ADBI Working Paper Series

TECHNOLOGY SPILLOVERS, ASSET REDEPLOYABILITY, AND CORPORATE FINANCIAL POLICIES

Phuong-Anh Nguyen and
Ambrus Kecskés

No. 1259
April 2021

Asian Development Bank Institute

Phuong-Anh Nguyen is an assistant professor of finance at the School of Administrative Studies of York University. Ambrus Kecskés is an associate professor of finance at the Schulich School of Business of York University.

Suggested citation:

Nguyen, P.-A. and A. Kecskés. 2021. Technology Spillovers, Asset Redeployability, and Corporate Financial Policies. ADBI Working Paper 1259. Tokyo: Asian Development Bank Institute. Available: https://www.adb.org/publications/technology-spillovers-asset-redeployability-corporate-financial-policies

Please contact the authors for information about this paper.

Email: anhvn@yorku.ca, akecskes@schulich.yorku.ca

Asian Development Bank Institute
Kasumigaseki Building, 8th Floor
3-2-5 Kasumigaseki, Chiyoda-ku
Tokyo 100-6008, Japan

Tel: +81-3-3593-5500
Fax: +81-3-3593-5571
URL: www.adbi.org
E-mail: info@adbi.org

Abstract

Prior research shows that technology spillovers across firms increase innovation, productivity, and value. We study how firms finance their own growth stimulated by technology spillovers from their technological peer firms. We find that greater technology spillovers lead to higher leverage. This is the result of technology spillovers increasing asset redeployability, as evidenced by more collateralized borrowing and asset transactions. Borrowing costs also decrease. Exogenous variation in the R&D tax credits of other firms allows us to identify the causal effect of technology spillovers on a given firm.

Keywords: innovation, technology spillovers, research and development, financial policies, capital structure, asset redeployability, cost of debt

JEL Classification: G12, G31, G32, G33, G34, O31, O33

Contents

1. INTRODUCTION

Innovation is perhaps the single most important driver of productivity and hence growth. However, firms do not innovate in isolation but rather within an ecosystem populated by technological peer firms (e.g., Lyandres and Palazzo 2016). Many classic studies demonstrate the importance to a given firm of the technologies of its peer firms, including Arrow (1962), Jaffe (1986), Romer (1990), and Grossman and Helpman (1991). More recently, Bloom, Schankerman, and Van Reenen (2013) ("BSV" hereafter) found that a given firm's innovation, productivity, and value all increase as a result of technology spillovers from other firms.

A number of recent studies provide evidence suggesting that technology spillovers affect corporate investment as well as the assets, both intangible and tangible, that they generate (e.g., Bena and Li 2014; Akcigit, Celik, and Greenwood 2016). Technologies can spill over across firms voluntarily, such as when firms choose to merge, or they can do so involuntarily, for instance when knowledge is transferred through patents, research papers, conferences, social networks, and employees changing firms.[1] Overall, as technologies spill over from one firm to another, they stimulate investment and generate assets for technologically related firms.

Taking as given the previously documented impact of technology spillovers on corporate assets, we study how firms choose the mix of debt and equity that they use in their financing. We hypothesize that technology spillovers to a firm increase the redeployability of its assets, and this ultimately leads the firm to increase its leverage. Our reasoning is as follows. In the standard capital structure framework, a key determinant of corporate leverage is the redeployability of the firm's assets, i.e., their value in alternative use (Williamson 1988; Shleifer and Vishny 1992).[2] Indeed, for innovative firms in particular, low asset redeployability may be one of the most important reasons for which leverage is low. This is because innovative firms tend to have many assets that are firm-specific (before considering technology spillovers) and few that are tangible. The specificity and intangibility of assets gives rise to a variety of frictions that leave potential lenders less willing to extend credit against the security of such assets (Hall 1992a). This is because these frictions increase losses to lenders in the event of bankruptcy.

Within the same standard framework, forces that increase asset redeployability reduce expected losses to lenders and thereby increase lending to firms. Activity in the same product market space as the firm is perhaps the most widely known of such forces for greater asset redeployability (e.g., Shleifer and Vishny 1992). Other firms in the same product market as a given firm may be willing to buy the firm's assets to bulk up on their own similar assets, to round out their own dissimilar assets, as a scale or scope deterrent to their competitors, or to otherwise expand their investment opportunities and output capabilities.

The foregoing logic and illustration also apply to activity in the technology space: firms with similar technologies may be willing to buy assets from each other. To the extent that the assets of a given firm incorporate technologies from other firms, i.e., technologies actually spill over across firms, the assets of the firm in question are of

[1] We discuss lasers and microprocessors, two popular illustrations of technology spillovers, in Appendix 1.

[2] Also see additional seminal papers in this area by Harris and Raviv (1990), Aghion and Bolton (1992), Hart and Moore (1994), and Bolton and Scharfstein (1996).

some use to the other firms, and these assets create value for those firms.[3] Therefore, other firms may be more willing to buy the firm's assets, which makes these assets more redeployable.[4] Thus, activity in the same technology space is another force for greater asset redeployability. It is worth stressing that the firm's assets generated by technology spillovers may be either intangible or tangible.[5] Similarly, what may change is not necessarily how much the firm invests but possibly only the extent to which its investment is stimulated by the technologies of other firms.[6]

Overall, within the standard framework, technology spillovers decrease the specificity of the firm's assets and increase their usefulness and value to other firms. Therefore, technology spillovers increase the redeployability of the firm's assets, both tangible and intangible, which leads to smaller losses to the firm's creditors in the event of bankruptcy. The firm's debt capacity rises, its borrowing costs fall, the firm borrows more, and in so doing it increases its leverage.

To test these predictions, we would ideally like to examine the details of the financing decisions corresponding to all assets resulting from technology spillovers that actually happened. However, no such data exist, not least because spillovers generate a wide variety of assets, many of which cannot be measured, but also because *actual* spillovers are almost impossible to measure. Nevertheless, we can take advantage of recent developments in the literature to measure *potential* technology spillovers.

Specifically, we study the effect of technology spillovers on corporate financial policies using a sample of 694 innovative publicly traded firms during the period 1981–2001. Following BSV, we capture potential technology spillovers to a firm (referred to hereafter without the "potential" qualifier) by taking into account both the extent of its technological similarity to other firms and the stock of knowledge of other firms. 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 of two firms. The technological proximity of two firms is measured as the distance between the technology activities of the firms in the same technology space or similar technology spaces. Technology activities and spaces are captured by patents and patent classes, respectively. Since the literature shows that our measure of technology spillovers results in higher corporate innovation, productivity, and value (BSV), it is reasonable to take as given that our measure captures actual technology spillovers. Moreover, our measure enables us to examine the direct effect of spillovers using a reduced-form approach.

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, as in BSV. We identify the effect of technology spillovers on financial policies using exogenous variation in federal and

[3] These other firms are not only those that were the initial source of technology spillovers to a given firm. For example, peer firm B may be the initial source of spillovers to firm A, but the resulting assets of firm A that incorporate technologies from firm B may in fact be useful to another peer firm C.

[4] As we discuss in Section 4.2, there is evidence in recent studies that is consistent with spillovers in technology space improving asset redeployability and facilitating borrowing.

[5] Such intangible assets can include patents, formulas, designs, business methods, trade secrets, etc. Tangible assets can include laboratory equipment, research facilities, communications hardware, machinery, factories, etc.

[6] Technology spillovers can affect the properties and value of the firm's assets without necessarily affecting how much it invests in R&D or PP&E. The firm's R&D spending could even fall as a result of technology spillovers if it is a substitute for the R&D of its technological peer firms. Of course, if the two are complements, then the firm's R&D spending will rise. As an empirical matter, BSV find that, for the average firm, the R&D of the firm's technological peer firms has no effect on its own R&D. The foregoing argument also applies to capital expenditures.

state R&D tax credits. For each firm-year, we project R&D stock on R&D tax credits, we calculate technology spillovers using the projected R&D stock, and we use this projected measure in our main regressions.

