Do Technology Spillovers Affect Corporate Financial Policies?

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Abstract

Prior research has shown that so called "technology spillovers" to a given firm from its technological peer firms increase the firm's own innovation, productivity, and value. We study how firms finance the growth stimulated by technology spillovers. We find that technology spillovers increase leverage, through both issuing more debt and less equity. Additional evidence supports two channels through which technology spillovers affect financial policies: greater asset redeployability (more collateralized borrowing and asset transactions) and equity undervaluation (positive earnings surprises and stock outperformance). Exogenous variation in R&D tax credits of other firms allows us to identify the causal effect of technology spillovers on a given firm.

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"'They just had no idea what they had,' [Steve] Jobs later said, after launching hugely profitable Apple computers using concepts developed by Xerox." (The Wall Street Journal (2012))

Bill Gates to Steve Jobs: "'[W]e both had this rich neighbor named Xerox and I broke into his house to steal the TV set and found out that you had already stolen it.'" (Isaacson (2011))

1. Introduction

Innovation is essential for prosperity, yet firms do not innovate and prosper in isolation but rather under the influence of their technological peer firms (e.g., Lyandres and Palazzo (2016)). To give a prominent example, Bloom, Schankerman, and Van Reenen (2013) ("BSV" hereafter) provide compelling evidence that a given firm's innovation, productivity, and value all increase as a result of technology spillovers from other firms.

By way of background, many classic studies demonstrate the importance to a given firm of the technologies of its peer firms, including Arrow (1962), Jaffe (1986), and Grossman and Helpman (1991). Recent studies provide evidence on the specific investments stimulated by technology spillovers as well as the assets they generate. For example, technology spillovers affect corporate innovation strategies (e.g., exploratory versus exploitative) (Akcigit and Kerr (2015)), technology transfers (Akcigit, Celik, and Greenwood (2016)), human capital investment (Rosenkopf and Almeida (2003)), tangible asset sales (Maksimovic and Phillips (2001)), strategic alliances (Li, Qiu, and Wang (2016)), and mergers and acquisitions (Phillips and Zhdanov (2013) and Bena and Li (2014)).[1] In summary, the consensus in the literature is that the technologies spill over from one firm to another, stimulating investment and generating assets for

[1] In addition to such voluntary spillovers, technology can also spill over involuntarily across firms, for instance, as knowledge transferred through patents, research papers, conferences, social networks, and employees changing firms.

technologically related firms.[2] Perhaps the most popular examples of technology spillovers are lasers and microprocessors. We discuss these in detail in Section 2.3.

Technology spillovers clearly have a significant impact on corporate growth. It is therefore essential to understand how firms choose the mixture of debt and equity that is used to finance the growth resulting from technology spillovers. We devote our study to answering this previously unexplored question.

We begin our study by considering why firms would choose debt versus equity to finance the assets generated by technology spillovers. Our reasoning is explained in detail in Section 5 and summarized briefly here. First, technology spillovers increase asset redeployability and thereby lead to higher leverage. Specifically, the assets of a firm generated by technology spillovers naturally derive in part from its technological peer firms. These corporate assets are therefore more productive for and valuable to peer firms. This asset redeployability increases the marketability of the firm's assets, to industrial users. Losses in the event of bankruptcy are lower, so the firm's creditors are willing to lend on more generous terms.[3] Since debt is cheaper, the firm borrows more.

Second, technology spillovers can potentially lead to mispricing of debt relative to equity, which would also affect leverage. In particular, the assets of the firm deriving in part from its technological peer firms could reasonably be characterized as long-term in nature, complex, and oftentimes intangible. Assets with such characteristics have a tendency to be mispriced by investors.[4] Given that equity is more sensitive to changes in firm value than debt, if investors

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[2] The technology assets generated by technology spillovers can be intangible, such as patents, formulas, designs, business methods, trade secrets, etc. These assets can also be tangible, such as laboratory equipment, research facilities, communications hardware, machinery, factories, etc.

[3] Patents, for example, are increasingly used as collateral for corporate borrowing (e.g., Mann (2016)).

[4] In a behavioral framework, such assets could in principle be undervalued or overvalued. For example, if investors extrapolate the future performance of an asset from its past performance, and if the asset only generates profits in the long run but not in the short run, then the representative heuristic would lead investors to undervalue the asset.

undervalue the firm's assets, the firm should finance itself with relatively less equity and more debt; conversely, if the firm's assets are overvalued, the firm should use relatively more equity financing than debt.

For our empirical analysis, we would ideally like to examine the details of the financing decisions corresponding to all investments stimulated by technology spillovers. Unfortunately, no such data exist, not least because technology spillovers generate a wide variety of assets, both tangible and intangible. Nevertheless, we can take advantage of recent developments in the literature to measure potential technology spillovers. Since the literature shows that our measure results in higher corporate innovation, productivity, and value, we can take as given the effect of technology spillovers on corporate growth. Finally, we can take a reduce form approach to examine the direct effect of our chosen measure on the firm's choice of debt versus equity financing.

To be specific, we study the effect of technology spillovers on corporate financial policies using a sample of 694 publicly traded firms during the years 1981-2001. Following BSV, we capture potential technology spillovers to a firm by taking into account both the extent of its technological similarity with other firms and the R&D of other firms. Specifically, our measure of technology spillovers to a firm is calculated as the sum of the weighted R&D stocks of other firms, where the weights are the technological proximities between two firms. The technological proximity between two firms is measured as the distance between the technology activities of the two firms in the same technology space or similar technology spaces. Technology activities and spaces are captured by patents and patent classes, respectively.

Indeed, numerous studies document a positive relationship between intangible assets and future stock returns, consistent with undervaluation.

In addition, in our empirical analysis, we always account for product market spillovers to separate the negative effect of the R&D of product market competitors from the positive effect of the R&D of technological peer firms. Similarly, we always account for the firm's own R&D, to ensure that we capture the incremental effect of other firms' R&D. Finally, following BSV, we identify the effect of technology spillovers on financial policies using exogenous variation in federal and state R&D tax credits. Simply put, for each firm-year, we calculate R&D tax credits, we project R&D stock on R&D tax credits, and we calculate technology spillovers using projected R&D stock. In our main regressions, we specifically remove all variation attributable to the firm's *own* R&D stock, the firm's *own* R&D tax credits, and unobserved heterogeneity across firms and over time. Our identification of technology spillovers to a given firm relies on the projected R&D of *other* firms based on *their* R&D tax credits.

We find that technology spillovers have a significant effect on financial policies. Leverage increases by 6 percentage points in response to a one-standard deviation increase in technology spillovers. Similarly, firms issue more debt and less equity. Additionally, in contrast to the well known negative relationship between leverage and a firm's own R&D (e.g., Titman and Wessels (1988) and Opler and Titman (1993)), the R&D of its peer firms increases the firm's own leverage. This is the case even though we control for the effect of firm's own R&D on leverage.[5]

We then consider two channels through which technology spillovers can affect financial policies. Beginning with the asset redeployability channel, we examine both asset collateralization and asset liquidity. We find that technology spillovers significantly increase the firm's total collateralized borrowing as well as its borrowing collateralized by a specific subset of

[5] Technology spillovers do not reliably affect the firm's own R&D spending, but they do increase its innovation output (BSV). Nevertheless, we control for the firm's own R&D to ensure that we only capture the direct effect of technology spillovers on the firm's leverage and not any indirect effect they may have through the firm's R&D.

technology assets, namely, patents. We also find a significant increase in the sale of patents as well as entire firms, suggesting an increase in the liquidity of both specific and general technology assets. Additionally, since greater asset redeployability implies a lower cost of debt, we also examine the effect of technology spillovers on bond and loan spreads. We find that for a one-standard deviation increase in technology spillovers, bond spreads decrease by roughly 6 basis points, and bank loan spreads decrease by 9 bps, results that persist for several years. Together, our findings suggest that technology spillovers increase the redeployability of the firm's technology assets.

Turning to the relative mispricing channel, we examine profitability surprises in the short run and the long run. Over a one year horizon, technology spillovers do not significantly affect realized earnings, which are in line with the market's expectations. Over a five year horizon, however, technology spillovers significantly increase realized earnings, and these realizations are significantly above the market's expectations. We also examine the effect of technology spillovers on stock valuation and performance. We find that market-to-book ratios are higher next year and continue to increase for several future years. This suggests that investors do incorporate the value created by technology spillovers into stock prices, but this price adjustment takes at least several years. Similarly, we find that abnormal stock returns increase by more than 10 percentage points per year, an effect that also persists for several few years. In summary, investors underestimate the long run profitability of the assets created by technology spillovers and it takes them several years to fully impound the value of these assets into stock prices. Collectively, our findings suggest that technology spillovers lead to equity undervaluation.

In summary, we find that technology spillovers increase leverage through both more debt issuance and less equity issuance. Further evidence supports two complementary channels through which technology spillovers affect financial policies: asset redeployability and undervaluation. The overall negative effect on the cost of debt indicates that asset redeployability dominates for debt, whereas the overall positive effect on abnormal stock returns indicates that undervaluation dominates for equity. In Section 8, we discuss alternative interpretations of our main findings, including information asymmetry, debt as a monitoring mechanism, signaling with debt, and cash flow risk.

Our study provides the first empirical evidence that technology spillovers have a significant causal impact on corporate financial policies. This is an important contribution because the literature documents that technology spillovers have great private and social benefits (e.g., Jaffe (1986), Grossman and Helpman (1991), and Bloom, Schankerman, and Van Reenen (2013)). To our knowledge, there is only one other study of technology spillovers and corporate policies, and it focuses exclusively on cash holdings. Qiu and Wan (2015) suggest that firms prefer internal to external financing for investments stimulated by technology spillovers. We study how firms choose their external financing mix and take a broader approach, studying capital structure, the cost of capital, and the various channels through which technology spillovers operate.

Similarly, our study improves our understanding of financial decision making in innovative firms. The financing of technology assets presents unique challenges (Hall (1992a) and Himmelberg and Petersen (1994)). However, the existing literature does not distinguish between technology assets derived from the firm's technological peer firms as opposed to the firm itself (e.g., Kortum and Lerner (2000) and Thakor and Lo (2015)). By contrast, we draw this distinction and study how firms finance the assets deriving from their technological peer firms.

Finally, we contribute to the emerging literature on peer effects and corporate policies (e.g., Foucault and Frésard (2014)). A few of these studies focus on financial policies as the outcome, and they examine peer effects among customers and suppliers (Kale and Shahrur (2007)) and product market competitors (MacKay and Phillips (2005) and Leary and Roberts (2014)). Instead, we examine the effect of technological peer firms' R&D on financial policies.

The rest of this paper is organized as follows. Section 2 presents the methodology and identification, while Section 3 presents the sample and data. Section 4 presents the results for capital structure. Section 5 presents the background for potential channels, while Section 6 and Section 7 present the results. Section 8 provides a discussion and concludes.

2. Methodology and Identification

2.1. Measuring Technology Spillovers

2.1.1. General Procedure

The technology spillover measures that we use are motivated by the insight that a firm is more likely to benefit from the R&D of other firms if it is closer to these firms in terms of technology. More precisely, the extent of technology spillovers from firm j to firm i depends on the technological proximity between firm i and firm j as well as the R&D stock of firm j. Aggregating across all other firms, technology spillovers to firm i are the sum of technology spillovers from all other firms j to firm i.

The calculation of technology spillovers entails three general steps. The first is to calculate the technological proximity between two firms. The literature uses two measure of technological proximity: the Jaffe measure (Jaffe (1986)) and the Mahalanobis measure (BSV). The Jaffe measure restricts technology spillovers to the same technology space whereas the Mahalanobis measure allows technology spillovers across different technology spaces. The second step is to calculate the R&D stocks of all other firms. The final step is to calculate the technology spillovers to a given firm from all other firms.

