R&D Spillovers in Canadian Industry: Results from a New Micro Database

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Introduction

Business investment in research and development (R&D) makes a key contribution to rising living standards. Firms undertaking the R&D are able to reduce production costs and introduce new products that provide benefits to consumers that are not fully captured in selling prices. Further, it is nearly impossible for R&D-performing firms to prevent some of the knowledge created from leaking out or spilling over to other firms. Since firms do not take these positive spillover benefits into consideration when making investment decisions, most governments subsidize business investment in R&D with the expectation that economic performance will improve as a result.

However, not all of the spillover benefits are positive. When firms bring new products to market and develop new production processes, the increase in sales can be at the expense of other firms, which reduces the spillover benefit of investment in R&D. In addition, firms sometimes compete to be the first to develop a particular innovation. The duplication of investment arising from the competition will absorb some or all of the social benefits of realizing the innovation. A further concern is that, in some circumstances, existing firms have an incentive to over-invest in R&D in order to delay the entry of competitors.

There is a rich empirical literature on the returns to R&D, covering private and social returns as well as the gap between the two, which is often described as the external return to R&D. Early analyses generally involved case studies, but the dominant approach now is econometric. Researchers typically estimate the parameters of a production or cost function that includes the owned stock of R&D, tangible capital and labour as inputs along with some measure of R&D that is external to the firm (or sector or country) as an additional factor affecting output. The coefficient on the stock of external R&D, or the spillover pool, can be used to calculate the external return to R&D. A positive spillover coefficient indicates that the social return to R&D exceeds the private return, suggesting that government support for R&D would be an appropriate policy response.

Researchers applying the econometric approach have to address a number of technical issues in order to be confident that coefficient estimates are robust. For example, inputs and output are simultaneously determined, but obtaining unbiased coefficients from a regression requires that the explanatory variables be predetermined. Measurement errors and firm-specific differences in such things as the quality of management, product lines and pricing strategies pose additional challenges for researchers. Another issue arises if an increase in investment in R&D reflects common technological opportunities. In this case, the estimated impact of spillovers on output would be overstated. Further, researchers also have to choose between including all firms or just R&D performers in the sample, in which case an adjustment for selection bias may be appropriate. When working with panel data sets, researchers have to choose between including only continuing firms in the sample (i.e. using a balanced sample) and including firms that enter and exit over the sample period.

The spillover pool is a weighted sum of R&D external to the firm, with the weights chosen to reflect the potential for benefiting from R&D performed by others. The wide range of weights that have been used in empirical work can be divided, with some simplification, into two categories: those based on economic transactions, such as intermediate input transactions, and those based on technological proximity, such as patenting activity in the same technology class. Weights based on economic transactions are likely to capture a mixture of knowledge spillovers and income transfers arising in part due to imperfect price measurement. Unless price indices are adjusted perfectly for quality changes, economic transactions between firms can result in spurious changes in real output and productivity. Using weights based on technological proximity is more likely to capture pure knowledge spillovers. It is now relatively common to weight external R&D by geographic distance, either as a separate measure or as an additional factor applied to other measures of proximity. Most researchers find that spillovers decline with distance, although separating pure distance effects from industry clustering effects is an issue. Some researchers (e.g. Higón and Antolín 2012) find a role for various measures of cultural affinity, such as sharing a common language or legal system, in mediating spillovers.

Even in the best of circumstances, the coefficient on the spillover pool is an imperfect measure of the external return on R&D. The consumer benefits arising from the introduction of new products that are not reflected in prices (consumer surplus) are at best partially captured in the econometric framework. On the other hand, to the extent that real output is correctly measured, social losses arising from "creative destruction", or the transfer of economic profits among firms due to product innovations, will not be captured.

Hall, Mairesse, and Mohnen (2010) provide a review of the issues surrounding the estimation of the private and external return to R&D as well as a comprehensive summary of the empirical literature. They report results from 29 studies examining domestic spillovers. Most of these studies report rates of return on external R&D, which are easier to compare than the unadjusted coefficient on the spillover pool. In addition, rates of return are more relevant to discussions of how much assistance should be provided for R&D. The median external rate of return in the 23 studies reporting this information is 29%, while the median private rate of return is 20%. We have found a further 12 studies analysing domestic spillovers published after the Hall, Mairesse and Mohnen survey. The results from these studies suggest an external rate of return of about 27% .

We have access to a longitudinal data base covering the period from 2000 to 2012 of all firms in Canada. We use a standard augmented production function approach in our analysis of spillovers, with real value added as the output measure. In this version of the paper, we estimate the production function (in logs) for an unbalanced panel of R&D performing firms using ordinary least squares estimators over the 13 years ending in 2012; the next version will report results using the system General Method of Moments (GMM) developed by Blundell and Bond (1998) to address endogeneity of inputs in a dynamic panel context.

Despite the richness of the empirical literature, there are some important gaps that this study attempts to fill. First, studies using Canadian data are not abundant. The only study of R&D spillovers using Canadian firm-level data was prepared 30 years ago by Bernstein (1988). Second, we define the spillover pool using a measure of technological proximity based on firms' reported expenditure in 28 research fields. This approach has a considerable advantage over the more usual approach of defining proximity in terms of patenting activities since it allows all R&D performers to be included in the analysis. Third, very little of the empirical analysis addresses how the external return to R&D varies by size of firm. We calculate separate spillover pools by size of firm, which allows us to assess whether the generation of spillovers, and hence the optimal subsidy rate, varies by size of firm. This is an important issue in Canada, which along with [6] other OECD member countries, subsidizes R&D performed by small firms at a substantially higher rate than R&D performed by larger firms.

Our empirical results are based on a fixed-effects estimator, which was more consistent with the data than the random-effects estimator. We obtain coefficients on the conventional inputs that are consistent with prior notions of income shares and, when R&D capital is included, constant returns to scale cannot be rejected. The estimated coefficient on internal R&D capital implies a rate of return of approximately 20 per cent, virtually the same as the median in the Hall, Mairesse, and Mohnen (2010) survey. Using our preferred measure of the spillover pool, the rate of return on external R&D is approximately 37%, higher than the median in the Hall, Mairesse and Mohnen survey but well within the range of estimates in the literature. Our estimates suggest that spillovers rise with firm size, although the hypothesis of a constant spillover rate by firm size cannot be rejected.

This paper is organized as follows. The next section presents an extended review of the literature, discussing the analytical framework and the econometric issues arising in empirical estimation of the returns to internal and external R&D. The section also discusses the definition of the spillover pool and summarizes the empirical work on rates of return. The data used in this study are described in the third section, which also includes a discussing of how the data were "cleaned" prior to performing the empirical work and how the spillover pool was calculated. Our estimation framework and results are presented in the fourth section, which is followed by some concluding remarks.

Literature review

Analytical framework

Following Lychagin et al. (2016),a general form of a production function that can be used to analyse the private and external rates of return on R&D is set out in equation 1.

(1) $Y_{it} = A_{it}\Omega_t \mathrm{H}_{it} U_{it} F_i(X_{it})$

where Y_{it} denotes output of firm (or industry) i at time t; A, Ω and U determine the level of productivity; and X is a vector of inputs. Firm productivity has a systematic component (A) and three random elements: aggregate shocks (Ω); firm-specific effects (H); and idiosyncratic shocks with a mean of zero (U).

The function F is most commonly specified as Cobb-Douglas in the recent empirical literature. With that assumption and taking logs, a potential estimating equation is:

(2) $y_{it} = a_{it} + \alpha c_{it} + \beta l_{it} + \theta_{it} m + \gamma k_{it} + \varphi s_{it} + \eta_{it} + \omega_t + u_{it}$

Where lower case letters represent natural logarithms and y is gross output, c is tangible capital, l is labour input, m is materials, k is the firm's internal stock of knowledge capital, and s is the stock of external capital relevant to the firm. In empirical work, it is relatively common to use sales as a proxy for gross output and to use value added instead of gross output. Hall, Mairesse, and Mohnen (2010) make the point that while theory suggests gross output is the preferred measure, practical considerations often make value-added the better option. For example, differences in the degree of vertical integration among firms cause variations in the materials-output ratio that are difficult to model.

Following the analysis of Cohen and Levinthal (1989), researchers frequently include a variable to capture a firm's capacity to absorb knowledge created by other firms. The most common approach in the literature is to interact the spillover pool with R&D capital or some other measure of the ability to absorb outside knowledge, such as the number of R&D professionals employed by the firm. This approach can be implemented by re-specifying the output elasticity of the spillover pool as $\varphi = \varphi_1 +$

$\varphi_2 AC_{it}$, where AC is some measure of absorptive capacity, which results in the following estimating equation:

$$(3) \quad y_{it} = a_{it} + \alpha c_{it} + \beta l_{it} + \theta_{it} m + \gamma k_{it} + \varphi_1 s_{it} + \varphi_2 s_{it} AC_{it} + \eta_{it} + \omega_t + u_{it}$$

Another possibility is to specify the weights used to aggregate external R&D to capture absorptive capacity as well as proximity.

The stock of knowledge capital (R&D) can formally be an element of X or be included in total factor productivity, A. If R&D is considered an input, and markets are competitive, γ should equal the income share accruing to R&D. The income share of R&D is not observed, so researchers often transform the estimated output elasticity to the private rate of return on R&D to assess the plausibility of the estimated parameter. Knowledge spillovers are almost always considered part of TFP.

In empirical work, equation 2 is frequently replaced with a TFP equation (Table 1). TFP can be calculated by constructing a productivity index (as in Lychagin et al. 2016) or by subtracting estimated values of factor inputs from actual output (Cardamone 2017). TFP is regressed against the variables not considered inputs in equation 2.

If equation 2 is estimated without the absorptive capacity term, the output elasticity of R&D will be the same for all firms. Since the marginal product of R&D can be calculated as the product of the output elasticity and the ratio of output to R&D capital, an increase in R&D intensity causes the marginal product of R&D to decline.[1] However, as pointed out by Hall, Mairesse, and Mohnen (2010), firms may be operating with different input shares, so it may be appropriate to assume constant rates of return rather than constant elasticities, by estimating the rate of return directly. The estimating equation relates the change in output (or TFP) to R&D intensity and the ratio of the spillover pool to output (among other variables); the coefficients on these variables represent gross rates of return. In empirical work, it is common to assume that the economic depreciation rate on R&D capital is zero, and to measure R&D intensity using gross investment in R&D.[2] Hall, Mairesse, and Mohnen (2010) demonstrate that using gross rather than net investment in a firm-level regression is likely to substantially understate the true rate of return on internal knowledge capital. The same point applies to the rate of return on the spillover pool.