In addition, in our main regressions, we always account for product market spillovers to ensure that we separate the negative effect of the knowledge stock of product market competitors from the positive effect of the knowledge stock of technological peer firms. We also control for the variation attributable to the firm's *own* R&D stock and its *own* R&D tax credits. Additionally, both technology spillovers and financial policies may be persistent over time within firms, and they may vary together within a given industry at a given point in time. Accordingly, we include firm fixed effects as well as industry-year fixed effects in our regressions. We therefore identify entirely off the time-series variation in technology spillovers within firms, after eliminating the variation common to firms within a given industry in a given year.

Turning to our results, we find that technology spillovers have a significant effect on financial policies. Leverage increases by 6 percentage points (or by about 0.4 standard deviations) in response to a one-standard deviation increase in technology spillovers. Firms issue more debt and less equity. In contrast to the well-known negative relationship between leverage and a firm's own R&D, which we also find, the R&D of its technological peer firms increases its own leverage. This is the case even though we control for the firm's own R&D. We also find a stronger effect of technology spillovers on leverage for firms with a higher credit rating. This is consistent with the notion that firms with greater access to the debt market can better exploit the collateralizability of their assets to use relatively cheap debt financing instead of equity.

We then consider the asset redeployability channel through which technology spillovers can affect financial policies. To this end, we examine two direct consequences of technology spillovers increasing the productivity and value of the firm's assets in alternative use: greater collateralization of, and market liquidity for, the firm's assets. These are consequences of greater asset redeployability because the more productive and valuable the firm's assets are to its technological peer firms, the more likely these assets are to be traded among firms and at a higher price. Potential lenders, in turn, should be more willing to accept these assets as collateral because, in the event of bankruptcy, the firm's creditors should be able to increase their recovery rate by selling these assets.[7] Therefore, we should observe more asset collateralization and greater asset liquidity resulting from technology spillovers.

The results of our tests confirm our predictions. We find that technology spillovers significantly increase the firm's borrowing that is collateralized by all of its assets in general as well as a specific subset of its 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.

Greater asset redeployability also implies lower borrowing costs. We therefore also examine the effect of technology spillovers on bond and loan spreads. We find that for a one-standard deviation increase in technology spillovers, spreads on bonds and bank loans decrease, respectively, by roughly 6 and 9 basis points (or about 7%–8% of a standard deviation). These results persist for several years, indicating a long-term impact of technology spillovers on the cost of debt.

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7 Indeed, redeployability of assets is often conceptualized and implemented in the literature as salability (e.g., Benmelech 2009) or liquidity (e.g., Gavazza 2011).

We also consider alternative interpretations of our results. We demonstrate that our collective results cannot be explained by an increase in future profitability, partly by showing empirically that the effect of technology spillovers on leverage is unaffected by whether we control for realized or expected future profitability. We also demonstrate that our results are inconsistent with theories of capital structure where the use of debt is motivated by managerial agency problems, information asymmetry, or cash flow risk.

Our study provides the first empirical evidence that technology spillovers have a significant impact on capital structure. The literature documents that technology spillovers have large private and social benefits (e.g., Jaffe 1986 and BSV). We document the financing mix chosen by firms for the assets that result from technology spillovers. In so doing, we complement the young but growing literature on the effect of technology spillovers on the real activities of firms. For example, Akcigit and Kerr (2018) study corporate innovation strategies; Akcigit, Celik, and Greenwood (2016) study technology transfers; Rosenkopf and Almeida (2003) study human capital investment; Maksimovic and Phillips (2001) study tangible asset sales; Li, Qiu, and Wang (2019) study strategic alliances; and Phillips and Zhdanov (2013) and Bena and Li (2014) study mergers and acquisitions.

Our study also improves our understanding of financial decision-making in innovative firms in particular. The financing of technology assets presents unique challenges (Hall 1992a; Himmelberg and Petersen 1994). However, the existing literature does not distinguish between assets generated by technological peer firms rather than the firm itself (e.g., Kortum and Lerner 2000; Thakor and Lo 2019). Our study does draw this distinction.

Finally, we contribute to the emerging literature on peer effects and corporate policies (e.g., Foucault and Frésard 2014). A few prior studies focus on financial policies as the outcome of interest, examining peer effects among customers and suppliers (Kale and Shahrur 2007) and product market competitors (MacKay and Phillips 2005; Leary and Roberts 2014). Instead, we study firms that are mutual technological peers.

2. METHODOLOGY AND IDENTIFICATION

2.1 Measuring Technology Spillovers

We begin by explaining the construction of the Jaffe (1986) measure of technology spillovers.[8] This measure restricts technology spillovers to the same technology space. First, the Jaffe measure of the technological proximity of two firms is constructed as follows. Each of the patents of a given firm is allocated by the USPTO to one or more technology class out of 426 possible classes. A firm's technology activity is then characterized by a vector $T_i=(T_{i1},T_{i2},\ldots,T_{i426})$, where $T_{i\tau}$ is the average share of the patents of firm *i* in technology class τ over the period 1970–1999.[9] The Jaffe proximity of firm *i* and firm *j* is then defined as the uncentered correlation between the two firms' technology activities:

[8] The methodology and identification, as well as the data and sample of the present paper, are closely related to those of BSV. The present paper also has an empirical framework in common with Nguyen and Kecskés (2020), but it focuses on different corporate consequences of technology spillovers, and it is written to be fully self-contained.

[9] 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 proximity measures. The data on patents allocated to 426 technology classes are understandably sparse for most firms in any given year, so it is common in the literature to use all available data. We follow this approach as well.

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

The Jaffe proximity measure ranges from zero to one. The higher 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 BSV and much of the literature, we set $\delta = 0.15$. Similarly, for the first year in which observe a firm, we set $G_0 = R_0/(\delta–g)$, where g = 0.05. This capitalizes the first R&D expenditure, which is then depreciated every year thereafter at the rate of δ.

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

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

Next, we explain the construction of the Mahalanobis measure of technology spillovers from BSV, which generalizes the Jaffe measure to allow technology spillovers across different technology spaces. The measure of the technological proximity of two firms now takes as an input a measure of the proximity of technology spaces. The literature captures the proximity of technology classes using the observed colocation of the technology classes within firms. The rationale is that technology classes that tend to colocate within firms are the result of related technologies, 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 (as for 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 $(\tau,\zeta)^{th}$ element equals $\Omega_{\tau\zeta}$. This matrix captures the proximity of technology classes.

The measure of the technological proximity of 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 the technological proximity of 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 the technological proximity of two firms.

The R&D stocks of all other firms are then calculated exactly as 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*:

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

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 opposing spillover effects on the firm itself: 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 of 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* equal 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. To briefly describe the construction of the Jaffe measure, the sales of a given firm are allocated to one or more industry segments using data from 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, the R&D stocks of all other firms, and the product market spillover measure are all calculated as before.

2.3 Identification Strategy

We use variation in federal and state R&D tax credits to identify the causal effects of technology spillovers on financial policies. There is a large body of accumulated evidence on the suitability of R&D tax credits for identification in our setting, which can be summarized as follows: changes in R&D tax credits do affect corporate policies, they are plausibly exogenous to corporate policies, and they vary across firms. We now describe the evidence in greater detail. First, a substantial literature shows that R&D tax credits stimulate large increases in R&D spending, both in the US and internationally (Hall 1992b; Berger 1993; Hines 1993; Bloom, Griffith, and Van Reenen 2002). Their relevance to corporate investment is therefore well established.