2.1.2. Jaffe Measure of Technology Spillovers

First, the Jaffe measure of technological proximity between two firms is constructed as follows. Each of the patents of a given firm is allocated by the USPTO to one or more of 426 possible technology classes. A firm's technology activity is then characterized by a vector T_i=(T_{i1},T_{i2},…,T_{i426}), where $T_{i\tau}$ is the average share of the patents of firm i in technology class τ over the period 1970-1999.[6] The Jaffe proximity between firm i and firm j is then defined as the uncentered correlation between the two firms' technology activities:

$$TECH_{ij}^{Jaffe} = T_i T_j' \Big/ \left(T_i T_i'\right)^{1/2} \left(T_j T_j'\right)^{1/2}$$

The Jaffe proximity measure ranges between zero and one. The higher is the measure, the closer are the technologies of the two firms.

Second, the R&D stocks of all other firms are calculated. The formula used to calculate a firm's R&D stock is $G_t = R_t + (1-\delta)G_{t-1}$, where R_t is the firm's R&D expenditures in year t and δ is the depreciation rate. Following the literature, δ=0.15.

Finally, the Jaffe measure of technology spillovers to firm i in year t is the sum of technology spillovers from all other firms j to firm i in year t:

$$TECHSPILL_{it}^{Jaffe} = \sum_{j \neq i} TECH_{ij}^{Jaffe} G_{jt}$$

[6] In calculating the proximity measure, one can either use all available data or only the data within a rolling window. The former approach benefits from greater precision, while the latter approach benefits from greater timeliness. Both approaches yield similar measures. The data on patents allocated to 426 technology classes is understandably sparse for most firms in any given year, so it is common to use all available data (e.g., BSV). We follow this approach as well.

2.1.3. Mahalanobis Measure of Technology Spillovers

The construction of the Mahalanobis measure of technology spillovers is somewhat more complicated than the Jaffe measure. This is because the measure of technological proximity between two firms takes as an input a measure of the proximity between technology spaces. The literature captures proximity between technology classes using the observed co-location of the technology classes within firms. The reasoning is that technology classes that tend to co-locate within firms are the result of related technologies and thus they reflect technology spillovers across technology classes.

To calculate the proximity of technology classes, the allocation of a technology class is determined by the vector $\Omega_\tau=(T_{1\tau},T_{2\tau},\ldots,T_{N\tau})$, where N is the number of firms and $T_{i\tau}$ is the average share of patents of firm i in technology class τ over the period 1970-1999. The proximity of the two technology classes, τ and ζ, is the uncentered correlation (the same as the Jaffe proximity measure) of the allocation vectors Ω_τ and Ω_ζ:

$$\Omega_{\tau\zeta} = \Omega_\tau \Omega'_\zeta \big/ \left(\Omega_\tau \Omega'_\tau\right)^{1/2} \left(\Omega_\zeta \Omega'_\zeta\right)^{1/2}$$

A 426×426 matrix Ω is then constructed such that its $(\tau,\zeta)^{\text{th}}$ element equals $\Omega_{\tau\zeta}$. This matrix captures the proximity of technology classes.

The measure of technological proximity between firm i and firm j is a function of the technology activities of the two firms (as captured by the vectors T_i and T_j in the Jaffe measure) and the proximity of technology classes. It is defined as follows:

$$TECH_{ij}^{Mahal} = \left(T_i \big/ \left(T_i T'_i\right)^{1/2}\right) \Omega \left(T'_j \big/ \left(T_j T'_j\right)^{1/2}\right)$$

This measure of technological proximity between two firms weights the overlap in technology activities between the two firms by the proximity of their technology classes. (It is worth noting the special case of $\Omega=I$, which implies that $\Omega_{\tau\zeta}=0$ for all $\tau\neq\zeta$. That is, technology spillovers can only occur within the same technology class. In this case, the Mahalanobis technological proximity measure is identical to the Jaffe technological proximity measure.) This completes the Mahalanobis measure of technological proximity between two firms.

The R&D stocks of all other firms are then calculated exactly like for the Jaffe measure of technology spillovers. Finally, the Mahalanobis measure of technology spillovers to firm *i* in year *t* is the sum of technology spillovers from all other firms *j* to firm *i* in year *t*:

$$TECHSPILL_{it}^{Mahal} = \sum\nolimits_{j \neq i} TECH_{ij}^{Mahal} G_{jt}$$

2.2. Measuring Product Market Spillovers

The effect of technology spillovers on a firm can be contaminated by the effect of product market spillovers because other firms that adopt similar technologies may also produce competing products. Therefore, the R&D activities of other firms have two separate and opposite spillover effects on the firm: technology spillovers, which positively affect its productivity, and product market spillovers, which negatively affect its market share. To isolate the effect of technology spillovers, we control for product market spillovers.

The product market spillover measures that we use are motivated by the insight that a firm's market shares in its various product markets are negatively affected by the R&D activities of other firms with which it competes. As with technology spillovers, the extent of product market spillovers from firm *j* to firm *i* depends on the product market proximity between firm *i* and firm *j* as well as the R&D stock of firm *j*. Aggregating across all other firms, product market spillovers to firm *i* are the sum of product market spillovers from all other firms *j* to firm *i*.

Both the Jaffe and Mahalanobis measures of product market spillovers are calculated analogously to the corresponding technology spillover measures. By way of brief description, the Jaffe measure of product market proximity is constructed as follows. The sales of a given firm are allocated to one or more industry segments according to Compustat. The firms in the sample cover 597 industries. A firm's product market activity is characterized by a vector $S_i=(S_{i1},S_{i2,}\ldots,S_{i597})$, where S_{ik} is the average share of the sales of firm i in industry k over the period 1993-2001 (shortened because of limitations on industry data). The Jaffe distance, R&D stocks of all other firms, and the product market spillover measure are all calculated as before.

2.3. Illustrative Examples of Spillovers

Technology spillovers to a firm are calculated as the weighted average R&D stocks of other firms, where the weights are the technological proximities between the firm and other firms. While the R&D of other firms is a straightforward concept, the notion of technological proximities between firms stands to benefit from some examples. We illustrate relationships in the technology space with reference to well known horizontal and vertical relationships in the product market space. These examples show that firms that are close in the technological space are not necessarily close in the product market space (horizontal or vertical).

We first compare and contrast technology relationships and horizontal product market relationships, following BSV. For simplicity, we use the Jaffe proximity measures in our examples. In our sample, the correlation between technological proximities and product market proximities is strong but only 0.47. IBM, for instance, is close to Apple, Intel, and Motorola in technology spaces (their proximities are 0.64, 0.76, and 0.46, respectively, on a scale of zero to one). However, only Apple is close to IBM in product market spaces (their proximity is 0.65), which reflects the fact that both firms produce personal computers (during our sample period). By contrast, Intel and Motorola are far from IBM in product market spaces (their proximities are both 0.01) because they produce semiconductors, whereas IBM's semiconductor production is modest. (Another illustration of the distinct relationship between technology spillovers and product market spillovers is provided by our Table 2.)

Second, we compare and contrast technology relationships and vertical product market relationships. For example, Coca-Cola Co. is close to both Liqui-Box Corp. and Tokheim Corp. in technology spaces (their proximities are 0.90 and 0.67, respectively). All three firms make some products that involve liquids and target consumers. Coca-Cola and Liqui-Box are vertically related in product market spaces because Coca-Cola makes beverage products and Liqui-Box makes packages for liquid products (e.g., bottles for drinks). However, Coca-Cola and Tokheim are not vertically related in product market spaces because Tokheim makes fuel dispensing systems (e.g., gasoline pumps).

By their nature, technology relationships are more easily understood by insiders than outsiders. These relationships can be explicit (as in the case of Apple and Samsung in consumer electronics, for example) or implicit (for instance, the many software developers that benefit from technological advances in computer operating systems). Similarly, as the following examples illustrate, it can take a long time for technology spillovers to become noticeable to outsiders of the firms they affect.

In the first famous example, lasers were first invented in 1960 by the Hughes Aircraft Company (now owned by the Raytheon Company). The original purpose of the technology was to amplify visible light, but it has since spread to many consumer and business uses, including disk drives, printers, barcode scanners, lighting displays, medicine and surgery, fiber optic cables, construction, manufacturing, in addition to military and law enforcement applications.

Microprocessors are another famous example of technology spillovers. Invented concurrently in 1971 by three firms (Garrett AiResearch, Texas Instruments, and Intel), they revolutionized the computer industry. However, the technology also spilled over into unrelated industries such as communications (e.g., satellites and mobile phones), household appliances (e.g., washing machines, refrigerators, and microwave ovens), automobiles, entertainment equipment (e.g., televisions and sound systems), games and toys, and household accessories (e.g., light switches and smoke alarms).

A related example is provided by open source software. In the history of computers, it was initially ubiquitous, then challenged by licensed software in the 1970s and 1980s, and has once again become widely deployed in computers. Prominent examples of open source products include the Linux and Android operating systems, the Apache web server, and the Firefox and Chrome internet browsers. Countless technology firms use open source output contributed by other firms (e.g., Google). Some make money by customizing the software for their clients (e.g., IBM). Others use the software to power their hardware (e.g., Samsung). Still others use the resulting technology products for their non-technology businesses (e.g., Amazon). We refer the reader to Rosenberg (1979) for additional examples.

2.4. Identification Strategy

We use variation in federal and state R&D tax credits to identify the causal effects of technology spillovers on financial policies. The accumulated evidence suggests that changes in R&D tax credits do affect corporate policies, and they are plausibly exogenous to corporate policies, but they vary heterogeneously across firms. First, a large literature shows that R&D tax credits generate large increases in R&D investment, both in the U.S. and internationally (Hall (1992b), Berger (1993), Hines (1993), and Bloom, Griffith, and Van Reenen (2002)). Their relevance to investment is well established.

Second, the exogeneity of these tax policies to corporate policies is demonstrated in the literature. For example, BSV provide compelling evidence that changes in economic or political conditions cannot explain changes in R&D tax policies (also see Cummins, Hassett, and Hubbard (1994) and Chirinko and Wilson (2013)). Indeed, the impact of R&D tax credits on government finances is relatively modest. Rather, R&D tax credits have gradually increased across states and over time. Nevertheless, there is substantial variation in R&D tax credits across states and over time, including at the federal level.

Finally, R&D tax credits vary greatly across firms. This heterogeneity arises at the federal level because effective federal tax credits are determined by the difference between the actual R&D expenditures of the firm and a base amount that varies across firms and time according to the applicable federal tax rules. Moreover, the amount that a firm can claim depends on the extent to which the credits exceed the firm's profits, and other factors such as deduction rules, the corporate tax rate, and so forth. At the state level, heterogeneity in tax credits arises because state tax credits are determined by the location of the firm's R&D activities.

We refer to spillover measures constructed in Section 2.1 as "raw" to distinguish them from "purged" spillover measures. The purged measures are constructed below in a manner that removes the variation in R&D investment that is endogenous to corporate policies and retains the variation that is exogenous. A detailed description is provided by BSV, but to briefly summarize here, federal and state R&D tax credits are calculated at the firm-year level using the Hall-Jorgenson user cost of capital approach (Hall and Jorgenson (1967)). For firms that operate in more than one state in a given year, tax credits are aggregated to the firm-year level as the sum of the weighted state-level tax credits for the firm-year in question, where the weights are the average shares of the firm's inventors located in a given state.

