Measuring the Private and Social Returns to R&D: Unintended Spillovers versus Technology Markets

Pere Arqué-Castells
University of Groningen

Daniel F. Spulber
Northwestern University

The canonical approach to measuring private and social returns to R&D assumes diffusion through spillovers. We develop a general framework that allows R&D to diffuse through both spillovers and voluntary technology transfers. To operationalize the framework, we create a data set of interactions in the market for technology between publicly held US firms. We use changes in tax incentives for R&D to identify causal effects. Taking market channels into account decreases the observed difference between social and private returns to R&D as compared with the canonical approach. The analysis suggests significant gains from trade in markets for technology.

I. Introduction

The knowledge capital model proposed by Griliches (1979) has long been the dominant approach for estimating the private and social returns to R&D. We thank Chad Syverson and four anonymous referees for helpful and constructive comments. We are grateful to Pol Antràs, Justus Baron, Christian Fons-Rosen, Alberto Galasso, Dietmar Harhoff, Christian Helmers, Hong Luo, Marti Mestieri, Pierre Mohnen, Mikko Packalen, David Perez-Castrillo, Carlos Serrano, and Joel Stieber for helpful comments. We are grateful to Stuart Graham for sharing the US Patent and Trademark Office Patent Data.

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corporate R&D. The knowledge capital model assumes the vertical integration of R&D and production, which describes the organization of innovation in the mid-twentieth century. An important feature of this model is that it implicitly assumes knowledge to be nontradable. An immediate consequence of this assumption is that firms extract value from their R&D activities only by serving downstream product markets. A second implication is that firms benefit from external R&D only through spillovers. Formally, the knowledge capital model is represented by a production function augmented with a measure of in-house R&D and another one augmented with a measure of external R&D that is assumed to be absorbed purely through unintended spillovers. This influential approach has been applied in hundreds of studies that find pervasive spillovers and a large wedge between the social and private returns to R&D (Jaffe 1986; Hall, Mairesse, and Mohnen 2010; Bloom, Schankerman, and Van Reenen 2013).

The current innovation landscape, however, is characterized by vertical separation, active intellectual property (IP) enforcement, and frequent exchange in technology markets (see Arora, Fosfuri, and Gambardella 2001; Spulber 2013, 2015; Arora, Cohen, and Walsh 2016). IP rights and technology markets allow firms to control knowledge flows strategically, minimizing the role of unintended externalities (Cassiman and Veugelers 2002). In particular, technology markets serve a dual role that must be taken into account when measuring the returns to R&D. First, technology markets provide a secondary revenue opportunity that allows firms to monetize their R&D efforts by selling knowledge directly to other firms. For instance, International Business Machines (IBM) obtained almost $1.2 billion in royalty payments in 2017. Second, technology markets give firms access to a potentially large pool of technologies, including patents and know-how that might be critical to the successful utilization of external inventions.

Understanding the precise channels through which knowledge is transmitted is necessary to inform sound innovation policies. If spillovers...
dominate technology transfers, then public policy makers should pursue increased enforcement of IP and consider R&D subsidies and tax credits to align private investments with the social optimum. Alternatively, if technology transfers dominate spillovers, oversubsidizing R&D could be harmful, as it would reinforce superstar trends (Autor et al. 2020) in firms that are already capable of internalizing the multilateral effects of their research. If technology transfers dominate spillovers, public policies should maintain enforcement of IP and help facilitate technology transfers.

The contribution of this paper is to develop and estimate a new framework that generalizes the canonical knowledge capital framework by including technology markets. Our augmented framework allows firms to benefit from external R&D through both involuntary spillovers and voluntary technology transfers. To operationalize the general framework, we create a new data set of interactions in the market for technology between publicly listed firms in the United States that draws on a combination of US Securities and Exchange Commission (SEC)–mandated material disclosures and voluntary disclosures to the US Patent and Trademark Office (USPTO). The data set is also an important contribution of the paper. It offers a broad coverage over time and across sectors, technologies, and contractual forms of exchange (i.e., patent transfers, licensing, cross-licensing, and R&D alliances). This new data set reveals that central actors in the market for technology are a very important source of knowledge creation and diffusion, with the top 2% of technology providers accounting for more than 70% of total R&D investments in Compustat. This empirical fact emphasizes the importance of accounting for the heterogeneous structure of the technology supply chain and confirms the convenience of accounting for firms’ ability to internalize the effects of their research.

To study how technology markets change incentives to invest in R&D, we develop a basic model that examines voluntary and involuntary technology transfers between a technology provider and a technology adopter. We derive optimal R&D investment decisions by the two firms as well as the voluntary technology transfer decision. This allows us to obtain analytical expressions for private and social rates of return to R&D under the general framework and study how these change depending on whether there is a voluntary transfer.

The model reveals that ignoring technology markets when measuring the returns to R&D generates two problems. The first problem arises from the misspecification of the analytical expressions used to calculate the private and social returns. When there is a voluntary technology transfer, the canonical model underestimates the private returns to R&D because it relies on expressions that ignore technology market revenue. Assuming that the spillover estimates obtained in previous studies are reliable, the canonical framework also underestimates the social returns to R&D (and the wedge between the social and private returns) because it ignores effects
diffusing through voluntary transfers that can be only partially internalized by the provider. The second problem concerns the reliability of the spillover elasticities estimated from production functions that ignore voluntary technology transfers. Our model indicates that the weights used to capture spillovers are positively correlated with voluntary technology transfer decisions. Therefore, spillover elasticities obtained from traditional specifications without technology markets are likely to be upward biased because of an omitted variable bias. The wedge between the social and private rates of return reported in earlier studies might be artificially inflated if the spillover elasticity conflates compensated transfers. Ultimately, whether the canonical model overstates or understates the wedge between the social and private returns is an empirical matter.

The empirical implementation involves two steps. In a first stage, for a panel of publicly traded US firms over the period 1990–2014, we estimate a product market revenue equation augmented with the conventional spillover pool and a newly constructed market-for-technology pool. The main goal is to estimate (for the first time in the literature) the elasticity of the market-for-technology pool. A second goal is to explore whether the spillover elasticity remains unchanged after controlling for technology transfers. The spillover pool is defined in a standard fashion as the sum of external R&D stocks weighted by technological proximity. The market-for-technology pool is defined analogously as the sum of R&D stocks by upstream providers in the market for technology.

Following the tradition in the spillovers literature, we work with time-invariant weights. This implies that we exploit only cross-sectional variation between firm dyads to tease out spillovers and technology transfers. The main reason for keeping the market-for-technology weight fixed is that we are particularly interested in studying whether the spillover weights are a catch-all measure that also picks up internalized transfers. This essentially involves studying whether the cross-sectional proximity links used to define the spillover pool correlate with the cross-sectional variation in the market-for-technology network. We define a market-for-technology weight that captures the extensive and intensive margins of connections between adopters and providers up to network distance four. The weight is modular and can be decoupled into subweights covering information up to distance one, two, and three. We construct market-for-technology pools based on all of these weights to study how the estimates change as we exploit an increasing amount of information from the network.

In a second instance, we use first-stage estimates along with the structure of interactions to calculate the private and social rates of return to R&D using the expressions for the general framework. An important challenge when measuring the private returns is that we must be able to assess the effects of own R&D not only on product market revenue but also on technology market revenue. The latter is not observed from financial
statements but can be approximated as a proportion of the gains from trade that a given provider generates through voluntary technology transfers. We calculate the gains from trade as the loss in product market revenue that an adopter would suffer if it was not connected to the provider. A proportion of this additional revenue is captured by the provider. This approach is convenient because it allows us to estimate unobserved technology market revenue purely from the effects of the provider’s R&D on the adopter’s product market revenue.

Identification of the elasticities of interest is achieved through within-firm variation in the spillover and market-for-technology pools, which are potentially correlated with the error term through two main channels. The first is the correlation between the error term and the weighting matrices (i.e., technological proximity matrix and market-for-technology network). The second is the possible correlation between the error term and external R&D stocks included in the pools. The first problem should not be severe in our case because we work with fixed weighting matrices and so the cross-sectional information of the structure of connections of a given adopter is absorbed by the firm fixed effect. The second issue is more problematic because all the within-firm variation in the pools is driven entirely by changes over time in the external R&D stocks. To deal with the possible endogeneity of external R&D investments, we follow the identification strategy in Bloom, Schankerman, and Van Reenen (2013). That is, we exploit supply-side shocks from tax-induced changes to the user cost of R&D capital to construct instruments for external R&D.

We apply the original instrumental variables (IV) strategy in Bloom, Schankerman, and Van Reenen (2013) and two corrections to mitigate concerns around potential endogenous variation in the instrument owing to aggregation across providers. The original IV strategy relies on a “double projection” procedure that involves three stages. First, the R&D of individual firms is projected on the state and federal component of the R&D cost. Second, the instrument for the external R&D pools is calculated as the weighted sum of presumably exogenous predicted R&D instead of actual R&D. Finally, the spillover and market-for-technology pools are projected on the corresponding instruments and on the other regressors. A problem with this strategy is that the instrument combines exogenous variation from changes in predicted R&D and potentially endogenous variation owing to changes in the composition of firms that invest in R&D. To address this issue, we propose a slightly different specification that controls for the weighted count of firms that contribute to the instrument. This specification exploits only intensive margin variation in the external R&D pools due to potentially exogenous tax credit shocks, holding the weighted number of firms that contribute to the pool constant. We also propose a second correction that consists in constructing the instrument directly as the weighted sum of federal and state tax prices, also controlling for
the weighted count of firms in the pools. The advantage of this strategy is that it allows for a more transparent direct projection of tax credits.

We obtain several findings of interest. First, the market-for-technology pool is a relevant input in the generation of product market revenue, with the elasticity of output with respect to the R&D of direct technology providers being only slightly lower than the elasticity of own R&D. Second, the weights traditionally used to capture spillovers are strongly correlated with proximity in the market-for-technology network. This implies that the spillover pool is correlated with the market-for-technology pool. As a consequence, ordinary least squares (OLS) estimates of the spillover elasticity are upward biased owing to an omitted variable bias and decline sharply when the market-for-technology pool is added in the regressions. Moreover, cleaner tests for pure externalities based on leveraging technologically close knowledge generated by distant providers in the market-for-technology network yield insignificant spillover effects. These results are important considering that most spillover elasticities in the literature are estimated by OLS (see Hall, Mairesse, and Mohnen 2010). IV estimates are less conclusive. With the double projection procedure, we obtain statistically significant estimates of the market-for-technology elasticity and statistically insignificant estimates of the spillover elasticity that are declining in the amount of information that we exploit from the market-for-technology network. With the direct projection procedure, we obtain statistically insignificant estimates of both the spillover and the market-for-technology elasticities, with the spillover elasticity being insensitive to the inclusion of the market-for-technology pool. Third, as a result of the previous points the canonical model substantially underestimates the private return and overestimates the wedge between the social and private returns to R&D. The private returns of prominent technology providers, which account for a large share of R&D in the economy, might be underestimated by as much as 30 percentage points. Finally, back-of-the-envelope estimates suggest that the gains from trade in the market for technology are larger than $1 trillion per year, accounting for at least 10% of total revenue in our sample of Compustat firms. Overall, our results suggest that knowledge diffusion takes place through more articulate channels than implied by the unintended spillovers narrative.

Related literature.—Our paper complements two important empirical literatures. The first group is the vast spillovers literature that builds on the knowledge capital model to estimate the returns to R&D (see Jaffe 1986; Bernstein and Nadiri 1988; Bottazzi and Peri 2003; Hall, Mairesse, and Mohnen 2010; Bloom, Schankerman, and Van Reenen 2013; Eberhardt, Helmers, and Strauss 2013; Colino 2016; Lychagin et al. 2016; Lucking, Bloom, and Van Reenen 2018; König, Liu, and Zenou 2019; Zacchia 2020). All the papers in this literature implicitly embrace the idea that the outcomes of R&D activities are nontradable and diffuse purely through
externalities. We emphasize that knowledge is tradable and that the weights used to capture pure externalities might also capture internalized transfers. This is true for the broad weights (e.g., technological proximity, market proximity, geographical proximity) used in most implementations (Jaffe 1986; Bloom, Schankerman, and Van Reenen 2013; Lychagin et al. 2016; Lucking, Bloom, and Van Reenen 2018) and for the more specific diffusion channels (e.g., inventor coauthorships, patent citations, and R&D alliances) leveraged in recent studies (Colino 2016; König, Liu, and Zenou 2019; Zacchia 2020). Therefore, the spillover pool should not be assumed to contribute purely to social returns to R&D. It also contributes to private returns to R&D.

The second group is an equally vast literature on the market for technology. This includes studies on the supply side of the market (see Arora and Fosfuri 2003; Fosfuri 2006; Gambardella, Giuri, and Luzzi 2007; Gambardella and Giarratana 2013), the demand side of the market (see Cecchignoli et al. 2010; Ali and Cockburn 2016), the specificities of patent transactions (Serrano 2010), and patent sale and purchase decisions as a function of firm-to-asset characteristics (Akcigit, Celik, and Greenwood 2016; Figueroa and Serrano 2019). We study firm-to-firm matching, which incorporates demand and supply aspects of the market for technology. To the best of our knowledge, we introduce this approach elsewhere (see Arqué-Castells and Spulber 2021). Firm-to-firm matching allows us to study how R&D diffuses through the market-for-technology network. A natural benefit of matched adopter-provider data is that we can measure the gains from trade in the market for technology by linking provider inputs to adopter outputs.

These two bodies of research have remained isolated so far, but there are two clear benefits to connecting them as we have done. The first is that the production function approach used in the spillovers literature is useful in estimating the gains from trade in the market for technology. The second is that it is not possible to tell whether a knowledge flow is a spillover unless it can be confirmed that it is transmitted through nonmarket channels. Some studies find that spillovers assumed to be nonpecuniary externalities stem from markets for technology. For instance, Zucker, Darby, and Armstrong (1998) find that the positive impact of research universities on nearby firms relates to identifiable market exchange and not spillovers. Similarly, Breschi and Lissoni (2009) find that localized spillovers primarily capture formal coinventor networks and not simply informal opportunities available “in the air.” Mowery and Ziedonis (2015) find knowledge flows through market transactions to be more geographically localized than those operating through nonmarket spillovers, which suggests that localized spillovers might indeed capture market transfers.

The remainder of the paper is organized as follows. Section II presents the basic two-firm model. Section III discusses the generalization of the
framework to a setting with multiple firms. Section IV presents the data. Section V discusses the empirical strategy. Section VI presents the econometric results. Section VII concludes.

II. Conceptual Framework

Firms share technology through a mixture of voluntary transfers and involuntary spillovers. Adopters obtain various benefits from voluntary transfers of technology in addition to benefits obtained from spillovers. The adopter may license or purchase IP to avoid penalties for infringement and additional legal costs. The adopter that licenses or purchases IP may experience increases in revenues, reductions in production costs, and improvements in transaction efficiencies. The adopter that licenses or purchases IP avoids costly workarounds and diminished product performance needed to conceal infringement. The adopter that licenses or purchases IP benefits by conforming to technology standards established by standards organizations. The adopter benefits from voluntary transfers when the provider bundles technology transfers with other goods and services that have value to the adopter. The provider may reveal additional know-how about how to implement inventions when making a technology market transfer that would not be available with a technology spillover. Finally, the adopter benefits from technology gains from trade when the provider makes reciprocal payments for cross-licensing the adopter’s technology.

Firms may also benefit from the R&D of other firms through various types of involuntary spillovers. “Involuntary spillovers” refers to technology transfers that are external to market transfers, even though the activities that generate the transfers may be voluntary. Firms benefit from other firms, revealing information about their inventions through patent claims. Firms benefit from observations of the technical publications and conference presentations of academics, research labs, and other firms. Firms benefit by observing and learning from the products, production technologies, and transaction methods of other firms. Based on this information, firms may imitate other firms or focus on more promising directions in R&D. Firms benefit from informal and formal disclosures by other firms in technical committees of standards organizations as well as technology standards published by standards organizations.

