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

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Abstract

Business investment in research and development (R&D) makes a key contribution to rising living standards. Firms undertaking the R&D can reduce production costs and introduce new products that provide benefits to consumers that are not fully captured in selling prices. Further, it is very difficult 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. Our study confirms the existence of substantial spillover benefits from R&D performed in Canada, so government support for R&D is justified. However, we do not find any empirical evidence to support the current policy of subsidizing R&D at a higher rate when it is performed by small firms than when it is performed by large firms. We also find much lower private rate of return on R&D performed by small firms than by large firms. Subsidies appear to be playing a key role in this result.

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

Table of Contents

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

Executive Summary

There is a sound public policy case for subsidizing R&D. When firms perform R&D, they create knowledge that allows them to introduce new products, improve existing goods and services or reduce production costs. However, some of the knowledge created inevitably leaks out or spills over to other firms, allowing them to reap benefits from the R&D performed by other firms. Firms do not consider these spillover benefits when deciding how much to invest in R&D, so a subsidy to encourage more R&D is the right policy response.

When deciding how much to subsidize R&D, governments should consider both the benefits and costs of the subsidy. The benefit to society from subsidizing R&D is determined by the knowledge spillovers, which are likely to be a constant share of the additional R&D induced by the subsidy. (The additional R&D induced by a subsidy has a direct effect on output, but this is offset by lower output in other sectors when taxes are increased, or spending is cut, to finance the subsidy.) On the cost side, the most important consideration is how the subsidy affects the commercial rate of return on the additional R&D performed. By lowering the hurdle rate for a profitable investment, subsidies allow R&D projects with less commercial potential to be undertaken, which lowers the value of output. The hurdle rate, or the required private rate of return on R&D, declines as the subsidy rate rises, so the loss in output becomes a larger share of the additional R&D as the subsidy rate rises.

Since increases in the subsidy rate generate benefits that are a constant share of the additional R&D induced by the subsidy and costs that are a rising share of the additional R&D, the net benefit has an inverted "U" shape: it initially rises along with the subsidy rate but eventually declines as the private return on R&D continues to fall. The maximum net benefit to society occurs when the subsidy rate is equal to the spillover rate. Note, however, that since governments incur costs to administer subsidy programs and firms spend money to comply with program requirements, the maximum net benefit may be negative.

Empirical analysis of spillovers can therefore make an important contribution to public policy by providing evidence on how much to subsidize R&D. In this paper, we employ a range of regression techniques to investigate the importance of R&D spillovers, making use of a data base consisting of all incorporated firms with employees performing R&D that was developed specifically for this study. Our analysis fills three gaps in the empirical literature on R&D spillovers. First, it is the only analysis using firm-level data covering all R&D performers in Canada. Second, we have access to detailed information on R&D spending by technological field, which allows us to investigate spillovers between firms operating in the same or similar technological fields. Almost all other empirical analyses of spillovers measure technological proximity using patenting activity, which has the disadvantage of limiting the analysis to firms that take out patents. Third, our study is one of three in the literature that provides evidence on spillovers by size of firm.

Our analysis confirms the existence of substantial spillover benefits from R&D performed in Canada, so governments are responding appropriately by subsidizing R&D. However, governments in Canada subsidize R&D performed by small firms at a much higher rate than R&D performed by larger firms. The federal government provides a 15% tax credit for R&D performed by large firms while all small and medium-sized Canadian-controlled private firms performing R&D receive a 35% refundable tax credit. Provincial programs reinforce this bias, raising the average small firm subsidy rate to almost 43% and the large firm rate to about 20%. In addition, about 2,000 small firms top up the SR&ED incentive, which is available to all firms performing R&D, with targeted assistance from the Industrial Research Assistance Program (IRAP), raising the subsidy rate to around 60% on average for these firms.

Our research does not support this policy bias in favour of small firms. Our analysis indicates that the subsidy rate on R&D performed by small firms is well above its optimal value while the large firm subsidy rate is below it. In fact, our research finds that small firms generate less spillovers than larger firms. Our research also shows that the rate of return on R&D performed by small firms is much lower than the rate of return for large firms. The higher subsidy rate for small firms accounts for a substantial portion of this gap in private rates of return by driving down the hurdle rate for investment further for small firms than for large firms. The lower private rate of return may also be a factor in the lower spillovers generated by small firms: projects with low commercial value to the performing firm may not provide much useful knowledge to other firms either.

The lower spillovers generated by small firms suggest that R&D performed by small firms should be subsidized less than R&D performed by larger firms. However, the development of small firms is impeded by several factors, including more burdensome costs of filing tax returns and applying for R&D support programs, barriers to entry erected by larger firms and tax policies that unintentionally hinder entrepreneurs. Perhaps more importantly, a few small firms are the source of innovations that have big impacts on living standards that are not captured in the spillover analysis. As a result, it would not be prudent to consider only the spillover rate when deciding how much to subsidize R&D performed by small firms.

Our research indicates that the all-firm average spillover rate is approximately 30%, which is about 10 percentage points above the small firm spillover rate. Adopting this as a common federal-provincial SR&ED subsidy rate would raise real income in Canada by lowering the small firm rate and increasing the large firm rate closer to their optimal levels. The federal government could achieve the target combined rate on its own by reducing the SR&ED small firm rate to 20% and raising the large firm rate to 25%. Thousands of small firms would continue to top up the SR&ED benefits with subsidies from IRAP, which could raise the subsidy rate slightly above 40% for these particularly promising firms.

R&D Spillovers in Canadian Industry: Results from a New Micro Database[1]

I. Introduction

Business investment in research and development (R&D) makes a key contribution to rising living standards. Firms undertaking the R&D can reduce production costs and introduce new products that provide benefits to consumers that are not fully captured in selling prices. Further, it is very difficult 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.

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. A positive coefficient on the stock of external R&D, or the spillover pool, indicates that that firms benefit from the knowledge created by other firms.

Our study adds to this empirical literature, filling three gaps. First, studies using Canadian data are not abundant. The only study of R&D spillovers using Canadian firm-level data was prepared 31 years ago by Bernstein (1988), covering selected manufacturing industries. Second, we define the spillover pool using a measure of technological proximity based on firms' reported expenditure in 147 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 7 other OECD member countries, subsidizes R&D performed by small firms at a substantially higher rate than R&D performed by larger firms.