Second, the exogeneity of these tax policies to corporate policies is also 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. Other studies perform similar analyses and come to the same conclusion (Cummins, Hassett, and Hubbard 1994; Chirinko and Wilson 2017; Moretti and Wilson 2017; Hombert and Matray 2018; Babina and Howell 2019). Indeed, since R&D tax credits have a relatively modest impact on government finances, it is unlikely that changes in these tax policies are caused by widely anticipated changes in corporate policies. 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, even those determined 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 a 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 the amount also depends on 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 hubs. Since firms can have R&D hubs in different states, their state R&D tax credits also vary across states.

We refer to spillover measures constructed in Section 2.1 as "raw" to distinguish them from "orthogonalized" spillover measures. These orthogonalized 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 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. The results are as in Column 3 of Table A.I. in Appendix B of BSV. 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 orthogonalized 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. BSV provide additional details, in Section B.3 of Appendix B, as do Wilson (2009) and Falato and Sim (2014). It is worth stressing 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.

2.4 Main Regression Specifications

Our regression specifications take the following general form:

$$Outcome_{i,j,t+1} = \alpha \cdot Tech\_Spill_{i,t} + \beta \cdot X_{i,t} + \gamma_i + \gamma_{j,t} + \varepsilon \quad (1)$$

where i indexes firms, j indexes industries, and t indexes years. $X_{i,t}$ is a vector of firm-level control variables, γ_i is a firm fixed effect, and $\delta_{j,t}$ is an industry-year fixed effect. Throughout our empirical analysis, we use four regression specifications for all our outcomes of interest. In the first two specifications, we capture spillovers with the raw and orthogonalized Jaffe spillover measures for both technology and product market spaces. In the last two specifications, we capture spillovers with the raw and orthogonalized 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. We always include technology spillovers, and we always control for product market spillovers and the firm's own R&D.[10] In specifications using orthogonalized spillover measures, we also control for the firm's own federal and state tax credits. Among other control variables, we include firm age to capture possible life cycle effects associated with technology and product market spillovers. All variables are defined in Appendix Table 1.

Additionally, in all firm-year regressions, we always include firm fixed effects and industry-year fixed effects. We thus identify entirely off the time-series variation of technology spillovers within firms across time, and within a given industry in a given year across firms. In all firm-deal regressions (e.g., for the cost of debt), we control for industry and year fixed effects because at the firm-deal level many firms appear only once.

Finally, we cluster standard errors by industry-year. 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 and Data Sources

We begin constructing our sample with all publicly traded US firms in CRSP and Compustat. We keep US 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 and product market spillovers. As a result, our sample is restricted to firms that had been issued at least one patent since 1963. Even so, our sample firms account for much of the R&D expenditures in the US: 62% in 1995, for example (BSV). Our final sample comprises 12,118 firm-year observations corresponding to 694 unique firms between 1981 and 2001.[11]

We obtain data on raw and orthogonalized technology and product market spillover measures from Nick Bloom (see BSV). We obtain patent data from the USPTO patent assignment database and from Noah Stoffman (see Kogan et al. 2017). Our stock trading data are from CRSP, and our accounting data are from Compustat. We obtain data on mergers and acquisitions from SDC. We also obtain bond issues data from SDC and bank loans data from Dealscan (the latter data start in 1987). We winsorize all continuous variables at the 1st and 99th percentiles.

[10] BSV find that technology spillovers do not reliably affect the firm's own R&D spending, but they do increase its innovation output. 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.

[11] We end our sample in 2001 due to data limitations. First and foremost, the NBER patent database becomes sparsely populated by the mid-2000s, and it ends completely in 2006. Patents are not included based on filing dates but based instead on grant dates. The NBER patent database becomes sparse by the mid-2000s because many of the patents filed in the early 2000s were not granted by 2006. We therefore end our sample in 2001 to ensure that we have accurate patent data with which to calculate technological proximity and hence technology spillovers. Second, some of our analyses require data for up to five years into the future. This requirement also limits our ability to extend our sample period. Nevertheless, we do have a large sample of innovative firms spanning more than two decades.

3.2 Descriptive Statistics

In Table 1, we present descriptive statistics for our sample. We start with technology spillovers. Since they are typically large in dollar value and right skewed, we use them in logarithmic form throughout the paper. However, we interpret them here in level form (not tabulated), which is more natural than interpreting them in logarithmic form. For the raw Jaffe measure, the value of technology spillovers is roughly $25 billion for the average firm (median of $20 billion), with a standard deviation of about $20 billion. These figures are close to the corresponding figures in BSV (Table II). Turning to our other three measures, the orthogonalized Jaffe measure is comparable in magnitude to the raw Jaffe measure, and the two Mahalanobis measures are roughly five times larger. The two Jaffe measures are naturally smaller than the two Mahalanobis measures since technology spillovers in the former are defined over a more restricted technology space than in the latter.

Table 1: Descriptive Statistics

	Mean	Standard Deviation	25th Percentile	Median	75th Percentile
Technology spillover variables					
• Raw Jaffe	9.7	1.1	9.2	9.9	10.4
• Orthogonalized Jaffe	9.6	1.0	9.1	9.8	10.3
• Raw Mahalanobis	11.3	0.9	10.8	11.4	11.9
• Orthogonalized Mahalanobis	11.3	0.8	10.8	11.4	11.8
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 (years)	24.6	18.1	11.7	20.1	31.5
• Total assets ($ millions)	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
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
Cost of debt 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

Note: 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 US 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.

Next, we turn to general firm characteristics. Given the manner in which we construct our sample, 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 a mean and median age of 25 and 20 years, respectively. Given their size and age, our firms are predictably profitable as reflected by their 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 (Baumol 2002).

Overall, while our firms are larger, older, more profitable, and more innovative than the typical publicly traded firm, they are comparable in terms of their leverage. In particular, their leverage averages out to 22% of total assets (median of 21%) compared to 24% (median of 22%) in Leary and Roberts (2014). Our firms are also 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 smaller firms and covers a somewhat later time period.

Table 2: Descriptive Statistics by Industry Sorted by Technology Spillovers

Industry	Obs.	Mean of Raw Jaffe Technology Spillovers	Standard Deviation of Raw Jaffe Technology Spillovers	Mean of Raw Jaffe Product Market Spillovers	Mean of R&D	Mean of Leverage
Communications (SIC=48)	61	10.50	1.09	9.42	56.8	23.7
Transportation equipment (SIC=37)	727	10.30	0.74	8.25	31.0	23.4
Chemicals and related products (SIC=28)	1,226	10.24	0.57	8.54	52.8	20.8
Electronic equipment excl. computers (SIC=36)	1,876	10.11	0.74	8.53	70.4	18.7
Construction products (SIC=32)	258	10.04	0.69	6.02	16.4	28.5
Consumer and business instruments (SIC=38)	1,086	9.98	0.69	8.15	101.4	17.1
Business services incl. technology (SIC=73)	166	9.94	0.78	7.73	74.9	16.1
Machinery and equipment incl. computers (SIC=35)	1,806	9.88	0.86	7.89	76.4	20.2
Paper and related products (SIC=26)	425	9.85	0.94	7.13	16.0	26.5
Rubber and plastic products (SIC=30)	261	9.79	1.01	7.74	25.1	18.9
Metal mining (SIC=10)	52	9.70	0.46	4.52	0.8	24.3
Primary metal industries (SIC=33)	392	9.59	0.86	6.47	9.7	22.3
Wood products excl. furniture (SIC=24)	84	9.56	0.83	4.77	0.0	31.9
Fabricated metal products (SIC=34)	735	9.42	0.97	6.74	17.4	20.7
Petroleum refining and related industries (SIC=29)	183	9.40	1.52	8.81	4.7	26.1