In the canonical framework, knowledge capital is the result of R&D performed in-house and external R&D absorbed purely through unintended spillovers. We develop a model that augments the canonical framework with technology markets. Our augmented model allows firms to benefit from external R&D through both involuntary spillovers and voluntary technology transfers. The technology market serves a dual role. First, it offers a secondary revenue opportunity for the provider. Second, it allows the
adopter to source external knowledge above and beyond spillovers. We study how these two functions of technology markets change the incentives to invest in R&D, potentially aligning the private and social returns to R&D. We derive expressions for the private and social returns to R&D for the general framework and compare them with the expressions used in the canonical framework with only spillovers. We discuss the implications of ignoring voluntary technology transfers when measuring the returns to R&D and potential underinvestment. The goal of the model is to guide empirical work.

**A. Model Setup**

We develop a basic model that examines voluntary and involuntary technology transfers between a technology provider $P$ and a technology adopter $A$. Both the adopter and the provider serve downstream product markets. To highlight the incentive effects of technology transfers, suppose that the provider and the adopter serve distinct product markets. This means that there are no business-stealing effects. Both the adopter and the provider invest in R&D to increase revenue in their respective product markets. Let $K_P$ and $K_A$ denote investment in R&D by the provider and the adopter, respectively. The provider is upstream in the technology supply chain. This implies sequential investment such that the provider invests in R&D before the adopter. The adopter can benefit from the provider’s R&D through both unintended spillovers and voluntary transfers in the market for technology. Unintended spillovers are exogenously determined and cannot be prevented if the adopter is sufficiently familiar with the provider’s research. Instead, the voluntary technology transfer is an explicit choice that must be validated by the two parties. Negotiating and implementing a technology transfer involves fixed transaction costs $C$. Without loss of generality, suppose that the provider bears these costs. If there is a voluntary technology transfer, the two firms bargain over the division of the gains from trade and the adopter pays a lump-sum royalty $R$ to the provider. We restrict attention to full-information bargaining without much loss of generality.\(^1\) The two firms decide how much to invest in R&D and whether to exchange technologies in the market for technology.

**Timing**—The model has three stages. In stage 1, the technology provider invests $K_P$ in R&D. If the technology provider expects that a market transfer of technology will not occur, R&D investment is $K_P^0$, and if the

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\(^1\) The main effect of asymmetric information on bargaining is that some negotiations break down even when there are gains from trade. This effect occurs when gains from trade are relatively low because there is an overlap of the range of buyer benefits and the range of seller costs (Myerson and Satterthwaite 1983; Spulber 1988).
technology provider anticipates that a market transfer of technology will occur, R&D investment is $K^{p*}$. In stage 2, the technology provider and adopter decide whether to arrange a market transfer of technology. If a market transfer occurs, they bargain over the lump-sum royalty and the equilibrium royalty $R$ is contingent on the adopter’s investment $K^a$. In stage 3, the technology provider invests $K^p$ in R&D. If the provider and the adopter do not engage in bargaining over a market transfer of technology, the provider’s R&D investment is $K^{p0}$. If the provider and the adopter engage in bargaining and a market transfer of technology has occurred, R&D investment is $K^{p*}$. The equilibrium royalty $R^*$ is realized. The model is solved by backward induction.

Unintended spillovers and voluntary technology transfers.—We propose definitions of spillovers and technology transfers that are consistent with the notion of weighted external R&D spillover pools used in the empirical literature. The unintentional spillover from the provider to the adopter is $q^{SP}K^p$, where $q^S$ represents technological proximity of the technologies of the provider and the adopter. The technological proximity weight reflects the observation that similar technologies provide greater spillover benefits than differentiated technologies. The proximity weight recognizes the difference between investment in R&D, which is a productive input, and the spillover, which is an output of R&D. The potential voluntary technology transfer from the provider to the adopter is defined analogously as $q^{MP}K^p$, where $q^M$ is a measure of the adopter’s ability to benefit from the provider’s R&D through the transfer. The weight again recognizes the difference between investment in R&D, which is a productive input, and voluntary technology transfer, which is an output of R&D. Note that there is an important difference between $q^S$ and $q^M$. The weight $q^S$ captures both the intensive and the extensive margins of spillovers (i.e., whether the adopter benefits from spillovers and how much of the provider’s R&D is absorbed through spillovers). Therefore, the unintended spillover is fully

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2 This timing is consistent with settings in which the provider invests in R&D ex ante to increase its own product market revenue regardless of whether there will be a transfer. Some of the R&D may then be of value to the adopter, which opens the door to ex post voluntary technology transfers. This setting is consistent with the behavior of large corporations responsible for the bulk of R&D in the world. However, it is also possible to think of technology exchanges—e.g., R&D joint ventures or contract R&D—in which the provider and the adopter agree on the transfer ex ante and the provider invests in R&D ex post. In such cases, the timing of the model would be slightly different, with the transfer taking place in stage 1 and the R&D investments in stages 2 and 3.

3 The weight is important because $100 of R&D investment expenditures will have different spillover effects depending on the relationship between the technology of the provider engaged in R&D and the technology of the adopter. For example, the technology generated by $100 of R&D investment in computer software is not the same as $100 of R&D investment in computer hardware. The spillover effects of $100 of R&D investment in computer software will differ depending on whether the adopter is a software firm or a hardware firm.
determined by $\omega^s$. Instead, $\omega^M$ captures only the intensive margin of the voluntary transfer (i.e., how much of the provider’s R&D is acquired through the transfer). The voluntary technology transfer decision is derived endogenously.

**Production function of the provider.**—The provider’s production function is

$$Y^P = F^P(K^P),$$

(1)

where $Y^P$ denotes product market revenue obtained from the provider’s output. Because this is a one-shot production function, investment in R&D determines the firm’s R&D capital stock. Suppose that all other inputs—such as capital equipment, labor, and resources—are optimized. Assume that the provider’s production function is differentiable, increasing, and concave in R&D, $F^P_1(K^P) > 0, F^P_{11}(K^P) < 0$.

**Production function of the adopter.**—The adopter’s production function is

$$Y^A = F^A(K^A, \omega^S K^P, \omega^M K^P),$$

(2)

where $Y^A$ denotes product market revenue. The adopter obtains positive revenues without a market transfer of technology, $F^A(K^A, \omega^S K^P, 0) > 0$. Assume that the adopter’s production function is differentiable, increasing, and concave in the adopter’s R&D investment and differentiable and increasing in unintentional spillovers and technology adoption. Also assume that the adopter’s marginal benefit from R&D investment is increasing in unintentional spillovers and voluntary technology transfers from the provider, $F_{12}^A > 0, F_{13}^A > 0$. Unintentional spillovers and technology adoption can have complementary effects, $F_{23}^A \geq 0$. These assumptions imply that own R&D, external R&D diffusing through spillovers, and external R&D acquired in the market for technology are strategic complements. This is consistent with the Cobb-Douglas production functions typically used in the empirical literature.

**Mechanisms.**—Importantly, we assume that spillovers and voluntary technology transfers are not mutually exclusive. The adopter can benefit from the provider’s R&D through pure spillovers and compensated transfers at the same time. This is consistent with the interpretation of spillovers in seminal endogenous growth models and with the unintended spillover narrative invoked in the empirical literature. Alternatively, we could allow for a mutually exclusive relationship between spillovers

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4 For example, according to Romer (1990, 84), “The owner of a design has property rights over its use in the production of a new producer durable but not over its use in research. If an inventor has a patented design for widgets, no one can make or sell widgets
and voluntary transfers. For example, in a setting with imperfect enforce-
ment, adopters can either infringe or pay for the technology. We do not
develop a model of technology enforcement partly because it is not in the
spirit of the spillovers literature and partly because we would not be able
to operationalize it with our data. This means that we are implicitly as-
suming perfect enforcement. That is, for those technologies that are ex-
cludable, the adopter either adopts through a compensated transfer or
does not adopt. Our model is valid for studying how technology markets
change the incentives to invest in R&D. However, it cannot explain how
technology markets limit rent-dissipating uses of technology due to
infringement.

B. The Equilibrium of the Model

The adopter and the provider decide how much to invest in R&D and
whether to bargain. We first derive the optimal R&D investments without
bargaining. We then solve the equilibrium with bargaining. The two firms
choose to bargain if the gains from trade at optimized R&D values are
positive.

No bargaining.—If the provider anticipates that there will not be any
bargaining over a possible market transfer, the provider invests in R&D
to maximize net revenue in stage 1. The provider solves the R&D invest-
ment problem max[Kp]\{F(Kp) - Kp\} so that F'(Kp0) = 1. Conditional on
having decided not to transact in stage 2, the adopter invests in R&D to
maximize net revenues in stage 3, taking into account the involuntary
spillover max[Ka]\{Fa(Ka, qaKp0, 0) - Ka\} so that Fa(Ka0, qaKp0, 0) = 1. Thus,
the equilibrium without bargaining is Kp0, Ka0.

Bargaining.—If the provider anticipates that there will be bargaining
over a possible market transfer, the provider chooses R&D Kp* before bar-
gaining occurs. The provider and adopter take Kp as given when negoti-
ating over royalties and the voluntary transfer qaKp*. The adopter invests
in R&D only after bargaining takes place so that the realization of the roy-
alty is contingent on the adopter’s R&D investment. The provider’s in-
vestment affects the adopter’s disagreement payoff in bargaining because
of unintended spillovers. If bargaining takes place and the provider and

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5 We do not know whether the estimated spillover effects are due to infringement, so
there is little gain in modeling the two channels. Of course, in practice there is infringe-
ment, so our estimates could be partly picking up infringement.
adopter disagree, the adopter would choose R&D investment $K^{AI}$ that solves $\max_K[F^A(K^A, \omega^S K^{PS}, 0) - K^A]$. The first-order condition for $K^{AI}$ is $F^A_1(K^{AI}, \omega^S K^{PS}, 0) = 1$. The adopter’s disagreement payoff in bargaining is

$$V(\omega^S K^P) = F^A(K^{AI}, \omega^S K^{PS}, 0) - K^{AI}. \quad (3)$$

The adopter’s R&D investment $K^{AI}$ will never be observed in equilibrium because bargaining results in a technology transfer. The disagreement payoff for the technology provider is zero because the provider does not receive any payments and does not incur any costs. Consider the Nash bargaining problem for the provider and adopter when there is a market transfer of technology. The gain from a voluntary technology transfer is the adopter’s revenue after a voluntary transfer net of R&D investment costs and net of the adopter’s disagreement payoff

$$\Delta = F^A(K^A, \omega^S K^P, \omega^M K^P) - K^A - V(\omega^S K^P). \quad (4)$$

Notice that $K^P$ has already been chosen in the first stage but $K^A$ has not yet been chosen. The bargaining problem is then $\max_R(\Delta - R) = a(\Delta - R) = (1 - a)(R - C)$. The total royalty is a weighted average of the adopter’s benefit and the transaction cost of a voluntary transfer,

$$R = a\Delta + (1 - a)C. \quad (5)$$

The three-stage interaction with bargaining is solved by backward induction as follows.

**Stage 3 (The adopter’s R&D investment).**—In the third stage, the adopter invests in R&D. The adopter’s net benefit from a market transfer of technology is

$$\Delta - R = (1 - a)[F^A(K^A, \omega^S K^P, \omega^M K^P) - K^A - V(\omega^S K^P) - C]. \quad (6)$$

Because bargaining results in profit sharing, royalties do not distort the adopter’s investment. With a voluntary technology transfer, the adopter chooses R&D to maximize $\Delta - R$. The first-order condition for the adopter’s problem with a voluntary technology transfer is

$$F^A_1(K^{AI}, \omega^S K^P, \omega^M K^P) = 1. \quad (7)$$

**Stage 2 (The technology transfer decision).**—In the second stage, the adopter and provider decide whether to make a market transfer of technology. The adopter’s benefit from a market transfer of technology is
A voluntary market transfer occurs only if the benefits are greater than or equal to transaction costs. The technology transfer decision is given by

\[ d = 1\{\Delta \geq C\}, \]  

(9)

where \( d \) is a dummy variable with value one if there is a voluntary transfer and zero otherwise and \( 1\{\cdot\} \) is the binary indicator function. If a voluntary technology transfer occurs, royalties depend on the provider’s R&D investment.

Stage 1 (The provider’s R&D investment).—In the first stage, the provider obtains revenue from production and voluntary technology transfers. The net revenue \( T \) obtained in the technology market is the lump-sum royalty minus transaction costs, which is equivalent to a share \( a \) of the gains from trade,

\[ T = (R - C) = a(\Delta - C). \]  

(10)

Voluntary transfers and involuntary spillovers take time. Both the provider and the adopter discount profits using a common discount factor \( r \), where \( 0 < r < 1 \). If the provider anticipates that a voluntary technology transfer will occur, the provider’s net present value of revenue is

\[ Y^p + \rho T = F^p(K^p) + \rho a(\Delta - C). \]  

(11)

The provider’s optimization problem is

\[ \max_{K^p} [F^p(K^p) + \rho a(\Delta - C) - K^p]. \]

Applying the envelope theorem and the adopter’s investment problem, the first-order condition for the provider’s problem is

\[ 1 - F^p(K^{p*}) = \rho a[f^p_2(K^{A*}, \omega^S K^{p*}, \omega^M K^{p*})\omega^S + f^p_3(K^{A*}, \omega^S K^{p*}, \omega^M K^{p*})\omega^M - V'(\omega^S K^{p*})\omega^S]. \]  

(12)

The marginal benefit of the adopter from the provider’s R&D is the sum of three effects: the spillover effect, the market transfer effect, and the opportunity cost effect of the spillover. Voluntary technology transfers occur only if there are gains from trade, \( \Delta \geq C \). The provider chooses investment \( K^{p*} \) if there are gains from trade. Otherwise, the provider chooses investment \( K^{p0} \).

Our analysis yields several interesting propositions that are worth discussing. We provide proofs in appendix A (apps. A–K are available online).

**Proposition 1.** The R&D investments of the provider and the adopter are greater with voluntary market transfers than without voluntary market transfers: \( K^{p0} < K^{p*} \), \( K^{A0} < K^{A*} \).
The result implies that R&D investments increase when the provider has a higher ability to internalize the results of its investment. The result also implies that total R&D is greater with technology markets $K_{A}^* + K_{P}^* > K_{A}^0 + K_{P}^0$. Because of strategic complementarity between spillovers and voluntary transfers, the adopter’s R&D also increases with voluntary technology transfers.

**Proposition 2.** The R&D investments of the provider and the adopter are increasing in provider bargaining power $a$ and in the discount factor $\rho$.

The result implies that the provider’s R&D investment $K_{P}^*$ is less than the social optimum. Because $a < 1$, the provider does not obtain the full marginal return to R&D investment. A higher bargaining power increases the provider’s ability to internalize the effects of its research and increases incentives to invest. With uncertain transfers and diverse adopters, there will be insufficient adoption, which will further lower R&D investment for both provider and adopter.

**Proposition 3.** The R&D investments of the provider and the adopter are increasing in technological proximity and technology market proximity.

The result implies that equilibrium investments depend on the adopter’s ability to extract value from the provider’s investment and generate higher gains from trade.

**Proposition 4.** The gain from technology transfer $\Delta$ is increasing in technological proximity and technology market proximity.

### C. Private and Social Returns to R&D

In this section, we derive the expressions for the marginal private return (MPR) and marginal social return (MSR) to the provider’s investment in R&D. The MPR is the increase in the provider’s revenue generated by a marginal increase in its own R&D stock. The MSR is the increase in aggregate output generated by a marginal increase in the provider’s R&D stock. The net present value of revenue with two firms is $Y_{P}^1 + \rho Y_{A}^1$, and the net present value of costs is $K_{P}^1 + \rho K_{A}^1 + \rho C$. Technology market revenue is a transfer and so does not enter the expression for aggregate output.