While a case can be made that assuming a constant rate of return is more plausible than assuming constant elasticities and hence a declining marginal product of R&D capital, most recent empirical work estimates elasticities. In the Hall, Mairesse, and Mohnen (2010) survey, about a third of the studies in the survey estimated elasticities. In the recent spillovers literature summarized in Table 1, only one of the 12 studies (Medda and Piga 2014) estimates the rates of return on R&D directly. Hall, Mairesse and Mohnen note that the rate of return estimates are less stable than the elasticity estimates, attributing this outcome to highly variable ex post returns to R&D.

An estimating equation is sometimes developed from equation 1 by assuming a translog production function. That approach allows the estimated output elasticities to vary with the level of other inputs –

[1] Inclusion of the absorptive capacity term in equation 2 causes inter-firm variance in the output elasticity without affecting the finding of diminishing returns to investment in R&D.

[2] See Donselaar, Koopmans, and others (2016) for a detailed comparison of estimating output elasticities and rates of return to R&D.

separability can be tested, not assumed. Badinger and Egger (2015), in a multi-country industry-level analysis, include both internal and external R&D as inputs, and cannot reject the hypothesis that both output elasticities are affected by the level of conventional inputs. Similarly, Aiello and Cardamone (2009), working with firm-level data in Italian manufacturing, find statistically significant coefficients on

Table 1: Key Characteristics of Recent Empirical Studies of Domestic R&D Spillovers

Author	Sample Description	Time Period	Estimator	Dependant variable[1]	Elasticity or rate of return
Industry level studies					
Acharya (2015)	17 OECD member countries; 28 industries (22 manufacturing)	1974-2002	Dynamic OLS	Log value added	Elasticity
Goodridge, Haskel & Wallis (2013)	7 UK industries	1992-2007	OLS with industry fixed effects	Smoothed TFP growth rate	Elasticity
Higon (2007)	8 UK manufacturing industries	1970-1997	Pooled mean group (Dynamic heterogeneous ECM panel)	Gross output growth rate	Elasticity
Firm level studies					
Aiello & Cardamone (2009)	Balanced panel of 1203 Italian mfg firms (R&D performers only; selection bias correction applied)	1998-2003	3SLS; 1-year lagged values as instruments	Log value added[2] & factor shares	Elasticity
Bloch (2013)	Unbalanced panel of all large firms and a sample of SMEs in Denmark	1997-2005	Fixed effects; lagged inputs	log value added per employee	Elasticity
Bloom, Schankerman and Van Reenen (2013)	Unbalanced panel of 715 US firms that patented at least once 1963 to 2001.	1981-2001	Fixed effects;[3] lagged inputs	Log sales	Elasticity
Lucking, Bloom & Van Reenen (2017)	Unbalanced panel of 1985 US firms that patented at least once 1970-2006	1985-2015	Fixed effects; lagged inputs	Log sales	Elasticity
Cardamone (2017)	3516 Italian mfg firms (cross-section)	2004-2006	Spatial autoregressive	Log TFP	Semi-elasticity
Lychagin et al (2016)	1383 US mfg firms that patented at least once 1970 to 2000	1980-2000	Fixed effects[4]	Log TFP	Elasticity
Medda & Piga (2014)	3077 Italian mfg firms in 21 industries; correction for non-random R&D performance	1998-2000	Instrumental variables	TFP growth rate	Rate of return
Ornaghi (2004)	Unbalanced panel of approximately 2000 Spanish mfg firms in 53 industries	1990-1999	SYS-GMM	Value added growth rate	Elasticity
Sena & Higón (2014)	8617 single plants in UK manufacturing (unbalanced panel; survivorship bias rejected)	1997-2002	SYS-GMM	Log gross output	Semi-elasticity

1. Unless otherwise stated production technology is assumed to be Cobb-Douglas and real values are obtained using industry deflators. 2. Translog production function. 3. R&D used in spillover pools instrumented. 4. Results also presented for GMM and Sys-GMM (with and without common factor restrictions) estimators.

the input interaction terms in the translog production function.

Econometric Issues

Estimating equation 2, which uses only the within-firm variation in the sample, presents a number of econometric challenges. These include simultaneity bias that occurs because inputs are endogenous rather than exogenous variables; selection bias if only continuing firms are included in the sample; and measurement bias caused by the absence of firm-level prices for output and inputs.[3]

Simultaneity bias

The simultaneity bias arises because firms decide on input levels based on demand and productivity shocks that they experience.[4] These productivity shocks are not observed by the researcher, but they are correlated with input choices. As a result, ordinary least squares (OLS) estimates are biased and inconsistent, causing coefficients on labour and materials to be overstated and coefficients on tangible and intangible capital to be understated, to the extent that they are positively correlated with the variable inputs.

Researchers use various techniques to address simultaneity bias. One approach is to assume that firm-specific productivity shocks are time-invariant and estimate equation 2 with a fixed-effects estimator. If firms are observed over a sufficiently long time period, this approach results in consistent estimates that are free of simultaneity bias. Further, if exit decisions are determined by firm fixed effects, this approach also addresses selection bias. While fixed-effects estimation can in principle be implemented through inclusion of dummy variables, equation 2 is usually estimated in first differences or in differences from mean values to eliminate firm-specific effects. This approach tends to increase the problems caused when variables are measured with error (Hall and Mairesse 1995).

One way to avoid making the assumption of time-invariant productivity shocks, which justifies use of a fixed effects estimator, is to instrument inputs when estimating variants of equation 2. Effective instruments must be correlated with the inputs, but not with unobserved productivity shocks, and can not enter the production function directly. Potential instruments include input and output prices, and variables that shift the demand for output and inputs. However, firm-level price data is not generally available and good quality “demand shifters” have been hard to find. As a result, “no clear contenders for ‘external’[5] instruments have emerged in the production function literature” (Eberhardt and Helmers 2016, 9). A number of researchers use one-period lags of inputs, ostensibly as instruments, with the fixed effects estimator in order to mitigate simultaneity problems (see Table 1). Hall and Mairesse (1995) state that in short panels, one-period lagged values of inputs remain correlated with the error term. Reed (2015)formally demonstrates that this approach generates inconsistent parameter estimates.

Olley and Pakes (1996) develop a consistent semiparametric estimator by using the firm’s investment decision as a proxy for unobserved productivity shocks that are correlated with input levels. More precisely, a non-parametric function (e.g. a higher order polynomial) of investment and capital is used to represent unobserved firm-specific productivity. Selection bias is explicitly addressed by including an exit rule in the estimating model. A weakness of this approach is that only observations with positive investment can be used, which can cause a substantial loss of efficiency in certain data sets (Van Beveren 2012). In order to avoid this limitation, Levinsohn and Petrin (2003a) use intermediate inputs, which are more likely to remain positive for all observations, as a proxy for unobserved productivity shocks.

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[3] See Van Beveren (2012) for a detailed review of the econometric issues encountered when estimating firm-level productivity equations.

[4] See Eberhardt and Helmers (2010) for a comprehensive and intuitive review of the issues raised when estimating production functions. Eberhardt and Helmers use the term “transmission” rather than “simultaneity” bias.

[5] That is, instruments that are not lagged variables or lagged transformed variables.

A further constraint is dealing with persistence or serial correlation in the data. For example, productivity shocks tend to be serially correlated, which induces serial correlation in factor inputs as they respond to these shocks. Arellano and Bond (1991) develop a methodology to estimate dynamic panel data models with the generalized method of moments (GMM) in order to recover consistent estimates of coefficients on inputs. This approach makes use of first-differencing (FD) or difference-from-means to eliminate individual-specific effects and uses lagged dependent and independent variables as instruments to correct for simultaneity. First-difference GMM exploits moment restrictions to obtain an optimal estimator of coefficients as the number of firms approaches infinity and the number of observations is small and constant. The estimator is developed assuming no serial correlation in the error term, so Arellano and Bond propose three tests of the underlying assumption of uncorrelated errors. This methodology has been used by a number of researchers examining the returns to R&D, with Hall and Mairesse (1995) being an early example.

While first-difference GMM performs better than a fixed-effect estimator, its performance suffers when the autoregressive component is moderately high and the number of time series observations is moderately low (Blundell and Bond 1998). In these circumstances the finite-sample bias is large and simulation studies indicate that coefficients are not precisely estimated. These problems arise because the first difference of a persistent or substantially autoregressive series contains little or no information as an instrument, so a first-difference GMM estimator would still be biased and inconsistent. It is worth emphasizing that with a short panel, inconsistency will not converge to zero as the number of cross-section observations increases. These weaknesses can be substantially reduced by using an extended, or system, GMM estimator that uses information on initial conditions. Estimation involves a combination of equations in first-differences with equations in *levels* (or levels with first differences) to exploit additional moment conditions. Based on Monte-Carlo simulations, Blundell and Bond (1998) and Blundell, Bond, and Windmeijer (2001)show that the system GMM estimator performs much better in the sense that finite sample bias is smaller and precision is greater compared to the standard GMM estimator.

The inclusion of lagged dependent and independent variables in GMM estimators implies some restrictions on their values. More precisely, the coefficients on the lagged regressors are non-linear combinations of the coefficients on their contemporaneous values and the coefficients on the lagged dependent variable. The implicit restrictions on their values – usually described as common factor restrictions – can be tested. If they are not rejected, the restrictions can be imposed through use of a non-linear least squares estimator [in order to improve the precision of the parameter estimates.][6]

Although the standard knowledge capital model set out in equation 2 recognizes that productivity is endogenous, the estimators discussed above make the simplifying assumption that changes in productivity are exogenous to the firm. Firm-level productivity follows a random (first-order Markov) process. Doraszelski and Jaumandreu (2013)draw attention to the role of investment in R&D in affecting a firm's productivity. In their approach, productivity at any point in time represents an expected component arising from R&D investment and an unexpected component arising from random shocks. That is, productivity continues to follow a random process that can be shifted by R&D investment. They develop an estimator in the spirit of Olley and Pakes (1996) that makes use of labour demand rather than investment demand to proxy firm-level productivity. The functional form of the proxy is derived from the first-order conditions for profit maximization.