continued on next page

Table 2 *continued*

Industry	Obs.	Mean of Raw Jaffe Technology Spillovers	Standard Deviation of Raw Jaffe Technology Spillovers	Mean of Raw Jaffe Product Market Spillovers	Mean of R&D	Mean of Leverage
Textile mill products (SIC=22)	185	9.34	1.12	4.06	9.5	27.7
Oil and gas extraction (SIC=13)	196	9.29	1.28	7.48	6.4	32.5
Wholesale durable goods (SIC=50)	216	9.16	1.03	7.66	20.2	24.4
Food and related products (SIC=20)	517	9.14	0.96	5.69	4.8	21.7
Printing, publishing, and related industries (SIC=27)	280	8.97	1.16	6.69	3.7	18.7
Furniture and fixtures (SIC=25)	236	8.94	1.07	4.50	15.6	20.5
Miscellaneous manufacturing industries (SIC=39)	318	8.54	1.36	7.11	12.3	21.3
Wholesale nondurable goods (SIC=51)	69	8.34	1.53	3.91	11.8	24.7
Apparel and related products (SIC=23)	224	8.27	1.29	1.64	0.7	23.2
Leather and related products (SIC=31)	122	7.05	1.41	0.96	16.5	19.5

Note: 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 US operating firms excluding financials and utilities. Only industries with at least five unique firms are included (97% of the sample). Industries are sorted and tabulated in descending order of mean raw Jaffe technology spillovers. All variables are defined in Appendix Table 1. R&D and leverage are multiplied by 100.

In Table 2, we present descriptive statistics by industry. More precisely, we group firms by their primary industries, and then we 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). Conversely, 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.

Furthermore, there is a positive correlation between technology spillovers and product market spillovers. This demonstrates the importance of controlling for product market spillovers. Finally, there is significant intra-industry variation in technology spillovers compared to their 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).

4. RESULTS

4.1 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; Leary and Roberts 2014). In addition to the features common to all of our regression specifications (Section 2.4), we control for sales, market-to-book of assets, cash flow, asset tangibility, and cash flow volatility.

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 used compared to equity increases by approximately 6 percentage points as a proportion of total assets. By way of comparison, the average firm has leverage of 22% (21% for the median firm) (Table 1).

Returning to our results in Table 3, 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. (though one of our coefficient estimates is admittedly statistically insignificant at the 10% level, albeit only marginally). In Panel C, equity issuance decreases by about 2 p.p. These results on debt and equity issuance are consistent with our leverage results, and they suggest that technology spillovers lead firms to adjust their leverage through their securities issuance decisions.

In contrast to technology spillovers, product market spillovers do not reliably 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. as a proportion of 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; Frank and Goyal 2009). The relative strength of our leverage results for technology spillovers compared to the firm's own R&D is an artifact of our rigorous regression specifications, but it is also consistent with the notion that technology spillovers can have a stronger and positive effect on asset redeployability (and hence leverage) compared to a weaker and negative effect for R&D.[12,13]

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[12] Instead of using product market spillovers constructed using SIC codes and sales weights, we also use as an alternative the Hoberg-Phillips product similarity measure (Hoberg and Phillips 2010, 2016). We construct product market spillovers as before with the exception of using as weights the pairwise similarity scores between two firms before multiplying by R&D stock and aggregating across firms. Although data availability does cause the sample size to shrink, our principal inferences are unchanged (see Internet Appendix).

[13] We also examine the possibility that our results may capture asset redeployability in product market space rather than just in technology space. We use a recently developed measure constructed for this purpose from Kim and Kung (2017) and include it as a control variable in our regressions. The sample size shrinks due to data availability, but our main inferences remain the same (see Internet Appendix).

Table 3: The Effect of Technology Spillovers on Capital Structure

Panel A: Leverage

	Dependent Variable is Leverage (t)			
	Raw Jaffe	**Orthogonalized Jaffe**	**Raw Mahalanobis**	**Orthogonalized Mahalanobis**
Technology spillovers (t-1)	6.52***	5.82**	6.46***	6.97***
	(3.12)	(2.28)	(3.41)	(3.14)
Product market spillovers (t-1)	1.07	4.59**	–0.20	5.13**
	(1.17)	(2.39)	(–0.17)	(2.09)
R&D (t-1)	–2.21***	–2.19***	–2.17***	–2.19***
	(–6.33)	(–6.37)	(–6.23)	(–6.39)
Control variables?	Yes	Yes	Yes	Yes
Firm fixed effects?	Yes	Yes	Yes	Yes
Industry-year fixed effects?	Yes	Yes	Yes	Yes
Observations	11,682	11,682	11,682	11,682
Adjusted R^2	0.607	0.608	0.607	0.608

Panel B: Debt Issuance

	Dependent variable is debt issuance (t)			
	Raw Jaffe	**Orthogonalized Jaffe**	**Raw Mahalanobis**	**Orthogonalized Mahalanobis**
Technology spillovers (t-1)	3.47**	3.85*	3.34**	2.77
	(2.22)	(1.86)	(2.14)	(1.56)
Product market spillovers (t-1)	0.61	1.93	–1.02	1.72
	(0.86)	(1.62)	(–1.03)	(0.94)
R&D (t-1)	–0.41*	–0.40*	–0.37	–0.37
	(–1.79)	(–1.73)	(–1.62)	(–1.61)
Control variables?	Yes	Yes	Yes	Yes
Firm fixed effects?	Yes	Yes	Yes	Yes
Industry-year fixed effects?	Yes	Yes	Yes	Yes
Observations	11,654	11,654	11,654	11,654
Adjusted R^2	0.233	0.233	0.233	0.233

Panel C: Equity Issuance

	Dependent variable is equity issuance (t)			
	Raw Jaffe	**Orthogonalized Jaffe**	**Raw Mahalanobis**	**Orthogonalized Mahalanobis**
Technology spillovers (t-1)	–1.81***	–2.47***	–1.98***	–1.63*
	(–2.60)	(–2.70)	(–2.66)	(–1.95)
Product market spillovers (t-1)	0.23	0.65	–0.24	–0.55
	(0.90)	(1.07)	(–0.59)	(–0.65)
R&D (t-1)	0.29*	0.29*	0.30*	0.28*
	(1.92)	(1.90)	(1.96)	(1.85)
Control variables?	Yes	Yes	Yes	Yes
Firm fixed effects?	Yes	Yes	Yes	Yes
Industry-year fixed effects?	Yes	Yes	Yes	Yes
Observations	11,654	11,654	11,654	11,654
Adjusted R^2	0.186	0.186	0.186	0.186

Note: 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 US 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 orthogonalized Jaffe and Mahalanobis measures. The independent variables are as follows: technology and product market spillovers; R&D; federal and state tax credits, but only in specifications using orthogonalized 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. Standard errors are clustered by industry-year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Only selected results are tabulated.

