Dechow and Dichev (2002), and Columns (5)-(8) use the information opaqueness measure of Hutton et al. (2009). We divide firms into Low (High) groups based on whether the proxy value is below (above) the sample median. Variable definitions are in Appendix Table A. Reported t-values are on an adjusted basis using robust standard errors corrected for firm-level clustering (Petersen 2009) and heteroskedasticity (White 1980). ***, ** and * respectively represent 1%, 5%, and 10% significance levels

Appendix Table A: Definition of Variables

Spillovers variables	
Lnspilltech	The log of the pool of R&D technology spillovers for firm *i* in year *t*: $Ln(\sum_{j\neq i} TECH_{ij} G_{jt})$. $Tech_{ij}$ is the technology closeness, defined as the uncentered correlation between all pairs: $TECH_{ij} = \frac{(T_i T_j')}{(T_i T_i')^{1/2}(T_j T_j')^{1/2}}$, where T_i is the vector of firms *i*'s technology activity, with the τ^{th} element being the average share of patents in USPTO technology class τ over the period 1976 to 2009. G_{jt} is firm *j*'s R&D capital, calculated using a perpetual inventory method with a 15% depreciation rate.
Lnspillsic	The log of the pool of R&D's product market effect for firm *i* in year *t*: $Ln(\sum_{j\neq i} SIC_{ij} G_{jt})$. SIC_{ij} is the product market closeness, defined as the uncentered correlation between all pairs: $SIC_{ij} = \frac{(S_i S_j')}{(S_i S_i')^{1/2}(S_j S_j')^{1/2}}$, where S_i is the vector of firms *i*'s product market activity, with the k^{th} element being firm *i*'s average share of sales in SIC four-digit industry *k* over the period 1976 to 2009. G_{jt} is firm *j*'s R&D capital, calculated using a perpetual inventory method with a 15% depreciation rate.
Dependent variables	
Ncskew	The negative of skewness of firm-specific weekly returns in a year.
Duvol	The ratio between the standard deviation of firm-specific weekly returns for all down-weeks and the standard deviation of weekly returns for all up-weeks.
Log(Volume)	The log of average monthly trading volume for a given firm in a year.
Ln(analysts)	The log of number of analysts plus one for a given firm in a year.
Control variables	
Dturn	The detrended share turnover in a year.
Sigma	The firm-specific weekly return volatility in a year.
Wret	The average firm-specific weekly return in a year.
Size	The logarithmic transformation of a firm's total assets at the end of a year.
MB	A firm's market-to-book ratio at the end of a year.
Lev	A firm's ratio of total liabilities to total assets at the end of a year.
ROA	A firm's ratio of net income to total assets at the end of a year.
Ln(1+grd)	The log of 1 plus a firm's total R&D stock at the end of a year.
Ln(1+xrd)	The log of 1 plus a firm's current year R&D spending.
Ln(1+npat)	The log of 1 plus a firm's total number of patent applications in a year.
Ln(1+ncite)	The log of 1 plus a firm's total citation number of patent applications in a year.
Cash_Flow	Cash flow from operations deflated by contemporaneous total assets.
1/Assets	The inverse of a firm's total assets.
Instrumental variables	
Lntectax	We first predict R&D flow by regressing the current year R&D expenditure on the user cost of R&D capital, accounting for federal and state-level R&D tax credit following Wilson (2009). Then we use the predicted R&D flow to generate predicted R&D stock $\widehat{G}_{jt}$ using a perpetual inventory method with a 15% depreciation rate and then generate the log of technology spillovers from predicted R&D stock for firm *i* in year *t*: $Ln(\sum_{j\neq i} TECH_{ij} \widehat{G}_{jt})$, following Bloom et al. (2013). $Tech_{ij}$ is the

	technology closeness, defined as the uncentered correlation between all pairs: $TECH_{ij} = \frac{(T_i T_j')}{(T_i T_i')^{1/2}(T_j T_j')^{1/2}}$, where T_i is the vector of firms i's technology activity, with the τ^{th} element being the average share of patents in USPTO technology class τ over the period 1976 to 2009.
Lnsictax	We first predict R&D flow by regressing the current year R&D expenditure on the user cost of R&D capital, accounting for federal and state-level R&D tax credit following Wilson (2009). Then we use the predicted R&D flow to generate predicted R&D stock $\hat{G}_{jt}$ using a perpetual inventory method with a 15% depreciation rate and then generate the log of product market effect from predicted R&D stock for firm *i* in year *t*: $Ln(\sum_{j \neq i} SIC_{ij} \hat{G}_{jt})$, following Bloom et al. (2013). SIC_{ij} is the product market closeness, defined as the uncentered correlation between all pairs: $SIC_{ij} = \frac{(S_i S_j')}{(S_i S_i')^{1/2}(S_j S_j')^{1/2}}$, where S_i is the vector of firms i's product market activity, with the k^{th} element being firm *i*'s average share of sales in SIC four-digit industry *k* over the period 1976 to 2009.
Group variables	
CEO Delta	The change in the dollar value of the CEO's wealth for a one percentage point change in stock price, following Coles et al. (2006).
Institutional Ownership	Institutional ownership concentration proxied by total share of institution holdings.
Abnormal Accruals	Absolute value of abnormal accruals, following Dechow and Dichev (2002).
Information Opaqueness	The prior three years' moving sum of the absolute value of discretionary accruals, following Hutton et al. (2009).