[6] See Eberhardt and Helmers (2010) for a discussion of this point.

In the Doraszelski and Jaumandreu approach R&D investment rather than capital enters the estimating equations. It is therefore not implicitly assumed that knowledge accumulates linearly (and with certainty) in proportion to spending on R&D, or that is depreciates by a fixed amount per period, as in the knowledge capital model. The Doraszelski-Jaumandreu model also has the advantage of capturing firm-level differences in the response to R&D, so that returns to R&D can be calculated for individual firms or for firms arranged in particular groups.[7]The Doraszelski-Jaumandreu approach has not yet been modified to include spillovers. [Explicitly modelling firm-level productivity shocks is clearly of interest, but further analysis and reflection is required to determine the advantages of the DJ approach over including R&D as a factor input in the production function. If R&D is considered an input and if it does affect firm TFP, the impact of unobserved productivity shocks would be diminished.]

While concerns about factor inputs, including R&D capital, being endogenous variables are universal, opinions are divided on whether the spillover pool is correlated with the error term. As mentioned earlier, it is plausible to assume that the spillover pool is exogenous in a competitive market, since firms would undertake R&D without considering the activities of other firms. However, even assuming that describing markets as competitive is realistic, firms may vary their spending on R&D in response to generally-perceived technological opportunities.[8]The resulting improvement in productivity could be incorrectly attributed to the spillover measure. In the recent literature, only Bloom, Schankerman, and Van Reenen (2013) test the exogeneity of the spillover pool. They develop an instrumental variable for R&D spending based on firm-specific changes in the user cost of R&D capital induced by tax changes. The estimated spillover output elasticity is not statistically different when spillovers are assumed to be endogenous rather than exogenous.

Despite the advances in econometrics, the fixed effects estimator finds considerable favour in the recent R&D spillover literature. Out of the 9 firm-level studies summarized in Table 1, four use fixed effects estimators (with inputs lagged one period), two use the system GMM estimator, two use instrumental variables and one researcher uses a spatial autoregressive estimator.

Two of the studies report results for more than one estimator. Bloom, Schankerman, and Van Reenen (2013) report results for OLS and fixed effects estimators in addition to the instrumental variable approach discussed above. Using the fixed-effect estimator causes the sign on the spillover coefficient to change from negative to positive. On the other hand, with the fixed effects estimator the sum of the output elasticities falls from .99 to .83.

Lychagin et al. (2016)assess a broader range of estimators. They report results using the Arellano-Bond first-difference GMM estimator, the system GMM estimator (with and without common factor restrictions) in addition to results using the fixed-effects estimator, which they describe as their baseline results. All specifications have econometric limitations but provide similar coefficient estimates for key variables. The instruments used in the first-difference GMM estimator have acceptable strength and first-order serial correlation is absent. On the other hand, the Hansen test rejects the null hypothesis of instrument validity for the Arellano-Bond estimator. The Hansen test is also rejected in the system-GMM estimator and the implied common factor restrictions on coefficients. Finally, there is evidence of second order serial correlation in the residuals from system-GMM estimation.

[7] The estimation form does not result in an estimated output elasticity or rate of return on R&D. These measures have to be calculated using estimated parameters and sample data.
[8] This is the “reflection problem” noted by Manski(1993).

Selection Bias

Selection bias has several dimensions. The most common issue discussed in the literature is what is often described as survivor bias. Firms that survive are likely to be more productive or to have more capital than firms that exit. This will cause a negative correlation between the error term and the capital input (tangible and intangible, presumably) causing the estimated coefficients on capital inputs to be biased downwards in a (balanced) sample that consists of continuing firms only. Potential bias of the spillover coefficient is not discussed in the literature, but it is possible that more productive firms, or firms that have more R&D capital, would be in a better position to absorb spillovers.

Olley and Pakes (1996) develop an estimator that explicitly takes account of firm-level survivor probability in a framework that also corrects for simultaneity. They obtain significantly different coefficients with a balanced panel, but the gains are small when the sample is unbalanced. The system-GMM estimator can be used with unbalanced panels, [although it appears better results are obtained with forward orthogonal differences than with first differences when working with an unbalanced sample.]

Selection issues also arise if the sample consists only of R&D performing firms. In this case the sample is no longer random, and the characteristics of firms that choose to invest in R&D may be systematically different from firms that do not invest in R&D. The sample may be limited to R&D performers by choice or as a result of spillover weighting schemes that implicitly restrict the sample by making the ability to benefit from spillovers conditional on performing R&D. Limiting the sample to R&D-performing firms would not be problematic if the regression results are used to make inferences about R&D-performing firms only. Aiello and Cardamone (2009) work with a sample of R&D performing firms. They address the selection bias issue by using a probit model to explain the decision to invest in R&D and use the fitted probabilities of investing as instruments when estimating the (translog) production function. Medda and Piga (2014)include both R&D performers and non-performers in their sample but use the predicted values from a Tobit R&D investment model as instruments for (endogenous) R&D in their TFP equation.

Restricting the sample to firms that patent their inventions also raises selection issues. Bloom, Schankerman, and Van Reenen (2013), Lychagin et al. (2016) and Lucking, Bloom, and Van Reenen (2017) restrict their sample to firms that have taken out at least one patent, but do not make any adjustment for selection bias.

Definition of the spillover pool

Early studies (e.g. Bernstein and Nadiri 1988) defined the spillover pool as the unweighted sum of the R&D performed by other firms in the same industry. Bernstein (1988) included pools to capture both intra- and inter-industry spillover effects, without weighting any of the outside R&D. It is now virtually universal practice to define the spillover pool as a weighted sum of R&D external to the firm, with the weights chosen to reflect the potential for firms to benefit from R&D performed by others. Most of weighting schemes used fall into three general categories: those based on economic transactions, and those based on technological or geographical proximity.

Weighting schemes based on economic transactions include inter-industry purchases of intermediate goods (Cardamone 2017; Goodridge, Haskel, and Wallis 2017), investment in capital goods (Wolff and Nadiri 1993), and patent flows between creators and users[9] (Los and Verspagen 2000). These weighting

[9] This weighting scheme is often described as the Yale Technology Matrix.

methods capture, at least in part, productivity gains transferred from other industries because producers were not able to appropriate all their benefits.[10] They also capture fictitious productivity transfers that arise when quality changes are poorly captured in official price data.

Measures of technological proximity provide a better indicator of pure knowledge transfers. (Jaffe 1986a) pioneered the use of patent data to allocate a firm's R&D spending by field of technology and developed a methodology to compare the distribution of spending – the technology position – across firms. The methodology restricts spillovers to knowledge transfers between firms operating in the same technological fields – knowledge transfers cannot occur between different fields, even if they are closely related. Bloom, Schankerman, and Van Reenen (2013) extend the Jaffe methodology to allow spillovers between closely-related fields in their "Mahalanobis extension". In addition, the Jaffe weighting matrix is symmetric – knowledge transfers from firm i to firm j are the same as transfers from firm j to firm i. Finally, note that under the Jaffe methodology, only firms performing R&D can benefit from spillovers.

The Jaffe methodology has been used frequently in recent empirical work (Table 2). In addition to the study by Bloom, Schankerman, and Van Reenen (2013) already mentioned, empirical work by Aldieri and Cincera (2009) and Lychagin et al. (2016) uses the Jaffe methodology, without the Mahalanobis extension. Bloch (2013) also applies the Jaffe methodology, but has access to data on R&D spending by 10 technological fields, which allows him to expand the scope of the analysis from R&D performers that patent to all firms that perform R&D. Aiello and Cardamone (2009) also adopt the Jaffe methodology, but use human capital weights to develop an asymmetric technological proximity measure.

The idea that knowledge transfers are affected by distance has considerable appeal. Despite the ease of electronic information flows, the opportunity for planned and spontaneous face-to-face meetings, which declines with distance, could facilitate knowledge spillovers. It is, however, important to distinguish what Lychagin et al. (2016) describe as the "declining contact with distance" from the "decreasing relevance with distance" hypotheses. In other words, knowledge transfers that appear to be related to geographic proximity may be the result of a grouping of firms with similar technological interests. In addition to facilitating knowledge transfers, agglomeration reduces costs by promoting better matches of workers and firms and the sharing of intermediate inputs. Confirming the existence of geographic spillovers requires isolating knowledge transfers and demonstrating that such spillovers exceed what would be expected given the existing distribution of R&D.[11]

Jaffe, Trajtenberg, and Henderson (1993) were the first to test for a geographic component of spillovers. Their study finds that patent citations are more likely to occur close to where the inventor resides, even after controlling for the existing concentration of technological activity. Buzard et al. (2017) obtain a similar result using a similar approach but are able to assign patents and citations to clusters of R&D labs rather than relying on information on the declared place of residence of the inventor. Bloom, Schankerman, and Van Reenen (2013) test for an independent impact of geography by including both a distance-weighted index of technological proximity and an unweighted measure as spillover variables in their production function. Both measures are statistically significant, which supports the existence of a pure distance effect. The sum of the coefficients on the two spillover variables is not, however, substantially different from the coefficient on the spillover variable when it enters the equation alone.

[10] Los and Verspagen assume the matrix captures rent spillovers only, which may be too restrictive.

[11] However, as noted by Jaffe, Trajtenberg, and Henderson (1993) the existing distribution of R&D activity may be affected by the potential for knowledge spillovers, so such a test is conservative.

Lychagin et al. (2016) report statistically significant coefficients on technological and geographical proximity spillover measures when entered in the same equation. However, the interaction of the two variables does not add to the explanatory power of the equation, suggesting that there is a distinct geographic component of knowledge spillovers. [reference to Lychagin (2016)?]