Then, using a firm-year panel, R&D expenditures are regressed on federal tax credits, state tax credits, and firm and year fixed effects. This regression is then used to calculate predicted R&D expenditures. The remaining calculations are the same as in Section 2.1. Predicted R&D expenditures are used to calculate the exogenous R&D stock for each firm-year. Finally, the purged spillover measures are calculated like the raw spillover measures but using the exogenous R&D stocks of other firms instead of their raw R&D stocks. For the details of this methodology, we refer the reader to Appendix B.3 in BSV as well as Wilson (2009) and Falato and Sim (2014). Note that our identification of technology spillovers to a given firm relies on the projected R&D of *other* firms based on *their* R&D tax credits and *not* on the firm's own R&D tax credits.

2.5. Main Regression Specifications

Throughout our empirical analysis, we use four regression specifications for all outcomes of interest. In the first two specifications, we capture spillovers with the raw and purged Jaffe spillover measures, for both the technology and product market spaces. In the last two specifications, we capture spillovers with the raw and purged Mahalanobis measures. We use both the Jaffe and Mahalanobis measures because each has various advantages. The Jaffe measure has been extensively used in the literature since it was popularized by Jaffe (1986), but it restricts technology spillovers to the same technology space. The Mahalanobis measure is a more recent contribution to the literature (BSV), but it allows technology spillovers across technology spaces rather than only within the same space.

Our regression specifications have several common features. In particular, we always include technology spillovers, our variable of interest, and product market spillovers, our control variable for the product market spillovers of other firms' R&D. Similarly, we always control for the firm's own R&D. In specifications using purged spillover measures, we also control for the firm's own federal and state tax credits. We also control for firm age to capture possible life cycle effects associated with technology and product market spillovers. Doing so allows us to rule out such possibilities as firms with greater technology spillovers having a greater debt capacity because they are more mature. We also include additional control variables that are standard in the literature for the outcome of interest. The independent variables at the firm-year level are lagged, and they are contemporaneous at the firm-deal level. All variables are defined in Appendix Table 1.

Additionally, in all firm-year regressions, we use firm and year fixed effects to control for time-invariant firm characteristics and time trends, respectively. In all firm-deal regressions (e.g., our cost of debt regressions), we control for industry and year fixed effects because at the firm-deal level many firms appear only once. As part of our robustness tests, we also control for industry-year fixed effects in our regressions, retaining firm fixed effects. Even though we double the number of fixed effects, the results are similar. Finally, we cluster standard errors by firm or industry-year, as appropriate, to reflect the structure of our data. We generally multiply the dependent variables by 100 for expositional simplicity. We standardize the independent variables so that each coefficient estimate captures the effect on the dependent variable of a one-standard deviation change in the corresponding independent variable.

3. Sample and Data

3.1. Sample Construction

We construct our sample as follows. We begin with all publicly traded U.S. firms in CRSP and Compustat. We keep U.S. operating firms defined as firms with CRSP share codes of 10 or 11. We drop firms that are financials or utilities. We then keep firms for which we have data on technology spillovers and product market spillovers. As a result, our sample is restricted to firms that were issued at least one patent since 1963. Nevertheless, our sample firms account for much of the R&D expenditures in the U.S., for instance, 62% in 1995 (see BSV). Our final sample comprises 12,118 firm-year observations corresponding to 694 unique firms between 1981 and 2001.[7]

3.2. Data Sources

We obtain data on raw and purged technology and product market spillover measures from Nicholas Bloom's website (see BSV). We obtain patent data from the USPTO patent assignment database and from Noah Stoffman's website (see Kogan, Papanikolaou, Seru, and Stoffman (2016)). Our stock trading data are from CRSP, our accounting data are from Compustat, and our analysts data are from I/B/E/S (the data begins in 1982). We obtain bond issues data from SDC and bank loans data from Dealscan (the latter data start in 1987). We also use SDC to obtain data on mergers and acquisitions. We winsorize all continuous variables at the 1st and 99th percentiles. The definitions of all variables are provided in Appendix Table 1.

3.3. Descriptive Statistics

[Insert Table 1 about here]

In Table 1, we present descriptive statistics for our sample. In light of sample construction, our firms invest heavily in R&D and they produce a large number of patents. Our firms have high valuations, with mean and median market-to-book of assets of 1.6 and 1.3, respectively. They are large, with mean and median total assets of $2.5 billion and $338 million, respectively. They are also mature, with mean and median age of roughly 25 and 20 years, respectively. Given their size and age, our firms are predictably profitable as reflected by their

[7] The NBER patent database is increasingly poorly populated by the mid-2000s and ends completely in 2006, so we end our sample in 2001. As an added benefit, our initial sample is the same as that of BSV and related papers.

cash flow of 15% of total assets (both mean and median). At the same time, the above characterization of our sample firms should not be surprising because much of the innovation in the economy is carried out by mature public firms (e.g., Baumol (2002)).

Overall, while our firms are larger, older, more profitable, and more innovative than a typical publicly traded firm, they are comparable in terms of their leverage. In particular, their leverage averages out to roughly 22% of total assets (median of 21%) compared to 24% (median of 22%) in Leary and Roberts (2014). Our firms are roughly similar to the typical publicly traded firm in terms of their cost of debt. Their bond issue spreads are 107 basis points and 83 bps in the mean and median, whereas the corresponding figures for their bank loan spreads are 126 bps and 75 bps. By comparison, Valta (2012) finds mean and median spreads of 180 bps and 150 bps, respectively, in a sample that includes firms from a somewhat later sample period.

[Insert Table 2 about here]

In Table 2, we present descriptive statistics by industry. More precisely, we group firms by their primary industries, and then sort industries by technology spillovers. We then compute descriptive statistics for each industry. Industries that are generally thought of as innovative cluster at the top of the table (high technology spillovers): e.g., communications, transportation equipment (automobiles, airplanes, etc.), and chemicals (including pharmaceuticals). Similarly, industries that are not typically considered to be innovative bunch at the bottom of the table (low technology spillovers): e.g., food, furniture, and clothing. Additionally, the most innovative industries, which have the highest technology spillovers, also have the highest R&D expenditures. This indicates that it is important to control for the firm's own R&D.

There is also a positive correlation between technology spillovers and product market spillovers. This demonstrates the importance of controlling for product market spillovers. Still, the industries with the highest technology spillovers are not always the industries with the highest product market spillovers. For instance, construction products have high technology spillovers whereas oil and gas extraction has low technology spillovers, yet both industries have roughly average product market spillovers.

Furthermore, there is significant intra-industry variation in technology spillovers compared to inter-industry variation. For example, a computer manufacturer (SIC=35) (high technology spillovers) at one standard deviation below the industry mean has lower technology spillovers than the average food producer (SIC=20) (low technology spillovers). Similarly, a furniture manufacturer (SIC=25) (low technology spillovers) at one standard deviation above the industry mean has higher technology spillovers than the average technology firm (SIC=73) (high technology spillovers). In short, at the firm level, there can be major differences between technology spillovers and product market industries.

Finally, comparing industry means, there is no relationship between technology spillovers and leverage. This suggests that any relationship between the two is more likely to occur at the firm level rather than at the industry level.

4. Results for Capital Structure

We begin our empirical analysis by examining the effect of technology spillovers on capital structure. Leverage is our main outcome of interest (debt-to-total assets), but we also examine debt issuance and equity issuance (both scaled by total assets). Our regression specifications follow the empirical literature on capital structure (e.g., Rajan and Zingales (1995), Lemmon, Roberts, and Zender (2008), and Leary and Roberts (2014)). In addition to the common features of our regression specifications, we control for firm age, sales, market-to-book of assets, cash flow, asset tangibility, and cash flow volatility.

Before we get to our results, we should note that product market spillovers and the firm's own R&D are the most relevant of our control variables. For this reason, we always report the results for these two variables. However, they are not the focus of our study, so we do not interpret our results for these two variables.

[Insert Table 3 about here]

Table 3 presents the results. Panel A shows that technology spillovers lead to an economically and statistically significant increase in leverage. In particular, as a result of a one-standard increase in technology spillovers, the amount of debt firm used compared to equity increases by approximately 6 percentage points relative to total assets. By way of comparison, the average firm has leverage of roughly 22% (21% for the median firm) (Table 1).

Moreover, Panel B shows that firms with greater technology spillovers increase their debt issuance, and Panel C shows that they decrease their equity issuance. In Panel B, debt issuance increases by roughly 3-4 p.p. In Panel C, equity issuance decreases by about 1-2 p.p., though the results are only statistically significant for three of the four specifications. These results on debt and equity issuance are consistent with our leverage results.

In contrast to technology spillovers, product market spillovers generally do not affect leverage. The firm's own R&D, however, is significantly related to leverage: a one-standard deviation increase in R&D is associated with a decrease in leverage of approximately 2 p.p. relative to total assets. Our findings are consistent with the negative relationship between R&D and leverage documented in the literature (e.g., Titman and Wessels (1988) and Frank and Goyal (2009)).

5. Background for Potential Channels

We find that greater technology spillovers lead to higher leverage (Table 3). We now provide some background on channels through which technology spillovers can affect financial policies. In the first, asset redeployability channel, the real investments made by a firm create assets using not only the technology of the firm itself but also the technology spillovers from other firms. Technology spillovers increase the value of these assets not only to the firm in question but also to other firms. The assets thus created are more valuable because these firms are technologically similar and the R&D of one increases the productivity of the assets of the others. By increasing their value in alternative use, technology spillovers increase the redeployability of a firm's technology assets, both intangible and tangible. As the theoretical literature argues, this decreases the losses to the firm's creditors in the event of bankruptcy, and thus increases the firm's debt capacity (e.g., Williamson (1988)).[8] Additionally, lower financial distress costs decrease the cost of capital. Confirming these predictions, the empirical literature documents that technology assets (specifically, patents) are increasingly important as collateral in corporate borrowing (Loumioti (2012) and Mann (2016)).[9] Additionally, technological similarity, a component of technology spillovers, is associated with greater liquidity of real assets (Bena and Li (2014)). Greater asset redeployability in turn decreases the cost of capital (Benmelech and Bergman (2009)). In summary, greater asset redeployability leads to higher debt capacity and a lower cost of capital, thus the firm increases its leverage (Modigliani and Miller (1958)).[10]

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[8] Other seminal papers in this area include Harris and Raviv (1990), Aghion and Bolton (1992), Hart and Moore (1994), and Bolton and Scharfstein (1996).

[9] For example, in the U.S., 21% of secured syndicated loans during 1996-2005 were collateralized by patents (Loumioti (2012)). Similarly, 16% of patents issued since 1980 were eventually collateralized (Mann (2016)).

[10] This channel can also be viewed through the lens of the stakeholder theory of capital structure. The firm's employees, customers, and suppliers, like its lenders, may bear significant losses in the event of the firm's

In the second, relative mispricing channel, the assets created by technology spillovers are undervalued by investors. There are a number of well known theoretical reasons for undervaluation of assets that are intangible and long-term. These reasons include limited investor attention (Hong and Stein (1999) and Hirshleifer and Teoh (2003)), ambiguity aversion (Bossaerts, Ghirardato, Guarnaschelli, and Zame (2010)), and various cognitive limitations (see the survey of Barberis and Thaler (2003)).[11] The empirical evidence indicates that the undervaluation of such assets and the increase in the cost of capital can be substantial.[12] Therefore, the assets created by technology spillovers should be similarly undervalued by investors. Moreover, in contrast to owners' residual payoffs, creditors' promised payoffs are well defined, thus debt is relatively less likely to be undervalued than equity (Hong and Sraer (2013)). To summarize, greater undervaluation of equity relative to debt leads to a higher cost of capital, especially for equity compared to debt, thus the firm finances itself with relatively less equity than debt (Baker and Wurgler (2002)).

6. Results for the Asset Redeployability Channel

We begin by studying asset redeployability. As a brief summary, technology spillovers can increase the productivity and value of the firm's assets to the firm's technological peer firms. This increase in asset redeployability decreases losses to the firm's creditors in the event of bankruptcy, so they lend on more generous terms. Consequently, technology spillovers lead to the firm using more debt and less equity.