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[1] Myeongwan Kim was an Economist at the Centre for the Study of Living Standards from September 2017 until July 2019. John Lester is a Senior Research Associate at the Centre for the Study of Living Standards. This project makes use of a micro database at the Canadian Centre for Data Development and Economic Research (CDER) at Statistics Canada developed by John Lester, Ryan MacDonald, Javad Sadeghzadeh and Weimen Wang. Development of the database was supported by funding from the Strategy, Research and Results Branch of the federal Department of Innovation, Science and Economic Development. Funding for this research was provided by the Productivity Partnership as supported by the Social Sciences and Humanities Research Council of Canada. While the research and analysis are based on data from Statistics Canada, the opinions expressed do not represent the views of the agency. More information on CDER is available at http://www.statcan.gc.ca/cder-cdre/index-eng.htm.
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We have access to a longitudinal data base covering the period from 2000 to 2012 of all incorporated firms with employees in Canada. We use a standard augmented production function approach in our analysis of spillovers, with real value added as the output measure. We estimate the production function (in logs) for an unbalanced panel of R&D performing firms using static and dynamic modelling approaches. Our preferred results are based on a static model with a fixed-effect estimator. While there is a compelling theoretical case for using a dynamic panel data model, it proved difficult to find an ideal specification in a generalized method of moments context. Nevertheless, our analysis with system generalized method of moments estimators based on a dynamic model supports the results from the static model.

We obtain coefficients on the conventional inputs that are consistent with income shares and, when R&D capital is included, the sum of the coefficients is close to one but constant returns to scale is rejected in our static production function but not in the dynamic version. The estimated coefficient on internal R&D capital implies a rate of return of 33%, which is substantially greater than the median obtained in our literature survey. The private rate of return on R&D performed by large firms is about 35% points higher than the private return to small firms. Subsidies appear to be playing a key role in this result. Using our preferred measure of the spillover pool, the rate of return on external R&D is approximately 33%, which is six percentage points higher than the median of estimates found in the literature. We find evidence that spillovers increase with the size of the firm performing the R&D. The external rate of return to R&D performed by large firms is 52% while the external return to R&D performed by small firms is 19%.

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. In section IV, we discuss how the spillover pool was calculated. Our estimation framework and results are presented in section V, which includes some robustness checks. Our analysis by size of firm is presented in section VI, which is followed by some concluding remarks.

II. Literature review

1. Analytical framework

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) $Y_{it} = A_{it}F_i(X_{it})$

where Y_{it} denotes output of firm (or industry) i at time t;$X$is a vector of inputs; and A is the Hicks-neutral efficiency level of firm i at time t.

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) $y_{it} = a_0 + \alpha c_{it} + \beta l_{it} + \theta m_{it} + \gamma k_{it} + \varphi s_{it} + v_{it} + u_{it}$

where lower case letters represent natural logarithms and$y$ is 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 knowledge capital relevant to the firm. We assume $\ln(A_{it})$ can be decomposed into the mean efficiency level across firms (a_0) and firm- and time-specific deviations from the mean observable to firms (v_{it}) and unobservable to firms (u_{it}) (*i.e.*$\ln(A_{it}) = \ a_0 + v_{it} + u_{it}$).[2]

Depending on the choice of estimation method, equation (2) can take different forms in order to capture productivity shocks unobserved to econometricians (*i.e.*$v_{it} + u_{it}$). For example, by assuming v_{it} can be decomposed into a firm-specific but time-invariant component (η_i) and a time-variant component affecting all firms (ω_t), we can estimate equation (2) using a fixed effects estimator with the following equation:

$$(3) \quad y_{it} = a_0 + \alpha c_{it} + \beta l_{it} + \theta m_{it} + \ \gamma k_{it} + \varphi s_{it} + \eta_i + \omega_t + u_{it}$$

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:

$$(4) \quad y_{it} = a_0 + \alpha c_{it} + \beta l_{it} + \theta m_{it} + \gamma k_{it} + \varphi_1 s_{it} + \varphi_2 s_{it} AC_{it} + \eta_i + \omega_t + u_{it}$$

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 the value of output calculated using observed factor inputs and estimated output elasticities from actual output(Cardamone

[2]We can denote log of firm-level productivity (or TFP) as $a_0 + v_{it}$. Following Olley and Pakes (1996), the productivity term is identified as such by assuming that $a_0 + v_{it}$ is a state variable that affects firms' production decisions. u_{it} is an *i.i.d.* component, reflecting unpredictable deviations from the mean due to external factors (*e.g.* unexpected delays in the delivery of intermediates) or measurement error.

2017). The TFP equation usually includes the spillover pool as an explanatory variable and includes the stock of own-R&D when it is not explicitly modelled as an input.

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 (2006)	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 is instrumented. 4. Results also presented for static and dynamic GMM estimators, with and without common factor restrictions.

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.[3] 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

[3] 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.

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 estimating this equation, it is common to measure R&D intensity using gross investment in R&D, which implicitly assumes that the economic depreciation rate on R&D capital is zero.[4] 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 – 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 the input interaction terms in the translog production function.

2. Econometric Issues

Estimating a demeaned version of equation 2 with OLS, which uses only the within-firm variation in the sample, presents several econometric challenges. These include simultaneity bias that occurs because inputs are endogenous rather than strictly 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.[5]

2-1. Simultaneity bias

The simultaneity bias arises because firms decide on input levels based on demand and productivity shocks that they experience.[6] These productivity shocks are not observed by econometricians, but they are correlated with input choices made by firms. As a result, ordinary least squares (OLS) estimates are biased and inconsistent. Levinsohn and Petrin(2003) analyse the case where input demand is affected by views on the productivity of the input. If productivity shocks are serially correlated, a positive shock will increase the demand for variable inputs, which introduces an upward bias to the coefficients on labour

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

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

[6] 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.

and materials. Capital is likely to be positively correlated with variable inputs. If so, the coefficient on capital will be biased downwards.

Researchers use various techniques to address simultaneity bias. One approach is to assume that there is a time-invariant component in firm-specific productivity shocks and estimate equation 2 with a fixed-effects estimator. If such assumption is correct and 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 for individual firms (equivalent to OLS on a demeaned equation), equation 2 can also be estimated in first differences to eliminate firm-specific effects. This approach tends to increase the problems caused when variables are measured with error (Hall and Mairesse 1995). In any case, in a typical situation characterized by a large number of cross-sectional units (N) and a short time period (T), using the OLS estimator on a transformed equation would result in biased and inconsistent coefficients if strict exogeneity assumptions for the factor inputs are not satisfied.

Another approach to addressing simultaneity bias 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 cannot 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’[7] 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.

