

Technology Spillovers and Corporate Cash Holdings

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This study examines the effect of technology spillovers on firms' cash holdings. It finds that firms facing greater technology spillovers hold higher cash balances. This effect is more pronounced among financially constrained firms and for firms that are likely to benefit more from diffused technology, e.g., those have newer patents, are more profitable, face better growth opportunities and are associated with greater product market fluidity. The spillover impact remains strong when product market competition and own-firm innovations are accounted for. Overall, our study identifies technology spillovers as an important factor in determining corporate cash policy.

Keywords: technology spillovers, product market competition, cash holdings

JEL Classifications: G32, G35, L10

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Abstract

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1. Introduction

Technology innovations are critical for firms to sustain competitive advantages and productivity growth. Innovations are characterized by strong elements of non-excludability and limited appropriability (Grossman and Helpman, 1992; Griliches, 1992; Steurs, 1994; and Llerena and Matt, 1999). Considerable knowledge spillovers could be generated through involuntary leakage (e.g., learning and imitation, upstream and downstream linkages, and mobility of workers) and voluntary transmission (e.g., technological licensing and R&D alliances). The diffusion of such beneficial externalities allows peers of the innovators to acquire technology at a lower cost than the cost of inventing it to enhance their productivity and innovative capability (Jaffe, 1986 and 1988) --- even in an environment of strict intellectual property protection (Bernstein and Nadiri, 1989; Griliches, 1979; Jaffe et al., 1993).² Meanwhile, innovations create significant product market threats by strengthening the inventors' competitive advantages and triggering market share reallocations.³ As a result, corporate innovations are featured with both non-rivalrous technology spillovers and product market threats. Preserving a liquid balance sheet thus is critical for firms to succeed in technological competition, allowing them to absorb diffused knowledge as it arises and react aggressively to competitive threats when they emerge.

The recent patent dispute between Apple and Samsung manifests the interaction among technology spillovers, product market rivalry and corporate liquidity management. In April 2011, Apple began litigating against Samsung in patent infringement suits, alleging that Samsung's Galaxy lineup and tablet computers "slavishly copied" its iPad/iPhone design and many other innovations. Samsung countersued, fuelling patent disputes that have been fought in about a

² Contracting over specific uses of technology, even well-defined intellectual property, is often difficult. This is manifested by some high-profile patent infringement litigations filed in 2011 and 2012, including Apple vs. Samsung, Oracle vs. Google over the Android mobile operating system, Verizon vs. ActiveVideo Networks for "sunset royalties", and AT&T vs. TiVo over digital video recording technology.

³ For instance, the competitive threat resulted from rivals' active R&D engagement is a key determinant of a firm's R&D expenditures (Reinganum, 1989 and Beath et al., 1995).

dozen countries. The dispute was a consequence of a long “frenemy” relationship between Apple and Samsung. Since the debut of the iPhones in 2007, Apple has squeezed the market shares of its competitors and become the dominant player in the US smartphone market. Apple’s innovations, however, have generated enormous knowledge externalities to its competitors. As Apple’s largest supplier of components (such as LCD panels and batteries) until 2012, Samsung has benefited greatly from Apple’s technology and market insights from knowledge flow through the supply-chain and other means. Samsung’s own financial strength at the same time plays a crucial role in its innovation. A *Wall Street Journal* article notes that: “The *deep-pocketed* Korean company has used a combination of engineering prowess, manufacturing heft and marketing savvy to create smartphones that can rival the iPhone in both sales and appeal”.⁴ Similarly, Apple has hoarded cash for years, recently reporting \$137 billion in cash, more than any other U.S. firm.

The patent dispute between Apple and Samsung highlights several unique features in technological competition. First, it epitomizes the concept of “coopetition” in technology competition (see, e.g., Brandenburger and Nalebuff, 1996): as firms compete for market share, they learn from each other and even collaborate in knowledge production. Hence, there are potentially dual advantages in maintaining solid liquidity in technology competition: to absorb technology spillovers when they arrive and to withstand product market competition when it materializes. Second, the fact that both Samsung and Apple are highly profitable firms thriving on technological advantages suggests that their marginal profit of innovation output is high.⁵ Consequently, they may be greatly motivated to utilize knowledge spillovers to facilitate

⁴ The article, written by Ian Sherr and Evan Ramstad, appeared January 26, 2013, on page B1 in the U.S. edition of *The Wall Street Journal*, with the headline “Has Apple Lost Its Cool to Samsung?”

⁵ For instance, gross margins on iPhone has been around 50% since its introduction, which was “an almost unheard of figure for a consumer electronics product” (Forbes, 9/11/2013).

innovations. Therefore, one would expect that the impact of technology spillovers on a firm's cash policy depends on the extent, to which cash could be used to enhance profit by absorbing external technology. Third, the value of innovative firms like Samsung and Apple consists of a large amount of intangible assets such as intellectual properties and human capital, which are difficult to be pledged as collateral for external borrowing, especially in the presence of intense competition that creates significant obsolescence risk.⁶ As a result, the concern of financial constraints could be an important consideration for innovative firms' cash management in coping with technological competition. Finally, since Samsung and Apple are highly innovative on their own, high cash balances of the two firms could be also related to their own innovation activities. To understand the spillover effect on cash holdings, it is thus important to take into account of own-firm innovations.

In this paper, we investigate whether and how technological competition, technology spillovers in particular, affects firms' cash holdings. The empirical identification of the effect of technology spillovers and that of market rivalry is difficult since peers from which a firm acquires knowledge are often its market rivals. Distinguishing these two effects thus requires separate measures that capture the uniqueness of knowledge diffusion in each space. We adopt the measures of Bloom, Schankerman and Van Reenen (2013, hereafter BSV) to achieve this goal. In BSV, a firm's positions in technology space and product market space are empirically distinguished by information on the distribution of its patenting across technology fields, and by its sales activity in a variety of industries. For an individual firm, the technology spillover effect is measured by the patent-weighted average of peers' R&D stocks, which quantifies

⁶ The significant obsolescence risk is manifested in the recent turmoil of another smart phone maker, BlackBerry. As the company lost its market share to the new generation of touchscreen smartphones, BlackBerry's cash balance shrank by almost 500 million in the first two quarters of 2013, a 20% decline from its total cash reverse at 2012 fiscal year-end.

technologically similar R&D available to the firm (i.e., the outside knowledge pool). The patent weights reflect the notion that a firm benefits more from technology produced by those with resembling patent filing patterns. The product market rivalry effect is measured by sales-weighted average of peers' R&D stocks, which captures business stealing effect due to competitors' technological advances. The sales-related weights are constructed using the information on firm-level industrial sales, gauging the degree of the overlap in sales.

We find that both technology spillovers and product market rivalry positively affect firms' cash holdings. Our estimates indicate that moving from the first technology spillovers (market rivalry) quartile to the third increases the cash-to-assets ratio by 7.6% (4.4%). Given the average cash-to-assets ratio in our sample is 10.4%, these effects are economically meaningful. The results suggest that, when facing large stock of outside R&D that is similar to a firm's own technology, the firm tends to hold more cash to preserve financial flexibility. The positive effect of market rivalry on cash reserves is consistent with studies showing that product market competition plays a key role in firm cash policy (e.g., Hoberg, Phillips and Prabhala, 2013, hereafter HPP; Schoubben and Van Hulle, 2010; and Morellec and Nikolov, 2009). It is also noteworthy that while the spillover and rivalry measures are correlated, our results indicate that each factor has independent incremental explanatory power on cash holdings.

To further identify the technology spillover effect on cash reserves, we examine subsamples of firms that are likely to benefit more from diffused knowledge. The idea is that the gain of holding cash for technology spillovers depends on the extent to which a firm can profit from its enhanced innovation productivity. A firm invests in R&D to produce innovation output (e.g., Smartphones and biotech drugs). Technology spillovers could improve innovation productivity of the firm's R&D investments. If the firm anticipates that the increased output of

the final product can be translated into higher profit, it would have greater incentives to build up cash reserves for external knowledge transfer to boost its production. Therefore, absorbing knowledge spillovers is more beneficial for firms with higher profit margin of innovation output, i.e., those can extract higher profit through enhanced innovation output. Indeed, we find that the impact of technology spillovers on cash holdings are stronger for firms that are more profitable, face better growth opportunities, have younger patent ages, and are associated with greater product market fluidity. To the extent that these subsamples of firms can derive greater profit from technology spillovers, our finding supports the notion that a firm's incentive to reserve cash for spillovers depends on the extent that the firm can utilize external technology to increase its marginal profit of innovation output.

We then examine the role of financial constraints in technology competition and find both the spillover and market rivalry effects are more pronounced for financially constrained firms, namely, those with poor credit ratings, smaller sizes or higher values of leading indices for constraints, namely the WW index (Whited and Wu, 2006), SA index (Hadlock and Pierce, 2010), and KZ index (Kaplan and Zingales, 1997). The finding indicates that a firm with limited access to external capital market hoards more cash to fund future investment needs in both technology and product market dimensions. This is consistent with the precautionary motive of cash holdings (Keynes, 1936, Almeida, Campello and Weisbach, 2004, Han and Qiu, 2008) that arises as constrained firms proactively save more to safeguard future investment needs.

Lastly, we conduct additional analysis to gain further insights on the role of technology spillovers in cash policy. First, while our results show that knowledge flowing from peers' R&D endeavor has a significant impact on a firm's cash balance, the firm's own innovative activities may also play a role in its financial policies (e.g., Kamien and Schwartz, 1978; Himmelberg and

Petersen, 1994; Hall, 2002). To control for the effect of own-firm innovations on cash holdings, we measure a firm's innovation performance using its patenting information. Our results indicate that, while own-firm innovations also have a positive impact on cash holdings, the technology spillover effect remains significant. Second, our analysis focuses on firms with observed patenting information. However, non-patenting firms may also engage in knowledge production, and thus are exposed to technology spillovers as well as product market rivalry caused by technology advances of patenting firms. To address the potential impacts of technological competition on non-patenting firm, we impute a non-patenting firm's technology spillover (market rivalry) effect as the average (or median) effect of all patenting firms within the same 4-digit SIC industry. We find that non-patenting firms, particularly those with positive R&D expenditures, also increase cash holdings in response to technology spillovers and product market rivalry. Third, we show that the identified positive spillover effect is robust to the use of alternative competition proxies (e.g., Herfindahl Index (HHI) and TNIC HHI proposed by Hoberg and Phillips, 2012) that capture the intensity of competitive rivalry in a broader sense. Finally, we address the potential endogeneity between cash balances and technology spillovers using instrumental variables (lagged values of spillovers) and find the results remain robust. Taken together, our findings underline the importance of technology spillovers, and its distinctions from product market rivalry, in determining cash holdings.