Table 4: The Effect of Technology Spillovers on Capital Structure: The Moderating Role of Debt Market Access

Panel A: Credit Rating of Long-Term Debt Only

	Dependent Variable is Leverage (t)			
	Raw Jaffe	**Orthogonalized Jaffe**	**Raw Mahalanobis**	**Orthogonalized Mahalanobis**
Technology spillovers (t-1)	12.85***	11.40***	16.35***	13.51***
	(5.08)	(3.49)	(7.00)	(4.77)
Tech. spill. (t-1) × Dummy variable (t-1)	-0.14	-0.04	-0.13	-0.24
for credit rating is noninvestment grade	(-0.14)	(-0.04)	(-0.12)	(-0.22)
Tech. spill. (t-1) × Dummy variable (t-1)	0.07	-0.28	-0.06	-0.23
for credit rating is BBB	(0.08)	(-0.30)	(-0.06)	(-0.23)
Tech. spill. (t-1) × Dummy variable (t-1)	2.50**	2.77***	3.15***	3.17***
for credit rating is A	(2.30)	(2.63)	(2.88)	(2.77)
Tech. spill. (t-1) × Dummy variable (t-1)	3.15	1.99	5.16***	4.18**
for credit rating is AA or AAA	(1.61)	(1.08)	(2.84)	(2.34)
Control variables?	Yes	Yes	Yes	Yes
Firm fixed effects?	Yes	Yes	Yes	Yes
Industry-year fixed effects?	Yes	Yes	Yes	Yes
Observations	9,070	9,070	9,070	9,070
Adjusted R^2	0.676	0.676	0.676	0.677

Panel B: Credit Rating of Both Short-Term and Long-Term Debt

	Dependent Variable is Leverage (t)			
	Raw Jaffe	**Orthogonalized Jaffe**	**Raw Mahalanobis**	**Orthogonalized Mahalanobis**
Technology spillovers (t-1)	12.95***	11.26***	16.38***	13.11***
	(5.19)	(3.51)	(7.15)	(4.66)
Tech. spill. (t-1) × Dummy variable (t-1)	-0.29	-0.09	-0.28	-0.26
for credit rating is noninvestment grade	(-0.28)	(-0.09)	(-0.26)	(-0.24)
Tech. spill. (t-1) × Dummy variable (t-1)	-0.07	-0.14	-0.01	0.08
for credit rating is BBB or A-2 or A-3	(-0.08)	(-0.15)	(-0.01)	(0.09)
Tech. spill. (t-1) × Dummy variable (t-1)	3.79***	3.60***	4.02***	4.01***
for credit rating is A or A-1	(3.12)	(3.00)	(3.24)	(3.17)
Tech. spill. (t-1) × Dummy variable (t-1)	4.52**	3.19*	5.30***	4.50**
for credit rating is AA or AAA or A-1+	(2.32)	(1.67)	(2.84)	(2.45)
Control variables?	Yes	Yes	Yes	Yes
Firm fixed effects?	Yes	Yes	Yes	Yes
Industry-year fixed effects?	Yes	Yes	Yes	Yes
Observations	9,070	9,070	9,070	9,070
Adjusted R^2	0.677	0.677	0.677	0.678

Note: This table presents the results of regressions of leverage on technology spillovers conditional upon the firm's credit rating. The regressions are the same as in Table 3 Panel A but every variable is interacted with each of five credit rating categories. In Panel A, the categories are based on the credit rating of long-term debt only. They are as follows: (1) no credit rating (the base category); (2) credit rating is noninvestment grade; (3) credit rating is BBB; (4) credit rating is A; and (5) credit rating is AA or AAA. In Panel B, the categories are based on the credit rating of both short-term and long-term debt. They are the same for categories (1) and (2) as in Panel A. For each of the other three categories, they are either the same as in Panel A based on long-term debt or they are as follows based on short-term debt: (3) A-2 or A-3; (4) A-1; and (5) A-1+. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Only selected results are tabulated.

We further examine how access to the debt market moderates the impact of technology spillovers on leverage. We measure debt market access using credit ratings. We obtain data on S&P corporate credit ratings from Compustat. We sort the firms in our sample into five categories based on their credit ratings. We principally use the credit rating of long-term debt, but we also use the credit rating of short-term debt as a refinement.

Our five categories based on long-term credit ratings are as follows: no credit rating, which is the base category; noninvestment grade; BBB; A; and AA or AAA. We also use short-term credit ratings, which are available for firms with low credit risk, to refine our measure of debt market access compared to using only long-term credit ratings. The bottom two categories are the same as before. The top three categories are either the same as before based on long-term debt or they are as follows based on short-term debt: A-2 or A-3; A-1; and A-1+.[14] We run the same regressions as in Table 3 Panel A, but we interact every variable with each of the five credit rating categories.

Table 4 presents the results. In both Panel A (long-term credit ratings only) and Panel B (both short-term and long-term credit ratings), the base category indicates that technology spillovers lead to an increase in leverage.[15] Furthermore, in both panels, as credit ratings increase, there is a stronger impact of technology spillovers on leverage. For firms rated A (long-term debt) or A-1 (short-term debt), as a result of a one-standard deviation increase in technology spillovers, the incremental increase in leverage is approximately 3 percentage points as a proportion of total assets. This incremental increase is, on balance, slightly stronger for firms rated AA or AAA (long-term debt) or A-1+ (short-term debt), which is the top category. Overall, the results are consistent with debt market access strengthening the impact technology spillovers on leverage.

4.2 Asset Redeployability

Having established that greater technology spillovers lead to higher leverage, we now consider whether asset redeployability is the channel through which this happens.[16] Assets that are more redeployable are more productive and valuable to firms that are mutual technological peers, so such assets are more likely to be traded and at a higher price among such firms. This increases recovery rates to creditors from selling the firm's assets in the event of bankruptcy, which should increase the willingness of potential lenders to extend credit to the firm. We therefore should see that technology spillovers result in greater asset collateralization and asset liquidity.

[14] About 60% of our sample firms have no long-term credit rating and less than 10% are rated noninvestment grade. About 10% are rated BBB, and there are about twice as many A rated firms as firms that are rated AA or AAA. More than three quarters of our sample firms have no short-term credit rating, and virtually none of them are rated less than A-3. The remaining quarter of our sample firms are A-3 or A-2 (very few are rated A-3), A-1, and A-1+ in roughly equal proportion.

[15] The sample size shrinks and the economic magnitude of the effect is larger than in Table 3, both of which are due to the availability of data on credit ratings.

[16] 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 creditors, may bear significant losses in the event of the firm's bankruptcy (Titman 1984; Maksimovic and Titman 1991). Technology spillovers can decrease these losses by increasing the redeployability of these stakeholders' assets embedded in the firm.

To test these two predictions, we would ideally like to observe the assets specifically generated by technology spillovers being used as collateral for corporate borrowing and being traded among firms. Since such data do not exist, we must instead use close approximations. Our approach is supported by evidence from the literature that technology assets are increasingly important as collateral in corporate borrowing (Loumioti 2012; Mann 2018; Hochberg, Serrano, and Ziedonis 2018), and that technological similarity is associated with greater liquidity of real assets (Bena and Li 2014; Serrano and Ziedonis 2018). For both asset collateralization and asset liquidity, we consider two groups of assets. The broad group captures the entire firm, including all of the firm's technology assets. By contrast, the narrow group only captures a subset of technology assets, namely patents. However, patents are among the most valuable of technology assets, and they are often used as collateral or sold.[17]

We begin our tests with the asset collateralization prediction. We consider both the extent to which the firm's borrowing is collateralized by all of its assets in general and the extent to which the firm's patents are used as collateral for its 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.[18]

In our regression specifications, we follow the empirical literature on capital structure and patent collateralizations (e.g., Leary and Roberts 2014; Mann 2018). In addition to the features common to all of our regression specifications (Section 2.4), we control for sales, market-to-book of assets, cash flow, asset tangibility, cash flow volatility, and other variables as appropriate.[19] Importantly, for regressions with patent flow as an outcome, we control for patent stock to eliminate any mechanical relationship between flows and stocks (e.g., firms that have more patents also tend to collateralize or sell more patents).