With the difficulty in finding good external instruments as well as the limited success from using one-period lagged values of inputs as "instruments", an alternative strategy is to make use of a set of internally available instruments. Arellano and Bond (1991) formally 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 forward-orthogonal deviation (FOD) to transform the production equation, which eliminates firm fixed effects. Then, one can use suitably lagged dependent and independent variables in levels as instruments to correct for simultaneity. Therefore, in theory, we can obtain a consistent estimator for panel data with a large number of observations (N) over a short period of time (T). Arellano and Bond GMM has been adopted by a number of researchers examining the returns to R&D, with Hall and Mairesse (1995) being an early example.

While Arellano and Bond GMM can mitigate the simultaneity bias in theory, its performance suffers in practice when the autoregressive component in each regressor is high (Blundell and Bond 1998). Simulation studies indicate that in these circumstances the finite-sample bias is large and coefficients are not precisely estimated. These problems arise because the first difference of a persistent series is weakly correlated with its lagged levels. They can be substantially reduced by using an extended, or system, GMM estimator that assumes stationary initial conditions so that the initial first differences of

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

the variables are uncorrelated with the fixed effect. Estimation involves a combination of transformed equations with equations in *levels* to exploit additional instruments in suitably lagged first differences. 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 Arellano and Bond 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 a minimum distance procedure.[8]

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 (2003) use intermediate inputs, which are more likely to remain positive for all observations, as a proxy for unobserved productivity shocks.

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.

In the Doraszelski and Jaumandreu (DJ) 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 DJ 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 groups.[9]The DJ 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.

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[8] See Eberhardt and Helmers (2016) for a discussion of this point.

[9] The estimation form does not result in an estimated output elasticity or rate of return on R&D. These measures must be calculated using estimated parameters and sample data.

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 if characterizing markets as competitive is realistic, firms may vary their spending on R&D in response to generally perceived technological opportunities.[10] 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 0.99 to 0.83.

Lychagin et al. (2016) assess a broader range of estimators. They report results using the Arellano-Bond first difference GMM estimator for both static and dynamic specifications of a total factor productivity equation (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 (qualitatively) similar coefficient estimates for key variables.[11]

2-2. 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.

[10] This is the "reflection problem" noted by Manski (1993).

[11] In all GMM specifications, the validity of the moment conditions they impose is rejected. Moreover, they find evidence of serial correlation in the error term, further indicating that the moment conditions imposed (*i.e.* the adopted lag structure of instruments) are invalid. The implied common factor restrictions imposed on coefficients in their dynamic model are also rejected.

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 is not 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.

2-3. Other sources of bias

Firm-level prices are not usually available, so most researchers deflate the nominal values of output and the factors of production by industry-level price indices. Unless firms produce a single product and operate in competitive markets, firm output and input prices will deviate from industry average price levels. If, as seems likely, input choice is correlated with these deviations, input coefficients will be biased. More specifically, there will be a downward bias in the estimated coefficients on labour and materials and an upward bias in the coefficient on tangible capital (Van Beveren 2012).

Estimating equation 2 in the presence of multi-product firms causes input coefficients to be biased in an unknown direction (Van Beveren 2012). Multi-product firms are likely to use different production techniques across their product line and are likely to face different demand conditions for each product. Equation 2 assumes identical production techniques for all products and, by using industry output price deflators, identical final demand for all products.

3. 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. The most common practice now is 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[12] (Los and Verspagen 2000). These weighting methods capture, at least in part, productivity gains transferred from other industries because

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

producers were not able to appropriate all their benefits.[13] 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.[14]

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. Lychagin et al. (2016) report statistically significant coefficients on technological and geographical

[13] Los and Verspagen assume the matrix captures rent spillovers only, which may be too restrictive.
[14] 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.

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. Lychagin et al. (2016) demonstrates that differences in absorptive capacity influence location decisions, which in turn affects estimates of how quickly spillovers decay with distance.

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 formally analyse 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.[15]

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.

[15] 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.

4. Empirical estimates of private and external returns to R&D

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 20 studies examining domestic spillovers, two of which contain multiple estimates of 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.[16] Most of these studies report rates of return on own and external R&D. Of the 22 estimates available, the median private rate of return is 19% and the external return is 29%. The private rate of return is gross of depreciation. With a 15% depreciation rate, the median net private rate of return appears low. This could be the result of the widespread availability of subsidies for performing R&D. 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, excluding the impact of subsidies on the private rate of return.

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, which suggests that the private incentive to undertake R&D is substantially understated by the estimated/calculated rates of return found in the literature.

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

[16] 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.

studies (Cardamone 2017; Sena and Higon 2014) estimate the semi-elasticity of the spillover pool. We use information provided by Cardamone to calculate the private and external rates of return on R&D from the estimated semi-elasticities in her study. The median private and external rates of return in the five studies for which rates of return are available are 15% and 22.5%, respectively. Using the estimates from all studies, the median private rate of return is 19% and the median external rate of return is 27%.

A range of estimates for the impact of external R&D is shown for the studies by Acharya (2015) and Goodridge, Haskel and Wallis (2013). 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 average of the two spillover coefficients.

Two of the studies (*i.e.* Bloom, Schankerman, and Van Reenen, 2013; Ornaghi,2006) 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 R&D performed by smaller firms could be more important than spillovers from large firms. There is some empirical support for the view that large firms do more R&D focussed on process and incremental product innovation than small firms, which focus more on the development of new products;[17] 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.

[17] See Choi and Lee (2018) for a brief discussion of the literature.

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]						
			Internal R&D	External R&D					External / Internal Return
				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 (2006)	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	*0.012*		*.0052*[4]				--

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.
4. Semi-elasticity

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.

III. Data

1. 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 was designed to analyse firm and employment dynamics, so the data are adjusted to eliminate spurious entries and exits caused by mergers, acquisitions and legal restructurings. For example, when two enterprises merge, the new entity is assumed to have existed since the organic birth of the oldest of the two firms. This approach facilitates the analysis of firm exit and entry, but as discussed below, the "disappearance" of firms that eventually merge could affect the ability to analyse some issues.

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 Information (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 as operating revenue less operating expenses adjusted to exclude depreciation, interest and taxes. Operating expenses are also 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 tangible capital is attributed to the firm using the capital rather than the owner of the capital.[18]

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.[19]The productivity database provides information for 3-digit North American Industry Classification System (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.[20] Firms report in GIFI the book value of tangible capital in use along with the accumulated depreciation charges against those assets. The GIFI data are available starting in 2000. Unfortunately, there is no completely satisfactory way to calculate the real value of the net stock of tangible capital in the base year. 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.