This study makes several contributions to the literature. First, we contribute to the growing literature on cash holdings. Bates, Kahle and Stulz (2009) demonstrate that the average cash-to-assets ratio for U.S. industrial firms has more than doubled in the last three decades. Lyandres and Palazzo (2012) show that the increase in average cash holdings is driven almost solely by firms which invest heavily in R&D. Our study indicates that technology spillovers and market

rivalry induced by rivals' R&D effort help to explain why innovative companies have stockpiled cash. Second, our study adds to the literature on how product market environment affects financial policies. Closely related to our paper, HPP has developed the text-based fluidity measure and find a strong interaction between product market competition and firms' payout and cash policies.⁷ Our empirical results complement HPP's findings by showing that an important dimension of product market threats, rivalry induced by competitors' R&D efforts, has a significant effect on cashing holdings. Third, recent studies have presented evidence that corporate innovations play an important role in equity market and corporate mergers and acquisitions (e.g., Hsu, 2009; Hirshleifer et al., 2013; Bena and Li, 2013; Fresard, Hoberg and Phillips, 2013). However, the role of firm-level R&D spillovers in determining corporate financial decisions has received insufficient attention. Our study fills this gap by probing the ways in which a firm's relative position in technology space, along with its product market closeness to peers, determines its cash holdings.

The remainder of the paper proceeds as follows. Section 2 motivates and develops our testable hypotheses regarding the effect of technology spillovers on cash holdings. Section 3 details the identification of technology spillovers and product market rivalry and the data used for our empirical analysis. Sections 4 empirically investigates the impact of technological competition on cash holdings. Section 5 concludes.

2. Hypothesis development: the impact of technology Spillovers on cash holdings⁸

A major advantage for innovative firms to hoard cash is to allow them to undertake valuable R&D projects when they arise. This stems from the precautionary motive of cash holdings

⁷ The usefulness of text-based analysis in finance has also been illustrated in Hanley and Hoberg (2010), Hoberg and Phillips (2010a, 2010b and 2012).

⁸ In Appendix A, we consider a simple extension of BSV's (2013) analytic model and derive propositions that are consistent with hypotheses developed in this section.

originally proposed by Keynes (1936). However, accumulating cash is not costless as it might force a firm to give up current positive-NPV projects or aggravate agency costs (Jensen, 1986; Dittmar, Mahrt-Smith, and Servaes, 2003). Therefore, a firm's cash reserves for future R&D investments are dictated by a tradeoff between the benefit and cost of holding cash. It reaches the optimal level when the marginal cost of increasing one unit of today's cash balances is equal to the expected marginal profit of hoarding cash for future R&D projects (Almeida, Campello and Weisbach, 2004, Kim, Mauer, Sherman, 1998, Han and Qiu, 2008). This can be concisely depicted as follows:

$$\left(\frac{\Delta Cost}{\Delta Cash} \right)_t = E \left(\frac{\Delta Profit}{\Delta R \& D Investment} \right)_{t+1} \quad (1)$$

where $(\Delta Cost / \Delta Cash)_t$ is the marginal cost incurred to increase cash holding at time t , while $E(\Delta Profit / \Delta R \& D Investment)_{t+1}$ is the expected marginal profit of carrying cash for R&D investment at time $t+1$. Eq. (1) indicates that a firm would hold more cash when it anticipates an increase in its marginal profit of R&D investments, which is determined by two factors: the marginal productivity of R&D ($\Delta Innovation output / \Delta R \& D investments$) and the marginal profit of innovation output ($\Delta Profit / \Delta Innovation output$). That is,

$$\left(\frac{\Delta Profit}{\Delta R \& D Investments} \right)_{t+1} = \left(\frac{\Delta Innovation Output}{\Delta R \& D Investments} \times \frac{\Delta Profit}{\Delta Innovation Output} \right)_{t+1} . \quad (2)$$

Existing literature provides strong evidence that technology spillovers enhance R&D productivity (e.g., Griliches, 1979). The presence of significant technology spillovers is exemplified by the observation that most patents cites and are cited by peers', indicating that technology is built on others'. Moreover, Jaffe, Trajtenberg and Henderson (1993) show that a firm's patents are more frequently cited by others that are geographically closer, demonstrating the existence of considerable knowledge spillovers through the interaction and flow of local

human capital. In particular, Tambe and Hitt (2013), relying on employee micro-data and focusing on information technology (IT) alone, report that spillovers from peer firms' IT-related innovations have contributed 20-30% as much to a firm's productivity growth. Therefore, technology spillovers are expected to enhance a firm's marginal productivity of R&D ($\Delta Innovation\ output/\Delta R\&D\ investments$). Equation (2) further indicates that firms with a higher marginal profit of innovation output ($\Delta Profit / \Delta Innovation\ output$) would be able to profit more from the enhanced productivity of R&D through absorbing technology spillovers. Those firms would have greater incentive to store more cash to utilize external knowledge.⁹ This leads to our first hypothesis.

HYPOTHESIS 1: *Ceteris paribus, firms would hold more cash in response to technology spillovers; and the positive effect of spillovers on cash holdings is stronger for firms with higher marginal profit of innovation output.*

Optimal cash holdings are also influenced by the extent to which firms can access external capital market, i.e., being financially constrained or not. A firm's degree of financial constraints depends on many factors, such as asset tangibility, informational asymmetry and legal environment (Kaplan and Zingales, 1997). For firms with unrestricted access to external funds, cash policy becomes irrelevant as there is no need to reserve cash for technology spillovers. However, innovative activities rely on and produce large stock of intangible assets, including human capital, patents and technological know-how, the value of which is hard to ascertain and subject to significant obsolescence risk. Such a unique feature of asset composition renders

⁹ A potential counter-effect for the positive impact of technology spillover on cash holdings is that knowledge externalities produced by rivals' R&D could potentially free the firm from spending on the same technology (i.e., reducing knowledge production) and thus lower its need to save cash. For example, despite potential patent infringement, Samsung is exempted from spending on the same technology given Apple's innovations of the capacitive sensing and multi-touch technology. However, even though Samsung was free from spending on the particular technology, the externality could stimulate R&D investments for innovations in related areas and thus motivate cash hoarding. As such, our results could be viewed as a net effect of technology spillovers.

innovative firms more susceptible to financial constraints, especially when technology competition intensifies. The concern of not being able to raise sufficient fund to take advantage of diffused technology would compel firms to increase their cash reserves. As such, financial constraints could play an important role in innovative firms' cash consideration in response to technology spillovers and induced competitive pressure.

HYPOTHESIS 2: *The positive effect of technology spillovers on cash holdings is stronger for firms facing greater financial constraints.*

Rival firms' R&D activities could not only yield positive technology spillovers but also intensify product market competition as firms often interact in both technology space and product space. A recent important study by Hoberg, Phillips and Prabhala (2013) shows that product market competition has a significant bearing on firms' cash and dividend policies. They develop a novel measure of competitive threats (referred as product market fluidity) that quantifies how a firm's products overlap with changes in rivals' and show that product market fluidity is positively (negatively) associated with a firm's cash reserves (dividend payout). This finding highlights liquidity preference when there is greater uncertainty in future cash flows (e.g., Bates et al, 2009). Since peers' technological advances could also intensify competition in product space, it is thus important to account for the product market rivalry effect when analyzing the technology spillover effect on cash holdings.

3. The Identification of technological competition and variable construction

In this section, we detail the identification of technological competition in technology space and product market space, then describe the data used in our empirical analysis.

3.1 Measuring spatial proximity

The challenge in the identification of the separate effects of technology spillovers and market

rivalry lies in the correlation between them. We follow BSV to empirically distinguish a firm's position in technology space and product market space using firm-level data on the distribution of its patenting across technology fields, and its sales across industries. More specifically, firm i 's activity in technology space is measured by its share of patents across 426 United States Patent and Trademark Office (USPTO) technology classes, $T_i = (T_{i,1}, T_{i,2}, \dots, T_{i,426})$.¹⁰ Following Jaffe (1986), define the weight ω_{ij} as the uncentered correlation between all firm i, j pairings:

$$\omega_{ij} = T_i T_j / \sqrt{T_i T_i \times T_j T_j}. \quad (3)$$

ω_{ij} , bounded from 0 to 1, captures the technology proximity between firm i and j as reflected through their patent positioning across technology classes. For instance, if patents of two firms are similarly distributed across technology classes, the value of ω would be close to 1 to reflect the two firms' proximity in technology space. Then, the outside technology pool available to firm i at time t ($Spill_Tech_{i,t}$) is calculated as the weighted sum of all its rivals' R&D stock, denoted as G ,¹¹

$$Spill_Tech_{i,t} = \sum_{j \neq i} \omega_{ij} \times G_{j,t}. \quad (4)$$

Thus, $Spill_Tech$ provides a "R&D-equivalent" dollar-amount measure for knowledge spillovers.

Similarly, the market rivalry measure takes into account the product market closeness captured by the overlaps between a firm and its rivals' sales across four-digit SIC industries.

¹⁰ The aggregation of rival's R&D is performed at the firm level instead of the technology class level. This is mainly due to the fact that one cannot determine the distribution of a firm's R&D spending across technology classes. Appendix C provides a brief summary of USPTO technology classes and the patent filing pattern of the sample firms.

¹¹ As in BSV and Hall et al. (2005), R&D stocks are calculated using a perpetual inventory method with a 15% depreciation rate. That is $R\&D_t = R_t + (1 - \rho)R\&D_{t-1}$ where R is the R&D expenditure in year t and $\rho = 0.15$.

Denoted as $Spill_Sale_{i,t}$, the product market rivalry presented to firm i is

$$Spill_Sale_{i,t} = \sum_{j \neq i} \tau_{ij} \times G_{j,t}. \quad (5)$$

where the proximity between firm i and j in product market space is calculated as

$$\tau_{ij} = S_i S'_j / \sqrt{S_i S'_i \times S_j S'_j}. \quad (6)$$

$S_i = (S_{i,1}, S_{i,2}, \dots)$ is a row vector, in which the k^{th} element, $S_{i,k}$ is the share of firm i 's sales in the four-digit SIC industry k .¹²

To summarize, the identification of R&D competition relies on the proximity measures that quantify the relatedness among firms in technology space and product market space. Therefore, the key difference between the two measures rests on their weighting schemes (Eq. (3) vs. Eq. (6)). Specifically, for firm i , $Spill_Tech$ measures its rivals' R&D stock aggregated by pairwise spatial closeness in technology space, which is proxied by the correlation in patent application filings as specified in Eq. (3). Similarly, $Spill_Sale$ quantifies technology induced competition using the weighted sum of rival's R&D stock. The weight, defined in Eq. (6) captures the spatial distance in product market space as revealed from the distribution of sales across industries. BSV's framework uses firms' average share of patents in each technology class to calculate technology closeness. Thus, firms that have no patent granted are dropped.¹³ As a result, our final sample includes 638 firms with an average number of annual observations of 16.8 per firm (10690 observations in total).