[17] For example, 21% of secured syndicated loans during the period 1996–2005 were collateralized by patents (Loumioti 2012). Similarly, 16% of patents issued since 1980 were eventually collateralized (Mann 2018). Among venture capital-backed startups in three selected innovation-intensive industries, 36% of firms founded from 1987 to 1999 received venture debt (Hochberg, Serrano, and Ziedonis 2018). Within the same group of startups but restricted to those that failed between 1988 and 2008, 83% of their patents were sold within one year of failure (Serrano and Ziedonis 2018).

[18] While patent collateralizations and sales would appear to be rare events in absolute terms, they are in fact quite common relative to patent grants per year. For instance, the average firm collateralizes about 1.5 patents per year and sells about 2.1 patents per year (Table 1), which should be compared to an average of roughly 15 patent grants per year (the ratio of the firm's patent stock to its age). On an annual basis, then, the patent collateralization rate is about 10% of the patent grant rate, and the sales rate is about 15% of the grant rate. As a basis of comparison, Mann (2018) documents that 16% of patents were collateralized at some point during their lifetime (as opposed to on an annual basis).

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

Table 5: The Effect of Technology Spillovers on Asset Collateralization

Panel A: Collateralized Debt

	Dependent Variable is Collateralized Debt (t)			
	Raw Jaffe	**Orthogonalized Jaffe**	**Raw Mahalanobis**	**Orthogonalized Mahalanobis**
Technology spillovers (t-1)	2.83***	1.76	2.57***	2.35**
	(3.32)	(1.53)	(2.79)	(2.13)
Product market spillovers (t-1)	–0.15	0.91	–0.30	0.89
	(–0.27)	(0.97)	(–0.36)	(0.62)
R&D (t-1)	–0.92***	–0.90***	–0.90***	–0.90***
	(–5.45)	(–5.41)	(–5.35)	(–5.43)
Control variables?	Yes	Yes	Yes	Yes
Firm fixed effects?	Yes	Yes	Yes	Yes
Industry-year fixed effects?	Yes	Yes	Yes	Yes
Observations	11,682	11,682	11,682	11,682
Adjusted R^2	0.436	0.436	0.436	0.436

Panel B: Patent Collateralizations

	Dependent Variable is ln(Number of Patents Collateralized) (t)			
	Raw Jaffe	**Orthogonalized Jaffe**	**Raw Mahalanobis**	**Orthogonalized Mahalanobis**
Technology spillovers (t-1)	18.98**	27.32***	15.41*	19.66**
	(2.06)	(2.69)	(1.87)	(2.20)
Product market spillovers (t-1)	9.36**	–6.99	16.54***	0.90
	(2.27)	(–0.89)	(2.68)	(0.08)
R&D (t-1)	0.22	0.32	0.18	0.46
	(0.10)	(0.14)	(0.08)	(0.20)
Control variables?	Yes	Yes	Yes	Yes
Firm fixed effects?	Yes	Yes	Yes	Yes
Industry-year fixed effects?	Yes	Yes	Yes	Yes
Observations	11,687	11,687	11,687	11,687
Adjusted R^2	0.204	0.204	0.205	0.204

Note: This table presents the results of regressions of collateralized debt 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 US 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 orthogonalized Jaffe and Mahalanobis measures. 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 orthogonalized 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 includes the natural logarithm of total assets, leverage, asset tangibility, cash flow volatility, and the stock of patents. All variables are defined in Appendix Table 1. In Panel A, the dependent variables are scaled by total assets. In Panel B, the natural logarithm is taken after adding one to the dependent variables. All dependent variables are multiplied by 100. The independent variables are lagged and standardized. Standard errors are clustered by industry-year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Only selected results are tabulated.

Table 5 presents the results. Panel A shows that collateralized borrowing increases by roughly 2–3 percentage points as a proportion of total assets. This amounts to a bit under half the increase in total borrowing resulting from technology spillovers, which is approximately 6 p.p. as a proportion of total assets (Table 3). Indeed, the increase in borrowing (as opposed to its level) stems disproportionately from collateralized borrowing. The unconditional average collateralized borrowing of the firm is 3% of total assets (Table 1), which roughly doubles as a result of technology spillovers. By contrast, the firm's unconditional average uncollateralized borrowing is about 19%–20% (22% minus 2%–3%), which increases by a relatively smaller 3–4 p.p. (6 p.p. minus 2–3 p.p.).

Panel B of Table 5 shows that firms also use a larger number of patents to secure their borrowing. In particular, technology spillovers increase the number of patents used to collateralize debt by roughly 15%–25%. We also take the simpler approach of examining whether a firm collateralizes any patents in a given year (as captured by a dummy variable). In line with the previous results, we find that the rate of patent collateralizations increases, by 5–9 p.p., which compares with its unconditional rate of 6% (see Internet Appendix).

Overall, greater technology spillovers appear to increase the collateralization of debt. However, we wish to understand this increase better. It could be the case that the firm's assets become more redeployable, so lenders are more willing to accept them as collateral. But perhaps the firm's assets become harder to sell, so lenders require more of these assets as collateral.

We therefore proceed to testing the asset liquidity prediction. We examine the sales of patents as well as the sales of entire firms. To capture the sale of specific technology assets, we use 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 acquirer and 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 6 presents the results. Panel A shows that the number of patents sold increases as a result of technology spillovers, very roughly, by 15%. We again take a simpler approach and examine whether a firm in a given year sells any patents (as captured by a dummy variable). The rate of patent sales is higher, by about 4 p.p., which compares with its unconditional rate of 8% (results not tabulated). As a basis of comparison, Serrano and Ziedonis (2018) document that 83% of the patents granted to failed venture capital-backed technology startups were sold within one year of failure.

The next two panels of Table 6 show that technology spillovers also increase mergers and acquisitions activity. While the results vary in economic and statistical significance, Panel B shows that the number of M&As increases by 10%, very roughly. Similarly, Panel C shows that the value of M&As also increases, by approximately 2 p.p. as a proportion of total assets, which compares with its unconditional mean of 2% of total assets. We also confirm that the rate of M&As is higher, by 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.

Table 6: The Effect of Technology Spillovers on Asset Liquidity

Panel A: Patent Sales

	Dependent Variable is ln(Number of Patents Sold) (t)			
	Raw Jaffe	**Orthogonalized Jaffe**	**Raw Mahalanobis**	**Orthogonalized Mahalanobis**
Technology spillovers (t-1)	15.71*	18.74*	12.65*	15.49
	(1.81)	(1.72)	(1.67)	(1.58)
Product market spillovers (t-1)	2.46	–18.73**	5.79	–12.48
	(0.74)	(–2.35)	(0.94)	(–1.27)
R&D (t-1)	–1.98	–1.79	–1.93	–1.69
	(–1.45)	(–1.32)	(–1.40)	(–1.25)
Control variables?	Yes	Yes	Yes	Yes
Firm fixed effects?	Yes	Yes	Yes	Yes
Industry-year fixed effects?	Yes	Yes	Yes	Yes
Observations	11,687	11,687	11,687	11,687
Adjusted R^2	0.343	0.343	0.343	0.343

Panel B: Number of Mergers and Acquisitions

	Dependent Variable is ln(Number of Mergers and Acquisitions) (t)			
	Raw Jaffe	**Orthogonalized Jaffe**	**Raw Mahalanobis**	**Orthogonalized Mahalanobis**
Technology spillovers (t-1)	8.53**	16.86***	7.28**	9.06**
	(2.58)	(3.58)	(2.18)	(2.21)
Product market spillovers (t-1)	2.07	–4.90	3.99	1.86
	(1.17)	(–1.27)	(1.49)	(0.39)
R&D (t-1)	–1.83***	–1.81***	–1.81***	–1.71**
	(–2.67)	(–2.60)	(–2.63)	(–2.48)
Control variables?	Yes	Yes	Yes	Yes
Firm fixed effects?	Yes	Yes	Yes	Yes
Industry-year fixed effects?	Yes	Yes	Yes	Yes
Observations	11,773	11,773	11,773	11,773
Adjusted R^2	0.206	0.206	0.206	0.205