**Marginal returns to R&D without a voluntary technology transfer.** — If $\Delta < C$ at optimized values $K_{p}^*$ and $K_{A}^*$, there is no technology transfer in the market for technology. The marginal private and social returns to the provider’s R&D investment are

\[
\text{MPR}^0 = \frac{\partial Y_{P}^1}{\partial K_{P}^1} = F_{P}^0(K_{P}^1), \quad (13)
\]

\[
\text{MSR}^0 = \frac{\partial Y_{P}^1}{\partial K_{P}^1} + \rho \frac{\partial Y_{A}^1}{\partial K_{P}^1} = F_{P}^0(K_{P}^1) + \rho F_{A}^1(K_{A}^0, \omega^S K_{P}^0, 0) \omega^S. \quad (14)
\]
These are the expressions traditionally used in the literature for calculating the marginal private and social rates of return. The MPR includes the marginal effect of the provider’s R&D on its own product market revenue. The MSR includes the effect of the provider’s R&D on its own revenue plus the effect on the product market revenue of the adopter diffusing through spillovers. The wedge between the social and private returns is explained entirely by spillovers:

\[
\text{MSR} - \text{MPR} = \rho \frac{\partial Y^A}{\partial K^P} = \rho F^A(K^{A_0}, \omega^S K^P, 0)\omega^S. \tag{15}
\]

Marginal returns to R&D with a voluntary technology transfer.—If \( \Delta > C \) at optimized values \( K^{P_0} \) and \( K^{A_0} \), there is voluntary technology exchange. The provider’s net present value of revenue is \( Y^P + \rho T \), so the marginal private and social returns are now given by

\[
\text{MPR}^1 = \frac{\partial Y^P}{\partial K^P} + \rho \frac{\partial T}{\partial K^P}
= F^P(K^P) + \rho a[F^A(K^{A_0}, \omega^S K^P, \omega^M K^P)\omega^S + F_3^A(K^{A_0}, \omega^S K^P, \omega^M K^P)\omega^M - F_2^A(K^{A_1}, \omega^S K^P, 0)\omega^S], \tag{16}
\]

\[
\text{MSR}^1 = \frac{\partial Y^P}{\partial K^P} + \rho \frac{\partial Y^A}{\partial K^P}
= F^P(K^P) + \rho [F^A(K^{A_0}, \omega^S K^P, \omega^M K^P)\omega^S + F_3^A(K^{A_0}, \omega^S K^P, \omega^M K^P)\omega^M]. \tag{17}
\]

Both the MPR and the MSR are larger than in the case without voluntary transfers. The MPR includes the marginal effect of the provider’s R&D on its own product market revenue as well as on its technology market revenue. The MSR includes the effect of the provider’s R&D on its own product market revenue, the effect on the product market revenue of the adopter diffusing through spillovers, and the effect on the product market revenue of the adopter taking place through technology transfers. A portion \( a \) of the latter effect is internalized by the provider through transfers in the market for technology. The wedge between the marginal social and private returns is

\[
\text{MSR}^1 - \text{MPR}^1 = \rho \left( \frac{\partial Y^A}{\partial K^P} - \frac{\partial T}{\partial K^P} \right)
= \rho (1 - a)[F^A(K^{A_0}, \omega^S K^P, \omega^M K^P)\omega^S + F_3^A(K^{A_0}, \omega^S K^P, \omega^M K^P)\omega^M]
+ \rho aF^A(K^{A_1}, \omega^S K^P, 0)\omega^S. \tag{18}
\]
The wedge is a share \((1 - a)\) of transferred knowledge (unintended spillovers and technology transfers) that cannot be internalized due to the provider’s bargaining power being below one plus a share \(a\) of the spillovers that the adopter would enjoy under the outside option of no market transfer. The latter cannot be internalized by the provider because it is part of the adopter’s disagreement payoff in bargaining.

**Proposition 5.** The wedge is larger with a voluntary transfer than without a voluntary transfer: \(\text{MSR}^1 - \text{MPR}^1 > \text{MSR}^0 - \text{MPR}^0\).

With a voluntary transfer, the adopter enjoys spillovers that cannot be internalized plus voluntary transfers that can be internalized only partially by the provider. Because of strategic complementarities, the effect of spillovers is magnified when the adopter also benefits from voluntary transfers.

### D. Discussion

The canonical knowledge capital model used to estimate the external effects of R&D is a restricted version of our model that assumes the market for technologies away by imposing \(F_3^4 = 0\). What are the implications of ignoring voluntary technology transfers when measuring the returns to R&D and potential underinvestment? Empirically measuring the private and social returns to R&D involves two steps. First, it is necessary to obtain reliable estimates of the empirical counterparts of \(F_2^4\) and \(F_3^4\). Second, it requires deriving the correct expressions for the MSR and MPR. Our analysis implies that ignoring technology markets generates problems in both stages.

First, when there are voluntary technology transfers, the expressions for the private and social returns derived under the canonical model with only spillovers are misspecified. The correct expressions are (16)–(18), whereas the canonical model uses (13)–(15). The canonical model clearly underestimates the private returns to R&D because it uses an expression for the private returns that ignores technology market revenue. To incorporate technology markets into the measurement, it is necessary to obtain estimates of \(F_3^4\). The implications for the measurement of the social returns are less straightforward. If the estimates of \(F_3^4\) obtained in the literature are accurate (i.e., \(\tilde{F}_3^4 \approx F_3^4\)), then the canonical model would underestimate the social returns to R&D because it relies on an expression that ignores the effects of voluntary transfers on the adopter’s revenue. It would also underestimate the wedge between the social and private returns because it ignores spillovers that cannot be internalized plus voluntary transfers that can be only partially internalized.

The second problem concerns the reliability of the spillover elasticities estimated with production functions that ignore technology markets. The exclusion of internalized transfers from empirical specifications could result in upward-biased estimates of the effect of spillovers \(\tilde{F}_2^4 > F_2^4\) due to an...
omitted variable bias. An omitted variable bias is likely if the weights commonly used to capture spillovers are positively correlated with the voluntary decision to transfer technologies. Proposition 4 suggests that this is a possibility. In such a case, the spillover pool used to capture externalities could become a catch-all measure capturing both spillovers and internalized transfers. This could result in an overestimate of the wedge between social and private returns to R&D.

III. Empirical Operationalization

In this section, we propose an empirical framework for estimating the knowledge capital model augmented with technology transfers. The framework adapts the main insights presented in the basic two-firm model to a setting with many firms. In practice, the market-for-technology supply chain is longer than in the two-stage case considered in the model. Most innovative firms occupy intermediate positions in the supply chain, acting as both technology providers and technology adopters. Accordingly, we consider a setting in which innovating firms have an adopter-provider role and obtain revenue from the product market and the technology market. We assume that links in the market for technology are formed vis-à-vis between providers and adopters according to the positive gains-from-trade rule in equation (9).

Formally, we represent this setup with a product market revenue production function augmented with own R&D, a standard spillover pool, and a newly constructed market-for-technology pool. The latter captures R&D diffusing through the market-for-technology network. Estimates of the product market revenue production function combined with information on the network of interactions are sufficient to calculate both the private and the social returns to R&D. The empirical operationalization involves three steps. First, we estimate the product market revenue equation augmented with a spillover pool and a market-for-technology pool. Second, we use the estimates of the product market revenue equation to measure technology market revenue. Finally, we calculate the expressions for the private and social returns. We provide the details of each step below.

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The two-firm bargaining setup is likely to apply in a context with many firms if transfers are staged and the information set is taken as given at the moment of bargaining. There is considerable evidence that providers and adopters negotiate most technology transfer agreements bilaterally (Spulber 2016). The positive gains-from-trade rule is valid for most of the exchange modes covered in this study (e.g., nonexclusive licensing, cross-licensing, and R&D alliances), and we argue that it is a reasonable approximation to exchange modes involving congestion (e.g., patent trades and exclusive licensing) also covered in this study because we do not model firm-to-asset-to-firm matching but firm-to-firm matching. Most firms in our sample own fairly large patent portfolios and can sell patents (grant exclusive licenses) to different adopters. Although there may be congestion at the asset level, there should be less congestion at the firm-to-firm level.
A. Revenue Generated in the Product Market

Product market revenue is generated with a standard Cobb-Douglas function that includes conventional inputs as well as knowledge capital. The latter is produced with in-house R&D, external R&D absorbed through spillovers, and external R&D acquired in the market for technology:

$$Y_{it} = G_{it}^{\bar{h}} S_{it}^{\bar{h}} M_{it}^{\bar{h}} X_{it}^{\bar{a}} \varepsilon^\alpha,$$  \hspace{1cm} (19)

where $Y_{it}$ represents product market revenue, $G_{it}$ represents the R&D stock of the firm calculated according to the perpetual inventory method, $S_{it}$ represents the pool of external knowledge available through spillovers, $M_{it}$ represents the pool of external knowledge purchased in the market for technology, with some abuse of notation $X_{it}$ accounts for standard inputs (i.e., labor and capital) and other controls that capture demand shifters, and $\varepsilon_{it} = \phi_{i} + \phi_{t} + u_{i}$ represents a firm-specific shock that subsumes year and firm fixed effects as well as an idiosyncratic error term.

**Spillover pool.**—Following the related literature, the spillover pool is defined as

$$S_{it} = \sum_{j \neq i} \omega_{ij}^{S} G_{jt},$$  \hspace{1cm} (20)

where $\omega_{ij}^{S}$ is a knowledge-weighting matrix applied to R&D stocks of other firms. The most popular weight is technological proximity, but other metrics such as geographical proximity, market proximity, or patent citations have also been used. The exact definition of the weight used to construct the spillover pools is provided in section IV.C.1.

**Market-for-technology pool.**—Similarly, the market-for-technology pool is defined as the sum of external R&D stocks weighted by the strength of connections in the market-for-technology network:

$$M_{it} = \sum_{j \neq i} \omega_{ij}^{M} G_{jt},$$  \hspace{1cm} (21)

where $\omega_{ij}^{M}$ is a weight capturing the importance of $j$ as an upstream supplier of $i$ in the market for technology. Note that this definition of the

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7 If a firm’s main activity is to license technologies to downstream manufacturers, then licensing will be the ordinary activity of the firm and royalty payments will be recorded as operating income in the Standard Industrial Classification (SIC) class 6794 (patent owners and lessors). To match the data to our model and make sure that $Y_{it}$ includes only product market revenue, we drop firms whose main activity is in the SIC code 6 (finance, insurance, and real estate). For the remaining firms, we define $Y_{it}$ as total sales minus sales in the SIC class 6794 capturing royalty income (even though in practice only a few firms report sales in this sector).

8 The perpetual inventory method imposes $G_{it} = R_{it} + (1 - \delta) G_{it-1}$, where $R_{it}$ represents the R&D flow (in 2010 prices) and $\delta = 0.15$ is a 15% depreciation rate. In the first year that we observe a firm, we assume that it is in steady state, so $G_{i0} = R / (\delta + g)$, where $g = 0.05$ gives the steady state growth rate of the R&D stock, which is assumed to be 5%.
market-for-technology weight is slightly different from the one used in the model. Let $d_{ij}$ be a dummy variable with value one if $i$ is a direct provider of $j$ in the market for technology and value zero otherwise. Then, the simplest possible definition of the weight would be $\omega_{ij}^M = d_{ij}$. However, it is possible to construct more sophisticated weights capturing both extensive margin (i.e., number of providers) and intensive margin (i.e., quantity of interactions with a given provider) information. It is also possible to exploit links between adopters and indirect providers (e.g., providers of providers) to capture the length of the technology supply chain. The baseline weight used in the main regressions exploits information along all these dimensions to capture the breadth and depth of the market-for-technology network. The weight used to construct the market-for-technology pools is defined in section IV.C.2.

**Time-invariant weights.**—Following the tradition in the spillovers literature, we work with time-invariant weights $\omega_{ij}^S$ and $\omega_{ij}^M$. This implies that we exploit only cross-sectional variation between firm dyads to tease out spillovers and technology transfers. Regarding the spillover weight, the main reason for setting technological proximity fixed in past studies has been that technology positions are drawn from information contained in patents, which is rather sparse because many firms patent only occasionally. To retain a reasonable sample size, we also stick to the common practice in the literature of defining time-invariant proximity weights. There are several reasons for setting the market-for-technology weight fixed as well. The most important reason is that we are particularly interested in studying whether the spillover weights are a catch-all measure that also picks up internalized transfers. This essentially involves studying whether the cross-sectional proximity links used to define the spillover pool correlate with the cross-sectional variation in the market-for-technology network. A second important reason is that there are some inherent limitations in our ability to separate spillovers and voluntary transfers from within-pair variation in the timing of transactions over time due to conceptual reasons. Third, for some exchange modes in our data there is a lack of clarity in the sampling criteria used to collect the transactions, which makes it difficult to reliably track transactions over time for a given pair. Finally, we do not have good instruments for network formation and our identification strategy builds on using time-invariant weights and time-varying external R&D stocks.

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The main challenge is that effective transaction dates do not indicate with precision the exact point in time when an adopter starts or stops benefiting from the provider’s R&D through voluntary transfers or spillovers. Adopters might benefit from the provider’s R&D without compensation well before a market transfer, so flows that are eventually internalized might be incorrectly interpreted as spillovers. Similarly, adopters might benefit from the provider’s R&D through spillovers after a market transfer because certain types of benefits cannot be internalized, so genuine spillovers could be incorrectly interpreted as voluntary transfers.
Parameters of interest.—The related literature has provided estimates for $\beta_1$ and $\beta_2$, both of which have generally been found to be positive and statistically significant (see Hall, Mairesse, and Mohnen 2010). Our data set on interactions in the market for technology allows us to construct $M_i$ and obtain the first estimates of $\beta_3$ in the literature. Importantly, estimates of the spillover elasticity $\beta_2$ may be affected by the inclusion of market-for-technology pool in the regressions. A positive correlation between the weights $\omega_{ij}^M$ and $\omega_{ij}^S$ would in turn result in a positively correlated relationship between $S_i$ and $M_i$. In such a case, the omission of $M_i$ in the regressions is likely to result in upward-biased estimates of $\beta_2$ due to an omitted variable bias. Therefore, our regressions also allow us to assess the extent to which the spillover elasticity is capturing internalized transfers. We discuss important identification considerations in section V.

B. Revenue Generated in the Technology Market

We measure technology market revenue of a given provider by adapting equation (10) to our setting with many firms. Technology market revenue is a proportion of the gains from trade generated by the market transfer. With an estimate of the market-for-technology elasticity $\beta_3$ in equation (19) and the information in the market-for-technology pool $M_{ij}$, we can measure the exact contribution of the provider’s R&D to every adopter’s product market revenue. We calculate the gains from trade as the revenue loss (net of the R&D investment) that each of the adopters would suffer if it were not connected to the provider. A fixed fraction $a$ of this additional revenue is captured by the provider. Technology market revenue for provider $i$ is the sum of all such revenues:

$$ T_i = a \sum_{j \neq i} \{ \omega_{ij}^M > 0 \} \left[ (\Delta_{ij} - C_{ij}) \right], $$

where $\Delta_{ij} = [Y_i(\omega_{ij}^M > 0) - G_{ij}^p] - [Y_i(\omega_{ij}^M = 0) - G_{ij}^p]$ gives the increase in product market revenue of adopter $j$ owing to the technology transfer from $i$, $\omega_{ij}^M$ is the weight measuring the strength of the connection in the market for technology between the adopter $j$ and the provider $i$, and $a \in [0, 1]$ is a measure of the provider’s bargaining power, which captures the percentage of firm $j$’s increase in product market revenue that $i$ appropriates through payments. In principle, $a$ should be adopter-provider specific, but we assume it to be constant across pairs because we do not have information on the provider’s actual bargaining power. We provide results for $a$ equal to 25%, 50%, and 75%. Note that our definition of revenue in the market for technology is broader than simply royalty income. It subsumes royalties, patent prices, compensation within alliances, and reduction of royalty payments in exchange for granting reciprocal access to own technologies. An important advantage of this approach is that it allows us to measure technology
market revenue from product market revenue data alone. This is convenient because product market revenue is easily traceable from financial statements, while technology market revenue is not.\(^{10}\)

C. Private and Social Returns with Many Firms

Now that the two main sources of revenue stemming from R&D have been defined, we are in a good position to derive the private and social rates of return to R&D. With multiple firms and assuming that \(\rho = 1\), as is customary in the literature, aggregate output in year \(t\) is given by \(Y_t = \sum Y_i\). The marginal private and social returns to R&D for firm \(i\) are given by the following expressions:

\[
\text{MPR}_i = \frac{\partial Y_i}{\partial G_i} + \frac{\partial T_i}{\partial G_i},
\]

\[
\text{MSR}_i = \frac{\partial Y_i}{\partial G_i} + \sum_{j \neq i} \left[ \frac{\partial Y_j}{\partial S_j} \frac{\partial S_j}{\partial G_i} + \frac{\partial Y_j}{\partial M_j} \frac{\partial M_j}{\partial G_i} \right].
\]

The MPR includes the effect of firm \(i\)'s R&D on its own product market revenue as well as on its technology market revenue. The MSR includes the effect of firm \(i\)'s R&D on its own product market revenue, the effect on the product market revenue of other firms diffusing through spillovers, and the effect on the product market of other firms taking place through technology transfers. A portion of the latter effect is recovered by firm \(i\) through transfers in the market for technology. The analytical expressions are reported in appendix B.