3.2 Examples and summary statistics

¹² For conglomerate i , its sales are represented by a row vector $S_i = (S_{i,1}, \dots, S_{i,k}, \dots, S_{i,N})$, where N is the number of four-digit SIC industries. The k^{th} element of S_i , $S_{i,k}$ is the *average* share of firm i 's sales in the four-digit SIC industry k reported over the sample period. That is, $S_{i,k} = \frac{1}{T} \sum_{t=1}^T S_{ikt}$, where S_{ikt} is firm i 's market share in four-digit SIC industry k in year t . T is the number of years of the sample period. If a segment with sales in industry k vanishes in year t , it will not be included in the calculation of S_{ikt} (essentially, its sales in industry k in year t are 0).

¹³ In Section 4.5, we consider a generalization of our analysis to include non-patenting firms.

Firms could interact quite differently with each other in technology and product market spaces. The spillover and rivalry measures defined in Eq. (4) and (5) allow us to capture different patterns of firm interactions in technology space and product market space. For instance, Apple Inc. is close to Microsoft in technology space, evidenced by their highly similar patent-filing patterns (the technological spatial proximity ω , defined in Eq. (3), is 0.88). This is not surprising given both firms develop operating systems (OS) and software suites. Turning to product market space, despite Microsoft recent attempts to edge in the mobile market, it still remains largely as a software company.¹⁴ Apple however has a strong presence in the market of computer hardware and personal computers. Correspondingly, we find that Apple and Microsoft are only modestly correlated in product market space with a closeness measure, τ (defined in Eq. (6)) of 0.31, which is mainly driven by their overlapped sales in OS.

Another example to illustrate the disparity of firms' spatial proximity in the two spaces involves two leading healthcare firms, Pfizer and Genentech. They are relatively distant in technology space with the value of ω 0.39. This is because that Pfizer mainly relies on traditional pharmaceutical research and works with chemical based compounds; while, Genentech, uses advances in genetics research and manufactures products in living organisms. Given the two firms use different methods in drug development, one might thus benefit less from the other's knowledge production. However, the two firms strive against each other head to head in the product market with very similar products, which is indicated by a close-to-unit sales similarity ($\tau=0.93$). Interesting, while Genentech uses extremely similar technology with another biotech firm, Biogen ($\omega=0.99$), their product market correlation ($\tau=0.07$) is far from perfect since Biogen's sales are concentrated in drugs for treatment of multiple sclerosis.

¹⁴ The two biggest product lines at Microsoft are Windows and Office suite.

In Table 1, we report top ten firms (and their industry membership¹⁵) that had experienced largest (Panel A) and lowest (Panel B) growth in the magnitude of $Spill_Tech / Spill_Sale$. Remarkably, Panel A.1 shows that firms of the pharmaceutical products industry had seen dramatic increase in $Spill_Tech$. This coincided with great technological advancements of the industry during the same period, including the development of breakthrough therapies for HIV/AIDS, the introduction of biotech medicines and advanced cancer treatment.¹⁶ As suggested by Panel A.2, the competitive pressure for firms of the electronic equipment industry had steadily built up, which was partly fueled as firms competed head-to-head in high-speed network equipment and telecommunications products. In addition, Panels B.1 and B.2 show that the industry membership of firms that underwent the least growth in $Spill_Tech / Spill_Sale$ is much dispersed. And not surprisingly, we see a few low-tech firms, i.e., apparel manufacturers and transportation companies, are among those, which witnessed the smallest changes in technology induced market completion.

[Table 1 about here]

To further assess the relationship between the measures of technology spillovers and market rivalry, in each year, we divide the sample firms into quintiles according to the value of $\ln(Spill_Tech)$ and $\ln(Spill_Sale)$. Table 2 reports the average value of $\ln(Spill_Tech)$ and $\ln(Spill_Sale)$ in each quintile. Among firms facing the lowest level of technology diffusion (Q1 of $\ln(Spill_Tech)$ -sorted portfolio), the average level of $\ln(Spill_Sale)$ is more than doubled (from 4.26 to 9.90) as we move from Q1 to Q5 of $\ln(Spill_Sale)$. In other quintiles of

¹⁵ Firms are assigned into 48 industries according to Fama and French's (1988) classification scheme.

¹⁶ A few legislation and regulation changes had also greatly spurred R&D endeavor of the industry. For instance, in 1980, in a pivotal Supreme Court decision, the justices decided that genetically manipulated organisms could be patented. In the same year, Congress passed the Bayh-Dole Act, allowing recipients of federal research funding to secure patents.

$\ln(\text{Spill_Tech})$, the increment in the average value of $\ln(\text{Spill_Sale})$ varies from 40% to 73% as one moves from Q1 to Q5 of $\ln(\text{Spill_Sale})$. Similarly, within each quintile of $\ln(\text{Spill_Sale})$, the average value of $\ln(\text{Spill_Tech})$ varies considerably, with a magnitude ranging from 8% to 78%. These results show that, although $\ln(\text{Spill_Tech})$ is positively correlated with $\ln(\text{Spill_Sale})$, there are still substantial independent variations in the two measures. The correlation coefficients between $\ln(\text{Spill_Tech})$ and $\ln(\text{Spill_Sale})$ is 0.47, which is well below the unity.

[Table 2 about here]

3.3 Other control variables

We follow the literature on the construction of other explanatory variables of cash holdings. We extract firm-level accounting information from the Compustat annual files and merge it with firm-level R&D spillover measures (Spill_Tech and Spill_Sale) to form our sample. Financial firms (SIC codes 6000-6999) and utilities (SIC codes 4900-4999) are excluded. The sample period is from 1982 to 2001. The detailed definitions of variables used in this study are listed in Appendix B. Table 3 presents descriptive statistics of all these variables. All continuous variables are winsorized at the 1% and 99% levels to reduce the influence of outliers.

[Table 3 about here]

4. Empirical analysis: technology spillovers, product market rivalry and cash holdings

4.1 Baseline results

We begin by investigating how technology spillovers, accounting for product market rivalry, affect corporate cash holdings. Our baseline econometric model is in line with the literature (e.g. Bates et al, 2009; and HPP) and is specified as follows:

$$cash_{i,t} = \beta_1 \ln(Spill_Tech_{i,t-1}) + \beta_2 \ln(Spill_Sale_{i,t-1}) + \gamma' X_{i,t-1} + \eta_i + \tau_t + \varepsilon_{i,t}, \quad (7)$$

where i and t are firm and time subscripts, respectively. The dependent variable *cash* is measured as cash plus equivalents dividend by book assets. The magnitude of technology spillovers and product market rivalry effects are measured by *Spill_Tech* and *Spill_Sale*, respectively. X is a vector of a constant term and other firm-level control variables suggested by related literature. η_i and τ_t capture the firm and time fixed effects. $\varepsilon_{i,t}$ is the error term.

[Table 4 about here]

Table 4 reports the firm-level fixed effects results of equation 7. As in BSV, the statistical inference is drawn based on the robust standard errors that are consistent to potential heteroscedasticity and to potential serial correlation. Column 1 shows the impact of technology spillovers on cash-to-assets ratio. The coefficient of $\ln(Spill_Tech)$ is positive and significant at a 1% level. This suggests that technology spillovers are positively related to firms' cash holdings. Column 2 assesses the impact of market rivalry on cash holdings. We find that the coefficient of $\ln(Spill_Sale)$ is positive and highly significant. This is consistent with the recent literature reporting that product market threats lead to higher cash balances. Column 3 reports the regression results where both $\ln(Spill_Tech)$ and $\ln(Spill_Sale)$ are present. We find that both the technology spillover and market rivalry effects remain statistically significant, so they both impinge on cash holdings. However, the presence of $\ln(Spill_Sale)$ reduces the coefficient estimate of $\ln(Spill_Tech)$ by 33% (from 0.097 in Column 1 to 0.073). The result indicates the importance of accounting for the product market rivalry effect when assessing the technology spillover effect. Column 4 uses the logarithm of cash-to-assets ratios as the

dependent variable.¹⁷ Both $\ln(\text{Spill_Tech})$ and $\ln(\text{Spill_Sale})$ remain positive and statistically significant. The impact of technology spillovers on cash holdings is noted to be more than twice as large when compared with that of market rivalry, which demonstrates the vital importance of technology spillovers, alongside product market threats in shaping corporate cash policy.

In terms of economic significance, Column 3 indicates that, *ceteris paribus*, moving from the first quartile of technology spillovers (market rivalry) to the third quartile increases a firm's cash-to-assets ratio by 7.6% (4.4%).¹⁸ Given the average cash holdings in our sample is 10.4%, the effects of technology spillovers and market rivalry are substantial. In comparison, moving from the first to third quartile in technology spillovers (market rivalry) has a similar relation with cash holdings as decreasing the proportion of tangible assets by 34 percentage points.¹⁹ Moreover, the elasticity estimation in Column 4 indicates that a 1% increase in the technology spillover level is associated with a 0.69% increase in cash holdings and a 1% increase in the product rivalry effect leads to a 0.29% increase in cash holdings. The result demonstrates that cash holdings are sensitive to technological competition, particularly technology spillovers.

As another robustness check, Column 5 shows the fixed effects result obtained using the spillover measure constructed based on Mahalanobis (1936) distance metric.²⁰ The potential limitation of the two technological competition measures that we rely on so far is that they are calculated based on Jaffe's (1986) distance metric (the "cosine" similarity), which assumes that

¹⁷ For the log-log model, the coefficient of an explanatory variable gives a direct estimate of the elasticity of the dependent variable with respect to the given explanatory variable.

¹⁸ The impact of technology spillovers is obtained by multiplying the estimated coefficient of $\ln(\text{Spill_Tech})$ (0.073) with the difference between the 3rd and 1st quartiles of $\ln(\text{Spill_Tech})$ ($= 11.91 - 10.87$) presented in Table 2. Similarly, the impact of market rivalry is obtained by multiplying the estimated coefficient of $\ln(\text{Spill_Sale})$ (0.023) with the difference between the 3rd and 1st quartiles of $\ln(\text{Spill_Sale})$ ($= 9.678 - 7.76$).

¹⁹ Given a coefficient of -0.221, a decrease in asset tangibility by 34% (20%) would lead to an increase in cash-to-assets ratio by 7.4% ($= 0.221 \times 0.344$) or 4.4% ($= 0.221 \times 0.2$), respectively.