2. 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.[21] 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

[18] In the GIFI accounts, capital lease payments are recorded as income by the owner of the capital, but the leased capital appears on the user's balance sheet. In order to align receipt of capital income and ownership of capital, capital lease income is removed from the owner's account and capital lease payments are treated as capital income of the user. (Note that when capital is rented through an operating lease in which the owner retains responsibility for repair and maintenance, ownership and the rental income are attributed to the lessor.) A similar issue arises with respect to R&D capital, but it is not possible to make a completely satisfactory adjustment in this case.

[19] This database provides information from 1961 to 2014 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.

[20] Tangible capital includes assets with a physical form (*e.g.* buildings, land, and machinery and equipment). R&D is the only intangible asset included in our analysis.

[21] 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. We do not capture spending on R&D outsourced to non-residents.

Data on R&D spending is also available from Statistics Canada's survey program *Research and Development in Canadian Industry (RDCI).* As discussed in Box 1, the RDCI is a more comprehensive 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 is not 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.

Box 1: 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 a more comprehensive source. On the other hand, since firms have a financial incentive to report R&D spending to the tax authority, the tax data may capture more firms than the RDCI survey.

The main differences between the two data sources are:

- The RDCI includes R&D outsourced by Canadian firms to non-residents. On average from 2000 to 2012, foreign outsourcing amounted to 6.3% of other owned R&D performed in-house.
- 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.
- As of 2008, the tax data includes, in certain circumstances, R&D performed by a foreign affiliate/subsidiary outside of Canada.
- In the tax data, firms have the option of reporting overhead expenses as incurred or as a percentage of wage costs. Having this option may result in higher reported expenditures on R&D.

At an aggregate level, the tax data used in this report capture owned R&D that is performed in Canada. The tax data is greater than the corresponding measure obtained from the RDCI survey in nine of the thirteen years in our sample. The average difference relative to the RDCI data is 1.2% and the range is 5.1 % to -5.4%.

The real value of spending on R&D is calculated using industry-specific implicit deflators developed by Statistics Canada. These deflators are based on a subset of input costs – labour costs of R&D personnel and the cost of intermediate materials. The deflator for labour costs is based on an index of hourly compensation in occupations likely to be involved in the performance of R&D. The deflator for materials is a weighted average of the KLEMS price indices for the materials used in the performance of R&D.

2-1. Depreciation and the stock of knowledge capital

Data on firm-level spending on R&D are available from 2000 to 2012. In order to calculate the net stock over this period, we need an estimate of the depreciation rate and of the beginning-of-year stock in 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, Mairesse, and Mohnen (2010) makes the point that the depreciation rate used will not have much impact on the estimated parameters of a production function if firm-level growth in R&D spending and depreciation rates 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.[22] As a result, we make the conventional assumption that knowledge capital depreciates at 15% per year.

The standard approach in the literature to estimating the initial capital stock is summarized in equation 5, which is derived assuming that the growth rate of the capital stock can be approximated by the growth rate of investment.[23]

$$(5) \quad K_{i2000} \approx \frac{\bar{I}_i}{g_i^* + \partial_i}$$

In equation 5, $\bar{I}_i$ and g_i^* are measures of the equilibrium level and growth rate of investment in R&D by firm *i,* respectively. These equilibrium values are usually approximated using partial or whole period sample averages of firm-level data. We estimate $\bar{I}_i$ as the average R&D investment over the 2000-2002 period. As discussed below, we use an alternative approach that makes use of both firm and industry-level growth rates to calculate g_i^*.

Equation 5 can only be used with confidence for firms that perform R&D consistently over the 2000-12 period and that have been in existence for long enough that their initial investment is fully depreciated by 2000. 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 can therefore use equation 5 to calculate the initial R&D stock for firms born in 1984 or earlier. In doing so, we are assuming that R&D spending grew at an average annual rate g_i^* over this period.

For firms that were born from 1985 to 1999 and that performed R&D continuously from 2000 to 2012, we adjust equation 5 to account for the shorter investment period.[24] We also adjust the trend growth rate of R&D for firms that did not perform R&D continuously from 2000 to 2012. The trend growth rate

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[22] 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.

[23] The accounting identity $\frac{K_t - K_{t-1}}{K_{t-1}} = \frac{I_t}{K_{t-1}} - \partial$ can be solved for the lagged net capital stock $K_{t-1} = \frac{I_t}{g_k + \partial}$, where g_k is the growth rate of the capital stock. In equation 4 in the text, g_k has been replaced by the growth rate of investment. See Berlemann and Wesselhöft (2014) for a discussion of various ways to approximate the initial capital stock.

[24] We use a standard formula for the future value of a series growing at a constant rate g for n periods and depreciating at a constant rate δ. $K_{i2000} = \bar{I}_i/(1+g_i)^n \left[\frac{(1-\partial)^n - (1+g_i)^n}{-\partial - g_i}\right]$

for these firms is more likely to take a negative value than for continuous performers, which will cause the estimate of the initial stock to take on negative or extremely large positive values when the absolute value of the growth rate is greater than or smaller than but close to the depreciation rate.[25] For firms born in 2000 or later, the R&D capital stock is calculated using observed R&D investment starting in their birth year.

In calculating the g_i^*, we depart from the standard practice of using average firm-level growth rates in favour of what has become known as James-Stein Estimators (JSE). Stein (1956) proved the counter-intuitive proposition that the arithmetic average is not always the best estimator of unobserved quantities. This insight has been applied in several fields; in our case the implication is that the best estimator of future growth in R&D spending by a firm may not be the average of its past growth rates. Better estimates, in the sense of lower mean squared error, may be obtained by "shrinking" the mean values to a point selected based on prior notions of the true equilibrium growth rate.

We experiment with various shrinkage points and assess their performance by comparing the resulting estimate of the aggregate R&D stock in 2000 with its value calculated from official surveys of R&D spending. We also compare estimates derived from maximum likelihood estimators, such as the firm-level sample average. Our firm-level methodology estimates the stock of R&D capital of firms in existence in 2000, but the estimate using aggregate data includes R&D performed by firms that exited over the 1984-99 period. To get an idea of the importance of this bias, we calculated the percentage increase in the stock of R&D capital in 2012 when we include the R&D performed by firms that exited over the 2000-12 period.