In contrast to the above studies finding evidence of a pure distance effect, Orlando (2004) presents evidence suggesting that reported knowledge spillovers may instead be the result of general agglomeration effects. Orlando examines spillovers in a narrowly-defined industry. He finds that spillovers between firms in the same detailed (4-digit) category are not attenuated by distance, but spillovers from outside this category are attenuated by distance.

In order to benefit from knowledge spillovers, firms must have the ability to identify, assimilate and exploit the ideas generated by other firms. Cohen and Levinthal (1989) appear to be the first to draw attention to the “two faces” of R&D: one to create knowledge and the other to enhance the firm’s ability to absorb new ideas developed elsewhere. Despite its intuitive appeal and the typical finding of a positive role for absorptive capacity, not all researchers include it in their empirical analyses of spillovers.[12]As stated earlier, absorptive capacity can be modelled as augmenting either the private or external return to R&D.

A variety of measures of absorptive capacity is found in the literature. A number of researchers measure absorptive capacity by including the product of R&D intensity and the spillover variable in the estimating equation (Kinoshita 2001, Grünfeld 2004). Aldieri and Cincera (2009) re-specify the spillover output elasticity to include an interaction with the stock of R&D, instead of R&D intensity. The estimated coefficient on the interaction term is positive and statistically significant. The output elasticities of internal R&D and the spillover pool are unchanged but including the interaction term substantially raises the output elasticity of tangible capital.

Bloch (2013)uses the share of R&D personnel in total firm employment and the existence of an R&D department as indicators of absorptive capacity, interacted with the spillover variable. While the coefficient on the interaction terms with technological spillovers is positive and statistically significant, the overall output elasticity of the spillover pool does not change from its value when spillovers enter without the interaction term. Sena and Higon (2014) use a measure of the quality of the firm’s workforce as an indicator of absorptive capacity. When interacted with the spillover variable, the labour quality gap has a statistically-significant positive role. The impact is, however, small: the output elasticity of spillovers rises 10-15% when interacted with the labour quality variable.

Ornaghi (2006) hypothesizes that absorptive capacity rises with firm size. She calculates a size-weighted intra-industry spillover pool and obtains a small but statistically significant output elasticity. Aiello and Cardamone (2009) define the spillover pool using the Jaffe methodology to determine technological proximity but impose asymmetric weights by assuming the ability to absorb outside knowledge is affected by the level of human capital at each firm. The output elasticity of internal R&D increases substantially while the spillover elasticity falls approximately in half when the symmetric measure is replaced with the asymmetric version. [In addition, the spillover variable is included as in input in a translog production function, so the estimated elasticity varies with the level of the other inputs, which implicitly captures absorptive capacity.]

[12] Out of 11 analyses of domestic spillovers published since 2004, only 3 include a measure of absorptive capacity.

The spillover variables discussed above are not intended to capture the social loss associated with 'creative destruction' arising from the introduction of new products. A new product generates a social benefit because consumers place a higher value on the new product than its production cost. This "consumer surplus" is typically shared with firms because the product is priced above its marginal production costs -- firms earn rents on new products. Some of this social benefit is at the expense of the products that are displaced, and this loss is part of the external return to R&D. These considerations lead some researchers (Lychagin et al. 2016) to include a "product market rivalry" spillover measure in the production function. However, as pointed out by Bloom, Schankerman, and Van Reenen (2013), product market rivalry does not affect production possibilities, so there is no reason to expect it to play a role in the production function, provided that output is correctly measured.

Bloom, Schankerman, and Van Reenen (2013) capture product market rivalry effects on the external return to R&D through a separate equation for the market value of firms. In their model, product market rivalry raises the private return to R&D without affecting the social return, so the external return on R&D is lower when product market rivalry is included in the analysis.

Empirical estimates of spillovers

Hall, Mairesse, and Mohnen (2010) presents a comprehensive review of the literature on estimating the private and public returns to R&D, including a review of the theory, practical estimation problems and a summary of the empirical results. They report results from 29 studies examining domestic spillovers. These studies report the output elasticity of the spillover pool, the rate of return on the pool or both. The rates of return were estimated directly or calculated from the output elasticity.[13]Most of these studies report rates of return on own and external R&D. In the 23 studies reporting this information, the median private rate of return is 20% and the external return is 29%. These are gross (of depreciation) rates of return. With a 15% depreciation rate, the median private rate of return appears low. This could be the result of the widespread availability of subsidies for performing R&D. This point is discussed in more detail below.

We have found a further [12] studies analysing domestic spillovers published after the Hall, Mairesse and Mohnen survey (Table 2).Only one of these studies, Medda and Piga (2014), estimates the rate of return directly. Another three studies (Acharya 2015;Bloom, Schankerman, and Van Reenen 2013;Lucking, Bloom, and Van Reenen 2017) transform estimated elasticities to rates of return. Two studies (Cardamone 2017; Sena and Higon 2014) estimate the semi-elasticity of the spillover pool. We use information provided by the authors to calculate the private and external rates of return on R&D. [The median private and external rates of return in these six studies are 15% and 22.5%, respectively.]

The remaining six studies estimate output elasticities, which range from near zero to almost 1.5. While the level is difficult to interpret, the ratio of the spillover elasticity to the own-R&D elasticity gives a reading on the importance of spillovers. The median value of the external-internal ratio of the six studies is 2.3. Since the ratio of the elasticities equals the ratio of the rates of return, this result implies that the external rate of return is 2.3 times larger than the private return. Using the median private rate of return

[13] The rate of return is obtained by taking the product of the output elasticity and the ratio of output to R&D capital. See Donselaar, Koopmans, and others (2016) for a derivation of this result. Researchers use either the sample means or medians of output and R&D capital in the calculation. In the more recent literature, Bloom, Schankerman, and Van Reenen (2013) and Lucking, Bloom, and Van Reenen (2017) use an R&D-weighted output measure.

obtained from Table 2, the external rate of return in the six elasticity-based studies would be 34.8%, compared to 22.5% in the rate-of-return based studies. Taken together, the median external rate of return in the 12 studies is 26.9%.

A range of estimates for the impact of external R&D is shown for the studies by Acharya and Goodridge, Haskel and Wallis. In these industry-level studies, it is not possible to separate intra-industry spillovers from the return to internal R&D.[When calculating the ratio of external to internal returns in Acharya, we assume the internal return includes intra-industry spillover effects.]Goodridge, Haskel and Wallis decompose the output elasticity of inside R&D into its factor share and a second component representing elements that raise the elasticity above the factor share, such as deviations from perfect competition, increasing returns and spillovers. These two components are shown in Table 2 for consistency with other results, but the ratio of external to internal elasticities is calculated assuming intra-industry spillovers are all internal, following the authors' approach.

Interpreting the return to the spillover pool is not clear-cut when multiple measures are included in the same equation. If the measures are not at all correlated, their individual impacts can in principle be identified and the overall impact would be given by the sum of the coefficients on the two variables. If the two measures are highly correlated, their individual impacts will be difficult to separate and it will be difficult to justify summing the coefficients to obtain the overall impact. Aiello and Cardamone (2009) take an average of their technological and geographic spillover variables when both measures are included in the estimating equation. The coefficient on the average measure is approximately the same as when the geographic measure enters alone, which is almost three times larger than the coefficient on the technological spillover variable when it appears in the equation. Lychagin et al. (2016) include three spillover measures in their equation, capturing technological, geographic and product market rivalry. Only the technological and geographical measures are shown in Table 2 since product market rivalry is not expected to affect production possibilities. The overall effect shown in Table 2 is the sum of the two spillover coefficients.

Two of the studies summarized in Table 2 provide information on spillovers by size of firm, which is useful to have when assessing the desirability of differentiating subsidy rates by size of firm. Some considerations suggest that spillovers from smaller to larger firms could be more important than spillovers from large to small firms. Small firms tend to perform more R&D related to the development of new processes and products while larger firms tend to focus more on improving existing products and processes;[14] everything else equal this would suggest higher spillovers from smaller firms. Larger firms are also likely to be able to make better use of patents and the development of complementary technologies to protect their intellectual property. Knowledge transfer resulting from employee turnover may also be less of an issue for larger firms. On the other hand, larger firms may perform more basic research than smaller firms and are more active in collaborative research, which would favour greater spillovers. Finally, it is possible that the quality of R&D rises with the amount of R&D performed, which would likely result in spillovers rising with firm size.

[14] Need a reference

Table 2: Recent Empirical Estimates of Domestic R&D Spillovers

Author	Definition of the spillover pool	Absorptive Capacity Modelled	*Output elasticity* or **rate of return** on:[1]						External / Internal Return
			Internal R&D	External R&D					
				Intra-Industry	Inter-industry	Techno-logical Proximity	Geograph-ical Proximity	Total External	
Industry level studies									
Acharya (2015)	R&D of the 10 most R&D intensive industries, accounting for 77% of R&D	No	**8.5 to 21.5**	**0 to 13**	**16**			**16 to 29**	**0.7**
Goodridge, Haskel & Wallis (2013)	Flows of intermediate consumption	Yes[2]	*.017 to .117*	*0 to 0.1*	*0.21*			*0.21 to 0.31*	1.8
Higon (2007)	I/O based estimates of sectoral flows of technology.	No	0.331		*0.942*			*0.942*	2.8
Firm level studies									
Aiello & Cardamone (2009)	Technological proximity: human-capital weighted similarity index (asymmetric Jaffe). Geographic: distance between capitals of provinces where firms operate.	Yes	0.105			*0.136*	*0.353*	*0.348*[3]	3.3
Bloch (2013)	Jaffe technological proximity based on declared field of research (10 fields)	Yes	0.198			*0.096*		0.096	0.5
Bloom, Schankerman and Van Reenen (2013)	Jaffe technological proximity based on patenting activity (426 categories)	No	**20.7**			**34.3**		**34.3**	**1.7**
Lucking, Bloom & Van Reenen	Jaffe technological proximity based on patenting activity (426 categories)	No	**13.6**			**44.1**		**44.1**	**3.2**
Cardamone (2017)	Technological proximity: intermediate input shares; geographic: distance between cities where firms are located.	No	**0.9**	**[8.0]**	**[0]**		**[8.7]**	**16.7**	**18.6**
Lychagin et al (2016)	Jaffe technological proximity based on patenting activity (410 categories); geographic based on inventor location.	No	*0.005*			*0.627*	*0.765*	*1.392*	278.4
Medda & Piga (2014)	Sum of industry R&D	No	**119.7**	**5.5**				**5.5**	**0.0**
Ornaghi (2004)	Intra-industry size-weighted (6 size categories)	Yes	*0.098*	*0.021*				*0.021*	*0.2*
Sena & Higon (2014)	I/O based estimates of sectoral flows of technology.	Yes							

1. Rates of return in square brackets were calculated by the authors of this study. 2. Tested but not significant. 3. The combined effect is the coefficient on the average of the two spillover measures

Bloom, Schankerman, and Van Reenen (2013) report that spillovers generated rise with firm size. The spillovers generated by firms in the top quartile are almost 75% higher than those generated by firms in the bottom quartile. The explanation advanced for this finding is that smaller firms tend to operate in technological niches, reducing the scope for knowledge spillovers. The dataset used does not include very small firms; the median number of employees in the bottom quartile is 370.