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bankruptcy (Titman (1984) and Maksimovic and Titman (1991)). Technology spillovers can decrease these losses by increasing the redeployability of these stakeholders' assets in the firm.

[11] As a behavioral example given by Barberis and Thaler (2003), consider the representative heuristic. In one of its manifestations, investors use the recent performance of an asset to infer its future performance. Additionally, intangible and long-term assets typically do not generate profits in the short run but rather do so in the long run. Taken together, these two tendencies mean that investors undervalue the asset.

[12] For evidence on R&D spending, see Lev and Sougiannis (1996), Chan, Lakonishok, and Sougiannis (2001), and Eberhart, Maxwell, and Siddique (2004). For innovation, see Hirshleifer, Hsu, and Li (2013) and Cohen, Diether, and Malloy (2013).

We perform two sets of empirical tests: the first examines asset collateralization, while the second examines asset liquidity. The first set of tests is motivated by the fact that if technology spillovers increase the redeployability of assets, then the firm's assets are more valuable as collateral to the firm's creditors, and more of the firm's debt can be collateralized. We examine whether technology spillovers result in greater collateralization of debt. For asset collateralization, we consider both the extent of the firm's total borrowing that is collateralized and the extent to which the firm's patents are used as collateral for the firm's borrowing. The former approach uses assets in general while the latter approach uses a specific subset of technology assets.

Greater asset collateralization by itself can arise from an increase in the redeployability of the firm's assets, but it can also arise from an increase in assets demanded by creditors as a result of a perceived increase in risk. In our second set of tests, we examine whether technology spillovers increase the redeployability of the firm's assets by examining asset liquidity. If the market for assets becomes more liquid, then in the event of bankruptcy, the firm's creditors should be able to sell assets more quickly and at a higher price. Technology spillovers, then, should increase asset liquidity. Ideally, we would like to observe the market for the real assets that are affected by technology spillovers. Since these ideal data do not exist, we instead take two related approaches using the data that are available. In the first, narrower approach, we examine sales of patents issued to the firm, which captures a reasonable subset of the firm's technology assets. In the second, broader approach, we examine the sales of entire firms, which captures all of the firm's technology assets, albeit alongside other assets besides.

We now turn to our empirical analysis, beginning with collateralized borrowing. To capture the generalized collateralization of assets, we use collateralized debt (net of capital leases) divided by total assets, from Compustat. To capture collateralization specifically of technology assets, we use patent collateralizations from the USPTO database. Owing to the nature of the patent database, the patent collateralizations and sales that we capture involve patents issued to the firm and subsequently collateralized or sold. In our regression specifications, we follow the empirical literature on capital structure and patent collateralizations (e.g., Leary and Roberts (2014) and Mann (2016)). In addition to the common features of our regression specifications, we control for firm age, sales, market-to-book of assets, cash flow, asset tangibility, cash flow volatility, and other variables as appropriate.[13] Importantly, for regressions with patent flow as an outcome, we control for patent stock to eliminate any mechanical relationship between flows and stocks.

[Insert Table 4 about here]

Table 4 presents the results in the first two panels. Panel A shows that collateralized borrowing increases by very roughly 3 percentage points relative to total assets. This amounts to roughly half the increase in total borrowing resulting from technology spillovers, which is approximately 6 p.p. higher debt as a proportion of total assets (Table 3). Indeed, the increase in borrowing arises disproportionately from collateralized borrowing. The unconditional average collateralized borrowing of the firm is about 3% of total assets (Table 1), which doubles as a result of technology spillovers. By contrast, the firm's unconditional average uncollateralized borrowing is about 18% (22% minus 3%), which increases by a relatively smaller 3 p.p. (6 p.p. minus 3 p.p.).

Panel B of Table 4 shows that firms also use a larger number of their patents to support their borrowing. In particular, technology spillovers increase the number of patents used to

[13] Specifically, for regressions without leverage as a dependent variable, we control for leverage. For regressions with patent collateralizations or sales as a dependent variable, we control for the stock of patents. Finally, for regressions with mergers and acquisitions as a dependent variable, we control for stock returns and cash holdings.

collateralize debt by roughly 20%-25%. We also take the simpler approach of examining whether a firm collateralizes any of its patents in a given year (as captured by a dummy variable). Consistent with the previous results, we find that the rate of patent collateralizations increases, by 6-8 p.p., or roughly double unconditional rate of about 6% (results not tabulated). Overall, greater technology spillovers appear to result in greater collateralization of debt.

We next turn to our empirical analysis of asset liquidity. We capture the sale of specific technology assets using patent sales from the USPTO database. To capture the sale of assets in general, we use data on mergers and acquisitions from SDC, specifically, the number of deals as well as the value of deals as a proportion of total assets. Our sample firms must be involved in deals as either the target of an acquisition or a party to a merger (because in a merger of equals the classification of the acquirer and the target is arbitrary). Our regression specifications follow the literature on asset sales (e.g., Harford (1999), Schlingemann, Stulz, and Walkling (2002), Bates (2005), and Fich, Harford, and Tran (2015)).

Table 4 presents the results in the last three panels. Panel C shows that the number of patents sold increases as a result of technology spillovers, very roughly, by 20%. We again take a simpler approach and examine whether a firm in a given year sells any of its patents (as captured by a dummy variable). The rate of patent sales is higher, by 5-7 p.p., which compares with the unconditional rate of patent sales of roughly 8% (results not tabulated). The next two panels show that technology spillovers lead to greater mergers and acquisitions activity. While the results vary in economic and statistical significance, Panel D shows that the number of M&As increases by 5%-10%, very roughly. Similarly, Panel E shows that the value of M&As also increases, by approximate 2-4 p.p. relative to total assets, which compares with its unconditional mean of roughly 2% of total assets. We also confirm that the rate of M&As is higher, by about

10%, very roughly, compared to the unconditional rate of 12% for a given firm in a given year (results not tabulated). Overall, asset liquidity appears to increase as a result of technology spillovers.

In our final test, we examine the cost of debt. We measure the cost of debt using bond issue spreads and bank loan spreads. In our regression specifications, we follow the empirical literature on the cost of debt. (For bond issues, see Ortiz-Molina (2006), Francis, Hasan, John, and Waisman (2010), and Qi, Roth, and Wald (2010). For bank loans, see Graham, Li, and Qiu (2008), Chava, Livdan, and Purnandam (2009), and Valta (2012).) In addition to the common features of our regression specifications, we include firm-level control variables: firm age, total assets, leverage, market-to-book of assets, cash flow, asset tangibility, and cash flow volatility. We also include deal-level control variables: the proceeds/amount of the bond/loan; the maturity of the bond/loan; the credit rating of the bond/firm; and the type of bond/loan.

[Insert Table 5 about here]

Table 5 presents the results. Panel A shows that technology spillovers decrease spreads on bond issues by 6-7 basis points. Panel B shows a similar effect on bank loan spreads, which decrease by 8-10 bps as a result of technology spillovers. All of the results are statistically significant. As for economic significance, bond issues and bank loans have average spreads of roughly 107 and 126 bps (median of 83 and 75 bps, respectively) (Table 1). Consequently, the cost of debt falls by about 5%-10% as a result of technology spillovers. For comparison purposes, Valta (2012) finds a similar increase in the cost of debt (about 10 bps) for a comparable increase in product market competition.[14]

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[14] Our results capture the net effect of technology spillovers on the cost of debt, accounting for the increase in leverage. The gross effect of technology spillovers on the cost of debt would be even more negative if leverage did not increase.

Product market spillovers, in contrast to technology spillovers, have no effect on bond issue spreads. They do, however, increase the spreads on bank loans, by about 6-8 bps. Our results on bank loan spreads suggest the firm's lenders have an unfavorable view of product market spillovers. The firm's own R&D is also significantly related to the cost of debt. For both bond issues and bank loans, R&D is associated with an increase in spreads of roughly 10-12 bps. This suggests that both bondholders and lenders view R&D unfavorably in pricing the firm's debt.

We also examine whether technology spillovers affect the cost of debt not only in the short run but also in the long run. To this end, we examine bond issues and bank loans over horizons of up to five years. We find that debt spreads are also negative in the long run like in the short run, but they are somewhat less economically and statistically significant as the horizon increases (results not tabulated). In summary, our results suggest that technology spillovers decrease the cost of debt. This is the case after accounting for the increase in leverage resulting from greater technology spillovers.

Taken together, our analysis shows that technology spillovers lead to more collateralized borrowing and asset transactions (Table 4) and a lower cost of debt (Table 5). The results are thus consistent with the asset redeployability channel through which technology spillovers impact financial policies.

7. Results for the Relative Mispricing Channel

We continue by studying the relative mispricing of equity versus debt. To summarize briefly, it is possible that investors underestimate the positive value implications of technology spillovers, more so for equity than debt. Managers respond by financing with debt instead of equity. As a result, technology spillovers lead to higher leverage.

We first examine whether profitability surprises are higher as a result of technology spillovers. Profitability surprises are defined as the difference between realized and expected profitability. Since the assets generated by technology spillovers tend to be long lived, we examine profitability both in the short run and the long run (typically five years). The maintained assumption is that equity is more sensitive to changes in firm value than debt (e.g., if there is new information about the firm's profitability). This implies that if investors undervalue the cash flows of the firm as a whole, then they undervalue cash flows to equity more than cash flows to debt.

We begin by testing whether technology spillovers lead to higher realized earnings. We then test whether market participants have commensurately higher earnings expectations as a result of technology spillovers. Finally, we test whether the difference between realized and expected earnings is greater. We use earnings for the following year and long-term earnings growth rates for the following five years. In our regression specifications, we follow the literature on realized and expected profitability (e.g., Core, Guay, and Rusticus (2006), Edmans (2011), and Giroud and Mueller (2011)). In addition to the common features of our regression specifications, we control for firm age, market capitalization, and market-to-book of equity.

[Insert Table 6 about here]

Table 6 presents the results.[15] Starting with the short run (one year horizon), Panel A shows that realized earnings relative to total assets are higher, by about 1%-3%, but they are statistically significant in only two of the four regressions. To put these magnitudes into perspective, average realized earnings are about 7% of total assets (Table 1), and average expected earnings are about one p.p. higher than that. Panel B shows that the market appears to

[15] The difference between realized and expected earnings is not identical to the earnings surprise because the sample sizes are different, more so five years out than one year out. Our results are similar if we use an overlapping sample.

anticipate comparably higher earnings as a result of technology spillovers. Indeed, the market is approximately correct and earnings surprises are economically and statistically insignificant in the short run (Panel C). By contrast, short-term earnings estimates tend to be overly optimistic as a general rule (e.g., Hong and Kubik (2003)).

Moving on to the long run (five year horizon), Panel A shows that the realized earnings growth rate is significantly higher, by roughly 10-13 p.p. By comparison, the unconditional standard deviation of the realized earnings growth rate is approximately 23%. However, the market anticipates a lower earnings growth rate, by 1-6 p.p. or so, as shown in Panel B. The net effect is that, in the long run, the market's expectations fall short of realizations by approximately 12-21 p.p. These magnitudes can be put into perspective by comparison to typical earnings growth rate realizations and expectations: around 9% and 15%, on average, respectively. Note that this large average performance shortfall is well documented (Chan, Karceski, and Lakonishok (2003)).

It is significant that technology spillovers lead to positive profitability surprises not in the short run but rather in the long run. The absence of profitability surprises in the short run is consistent with the increase in valuations documented in the literature (e.g., BSV). However, presence of substantial profitability surprises in the long run is inconsistent with valuations fully adjusting in a timely fashion. Rather, it suggests that while valuations may be higher, they are still too low.