²⁰ The construction of Mahalanobis' (1936) distance metric-based spillover measures is notationally involved. We thus direct interested readers to the appendix C of BSV for more details.

the spillovers only occur within the same technology (patent) class, thus rules out spillovers between different classes. In particular, the “cosine” measure partitions technology space according to 426 UPSTO technology classes, and assumes that technology classes are orthogonal to each other. As a result, in the case that two firms have no patents filed in overlapping classes (i.e., $\omega_j = 0$), the spillover effect between the two would be assigned as zero. However, knowledge may flow not only within a class, but also across classes. Therefore, to better reflect knowledge complementarity across different technology classes, we follow BSV and employ the Mahalanobis distance measure to construct an alternative spillover measure. The basic idea of Mahalanobis closeness measure is to weigh the overlap in patent shares between firms (the cosine similarity) by how close their different patent shares are to each other. In essence, the cosine similarity between two firms (Jaffe’s metric) is the dot product of the two vectors representing the distribution of firms’ patent shares across technology classes. Hence, by construction, the product of patent shares in the same classes is given a weight of 1, and that of different patent classes is completely discounted by assigning a weight of 0. The key difference between Jaffe’s and Mahalanobis’s measures is that, in the calculation of Mahalanobis’s metric, the weight allocated for the latter case (i.e., multiplication across two different technology classes) is determined by how frequently the different patent classes overlap within the same firm. If the two patent classes tend to be filed frequently by the same firm, a close-to-1 weight would be assigned to recognize that these classes are highly correlated and technological spillover among them are more likely.

Using Mahalanobis measures that take into account of cross-class spillovers, we find that our previous findings that firms’ cash-to-assets ratios are positively affected by firms’ exposure to diffused knowledge and their competitive position in product market space are fully retained.

Specifically, Column 5 shows that the coefficient of the Mahalanobis spillover measure is 0.074, slightly higher than the one on Jaffe's spillover measure (0.068 shown in Column 3). This suggests that a firm may also benefit from patents filed outside of its own technology field. Lastly, in Column 6, we replace the dependent variable as the "net" cash holdings to alleviate the concern that high cash balances are due to more aggressive borrowing and find that previous findings are fully retained.²¹

4.2 Heterogeneity in the impact of technology spillovers on cash holdings

We have shown that technology spillovers have a positive effect on firms' cash holdings. Hypothesis 1 further states that such an effect is stronger for firms that have higher marginal profit of innovation output so that they can profit more from enhanced output through spillover transfer.

To investigate the heterogeneity in the impact of technology spillovers on cash holdings, we classify firms into two groups that are likely to differ in their marginal profit of innovation output. We then examine whether technology spillovers have differential impacts on cash holdings of these two groups. To capture a firm's marginal profit of innovation output, we use several proxies. First, a new technological innovation is likely to be rewarded with a high marginal profit. We thus expect that cash holdings of firms with "younger" patents are more responsive to technology spillovers. We measure a firm's patent age as the average number of years for which a firm's patents have been granted. Then, we sort firms in a given year based on their patent age and define a firm with younger patents if its average patent age is lower than the median. Second, we use a firm's profitability to proxy its marginal profit of output. Arguably, firms with higher profitability are more likely to have a higher marginal profit of output. We sort firms in a given year based on their profitability (i.e., operating income divided by assets), and define profitable

²¹ The "net cash" is defined as total cash subtracts debt and scaled by book assets, i.e., $[\text{che} - (\text{dltt} + \text{dlc})] / \text{at}$.

firms as those with profitability higher than the median. Third, we employ market to book ratio to capture a firm's earnings potential and split the sample based on its median. Compared with accounting-based profitability measures, a major advantage of market to book ratio is that it embodies the present value of future cash flow that could be generated from innovation output and thus a higher market to book ratio reflects a greater earning potential of a firm's output. Lastly, we divide firms into two groups based on the median of their product market fluidity (HPP, 2013). High fluidity indicates that a firm's products have greater overlap with changes of rivals' products. As pointed out by HPP, a large value of fluidity suggests that the firm faces intensified market competition; and its product is likely to be on the early stage of lifecycle. In particular, HPP show that fluidity is positively correlated with the business descriptions of IPO and venture-capital-backed firms, suggesting new firms are inclined to enter the product market encompassed by high fluidity firms. To the extent that a product tends to have a large profit margin during its early stage of life cycle and firm entry also hints high profitability, a stronger spillover effect on cash holdings is anticipated among firms with greater-than-the-median fluidity.²²

[Table 5 about here]

The results of the aforementioned subsample analysis are reported in Table 5. Columns 1 and 2 present the results of firm-level fixed effects regressions for subsamples with young vs. old patents, respectively. We find that technology spillover effect is positive and statistically significant only among firms with younger patents. Respectively, Columns 3 and 4 show the results for subsamples split by profitability, Columns 5 and 6 are by market-to-book ratio, and

²² We thank HPP for making their fluidity data available online. After merging with the fluidity measure, our sample size is shrank as the measure is available from 1997.

Columns 7 and 8 are for high vs. low fluidity firms.²³ To the extent that marginal profit of innovation output is relatively high among those subsamples presented in odd numbered columns, the finding presented in Table 5 provides further support to Hypothesis 1 and highlights the great importance of technology spillovers among profitable firms, and those that possess new technology or are in the early life span of products.

4.3 The role of financial constraints

By far, we find strong support to Hypothesis 1: an economically and statistically significant relationship between technology spillovers and cash holdings. We now turn to examine Hypothesis 2 that concerns the role of financial constraints in the spillover effect.

To see how the concern of financial constraints affects the spillover effect, we separate firms according to indirect proxies (asset size and credit rating) and a few leading indices of the degree of financial constraints (i.e., WW index (Whited and Wu, 2006), SA index (Hadlock and Pierce, 2010), and KZ index (Kaplan and Zingales, 1997)). To partition the sample based on firm size, every year, we rank firms' asset size and assign to the financial constrained (unconstrained) group those firms in the lower (upper) half of the size distribution. Using bond ratings, constrained firms are defined as companies with below investment-grade ratings. By construction, the three indicators of financial constraints, WW, SA and KZ indices, are higher for more financially constrained firms. Therefore, using each index, we sort firms in a given year based on the index level, and define constrained firms as those with their index values exceeding the median in a year.

[Table 6 about here]

Table 6 reports the result of this subsample analysis. All specifications also include year and firm-level fixed effects. Throughout all subsamples, we find that the technology spillover effect

²³ Due to the fact the fluidity measure is available from 1997, the merged sample has fewer observations.

is more pronounced for the constrained firms as they rely more heavily on their internal fund to take advantage of diffused knowledge. The results thus support Hypothesis 2 that financial constraints matter in the impact of technology spillovers on cash holdings.

4.4 Own-firm innovation

While our results show that technology spillovers from peer firms have a significant bearing on a firm's cash holdings, a firm's own innovation activity may also play a key role in its financial policies. Kamien and Schwartz (1978) note that firms engaging in ambitious R&D projects have a great need for cash. Himmelberg and Petersen (1994) and Hall (2002) point out that R&D activity is associated with higher adjustment costs. Brown and Petersen (2011) show that, to limit adjustment cost, R&D intensive firms have strong incentives to hold more cash in order to maintain a relatively smooth path of R&D spending. In addition, given that firms might be quite reluctant to disclose detailed information about their R&D projects, one would expect a high degree of information asymmetry between outside lenders and firms engaged in large-scale innovations. This would create a large wedge between the costs of internal and external financing (Myers and Majluf, 1984; Diamond and Verrecchia, 1991) and consequently motivate cash accumulation. Pinkowitz and Williamson (2007) find that the market value of the marginal dollar of cash is highest in R&D-intensive industries, suggesting that it is more beneficial for innovative firms to hold more cash.

To control for own firm innovation effect on cash holdings, following the literature of firm innovations (e.g., Fang, Tian and Tice, 2013; Hsu, 2013; and He and Tian, 2013), we measure a firm's innovation using the number of patents filed and the average number of citations the firm's patents receive in subsequent years. The number of patents captures a firm's overall innovation productivity and the number of citations per patent captures the significance and

quality of its innovation output. Specifically, we use the following four proxies:

1. *count* is defined as the total number of patent filings that are eventually granted in a year;
2. *count_{adj}* is the citation-weighted total number of patent filings in a year;
3. *cite* is the average number of citations received by patents filed in a year;
4. *cite_{adj}* is the average number of citations at the per patent level with the self-citations excluded.

To account for the long-term nature of innovation, we calculate a firm's five-year discounted sum of patenting activities.²⁴ Specifically, for firm *i* in year *t*, its weighted innovativeness (WI) is calculated as

$$WI_{i,t-1} = \sum_{j=1}^5 innovation_{i,t-j} \times (1 - \delta)^j, \quad (8)$$

where $innovation_{i,t}$ is one of the four proxies (*count*, *count_{adj}*, *cite* or *cite_{adj}*).²⁵ δ is the discount factor of past innovation output. We choose δ as 0.15, the same value as the depreciation rate of firm R&D stock.²⁶ Finally, the natural logarithm of (1 + WI) is used in our analysis.

[Table 7 about here]

The table 7 reports the fixed-effects regression results as we further control for own-firm

²⁴ Lev and Sougiannis (1996) document that technology cycles measured by the duration of the benefits of R&D outlays are about five years.

²⁵ One potential issue of using citation-related measures (*count_{adj}*, *cite* and *cite_{adj}*) is that a firm does not know the exact number of citations of its patents filed at the end of year $t - 1$ when making decisions on its cash holdings. Nevertheless, to the extent that a firm has a proper assessment on the importance of its patents, the citation-related measures could be viewed as proxies for the firm's appraisal of the importance of its own patents. Another potential concern is that the forward looking information captured in the citation count might cause reverse causality, in which a firm's cash holdings in year *t* affect the number of subsequent citations. However, given that (self-excluded) citations are made by *peer firms*, the firm's cash balances at the end of year *t* are unlikely to affect the reference of its patents filed in previous years. In addition, we follow the standard practice (e.g., Hall, Jaffe, and Trajtenberg, 2001 and 2005) in dealing with the potential truncation problems with patent counts and patent citations.

²⁶ The choice of the value of δ has no material impact on our regression results. Since our regressions already control for firm-level R&D, to avoid potential multicollinearity, we do not use a firm's R&D as weights in calculating the sum of patents.

innovation in examining the technology spillover and market rivalry effects on cash holdings. Compare with our baseline result presented in Table 4, Column (3), we find that the effects of technology spillovers and market rivalry are strikingly robust. Notably, the coefficient of $\ln(\textit{Spill_Tech})$ and that of $\ln(\textit{Spill_Sale})$ remain statistically significant and their magnitudes are almost unaffected (0.071 and 0.022, respectively) compared with the baseline result (0.073 and 0.023, respectively). In addition, Table 7 shows that the coefficient of various firm-level innovation proxy is positive and statistically significant (at a 5% or 10% level).²⁷ Overall, our results indicate that a firm's innovation activity has a considerable impact on its cash holding policy. The technology spillover effect remains significant after controlling for firm-level innovations.