Panel C: Value of Mergers and Acquisitions

	Dependent Variable is Value of Mergers and Acquisitions (t)			
	Raw Jaffe	**Orthogonalized Jaffe**	**Raw Mahalanobis**	**Orthogonalized Mahalanobis**
Technology spillovers (t-1)	1.02	3.66**	2.07*	3.05**
	(0.94)	(2.48)	(1.90)	(2.43)
Product market spillovers (t-1)	0.74	0.56	0.13	1.44
	(1.26)	(0.55)	(0.15)	(0.98)
R&D (t-1)	–0.60**	–0.64**	–0.61**	–0.63**
	(–2.39)	(–2.47)	(–2.41)	(–2.41)
Control variables?	Yes	Yes	Yes	Yes
Firm fixed effects?	Yes	Yes	Yes	Yes
Industry-year fixed effects?	Yes	Yes	Yes	Yes
Observations	11,773	11,773	11,773	11,773
Adjusted R^2	0.083	0.084	0.083	0.084

Note: This table presents the results of regressions of 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 US 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 orthogonalized Jaffe and Mahalanobis measures. 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 orthogonalized 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 total assets, leverage, asset tangibility, cash flow volatility, and the stock of patents; Panel B and Panel C include the natural logarithm of total assets, stock returns, leverage, and cash holdings. All variables are defined in Appendix Table 1. In Panel C, the dependent variables are scaled by total assets. In Panel A and Panel B, 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. Standard errors are clustered by industry-year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Only selected results are tabulated.

Beyond technology spillovers, product market spillovers do not have a reliable effect on either asset collateralization or asset liquidity. By contrast, the firm's own R&D is significantly related to both collateralized borrowing and mergers and acquisitions activity, although it is not significantly related to either patent collateralizations or patent sales. Collateralized borrowing decreases by approximately 1 p.p. as a proportion of total assets. Similarly, the number of M&As decreases by about 2%, and the value of M&A decreases by roughly 0.6 p.p. as a proportion of total assets. Overall, there is some evidence consistent with the notion that the redeployability of a firm's assets is reduced by the firm's own R&D.

4.3 The Cost of Debt

In our final analysis, we examine the cost of debt. Borrowing costs should decrease as a result of greater technology spillovers as long as the beneficial effect of greater asset redeployability is not completely offset by the detrimental effect of higher leverage. 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.[20] In addition to the features common to all of our regression specifications (Section 2.4), we include firm-level control variables: 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 (private versus public / term loan versus credit line).

Table 7 presents the results. Panel A shows that technology spillovers decrease spreads on bond issues by roughly 6 basis points. Panel B shows a similar effect on bank loan spreads, which decrease by about 9 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 bps and 126 bps, respectively (median of 83 bps and 75 bps, respectively) (Table 1). Consequently, the cost of debt falls by about 5%–10% relative to its unconditional mean as a result of technology spillovers. To place these magnitudes in the context of prior work on peer effects, Valta (2012) finds a similar increase in the cost of debt (about 10 bps) for a comparable increase in product market competition. Chang et al. (2020) likewise find a 28 bps increase associated with a comparable magnitude decrease in bankruptcy recovery rates for product market peers. We should note that the decrease in the cost of debt that we find is consistent with the firm's assets becoming more redeployable and hence more valuable to its creditors.

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 bank 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 the firm's own R&D is viewed unfavorably by both bondholders and bank lenders in determining the firm's borrowing costs.

[20] For bond issues, see Ortiz-Molina (2006), Francis et al. (2010), and Qi, Roth, and Wald (2010). For bank loans, see Graham, Li, and Qiu (2008), Chava, Livdan, and Purnandam (2009), and Valta (2012).

Table 7: The Effect of Technology Spillovers on the Cost of Debt

Panel A: Bond Issues				
	Dependent Variable is Spread (t)			
	Raw Jaffe	**Orthogonalized Jaffe**	**Raw Mahalanobis**	**Orthogonalized 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)	(2.18)	(2.44)
Control variables?	Yes	Yes	Yes	Yes
Industry fixed effects?	Yes	Yes	Yes	Yes
Year fixed effects?	Yes	Yes	Yes	Yes
Observations	2,205	2,205	2,205	2,205
Adjusted R^2	0.557	0.558	0.558	0.558
Panel B: Bank Loans				
	Dependent Variable is Spread (t)			
	Raw Jaffe	**Orthogonalized Jaffe**	**Raw Mahalanobis**	**Orthogonalized 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)	(3.00)
Control variables?	Yes	Yes	Yes	Yes
Industry fixed effects?	Yes	Yes	Yes	Yes
Year fixed effects?	Yes	Yes	Yes	Yes
Observations	2,724	2,724	2,724	2,724
Adjusted R^2	0.558	0.561	0.557	0.560

Note: 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 US 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 orthogonalized Jaffe and Mahalanobis measures. 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 orthogonalized 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 is 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. Standard errors are clustered by industry-year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Only selected results are tabulated.

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, as 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 even accounting for the increase in leverage resulting from greater technology spillovers, which by itself would tend to increase the cost of debt.

5. DISCUSSION OF ALTERNATIVE INTERPRETATIONS

We provide a substantial volume of evidence supporting asset redeployability as the channel through which technology spillovers lead to higher leverage. Nevertheless, we now examine alternative interpretations of the positive effect of technology spillovers on leverage. We show that our results as a whole cannot be explained by these alternative channels.

Under the tradeoff theory of capital structure, one possibility is that an increase in future profitability leads to an increase in leverage today. Higher cash flows translate into a higher tax shield benefit of debt, which firms may exploit by increasing leverage. While related work does show that technology spillovers lead to higher profitability in the long run (over a five-year horizon), profitability in the short run is unchanged (Nguyen and Kecskés 2020). Since a firm needs higher cash flows to be able to make higher interest payments, the increase in the firm's debt (and hence its interest payments) should normally occur roughly around the same time as the increase in its cash flows. Since this is not supported by the extant evidence, a pure future profitability interpretation is problematic.[21] Nevertheless, in Appendix 2, we test the key prediction of the future profitability interpretation, which is that controlling for future profitability should subsume at least some of the effect of technology spillovers on leverage. The results, presented in Appendix Table 2, are also inconsistent with the future profitability interpretation.

A closely related possibility, still under the tradeoff theory, is that technology spillovers may decrease cash flow risk, which leads to lower costs of financial distress, higher debt capacity, and ultimately to higher leverage. In fact, related work suggests that cash flow risk actually increases as a result of the innovation risk that may be associated with technology spillovers (Tseng 2018). This evidence is inconsistent with a cash flow risk interpretation of the effect of technology spillovers on leverage.

Another possibility, under the managerial agency theory of capital structure, is that debt may be used as a managerial disciplinary mechanism. Higher cash flows present greater opportunities for managers to invest in projects that enrich themselves at the expense of shareholders. It is in the interests of shareholders to prevent managers from wasting the cash flows stemming from technology spillovers. Therefore, shareholders force managers to issue debt, the interest payments on which will be made using the cash flows from technology spillovers, and to pay out the issuance proceeds to shareholders. In additional empirical analyses, we find that technology spillovers do lead to higher cash holdings (in line with Qiu and Wan 2015) but not to any change in payouts to shareholders (results not tabulated). This evidence is inconsistent with the disciplinary mechanism interpretation.