We examine whether abnormal stock returns are higher as a result of technology spillovers. Following the literature, we account for both risk factors as well as firm characteristics (Faulkender and Wang (2006), Dittmar and Mahrt-Smith (2007), and Denis and Sibilkov (2010)). Specifically, we run regression of future abnormal stock returns on our variables of interest as well as the standard explanatory variables in the empirical literature on stock returns. These latter variables include market capitalization, the market-to-book of equity, cash flow, stock returns, and the volatility of stock returns. Since the effect of technology spillovers may take time to be impounded into stock prices, we examine stock returns over horizons of one to five years. In addition to the common features of our regression specifications, we control for firm age and the asset pricing variables listed above.

[Insert Table 7 about here]

Table 7 presents the results. Technology spillovers lead to a significant increase in abnormal stock returns. At the one year horizon (Panel A), stock returns are higher by approximately 12-18 percentage points. By comparison, the unconditional standard deviation of stock returns is around 38%. The results are statistically significant in three of the four specifications, and just marginally insignificant in the fourth. At the five year horizon (Panel B), the results are higher by a comparable magnitude, roughly 11-19 p.p., and they are statistically significant in all four specifications. The results are similar at the two, three, and four year horizons, and they too are all statistically significant (not tabulated). We find similar results whether we estimate abnormal returns using the market model or the four-factor model.

Product market spillovers do not reliably increase or decrease stock returns. However, the firm's own R&D is generally positively related to stock returns, and our results are consistent with the literature.[16] As the horizon increases, the results for R&D weaken in both economic and statistical significance.

Taken as a whole, our analysis shows that technology spillovers lead to positive profitability surprises in the long run (Table 6) and persistently higher abnormal stock returns

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[16] As a basis of comparison, Chan, Lakonishok, and Sougiannis (2001) find that R&D-to-sales ratios spread future excess stock returns by roughly 3 p.p.; for R&D-to-market capitalization, the spread is about 11 p.p.

(Table 7). The results are thus consistent with the relative mispricing channel through which technology spillovers impact financial policies.

8. Discussion and Conclusion

Our main results suggest that technology spillovers increase leverage (Table 3). Additional results suggest two channels for why this happens. According to the asset redeployability channel, technology spillovers increase collateralized borrowing, in general and using technology assets in particular. They also increase the liquidity of the firm's assets, of technology assets specifically and all assets generally. These results (Table 4), together with the decrease in the cost of debt (Table 5) suggest that asset redeployability increases, which in turn decreases financial distress costs. According to the static tradeoff theory, firms should increase their leverage.

The results for profitability (Table 6), however, suggest the relative mispricing channel as a second explanation. Realized profitability increases, thus both debt and equity increase in value. However, creditors' promised payoffs are well defined whereas owners' residual payoffs are not, thus debt is likely to be relatively less undervalued than equity. Indeed, the market correctly anticipates the increase in profitability in the short run, but it dramatically underestimates profitability in the long run. The relative undervaluation of equity compared to debt explains both the increase in abnormal returns (Table 7) and the increase in profitability surprises (Table 6). Firms should therefore increase their leverage, according to the market timing theory of capital structure.

Both channels can explain the increase in leverage that results from technology spillovers. However, the negative net effect on the cost of debt (Table 5) suggests that the asset redeployability channel dominates in the case of debt. By contrast, in the case of equity, the positive net effect on abnormal stock returns (Table 7) suggests that the relative mispricing channel dominates.

Though not the focus of our study, we find that the firm's own R&D is negatively related to leverage (Table 3), consistent with the literature. R&D can affect leverage through a number of channels, including the ones that we study in this paper. R&D decreases asset redeployability and increases relative mispricing (Hall (2002)). Our results (Table 4 through Table 6) are broadly consistent with these predictions. They suggest that the leverage decreasing effects of R&D (e.g., lower asset redeployability) dominate its various leverage increasing effects (e.g., relative mispricing).

We now discuss several other potential interpretations of the effect of technology spillovers on financial policies. In the first interpretation, technology spillovers make a firm more difficult to understand and value for outsiders of the technology spaces in which the firm operates. Since equity is relatively more sensitive to changes in firm value than debt, the increase in information asymmetry caused by technology spillovers increases the cost of equity more than the cost of debt, so the firm increases its leverage. While this interpretation in consistent with our leverage result, it would by itself imply an increase in the costs of both debt and equity, albeit a relatively greater increase in the latter compared to the former. Additionally, while it would be consistent with more dispersed investor expectations, it would be inconsistent with biased expectations. In fact, we find that investors significantly underestimate the impact of technology spillovers on earnings in the long run, which suggests that information asymmetry by itself cannot explain our results.

In another interpretation, firms use debt as a monitoring mechanism. Technology spillovers increase cash flow, which managers might spend on unprofitable projects. To prevent this, investors pressure firms issue debt and pay out the proceeds to shareholders. In untabulated results, we find that technology spillovers increase cash holdings, and they do not increase payouts to shareholders. These results suggest that using debt as a monitoring mechanism is not the main reason for firms with greater technology spillovers to increase their leverage.

In yet another interpretation, firms use debt to signal to investors that technology spillovers increase cash flow. Our results show that the market is very positively surprised by the firm's earnings, and abnormal stock returns are strongly positive, in both cases for several years into the future. This suggests that if firms are trying to signal with debt, then they are not very successful at doing so.

In the final interpretation, greater technology spillovers increase cash flow risk (e.g., Tseng (2014)). As a result, financial distress costs increase and thus debt capacity decreases. However, this would imply a decrease in leverage, which is opposite to what we observe. An increase in fundamental risk (as distinct from information risk) is inconsistent with our results.

In conclusion, our paper demonstrates the importance of technology spillovers in explaining corporate financial policies. Technology spillovers lead to changes in capital structure and the cost of capital. They operate through the redeployability of the firm's assets, its information environment, and the mispricing of its debt versus equity.

References

Aghion, Philippe, and Patrick Bolton, 1992, An incomplete contracts approach to financial contracting, *Review of Economic Studies* 59, 473-494.

Akcigit, Ufuk, and William R. Kerr, 2015, Growth through heterogeneous innovations, working paper.

Akcigit, Ufuk, Murat Alp Celik, and Jeremy Greenwood, 2016, Buy, keep or sell: Economic growth and the market for ideas, *Econometrica* 84, 943-984.

Arrow, Kenneth, 1962, *The Rate and Direction of Inventive Activity: Economic and Social Factors*, Princeton University Press.

Baker, Malcolm, and Jeffrey Wurgler, 2002, Market timing and capital structure, *Journal of Finance* 57, 1-32.

Barberis, Nicholas, and Richard Thaler, 2003, A survey of behavioral finance, in George M. Constantinides, Milton Harris and René M. Stulz, eds.: *Handbook of the Economics of Finance*.

Bates, Thomas W., 2005, Asset sales, investment opportunities, and the use of proceeds, *Journal of Finance* 60, 105-135.

Baumol, William J., 2002, *The Free-Market Innovation Machine: Analyzing the Growth Miracle of Capitalism*, Princeton University Press.

Bena, Jan, and Kai Li, 2014, Corporate innovations and mergers and acquisitions, *Journal of Finance* 69, 1923-1960.

Benmelech, Efraim, and Nittai K. Bergman, 2009, Collateral pricing, *Journal of Financial Economics* 91, 339-360.

Berger, Philip G., 1993, Explicit and implicit tax effects of the R&D tax credit, *Journal of Accounting Research* 31, 131-171.

Bloom, Nicholas, Mark Schankerman, and John Van Reenen, 2013, Identifying technology spillovers and product market rivalry, *Econometrica* 81, 1347-1393.

Bloom, Nick, Rachel Griffith, and John Van Reenen, 2002, Do R&D tax credits work? Evidence from a panel of countries, 1979-1997, *Journal of Public Economics* 85, 1-31.

Bolton, Patrick, and David Scharfstein, 1996, Optimal debt structure and the number of creditors, *Journal of Political Economy* 104, 1-26.

Bossaerts, Peter, Paolo Ghirardato, Serena Guarnaschelli, and William R. Zame, 2010, Ambiguity in asset markets: Theory and experiment, *Review of Financial Studies* 23, 1325-1359.

Chan, Louis K. C., Jason Karceski, and Josef Lakonishok, 2003, The level and persistence of growth rates, *Journal of Finance* 58, 643-684.

Chan, Louis K. C., Josef Lakonishok, and Theodore Sougiannis, 2001, The stock market valuation of research and development expenditures, *Journal of Finance* 56, 2431-2456.

Chava, Sudheer, Dmitry Livdan, and Amiyatosh Purnandam, 2009, Do shareholder rights affect the cost of bank loans?, *Review of Financial Studies* 22, 2973-3004.

Chirinko, Robert S., and Daniel J. Wilson, 2013, Tax competition among U.S. States: Racing to the bottom or riding on a seesaw?, working paper.

Cohen, Lauren, and Dong Lou, 2012, Complicated firms, *Journal of Financial Economics* 104, 383-400.

Cohen, Lauren, Karl Diether, and Christopher Malloy, 2013, Misvaluing innovation, *Review of Financial Studies* 26, 635-666.

Core, John H., Wayne R. Guay, and Tjomme O. Rusticus, 2006, Does weak governance cause weak stock returns? An examination of firm operating performance and investors' expectations, *Journal of Finance* 61, 655-687.

Cummins, Jason G., Kevin A. Hassett, and R. Glenn Hubbard, 1994, A reconsideration of investment behavior using tax reforms as natural experiments, *Brookings Papers on Economic Activity* 2, 1-60.

Denis, David J., and Valeriy Sibilkov, 2010, Financial constraints, investment, and the value of cash holdings, *Review of Financial Studies* 23, 247-269.

Dittmar, Amy, and Jan Mahrt-Smith, 2007, Corporate governance and the value of cash holdings, *Journal of Financial Economics* 83, 599-634.

Eberhart, Allan C., William F. Maxwell, and Akhtar R. Siddique, 2004, An examination of long-term abnormal stock returns and operating performance following R&D increases, *Journal of Finance* 59, 623-650.

Edmans, Alex, 2011, Does the stock market fully value intangibles? Employee satisfaction and equity prices, *Journal of Financial Economics* 101, 621-640.

Falato, Antonio, and Jae W. Sim, 2014, Why do innovative firms hold so much cash? Evidence from changes in state R&D tax credits, working paper.

Faulkender, Michael, and Rong Wang, 2006, Corporate financial policy and the value of cash, *Journal of Finance* 61, 1957-1990.

Fich, Eliezar M., Jarrad Harford, and Anh L. Tran, 2015, Motivated monitors: The importance of institutional investors' portfolio weights, *Journal of Financial Economics* 118, 21-48.

Foucault, Thierry, and Laurent Frésard, 2014, Learning from peers' stock prices and corporate investment, *Journal of Financial Economics* 111, 554-577.

Francis, Bill B., Iftekhar Hasan, Kose John, and Maya Waisman, 2010, The effect of state antitakeover laws on the firm's bondholders, *Journal of Financial Economics* 96, 127-154.

Frank, Murray Z., and Vidhan K. Goyal, 2009, Capital structure decisions: which factors are reliably important?, *Financial Management* 38, 1-37.

Giroud, Xavier, and Holger M. Mueller, 2011, Corporate governance, product market competition, and equity prices, *Journal of Finance* 66, 563-600.

Graham, John R., Si Li, and Jiaping Qiu, 2008, Corporate misreporting and bank loan contracting, *Journal of Financial Economics* 89, 44-61.

Grossman, Gene M., and Elhanan Helpman, 1991, Trade, knowledge spillovers, and growth, *European Economic Review* 35, 517-526.

Hall, Bronwyn H., 1992a, Investment and research and development at the firm level: Does the source of financing matter?, working paper.