4.5 Non-patenting firms

Our analysis focuses on firms with observed patent filing history as it is difficult to gauge the innovation capability of non-patenting firms. However, non-patenting firms may also engage in innovation activities and be affected by technology spillovers and product market competition caused by technology advances of patenting firms. Arguably, all non-patenting firms operating in the same industry are likely to benefit from same types of diffused technology and face a similar competition effect from their more innovative peers. Therefore, to capture the potential impacts of technology spillover and product market rivalry on non-patenting firms, we assign a non-patenting firm's technology spillover (market rivalry) measure as the average (or median) effect of all patenting firms within the same 4-digit SIC industry.²⁸

²⁷ Own-firm innovations (i.e., patents and citations) are persistent with low within-firm variations. Its effect on cash holdings could be largely absorbed by firm fixed effects.

²⁸ For conglomerates reporting sales in more than one SIC industry, a sales-weighted average of their segment peers is assigned.

Table 9, Panel A reports the summary statistics of non-patenting firms. The corresponding statistics of patenting firms are also listed. Compared with patenting firms, non-patenting firms hold about 50% less cash and are considerably smaller (measured by $\ln(\text{sales})$). The non-patenting firms are much younger and growth firms (higher sales growth) with lower profitability (e.g., lower ROA and lower stock returns). Clearly, patenting firms are larger, more mature, and more profitable firms that have greater cash reserves. This is consistent with the impression that patenting firms generally are more successfully industrial innovative leaders.

[Table 8 about here]

To examine the impacts of technological competition on non-patenting firms, we regress firms' cash-to-asset ratios on the imputed spillover and rivalry measures and other controls included in Table 4. Table 8, Panel B reports the regression results.²⁹ The coefficient of the average or median spillover effect and that of the average/median rivalry effect (shown in Columns 1 and 3, respectively) are found to be positive and statistically significant. Columns 2 and 4 restrict the sample to non-patenting firms with positive R&D. R&D not only generates new knowledge but determines the firm's ability to recognize and assimilate diffused technology (Cohen and Levinthal, 1989 and 1990). As such, among non-patenting firms, the impacts of technological competition could be more pronounced for firms with an active R&D engagement (i.e., positive R&D expenditure). The results show that, for non-patenting firms with positive R&D, the estimated spillover and rivalry effects are more than 30% higher compared with those of all non-patenting firms. The results suggest that, just like patenting firms, non-patenting firms, particularly those with positive R&D expenditures, also increase cash holdings in response to technology spillovers and product market rivalry.

²⁹ Given the average spillover/rivalry effect lacks of variations at a firm level, the fixed-effect regression is not applicable.

4.6 Further analysis

In this section, we consider a few extensions to shed light on the effect of technology spillovers on financial flexibility.

Our measure of product market rivalry (*Spill_Sale*) is the sales-weighted sum of rivals' R&D stock and captures the competitive pressure induced mainly by competitors' technology advances. To capture the intensity of product market competition in a broader sense, we employ two proxies: 1) the Herfindahl-Hirschman Index (HHI) that is computed using firms' market shares as measured by three-digit SIC sales; and 2) the HHI calculated using the text-based network industry classification (TNIC) developed by Hoberg and Phillips (2012).³⁰ Compared with static industry classifications (e.g., SIC or NAICS) that cannot reflect the evolution of product markets over time nor easily accommodate innovations that create entirely new product markets, the TNIC defines a dynamic industry classification based on product descriptions of annual 10-K filings and allows each firm to have its own potentially unique set of competitors.

[Table 9 about here]

Table 9, Columns 1 and 2 report the regression results.³¹ A higher HHI implies weaker competition. Therefore, the negative and highly significant coefficient of HHI is consistent with our previous finding that firms facing great market rivalry (i.e., lower HHI) maintain high cash balances. Moreover, the coefficient of $\ln(\text{Spill_Tech})$ remains positive and significant at a 1% level, indicating a strong positive effect of technology on cash holdings. Column 2 provides further support to our main finding as we observe that, after controlling for market competition proxied by the TNIC HHI, the positive effect of technology spillovers is fully retained.

³⁰ Our spillover proxy uses the distribution of patent filings to aggregate R&D stock in technology space at one point of time. Hence, its correct counterpart is the static product market competition measure in the product text literature.

³¹ The firm-level fixed effects are dropped given the lack of firm-level variation in the traditional HHI. After merging our data with the TNIC HHI that is available from 1996, we end up with a smaller dataset as shown in Column 2. We thank Hoberg and Phillips for making their TNIC HHI available on line.

Furthermore, in Column 3, we conduct an instrumental analysis to address the concern with potential endogeneity. Our set of instruments for the two key variables, lagged $\ln(\text{Spill_Tech}_{t-1})$ and $\ln(\text{Spill_Sale}_{t-1})$, includes their two-year and three-year lags (four instruments), which are less likely to be influenced by a firm's current cash policy. The IV results presented in Column 3 fully agree with our previous findings as we find that the coefficient of $\ln(\text{Spill_Tech})$ and that of $\ln(\text{Spill_Sale})$ remain positive and statistically significant with a similar magnitude as the baseline result reported in Table 5, Column 3. Durbin-Wu-Hausman's χ^2 test alleviates the endogeneity concern as the null hypothesis that $\ln(\text{Spill_Tech})$ and $\ln(\text{Spill_Sale})$ are exogenous cannot be rejected at a 10% significance level.³²

In summary, our analysis in this section strongly indicates the robustness of our finding that technology spillovers positively impinge on cash holdings.

5. Conclusion

The importance of technology innovations and its spillovers for long-run economic growth cannot be overstated. Corrado, Hulten, and Sichel (2009) and Corrado and Hulten (2010) document that technological progress and the accumulation of intangible capital have together accounted for half of the increase in output per hour in the United States over the past several decades. While the importance of corporate innovations and technology proximity between firms has been gradually recognized in asset pricing and M&A literature, their implications for major corporate policy decisions have been left unexplored. This paper fills in this gap and investigates how technological competition, particularly technology spillovers, shapes firms' cash holdings.

³² The first-stage F-statistic is highly significant (p-value<0.00), indicating the relevance of the four IVs. We also conduct Hansen's J overidentification test. The validity of IVs is supported by the fact that we cannot reject the null hypothesis, given a test statistic of 1.43 (p-value=49%).

Our results show that the positive effect of technology spillovers on cash holdings is of economic and statistical significance. Furthermore, we show that, a firm's cash balance is positively affected by spillovers to a greater extent when it's financially constrained, and when marginal profit of innovation output is large so that the firm can greatly enhance profit through improved marginal productivity. The effects remain robust when own-firm innovations are controlled for, among non-patenting firms with their spillover measures imputed as industry averages, and with alternative market competition proxies used to capture the intensity of competitive rivalry in a broader sense. Taken together, the evidence provided in this paper highlights the unique role of technology spillovers in determining corporate cash policy.

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Table 1. Sample firms that experienced highest/lowest growth in *Spill_Tech* and *Spill_Sale*

Panel A.1 (A.2) lists top ten sample firms that had experienced the highest growth in *Spill_Tech* (*Spill_Sale*). Panel B.1 (B.2) lists top ten sample firms that had experienced the lowest growth in *Spill_Tech* (*Spill_Sale*). Firms are assigned into 48 industries according to Fama and French's (1988) classification scheme.

Panel A. Top ten firms that experienced highest growth

A.1 Firms that experience highest growth in *Spill_Tech*

Company	Industry membership
GENENTECH INC	Pharmaceutical Products
SCHERING-PLOUGH	Pharmaceutical Products
LILLY (ELI) & CO	Pharmaceutical Products
GENERAL DATACOMM INDS	Electronic Equipment
BIOGEN INC	Pharmaceutical Products
AUTO-TROL TECHNOLOGY CORP	Computers
PFIZER INC	Pharmaceutical Products
FOREST LABORATORIES -CL A	Pharmaceutical Products
ABBOTT LABORATORIES	Pharmaceutical Products
DEL LABORATORIES INC	Consumer Goods

A.2 Firms that experience highest growth in *Spill_Sale*

Company	Industry membership
NIKE INC -CL B	Apparel
GUILFORD MILLS INC	Textiles
FLEXSTEEL INDS	Consumer Goods
GENERAL DATACOMM INDS	Electronic Equipment
NATIONAL SEMICONDUCTOR CORP	Electronic Equipment
TELLABS INC	Electronic Equipment
MILLER (HERMAN) INC	Business Supplies
SILICONIX INC	Electronic Equipment
ADVANCED MICRO DEVICES	Electronic Equipment
SEMTECH CORP	Electronic Equipment

Panel B. Top ten firms that experienced lowest growth

B.1 Firms that experience lowest growth in *Spill_Tech*

Company	Industry membership
CONOCO INC	Petroleum and Natural Gas
FAIRMOUNT CHEMICAL CO INC	Chemicals
KREISLER MANUFACTURING CORP	Aircraft
VALENCE TECHNOLOGY INC	Electrical Equipment
ALLIANCE PHARMACEUTICAL CP	Pharmaceutical Products
BUTLER NATIONAL CORP	Aircraft
COLUMBUS MCKINNON CORP	Machinery
THORATEC CORP	Medical Equipment
HARDINGE INC	Machinery
LEXMARK INTL INC -CL A	Computers

B.2 Firms that experience lowest growth in *Spill_Sale*

Company	Industry membership
REEBOK INTERNATIONAL LTD	Apparel
BURLINGTON NORTHERN RR CO	Transportation
CSX CORP	Transportation
GEORGIA-PACIFIC CORP	Business Supplies
GARAN INC	Apparel
HERSHEY FOODS CORP	Food Products
CONOCO INC	Petroleum and Natural Gas
BELLSOUTH CORP	Communication
HAMPTON INDUSTRIES	Apparel
US HOME CORP	Construction

Table 2: **The Correlation Between $\ln(\text{Spill_Tech})$ and $\ln(\text{Spill_Sale})$**

In each year, we divide the sample firms into quintiles according to the value of $\ln(\text{Spill_Tech})$ ($\ln(\text{Spill_Sale})$). The first row of each cell shows the average value of $\ln(\text{Spill_Tech})$ and the second report that of $\ln(\text{Spill_Sale})$ for each quintile with the corresponding standard deviations in parentheses.