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[21] To be precise, we do find a decrease in the cost of debt in addition to the increase in leverage. If the former effect dominates the latter, then interest payments will decrease. However, our results show that the decrease in the cost of debt (6–9 bps from Table 7) has a much smaller effect on interest payments than the increase in leverage (6 percentage points from Table 3). To illustrate the overall effect, assume that for the typical firm the cost of debt decreases by as much as 10 basis points, the spread is only 100 basis points, and the yield on a duration-matched government bond is only 3%. In this case, interest payments would decrease by at most 2.5% (= -10 bps ÷ 400 bps). By comparison, for the typical firm with leverage of 20%, a mere 0.5 p.p. increase in leverage (i.e., a 2.5% increase) would be more than sufficient to offset the decrease in the cost of debt and increase interest payments overall. In fact, we find a much larger increase in leverage than required by the foregoing calculations.

A final possibility, under the pecking order theory, is that greater information asymmetry leads to higher leverage. Technology spillovers increase the complexity and uncertainty of value-relevant information about the firm, which makes the firm more difficult to value, especially for outsiders compared to insiders (Nguyen and Kecskés 2020). The resulting increase in information asymmetry can lead to higher leverage, but it requires an increase in the cost of debt and by less than the increase in the cost of equity. Since we find that borrowing costs in fact decrease (Table 7), a pure information asymmetry interpretation cannot explain our results.

6. CONCLUSION

This paper is motivated by prior research showing that technology spillovers across firms increase the innovation, productivity, and value of these firms. Building on this evidence, we first argue that the growth stimulated by technology spillovers to a given firm from its technological peer firms increases the redeployability of the firm's own assets. This increase in asset redeployability leads to smaller losses to the firm's creditors in the event of bankruptcy. The firm's debt capacity thereby increases, the firm borrows more, and its leverage thus increases.

We then take advantage of recent developments in the literature to test our predictions. We implement an empirical framework that allows us to measure technology spillovers, and to identify their causal effect on a given firm based on exogenous variation in the R&D tax credits of other firms. We find that greater technology spillovers lead to higher leverage. This effect is stronger for firms with greater debt market access. Moreover, we also find more collateralized borrowing and asset transactions, and also a decrease in borrowing costs. Taken together, our results are consistent with our argument that technology spillovers increase leverage by increasing asset redeployability. Overall, our paper demonstrates the importance of technology spillovers in explaining corporate financial policies.

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APPENDIX 1: 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 of the firm and other firms. While the R&D of other firms is a straightforward concept, the notion of technological proximities of firms stands to benefit from some examples. We illustrate relationships in technology space with reference to well-known horizontal and vertical relationships in product market space. These examples show that firms that are close in technology space are not necessarily close in 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, the Coca-Cola Co. is close to both the Liqui-Box Corp. and the 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).

Finally, we offer several examples of technology spillovers. The manner in which technologies diffuse throughout the economy, across firms and over time, is instructive. The diffusion process itself shows that the assets generated by technological diffusion are more useful and therefore more valuable to technological peer firms than assets generated by technologies that are specific to a given firm.

In the first famous example, lasers were 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 a wide variety of consumer and business uses. These applications include drives, printers, barcode scanners, lighting displays, medicine and surgery, fiber-optic cables, construction, and 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).

Appendix Table 1: Variable Definitions

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.†
• Orthogonalized Jaffe • Orthogonalized Mahalanobis	Computed like the corresponding raw variables except that the R&D stock of other firms is first orthogonalized 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 orthogonalized R&D stock corresponding to each firm-year.†
Capital structure variables	
• Leverage	(DLTT+DLC)/AT*
• Debt issuance	DLTIS/AT*
• Equity issuance	SSTK/AT*
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 (2018).
• Number of patents sold	Number of patents issued to the firm and subsequently sold. See Serrano (2010) and Akcigit, Celik, and Greenwood (2016).
• 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
Cost of debt variables	
• Bond issue spreads	Bond issue spread related to a duration-matched government bond
• Bank loan spreads	Bank loan spread over the benchmark rate
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-to-book of assets	(AT-(TXDITC+CEQ)+PRCC_F×CSHO)/AT*
• 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*
• Realized future profitability	Mean OIBDP/AT during the next five years*
• Expected future profitability	Analysts' long-term earnings growth rate estimates

Note: 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).

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 dominant. 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 nontechnology businesses (e.g., Amazon). We refer the reader to Rosenberg (1979) for additional examples.

APPENDIX 2: THE FUTURE PROFITABILITY INTERPRETATION OF THE RESULTS

The future profitability interpretation has a key prediction that we test here. Specifically, if future profitability can explain our results, then reasonable proxies for future profitability should at a minimum partially subsume the effect of technology spillovers on leverage, and therefore our main results should become noticeably weaker or disappear.

In our empirical test of this prediction, we capture future profitability using two proxies. First, to capture realized future profitability, we use mean cash flow during the next five years. Second, to capture expected future profitability, we use analysts' long-term earnings growth rate estimates.

The results, which are presented in Appendix Table 2, are economically and statistically significant for our measures of technology spillovers. Moreover, the coefficient estimates on our technology spillover measures are comparable to those in Table 3. This evidence is inconsistent with the future profitability interpretation, which predicts weaker or entirely insignificant estimates on technology spillovers.[1]

Appendix Table 2: Replication of Baseline Capital Structure Results Controlling for Future Profitability

Panel A: Controlling for Realized Future Profitability

	Dependent Variable is Leverage (t)			
	Raw Jaffe	**Orthogonalized Jaffe**	**Raw Mahalanobis**	**Orthogonalized Mahalanobis**
Technology spillovers (t-1)	6.75***	5.83**	6.60***	6.99***
	(3.27)	(2.29)	(3.51)	(3.16)
Product market spillovers (t-1)	1.04	4.55**	–0.20	5.12**
	(1.15)	(2.41)	(–0.16)	(2.11)
R&D (t-1)	–2.24***	–2.21***	–2.19***	–2.21***
	(–6.37)	(–6.38)	(–6.26)	(–6.41)
Control variables?	Yes	Yes	Yes	Yes
Firm fixed effects?	Yes	Yes	Yes	Yes
Industry-year fixed effects?	Yes	Yes	Yes	Yes
Observations	11,681	11,681	11,681	11,681
Adjusted R^2	0.607	0.608	0.607	0.608

Panel B: Controlling for Expected Future Profitability

	Dependent Variable is Leverage (t)			
	Raw Jaffe	**Orthogonalized Jaffe**	**Raw Mahalanobis**	**Orthogonalized Mahalanobis**
Technology spillovers (t-1)	6.02**	10.20**	5.17**	10.17***
	(2.16)	(2.50)	(2.14)	(3.12)
Product market spillovers (t-1)	–1.36	–4.35	–1.63	0.40
	(–0.84)	(–1.24)	(–0.88)	(0.09)
R&D (t-1)	–2.59***	–2.57***	–2.55***	–2.59***
	(–5.85)	(–5.81)	(–5.79)	(–5.88)
Control variables?	Yes	Yes	Yes	Yes
Firm fixed effects?	Yes	Yes	Yes	Yes
Industry-year fixed effects?	Yes	Yes	Yes	Yes
Observations	6,968	6,968	6,968	6,968
Adjusted R^2	0.645	0.647	0.644	0.647

Note: This table presents the results of regressions of leverage on technology spillovers. The regressions are the same as in Table 3 but with slight modifications as indicated. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Only selected results are tabulated.

[1] It is possible that measures of total factor productivity (TFP) are better at capturing the theoretical notion of future profitability than our previous two measures. As a robustness check, we obtain TFP data from Şelale Tüzel (see İmrohoroğlu and Tüzel 2014 for details), and we rerun the regressions in Appendix Table 2 with two modifications. In particular, we use mean TFP during the next five years instead of mean cash flow, and we control for lagged TFP. Our inferences remain unchanged.