Hall, Bronwyn H., 1992b, R&D tax policy during the 1980s: Success or failure?, in *Tax Policy and the Economy* 7, 1-36.

Hall, Bronwyn H., 2002, The financing of research and development, *Oxford Review of Economic Policy* 18, 35-51.

Hall, Robert E., and Dale W. Jorgenson, 1967, Tax policy and investment behavior, *American Economic Review* 57, 391-414.

Harford, Jarrad, 1999, Corporate cash reserves and acquisitions, *Journal of Finance* 54, 1969-1997.

Harris, Milton, and Artur Raviv, 1990, Capital structure and the informational role of debt, *Journal of Finance* 45, 321-349.

Hart, Oliver, and John Moore, 1994, A theory of debt based on the inalienability of human capital, *Quarterly Journal of Economics* 109, 841-879.

Himmelberg, Charles P., and Bruce C. Petersen, 1994, R&D and internal finance: A panel study of small firms in high-tech industries, *Review of Economics and Statistics* 76, 38-51.

Hines, James R., 1993, On the sensitivity of R&D to delicate tax changes: The behavior of U.S. multinationals in the 1980s, in Alberto Giovannini, R. Glenn Hubbard, and Joel Slemrod, eds.: *Studies in International Taxation*, University of Chicago Press.

Hirshleifer, David, and Siew Hong Teoh, 2003, Limited attention, information disclosure, and financial reporting, *Journal of Accounting and Economics* 36, 337-386.

Hirshleifer, David, Po-Hsuan Hsu, and Dongmei Li, 2013, Innovative efficiency and stock returns, *Journal of Financial Economics* 107, 632-654.

Hong, Harrison, and David Sraer, 2013, Quiet bubbles, *Journal of Financial Economics* 110, 596-606.

Hong, Harrison, and Jeffrey D. Kubik, 2003, Analyzing the analysts: Career concerns and biased earnings forecasts, *Journal of Finance* 58, 313-351.

Hong, Harrison, and Jeremy C. Stein, 1999, A unified theory of underreaction, momentum trading, and over reaction in asset markets, *Journal of Finance* 54, 2143-2184.

Isaacson, Walter, 2011, Steve Jobs (Simon and Schuster, New York, NY).

Jaffe, Adam B., 1986, Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value, *American Economic Review* 76, 984-1001.

Kale, Jayant R., and Husayn Shahrur, 2007, Corporate capital structure and the characteristics of suppliers and customers, *Journal of Financial Economics* 83, 321-365.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, Noah Stoffman, 2016, Technological innovation, resource allocation, and growth, forthcoming *Quarterly Journal of Economics*.

Kortum, Samuel, Josh Lerner, 2000, Assessing the contribution of venture capital to innovation, *RAND Journal of Economics* 31, 674-692.

Leary, Mark T., and Michael R. Roberts, 2014, Do peer firms affect corporate financial policy?, *Journal of Finance* 69, 139-178.

Lemmon, Michael L., Michael R. Roberts, and Jaime F. Zender, 2008, Back to the beginning: Persistence and the cross-section of corporate capital structure, *Journal of Finance* 63, 1575-1608.

Lev, Baruch, and Theodore Sougiannis, 1996, The capitalization, amortization, and value-relevance of R&D, *Journal of Accounting and Economics* 21, 107-138.

Li, Kai, Jiaping Qiu, and Jin Wang, 2016, Technological competition and strategic alliances, working paper.

Loumioti, Maria, 2012, The use of intangible assets as loan collateral, working paper.

Lyandres, Evgeny, and Berardino Palazzo, 2016, Cash holdings, competition, and innovation, forthcoming *Journal of Financial and Quantitative Analysis*.

MacKay, Peter, and Gordon M. Phillips, 2005, How does industry affect firm financial structure?, *Review of Financial Studies* 18, 1433-1466.

Maksimovic, Vojislav, and Sheridan Titman, 1991, Financial policy and reputation for product quality, *Review of Financial Studies* 4, 175-200.

Maksimovic, Vojislav, and Gordon Phillips, 2001, The market for corporate assets: Who engages in mergers and asset sales and are there efficiency gains?, *Journal of Finance* 56, 2019-2065.

Mann, William, 2016, Creditor rights and innovation: Evidence from patent collateral, working paper.

Modigliani, Franco, and Merton H. Miller, 1958, The cost of capital, corporation finance, and the theory of investment, *American Economic Review* 48, 655-669.

Opler, Tim, and Sheridan Titman, 1993, The determinants of leveraged buyout activity: Free cash flow vs. financial distress costs, *Journal of Finance* 48, 1985-1999.

Ortiz-Molina, Hernán, 2006, Top management incentives and the pricing of corporate public debt, *Journal of Financial and Quantitative Analysis* 41, 317-340.

Phillips, Gordon M., and Alexei Zhdanov, 2013, R&D and the incentives from merger and acquisition activity, *Review of Financial Studies* 26, 34-78.

Qi, Yaxuan, Lukas Roth, and John K. Wald, 2010, Political rights and the cost of debt, *Journal of Financial Economics* 95, 202-226.

Qiu, Jiaping, and Chi Wan, 2015, Technology spillovers and corporate cash holdings, *Journal of Financial Economics* 115, 558-573.

Rajan, Raghuram G., and Luigi Zingales, 1995, What do we know about capital structure? Some evidence from international data, *Journal of Finance* 50, 1421-1460.

Rosenberg, Nathan, 1979, Technological interdependence in the American economy, *Technology and Culture* 20, 25-50.

Rosenkopf, Lori, and Paul Almeida, 2003, Overcoming local search through alliances and mobility, *Management Science* 49, 751-766.

Schlingemann, Frederik P., René M. Stulz, and Ralph A. Walkling, 2002, Divestitures and the liquidity of the market for corporate assets, *Journal of Financial Economics* 64, 117-144.

Serrano, Carlos J., 2010, The dynamics of the transfer and renewal of patents, *RAND Journal of Economics* 41, 686-708.

Thakor, Richard T., and Andrew W. Lo, 2015, Competition and R&D financing decisions: Theory and evidence from the biopharmaceutical industry, working paper.

Titman, Sheridan, 1984, The effect of capital structure on a firm's liquidation decision, *Journal of Financial Economics* 13, 137-151.

Titman, Sheridan, and Roberto Wessels, 1988, The determinants of capital structure choice, *Journal of Finance* 43, 1-19.

Tseng, Kevin, 2014, Knowledge network and the cross-section of expected returns, working paper.

Valta, Philip, 2012, Competition and the cost of debt, *Journal of Financial Economics* 105, 661-682.

The Wall Street Journal, 2012, Gordon Crovitz: Who Really Invented the Internet?, July 12.

Williamson, Oliver E., 1988, Corporate finance and corporate governance, *Journal of Finance* 43, 567-591.

Wilson, Daniel J., 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.

Table 1
Descriptive Statistics

This table presents descriptive statistics for technology spillover variables, firm characteristics variables, and all dependent variables. The sample comprises 12,118 firm-year observations corresponding to 694 unique firms between 1981 and 2001. The firms in the sample are publicly traded U.S. operating firms excluding financials and utilities. All variables are defined in Appendix Table 1. All variables are multiplied by 100 except for the technology spillover variables, the stock of patents, firm age, total assets, the market-to-book of assets, the number of patents collateralized, the number of patents sold, and the number of mergers and acquisitions.

	Mean	Standard deviation	25^{th} percentile	Median	75^{th} percentile
Technology spillover variables					
- Raw Jaffe	9.7	1.1	9.2	9.9	10.4
- Purged Jaffe	7.3	2.3	6.3	7.6	9.0
- Raw Mahalanobisp	11.3	0.9	10.8	11.4	11.9
- Purged Mahalanobis	8.5	1.7	7.8	8.8	9.7
Firm characteristics variables					
- R&D	44.9	68.9	0.0	19.9	59.5
- Patent stock	611	1,935	5	28	175
- Firm age	24.6	18.1	11.7	20.1	31.5
- Total assets	2,507	6,366	90	338	1,648
- Market-to-book of assets	1.6	1.0	1.0	1.3	1.8
- Cash flow	15.0	8.7	10.3	15.2	20.1
- Asset tangibility	31.4	16.2	19.5	28.8	40.0
- Cash flow volatility	3.5	3.3	1.3	2.5	4.5
Capital structure variables					
- Leverage	21.7	15.6	9.0	20.6	31.5
- Debt issuance	5.6	9.8	0.0	1.1	7.1
- Equity issuance	1.5	4.1	0.0	0.2	0.9
Cost of capital variables					
- Bond issue spreads	107.1	93.4	55.0	83.0	130.0
- Bank loan spreads	125.5	118.9	32.5	75.0	200.0
- Abnormal stock returns	7.3	37.7	-14.5	5.8	26.5
Asset redeployability variables					
- Collateralized debt	3.2	7.7	0.0	0.0	2.0
- Number of patents collateralized	1.5	7.5	0.0	0.0	0.0
- Number of patents sold	2.1	10.1	0.0	0.0	0.0
- Number of mergers and acquisitions	0.2	0.5	0.0	0.0	0.0
- Value of mergers and acquisitions	1.8	8.1	0.0	0.0	0.0
Profitability variables					
- One year realized earnings	6.9	7.6	3.2	6.5	10.4
- One year expected earnings	8.6	6.3	4.7	7.5	11.2
- One year earnings surprise	-1.7	5.1	-2.4	-0.5	0.4
- Five year realized earnings growth rate	9.0	23.3	-3.2	8.0	17.9
- Five year expected earnings growth rate	14.9	6.4	10.9	13.5	17.3
- Five year earnings growth rate surprise	-6.1	21.4	-16.9	-6.0	3.0

Table 2
Descriptive Statistics by Industry Sorted by Technology Spillovers

This table presents descriptive statistics by industry sorted by technology spillovers. The sample comprises 12,118 firm-year observations corresponding to 694 unique firms between 1981 and 2001. The firms in the sample are publicly traded U.S. operating firms excluding financials and utilities. Only industries with at least five unique firms are included (97% of the sample). All variables are defined in Appendix Table 1. R&D and leverage are multiplied by 100.