IV. Data

We construct a firm-level panel data set for the period 1990–2014 that combines accounting data from US Compustat, patent data from the USPTO Patent Assignment Dataset (PAD), information on interactions in the market for technology, and R&D tax credit information. We describe the main data sources in section IV.A, describe the market-for-technology network data sources in section IV.B, and report the analytical expressions.

\(^{10}\) Technology market revenue is generally considered an extraordinary source of revenue that is recorded in the nonoperating income account along with many other concepts. The absence of detailed reporting prevents researchers from identifying revenue in the market for technology from financial statements. Even if licensing income is readily reported in financial statements, it should be noted that royalty payments do not represent total revenue in the market for technology because firms often reduce or eliminate payments in exchange for access to other firms’ patent portfolios, a common practice in cross-licensing agreements. In such cases, technology market revenue is expensed before it is even recorded. According to IBM, the value of access might be an order of magnitude larger than that of licensing income (Grindley and Teece 1997).
in section IV.B, describe the construction of the spillover and market-for-technology pools in section IV.C, and provide descriptive statistics of the data set used in the econometric analysis in section IV.D.

A. Sources

In this subsection, we describe the four data sets used to construct the final data used in the regressions. We also describe the match between all the different data sources.

Data set on interactions in the market for technology.—We collect a large list of transactions in the market for technology with broad coverage over six modes of exchange, including patent trades, licensing, cross-licensing, licensing between firms in joint ventures, cross-technology exchanges between firms in joint ventures, and R&D alliances. The construction of the list of deals on each mode of technology exchange is described in appendix C. For each transaction, we observe the identity of at least one party on each end of the agreement. The collected list of transactions was extracted from voluntarily recorded patent assignments at the USPTO and compulsory disclosures to the SEC. The exact sources include the USPTO PAD (for patent trades), ktMINE (for licensing deals), direct searches over SEC filings (for cross-licensing deals), and information from Securities Data Company (SDC) Platinum, which draws mostly on SEC disclosures (for licensing, cross-licensing, and R&D alliances between firms forming alliances or joint ventures). It is important to understand some features about the collected list of interactions. First, time coverage is acceptable for the post-1990 period. Second, with most of the deals coming from SEC filings, coverage is inevitably better for publicly traded firms. Third, despite our efforts to amass the broadest possible amount of deals, our data set is far from being a census, even for public firms.

11 We follow Arora and Gambardella (2010) in defining the market for technology broadly as explicit transactions involving a formal exchange of knowledge for money or additional knowledge. Patent trades and licensing involve exchanges of knowledge for money, while cross-licensing and R&D alliances involve exchanges of knowledge and perhaps also balancing payments.

12 This is necessarily the case for the licensing, cross-licensing, and R&D alliances data sets, which are exhaustive for the post-1990 period. The USPTO PAD covers the post-1980 period, but reassignments remain relatively low until the mid-1990s (see Graham, Marco, and Myers 2018).

13 Private firms do also show in deals disclosed to the SEC, but to a lesser extent. The filers of SEC filings are public firms. One of the parties of the deal is the filer itself (or a subsidiary). The other party can be either another public firm or a private one. Thus, SEC deals are public to public or public to private.

14 There are “nonmaterial” deals not disclosed to the SEC or even “material” deals that are disclosed with redacted terms. For instance, Lexmark states in some of its SEC filings
is the most comprehensive data set on interactions in the market for technology that can be put together for public firms. Finally, the data are better suited to capture the extensive margin (i.e., whether two firms ever interact) than the intensive margin (i.e., the number of interactions between firms) of the market for technology. Basic descriptive statistics of the data set on interactions are provided in appendix C.

**USPTO PAD.**—The USPTO PAD (see Graham, Marco, and Myers 2018) provides detailed information on the changes in patent ownership. It is used for four different purposes. The first is to complement the data set on interactions in the market for technology by tracking patent trades between firms. The second is to measure the number of eventually granted utility patent applications per firm and year. Such patent flow is constructed as the yearly number of original employer assignments of granted (by 2013) utility patents with application date on or after 1980. The third purpose is to measure technological proximity between firms from the technology classes of their patents. To accomplish this, we import technology classes from the BASIC 13 file in the USPTO Patent Technology Monitoring Team Custom Extract 2013. The fourth purpose is to measure firms’ geographical distribution of innovative activities across states to infer the amount of statutory tax credit that can be claimed in each state.

**Compustat.**—We use the following balance sheet items in Compustat North America Fundamentals (Compustat mnemonics are in parentheses): sales (SALE), physical capital (PPENT), the number of employees (EMP), R&D expenditures (XRD), and investment (CAPX). We use deflators from multiple sources to deflate these variables. Sales are deflated with the gross output deflator from the European Union–level analysis of capital, labor, energy, materials, and service inputs (EU KLEMS) database (September 2017 release), physical capital and investment are deflated with the nonresidential fixed investment good deflator (line 9) from the

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15 The USPTO PAD is extensively described in Graham, Marco, and Myers (2018). We work with a version that covers 5,534,135 transactions recorded at the USPTO between January 1970 and January 2013 (inclusive). While the first transaction date is January 1970, the number of transactions recorded in the initial years is negligible. Data coverage seems sufficient for the years 1981–2012. Updated versions of the USPTO PAD can be found at http://www.uspto.gov/learning-and-resources/electronic-data-products/patent-assignment-dataset.

16 A transaction is defined as an employer assignment if it is the first transaction recorded for the patent, the execution date is before or on the grant date, and the conveyance text identifies the transaction as an “assignment of the assignor’s interest.” Overall, 3,031,098 utility patents are originally assigned from inventors to corporations.
national income and product accounts (NIPA) tables of the Bureau of Economic Analysis (BEA) satellite account, and R&D expenses are deflated using aggregate input price index for R&D performed by private businesses, published by the BEA as a part of the R&D satellite account. Finally, information in the Compustat Historical Segments data set is used for two different purposes. The main purpose is to construct an accurate measure of product market revenue. The second purpose is to measure product market proximity between firms to define an alternative spillover pool for robustness checks.

**Tax credits.**—We exploit supply-side shocks to firm-level R&D triggered by federal and state R&D tax credits to build instruments for the pools of external knowledge. To calculate the federal component of the firm-specific tax price of R&D, we exploit changes over time (in the definition of the base, the statutory tax credit, and deduction rules) in the research and experimentation tax credit as well as in the corporate tax rates (all of which are summarized in table 1 in Rao 2016). To calculate the federal component of the tax price of R&D, we take advantage of the data set produced by Wilson (2009), who calculates the user cost of R&D faced by a representative firm conducting R&D within a given state.

**Match between data sets.**—The four data sources are matched as follows. First, Compustat firms (with nonmissing information in the Compustat segment data set) are matched to USPTO PAD patents through the ASSIGNEE/OR-GVKEY file defined in the appendix of Arqué-Castells and Spulber (2021), which links standardized and disambiguated assignor/assignee names to Compustat GVKEYs. Second, Compustat firms with patents are matched to firms in the data set on interactions in the market for technology. For patent trades, which are obtained from the USPTO PAD, establishing such a link is automatic because the ASSIGNEE/OR-GVKEY link already matches firms involved in patent assignments or reassignments to Compustat. For the remaining forms of exchange, including licensing, cross-licensing, and R&D alliances, we match firms by name. Details on the match are provided in appendix D. Federal tax information required to build the tax price of R&D is linked to firms by year, while state tax information is linked to firms according to the geographical distribution of firm patents across US states. The broadest possible sample resulting from merging all the data sources includes 7,653 Compustat

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17 As argued earlier, most firms report royalty payments as nonoperating income, but a few firms specializing in patent licensing do report royalty income as operating revenue (or sales). We take two actions to purge sales from royalty payments. First, we exclude firms that have SIC code 6 (finance, insurance, and real estate) as their main sector of activity from the sample used in the regressions. Second, for the remaining firms that do not have SIC code 6 as their main sector of activity but might still have SIC class 6794 (patent owners and lessors) as a relevant secondary sector, we define sales as total sales minus sales in SIC class 6794.
firms linked to at least one patent (with application date on or after 1980), of which 3,897 interact in the market for technology with at least another firm in the sample in transactions with a known execution date.

B. Market-for-Technology Data

The matched sample includes 3,897 firms that interact in the market for technology with at least another firm in the sample (i.e., a Compustat firm with at least one issued patent with application date on or after 1980) and for which the deal has a known execution date. Most of these participants in the market for technology are both adopters and providers (664 are pure adopters, 523 are pure providers, and 2,710 are both adopters and providers). Such firms form 20,172 unique pairs that interact at least once. We think of pairs as directed interactions, with the first firm in the pair being the adopter and the second one the provider (i.e., if two firms exchange knowledge bilaterally, they are recorded twice as two different pairs). The average number of transaction records per pair is 8.4, and the total number of records is 168,935. However, the number of records in the raw data includes potential duplicates. To eliminate duplicates, we take a conservative approach and treat repeated transaction records between a pair in a given exchange mode and execution year as the same deal. The total number of cleaned transaction records (i.e., pair-mode-year observations) is 33,873. The distribution of the intensity of connections is highly skewed. Most pairs transact just once, with only slightly more than 30% of the pairs transacting twice or more. The average number of transactions (i.e., mode-year observations) per pair is 1.68. The pairs with the highest number of interactions are Hewlett-Packard (HP)—IBM and HP-Microsoft, with 27 transactions each. Below we describe the cross-sectional and longitudinal dimensions of the data. To construct the market-for-technology weight, we mostly exploit the cross-sectional dimension of the network. We use the longitudinal dimension to measure the intensity of connections between pairs but do not explicitly exploit network formation over time.

Note that this is a subsample of a slightly larger data set of transactions with two firms matched to Compustat, which also includes transactions with an unknown transaction date or pairs in which one of the two firms is not matched to patents. The broader sample includes 22,247 unique pairs that interact at least once, of which 22,114 have at least one transaction with a known transaction date. Only 20,172 of those pairs involve firms linked to patents. We restrict to transactions between those pairs in our analysis. The number of records in the raw data generally exceeds the number of unique deals because some deals are collected multiple times through different SEC filings or because some patent bundles are transferred through independent patent-by-patent transactions. More sophisticated disambiguation of unique transactions is complex because the only information available for some deals is the name of the parties and the execution year.
1. Cross-Sectional Dimension of the Network

The network of interactions in the market for technology is displayed in figure 1. Groups 3 (drugs and medical) and 2 (computers and communications) in the National Bureau of Economic Research Patent Data Project (NBER PDP) six-group aggregation of technology fields (see Hall, Jaffe, and Trajtenberg 2001)—on the left and right extremes of the network, respectively—dominate the market for technology. In between, there is a gradation of smaller technology clusters: chemical (group 1), others (group 6), mechanical (group 5), and electrical and electronic (group 4). The fact that firms heavily cluster by technology field suggests that technological proximity plays an important role in shaping the market-for-technology network. That is, firms try to internalize the effects of their R&D when spillovers are expected.

Firms connected to the network as technology adopters do of course access knowledge from their direct providers, but they are also indirectly connected to knowledge at further node distances owned by indirect providers. It takes only a few steps for connected adopters to reach most of the firms in the network. On average, an adopter is linked to 0.14% of the firms in the network in one step, 4% in two steps, 26% in three steps, 58% in four steps, 75% in five steps, and 81% in six steps, after which the number of connections barely increases. The potential for reaching further providers is exhausted after node distance 11, which defines the diameter of the network (i.e., the shortest distance between the two most distant nodes). The average path length is four (i.e., on average it takes four steps to connect two firms). Finally, it is important to highlight that our market-for-technology network has very little overlap with the product market network.22

The top 35 adopters and providers are listed in table 1. Table 2 shows that participation in the market for technology is highly skewed, with only 1% of firms adopting technologies from more than 50 different providers or providing technologies to more than 50 different adopters. However, such prominent actors in the market for technology are responsible for about 40% of total R&D investments and patent applications. This skewed distribution implies that those firms that are most active in generating knowledge are also active at protecting and enforcing such knowledge. Therefore, the returns to R&D might be considerably larger than typically assumed for central actors, which is a very important source of knowledge.

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21 Each node in the network represents a firm (with node size being proportional to the number of interactions of the firm), and each edge represents the number of interactions between a pair of firms (with edge size being proportional to the number of interactions between the pair). Nodes are arranged following the Fruchterman and Reingold (1991) algorithm. Firms that appear closer to each other in the graph are more strongly connected.

22 The product market network of Barrot and Sauvagnat (2016) includes 21,654 unique customer-supplier pairs (of Compustat firms), of which only 833 have an adopter-provider relationship in the market for technology.
creation and diffusion. When calculating the private and social returns to R&D, we take such heterogeneity in firms’ capacity to internalize the effects of their research into account.

2. Longitudinal Dimension of the Network

Figure 2 shows the distribution of cleaned transaction records (i.e., pair-mode-year observations) for the whole sample and for every contractual mode of exchange. The number of transactions is almost negligible for the pre-1990 and post-2014 years. Part of the variation in the number of transactions over time is driven by sampling choices, which seem to
differ considerably across exchange modes. For patent trades, the sampling criteria considered in the USPTO PAD is stable over the whole period, and this translates into an apparently logical sequence with patent trades increasing over time. Non-alliance-related licensing deals have been compiled by ktMINE from SEC disclosures, and sampling seems to be targeted at post-1995 deals. Non-alliance-related cross-licensing deals are self-compiled from SEC forms filed on or after 2000.23 The sampling criteria used by SDC Platinum to create the data on alliance-related deals (i.e., licensing and

23 SEC filings essentially provide information on active deals. Many licensing and cross-licensing deals have terms of >5 years, so post-2000 filings also provide a substantial amount of information for the 1995–2000 period.
cross-licensing deals and R&D alliances) is not explicit, so time consistency cannot be assumed. Sampling seems targeted around 1995. The sharp peak in the number of deals around 1995 and subsequent decay after 2000 seem too steep to be entirely driven by the crash of the dot-com bubble. The evolution in the number of deals seems driven mainly by sampling choices, which are unknown to us, rather than by actual underlying activity. Note that inconsistencies in sampling pose some limits to our ability to reliably track network formation over time. We do not explicitly exploit network formation in this study. We use longitudinal information mostly to measure the intensity of connections through aggregation of deals within adopter-provider pairs over time and across modes of exchange.