The JSE is presented in equations 6-8.

$$(6)\ g_i^* = \bar{g} + c_i(g_i - \bar{g})$$

where g_i^* represents our estimate of the equilibrium growth rate in R&D spending for firm i; $\bar{g}$ is the shrinkage point; g_i is the average annual growth rate from 2000 to 2012 for firm i; and c_i is the shrinkage factor, defined as:

$$(7)\ c_i = 1 - \frac{(n-3)\sigma_i}{\sum_{i=1}^{n}(g_i - \bar{g})^2}$$

where *n* is the number of firms and σ_i is the standard deviation in annual growth rates for firm i:

$$(8)\ \sigma_i = \frac{1}{T_i}\sum_{t=1}^{T_i}(g_{it} - g_i)^2$$

where T_i is the number of years firm i has a non-missing annual growth rate in R&D spending.

Equation 7 and 8 imply that the shrinkage factor would differ across firms, varying inversely with the standard deviation of firm-level annual growth rates. A large standard deviation implies a high degree of uncertainty in our measurement and hence, we attribute any large growth rate more to random fluctuations than to a genuinely large equilibrium rate.[26] Equation 8 also accounts for different degrees

[25] For non-continuous performers, we calculate the growth rate leaving out increases from zero and/or declines to zero. For all firms we set a floor for the average annual growth rate of -8.3% , which is the 2000-12 average annual growth rate based on the change in R&D investment from 2000 to 2012 (*i.e.* -100%/12) for a firm that performs R&D in 2000 but not in 2012.

[26] See Efron and Morris (1977) for detail. The authors provide an example for varying shrinkage factors using their analysis on the distribution of the disease toxoplasmosis in El Salvador at the city-level.

of uncertainty in estimating firm-level equilibrium growth rates stemming from different sample sizes for each firm (*i.e.* different numbers of annual observations within firms).

Note that the shrinkage factor (c) can take a negative value for some firms. As proposed in Baranchik (1964), we constrain the shrinkage factor to be positive, which is commonly called the positive-part James-Stein estimator.[27] This simple modification provides a JSE-dominating estimator (*i.e.* it performs better than the standard JSE based on some decision rule such as mean squared errors).

We calculated g_i^* using three different shrinkage points.

1. The "grand average" of firm-level growth rates – the average of all firm-level average annual growth rates.[28]
2. The unweighted average of firm-level average annual growth rates within industries.
3. The average annual growth rates in industry-level R&D spending.

It may not be correct to specify a single shrinkage point relevant for *all* firms. It may be that equilibrium rates are heterogeneous across industries. Hence, for the second and third choice, our prior notion is that the equilibrium growth rate in R&D investment can be related to the industry in which a given firm operates.[29] Specifically, we define the shrinkage point and the shrinkage factor for each firm using statistics defined based on the firm's 4-digit NAICS industry. That is, we use n_k and $\bar{g}_k$ where k denotes 4-digit NAICS industry.[30]

Using published aggregate investment data, we estimate that the stock of R&D capital in 2000 was $69.6 billion (in 2007 dollars). Including R&D performed by firms that exited over the 2000-12 period increases the stock of R&D capital in 2012 by 14.6%. If the same relationship applied in the 1984-99 period, our aggregate benchmark for the stock of R&D capital of firms in existence in 2000 should be reduced by 14.6% to $59.4 billion. All three estimates based on firm-level data are less than our adjusted benchmark. Using shrinkage points 1 and 2 results in initial stock estimates that are too low given our estimates of the R&D capital likely to be missed using our methodology. However, when the shrinkage point is defined as the average annual growth rate in industry-level R&D, the 2000 R&D capital is estimated to be $56.5 billion, which is only 4.8% lower than our benchmark level.

We also compare estimates of the initial stock obtained using the JSEs with various maximum likelihood estimators (MLEs). The first is setting g_i^* equal to the sample average annual growth rate of firm i. We also set g_i^* equal to the average of all firm-level average annual growth rates in a given industry and to the average annual industry level growth rate.[31] However, the three options result in estimates of the initial capital stock that are either very large or very small compared to our benchmark.

In our econometric analysis, we use estimates of the initial stock of R&D based on the third shrinkage point. As discussed below, however, the qualitative results for the rate of return on internal and external

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[27] This can be represented as: $c_i = \left(1 - \frac{(n-3)\sigma_i}{\sum_{i=1}^{n}(g_i-\bar{g})^2}\right)^+$. We replace any negative value for c_i with zero.
[28] This is similar to the approach adopted in Efron and Morris (1977).
[29] This is similar in nature to the multiple shrinkage framework suggested in George (1986).
[30] We also tried different levels of NAICS industries (*e.g.* 2-digit NAICS) but we found no difference in our estimates.
[31] The last two are equivalent to setting the shrinkage factor in variants 2 and 3 to zero.

R&D are not particularly sensitive to using estimates based on shrinkage points 1 and 2 and the three MLEs experimented above.

2-2. 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.[32] The argument is that the tangible capital and labour used to create R&D capital are also included in the conventional inputs. We 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.[33]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.

3. Data cleaning

Our data set consists of all firms that receive a tax credit for performing or purchasing R&D in Canada at least once over the 2000-12 period. From this population, we retain the firms that provide enough information to identify their technology position.[34] Based on this sample, we construct our spillover pool.

Our first step in cleaning this sample for the estimation of our regression equations was to remove any observations for which tangible capital is negative, zero or missing. Observations for which value added is missing are also dropped.[35] In our sample, a small number of observations have negative value added. Few of these observations appear to result from measurement error. In most cases, these observations arise because startups and firms facing competitive pressures experience losses that exceed their wage bill, resulting in negative value added. In principle, these observations should be kept in our sample, but since we estimate a production function in logs, negative observations must be excluded or transformed in some way. We experimented with the inverse hyperbolic sine transformation, which is of interest

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

[33] 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.

[34] We discuss the possibility of selection bias introduced by our sample selection in the following section.

[35] There are no observations with zero value added. Also, all observations of employment (proxied by an average labour unit) are positive in our sample. We set observations of R&D capital with zero value to one so that ln(R&D capital) = 0. Firms that start performing R&D after 2000 will have zero R&D capital until they start performing R&D. We include a dummy variable in the estimating equation indicating observations with zero R&D capital.

because it approximates the natural logarithm of a variable while allowing observations with values less than or equal to zero to be retained.[36] Results using this transformation were, however, unsatisfactory. The transformation resulted in implied output elasticities of factors inputs that are inconsistent with our prior knowledge -- we obtain very large positive or negative coefficients on the inputs.[37] As a result, we dropped all observations with value-added less than or equal to zero.