Ornaghi (2006) investigates spillovers among six employment-size-categories of firms, ranging from 20 employees or less to 500 or more. In order to distinguish between spillovers generated and received, she calculates 11 spillover variables. Ornaghi finds that diffusion occurs more from small to large firms than from large to small. Spillovers from small to large firms are up to two times as important as spillovers between firms of similar size. Spillovers from large firms to small firms were not statistically different from zero, while spillovers from large to medium-sized firms were about half a large as spillovers between firms of similar size. The ability to analyse spillovers generated and received by size of firm is an important advantage of Ornaghi's methodology. Her findings suggest that smaller firms should receive larger subsidies for performing R&D than larger firms

Data

Output and conventional inputs

The basic data source for our analysis is Statistics Canada's Longitudinal Employment Analysis Program (LEAP) data file linked to corporate income tax (T2) files. The LEAP file uses the statistical enterprise concept, which includes all entities controlled by the same corporation as the basis for its longitudinal structure. As a result, an enterprise may comprise more than one legal entity filing a tax return. The LEAP file is adjusted to eliminate spurious entries and exits caused by mergers, acquisitions and legal restructurings.[15]The other key data source is information from financial statements submitted by firms with their income tax return. These data are collectively described as the general index of financial indicators (GIFI). They include information on, among other items, the value of sales, costs, investment, depreciation and the capital stock.

We measure output as value-added. It is calculated as the sum of labour income from the LEAP file and capital income calculated from the GIFI data. While we would have preferred to calculate both measures from the same source, data on employment levels, which is used as the labour input in the production function, is only available from the LEAP file. To ensure consistency between employment levels and labour income, we also use the LEAP file as the source for labour income. Capital income is calculated from the GIFI data, adjusted to exclude R&D expenses that have not been capitalized by firms in order to avoid what Hall, Mairesse, and Mohnen (2010) describe as the "expensing bias" – understating capital income by calculating it net of what is treated as a balance sheet item. Finally, as recommended by (Moussaly and Wang 2014), we make adjustments to ensure that income generated by leased capital is attributed to the firm using the capital rather than the owner of the capital.[16]

[15]For example, when two enterprises merge, the new entity is assumed to have existed since the organic birth of both enterprises. For legal restructurings that result in enterprises continuing an existing business under a different name, payroll data is used to determine if most workers employed by the exiting firm are employed by a new firm within an adjacent time period.

[16] In the GIFI accounts, capital lease payments are recorded as income by the owner of the capital and an expense by the user. In order to correctly measure the capital income of the two parties, capital lease income is removed from the owner's account and capital lease payments are treated as capital income of the user.

We determine real value added using industry-specific implicit deflators calculated from data developed as part of Statistics Canada's industry productivity database, often denoted as the KLEMS database.[17] The productivity database provides information for 3-digit NAICS goods-producing industries and 2-digit service-producing industries.

We use GIFI balance sheet items to calculate the aggregate net stock of tangible capital for individual firms. Firms report the book value of tangible capital in use along with the accumulated depreciation charges against those assets. There is no completely satisfactory way to calculate the real value of the net capital stock. Book values of the stock and accumulated depreciation are a mixture of historical dollars so deflation by any price index will give inaccurate results. We use the industry-specific implicit deflators obtained from the industry productivity database to calculate the real net stock of tangible capital.

Ideally, the labour input would be measured by the number of hours worked. Unfortunately, reliable firm-level data on hours worked are not available, so we use an estimate of the number of employees developed for the LEAP data file. This estimate is developed by taking the ratio of total payroll to average annual earnings of a typical worker in the enterprise's 4-digit industry, province and enterprise size class.

Investment in research and development (R&D)

We use information submitted by firms in form T661 to claim the federal tax credit for investment in scientific research and experimental development (SR&ED) to estimate their spending on R&D. The eligibility criteria for the credit are consistent with the definition of R&D set out in the OECD's Frascati Manual. Firms report spending on wages and salaries, materials costs, equipment leasing, equipment purchase, expenditures on contracts and "third-party payments" for R&D.[18] Investment in structures used to perform R&D is not reported. We make a series of adjustments to obtain an estimate that includes R&D performed in-house for internal use; R&D performed under contract by other Canadian firms that the firm can exploit on an exclusive basis; and, R&D performed by third parties in Canada that

Box 2: The Research and Development in Canadian Industry Survey

R&D spending estimated from the tax data differs in coverage from Statistics Canada's survey program *Research and Development in Canadian Industry* (RDCI) which is, on balance, a slightly more comprehensive source. The main differences between the two data sources are:

- The RDCI includes spending on buildings and land, which are not in the tax data because such spending is not eligible for the SR&ED investment tax credit. However, in 2014, the first year such information is publicly available, spending on buildings and land amounted to just .4% of total R&D spending.
- The RDCI includes spending by firms that do not claim the SR&ED, either because they choose not to or because they are not-for-profit enterprises.
- The RDCI includes information on R&D purchased by Canadian firms from non-residents.
- As of 2008, the tax data includes, in certain circumstances, R&D performed by a foreign affiliate/subsidiary outside of Canada.

In principle, the RDCI would be a better source of R&D spending than the tax data. However, starting in 2014 the RDCI shifted from a census to survey approach. As a result, it will not be possible to construct a complete longitudinal data set of firms performing R&D after 2013, which makes the RDCI a less interesting source to use over the longer term.

[17] This database provides information from 1961 to 2012 for multifactor productivity based on gross output and value added. It also provides data on gross output, value added as well as capital, labour and intermediate inputs. The database is described in (Baldwin, Gu, and Yan 2007) and the data can be accessed through Cansim table 383-0032. The acronym KLEMS is used to draw attention to the fact that the database provides information on capital (K), Labour (L), energy (E), Materials (M) and services (S) inputs.

[18] Contracts and third-party payments are distinguished primarily by the degree of control over the performance of the R&D exercised by the payer and the right to use the R&D. In a contract, the payer has complete control and exclusive use of the R&D while in a third-party payment, the performer has control over the performance of the R&D and the payer has non-exclusive rights to exploit the results of the R&D.

the firm can exploit on a non-exclusive basis.

Depreciation and the stock of knowledge capital

Data on firm-level spending on R&D are available from 2000 to 2012. The real value of spending on R&D stock of R&D is calculated using the aggregate deflator for R&D developed in the system of national accounts.[19] This deflator is based on the real average wage rate of R&D personnel. In order to calculate the net stock over this period, we need an estimate of the stock in 1999 and knowledge of the depreciation rate. The standard approach in the literature to estimating the initial capital stock is to assume that R&D investment grows at a constant firm-specific rate g_i and that the knowledge capital loses value at a constant firm-specific rate δ_i (Hall 2005). With these assumptions, the stock of knowledge capital at time *t* for firm *i* can be calculated as follows:

$$(8) \quad K_{ti} \approx \frac{\bar{I}_i}{g_i + \partial_i}$$

where $\overline{I_\iota}$ is a measure of the equilibrium level of investment in R&D by firm *i*. It is calculated as the average level of investment over the three years ending in 2002. The equilibrium growth rate of R&D by firm i is calculated as the average growth rate of R&D over the entire sample period.

The above equation can only be used with confidence for firms that have been in existence and consistently performing R&D for long enough that their initial investment is fully depreciated by 2000. In the literature, a 15% depreciation rate is typically assumed, although the evidence is accumulating in favour of a higher rate. Huang and Diewert (2011) develop a model that incorporates imperfect competition and in which R&D is a technology shifter rather than an input to the production process. Estimating this model with US data, they obtain a depreciation rate of 29% for R&D undertaken in manufacturing. The results are described as preliminary. Li (2012)develops a forward-looking profit model to estimate depreciation rates for R&D undertaken in 10 US industries. The rates range from 10 to 43%, with only one estimate below 15%.

Hall (2005) makes the point that the depreciation rate used will not have much impact on the estimated parameters of a production function if g_i and δ_i are relatively stable over time. In this case, differences in the level of rates can be captured in firm fixed effects in the regression equation so the elasticity of output to the stock of knowledge capital will be little affected.[20] As a result, we make the conventional assumption that knowledge capital depreciates at 15% per year.

Firms can be identified in the T2-LEAP data base from 1984 forward. With a 15% depreciation rate, the value of R&D performed in 1984 would have fallen by about 93% by 1999. We therefore apply equation 1 without any adjustments to firms born in 1984 or earlier. For firms born after 1984 but before 2000, we multiply equation 8 by the ratio of the firm's age to 16 when calculating the initial capital stock. For firms born in 2000 or later, the initial capital stock is set to zero.

Double-counting of R&D inputs

Starting with Schankerman (1981), there is a long tradition in empirical work estimating the rate of return on R&D of correcting for the "double-counting" of R&D inputs.[21] The argument is that the tangible capital and labour used to create R&D capital are also included in the conventional inputs. We

[19] The deflator can be calculated from information presented in Cansim table 037-0007.

[20] On the other hand, the net returns to own and external R&D, which are calculated from the estimated elasticity, are affected by the depreciation rate.