$\ln(\text{Spill_Tech})$	$\ln(\text{Spill_Sale})$				
	Q1	Q2	Q3	Q4	Q5
Q1	9.867 (0.289) 4.262 (0.399)	10.11 (0.226) 6.404 (0.343)	10.35 (0.248) 7.790 (0.275)	10.14 (0.269) 8.616 (0.281)	10.18 (0.215) 9.896 (0.332)
Q2	11.03 (0.282) 5.764 (0.204)	11.03 (0.284) 7.614 (0.239)	11.02 (0.279) 8.460 (0.249)	11.02 (0.262) 8.942 (0.258)	11.07 (0.288) 9.992 (0.291)
Q3	11.40 (0.262) 6.466 (0.341)	11.44 (0.297) 7.971 (0.352)	11.44 (0.273) 8.603 (0.371)	11.45 (0.275) 9.282 (0.463)	11.46 (0.265) 10.26 (0.402)
Q4	11.79 (0.291) 7.331 (0.182)	11.81 (0.286) 8.538 (0.209)	11.78 (0.268) 9.006 (0.237)	11.80 (0.288) 9.615 (0.318)	11.82 (0.289) 10.29 (0.382)
Q5	12.22 (0.295) 7.588 (0.493)	12.25 (0.279) 9.057 (0.429)	12.37 (0.284) 9.672 (0.429)	12.37 (0.266) 10.17 (0.460)	12.31 (0.245) 10.68 (0.328)

Table 3: **Summary Statistics**

The table provides summary statistics of firm characteristics in the sample. Financial firms (SIC codes 6000-6999) and utilities (SIC codes 4900-4999) are excluded. The sample period is from 1982 to 2001. *Cash* is the cash-to-asset ratio, calculated as cash and marketable securities (#1) divided by total book assets (#6). The size of a firm is measured by the logarithm of total sales. Book-to-market is the ratio of book value of common shareholders' equity (#60) to market value of equity (#199 multiplied by #25) at fiscal year-end. Stock return is in the annual frequency. Return on Assets (ROA) is calculated as operating income before depreciation (#13) scaled by total assets (#6). Income volatility is calculated as the standard deviation of Net Earnings before Extraordinary Items (#18) from year t to t-3, scaled by total assets (#6).

	# of obs.	mean	s.d.	25 th	Median	75 th
Cash	10690	0.105	0.124	0.018	0.055	0.143
$\ln(\text{Spill_Tech})$	10690	11.33	0.832	10.87	11.42	11.91
$\ln(\text{Spill_Sale})$	10690	8.474	1.679	7.742	8.711	9.680
$\ln(\text{sales})$	10690	6.230	1.900	4.855	6.164	7.586
Book-to-market	10690	0.653	0.450	0.352	0.561	0.845
Stock return	10690	-0.005	0.405	-0.234	0.023	0.237
ROA	10690	0.051	0.076	0.024	0.058	0.092
Income volatility	10690	1.919	6.458	0.042	0.180	0.829
Sales growth	10690	0.074	0.166	-0.006	0.070	0.150

Table 4: **Technological Competition and Cash Holdings**

This table reports our baseline fixed-effects estimates from the following equation:

$$cash_{it} = \beta_1 \ln(Spill_Tech_{i,t-1}) + \beta_2 \ln(Spill_Sale_{i,t-1}) + \gamma' X_{i,t} + \eta_i + \tau_t + \varepsilon_{it},$$

where i and t are firm and time subscripts, respectively. In Columns (1), (2), (3) and (5), the dependent variable, $cash$ is measured as cash plus equivalents dividend by book assets. In Column (4), the dependent variable is the log of cash-asset ratios. In Column (6), Net Cash is defined as total cash subtracts debt and scaled by book assets, i.e., $[(che-(dltt+dlc)]/at$. The magnitude of technology spillovers and product market rivalry effects are measured by $Spill_Tech$ and $Spill_Sale$, respectively. $Spill_Tech_{Mah}$ and $Spill_Sale_{Mah}$ are Mahalanobis metric-based technology spillovers and market rivalry measures, respectively. X is a vector of other firm-level control variables suggested by related literature and a constant term. η_i and τ_t capture the firm and time fixed effects. ε_{it} is the error term. As in BSV, Standard errors in parentheses are robust to heteroskedasticity and first-order serial correlation using the Newey-West correction. ***, **, * indicate significance level at 1%, 5% and 10% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Cash	Cash	Cash	log(Cash)	Cash	Net Cash
$\ln(Spill_Tech)$	0.094*** (4.40)		0.068*** (2.95)	0.503** (2.24)		0.059** (2.12)
$\ln(Spill_Sale)$		0.034*** (5.13)	0.024*** (3.40)	0.358*** (4.30)		0.033*** (3.69)
$\ln(Spill_Tech_{Mah})$					0.074*** (3.57)	
$\ln(Spill_Sale_{Mah})$					0.022*** (3.36)	
$\ln(sales)$	-0.023*** (-7.25)	-0.024*** (-7.54)	-0.024*** (-7.63)	-0.177*** (-5.74)	-0.023*** (-7.32)	-0.030*** (-7.59)
Book-to-market	-0.012*** (-3.81)	-0.012*** (-3.82)	-0.012*** (-3.90)	-0.058 (-1.44)	-0.012*** (-3.86)	-0.005 (-1.16)
Stock return	0.005** (2.35)	0.005** (2.30)	0.005** (2.25)	0.087*** (3.44)	0.005** (2.21)	0.011*** (3.99)
ROA	0.160*** (8.66)	0.163*** (8.82)	0.162*** (8.77)	1.309*** (6.58)	0.163*** (8.76)	0.292*** (11.59)
Income volatility	0.001*** (5.10)	0.001*** (5.14)	0.001*** (4.97)	0.012*** (6.53)	0.001*** (4.94)	0.001*** (5.29)
Sales growth	-0.044*** (-7.07)	-0.043*** (-6.87)	-0.044*** (-6.90)	-0.493*** (-6.76)	-0.045*** (-7.04)	-0.048*** (-5.73)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
# of obs.	10690	10690	10690	10690	10604	10690
Adj. R ²	0.657	0.657	0.658	0.584	0.656	0.625

Table 5. **The heterogeneity in the impact of technological spillovers on cash holdings**

This table explores the potential interaction between the technology spillover effect and marginal profit of innovation output, as motivated in Hypothesis 1. In a given year, we categorize firms into two subsamples based on the median of average patent age (Col. 1 and 2), profitability (Col. 3 and 4), market-to-book ratio (Col. 5 and 6) and product fluidity (Col. 7 and 8). All specifications also include year and firm-level fixed effects. Standard errors in parentheses are robust to heteroskedasticity and first-order serial correlation using the Newey-West correction. ***, **, * indicate significance level at 1%, 5% and 10% level respectively.

	Avg. patent age		Profitability		M/B		Product fluidity	
	(1) Young	(2) Old	(3) High	(4) Low	(5) High	(6) Low	(7) High	(8) Low
$\ln(\text{Spill_Tech})$	0.146*** (2.64)	-0.059 (-1.18)	0.100*** (2.86)	0.035 (1.03)	0.123*** (3.33)	0.027 (0.86)	0.231* (1.76)	-0.216* (-1.70)
$\ln(\text{Spill_Sale})$	0.046** (2.46)	0.029** (2.34)	0.028*** (2.65)	0.024** (2.25)	0.027** (2.13)	0.022** (2.48)	0.074* (1.79)	0.010 (0.31)
$\ln(\text{sales})$	-0.023*** (-3.19)	-0.020*** (-3.53)	-0.014** (-2.50)	-0.028*** (-6.60)	-0.017*** (-3.48)	-0.039*** (-9.00)	-0.05 (-0.92)	0.015 (0.86)
Book-to-market	-0.014* (-1.65)	-0.004 (-0.97)	-0.013* (-1.92)	-0.012*** (-3.33)	-0.008 (-1.49)	-0.014*** (-3.42)	-0.016 (-1.45)	0.010 (0.95)
Stock return	0.011** (2.39)	0.007** (2.37)	0.004 (1.24)	0.004 (1.28)	0.006** (2.11)	-0.001 (-0.33)	0.006 (0.95)	0.007 (1.23)
ROA	0.151*** (3.92)	0.087*** (3.15)	0.209*** (5.66)	0.119*** (5.29)	0.118*** (4.73)	0.149*** (5.17)	0.011 (0.21)	0.030 (0.59)
Income volatility	0.001** (2.21)	0.001** (2.47)	0.001*** (2.90)	0.001*** (2.91)	0.001*** (2.81)	0.001** (2.34)	-0.001 (-1.55)	0.000 (0.21)
Sales growth	-0.035*** (-2.90)	-0.045*** (-4.58)	-0.040*** (-3.77)	-0.046*** (-5.72)	-0.037*** (-4.00)	-0.045*** (-5.14)	-0.020 (-1.11)	-0.045*** (-2.84)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of obs.	5346	5344	5346	5344	5346	5344	1258	1259
Adj. R ²	0.720	0.673	0.669	0.680	0.672	0.689	0.772	0.813

Table 6. **The role of financial constraints**

This table examines the role of financial constraints in the technology spillover effect. Sample firms are divided into categories according to indirect proxies (asset size and credit rating) and a few leading indices of the degree of financial constraints (i.e., WW index (Whited and Wu, 2006), SA index (Hadlock and Pierce, 2010), and KZ index (Kaplan and Zingales, 1997)). For firm size, the financially constrained (unconstrained) group consists of firms in the lower (upper) half of the size distribution. Using bond ratings, constrained firms are defined as companies with below investment-grade ratings. With one of the WW, SA and KZ indices, constrained firms are those with their index values exceeding the median in a year. Each specification also includes year and firm-level fixed effects. Standard errors in parentheses are robust to heteroskedasticity and first-order serial correlation using the Newey-West correction. ***, **, * indicate significance level at 1%, 5% and 10% level respectively.

	Firm size		Credit rating		WW index		SA index		KZ index	
	(1) Small firms	(2) Large firms	(3) Non-inv.	(4) Investment	(5) High	(6) Low	(7) High	(8) Low	(9) High	(10) Low
<i>ln(Spill_Tech)</i>	0.067** (2.14)	0.044 (1.21)	0.085*** (3.26)	0.039 (1.13)	0.083** (2.51)	-0.005 (-0.15)	0.063** (2.03)	-0.022 (-0.69)	0.064** (1.98)	0.024 (0.69)
<i>ln(Spill_Sale)</i>	0.029*** (2.67)	0.019* (1.85)	0.028*** (3.24)	0.018 (1.61)	0.035*** (3.00)	0.014* (1.67)	0.032*** (2.81)	0.035*** (3.94)	0.024** (2.52)	0.020* (1.75)
<i>ln(sales)</i>	-0.028*** (-5.38)	-0.017*** (-4.39)	-0.025*** (-6.57)	-0.026*** (-4.10)	-0.031*** (-6.27)	-0.021*** (-5.38)	-0.027*** (-5.04)	-0.019*** (-4.67)	-0.019*** (-4.98)	-0.034*** (-6.19)
Book-to-market	-0.015*** (-3.57)	-0.006 (-1.18)	-0.013*** (-3.73)	-0.007 (-1.07)	-0.018*** (-4.19)	0.003 (0.54)	-0.017*** (-3.75)	-0.002 (-0.51)	-0.007 (-1.62)	-0.013*** (-2.93)
Stock return	0.001 (0.40)	0.009*** (3.43)	0.003 (1.24)	0.009*** (2.72)	0.002 (0.54)	0.009*** (3.43)	0.000 (0.11)	0.011*** (3.87)	0.010*** (3.66)	-0.002 (-0.46)
ROA	0.195*** (8.05)	0.097*** (3.45)	0.186*** (8.74)	0.053 (1.40)	0.199*** (8.13)	0.078** (2.39)	0.193*** (7.61)	0.104*** (3.62)	0.078*** (2.84)	0.208*** (8.44)
Income volatility	0.002 (1.46)	0.001*** (5.01)	0.002*** (4.38)	0.001** (2.43)	0.001* (1.90)	0.001*** (5.09)	0.002** (2.03)	0.001*** (4.94)	0.001*** (4.83)	0.003 (1.48)
Sales growth	-0.053*** (-5.80)	-0.035*** (-4.42)	-0.050*** (-6.61)	-0.025** (-2.36)	-0.050*** (-5.37)	-0.035*** (-4.43)	-0.049*** (-5.17)	-0.040*** (-4.91)	-0.036*** (-4.53)	-0.049*** (-4.93)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of obs.	5344	5346	7821	2869	5189	5182	5350	5340	5054	5051
Adj. R ²	0.653	0.670	0.652	0.662	0.640	0.679	0.655	0.656	0.698	0.651

Table 7. Technological Competition and Cash Holdings: Own Firm Innovations

This table reports the fixed-effects regression results as we further control for own firm innovation capability in examining the technology spillover and market rivalry effects on cash holdings. The own-firm technological output is measured by a firm's five-year discounted sum of innovation activities (denoted as WI, see Equation 8). Each specification also includes a set of control variables as in Table (4) and time fixed effects. Standard errors in parentheses are robust to heteroskedasticity and first-order serial correlation using the Newey-West correction. ***, **, * indicate significance level at 1%, 5% and 10% level respectively.