The ratio of output to R&D capital (evaluated using mean values) is used to transform estimated output elasticities into rates of return. The impact of outliers on this statistic is therefore of interest. To test the sensitivity of this ratio to outliers, we examined the impact of removing successively larger slices of both tails of the distribution for the value added to R&D capital ratio. We found that removing successively larger slices of the top tail (observations with very low R&D intensity) affected the magnitude of the estimated coefficients while having no impact on the ratio. The opposite was found for removing successively larger slices of the bottom tail (observations with very high R&D intensity) – the ratio was affected without having a substantial impact on the coefficients. We dropped the top and bottom 2% of the distribution since subsequent 0.5%-point increases in the cut-off had little or no impact on the ratio and the coefficients.[38]

The trimmed sample is characterized by many 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 roughly 1% of the R&D stock while firms in the top percentile account for 75% (Table 3). Similar patterns are found in terms of R&D spending.

To investigate whether very small firms have an impact on estimated coefficients, 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 the output elasticity of labour.[39] This coefficient increased to a non-negligible extent when firms with less than one employee were removed but remained stable when additional smaller firms were trimmed from the sample. Removing these micro-firms raised the sum of all input coefficients closer to one, although constant returns to scale is still rejected. These mini firms were dropped from the regression sample as they appear to use a different production technology than the rest of the firms.[40]

[36] See Bellemare and Wichman (2018) for a discussion.

[37] The transformation is ideal when we have non-negative values or negative values close to zero. In our case, there are many observations with quite large negative values, resulting inan undesirable property (*i.e.* the transformation is convex over negative values when the assumption of diminishing marginal product is desirable) – see (Ravallion 2017). To avoid this, one can apply the ordinary hyperbolic sine transformation to negative observations and the inverse transformation to positive observations. However, this approach “de-stabilizes” (or increases) the variance of the transformed variable (Ravallion 2017).

[38] Trimming the data, however, has no effect on the qualitative results in this paper.

[39]The output to R&D capital ratio is unaffected.

[40]As we discuss later, dropping these mini firms does not change the qualitative results in this paper.

Table 3: Share of total R&D Stock by Firm Employment Size 2000-2012

Size Percentile Range	Share of Total R&D stock (%)	Share of Total R&D spending (%)	Mean Employment
<25%	1.3	2.2	3
25%<x<95%	23.3	28.5	41
95%<x	75.4	69.3	1,553

Note: Employment is in terms of average labour unit. See text for definition.

Dropping observations with negative value-added results in an asymmetric treatment of gains and losses from investing in R&D and tangible capital. For startups and other firms developing new products, we ignore losses in the development period, including only the period of positive returns, assuming the firm survives. For established firms suffering declining sales or downward pressure on prices, we do not include those observations for which the return to capital is sharply negative, but we do include the positive observations. This puts downward pressure on the rate of return to R&D. On the other hand, the observed elasticity of value-added to R&D could be spuriously highor low as value-added shifts from negative to positive due to rising sales. The net impact on the rate of return to R&D therefore cannot be determined a priori. As an empirical test, we estimated the production function excluding firms that experience negative value-added at any time over the sample period, observing an increase in the output elasticity of own-R&D.

IV. Constructing the spillover pool

1. 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 $\mathrm{F_i} = [\mathrm{F_{i1}} \mathrm{F_{i2}} \dots \mathrm{F_{ik}}]$ 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, denoted as P_{ij}, can be measured as the uncentred correlation of firms' technological positions:

$$(9)\; P_{ij} = F_i F_j' / [(F_i F_i')(F_j F_j')]^{1/2}$$

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.

Using the measure of technological proximity P_{ij}, we compute the spillover measure for firm i at time $t$as the weighted sum of R&D stock of all other firms:

$$(10)\ S_{it} = \sum_{j \neq i}^{J} P_{ij} K_{jt}$$

where K_{jt} is the R&D stock of firm $j \neq i$ at time t.

Note that the spillover measure at time t is constructed based on total R&D stock at time t weighted by a technological proximity weighting matrix. Our spillover measure does not keep the knowledge stock of exiting firms. If a firm exits, its knowledge is assumed to disappear from the economy.

However, R&D performed by firms that exit could still be a source of knowledge for the surviving firms in the economy. Hence, we experimented with an "augmented" spillover pool that includes the R&D capital stock of firms that exit.[41] Using this knowledge pool, neither the estimated coefficients for the aggregate spillover pool and the pool by size of performer nor their statistical significance changed.

2. 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 147 detailed technological fields (represented by a 5-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 the most detailed technology information (*i.e.* 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 eligible for the federal enhanced SR&ED investment tax credit were classified as small and those firms receiving the regular credit were classified as large.[42]This definition allows us to assess whether the different subsidy rates by firm size are appropriate.

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[41] We depreciate R&D capital of existing firms by 15 per cent annually. We construct the augmented spillover pool by size of performer. To determine the size group for firms that exit, we rely on the last observed size group. That is, we rely on the net income and tangible capital stock observed in the last observed year and apply the eligibility criteria for enhanced tax credit applicable to that year.

[42]Eligibility for the enhanced credit is determined by the amount spent on R&D, profits and assets. In 2012, the maximum amount of R&D spending eligible for the enhanced credit was $3 million. This amount was reduced to

The quality of the data on spending by technological field is good. Annually, about 70% - 77% of the firms that own R&D capital representing 90% - 98% of R&D capital provided complete information over the 2008-12 period. A small number of other firms provided enough information to allow us to develop completely satisfactory measures of their spending by technological field.[43] As a result, our technological proximity measures cover approximately 95% - 98% of R&D capital 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 in the 92% - 96% range over the 2000-07 period.[44]

We do not introduce any substantial selection bias by dropping firms without enough information for technology position.[45] The distributions of labour and capital inputs and value-added in our sample are very similar to those for R&D performers in T2-LEAP. In addition, distributions by size of firm (small versus large) and by industry are almost identical in the two data sets. 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, Schankerman, and Van Reenen (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;[46] they rarely enter a new field.

Table 4 provides some basic descriptive statistics for the key variables used in our analysis by size of firm. Compared to small firms, not surprisingly, large firms have larger means for output, tangible capital stock, and employment but with much more variation within the size group as indicated by the standard deviation. Moreover, we observe that large firms have much larger means for both R&D spending and stock. This is consistent with Table 3, which indicates that a small number of very large firms account for a disproportionately large share in total R&D stock, resulting in a high mean value for R&D capital. However, combined with their mean output level, larger firms have lower R&D intensity and therefore a higher output to R&D capital ratio.