[21] See for example, Cuneo and Mairesse (1983), Hall and Mairesse (1995), Peeters and Ghijsen (2000), and Hall, Mairesse, and Mohnen (2010).

are not persuaded that this correction is necessary. To see our point of view, it is useful to think of output as consisting of consumer and capital goods. The existing capital stock and labour are used to produce both types of output and the newly-produced capital becomes an input when it is available for use. The current labour input is always being used to produce output, so adjusting it to eliminate the labour used to create the capital asset would not be appropriate.[22]There is an exact parallel for R&D prepared under contract for another firm: output of the performing firm rises and the R&D capital of the purchasing firm increases. When a firm performs R&D in-house, its output rises when the expenditure is made, whether the R&D is capitalized or not.

This line of argument draws attention to the fact that newly-produced tangible and intangible capital may not be available to produce output in the period they are created. Li (2014, page 11) reports an average lag of two years between performing R&D and receiving revenue from investment in R&D for the US economy. Such a gestation lag suggests that only a small portion of current-period R&D will be used to produce output. Some tangible capital will also be in process over an extended period before it becomes available to produce output. As a result, lag structures on capital inputs should be explored when estimating production functions.

Data cleaning

Our first step in cleaning the data was to remove any observations for which value added, tangible capital or employment (proxied by an average labour unit) is negative or zero. In addition to eliminating obvious measurement errors, this step removes firms with no sales and highly unprofitable firms. We also removed all observations for which R&D capital is negative but set observations with zero value to one so that they could be included in a production function estimated in logs. [23]The number of observations after this step ranges from 18,000 to 28,000 annually over the 2000-12 period; the number of unique firms in the panel is about 38,000.

The next step in cleaning the data was to check for influential outliers by estimating equation 2 with robust least squares. We did not detect any influential outliers in this step. However, since the ratio of output to R&D capital (evaluated using mean values) is used to transform estimated output elasticities into rates of return, we also examined the impact of outliers on this statistic. In the full sample, which consists of R&D performers only, the ratio of output to R&D capital is approximately 12. To test the sensitivity of this ratio to outliers, we examined the impact of removing successively larger slices of the tails of the distribution for value added, tangible capital and R&D capital. With a 0.5% cut-off, the output to R&D capital ratio falls to just under eight. Subsequent .5%-point increases in the threshold had much smaller impacts on the ratio, so we used the 0.5% criteria to trim the data.

[22] Note also that when R&D is considered a capital rather than a current expenditure in the Canadian system of national accounts, adjustments are made to eliminate the “expensing bias” but no adjustments are made for double-counting the inputs used to create R&D.

[23] We also included a dummy variable indicating observations with zero capital stock.

The trimmed dataset is characterized by a large number of small firms accounting for a small share of the R&D performed in the economy and a small number of large firms accounting for a large share of the R&D performed. Firms in the bottom quartile account for less than 5% of total R&D performed while firms in the top percentile account for 40% of R&D performed (Table 3). To investigate whether these small firms have an impact on estimated coefficients that could be considered disproportionate relative to their share of R&D, we estimated the augmented production function with the trimmed sample and with successively larger slices of the smallest firms removed. The only coefficient affected by this process was on spillovers generated by small firms. This coefficient became statistically different from

Table 3: Share of total R&D Stock by Firm Employment Size 2000-2012		
Size Percentile Range	Share of Total R&D (%)	Mean Employment[1]
<25%	4.8	3.4
25%<x<90%	54.7	30.0
90%<	40.5	511.5
1. Average labour unit. See text for definition.		

zero when firms with less than one employee were removed but remained stable when more smaller firms were trimmed from the sample. These mini-firms, which account for 1% of all firms and less than .1% of R&D performed, were dropped from the regression sample.

Constructing the spillover pool

Technological proximity

In this paper, we use two measures of technological proximity. The now-standard approach developed by Jaffe (1986) defines technological proximity by comparing the distribution of R&D spending by technological category across firms. If there are K technology areas, the technology position of firm i can be characterized by a vector $\mathrm{F_i} = [\mathrm{F_{i1}} \mathrm{F_{i2}} \ldots \mathrm{F_{iK}}]$ where $\mathrm{F_{ik}}$ is the fraction of firm i's total research expenditure devoted to area k. The proximity of firm i and firm j can be measured as the uncentred correlation of firms' technological positions:

$$P_{ij} = F_i F_j' / [(F_i F_i')(F_j F_j')]^{1/2}$$

where F' is the transpose of F.

The proximity measure (a scalar) has the following properties: it is unity for firms whose position vectors are identical; it is zero for firms whose position vectors are completely unrelated, or orthogonal; and, it is bounded between 0 and 1 for all other pairs.

Bloom, Schankerman and Van Reenen (2013) introduce the "Mahalanobis extension" to overcome the restriction that knowledge transfers cannot occur between different fields, even if the fields are closely related. This extension allows spillovers between different technology areas by weighting the standard Jaffe measure by the closeness of different technology areas. The proximity of technological areas is based on how frequently they coincide within firms in the sample. For example, if many firms spend money on research in technology area x and y at the same time, then x and y would have a correlation coefficient that is close to 1.

This weighting scheme implies that firms with diverse research areas benefit from outside R&D to a greater extent than under the standard Jaffe method. A firm operating in several research fields has lower potential spillover benefits using the standard methodology because diversity reduces the size of each element of its position vector.

A technical description of the two proximity measures used in this paper is provided in the Appendix.

Measuring technological proximity

Since 2008, firms have been required to report spending by field of research when applying for R&D tax credits. Information is presented for four major categories, 28 sub-categories (represented by a 3-digit code) and 145 detailed technological fields (represented by a five-digit code). Having access to such data is unusual: to our knowledge, Denmark is the only other country that gathers such information, and only one researcher (Bloch 2013) has exploited it. Defining technological proximity in terms of R&D spending has a considerable advantage over the more usual approach of defining proximity in terms of patenting activities since it allows all R&D performers to be included in the analysis.

We constructed Jaffe-inspired technological proximity measures using 3 and 5-digit field codes, with and without the Mahalanobis extension developed by Bloom, Schankerman, and Van Reenen (2013) discussed above. We also constructed separate spillover pools generated by small and large firms. Firms receiving the federal enhanced SR&ED investment tax credit were classified as small and those firms receiving the regular credit were classified as large.

The quality of the data on spending by technological field is good. About 65% - 78% of R&D performers, representing 90% - 98% of R&D spending, provided complete information over the 2008-12 period. A small number of firms provided enough information to allow us to develop completely satisfactory measures of their spending by technological field.[24] As a result, our technological proximity measures cover approximately 95% - 98% of R&D spending on average over the 2008-12 period. When we extend the calculation back to 2000, the share of firms captured in our proximity measure falls since we cannot perform the calculation for firms that exited prior to 2008. However, the share of R&D captured remains above 90% - 95% over the 2000-07 period.

Nevertheless, extending the technological proximity measures to the 2000-07 period will provide useful results only if firms change research fields slowly over time. This is a plausible hypothesis since expertise in various areas is not easily acquired and involves large sunk costs. Bloom et al. (2013), compare results when proximity is measured using data over the whole sample (1963 to 2001) and using data from 1970 to 1980. The results are described as reasonably similar because firms changed research fields only slowly over time. In our sample, we observed that firms tend to operate in the same small number of fields over the 2008-2012 period;[25] they rarely enter a new field.

Estimation framework and results

In this version of the paper, we report results from estimating variants of equations 2 and 3 using ordinary least squares. The next version of the paper will explore the impact of using alternative econometric approaches, particularly General Method of Moments estimators. The baseline equation is reproduced below.

$$(2') \qquad y_{it} = a_{it} + \alpha c_{it} + \beta l_{it} + \gamma k_{it} + \varphi s_{it} + \eta_{it} + \omega_t + u_{it}$$

[24] We can calculate spending for firms that submit incomplete or missing spending by project provided that they are working in a single technological field. We cannot make approximations for two categories of firms: those for which field codes are missing, invalid or provided only for a subset of projects underway in a given year; and those working in more than one field providing complete field codes but incomplete expenditure data by project.

[25] On average over the 2008-12 period, firms undertook research in 1.33 fields.

In equation 2', y is value added, c is tangible capital, l is the labour input (employment, proxied by average labour units), k is R&D capital, s is the spillover pool, η represents aggregate productivity shocks, proxied by year dummies, ω captures time-invariant firm-fixed effects and u is a random error. All variables are in logs.

We began our empirical investigation by estimating equation 2' over the 2000-12 period for an unbalanced sample of R&D performers and using the Jaffe proximity weights calculated using five-digit technology field codes. While our dataset is adjusted for the effects of mergers, acquisitions and legal restructurings, entries and exits remain a potential source of selection bias, prompting us to work with an unbalanced panel. Our sample is restricted to R&D performers primarily because our modelling framework assumes that only R&D performers can benefit from spillovers. We experimented with industry dummy variables and industry-level value-added (as in Bloom, Schankerman, and Van Reenen 2013), but these variables had little impact on the results and were dropped from subsequent regressions.

The choice of estimation period involves a trade-off between measuring the R&D stock with error and reducing the efficiency of the fixed-effect estimator by shortening the length of the panel. As discussed above, initial stock of R&D for firms entering prior to 2000 is only an approximation, but the starting value becomes less important over time as a result of depreciation. For example, by 2010 about three-quarters of the imputed value of R&D capital in 2000 has been depreciated, causing the potential importance of measurement error to decline substantially. On the other hand, the efficiency of the fixed effect estimator falls dramatically as the length of the panel shrinks from 13 to 3 years. This loss in efficiency occurs because the fixed effect estimator uses variations over time within each firm rather than variations between firms.

The output elasticities for labour and tangible capital obtained at this stage were consistent with prior notions of income shares. In addition, the sum of the coefficients on all three inputs was not significantly different from one. That is, the hypothesis of constant returns to scale could not be rejected, a finding that was repeated in all equations subsequently estimated. We also used a random-effects estimator but conducting a Hausmann test led us to reject the null hypothesis that the unique errors are not correlated with regressors (i.e. reject the null that the random effect estimator is preferred). As a result, all of our subsequent econometric analysis is based on the fixed-effects estimator.