	(1)	(2)	(3)	(4)
	Cash	Cash	Cash	Cash
$\ln(\text{Spill_Tech})$	0.067*** (2.93)	0.067*** (2.94)	0.068*** (2.95)	0.068*** (2.95)
$\ln(\text{Spill_Sale})$	0.023*** (3.30)	0.024*** (3.36)	0.024*** (3.42)	0.024*** (3.41)
$\ln[1 + \text{WI}(\text{count})]$	0.003* (1.91)			
$\ln[1 + \text{WI}(\text{count}_{adj})]$		0.002** (2.12)		
$\ln[1 + \text{WI}(\text{cite})]$			0.002* (1.76)	
$\ln[1 + \text{WI}(\text{cite}_{adj})]$				0.001 (1.56)
Other controls		the same as in Table 4		
Year fixed effect	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
# of obs.	10690	10690	10690	10690
Adj. R ²	0.658	0.658	0.658	0.658

Table 8: Technological Competition and Cash Holdings: Non-Patenting Firms

This table analyzes the spillover and rivalry effects on cash holdings for non-patenting firms. Panel A provides summary statistics for non-patenting firms (40,067 firm year observations) and patenting firms (9,924 firm year observations). Panel B presents the OLS regression results. A non-patenting firm's technology spillover (market rivalry) measure is assigned as the average (or median) effect of all patenting firms within the same 4-digit SIC industry. For conglomerates reporting sales in more than one SIC industries, a sales-weighted average of their segment peers is assigned. Each specification also includes a full set of firm-specific explanatory variables and time dummies. Standard errors in parentheses are robust to heteroskedasticity and first-order serial correlation using the Newey-West correction. ***, **, * indicate significance level at 1%, 5% and 10% level respectively.

Panel A: Mean comparison: Non-patenting vs. patenting firms

	Non-patenting firms			Patenting firms			Diff. in mean
	mean	median	s.d.	mean	median	s.d.	
Cash holdings (\$m)	82.34	5.390	341.5	225.0	24.43	1021	-142.6*** (-14.29)
ln(sales)	4.258	4.260	2.468	6.230	6.164	1.900	-1.972*** (-93.11)
Book-to-market	0.662	0.562	0.994	0.653	0.561	0.450	0.010 (1.62)
Stock return	-0.075	-0.025	0.656	-0.005	0.023	0.405	-0.071*** (-14.67)
ROA	-0.080	0.025	0.375	0.051	0.058	0.076	-0.131*** (-74.09)
Income volatility	1.552	0.122	5.460	1.919	0.180	6.458	-0.367*** (-5.50)
Sales growth	0.087	0.074	0.412	0.074	0.070	0.166	0.013*** (5.54)

Panel B: The impact of average technological competition on cash holdings

	(1)	(2)	(3)	(4)
	With non-patenting firms proxied by the 4-digit SIC industry median		With non-patenting firms proxied by the 4-digit SIC industry average	
	All non-patenting firms	Non-patenting positive-R&D firms	All non-patenting firms	Non-patenting positive-R&D firms
ln(Spill_Tech)	0.020*** (13.80)	0.023*** (6.92)	0.013*** (8.79)	0.066** (2.03)
ln(Spill_Sale)	0.009*** (16.83)	0.017*** (13.09)	0.011*** (20.78)	0.022*** (16.97)
Other controls	the same as in Table 4			
Year fixed effect	Yes	Yes	Yes	Yes
Firm fixed effect	No	No	No	No
# of obs.	65871	28213	65871	28213
Adj. R ²	0.205	0.156	0.206	0.156

Table 9. **Robustness Check: Alternative measures of market competition and IV regressions**

Each specification also includes a set of control variables as in Table (4) and time fixed effects. Standard errors in parentheses are robust to heteroskedasticity and first-order serial correlation using the Newey-West correction. ***, **, * indicate significance level at 1%, 5% and 10% level respectively.

	Alternative market competition measures		IV
	(1) Cash	(2) Cash	(3) Cash
ln(Spill_Tech)	0.008*** (3.00)	0.013*** (3.07)	0.061** (2.23)
HHI	-0.054*** (-4.53)		
TNIC HHI		-0.084*** (-5.42)	
ln(Spill_Sale)			0.027*** (3.37)
ln(sales)	-0.025*** (-23.65)	-0.029*** (-13.77)	-0.023*** (-6.69)
Book-to-market	-0.031*** (-7.92)	-0.030*** (-3.94)	-0.016*** (-4.60)
Stock return	0.000 (0.01)	0.007 (1.05)	0.004* (1.77)
ROA	0.258*** (8.49)	0.264*** (5.46)	0.141*** (7.36)
Income volatility	0.003*** (10.86)	0.004*** (7.55)	0.001*** (4.14)
Sales growth	0.012 (1.12)	-0.024 (-1.29)	-0.046*** (-7.14)
Year fixed effect	Yes	Yes	Yes
Firm fixed effect	No	No	Yes
# of obs.	10690	2612	9627
Adj. R ²	0.140	0.154	0.694
Wu-Hausman test of exogeneity			1.847 (0.158)
Hansen J statistic			1.429 (0.490)
1 st stage F test			
ln(Spill_Tech)			53204.6 (0.000)
ln(Spill_Sale)			16186.6 (0.000)

Appendix A. The Model

We present a simple model to illustrate the effects of technology spillovers and product market rivalry on a firm's cash holdings. The model extends BSV's two-stage model into three stages. The key setup in Stages 1 and 2 are the same as BSV's. The new feature of our model is that, in Stage 0, the firm needs to decide the allocation of cash: saving for R&D spending in Stage 1 versus investing in a non-R&D project, of which the assets could be used as collateral to secure external financing.

A.1 The setup

As in BSV, there are three firms, j , τ and m . Firms j and τ overlap only in technology space but not in the product market while firms j and m overlap only in the product market.

Stage 0, Firm j is endowed with cash W_j . It can save cash C_j and invest the rest $i_j = W_j - C_j$ in a non-R&D project that yields a payoff $F(i_j)$ at Stage 2 ($F' > 0$ and $F'' < 0$). The assets generated by investment i_j can be used as collateral to borrow in Stage 1. That is:

$$B_j = qi_j,$$

where B_j is the value of external borrowing; and $q \in (0,1)$ is the collateralization rate, at which the non-R&D project can be pledged as the collateral to creditors. q captures firm j 's degree of financial constraints. A firm with low asset tangibility, great information asymmetry or operated in a poor legal environment will have a small collateralization rate q , therefore, limited access to external financing.

Stage 1. Firm j 's R&D spending r_j is supported by its internal cash reserve C_j and external borrowing capacity B_j :

$$r_j = C_j + B_j.$$

Firm j produces innovation output with its own R&D spending r_j . The firm may also benefit from technology spilled from its neighbor in technology space, firm τ . Firm j 's technology output, k_j is equal to

$$k_j = \phi(r_j, r_\tau),$$

where r_τ is the R&D investment of Firm τ . The knowledge production function is non-decreasing and concave in either argument.

Stage 2. Firms j and m compete in some variable x (e.g., price or quantity), conditional on their technology output levels, k_j and k_m , respectively. Firm j 's profit function is given by $\pi(x_j, x_m, k_j)$. The best responses of Firms j and m are given by $x_j^* = \arg \max_{x_j} \pi(x_j, x_m, k_j)$ and $x_m^* = \arg \max_{x_m} \pi(x_j, x_m, k_m)$, respectively. Solving for the second stage Nash decisions yields $x_j^* = f(k_j, k_m)$ and $x_m^* = f(k_m, k_j)$, where f is a generic term for a function. Therefore, the profit for Firm j is $\Pi(k_j, k_m) = \pi(k_j, x_j^*, x_m^*)$, where $\Pi_1 > 0$ and $\Pi_2 > 0$.

A.2 Analysis

At stage 0, the firm's optimization problem is to choose cash holdings C_j that maximize its total profit from R&D and non-R&D investments:

$$\begin{aligned} \text{Max}_{\{C_j\}} \quad & \Pi = F(i_j) + \Pi[k_j, k_m] - i_j - r_j - B_j \\ \text{s.t.} \quad & i_j = W_j - C_j \\ & r_j = C_j + B_j \\ & B_j = qi_j \\ & k_j = \phi(r_j, r_\tau) \end{aligned} \quad , \quad (\text{A1})$$

which is equivalent to

$$\underset{\{C_j\}}{\text{Max}} \Pi = F(W_j - C_j) + \Pi[\phi(qW_j + (1-q)C_j, r_\tau), k_m] - W_j \quad (\text{A2})$$

The optimal cash holding C_j^* satisfies the following first-order condition:

$$F'(W_j - C_j^*) + \Pi_1[\phi(qW_j + (1-q)C_j, r_\tau), k_m]\phi_1 q = \Pi_1[\phi(qW_j + (1-q)C_j, r_\tau), k_m]\phi_1. \quad (\text{A3})$$

The left hand side term of Eq. (A3) is the benefit of one additional unit of investment in the non-R&D project i_j at Stage 0 (at the cost of reducing cash holdings by one unit). The term has two components: 1) the marginal return from investment i_j , $F'(W_j - C_j^*)$; and 2) the additional pledgeable value q that can be used to invest in the R&D project and increase the profit by $\Pi_1\phi_1 q$. The right hand side shows the benefit of carrying one additional unit of cash to Stage 1, which is the marginal profit of the R&D investment, $\Pi_1\phi_1$. At the optimal level, C_j^* , the marginal benefit of investing in a non-R&D project equals to that of saving cash for the future R&D project.