The mean spillover pool (both aggregate and by size) is greater for small firms, implying that small firms have greater access to the external knowledge stock. Since the spillover pool is a technology-weighted sum of external R&D capital, the greater size implies that small firms perform R&D in the same or similar technological fields as other firms to a greater extent than larger firms.

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zero as taxable income increased from $500,000 to $800,000 and as capital increased from $10 million to $50 million.

[43] We can calculate spending for firms that submit incomplete or missing spending by project if 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.

[44] The number of observations in this sample ranges from 20,000 to 34,000 annually over the 2000-12 period; the number of unique firms in the panel is about 38,000. Based on this sample, we construct our spillover pool.

[45] See Appendix 1 for a detailed description of our sample selection process.

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

Table 4: Summary Statistics, Estimation Sample, Small and Large Firms, Millions of 2007 CAD, 2000-2012

	Small firms		Large firms	
	Mean	Std. Dev.	Mean	Std. Dev.
Value added	5.8	168	578	3,140
Tangible capital stock	20.3	3,750	1,550	19,300
Average labour unit	52	415	1,490	4,576
R&D spending	0.2	4.1	8.8	48.2
R&D stock	1.3	24.1	54.9	336.0
Spillover pool	5,600	5,390	5,080	4,600
Spillover pool by Small	2,710	2,590	2,280	2,190
Spillover pool by Large	2,890	3,470	2,800	2,940
Spillover pool (Mahalanobis)	6,250	5,640	5,670	4,860
Spillover pool by Small (Mahalanobis)	3,010	2,740	2,540	2,320
Spillover pool by Large (Mahalanobis)	3,240	3,580	3,130	3,060
Net income	0.2	44.7	110	553
Mean(value added)/Mean(R&D stock)	4.54		10.53	
No. Observations (firm x year)	272,355		10,835	

Note: Except for net income, all dollar-value variables are deflated using the KLEMS 4-digit NAICS output/input/R&D deflators. Other statistics such as median, min., and max. are not reported due to confidentiality constraints.

V. Estimation framework and results

In this section, we report the results from estimating a Cobb-Douglas production function based on a static and dynamic specification respectively. In the static specification, we adopt OLS with firm and year fixed effects to estimate the coefficients. However, even with fixed effects, we suspect endogeneity problems in the factor inputs as discussed in section II. To mitigate such problems, in the dynamic model in which we allow unobserved firm-level productivity shocks to follow an AR(1) process, we estimate the coefficients with a broader range of estimators (*i.e.* OLS, FE, and GMM).

1.Static specification

1-1. Model

We estimate variants of equations 2 using ordinary least squares with firm and year fixed effects. The baseline equation is reproduced below.

$$(3)\ y_{it} = a_0 + \alpha c_{it} + \beta l_{it} + \gamma k_{it} + \varphi s_{it} + \phi q_t + \eta_i + \omega_t + u_{it}$$

In equation 3, y is value added, a_0 is mean efficiency across all firms, 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 captures time-invariant firm-fixed effects, ω represents aggregate productivity shocks, proxied by year dummies, and u is a random error. As in Bloom, Schankerman, and Van Reenen (2013), we include industry-level value-added (q) to control for industry demand shocks. All variables are in logs.

We began our empirical investigation by estimating equation 3 over the 2000-12 period for an unbalanced sample of R&D performers and using both the Jaffe and Mahalanobis-extended proximity weights calculated using five-digit technology field codes (147 fields). 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.

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. An increased susceptibility to inconsistency is another cost of shortening the panel. As discussed above, the 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.

1-2. Results

The output elasticities for labour and tangible capital obtained at this stage were consistent with prior notions of income shares. The sum of the coefficients on all three inputs was close to one but the hypothesis of constant returns to scale was rejected, a finding that was repeated in all static production equations subsequently estimated. We also used a random-effects estimator but conducting a Hausman 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 our subsequent econometric analysis is based on the fixed-effects estimator.

Table 5: Production function regression results, static specification with fixed effects

	(1) Jaffe	(2) Mahalanobis
ln(Labour)	0.668*** (0.004)	0.688*** (0.004)
ln(Tangible capital)	0.238*** (0.003)	0.238*** (0.003)
ln(R&D capital)	0.040*** (0.002)	0.040*** (0.002)
ln(Spillover pool)	0.021 (0.014)	0.040** (0.020)

Note: The Jaffe proximity measure requires that firms operate in the same technological field for spillovers to occur; the Mahalanobis extension 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). Industrial value added is also included (coefficient omitted). The equation is estimated on an unbalanced panel of R&D performers in the 2000-2012 period. Standard errors, which are clustered by firm, are in parentheses. The number of observations (firm x year) is 283,190 and the number of firms is 31,205. *** p<0.01, ** p<0.05, * p<0.10

Results are summarized in Table 5. When we use the Jaffe measure of technological proximity to define the spillover pool, the output elasticity is not significantly different from zero. Allowing spillovers between firms operating in closely-related fields (the Mahalanobis extension) rather than requiring firms to be operating in identical fields (Jaffe methodology) results in a statistically significant spillover elasticity. The output elasticity of own-R&D is not affected by allowing greater scope for spillovers.

1-3 Robustness checks

Finding a positive spillover effect is robust to different sample periods. We estimated the equation for rolling 6-year sub-periods over the 2000-2012 period (*i.e.* 2000-2005, 2001-2006, ..., 2007-2012). The spillover effect remains positive across all sub-periods except for the sub-period 2000-2005 and 2007-2012 in which the coefficient is negative but not statistically different from zero.[47]

The estimates of own-R&D and external R&D output elasticities could be disproportionately affected by a small number of young firms or 'startups' for several reasons. First, since startups are likely to have a low ratio of sales to costs, the productivity of R&D performed by startups may be lower than for other firms. Second, to the extent that young firms are also small, their size may limit their capacity to absorb knowledge created by other firms. Third, there is evidence that some startups are more innovative than other firms. Kortum and Lerner (2000) find that startups funded by venture capitalists have a higher propensity to patent than other firms. Schnitzer and Watzinger (2014) compare the spillovers generated by venture capital funded startups with spillovers generated by other firms. They find substantially larger spillover effects from venture capital startups.