3. Important Remarks

We emphasize that our data set includes only a subset of all the voluntary technology transfers that involve compensated payments. This is partly because we do not consider important exchange modes of technology transfer, such as mergers and acquisitions (M&As) or the hiring of inventors. The main reason for excluding M&As from our sample is that our strategy for estimating the effect of voluntary transfers relies on tracking the effect of variation over time in the provider’s R&D on the adopter’s revenue. This requires focusing on exchange modes where the two sides of the deal

<table>
<thead>
<tr>
<th>Number of Firms Adopted From/Provided To</th>
<th>% R&amp;D</th>
<th>% Patents</th>
<th>% Sales</th>
<th>% Firms</th>
</tr>
</thead>
<tbody>
<tr>
<td>A. Relevance as an Adopter</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>6.1</td>
<td>2.9</td>
<td>38.3</td>
<td>83.2</td>
</tr>
<tr>
<td>1</td>
<td>3.3</td>
<td>2.2</td>
<td>9.7</td>
<td>6.4</td>
</tr>
<tr>
<td>Between 2 and 10</td>
<td>17.4</td>
<td>15.9</td>
<td>21.9</td>
<td>8.7</td>
</tr>
<tr>
<td>Between 11 and 20</td>
<td>14.8</td>
<td>12.2</td>
<td>11.0</td>
<td>1.0</td>
</tr>
<tr>
<td>Between 21 and 50</td>
<td>20.0</td>
<td>23.1</td>
<td>8.6</td>
<td>.5</td>
</tr>
<tr>
<td>More than 50</td>
<td>38.4</td>
<td>43.7</td>
<td>10.4</td>
<td>.3</td>
</tr>
<tr>
<td>B. Relevance as a Provider</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>6.7</td>
<td>3.0</td>
<td>41.7</td>
<td>84.0</td>
</tr>
<tr>
<td>1</td>
<td>2.9</td>
<td>2.3</td>
<td>9.8</td>
<td>5.7</td>
</tr>
<tr>
<td>Between 2 and 10</td>
<td>16.3</td>
<td>15.7</td>
<td>18.4</td>
<td>8.5</td>
</tr>
<tr>
<td>Between 11 and 20</td>
<td>15.1</td>
<td>13.4</td>
<td>11.1</td>
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<tr>
<td>Between 21 and 50</td>
<td>18.7</td>
<td>20.1</td>
<td>8.7</td>
<td>.5</td>
</tr>
<tr>
<td>More than 50</td>
<td>40.3</td>
<td>45.5</td>
<td>10.3</td>
<td>.3</td>
</tr>
</tbody>
</table>

Note.—This table groups firms by their prominence as adopters (measured as the number of providers a firm adopts from) in panel A and as providers (measured as the number of adopters a firm provides to) in panel B. For each group, we report the percentage of R&D investments, patent applications, sales, and firms out of the total. The sample used to produce this table includes all the available Compustat observations for the years 1990–2014.
preserve their legal form. The main reason for excluding inventor hires is that those involve a slightly different mechanism from the one considered in this paper. The hiring firm compensates the inventor through a higher

24 With M&A deals, the R&D of the target merges with financial data of the acquirer, which prevents us from tracking the effects of the target’s R&D on the acquirer’s revenue. Also, the revenues of the target merge with the revenues of the adopter, which adds noise in the outcome measure of the productivity equation.
salary but not the previous employer of the inventor. We mainly consider compensation between firms in our setup. Another reason why our data are not comprehensive is that we are able to collect only a subset of the deals through the exchange modes that we do target. This is partly because firms disclose material deals only to the SEC but keep many more deals secret and partly because our matching exercise favors including true positives at the expense of excluding some false negatives. The most important implication of such considerations is that any effects that we may capture with this data set are likely to be a lower bound for the true importance of technology markets.

C. Weights for the Spillover and Market-for-Technology Pools

In this subsection, we define the weights used to construct the spillover and market-for-technology pools given by equations (20) and (21). The weight used to define the spillover pool is based on the notion of technological proximity. The main intuition is that firms are better able to benefit from the R&D of firms operating in similar technological fields. The weight used to define the market-for-technology pool is based on the strength of connections in the market-for-technology network. The spillover weight is standard in the literature. The market-for-technology weight is novel and one of the main contributions of the paper. Following the tradition in the spillovers literature, we work with time-invariant weights. This implies that we exploit only cross-sectional variation between firm dyads to tease out spillovers and technology transfers.

1. Weight for the Spillover Pool \( (\omega^S_{ij}) \)

Our main weight for the spillover pool is the Jaffe (1986) technology closeness measure, calculated as the uncentered correlation between the respective technology classes of the two firms. This index ranges between zero (minimum closeness) and one (maximum closeness), depending on the degree of overlap in technology between firm pairings, and is time invariant. By way of robustness check we also use the Jaffe metric applied to alternative distance spaces commonly used in the literature, such as geographical proximity and proximity in the product market space. Additionally, we use the intensity of forward citations from \( i \) to \( j \) and an analogous binary indicator capturing whether the adopter ever cites the provider. The exact expressions for all these weights are provided in appendix E.

2. Weight for the Market-for-Technology Pool \( (\omega^M_{ij}) \)

The market-for-technology weight measures the importance of \( j \) as an upstream technology supplier of \( i \) using both extensive and intensive margin
information in the market-for-technology network. We exploit information up to network distance four—the average path length of the network—to capture the breadth and depth of the network.

We first define the strength of direct connections as follows. Let \( d_{ijzt} \) be a dummy variable with value one if provider \( j \) transfers technologies to adopter \( i \) through mode of exchange \( z \) in year \( t \) and value zero otherwise.\(^{25}\) The total count of technology transfers (i.e., exchange mode–year observations) from \( j \) to \( i \) over the whole sample period is \( D_{ij} = \sum_t^\Sigma_z d_{ijzt} \).\(^{26}\) The maximum possible number of technology transfers from \( j \) to \( i \) is \( D_{ij}^{\text{max}} = 6\Sigma_t^\text{overlap}_{ijt} \), where \( \text{overlap}_{ijt} \) is a dummy variable with value one if \( i \) and \( j \) are both active in Compustat in year \( t \) and six is the maximum possible number of transactions through different exchange modes per year between a given pair.\(^{27}\) We measure the importance of \( j \) as a direct technology provider of \( i \) as the total number of technology transfers out of the maximum possible number of transfers, \( n_{ij} = D_{ij}/D_{ij}^{\text{max}} \).

The ratio \( n_{ij} \) subsumes both intensive and extensive margin information and ranges between zero and one. It is equal to one if \( j \) supplies technologies to \( i \) every year through every mode of exchange and is equal to zero if it does not supply technologies to \( i \) at all. The mean value of this measure for connected pairs is 0.02, with minimum and maximum values of 0.005 and 0.3, respectively. That is, on average, adopters obtain technologies from a given provider in only 2% of all the possible mode-year observations. Note that while we try to capture the intensive margin through the aggregation of deals over time and across exchange modes within a given pair, we do not observe how much technology is transferred for a given deal because transaction prices or transacted assets are not observed. Therefore, our ability to measure the intensive margin is partial. This is an inherent limitation of our analysis. Despite this limitation, our measure of the strength of direct connections \( n_{ij} \) offers valuable information on

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\(^{25}\) Recall that the most fine-grained measure of cleaned transaction records is at the pair-mode-year level. The subscript \( z \) indexes the six modes of exchange in our data (patent transfers, licensing, cross-licensing, licensing between firms in a joint venture, cross-licensing between firms in a joint venture, and R&D alliances). The subscript \( t \) indexes the years 1980–2014. Most of the transactions take place in the post-1990 period, with only 3.4% of transactions having effective transaction dates before 1990.

\(^{26}\) For example, if we observe a licensing agreement between firms \( i \) and \( j \) in 1995 and another one in 1998, the number of technology transfers is two. Similarly, if \( i \) adopts technologies from \( j \) through patenting and cross-licensing in 1995, the number of transfers from \( j \) to \( i \) is again two. If \( i \) adopts technologies from \( j \) through three different licensing agreements in 2000, this will count as just one technology transfer because we have collapse transfers at the mode-year level to remove potential duplicates.

\(^{27}\) The number of years over which two firms overlap in Compustat is only a proxy for the number of years over which two firms coexist. In practice, firms are incorporated a few years before they go public, and such years are not reflected in our overlap measure. We set the minimum number of overlapping years at five (i.e., we replace \( \sum_{t=1980}^{2014} \text{overlap}_{ijt} \) with five whenever the value is positive but lower than five). This affects only 4% of the transacting pairs.
the intensive margin of connections. Values close to one mean that the adopter and the provider are highly integrated, in which case the R&D of the provider should be almost as powerful as own R&D.

The weight can then be obtained by combining the measure on the strength of direct connections with network information up to longer distances to capture relationships between distant firms up to network distance four:

$$\omega_{ij}^{M-DA} = n_{ij} + \sum_{k,l \neq i,j} n_{il} n_{lj} + \sum_{k,l} \sum_{i \neq j} n_{il} n_{lj} + \sum_{k,l,m} \sum_{i \neq j} n_{im} n_{ml} n_{lj} n_{kj},$$  (25)

where the first component on the right-hand side has already been described, the second component measures action at network distance two, the third component measures action at network distance three, and the last component measures action at network distance four. The contribution of a provider at a given node distance is given by the sum of nonredundant paths linking and at each distance, weighted by the relative importance of as a direct provider of the immediate adopter times the importance of the relative adopter as a provider of the next adopter, and so on. Figure 3 provides a graphical illustration of the weight for two hypothetical firms .

Exploiting distant information in the network increases the number of firms that contribute to the market-for-technology pool. Using links in the network beyond direct connections is relevant for two reasons. First, our market-for-technology network is not comprehensive owing to firms not disclosing most of their deals in their financial statements. Therefore, indirect connections between firms at longer distances could indeed be capturing direct connections that we simply failed to collect or that are not disclosed in the available data sources. Second, distant interactions capture a longer technology supply chain that extends beyond direct connections and allow us to better capture the breadth and depth of the network. The weight acknowledges that the contribution of distant providers is lower than that of closer providers.

Note that while the weight for the spillover pool is based on patented technologies, this is not necessarily the case for the weight for the market-for-technology pool (e.g., it could capture the transfer of tacit knowledge that could not possibly have been measured by patented inventions). In practice, though, all of the firms in our sample patent and many voluntary transfer deals are likely to involve patented technologies.

Consider the following examples. Provider sells patents to firm which in turn licenses such patents to firm . Alternately, provider engages in an R&D alliance with firm which in turn sells patents to firm . In both cases, R&D from diffuses through the market-for-technology supply chain to firm . To measure all the gains from trade resulting from 's R&D, we need to estimate the effect of 's R&D on both the product market revenue of the intermediate adopter and the downstream adopter . The latter will not be captured from the effect of 's R&D and on 's product market revenue.
Importantly, the weight is modular and can be easily decoupled into subweights covering information up to distance one ($\omega^M_{ij} = n_{ij}$), distance two ($\omega^M_{ij} = n_{ij} + \sum_{k \neq j} n_{ik} n_{kj}$), and distance three ($\omega^M_{ij} = n_{ij} + \sum_{k \neq j} n_{ik} n_{kj} + \sum_{l \neq i, j} n_{ikl} n_{lkj}$). This is an interesting property in our case because we are interested in studying whether the estimates of the
spillover elasticity are sensitive to the amount of information exploited in the market-for-technology network. We calculate four different market-for-technology pools based on each of the weighing matrices exploiting information between network distance one and four and obtain separate estimates for each of these. We also report results using unweighted direct connections between firms in robustness checks.

3. Relationship between the Spillover and Market-for-Technology Weights

Table 3 provides descriptive statistics of the weights for the spillover pool by node distance (i.e., the number of steps it takes to connect two firms) in the market for technology. The results essentially echo the main insights emerging from the network depicted in figure 1—namely, that the most popular spillover pool weights are strongly correlated with proximity in the market for technology. For instance, the Jaffe technological proximity measure is 0.336 between adopters and direct providers and declines by almost one-half to 0.151 between adopters and providers at node distance two, to 0.071 between firms at distance three, to 0.035 for providers at distance four, and further to 0.026 for more distant providers. Similar patterns emerge for other weights commonly used in the literature to calculate the spillover pool based on geographical proximity, market proximity, and forward citations. The main implication of these figures is that the weights assumed to capture pure externalities are also capturing internalized market transfers.

TABLE 3

Descriptive Statistics of the Pairwise Data Set

<table>
<thead>
<tr>
<th></th>
<th>( D1 )</th>
<th>( D2 )</th>
<th>( D3 )</th>
<th>( D4 )</th>
<th>( D5-D11 )</th>
<th>Unconnected</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technological proximity</td>
<td>( 0.336 )</td>
<td>( 0.151 )</td>
<td>( 0.071 )</td>
<td>( 0.035 )</td>
<td>( 0.026 )</td>
<td>( 0.026 )</td>
</tr>
<tr>
<td>Geographical proximity</td>
<td>( 0.241 )</td>
<td>( 0.187 )</td>
<td>( 0.167 )</td>
<td>( 0.148 )</td>
<td>( 0.123 )</td>
<td>( 0.103 )</td>
</tr>
<tr>
<td>Market proximity</td>
<td>( 0.224 )</td>
<td>( 0.104 )</td>
<td>( 0.052 )</td>
<td>( 0.025 )</td>
<td>( 0.017 )</td>
<td>( 0.020 )</td>
</tr>
<tr>
<td>Percentage of citations</td>
<td>( 0.014 )</td>
<td>( 0.002 )</td>
<td>( 0.000 )</td>
<td>( 0.000 )</td>
<td>( 0.000 )</td>
<td>( 0.000 )</td>
</tr>
<tr>
<td>At least one citation</td>
<td>( 0.567 )</td>
<td>( 0.178 )</td>
<td>( 0.036 )</td>
<td>( 0.010 )</td>
<td>( 0.005 )</td>
<td>( 0.004 )</td>
</tr>
<tr>
<td>Number of pairs</td>
<td>( 16,870 )</td>
<td>( 387,048 )</td>
<td>( 1,840,096 )</td>
<td>( 2,190,669 )</td>
<td>( 1,390,931 )</td>
<td>( 13,886,816 )</td>
</tr>
</tbody>
</table>

**Note.**—This table provides descriptive statistics of the weights used to construct the spillover pool by node distance in the market for technology. Such descriptive statistics are based on an initial pairwise expansion of size \( 7,653 \times (7,653 - 1) \) between all the firms matched to patents. These are the pairs for which technological proximity can be calculated. Next, we impose an additional filter and restrict to pairs where the two firms invest in R&D and overlap in Compustat in at least 1 year during the period 1990–2014. These are the pairs for which the provider can potentially contribute to the adopter’s R&D pool through the weighting matrices.
To estimate the separate effects of spillovers and technology markets, we need variation in the spillovers and market-for-technology weights across pairs. While both measures are positively correlated, they are far from perfectly collinear. Figure 4 shows that there is substantial dispersion in both weights across pairs. The raw correlation between the spillover and the market-for-technology weights based on information up to several node distances ranges between 0.06 and 0.079, values well below one. Generally, pairs with high values of the market-for-technology weight also tend to have relatively high values of the spillover weight, while this is not necessarily the case for the opposite. For example, almost 97% of the pairs with positive $\omega_{ij}^{M-D1}$ also have positive $\omega_{ij}^{S}$. By contrast, only 0.3% of the pairs with positive $\omega_{ij}^{S}$ have positive values of $\omega_{ij}^{M-D1}$. The percentages are less extreme for the weights exploiting information up to network distance four, with 51% of the pairs with positive $\omega_{ij}^{M-D4}$ having positive $\omega_{ij}^{S}$ and 38% of the pairs with positive $\omega_{ij}^{S}$ having positive values of $\omega_{ij}^{M-D4}$.

**Fig. 4.**—Correlation between the spillover and market-for-technology weights. This graph plots the pairwise weights used to construct the spillover pool and market-for-technology pool for a sample of 7,656,371 pairs that overlap in Compustat in at least 1 year and have positive values for at least one of the two weights.
These patterns imply that it is possible to identify spillover effects from pairs that are not connected through the market for technology; then, it is possible to identify market-for-technology effects from the remaining pairs that are connected in the market for technology and possibly also simultaneously benefit from spillovers.\textsuperscript{30} Consider three hypothetical firms: the focal adopter of interest $i$, a provider $k$ that is in close technological (but not market-for-technology) proximity to $i$, and another provider $l$ that is in close market-for-technology (and possibly also technological) proximity to $i$. When firm $k$ varies its R&D expenditures, $S$ will vary while $M$ remains constant. When firm $l$ changes its R&D expenditures, $M$ will vary and $S$ may vary as well. Differences in the weights therefore lead to independent variation in $i$’s spillover and market-for-technology pools.

\section*{D. Sample Used in the Econometric Regressions}

In the econometric regressions, we restrict to the years 1990–2014, for which coverage on interactions in the market for technology is satisfactory. We drop firms in the following sectors, which are heavily regulated or have licensing income as the main revenue source: agriculture, forestry, and fishing (SIC codes starting with 0); mining and construction (SIC codes starting with 1); electric, gas, and sanitary services (SIC codes starting with 49); finance, insurance, and real estate (SIC codes starting with 6); and public administration (SIC codes starting with 9). For the remaining firms, we clean and remove accounting years with extremely large jumps in sales, employment, or capital signaling merger and acquisition activity (when a year is removed the firm is treated as a new entity with a new identifier). We preserve all firms with at least one patent, which are observed for at least four consecutive years after the cleaning and with nonmissing information on the relevant variables (i.e., sales, capital, employment, and R&D).