Industry	Obs.	Mean of raw Jaffe technology spillover	Standard deviation of raw Jaffe technology spillover	Mean of raw Jaffe product market spillover	Mean of R&D	Mean of total assets	Mean of leverage
Communications (SIC=48)	61	10.50	1.09	9.42	56.8	29,123	23.7
Transportation equipment (SIC=37)	727	10.30	0.74	8.25	31.0	4,805	23.4
Chemicals and related products (SIC=28)	1,226	10.24	0.57	8.54	52.8	3,446	20.8
Electronic equipment excl. computers (SIC=36)	1,876	10.11	0.74	8.53	70.4	1,492	18.7
Construction products (SIC=32)	258	10.04	0.69	6.02	16.4	1,686	28.5
Consumer and business instruments (SIC=38)	1,086	9.98	0.69	8.15	101.4	1,613	17.1
Business services incl. technology (SIC=73)	166	9.94	0.78	7.73	74.9	1,845	16.1
Machinery and equipment incl. computers (SIC=35)	1,806	9.88	0.86	7.89	76.4	1,686	20.2
Paper and related products (SIC=26)	425	9.85	0.94	7.13	16.0	3,642	26.5
Rubber and plastic products (SIC=30)	261	9.79	1.01	7.74	25.1	1,202	18.9
Metal mining (SIC=10)	52	9.70	0.46	4.52	0.8	2,419	24.3
Primary metal industries (SIC=33)	392	9.59	0.86	6.47	9.7	1,418	22.3
Wood products excl. furniture (SIC=24)	84	9.56	0.83	4.77	0.0	4,405	31.9
Fabricated metal products (SIC=34)	735	9.42	0.97	6.74	17.4	809	20.7
Petroleum refining and related industries (SIC=29)	183	9.40	1.52	8.81	4.7	12,170	26.1
Textile mill products (SIC=22)	185	9.34	1.12	4.06	9.5	412	27.7
Oil and gas extraction (SIC=13)	196	9.29	1.28	7.48	6.4	3,960	32.5
Wholesale durable goods (SIC=50)	216	9.16	1.03	7.66	20.2	526	24.4
Food and related products (SIC=20)	517	9.14	0.96	5.69	4.8	3,453	21.7
Printing, publishing, and related industries (SIC=27)	280	8.97	1.16	6.69	3.7	2,082	18.7
Furniture and fixtures (SIC=25)	236	8.94	1.07	4.50	15.6	583	20.5
Miscellaneous manufacturing industries (SIC=39)	318	8.54	1.36	7.11	12.3	351	21.3
Wholesale non-durable goods (SIC=51)	69	8.34	1.53	3.91	11.8	850	24.7
Apparel and related products (SIC=23)	224	8.27	1.29	1.64	0.7	518	23.2
Leather and related products (SIC=31)	122	7.05	1.41	0.96	16.5	176	19.5

Table 3
The Effect of Technology Spillovers on Capital Structure

This table presents the results of regressions of leverage, debt issuance, and equity issuance on technology spillovers. The sample comprises 12,118 firm-year observations corresponding to 694 unique firms between 1981 and 2001. The firms in the sample are publicly traded U.S. operating firms excluding financials and utilities. For each dependent variable, four regressions are run, one for each measure of spillovers. In each regression, the same measure is used for technology spillovers and product market spillovers. The four spillover measures are the raw and purged Jaffe and Mahalanobis measures, as indicated. The independent variables are as follows: technology and product market spillovers; R&D; federal and state tax credits, but only in specifications using purged spillover measures; the natural logarithm of firm age; the natural logarithm of sales; the market-to-book of assets; cash flow; asset tangibility; and cash flow volatility. All variables are defined in Appendix Table 1. The dependent variables are expressed as a percentage of total assets. The independent variables are lagged and standardized. Fixed effects are included for firms and years. Standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Only selected results are tabulated.

Panel A: Leverage				
	Dependent variable is leverage (t)			
	Raw Jaffe	Purged Jaffe	Raw Mahalanobis	Purged Mahalanobis
Technology spillovers (t-1)	6.30***	5.87**	5.38***	6.68***
	(3.51)	(2.22)	(3.17)	(3.17)
Product market spillovers (t-1)	2.00**	2.66	1.12	1.07
	(2.51)	(1.48)	(1.07)	(0.47)
R&D (t-1)	-2.15***	-2.08***	-2.10***	-2.05***
	(-6.25)	(-6.09)	(-6.09)	(-6.01)
Observations	11,919	11,919	11,919	11,919
Adjusted R^2	0.597	0.597	0.597	0.597

Panel B: Debt Issuance				
	Dependent variable is debt issuance (t)			
	Raw Jaffe	Purged Jaffe	Raw Mahalanobis	Purged Mahalanobis
Technology spillovers (t-1)	3.15**	4.11**	2.50*	2.67*
	(2.37)	(2.26)	(1.82)	(1.69)
Product market spillovers (t-1)	1.15*	2.12*	0.82	1.50
	(1.73)	(1.85)	(0.94)	(0.95)
R&D (t-1)	-0.31	-0.28	-0.28	-0.25
	(-1.36)	(-1.26)	(-1.24)	(-1.09)
Observations	11,892	11,892	11,892	11,892
Adjusted R^2	0.228	0.228	0.228	0.228

Panel C: Equity Issuance				
	Dependent variable is equity issuance (t)			
	Raw Jaffe	Purged Jaffe	Raw Mahalanobis	Purged Mahalanobis
Technology spillovers (t-1)	-1.38**	-1.69**	-1.60**	-0.91
	(-2.21)	(-2.00)	(-2.31)	(-1.14)
Product market spillovers (t-1)	0.56**	0.74	0.38	-0.05
	(2.11)	(1.28)	(0.97)	(-0.06)
R&D (t-1)	0.35**	0.35**	0.35**	0.34**
	(2.16)	(2.15)	(2.19)	(2.12)
Observations	11,892	11,892	11,892	11,892
Adjusted R^2	0.183	0.182	0.183	0.182

Table 4
The Effect of Technology Spillovers on Asset Redeployability

This table presents the results of regressions of collateralized debt measures and asset liquidity measures on technology spillovers. The sample comprises 12,118 firm-year observations corresponding to 694 unique firms between 1981 and 2001. The firms in the sample are publicly traded U.S. operating firms excluding financials and utilities. For each dependent variable, four regressions are run, one for each measure of spillovers. In each regression, the same measure is used for technology spillovers and product market spillovers. The four spillover measures are the raw and purged Jaffe and Mahalanobis measures, as indicated. The independent variables common to all panels are as follows: technology and product market spillovers; R&D; federal and state tax credits, but only in specifications using purged spillover measures; the natural logarithm of firm age; the market-to-book of assets; and cash flow. Additional independent variables specific to each panel are as follows: Panel A includes the natural logarithm of sales, asset tangibility, and cash flow volatility; Panel B and Panel C include the natural logarithm of total assets, leverage, asset tangibility, cash flow volatility, and the stock of patents; and Panel D and Panel E include the natural logarithm of total assets, stock returns, leverage, and cash holdings. All variables are defined in Appendix Table 1. In Panel A and Panel E, the dependent variables are scaled by total assets. In Panel B through Panel D, natural logarithms are taken after adding one to the dependent variables. All dependent variables are multiplied by 100. The independent variables are lagged and standardized. Fixed effects are included for firms and years. Standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Only selected results are tabulated.

Panel A: Collateralized Debt

	Dependent variable is collateralized debt (t)			
	Raw Jaffe	Purged Jaffe	Raw Mahalanobis	Purged Mahalanobis
Technology spillovers (t-1)	3.20***	2.31**	2.67***	2.46**
	(4.12)	(2.19)	(3.19)	(2.45)
Product market spillovers (t-1)	0.76	1.31	1.01	0.56
	(1.41)	(1.46)	(1.41)	(0.43)
R&D (t-1)	-0.88***	-0.85***	-0.87***	-0.83***
	(-5.35)	(-5.17)	(-5.28)	(-5.10)
Observations	11,919	11,919	11,919	11,919
Adjusted R^2	0.425	0.425	0.425	0.424

Panel B: Patent Collateralizations

	Dependent variable is ln(number of patents collateralized) (t)			
	Raw Jaffe	Purged Jaffe	Raw Mahalanobis	Purged Mahalanobis
Technology spillovers (t-1)	22.30***	18.91**	20.00***	25.19***
	(2.74)	(2.06)	(2.59)	(2.95)
Product market spillovers (t-1)	14.06***	-9.52	19.25***	-19.50**
	(3.54)	(-1.31)	(3.41)	(-2.02)
R&D (t-1)	0.01	0.54	-0.01	0.68
	(0.00)	(0.25)	(-0.00)	(0.31)
Observations	11,924	11,924	11,924	11,924
Adjusted R^2	0.208	0.207	0.208	0.207

Panel C: Patent Sales				
	Dependent variable is ln(number of patent sold) (t)			
	Raw Jaffe	Purged Jaffe	Raw Mahalanobis	Purged Mahalanobis
Technology spillovers (t-1)	25.55***	16.94*	21.89***	26.08***
	(3.46)	(1.80)	(3.15)	(2.90)
Product market spillovers (t-1)	9.97***	-21.58***	14.70***	-26.17***
	(3.20)	(-3.09)	(2.76)	(-3.02)
R&D (t-1)	-3.13**	-2.41*	-3.08**	-2.36
	(-2.16)	(-1.68)	(-2.12)	(-1.64)
Observations	11,924	11,924	11,924	11,924
Adjusted R^2	0.343	0.343	0.343	0.343

Panel D: Number of Mergers and Acquisitions				
	Dependent variable is ln(number of mergers and acquisitions) (t)			
	Raw Jaffe	Purged Jaffe	Raw Mahalanobis	Purged Mahalanobis
Technology spillovers (t-1)	4.99	12.25***	8.30**	10.06**
	(1.59)	(2.73)	(2.50)	(2.44)
Product market spillovers (t-1)	2.98*	-1.73	1.97	-1.41
	(1.65)	(-0.49)	(0.80)	(-0.32)
R&D (t-1)	-1.51**	-1.49**	-1.55**	-1.42**
	(-2.36)	(-2.31)	(-2.40)	(-2.21)
Observations	12,007	12,007	12,007	12,007
Adjusted R^2	0.194	0.194	0.194	0.194

Panel E: Value of Mergers and Acquisitions				
	Dependent variable is value of mergers and acquisitions (t)			
	Raw Jaffe	Purged Jaffe	Raw Mahalanobis	Purged Mahalanobis
Technology spillovers (t-1)	1.77*	3.80***	3.18***	4.23***
	(1.76)	(2.77)	(3.01)	(3.33)
Product market spillovers (t-1)	0.97*	0.82	0.22	0.31
	(1.69)	(0.81)	(0.29)	(0.23)
R&D (t-1)	-0.48**	-0.49**	-0.49**	-0.47**
	(-2.07)	(-2.07)	(-2.08)	(-1.99)
Observations	12,007	12,007	12,007	12,007
Adjusted R^2	0.071	0.071	0.071	0.071

Table 5
The Effect of Technology Spillovers on the Cost of Debt

This table presents the results of regressions of bond issue spreads and bank loan spreads on technology spillovers. The sample comprises 12,118 firm-year observations corresponding to 694 unique firms between 1981 and 2001. The firms in the sample are publicly traded U.S. operating firms excluding financials and utilities. For each dependent variable, four regressions are run, one for each measure of spillovers. In each regression, the same measure is used for technology spillovers and product market spillovers. The four spillover measures are the raw and purged Jaffe and Mahalanobis measures, as indicated. The independent variables at the firm level are as follows: technology and product market spillovers; R&D; federal and state tax credits, but only in specifications using purged spillover measures; the natural logarithm of firm age; the natural logarithm of total assets; leverage; the market-to-book of assets; cash flow; asset tangibility; and cash flow volatility. The independent variables at the firm-deal level are as follows: the natural logarithm of the proceeds of the bond issue or the amount of the bank loan; the natural logarithm of the maturity of the bond or the loan; the credit rating of the bond issue or the credit rating of the firm; a dummy variable that equals one if the credit rating is missing and zero otherwise; and a dummy variable that equals one if the bond issue private rather than public or the bank loan is a term loan rather than a credit line. All variables are defined in Appendix Table 1. The dependent variables are multiplied by 100. The independent variables are lagged and standardized. Fixed effects are included for industries and years. Standard errors are clustered by industry-year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Only selected results are tabulated.