A surprising result at this stage was a negative and statistically significant coefficient on the spillover variable. While R&D performed by competitors could have negative effects on profits by destroying rents, a direct negative effect on productivity would not be expected. Similarly, firms may compete in research effort to be the first to bring an innovation to market, but this would be more likely to show up in a lower return to own R&D than a direct negative impact on productivity from R&D performed by other firms.

One possible explanation for the negative coefficient is that the distribution of R&D spending by detailed technological field is not stable over time, so that the spillover variable is calculated with error, causing the coefficient to be biased towards zero. If changes in the composition of R&D spending are affecting the spillover coefficient, we would expect the output elasticity of own R&D to be affected as well. When we shortened the estimation period by starting in 2004, the spillover coefficient changed sign while remaining significantly different from zero, but the output elasticity of internal R&D was not affected. Further, when we calculated technological proximity using 3-digit field codes (28 instead of 145 categories) we obtained a positive coefficient on the spillover pool for both estimation periods. While we use proximity measures based on 3-digit field in all subsequent regressions, we plan to analyse the impact of switching to a more aggregate proximity measure in the next version of this paper using GMM estimators, which provide more consistent coefficient estimates when working with short panels.[26]

Results based on the 3-digit proximity measure are summarized in Table 4. When we use the Jaffe measure of technological proximity to define the spillover pool, the internal and external output elasticities are similar in size.[27] Allowing spillovers between firms operating in closely-related fields (the Mahalanobis extension) rather than requiring firms to be operating in identical fields (Jaffe methodology) raises the output elasticity of external R&D by about 60%. The output elasticity of own-

Table 4: Production Function Regression Results using a Fixed-Effects Estimator
(Estimated using an unbalanced sample of R&D performers 2000-12)

Dep. Var: Ln(value added)	(1)	(2)	(3)
Proximity measure (3-digit)	Jaffe	Mahalanobis	Mahalanobis
Ln(Employment)	***0.684***	***0.684***	***0.681***
	(0.004)	(0.004)	(.004)
Ln(Tangible Capital)	***0.236***	***0.236***	***0.235***
	(.002)	(.002)	(.002)
Ln(R&D Capital)	***0.025***	***0.025***	***0.0162***
	(0.002)	(0.002)	(.002)
Ln(SpilloverPool)	***0.029***	***0.047***	***0.043***
	(0.009)	(0.011)	(.011)
Ln(SpilloverPool)*(R&D Capital)			***7.33E-10***
			(9.16e-11)

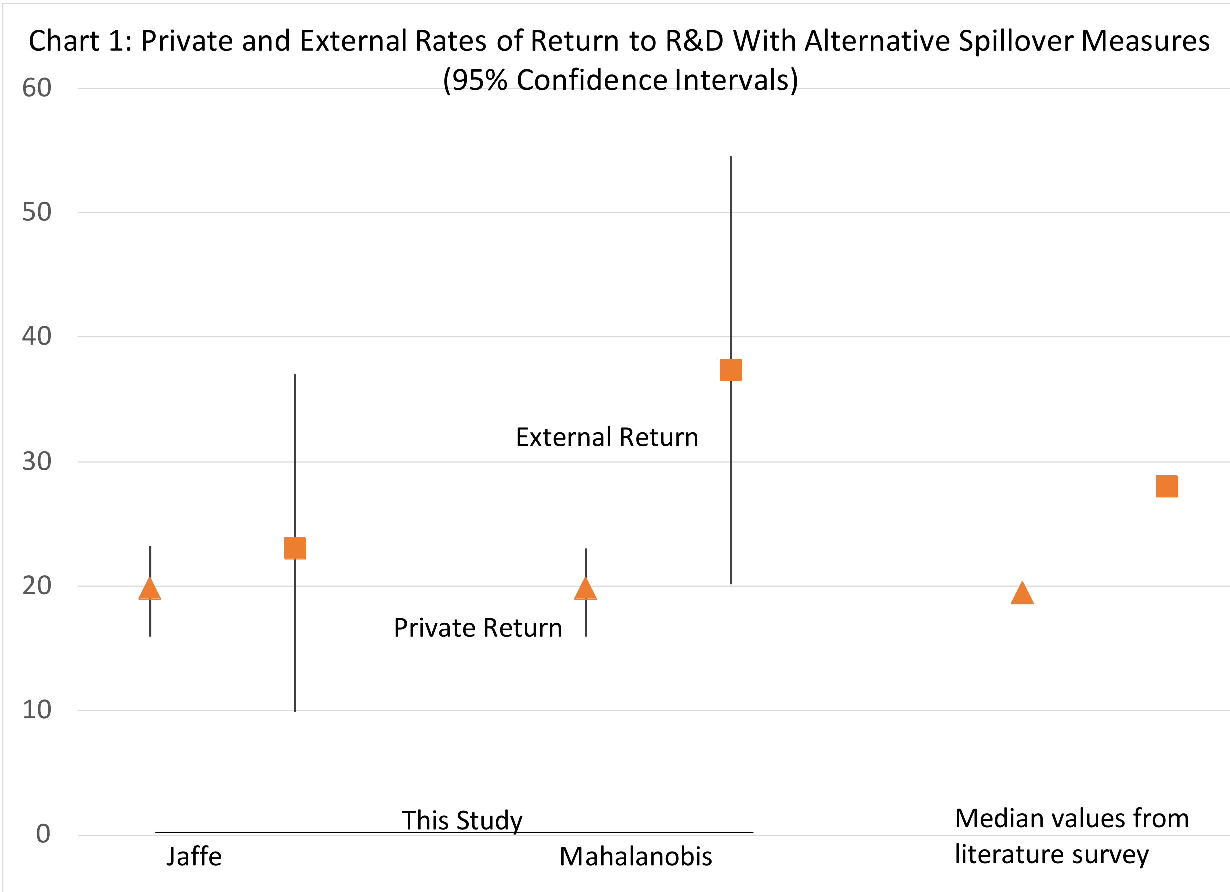
The Jaffe proximity measure requires that firms operate in the same technoloical field for spillovers to occur; the Mahlanobis exttension allows spillovers among closely-related fields. All regressions include firm and year fixed effects along with a dummy variable for observations where the stock of R&D capital is zero (coefficients not shown). Coefficients in ***bold italics*** have p<.01; in **bold** p<.05; in *italics* p<.10. Standard errors, which are clustered by firm, are in parentheses. The number of observations in all regressions is 296,841.

R&D is not affected by allowing greater scope for spillovers.

[26] A concern with aggregating technology fields may be that it would increase measured proximity and hence have a direct impact on the spillover elasticity. However, aggregation does not necessarily increase the proximity measure since we are normalizing the correlation by the standard deviations of technology position vectors. For a discussion see Bloom, Schankerman, and Van Reenen (2013, Appendix C.1).

[27] Without firm fixed effects, the output elasticity of own-R&D is about five times larger than shown in Table 4, which implies an implausibly large income share for R&D capital.

The estimated elasticities imply a private rate of return on R&D of about 20% (Chart 1). This rate of return is approximately the same as the median value of estimates reported by Hall, Mairesse, and



Mohnen (2010), which is slightly higher than the median obtained from six more recent studies summarized in Table 2. As mentioned earlier, a gross private rate of return to R&D of around 20% implies a low rate of return for investors in the context of a 15% depreciation rate. The prevalence of R&D subsidies likely contributes to the low market rate of return to investors. The estimated/calculated rates of return represent marginal ex post rates of return to R&D. Over the longer term, ex post and ex ante rates of return will coincide, so the estimated/calculated rates of return approximate the required gross rate of return on the marginal investment in R&D. The required gross rate of return is net of subsidies.

Almost all members of the Organisation for Economic Co-operation and Development provide substantial tax incentives for performing R&D. In 2017, the median tax-based subsidy rate for large firms was 14.8% (Lester and Warda 2018) and many countries offer subsidies delivered through spending programs as well. In Canada, the combined federal-provincial tax-based subsidy rate for all firms averaged more than 30% of the user cost of capital over the 2010-2012 period (Table 5), suggesting that the private incentive to undertake R&D is substantially understated by the estimated rate of return.

The implied external rate of return on R&D ranges from about 23% to about 37%, depending on how technological proximity is measured (Chart 1). The result using the standard Jaffe measure of proximity is slightly below the median result of the existing studies surveyed. While the rate of return obtained using the Mahalanobis extension is substantially higher than the median, it is well within the range of

Table 5: Federal and Provincial SR&ED Investment Tax Credit Rates
(2010-12 in percentage)

	Federal	Provincial[1]	Combined[2]
SMEs	35.0	13.3	43.6
Other firms	20.0	6.3	25.0
All firms[3]	25.1	8.6	31.6

1. Expenditure-weighted sum of provincial statutory rates.
2. The base for the federal credit is reduced by the amount of provincial assistance provided.
3. Weights were developed from federal tax expenditures by firm type.

estimates obtained.[28]

Column 3 of Table 4 shows the impact of including a measure of absorptive capacity when technological proximity is calculated using the Mahalanobis extension. The absorptive capacity term is captured by interacting the log of the spillover pool and the level of own-R&D. With respect to equation 2', this is implemented by re-specifying the output elasticity of spillovers as $\varphi = \varphi_1 + \varphi_2 K_{it}$, which results in the following estimating equation:

$$(3') \quad y_{it} = a_{it} + \alpha c_{it} + \beta l_{it} + \gamma_1 k_{it} + \varphi_1 s_{it} + \varphi_2 s_{it} K_{it} + \eta_{it} + \omega_t + u_{it}$$

We obtain a positive and statistically significant coefficient on the interaction term, which indicates that the ability to benefit from external R&D rises with the level of internal R&D performed.[29] However, the coefficient is very small and its impact is not quantitatively important: including the interaction effect causes the spillover elasticity to vary by plus or minus .001 as firm R&D (K_i) ranges from the top to the bottom 5% of the sample. Our qualitative finding is consistent with results in the empirical literature, although few studies model absorptive capacity exactly as we have done. Our formulation follows Aldieri and Cincera (2009) who obtain a positive coefficient on the interaction term. Jaffe (1986b) interacts the log of internal R&D with the log of the spillover pool and obtains a positive coefficient. Most other studies use measures other than internal R&D when testing the importance of absorptive capacity. Note that unless the interaction term is developed by re-specifying the output elasticity, it cannot be derived from the production function.