These filters leave us with 3,049 firms and 34,607 firm-year observations for which the spillover pool can be created and the product market revenue equation can be estimated. One of the main goals of the empirical exercise is to identify the elasticity of the market-for-technology pool. Such a pool can be created only for firms that are connected to the market for technology as adopters. To obtain the main sample used in the regressions, we apply one last filter and restrict to firms connected to direct providers that invest in R&D in all the years in which the firm is in the sample. This filter ensures that the market-for-technology pools of connected firms are not empty. We exclude from the main sample firms that are unconnected to the network or that are connected to the network but to direct

\textsuperscript{30} Even the latter pairs provide useful variation for identifying both coefficients given the substantial dispersion in technological proximity for pairs with similar values of the market-for-technology weight.
providers that do not invest in R&D in any of the sample periods in which they are available.31 We refer to the latter group as unconnected firms for simplicity.

The final sample includes 1,796 firms (21,893 firm-year observations) that account for 97% of the R&D investments in the broader sample of 3,049 firms (34,607 firm-year observations) and 78% of total R&D investments by Compustat firms during the sample years. Descriptive statistics are provided in table 4. The firms in the main sample are on average substantially larger (in sales, number of employees, and capital), have higher R&D expenditures, patent more, and have access to a larger spillover pool. Finally, note that to calculate the spillover and market-for-technology pools we use all the available R&D observations in Compustat.

V. Empirical Strategy

To estimate equation (19), we consider a specification with just two conventional inputs: labor and capital. This is a specification commonly used in related studies interested in estimating the effect of R&D spillovers (see Bloom, Schankerman, and Van Reenen 2013; Colino 2016; Zacchia 2020). Another possibility would be to also include materials in the specification, as in Lychagin et al. (2016). We opt for the first specification without materials because the best possible measure of materials that can be constructed with Compustat data already subsumes R&D expenditures as well as payments for technology.32 Including such a measure of materials in the regressions is not compatible with our goal of obtaining separate identification of the coefficients of own R&D and the market-for-technology pool, because it already absorbs all the variation required to identify both coefficients, which are needed to measure the private returns to R&D. Therefore, we argue that studies interested in measuring both the private and the social returns to R&D with Compustat data should use specifications without materials, similar to the one proposed by Bloom, Schankerman, and Van Reenen (2013). Instead, studies interested in estimating only pure spillover effects, such as Lychagin et al. (2016), can use specifications with materials. The materials measure will partly control for

31 The market-for-technology pools of those connected firms could be positive if the direct providers have invested in R&D in the past but the stocks have not fully depreciated or if indirect providers invest in R&D during the sample period.

32 The Compustat measure is considerably broader than more conventional definitions that typically include only raw materials. The standard definition of materials with Compustat data is cost of goods sold (COGS, Compustat item 41) plus administrative expenses (XSGA, Compustat item 189) less depreciation (DP, Compustat item 14) less wage expenditures (calculated as number of employees times the average industry sales extracted from databases such as EU KLEMS). XSGA includes R&D expense, while COGS includes licenses and royalty expense. This definition has been used, e.g., by Bresnahan, Brynjolfsson, and Hitt (2002), Keller and Yeaple (2009), and Lychagin et al. (2016).
internalized technology flows, possibly leading to more reliable estimates of pure spillover effects.

To address the endogeneity of conventional inputs, we estimate the coefficients of labor and capital following the procedure described by De Loecker (2013). This procedure builds on the control function approach proposed by Olley and Pakes (1996) with the correction advocated by Ackerberg, Caves, and Frazer (2015). It also allows the productivity process to be endogenously shifted by policy variables of interest, as in Doraszelski and Jaumandreu (2013). In our case, productivity is allowed to

---

**TABLE 4
Descriptive Statistics of the Firm-Level Data Set**

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>A. Connected</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sales</td>
<td>6,758</td>
<td>400</td>
<td>25,701</td>
<td>.001</td>
<td>532,726</td>
</tr>
<tr>
<td>Labor</td>
<td>17</td>
<td>2</td>
<td>45</td>
<td>.001</td>
<td>761</td>
</tr>
<tr>
<td>Capital</td>
<td>1,791</td>
<td>74</td>
<td>7,785</td>
<td>.001</td>
<td>186,470</td>
</tr>
<tr>
<td>Patent flow</td>
<td>41</td>
<td>2</td>
<td>179</td>
<td>.000</td>
<td>4,355</td>
</tr>
<tr>
<td>Cite weighted patents</td>
<td>205</td>
<td>7</td>
<td>1,016</td>
<td>.000</td>
<td>29,881</td>
</tr>
<tr>
<td>R&amp;D</td>
<td>303</td>
<td>22</td>
<td>977</td>
<td>.003</td>
<td>14,114</td>
</tr>
<tr>
<td>R&amp;D stock</td>
<td>1,502</td>
<td>137</td>
<td>5,080</td>
<td>.020</td>
<td>60,017</td>
</tr>
<tr>
<td>Spillover pool (S)</td>
<td>136,626</td>
<td>109,430</td>
<td>102,860</td>
<td>247</td>
<td>603,514</td>
</tr>
<tr>
<td>Market-for-technology pool (M):</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$D_1$</td>
<td>1,074</td>
<td>203</td>
<td>2,990</td>
<td>.002</td>
<td>42,827</td>
</tr>
<tr>
<td>$D_2$</td>
<td>2,214</td>
<td>383</td>
<td>6,564</td>
<td>.002</td>
<td>88,653</td>
</tr>
<tr>
<td>$D_3$</td>
<td>3,495</td>
<td>573</td>
<td>10,718</td>
<td>.002</td>
<td>141,787</td>
</tr>
<tr>
<td>$D_4$</td>
<td>4,919</td>
<td>760</td>
<td>15,397</td>
<td>.002</td>
<td>198,684</td>
</tr>
<tr>
<td>Number of firms</td>
<td>1,796</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of observations</td>
<td>21,893</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>B. Unconnected</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sales</td>
<td>879</td>
<td>74</td>
<td>4,080</td>
<td>.001</td>
<td>96,925</td>
</tr>
<tr>
<td>Labor</td>
<td>3</td>
<td>0</td>
<td>11</td>
<td>.001</td>
<td>212</td>
</tr>
<tr>
<td>Capital</td>
<td>225</td>
<td>11</td>
<td>1,079</td>
<td>.001</td>
<td>20,298</td>
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<tr>
<td>Patent flow</td>
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<td>.000</td>
<td>108</td>
</tr>
<tr>
<td>Cite weighted patents</td>
<td>7</td>
<td>0</td>
<td>29</td>
<td>.000</td>
<td>752</td>
</tr>
<tr>
<td>R&amp;D</td>
<td>15</td>
<td>4</td>
<td>44</td>
<td>.001</td>
<td>1,243</td>
</tr>
<tr>
<td>R&amp;D stock</td>
<td>65</td>
<td>16</td>
<td>210</td>
<td>.008</td>
<td>5,288</td>
</tr>
<tr>
<td>Spillover pool (S)</td>
<td>68,489</td>
<td>50,578</td>
<td>64,556</td>
<td>103</td>
<td>519,148</td>
</tr>
<tr>
<td>Market-for-technology pool (M):</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$D_1$</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>.000</td>
<td>32</td>
</tr>
<tr>
<td>$D_2$</td>
<td>0</td>
<td>0</td>
<td>8</td>
<td>.000</td>
<td>223</td>
</tr>
<tr>
<td>$D_3$</td>
<td>1</td>
<td>0</td>
<td>15</td>
<td>.000</td>
<td>445</td>
</tr>
<tr>
<td>$D_4$</td>
<td>1</td>
<td>0</td>
<td>28</td>
<td>.000</td>
<td>727</td>
</tr>
<tr>
<td>Number of firms</td>
<td>1,255</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of observations</td>
<td>12,714</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Note.**—This table reports summary statistics of the variables used in the regressions for the main sample of firms connected to the network (panel A) and for the sample of unconnected firms (panel B). Values are in millions of 2010 dollars.
be impacted by the variables contributing to the firm’s knowledge capital (i.e., own R&D as well as the external R&D pools). The proxy variable that we use to instrument for productivity is log investment. We provide more details of the estimation procedure in appendix F. The coefficients on labor and capital obtained from this specification are estimated to be 0.7 and 0.24, respectively, for the main sample of connected firms. In our main empirical specification below, we use the measure of logged total factor productivity \( \ln TFP \) resulting from such coefficient estimates as the dependent variable:

\[
\ln TFP_{it} = \ln Y_{it} - 0.7 \ln L_{it} - 0.24 \ln K_{it},
\]

where \( G_{it} \) represents the firm’s R&D stock, \( S_{it} \) represents the standard spillover pool, \( M_{it} \) represents the market-for-technology pool, \( \phi_i \) represents a full set of year fixed effects, \( \phi_i \) represents a firm fixed effect, and \( u_{it} \) represents the error term. We lag own R&D and the external R&D pools by 1 period to account for the fact that the effects of R&D materialize with a temporal lag. The outcome of the revenue production function is deflated product market revenue, as is customary in the literature. The deflator, however, conflates both supply and demand factors. To control for the latter, we include the logged current industry prices among the set of regressors, as in Bloom, Schankerman, and Van Reenen (2013) and Zacchia (2020). This is similar to controlling for industry-year effects. Related studies take a similar approach and control for trends for the computer industry and semiconductors, which have experienced a huge decline in prices over the sample period (see Griliches and Mairesse 1995; Keller and Yeaple 2009).

### A. Identification Challenges

The parameters of interest are \( \beta_2 \) and \( \beta_3 \), which capture the elasticity of the outcome variable with respect to the spillover and market-for-technology pools, respectively. Identification of these parameters is achieved through within-firm variation in the spillover and market-for-technology pools. The pools are the interaction of dyad-specific weights that are held fixed over time and time-varying R&D investments. Firms are subject to differential shocks in R&D over time, and the effect of such a change in R&D will be heterogeneous across firms depending on the weights. Thus, identification comes from the interaction between a time-invariant weight and a time-varying shock. Figure 5 shows that there is enough independent within-firm variation across both measures to separately identify the contributions of the spillover and market-for-technology pools to revenues. The figure shows the distribution of within-firm correlation between detrended spillover and market-for-technology measures. Although correlation is high
for some firms, there are a substantial number of firms for which correlation is low or negative.

The external R&D pools are potentially correlated with the error term through two channels. The first is the possible correlation between the weights and the error term—that is, $E[\omega_j : u_i] \neq 0$ and $E[\omega_M : u_i] \neq 0$. The spillover weight is potentially correlated with the error term because firms might decide to operate in certain technology spaces in response to unobserved technological shocks. Similarly, the market-for-technology weight is potentially correlated with the error term because transaction decisions depend on unobserved profitability shocks. This problem should not be severe in our setting because we do not directly exploit connection formation over time. We exploit only cross-sectional information in the weighting matrices. Cross-sectional information on the structure of connections $\Sigma_{ij}, \omega_j^S$ and $\Sigma_{ij}, \omega_j^M$ remains constant over time for a given adopter and should be absorbed by the firm fixed effect. This is not to say that network formation does not generate endogeneity issues with time-invariant

Fig. 5.—Within-firm correlation between the spillover and market-for-technology pools. Correlations are computed by removing the respective year means from the respective pools and finding their correlation coefficient for every firm.
weights. It does, but such endogeneity issues manifest through the channel that we describe below.

The second is the possible correlation between the error term of the adopter and the R&D of its technology providers—that is, \( E[G_{jt-1} \cdot u_t] \neq 0 \). The R&D of technology providers is potentially correlated with the error term for two reasons. First, the provider takes into account the adopter’s future benefits from the technology transfer when deciding how much to invest in R&D. If the provider has information about future profitability shocks of the adopter, then those will be incorporated in the first-order condition for the provider’s optimal R&D investment. If such profitability shocks are not observed by the econometrician (i.e., are embedded in the error term), then the provider’s lagged R&D stock will be correlated with the error term. Second, the time-varying component of the weight that we do not explicitly exploit can be regarded as an omitted variable that ends up subsumed in the error term. This omitted variable captures changes in network formation and is a function of unobserved shocks to the provider and the adopter. Therefore, by relying on collapsed weights we address the potential correlation between the weight and the error term at the expense of possibly generating an additional source of correlation between the provider’s R&D and the error term.

In short, with time-invariant weights, all the within-firm variation in the external R&D pools is driven entirely by changes over time in the external R&D stocks \( G_{jt-1} \), which are potentially correlated with the error term. The main advantage of not exploiting network formation is that it should allow us to address the endogeneity of the external R&D pools by instrumenting only the external R&D stocks. This is important in our case because we do not have good instruments for the evolution of the network.

B. IV Strategy with R&D Tax Price Instruments

To deal with the possible endogeneity of external R&D investments, we follow the identification strategy in Bloom, Schankerman, and Van Reenen (2013). That is, we exploit changes in the tax price of R&D induced by federal and state R&D tax credits to construct instruments for the R&D investments in the pool.  

The federal tax price, denoted by \( r_{jt}^F \), is firm specific because it depends on the interaction between actual R&D and a firm-specific base that depends on firm age and other firm-specific attributes. Moreover, it displays variation over time because of changes in the definition

Both have been shown to be important drivers of corporate R&D expenditure. The federal R&D tax credit has a strong effect on corporate R&D. The elasticities found in the literature are broadly around unity or larger. This evidence includes Hall (1993), Bloom, Griffith, and Van Reenen (2002), Rao (2016), and other papers reviewed in Becker (2015). State R&D tax credits also increase R&D within affected states, as shown by Wilson (2009) among others, with the estimated elasticity also being above one.
of the base, the statutory tax credit, the corporate tax rates, and deduction rules. The firm’s state-level tax price, denoted by $r_{Sit}$, also varies across firms because the geographical distribution of economic activity—and hence the extent to which firms can benefit from state-specific R&D tax credits—varies across firms. Details on the measurement of the tax prices are provided in appendix G. We shock external R&D stocks with tax credits and let the shock diffuse through fixed weights to identify $\beta_1$ and $\beta_n$. We use the original IV strategy in Bloom, Schankerman, and Van Reenen (2013) and also apply two corrections to mitigate concerns around potential endogenous variation in the instrument owing to aggregation across providers and to the double projection procedure.

1. Double Projection with Predicted R&D

In our baseline IV regressions, we implement the strategy proposed in Bloom, Schankerman, and Van Reenen (2013). That is, we regress (logged) R&D on (logged) $r_{Sit}$ and $r_{Fit}$ controlling for firm and year fixed effects (details on the estimates used to construct predicted R&D stocks are provided in app. G). Then we use the resulting estimates to calculate the predicted R&D, $R_{jt}^{\text{TAX}}$. Note that we use all the right-hand-side variables to calculate predicted R&D following the original procedure in Bloom, Schankerman, and Van Reenen (2013). We partial out only the error term, which includes potentially endogenous shocks. The inclusion of firm and time fixed effects improves the fit of the prediction and therefore the strength of the instrument, but it also generates nonlinear interactions that are fed into the second stage. The instruments for the external R&D pools are then obtained as in equations (20) and (21) but using predicted R&D instead of actual R&D stocks: $STAX_{jt} = \sum_{Sit} \omega_{ij} \times \{R_{jt} > 0\} \times R_{jt}^{\text{TAX}}$ and $MTAX_{jt} = \sum_{Sit} \omega_{ij} \times \{R_{jt} > 0\} \times R_{jt}^{\text{TAX}}$. We write these expressions as a function of the binary indicator $\{R_{jt} > 0\}$ to make it explicit that the instruments condition on whether firm $j$ invests in R&D.