Panel A: Bond Issues

	Dependent variable is spread (t)			
	Raw Jaffe	Purged Jaffe	Raw Mahalanobis	Purged Mahalanobis
Technology spillovers (t-1)	-6.55**	-5.91**	-6.63**	-6.35**
	(-2.09)	(-2.21)	(-2.21)	(-2.10)
Product market spillovers (t-1)	-0.36	-2.79	-1.49	-2.71
	(-0.17)	(-0.95)	(-0.56)	(-0.94)
R&D (t-1)	10.26**	11.73**	10.63**	11.75**
	(2.08)	(2.43)	(2.17)	(2.44)
Observations	2,206	2,206	2,206	2,206
Adjusted R^2	0.562	0.562	0.562	0.562

Panel B: Bank Loans

	Dependent variable is spread (t)			
	Raw Jaffe	Purged Jaffe	Raw Mahalanobis	Purged Mahalanobis
Technology spillovers (t-1)	-9.52***	-9.63***	-8.76***	-8.95***
	(-2.92)	(-3.08)	(-2.75)	(-2.85)
Product market spillovers (t-1)	6.35**	8.17***	5.49*	5.50*
	(1.98)	(2.71)	(1.77)	(1.76)
R&D (t-1)	10.57***	9.92***	10.71***	10.56***
	(2.90)	(2.77)	(2.99)	(2.99)
Observations	2,728	2,728	2,728	2,728
Adjusted R^2	0.558	0.561	0.557	0.559

Table 6
The Effect of Technology Spillovers on Profitability

This table presents the results of regressions of realized, expected, and unexpected profitability on technology spillovers. The sample comprises 12,118 firm-year observations corresponding to 694 unique firms between 1981 and 2001. The firms in the sample are publicly traded U.S. operating firms excluding financials and utilities. For each dependent variable, four regressions are run, one for each measure of spillovers. In each regression, the same measure is used for technology spillovers and product market spillovers. The four spillover measures are the raw and purged Jaffe and Mahalanobis measures, as indicated. The independent variables are as follows: technology and product market spillovers; R&D; federal and state tax credits, but only in specifications using purged spillover measures; the natural logarithm of firm age; the natural logarithm of market capitalization; and the natural logarithm of the market-to-book of equity. All variables are defined in Appendix Table 1. At the one year horizon, natural logarithms are taken after adding one to the dependent variables. All dependent variables are multiplied by 100. The independent variables are lagged and standardized. Fixed effects are included for firms and years. Standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Only selected results are tabulated.

Panel A: Realized Earnings

	One year horizon				Five year horizon			
	Dependent variable is ln(realized earnings) (t)				Dependent variable is realized earnings growth rate (t)			
	Raw Jaffe	Purged Jaffe	Raw Mahalanobis	Purged Mahalanobis	Raw Jaffe	Purged Jaffe	Raw Mahalanobis	Purged Mahalanobis
Technology spillovers (t-1)	0.80	1.16	3.86***	3.37**	13.31***	10.35**	13.05***	13.48***
	(0.65)	(0.75)	(3.12)	(2.21)	(3.64)	(2.00)	(3.62)	(2.88)
Product market spillovers (t-1)	-1.68***	-0.69	-2.18***	-1.66	2.60	-1.37	5.15*	1.04
	(-2.63)	(-0.34)	(-2.78)	(-0.77)	(1.23)	(-0.30)	(1.93)	(0.18)
R&D (t-1)	0.27	0.23	0.22	0.22	-0.96	-0.71	-1.01	-0.79
	(1.00)	(0.87)	(0.80)	(0.81)	(-1.13)	(-0.84)	(-1.19)	(-0.94)
Observations	8,562	8,562	8,562	8,562	8,557	8,557	8,557	8,557
Adjusted R^2	0.530	0.532	0.531	0.532	0.236	0.234	0.236	0.234

Panel B: Expected Earnings								
	One year horizon				Five year horizon			
	Dependent variable is ln(expected earnings) (t)				Dependent variable is expected earnings growth rate (t)			
	Raw Jaffe	Purged Jaffe	Raw Mahalanobis	Purged Mahalanobis	Raw Jaffe	Purged Jaffe	Raw Mahalanobis	Purged Mahalanobis
Technology spillovers (t-1)	0.07	0.95	2.80***	2.67***	-6.36***	-3.78***	-3.69***	-1.37
	(0.10)	(0.82)	(3.70)	(2.78)	(-5.57)	(-2.76)	(-2.86)	(-0.96)
Product market spillovers (t-1)	-1.09***	0.77	-1.82***	0.09	2.15***	6.56***	0.73	4.43***
	(-2.66)	(0.80)	(-3.81)	(0.09)	(4.09)	(5.33)	(1.11)	(3.13)
R&D (t-1)	0.33*	0.28*	0.28*	0.26	-0.36*	-0.51**	-0.40*	-0.53**
	(1.93)	(1.67)	(1.68)	(1.57)	(-1.67)	(-2.37)	(-1.88)	(-2.45)
Observations	8,654	8,654	8,654	8,654	7,161	7,161	7,161	7,161
Adjusted R^2	0.705	0.706	0.706	0.706	0.620	0.618	0.618	0.617

Panel C: Earnings Surprise								
	One year horizon				Five year horizon			
	Dependent variable is ln(earnings surprise) (t)				Dependent variable is earnings growth rate surprise (t)			
	Raw Jaffe	Purged Jaffe	Raw Mahalanobis	Purged Mahalanobis	Raw Jaffe	Purged Jaffe	Raw Mahalanobis	Purged Mahalanobis
Technology spillovers (t-1)	0.56	-0.48	0.97	0.97	20.75***	11.52	17.60***	16.39***
	(0.53)	(-0.34)	(0.87)	(0.66)	(3.81)	(1.56)	(3.48)	(2.69)
Product market spillovers (t-1)	-0.55	-2.02	-0.33	-2.95	2.67	-11.19	7.48**	-8.36
	(-0.92)	(-1.04)	(-0.48)	(-1.40)	(0.92)	(-1.40)	(2.41)	(-0.94)
R&D (t-1)	-0.01	0.01	-0.03	0.01	1.09	1.74*	1.13	1.66
	(-0.06)	(0.05)	(-0.11)	(0.03)	(1.05)	(1.67)	(1.10)	(1.58)
Observations	8,562	8,562	8,562	8,562	5,504	5,504	5,504	5,504
Adjusted R^2	0.423	0.424	0.423	0.424	0.242	0.238	0.242	0.239

Table 7
The Effect of Technology Spillovers on Abnormal Stock Returns

This table presents the results of regressions of abnormal stock returns on technology spillovers. The sample comprises 12,118 firm-year observations corresponding to 694 unique firms between 1981 and 2001. The firms in the sample are publicly traded U.S. operating firms excluding financials and utilities. For each dependent variable, four regressions are run, one for each measure of spillovers. In each regression, the same measure is used for technology spillovers and product market spillovers. The four spillover measures are the raw and purged Jaffe and Mahalanobis measures, as indicated. The dependent variables are abnormal stock returns estimated using the market model and annualized. Abnormal stock returns are measured over horizons of one and five years in Panel A and Panel B, respectively. The independent variables are as follows: technology and product market spillovers; R&D; federal and state tax credits, but only in specifications using purged spillover measures; the natural logarithm of firm age; the natural logarithm of market capitalization; the market-to-book of equity; cash flow; stock returns; and stock return volatility. All variables are defined in Appendix Table 1. The dependent variables are multiplied by 100. The independent variables are lagged and standardized. Fixed effects are included for firms and years. Standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Only selected results are tabulated.

Panel A: One Year Horizon

	Dependent variable is abnormal stock returns (t)			
	Raw Jaffe	Purged Jaffe	Raw Mahalanobis	Purged Mahalanobis
Technology spillovers (t-1)	11.57*	12.61	14.59**	17.73**
	(1.82)	(1.53)	(2.28)	(2.34)
Product market spillovers (t-1)	4.63	-12.81*	8.35*	-15.26*
	(1.37)	(-1.81)	(1.83)	(-1.69)
R&D (t-1)	2.60**	2.89**	2.50**	2.92**
	(2.20)	(2.45)	(2.12)	(2.47)
Observations	11,817	11,817	11,817	11,817
Adjusted R^2	0.203	0.204	0.204	0.204

Panel B: Five Year Horizon

	Dependent variable is abnormal stock returns (t)			
	Raw Jaffe	Purged Jaffe	Raw Mahalanobis	Purged Mahalanobis
Technology spillovers (t-1)	17.02***	10.74***	18.91***	16.41***
	(7.91)	(3.84)	(8.60)	(6.14)
Product market spillovers (t-1)	2.57*	-4.30**	5.90***	-5.73**
	(1.80)	(-2.03)	(3.24)	(-2.16)
R&D (t-1)	0.48	0.76*	0.44	0.75*
	(1.16)	(1.82)	(1.07)	(1.82)
Observations	11,262	11,262	11,262	11,262
Adjusted R^2	0.559	0.555	0.561	0.556

Appendix Table 1
Variable Definitions

This table presents variable definitions. Variables are computed for every firm-year except for spreads on bond issues and bank loans. In these latter cases, variables are computed for every firm-deal. Industry is defined using two-digit SIC codes. * indicates that the variable is defined using Compustat data items. † indicates that the variable is computed as in Bloom, Schankerman, and Van Reenen (2013).

Name	Definition
Spillover variables	
- Raw Jaffe - Raw Mahalanobis	The Jaffe or Mahalanobis distances in the technology or product market spaces are computed for each pair of firms. Then the stock of R&D is computed for every firm-year. Finally, the spillover variables for a firm are computed as the natural logarithm of the sum of the R&D stock of each of the other firms weighted by the distance between the firm in question and each of the other firms. †
- Purged Jaffe - Purged Mahalanobis	Computed like the corresponding raw variables except that the R&D stock of other firms is first purged before weighting and summing. Specifically, R&D tax credits are computed for each firm-year, and the R&D stock is regressed on the R&D tax credits. The resulting predicted values are used as the purged R&D stock corresponding to each firm-year. †
Capital structure variables	
- Leverage	(DLTT+DLC)/AT *
- Debt issuance	DLTIS/AT *
- Equity issuance	SSTK/AT *
Cost of capital variables	
- Bond issue spreads	Bond issue spread related to a duration matched government bond
- Bank loan spreads	Bank loan spread over the benchmark rate
- Abnormal stock returns	Abnormal stock returns estimated using the market model implemented using daily returns and then annualized
Asset redeployability variables	
- Collateralized debt	(DM+DCLO)/AT *
- Number of patents collateralized	Number of patents issued to the firm and subsequently used as collateral for borrowing. See Mann (2016) for details.
- Number of patents sold	Number of patents issued to the firm and subsequently sold. See Serrano (2010) and Akcigit, Celik, and Greenwood (2016) for details.
- Number of mergers and acquisitions	Number of mergers and acquisitions involving the firm
- Value of mergers and acquisitions	Value of mergers and acquisitions involving the firm scaled by total assets
Profitability variables	
- One year realized earnings	Actual earnings times shares outstanding all scaled by total assets
- One year expected earnings	Analysts' earnings estimates times shares outstanding all scaled by total assets
- One year earnings surprise	Difference between realized and expected earnings at the one year horizon
- Five year realized earnings growth rate	Five year growth rate of (IB/CSHO)/AJEX *
- Five year expected earnings growth rate	Analysts' long-term earnings growth rate estimates
- Five year earnings growth rate surprise	Difference between realized and expected earnings growth rate at the five year horizon

Control variables	
- R&D	Stock of the firm's R&D accumulated up to a given firm-year adjusted for depreciation and scaled by the firm's stock of physical capital †
- Federal tax credits - State tax credits	Natural logarithm of the firm's federal and state tax credits in a given firm-year †
- Firm age	Number of years as a publicly traded firm
- Patent stock	Stock of the firm's patents accumulated up to a given firm-year
- Total assets	AT *
- Sales	SALE *
- Market capitalization	PRCC_F×CSHO *
- Market-to-book of assets	(AT-(TXDITC+CEQ)+PRCC_F×CSHO)/AT *
- Market-to-book of equity	(PRCC_F×CSHO)/(TXDITC+CEQ) *
- Cash flow	OIBDP/AT *
- Asset tangibility	PPENT/AT *
- Cash flow volatility	Standard deviation of cash flow computed using three years of annual data *
- Stock returns	Annualized mean daily stock returns
- Leverage	(DLTT+DLC)/AT *
- Cash holdings	CHE/AT *
- Stock return volatility	Annualized standard deviation of daily stock returns