The results summarized in Table 6 provide a perspective on whether spillovers vary by size of firm. If small firms generate more spillovers than larger firms, there would be a strong case for providing higher

[28] The median rates of return on internal and external R&D are calculated using estimates from the studies included in the Hall, Mairesse, and Mohnen (2010) survey as well as the estimates shown in Table 2.

[29] We also experimented with an alternative approach in which the internal R&D output elasticity was re-specified as $\gamma = \gamma_1 + \gamma_2 S_{it}$, which gave an interaction term between the log of internal R&D capital and the level of the spillover pool. In this case the coefficient on the interaction term was negative, implying that the productivity of internal R&D declines as external R&D rises. We are reviewing possible explanations for this unexpected result.

subsidies for small firms, as is done in Canada and several other OECD member countries. We tested this hypothesis by including separate pools for spillovers generated by small and large firms in the regression equation. Firms eligible for the federal enhanced SR&ED investment tax credit were classified as small while all other firms were classified as large. For both measures of technological proximity we find that the coefficients on spillovers generated by small firms are significantly different from zero at the 10% level while the coefficients on large firm spillovers are significant at the 1% level. The correlation between the two measures is .3 over the 2000-12 period, so there is little reason to be concerned about the precision of the coefficient estimates. While the point estimates of the coefficients indicate that spillovers generated rise with firm size, we cannot reject the hypothesis that the two coefficients have the same value at the 5% significance level. Note that the overall spillover elasticity implied by the results for small and large firms is lower than the base-case elasticity.

Our finding supports results in Bloom, Schankerman, and Van Reenen (2013), which, based on a sample of publicly-listed US firms, found a statistically significant positive relationship between spillovers and firm size. While the comparison is not exact, our finding contrasts with that of Ornaghi (2006), who, working with Spanish data, found that spillovers from small to large firms were more important than spillovers from large to small.

Our preliminary results do not offer any support for the proposition that small firms generate more substantial spillovers than large firms. Since the optimal subsidy rate rises with the spillover rate, this finding weakens the case for providing higher subsidies for small firms. However, there is some evidence that small firms respond more strongly to R&D incentives than larger firms, so preferential treatment of small firms could still be justified.[30]

[30] [See Lester (Forthcoming) for a brief summary of this literature.]

Table 6: Production Function Regression Results using a Fixed-Effects Estimator (Estimated using an unbalanced sample of R&D performers 2000-12)				
Dep. Var: Ln(value added)	(1)	(2)	(3)	(4)
Proximity measure (3-digit)	Jaffe	Jaffe	Mahalanobis	Mahalanobis
Ln(Employment)	***0.684***	***0.684***	***0.684***	***0.684***
	(0.004)	(0.004)	(0.004)	(.004)
Ln(Tangible Capital)	***0.236***	***0.236***	***0.236***	***0.236***
	(.002)	(.002)	(.002)	(.002)
Ln(R&D Capital)	***0.025***	***0.025***	***0.025***	***0.025***
	(0.002)	(0.002)	(0.002)	(.002)
Ln(SpilloverPool)	***0.029***		***0.047***	
	(0.009)		(0.011)	
Ln(SpilloverPool_small)		*0.014*		*0.021*
		.007		.009
Ln(Spillover pool_large)		***0.023***		***.038***
		.007		.009

The Jaffe proximity measure requires that firms operate in the same technological field for spillovers to occur; the Mahlanobis exttension allows spillovers among closely-related fields. All regressions include firm and year fixed effects along with a dummy variable for observations where the stock of R&D capital is zero (coefficients not shown). Coefficients in ***bold italics*** have p<.01; in **bold** p<.05; in *italics* p<.10. Standard errors, which are clustered by firm, are in parentheses. The number of observations in all regressions is 296,841.

As discussed above, there are a number of considerations that suggest spillovers should fall with firm size. In contrast, Bloom, Schankerman, and Van Reenen (2013) report that small firms operate in "technological niches" that limit the applicability of their research to other firms. This channel of influence is not a factor in our results: the technological proximity indexes we calculated do not vary substantially by size of firm.[31] The higher subsidy rate available to small firms could be influencing the result. The combined federal-provincial subsidy rate on R&D performed by small firms is almost 19 percentage points higher than the rate for larger firms. As a result of this differential, the "hurdle rate" for undertaking an R&D project will be substantially lower for smaller firms. While a low (net of subsidy) private return does not necessarily result in a low external return, projects with low commercial value to the performing firm may not provide useful knowledge to other firms either. An additional factor influencing the result is that small firms appear to perform less basic research and more experimental development than larger firms.[32] Spillovers are generally thought to be higher for basic research than for other forms of R&D.

Conclusion

This paper makes three contributions to the extensive literature on R&D spillovers. First, it provides estimates of the rate of return to external R&D using recent firm-level data for Canada. The most recent estimates were prepared thirty years ago by Bernstein (1988) and only covered selected manufacturing industries. Second, this paper makes use of data on R&D spending by technological field to calculate technological proximity measures. This approach has a considerable advantage over the more usual approach of defining proximity in terms of patenting activities since it allows all R&D performers to be included in the analysis. Third, we calculate separate spillover pools by size of firm, which allows us to assess whether the generation of spillovers varies by size of firm.

[31] The aggregate indexes for large and small firms have very similar values over the 2008-11 period, although the measure is slightly greater for larger firms; in 2012, the small firm measure is slightly greater than the measure for larger firms.

[32] Presently, we can only calculate the share of firms performing basic research by size of firm.

Our preferred measure of the spillover pool indicates that the rate of return on external R&D is about 37 per cent, which is higher than typically found in the literature. However, when spillover pools generated by large and small firms are included in the regression equation, the implicit aggregate spillover rate declines. More importantly, the point estimates on the spillover pools imply that the rate of return on external R&D rises with firm size, although the difference is not statistically significant. This finding substantially weakens the case for subsidizing R&D performed by small firms at a higher rate than R&D performed by larger firms, as is done in Canada and several other OECD member nations.

These results are preliminary. They are based on a fixed-effects estimator applied to a relatively short panel. We may therefore obtain different results in the next version of the paper when we will use first-difference and system-GMM estimators.

Appendix: Measures of Technological Proximity

The Jaffe proximity measure

Denote N = the total number of firms

Denote K = the total number of technology fields

Define a technology position vector for firm n across K technology fields.

$$F_n = [\,F_{n1} \quad F_{n2} \quad \ldots F_{nK}]_{(1xK)}$$

where F_{nk} is the share of technology field k in the total R&D expenditure of firm n. Let RD_n denote the total R&D expenditure of firm n. Then, we have $RD_n = \sum_k^K RD_{nk}$ and $F_{nk} = \frac{RD_{nk}}{RD_n}$.

Stacking F_n for all n vertically…

$$ff = \begin{bmatrix} F_{11} & \cdots & F_{1K} \\ \vdots & \ddots & \vdots \\ F_{N1} & \cdots & F_{NK} \end{bmatrix}_{(NxK)}$$

Note that the Jaffe proximity measure is essentially an uncentered correlation coefficient for a given pair of technology position vectors. Therefore, in the next step, we normalize each element by the standard deviation of the corresponding technology position vector.

$$ff\_n = \begin{bmatrix} F_{11}/(F_1F_1')^{0.5} & \cdots & F_{1K}/(F_1F_1')^{0.5} \\ \vdots & \ddots & \vdots \\ F_{N1}/(F_NF_N')^{0.5} & \cdots & F_{NK}/(F_NF_N')^{0.5} \end{bmatrix}_{(NxK)}$$

$$\tilde{F} = ff\_n * ff\_n'$$

$$\tilde{F} = \begin{bmatrix} 1 & \cdots & F_1F_N/[(F_1F_1')(F_NF_N')]^{0.5} \\ \vdots & \ddots & \vdots \\ F_NF_1/[(F_1F_1')(F_NF_N')]^{0.5} & \cdots & 1 \end{bmatrix}_{(NxN)}$$

Replace the diagonal of $\tilde{F}$ with zeroes to exclude self-influence.

$$\tilde{F} = \begin{bmatrix} 0 & \cdots & F_1F_N \big/ [(F_1F_1')(F_NF_N')]^{0.5} \\ \vdots & \ddots & \vdots \\ F_NF_1 \big/ [(F_NF_N')(F_1F_1')]^{0.5} & \cdots & 0 \end{bmatrix}_{(NxN)}$$

$\tilde{F}$ contains the standard Jaffe proximity measure between firms.

Mahalanobis normed proximity measure

Define a vector containing the distribution of technology k across N firms.

$$T_k = [\,F_{1k} \quad F_{2k} \quad \ldots F_{Nk}]_{(1XN)}$$

Stacking T_k for all k vertically…

$$tt = \begin{bmatrix} F_{11} & \cdots & F_{N1} \\ \vdots & \ddots & \vdots \\ F_{1K} & \cdots & F_{NK} \end{bmatrix}_{(KxN)}$$

*Note that $tt = ff'$

$$tt\_n = \begin{bmatrix} F_{11} \big/ (T_1T_1')^{0.5} & \cdots & F_{1N} \big/ (T_1T_1')^{0.5} \\ \vdots & \ddots & \vdots \\ F_{K1} \big/ (T_KT_K')^{0.5} & \cdots & F_{KN} \big/ (T_KT_K')^{0.5} \end{bmatrix}_{(KxN)}$$

$$O = tt\_n * tt\_n'$$

$$O = \begin{bmatrix} 1 & \cdots & T_1T_K \big/ [(T_1T_1')(T_NT_N')]^{0.5} \\ \vdots & \ddots & \vdots \\ T_KT_1 \big/ [(T_NT_N')(T_1T_1')]^{0.5} & \cdots & 1 \end{bmatrix}_{(KxK)}$$

O can be interpreted as the standard Jaffe proximity measure defined for technology fields.

$$\tilde{P} = ff\_n * O * ff\_n'$$

Similarly, we replace the diagonal of $\tilde{P}$ with zeroes to exclude self-influence. $\tilde{P}$ is an (NxN) matrix that contains the Mahalanobis normed proximity measures defined for firms.

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