2. Double Projection Controlling for Weighted Counts of Firms in the Pool

One caveat with the original tax instrument is that the extensive margin decision $\{R_{jt} > 0\}$ is potentially endogenous and is not instrumented

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34 We prefer to build instruments in levels rather than stocks in our baseline estimates to mitigate endogeneity concerns owing to aggregation over time. We report robustness checks using stock-based instruments. As noted by Hall, Mairesse, and Mohnen (2010), current R&D investments should be a good proxy of R&D stocks. If R&D grows at a constant rate $g$ and knowledge capital depreciates at a rate $\delta$, then $G_{it} = R_{it}/(g + \delta)$ and $\ln G_{it} = \ln R_{it} - \ln (g + \delta)$. That is, the logged R&D stock can be expressed as the logged investment plus the logged growth rate and depreciation, which will be incorporated in the firm fixed effect as long as they do not change very much within firm over time.
for. The exogenous component $R_{jt}^{\text{TAX}}$ enters the instrument conditional on firm $j$ investing in R&D. This means that the instrument combines presumably exogenous variation from the R&D tax credits of the providers that invest in R&D and potentially endogenous variation from the aggregation across providers with positive R&D investments. If we turn off the exogenous variation by setting $R_{jt}^{\text{TAX}} = 1$, the instruments become a weighted sum of firms that contribute to the pool: $\text{STAX}_N = \sum_{j\neq i} \omega_{ij}^N \times 1 \{ R_{jt} > 0 \}$ and $\text{MTAX}_N = \sum_{j\neq i} \omega_{ij}^M \times 1 \{ R_{jt} > 0 \}$. This information is potentially endogenous because selection into R&D responds to profitability shocks.35

To remove endogenous variation in the instrument caused by aggregation across providers, we propose a different specification that explicitly includes the weighted count of firms that contribute to the instrument $\text{STAX}_N$ and $\text{MTAX}_N$ as controls. This specification exploits a different type of variation in the external R&D pools for identification of the parameters of interest. In particular, it exploits only intensive margin variation in the external R&D pools, holding the extensive margin constant. The obvious advantage of this strategy is that it guarantees that we exploit only arguably exogenous variation in the instrument. A potential problem is that it might neutralize useful identifying variation if an important part of the within variation in the external R&D pools comes from changes over time in the composition of the pool.

3. Direct Projection Controlling for Weighted Counts of Firms in the Pool

Another possibility is to implement the same strategy above but constructing the instrument directly with the weighted sum of R&D tax prices. In this case, we have two instruments for the spillover pool: $\text{STAX}_F = \sum_{j\neq i} \omega_{ij}^F \times 1 \{ R_{jt} > 0 \} \times \rho_{jt}$ and $\text{STAX}_S = \sum_{j\neq i} \omega_{ij}^S \times 1 \{ R_{jt} > 0 \} \times \rho_{jt}$. We also

35 Tax-driven changes in the marginal cost of R&D could tip some firms on the margin from zero to positive R&D, but the instruments are not designed to explain such extensive margin effects. In principle, an instrument redefined to include tax-driven variation in R&D for all the firms (and not only for R&D-active firms)—i.e., $\text{STAX}_F = \sum_{j\neq i} \omega_{ij}^F \times R_{jt}^{\text{TAX}}$—could potentially explain both intensive and extensive margin decisions. In practice, however, both the federal and the state tax prices have very limited explanatory power for the extensive margin. Identifying variation for the federal tax price stems mostly from changes in the interaction between firm R&D and the base level of R&D spending, both of which remain fixed over time for firms that do not invest in R&D. Therefore, the federal tax price does not offer within-firm variation for identifying potential extensive margin effects. The state tax price has within-firm variation for firms that do not invest in R&D, but supplementary regressions not reported in this study return zero extensive margin effects. Therefore, the federal and state tax prices have explanatory power only for the intensive margin decision of how much to invest in R&D, which justifies the design of the instrument based on conditioning on positive R&D.
have two instruments for the market-for-technology pool: $MTAX_{Fu} = \sum_{m} \omega_{m}^{H} \times 1\{R_{u} > 0\} \times \rho_{u}^{\sigma}$ and $MTAX_{Su} = \sum_{mu} \omega_{u}^{H} \times 1\{R_{u} > 0\} \times \rho_{u}^{\sigma}$. Such instruments capture the weighted exposure to federal and state R&D tax credits. To make sure that the instruments are exogenous, we still have to control for the weighted count of firms that contribute to the instruments $STAX_{N_{u}}$ and $MTAX_{N_{u}}$. The main advantage of the direct projection is that it is more transparent than the double projection procedure because it does not feed into nonlinear formulas to predict right-hand variables for the second stage. A potential disadvantage is that the strength of the instrument is likely to be lower.

C. Discussion of Alternative Identification Strategies

Explicitly exploiting network formation would involve having to instrument for the evolution of the network. Valid opportunities for instrumenting network formation could be found in institutional changes affecting transaction costs in the market for technology. Patents serve as the foundation of the market for technology, so institutional changes affecting patent protection would be natural candidates. For example, the formation of the Court of Appeal for the Federal Circuit (CAFC) is possibly the most relevant institutional change affecting transaction costs in the market for technology in the United States. The establishment of the CAFC strengthened patent protection and reduced uncertainty surrounding the scope of IP rights (see Galasso and Schankerman 2010). However, the CAFC was established in 1982, long before the sample period covered in this study, and cannot be leveraged in our context. More generally, we find it hard to leverage such institutional shocks because it is unclear how they may have heterogeneous effects on the transaction costs of individual firms and—more importantly—dyads of firms.

Related papers that explicitly exploit network formation of the weighting matrices used to calculate the spillover pool use other strategies. For instance, Zacchia (2020) relies on network spatial lags to instrument for both network formation and external R&D investments. Colino (2016) uses past network structures to instrument for current network formation and the tax instruments proposed by Bloom, Schankerman, and Van Reenen (2013) to instrument for external R&D stocks. Acemoglu, Akcigit, and Kerr (2016) use past network structures to predict network formation in the structure of patent citations. Such strategies would not be optimal in our case, partly because our network is not comprehensive and partly because we do not observe the presample network. Spatial network lags may include direct interactions rather than actual spatial lags, which would result in a violation of the exclusion restriction needed for identification in second-stage IV estimates. Past network structures might fail to capture links that do exist due to our market-for-technology
network being incomplete. The latter is not a problem with patent citation networks built from the whole universe of patent citations. Finally, note that our analytical model suggests that past network structures might not be a totally valid instrument because the decision to transact at a given point in time is a function of future expected profits.

VI. Results

In this section, we present the empirical results of the paper. The section is divided into six parts. First, we present OLS results. Second, we present results based on the tax credit IV strategy. Third, we briefly discuss the main insights from the OLS and IV results. Fourth, we report robustness checks and additional extensions. Fifth, we use our estimates to measure the private and social rates of return to R&D. Finally, we obtain back-of-the-envelope estimates of the gross gains from trade in the market for technology.

A. OLS Results

Table 5 presents OLS results. Columns 1 and 2 report results for a specification that includes only own R&D and the spillover pool, estimated on the samples of unconnected and connected firms, respectively. The coefficient on \( G \) is positive but statistically insignificant, a common result in specifications with firm fixed effects and in the lower end of estimates.

<table>
<thead>
<tr>
<th>( \ln(G) )</th>
<th>( \ln(S) )</th>
<th>( \ln(M - D#) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( (0.16) )</td>
<td>( (0.142) )</td>
<td>---</td>
</tr>
<tr>
<td>( 0.024 )</td>
<td>( 0.265^* )</td>
<td>( 0.027*** )</td>
</tr>
<tr>
<td>( 0.013 )</td>
<td>( 0.255*** )</td>
<td>( 0.071*** )</td>
</tr>
<tr>
<td>( 0.012 )</td>
<td>( 0.227*** )</td>
<td>( 0.098*** )</td>
</tr>
<tr>
<td>( 0.012 )</td>
<td>( 0.195*** )</td>
<td>( 0.029 )</td>
</tr>
<tr>
<td>( 0.013 )</td>
<td>( 0.181*** )</td>
<td>( 0.114*** )</td>
</tr>
<tr>
<td>( 0.013 )</td>
<td>( 0.178*** )</td>
<td>( 0.033 )</td>
</tr>
</tbody>
</table>

Firm and year fixed effects | Yes | Yes | Yes | Yes | Yes
Firms | 1,253 | 1,796 | 1,796 | 1,796 | 1,796
Observations | 12,714 | 21,893 | 21,893 | 21,893 | 21,893

Note.—The dependent variable is \( \ln(TFP) \). All the regressions include industry price deflator controls. Standard errors (shown in parentheses) are clustered at the firm and headquarters’ state level.

* Significant at the 10% level.
*** Significant at the 1% level.
found in the literature, which range from 0.01 to 0.25 but are centered on 0.08 (see Hall, Mairesse, and Mohnen 2010). The estimated spillover elasticity is statistically significant with a value well within the range of estimates in the literature. The estimates are similar in magnitude in both samples, which suggests that sampling considerations do not bias the estimates in any substantial way due to selection issues. Focusing on the main sample of connected firms is likely to be sufficient to provide an accurate qualitative characterization of the relationship between spillovers and technology markets. A full-fledged quantitative assessment would require working with the comprehensive network of interactions in the market for technology.

The remaining columns report results for a specification that includes the market-for-technology pool, using four different measures of $M$ based on weights that exploit an increasing amount of information in the network, ranging from only direct connections to connections up to network distance four. The primary result is that the newly constructed market-for-technology pool $M$ has a positive and statistically significant coefficient. The second result of interest is that the coefficient of the spillover pool $S$ declines considerably, between 3 and 8 percentage points, when the market-for-technology pool is included among the set of regressors. The decline in the spillover elasticity when controlling for technology markets suggests that the conventional spillover pool captures knowledge transmitted through internalized transfers and not only pure externalities. The decline in the spillover coefficient is remarkable considering that our data set on interactions in the market for technology comprises only a subsample of the universe of transactions.

In appendix H, we report results for a specification that uses logged product market revenue as the dependent variable (instead of logged TFP) and includes conventional inputs on the right-hand side, either lagged or in current values as in related studies (e.g., Bloom, Schankerman, and Van Reenen 2013; Zacchia 2020). The spillover and market-for-technology elasticities remain very stable across specifications, but the R&D elasticity fluctuates quite heavily from a statistically insignificant point estimate of 0.018 (when labor and capital are lagged by 1 period) to a statistically significant point estimate of 0.103 (when labor and capital

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36 A selection bias could be present if firms self-select into technology markets only when they cannot access external knowledge through spillovers. In such a case, spillovers would be underestimated in our sample of connected firms. This does not seem to be the case. Note that unconnected firms are not truly unconnected firms. The sample of unconnected firms includes some firms connected to the network but to providers that do not invest in R&D during the sample period, leading to empty pools. It also possibly includes firms that we have not been able to match to the network because our data gathering and matching exercise favors false negatives.
are in current values). Such results suggest that our point estimate of the R&D elasticity is a lower bound. We keep that in mind when discussing the private returns to R&D or comparing the effectiveness of own R&D versus acquired R&D. The wedge between the social and private returns is unaffected by the elasticity of own R&D.

Because the spillover and market-for-technology pools aggregate R&D stocks of several firms, it is difficult to gauge an accurate idea of the relative importance that own R&D, spillovers, and markets for technology have on the generation of revenues from the estimated coefficients. To obtain comparable magnitudes, we calculate the elasticity of $i$’s output with respect to the external R&D stock of just one firm $j$, which is given by the following expression:

$$
\varepsilon^Y_{G_j} = \frac{\partial Y_i}{\partial G_j} \frac{G_j}{Y_i} = \beta_2 \omega^S_{ij} \frac{G_j}{S_i} + \beta_3 \omega^M_{ij} \frac{G_j}{M_i}.
$$

(27)

Such elasticity is evaluated at mean values for nonproviders ($\omega^S_{ij} = 0.052$, $G_j/S_i = 0.015$, $\omega^M_{ij} = 0$, $G_j/M_i = 387.45$) and direct providers ($\omega^S_{ij} = 0.34$, $G_j/S_i = 0.048$, $\omega^M_{ij} = 0.02$, $G_j/M_i = 13.38$) in the market for technology using the OLS estimates in column 3. The elasticity by a nonprovider is 0.00017. This value is 70 times smaller than the elasticity of own R&D, which ranges between 0.012 and 0.013. The elasticity of the R&D stock of a direct provider is much higher, at 0.011, only slightly smaller than our admittedly low estimate of the elasticity of own R&D and about eight times smaller than the most common estimates in the literature (centered on 0.08). Interestingly, an important fraction of the elasticity of R&D by direct providers is due to technology transfers (the elasticity of revenue with respect to spillovers is $\beta_2 \omega^S_{ij} (G_j/S_i) = 0.0037$, whereas the elasticity with respect to market transfers is $\beta_3 \omega^M_{ij} (G_j/M_i) = 0.0072$).

**B. IV Results**

Table 6 presents IV results based on the original double projection strategy discussed in section V.B.1. Panels B and C report the results of the first-stage regressions. The instruments are strongly positively correlated with the instrumented variables $\ln(S)$ and $\ln(M)$. The measured $F$-statistics are high, above 60 in the specifications with the market-for-technology pool.

---

37 When conventional inputs and R&D are both measured in lags, conventional inputs possibly pick up part of the effect of own R&D due to double counting of R&D activities (e.g., the labor measure including inventors or the capital measure including laboratories). It is also possible that the control function approach used to calculate the elasticities of conventional inputs in the first stage allocates a higher weight to conventional inputs, leaving a lower fraction of revenue to be explained by R&D in the second stage. The elasticity estimates obtained with plain OLS and the control function approach are indeed higher than the estimates obtained with firm fixed effects, which is consistent with this view.
Panel A displays the results from the two-stage least squares (2SLS) estimates. The point estimates are similar to the ones obtained by OLS, but the coefficients of the spillover pool are no longer statistically significant. One caveat with this strategy is that the instruments incorporate potentially endogenous variation from aggregation over providers. In appendix I.1, we show that placebo instruments that exploit only endogenous variation in the original instrument—that is, the weighted sum of firms that contribute to the instruments STAX_Ni and MTAX_Ni—are responsible for a substantial part of the variation in the original instrument and return results that are similar to the ones obtained with the main instrument.

To mitigate concerns, table 7 reports IV results based on the double projection strategy presented in section V.B.2 but explicitly controlling for the
## TABLE 7
**IV Results—Double Projection Controlling for Weighted Counts**

<table>
<thead>
<tr>
<th>M up to Node Distance:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
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<tr>
<td><strong>A. Second Stage</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(G)</td>
<td>.016</td>
<td>.018</td>
<td>.015</td>
<td>.015</td>
<td>.015</td>
<td>.015</td>
</tr>
<tr>
<td>(          )</td>
<td>(.018)</td>
<td>(.014)</td>
<td>(.014)</td>
<td>(.013)</td>
<td>(.013)</td>
<td>(.013)</td>
</tr>
<tr>
<td>ln(S)</td>
<td>.605**</td>
<td>-.059</td>
<td>-.090</td>
<td>-.089</td>
<td>-.103</td>
<td>-.110</td>
</tr>
<tr>
<td>(          )</td>
<td>(.253)</td>
<td>(.196)</td>
<td>(.191)</td>
<td>(.197)</td>
<td>(.201)</td>
<td>(.207)</td>
</tr>
<tr>
<td>ln(M) − D#</td>
<td>.052*</td>
<td>.103***</td>
<td>.160****</td>
<td>.199***</td>
<td>(. .029)</td>
<td>(. .040)</td>
</tr>
<tr>
<td>ln(STAX_N)</td>
<td>-.068</td>
<td>.269***</td>
<td>.258****</td>
<td>.244**</td>
<td>.240**</td>
<td>.238**</td>
</tr>
<tr>
<td>(          )</td>
<td>(.101)</td>
<td>(.095)</td>
<td>(.092)</td>
<td>(.094)</td>
<td>(.095)</td>
<td>(.096)</td>
</tr>
<tr>
<td>ln(MTAX_N) − D#</td>
<td>.003</td>
<td>.023</td>
<td>.024</td>
<td>.025</td>
<td>(. .022)</td>
<td>(. .021)</td>
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<tr>
<td><strong>B. First Stage for ln(S)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(STAX)</td>
<td>.434***</td>
<td>.390***</td>
<td>.390***</td>
<td>.384***</td>
<td>.384***</td>
<td>.384***</td>
</tr>
<tr>
<td>(          )</td>
<td>(.040)</td>
<td>(.055)</td>
<td>(.055)</td>
<td>(.056)</td>
<td>(.056)</td>
<td>(.056)</td>
</tr>
<tr>
<td>ln(MTAX) − D#</td>
<td>-.001</td>
<td>.010</td>
<td>.011</td>
<td>.013</td>
<td>(. .004)</td>
<td>(. .012)</td>
</tr>
<tr>
<td>ln(STAX_N)</td>
<td>.174***</td>
<td>.332***</td>
<td>.330***</td>
<td>.329***</td>
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<td>.329***</td>
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<tr>
<td>(          )</td>
<td>(.028)</td>
<td>(.046)</td>
<td>(.047)</td>
<td>(.046)</td>
<td>(.045)</td>
<td>(.045)</td>
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<tr>
<td>ln(MTAX_N) − D#</td>
<td>.007</td>
<td>.012</td>
<td>.018</td>
<td>.022*</td>
<td>(. .007)</td>
<td>(. .009)</td>
</tr>
<tr>
<td><strong>C. First Stage for ln(M)</strong></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(STAX)</td>
<td>-.066</td>
<td>-.171</td>
<td>-.148</td>
<td>-.124</td>
<td>(. .177)</td>
<td>(. .153)</td>
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<tr>
<td>ln(MTAX) − D#</td>
<td>.550***</td>
<td>.539***</td>
<td>.544***</td>
<td>.528***</td>
<td>(. .045)</td>
<td>(. .034)</td>
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<tr>
<td>ln(STAX_N)</td>
<td>.349***</td>
<td>.290***</td>
<td>.251***</td>
<td>.224***</td>
<td>(. .098)</td>
<td>(. .059)</td>
</tr>
<tr>
<td>ln(MTAX_N) − D#</td>
<td>.054</td>
<td>.066***</td>
<td>.069***</td>
<td>.076***</td>
<td>(. .034)</td>
<td>(. .025)</td>
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<td><strong>Firm and year fixed</strong></td>
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<td></td>
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<tr>
<td>effects</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>First-stage F-test</td>
<td>120</td>
<td>49</td>
<td>24</td>
<td>24</td>
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<td>23</td>
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<tr>
<td>Firms</td>
<td>1,253</td>
<td>1,796</td>
<td>1,796</td>
<td>1,796</td>
<td>1,796</td>
<td>1,796</td>
</tr>
<tr>
<td>Observations</td>
<td>12,714</td>
<td>21,893</td>
<td>21,893</td>
<td>21,893</td>
<td>21,893</td>
<td>21,893</td>
</tr>
</tbody>
</table>