Comparative statics analysis yields the impact of technology spillovers and product market rivalry on the firm's cash holdings shown as follows.

$$\frac{\partial C_j^*}{\partial r_\tau} = -\frac{(\Pi_{11}\phi_{12} + \Pi_{11}\phi_1\phi_2)(1-q)}{A}, \quad (\text{A1})$$

and

$$\frac{\partial C_j^*}{\partial k_m} = -\frac{\Pi_{12}\phi_1(1-q)}{A}, \quad (\text{A2})$$

where $A = F_{11} + (\Pi_{11}\phi_1^2 + \Pi_{11}\phi_1)\phi_1(1-q)^2 < 0$ by the second order condition. The key determinant of the sign of $\partial C_j^*/\partial r_\tau$ is ϕ_{12} , which captures the impact of knowledge externalities (diffused from firm τ) on firm j 's marginal technology productivity. $\partial C_j^*/\partial r_\tau$ is positive if $\phi_{12} > 0$, which

means that firm j 's R&D is positively related to the R&D conducted by firms in the same technology space. As shown in Eq. A1, *ceteris paribus*, the spillover effect would be stronger for firms with a large value of Π_1 .³³

The impact of financial constraints on the cash holding sensitivities to technology spillovers and product market rivalry are as the follows:

$$\frac{\partial^2 C_o^*}{\partial r_\tau \partial q} = \frac{(\Pi_1 \phi_{12} + \Pi_{11} \phi_1 \phi_2)}{A} \quad (\text{A3})$$

$$\frac{\partial^2 C_o^*}{\partial k_m \partial q} = \frac{\Pi_{12} \phi_1}{A} \quad (\text{A4})$$

The above comparative static analyses lead to the following two main propositions.

Proposition 1: Technology spillover has a positive effect on a firm's cash holdings, i.e., $\partial C_j^* / \partial r_\tau > 0$ (Eq. A1); and, *ceteris paribus*, this positive effect is stronger for firms with large marginal profit (Π_1).

Proposition 2: The positive technology spillover effect on cash balances would be strengthened

for financially constrained firms (with a smaller q) given $\frac{\partial^2 C_o^*}{\partial r_\tau \partial q} < 0$ as shown in Eq. A3.

Turning to the market rival effect, the sign of $\partial C_j^* / \partial k_m$ is same as that of Π_{12} , which is positive if k_j and k_m are strategic complements as generally assumed in the literature (e.g., Lee and Wilde, 1980, and Aghion, Harris, and Vickers, 1997). In parallel with Proposition 2, such an effect will be heightened for financially constrained firms; that is, $\frac{\partial^2 C_o^*}{\partial k_m \partial q} < 0$ as shown in Eq. A4.

³³ A minor condition for this to hold is that the firm faces non-decreasing marginal return in innovation output ($\Pi_{11} \geq 0$) or the decreasing marginal return in innovation output is not "too strong" (i.e., Π_{11} is not too negative so that $\Pi_1 \phi_{12} + \Pi_{11} \phi_1 \phi_2$ remains positive). Nadiri (1993) shows that the possibility of diminishing returns to innovative activities seems implausible.

Appendix B: Definition of Variables

1. *Cash* is measured as cash-to-assets and marketable securities divided by total book assets. We also use the logarithm of cash-to-assets ratio in our robustness checks.
2. $\ln(\text{Sales})$ is the logarithm of total sales.
3. *Book-to-market* is the ratio of book value of common shareholders' equity to market value of equity at fiscal year-end.
4. *Stock return* is in the annual frequency.
5. *ROA*. Return on Assets is calculated as operating income before depreciation scaled by total assets.
6. *Tangibility* is calculated as Net Property, Plant and Equipment divided by total assets.
7. *Income volatility* is the standard deviation of Net Earnings before Extraordinary Items from year t to $t - 3$, scaled by total assets.
8. $\ln(\text{firm age})$ is the number of years for which the firm is listed in Compustat).
9. Following Hadlock and Pierce (2010), the SA index is calculated as

$$(-0.737 \times \text{Size}) + (0.043 \times \text{Size}^2) - (0.040 \times \text{Age}),$$

where Size equals the log of inflation-adjusted book assets, and Age is the number of years the firm is listed with a non-missing stock price on Compustat. In calculating the index, we follow Hadlock and Pierce and cap Size at (the log of) \$4.5 billion and Age at 37 years.

10. Following Whited and Wu (2006), the WW index is computed according to the following formula:

$$\begin{aligned} \text{WW} = & -0.091 \times \text{CF} - 0.062 \times \text{DIVPOS} + 0.021 \times \text{TLTD} - 0.044 \times \text{LNTA} + 0.102 \\ & \times \text{ISG} - 0.035 \times \text{SG}, \end{aligned}$$

where CF is the ratio of cash flow to total assets; DIVPOS is an indicator that takes the

value of one if the firm pays cash dividends; TLTD is the ratio of the long-term debt to total assets; LNTA is the natural log of total assets; ISG is the firm's three-digit industry sales growth; and SG is firm sales growth.

11. KZ Index is constructed following Lamont, Polk, and Saá-Requejo (2001) as

$$-1.002 \times CF + 3.139 \times TLTD - 39.368 \times TDIV - 1.315 \times CASH + 0.283 \times Q,$$

where TDIV is the ratio of total dividends to assets and Q is Tobin's q. other variables are defined as in the WW index.

Appendix C: A brief summary of USPTO technology classes and the patent filing pattern of the sample firms

Patents are assigned into classes based on their common subject matter according to the U.S. Patent Classification (USPC) System, used and maintained by the United States Patent and Trademark Office (USPTO) to provide guidance for the classification.³⁴ The USPTO was established as a distinct governmental bureau in 1802. The USPTO is now part of the Commerce Department. Below we provide a summary of the patent filing pattern of our sample firms.

The table A1 lists the top 10 patent classes, in which patents are most frequently filed.³⁵ The 10 classes represent 12.38% of all patents filed by our sample firms over the sample period.

Table C1. Top 10 most frequently filed patent classes

Rank	Patent class	Class description	Patent count	Patent share (%)
1	No. 438	Semiconductor Device Manufacturing: Process	12564	3.23
2	No. 257	Active Solid-State Devices	8120	2.09
3	No. 370	Multiplex Communications	5782	1.49
4	No. 514	Drug, Bio-Affecting And Body Treating Compositions	4842	1.25
5	No. 709	Electrical Computers And Digital Processing Systems: Multicomputer Data Transferring	4061	1.04
6	No. 430	Radiation Imagery Chemistry: Process, Composition, Or Product Thereof	3840	0.99
7	No. 428	Stock Material Or Miscellaneous Articles	3812	0.98
8	No. 707	Data Processing: Database And File Management Or Data Structures	2769	0.71
9	No. 711	Electrical Computers And Digital Processing Systems: Memory	1250	0.32
10	No. 525	Synthetic Resins Or Natural Rubbers	1095	0.28
Total			48135	12.38

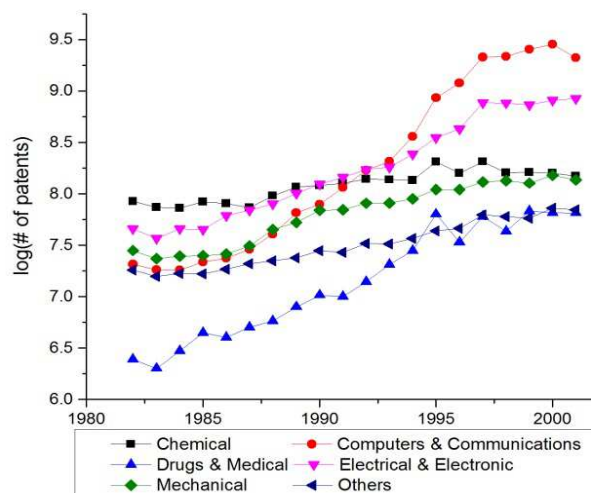
To provide an overview of the patent filing patterns over the more than 400 patent classes, we have consulted the higher-level classification proposed by Hall, Jaffe and Trajtenberg (2001,

³⁴ The USPC System has been replaced with the Cooperative Patent Classification (CPC) system as of Jan. 1, 2013 to harmonize the patent classifications systems between the European Patent Office (EPO) and USPTO.

³⁵ The details of technology classes can be found at <http://www.uspto.gov/web/offices/ac/ido/oeip/taf/cbcby.htm>.

NBER) to aggregate patent classes into six main technological categories.³⁶ Figure A1 shows the logarithm of the numbers of patents filed in each of the six categories by our sample firms over our sample period. We see the most dramatic growth of patent filings in categories of Computers & Communications and Drugs & Medical.

Figure C1. Logarithm of the number of patents filed in six main technological categories



The average number of patent classes in which a firm filed patent applications in a year is 54.2 with a median of 37 and the maximum of 273. The patent filing pattern is rather stable. In our sample, 77.3% of firms filed at least one patent in the same class in which they had filed one year before, and that 93.3% firms filed patents in the same class within 5 years. This number is 96.6 for the 10-year window.

Table C2 reports the distribution of the average size (measured by sales) across six technological classes. Given a single firm may file patents in dozens and even hundreds of different patent classes in a year, in the calculation of the average firm size of a category, we

³⁶ The six main technological categories are: 1. Chemical, 2. Computers & Communications, 3. Drugs & Medical, 4. Electrical & Electronic, 5. Mechanical and 6. Others. Patent classes are not evenly distributed across the six technological categories. For instance, the category of Drugs & Medical only has 14 patent classes; while the number is 117 for the category of Mechanical.

weigh a firm size by the ratio of the firm's patents filed in the category to its total number of patents filed that year. Thus, if a firm filed few of its patents in a category, its size would weigh less in the calculation of the average firm size of the technology category. We find that among the first five categories, firms in the category of Drugs & Medical have the largest size. Notably, the distribution of firm size in each category is positively skewed.

Table C2. Summary statistics of firm size (measured by sales in millions of dollars) across six technological classes

	mean	s. d.	sk.	kurt.	Q1	Q2	Q3
1. Chemical	268.3	553.0	6.930	80.45	49.51	104.2	253.4
2. Computers & Communications	343.8	1123.9	18.32	587.15	40.66	97.03	278.1
3. Drugs & Medical	351.3	822.3	6.514	65.93	44.17	106.0	289.7
4. Electrical & Electronic	238.6	612.8	13.05	300.5	39.97	87.72	212.4
5. Mechanical	289.6	855.4	16.21	412.4	49.36	103.2	257.8
6. Others	386.1	1505.9	31.81	1634.0	53.95	115.5	303.1