**Note.**—The dependent variable in the second-stage 2SLS regressions is ln(TFP). The instrumented variables are ln(S) and ln(M). All the regressions include industry price deflator controls and the firm’s own federal and state R&D tax credit values among the set of controls. Standard errors (shown in parentheses) are clustered at the firm and headquarters’ state level. The first-stage F-test is the Kleibergen and Paap (2006) rk Wald F-statistic for the joint significance of the tax-based IVs from the first stage.

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.
weighted count of firms that contribute to the instrument $STAX_{\alpha}$ and $MTAX_{\alpha}$. This specification exploits intensive margin variation in the external R&D pools caused by tax shocks, holding the number of firms in the pool constant, therefore relying on arguably exogenous variation in the instruments. Panels B and C show that the instruments are positively correlated with the instrumented variables. The $F$-statistics are considerably lower than in the original strategy but with values still above 20. Second-stage results displayed in panel A show that the spillover coefficient declines considerably, turning negative, but with a statistically insignificant coefficient. The estimated coefficients of the market-for-technology pools remain similar in magnitude and are generally statistically significant.

Table 8 reports IV results based on a direct projection of the weighted sum of tax prices discussed in section V.B.3, also controlling for the weighted count of firms in the instruments. The tax instruments now enter the first-stage regressions for the respective instrumented variables with the expected negative coefficient, meaning that increases in the tax price of R&D of providers lead to declines in the R&D investments by such providers. We show in appendix I.2 that the coefficients turn positive when the weighted counts are not included as controls, which suggests that in the absence of such controls the instruments mostly capture changes in the composition of the pool over time rather than changes in exposure to tax credits. The instruments are weaker than in the previous regressions, with the $F$-statistic on occasion being below 20. The second-stage estimates reported in panel A are statistically insignificant. In terms of magnitude, the spillover elasticity is larger than in previous estimates and insensitive to the amount of information exploited from the market-for-technology network, while the market-for-technology elasticity is lower.

Appendix I.3 shows that all the IV estimates are fairly robust to using instruments in stocks rather than in levels. The main difference is that the spillover elasticity is larger when the instruments are measured in stocks. In the double projection without weighted count controls, the spillover elasticity turns statistically significant. In the double projection with weighted counts, the spillover elasticity turns positive but remains statistically insignificant. In the direct projection with weighted count controls, the spillover elasticity is larger but remains statistically insignificant. In the direct projection, the positive sign of the coefficient of the state component of the tax price in the first-stage regressions suggests that stocks may generate endogenous variation because of aggregation over time.

C. Recap of OLS and IV Results

All the OLS estimates of the spillover and market-for-technology elasticities are positive and statistically significant. The IV estimates are less conclusive than the OLS ones. All the IV estimates of the spillover elasticity are
<table>
<thead>
<tr>
<th></th>
<th>A. Second Stage</th>
<th></th>
<th>B. First Stage for ln(S)</th>
<th></th>
<th>C. First Stage for ln(M)</th>
</tr>
</thead>
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<td>M up to Node Distance:</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
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<td>ln(G)</td>
<td>.006 (.026)</td>
<td>.002 (.012)</td>
<td>.001 (.012)</td>
<td>.000 (.012)</td>
<td>.000 (.012)</td>
</tr>
<tr>
<td>ln(S)</td>
<td>1.120 (.821)</td>
<td>.433* (.214)</td>
<td>.284 (.217)</td>
<td>(.218) (.214)</td>
<td>(.219) (.214)</td>
</tr>
<tr>
<td>ln(M) - D#</td>
<td>.013 (.059)</td>
<td>.046 (.101)</td>
<td>.066 (.118)</td>
<td>.088 (.129)</td>
<td>.088 (.129)</td>
</tr>
<tr>
<td>ln(STAX_N)</td>
<td>-.299 (.224)</td>
<td>.062 (.106)</td>
<td>.056 (.104)</td>
<td>.033 (.102)</td>
<td>.033 (.102)</td>
</tr>
<tr>
<td>ln(MTAX_N) - D#</td>
<td>.018 (.029)</td>
<td>.030 (.034)</td>
<td>.037 (.039)</td>
<td>.038 (.042)</td>
<td>.038 (.042)</td>
</tr>
<tr>
<td>ln(STAX_F)</td>
<td>-.165 (.110)</td>
<td>-.844*** (.226)</td>
<td>-.815*** (.233)</td>
<td>-.807*** (.234)</td>
<td>-.805*** (.234)</td>
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<tr>
<td>ln(STAX_S)</td>
<td>-1.472*** (.373)</td>
<td>-2.713*** (.502)</td>
<td>-2.790*** (.483)</td>
<td>-2.809*** (.481)</td>
<td>-2.812*** (.483)</td>
</tr>
<tr>
<td>ln(MTAX_F) - D#</td>
<td>-.043* (.020)</td>
<td>-.062** (.029)</td>
<td>-.071** (.034)</td>
<td>-.075** (.037)</td>
<td>-.075** (.037)</td>
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<tr>
<td>ln(MTAX_S) - D#</td>
<td>.097 (.099)</td>
<td>.113 (.121)</td>
<td>.115 (.136)</td>
<td>.121 (.148)</td>
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<tr>
<td>ln(STAX_N)</td>
<td>1.891*** (.390)</td>
<td>3.930*** (.469)</td>
<td>3.975*** (.461)</td>
<td>3.984*** (.461)</td>
<td>3.986*** (.461)</td>
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<tr>
<td>ln(MTAX_N) - D#</td>
<td>-.046 (.103)</td>
<td>-.033 (.128)</td>
<td>-.020 (.144)</td>
<td>-.017 (.156)</td>
<td>-.017 (.156)</td>
</tr>
<tr>
<td>ln(STAX_F)</td>
<td>-.126 (.749)</td>
<td>.782*** (.366)</td>
<td>.954*** (.293)</td>
<td>.984*** (.269)</td>
<td>.984*** (.269)</td>
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<tr>
<td>ln(STAX_S)</td>
<td>-1.579 (1.987)</td>
<td>-1.650 (1.273)</td>
<td>-1.773 (1.103)</td>
<td>-1.643 (1.002)</td>
<td>-1.643 (1.002)</td>
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<td>ln(MTAX_F) - D#</td>
<td>-.950*** (.100)</td>
<td>-.701*** (.094)</td>
<td>-.622*** (.085)</td>
<td>-.570*** (.085)</td>
<td>-.570*** (.085)</td>
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<tr>
<td>ln(MTAX_S) - D#</td>
<td>-2.478 (.568)</td>
<td>-.518 (.485)</td>
<td>-.350 (.436)</td>
<td>-.185 (.404)</td>
<td>-.185 (.404)</td>
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<tr>
<td>ln(STAX_N)</td>
<td>1.976 (1.814)</td>
<td>1.064 (1.234)</td>
<td>.988 (1.074)</td>
<td>.816 (0.979)</td>
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<td>1.894*** (.564)</td>
<td>1.498*** (.516)</td>
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<td>1.011*** (.402)</td>
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<td>fixed effects</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>First-stage F-test</td>
<td>9 33</td>
<td>33</td>
<td>25</td>
<td>20</td>
<td>21</td>
</tr>
<tr>
<td>Firms</td>
<td>1,253 1,796</td>
<td>1,796</td>
<td>1,796</td>
<td>1,796</td>
<td>1,796</td>
</tr>
<tr>
<td>Observations</td>
<td>12,714 21,893</td>
<td>21,893</td>
<td>21,893</td>
<td>21,893</td>
<td>21,893</td>
</tr>
</tbody>
</table>

**Note.**—See table 7 note.  
* Significant at the 10% level.  
** Significant at the 5% level.  
*** Significant at the 1% level.
statistically insignificant. The IV estimates of the market-for-technology elasticity based on the double projection are positive, statistically significant, and similar in magnitude to the OLS ones. The estimates based on the direct projection—the strategy that most plausibly exploits exogenous variation in the instruments—are statistically insignificant and lower in magnitude than the OLS estimates. It is worth noting that the direct projection also has limitations, as it exploits only a subset of the variation in the R&D pools stemming from changes in the intensity of R&D investments, holding the number of firms in the pool constant. Variation caused by changes in the composition of the firms in the pools is potentially important because R&D entrants are likely to own new technologies of particular interest to incumbent firms. Such variation is also leveraged in the OLS estimates. In appendix I.4, we report OLS results for a specification that controls for the weighted counts of firms in the R&D pools. The weighted counts enter the regressions with a positive sign and cause a decline in the spillover and market-for-technology coefficients, which suggests that a substantial part of the variation in the external R&D pools is due to variation in composition of the firms in the pools. Overall, the combination of OLS and IV results lends support to a possibly causal interpretation of the estimates.

D. Extensions and Robustness Checks

In appendix J, we report numerous extensions and robustness checks. We report results using the cumulative number of technology adoptions as well as before/after estimates. We use alternative weights for the market-for-technology and spillover pools. We offer results by mode of exchange and carry out placebo tests with randomized links. We also study heterogeneity over time and across industries. Finally, we report results for alternative specifications that include materials as a conventional input.

E. Private and Social Returns to R&D

To measure the private and social returns, we make the simplifying assumption that optimal R&D investments remain constant with the level of technology adoption. This assumption is supported by supplementary regressions reported in appendix K, which show that R&D investments are insensitive to the market-for-technology pool. This result implies that technology acquisitions neither stimulate nor crowd out internal R&D investments. Technology transfers increase the provider’s incentive to invest in R&D without reducing the adopter’s investment through a substitution mechanism. Therefore, the net effects of technology markets on the overall amount of R&D in the economy should be positive and driven by incentive effects for the provider.
Table 9 presents estimates (median values) of the rates of return calculated according to the canonical model with only spillovers (using the OLS estimates in col. 2 of table 5) and the general framework with both spillovers and technology (using the OLS estimates in col. 5 of table 5 and the market-for-technology pool that exploits information up to distance three). Prominent technology providers account for a small share of firms in the economy but represent a large share of R&D investments (see table 2). To correctly assess firms’ incentives to invest in R&D, we provide heterogeneous results for different subsamples of firms grouped by their relevance as providers in the market for technology. Results for the pooled sample are also reported at the bottom of the table.

According to the canonical model, the MPR and MSR are 3% and 42%, respectively, when pooling all providers together (i.e., a $1 increase in a firm’s R&D stock increases its own output by $0.03 and total output by $0.42). This represents a wedge of 39 percentage points between the social and private returns that mirrors previous results in the literature. The MPR remains constant across groups of providers in the canonical model, but the MSR increases with provider relevance because prominent providers operate in more diversified technology classes and send spillovers to a larger number of firms. For the most prominent providers, there is an 80 percentage point divergence between the social and private returns.

The general framework results in larger estimates of the private return and lower estimates of the social return. The private returns are higher because now revenue obtained in technology markets is factored in. The social returns are lower, despite the fact that we now also take into account additional flows diffusing through voluntary transfers, because the spillover elasticity is lower when the market-for-technology pool is included in the regressions. For the pooled sample, the MPR ranges between 5% and
7% depending on the assumed bargaining power of the provider, while the MSR is 37%. The wedge between the social and private returns is 30%, considerably lower than in the canonical model. For the group of prominent providers, both the private and the social returns are considerably higher than in the canonical model, at 41% and 127%, respectively, when assuming a 50-50 split, with the wedge also being higher at 86%.

F. Gains from Trade in the Market for Technology

Finally, we use the parameter estimates to obtain back-of-the-envelope estimates of the gross (of transaction costs) gains from trade (GFT) in the market for technology. Assuming that optimal R&D investments remain constant with the level of technology adoption, the gross gains from trade for a given adopter can be calculated following equation (4) as the difference in its product market revenue when it has access to the market-for-technology pool versus when it does not: \( GFT_a = Y_a - Y_a(\beta_3 = 0) \). Then, the total gains from trade (TGFT) in our sample are calculated as \( TGFT_t = \sum GFT_a \) for every year in the period 1990–2014. When only direct links are considered, the TGFT are estimated at between $538 and $1,425 billion (beginning and end of period, in 2010 dollars). For the broader weight that captures downstream propagation up to distance four, the TGFT are estimated at between $1,741 and $4,368 billion (beginning and end of period, in 2010 dollars). For comparison, total output and total R&D range between $3,633 and $8,504 billion and between $138 and $389 billion, respectively, during the sample period. These figures suggest that more than 10% of total revenue in our sample of Compustat firms is generated through exchange in the market for technology.

VII. Conclusion

This paper generalizes the canonical knowledge capital model used to measure the returns to R&D with technology markets. The extended framework acknowledges that firms extract returns from R&D by selling knowledge directly to other firms and similarly benefit from other firms’ R&D investments through formal transactions. To operationalize the model, we collect a new data set on interactions in the market for technology between publicly held firms in the United States. This new data set allows us to measure the pool of external R&D accessed through technology markets. We include this newly constructed variable in a product market revenue equation along with a standard traditional spillover pool measured as the sum of external R&D stocks weighted by technological proximity. To identify causal effects, we exploit within-firm variation in tax incentives to R&D, holding the weights used to construct the spillover and market-for-technology pools fixed.
We obtain several findings of interest. First, the market-for-technology pool enters the product market revenue equation with a positive and statistically significant sign. This implies that technology markets serve an important function by granting access to valuable production inputs. Second, the prevalence of genuine spillovers is ambiguous after accounting for technology markets because the weights used to construct standard spillover pools are correlated with matching in the market for technology. This finding cautions against the common practice of assuming that spillover pools contribute purely to the social returns. Standard versions of external knowledge pools are contaminated with transfers and therefore also contribute to the private returns. Third, the private return to R&D is considerably larger (particularly for prominent technology providers) in the general framework than in the canonical model. As a result, the wedge between the social and private returns to R&D is smaller than estimated in earlier studies. Finally, back-of-the-envelope estimates suggest that the gains from trade in the market for technology are larger than $1 trillion per year and account for at least 10% of total output. Overall, knowledge diffusion seems to take place through more channels than suggested by the unintended spillovers narrative.

References