Excluding firms that are less than five years old, accounting for roughly 19% of our sample, has some impact on the spillover and own-R&D coefficients. The spillover coefficient increases while, contrary to our conjecture above, the own R&D coefficient decreases.[48] These observations imply that, compared to established firms, startups tend to benefit more from their own R&D stock but less from R&D performed by other firms in the economy. To show this explicitly, we estimate a production function in which we interact the aggregate spillover pool and own R&D stock with the indicator for startups.

Table 6 summarizes the results. We find that the own R&D coefficient is about a sixth greater for startups than for established firms (row 1). This difference is statistically significant. The startups in our sample are mostly profitable firms since we dropped all observations with negative value added.[49] A higher own-R&D output elasticity for startups may therefore be capturing very rapid sales growth from a small base when new products are introduced.

In contrast, spillovers received by startups from all firms are slightly smaller than for established firms and the estimate is less precise (row 2). As a second test, we constructed a spillover pool based on firms net of startups and estimated the output elasticity with respect to this pool. The spillover effect of this pool on all firms in our sample is slightly larger than the impact of the aggregate spillover pool (0.044 vs. 0.040). We also included a separate spillover pool based on startups in the production equation. The coefficient on the pool generated by startups and received by all firms is still positive and significant but very small (row 3). A possible explanation for this finding is that startups perform R&D in a narrower

[47] The output elasticity with respect to own R&D remained positive and statistically significant across all sub-periods.
[48] We find similar results when we define startups as firms less than three years old.
[49] The share of firms with negative value added is larger for total startups than for established firms. As a result, dropping observations with negative value-added leaves disproportionately more profitable start-ups in our sample.

range of technological fields than established firms as they focus on bringing a limited range of products to market.

Table 6: Output elasticities for R&D capital and spillover, startups vs. established firms, FE estimates, Mahalanobis distance measure

	Startups	Established firms
(1) R&D capital	0.048*** (0.003)	0.041*** (0.002)
(2) Spillovers to	0.038* (0.020)	0.041** (0.020)
(3) Spillovers generated by	0.008** (0.017)	0.044*** (0.017)

Note: Standard errors clustered by firm are in parentheses. The coefficients in row 1 and 2 are obtained from estimating a Cobb-Douglas production equation in which we interact own R&D and the aggregate spillover pool with the indicator for startups. The results are very similar if we estimate the production function separately for startups and established firms. The coefficients in row 3 are obtained from estimating a production function that includes separate spillover pools generated by established firms and startups. The number of startup observations is 53,296 and the number of established firm observations is 229,894. *** p<0.01, ** p<0.05, * p<0.10

A small number of industries are driving the results. Four two-digit industries—manufacturing,[50] wholesale trade, information and cultural industries, and professional, scientific, and technical services -- account for 89.6% of the total R&D stock in our sample but 69.4% of the observations.[51] The shares in total R&D stock of these industries range from 10% to 30%. The shares of the other industries are almost all below 1%.

We estimate equation 3 by interacting own R&D and the spillover pool by the dummy for these key R&D performing industries.[52] The spillover output elasticity of these industries is about 15% larger than the baseline elasticity of 0.040 (column1 in Table 7). For other industries, the spillover coefficient is positive but insignificant. Also, note that the output elasticity of own R&D is greater for the key industries than it is for other industries, implying that internal R&D experience is positively associated with the capacity to benefit from it. For both the own R&D and the spillover coefficient, the null hypothesis that the two groups exhibit the same magnitude is rejected (p-value = 0.001 and 0.067 respectively).

Further, when equation 3 is estimated including a separate spillover pool generated by each of the groups (column 2 in Table 7), we find that the spillover effect generated by these key R&D-performing industries is about 40% larger than the aggregate spillover effect in our baseline specification (0.056 vs. 0.040). In contrast, the coefficient on the pool generated by other industries is positive but not statistically significant. These findings strongly support the conclusion that the aggregate spillover effect we estimate in Table 5 is driven by the key R&D-performing industries. This result could be a sign of

[50] Excluding food, beverages, textiles and leather manufacturing (NAICS 31).
[51] It may be surprising that wholesale trade is a large R&D-performing industry. Note, however, that two subsectors in NAICS 41-- NAICS 4145 (pharmaceuticals, toiletries, cosmetics and sundries) and NAICS 4173 (computer and communications equipment and supplies) -- account for 71% of the R&D stock of wholesalers but 14% of the total observations in the industry. We suspect that most of the R&D performed in these subsectors is intended to develop new products and processes in sectors other than wholesale trade.
[52] The coefficients for the factor inputs are very similar if we estimate a production function separately for the key industries and the others.

asymmetric spillovers arising from different absorptive capacities since firms in these industries tend to have not only a larger R&D stock but also a higher propensity to conduct R&D than firms in other industries.[53]

Table 7: Production function regression results, Static specification with fixed effects, Key R&D performing industries, Mahalanobis distance measure

	1	2
ln(Labour)	0.668***	0.668***
	(0.004)	(0.004)
ln(Tangible capital)	0.238***	0.238***
	(0.003)	(0.003)
ln(R&D capital)		0.040***
	-	(0.002)
ln(R&D capital) x key industries	0.046***	
	(0.003)	-
ln(R&D capital) x other industries	0.030***	
	(0.004)	-
ln(Spillover pool) x key industries	0.046***	
	(0.020)	-
ln(Spillover pool) x other industries	0.029	
	(0.021)	-
ln(Spillover pool generated by key industries)		0.056***
	-	(0.019)
ln(Spillover pool generated by other industries)		0.007
	-	(0.015)

Note: Key R&D performing industries are NAICS 32-33 (Manufacturing excluding food, beverages, textiles and leather manufacturing), 41 (Wholesale trade), 51(Information and cultural industries), and 54 (Professional, scientific, and technical services). The number of key industries observations is 196,405. The number of the total observations is 283,190. For details of the specification, refer to the footnote in Table 5.
*** p<0.01, ** p<0.05, * p<0.10

2. Dynamic specification

With fixed T, our estimator based on OLS with firm fixed effects will be biased and inconsistent if the strict exogeneity assumptions for the factor inputs are violated. Hence, we adopt more advanced techniques that do not require the assumption of strict endogeneity to isolate useful information in our data. Specifically, we allow some of the factor inputs to be endogenous with respect to unobserved productivity shocks. Then, we use past values of the factor inputs as instruments to identify the parameters of interest after removing fixed effects through appropriate transformations.

2-1. Model

The GMM estimator introduced in Arellano and Bond (1991) - henceforth, AB GMM - has its origin in the study of dynamic equilibrium relationships. The estimator is relevant if productivity shocks are persistent (*i.e.* serially correlated) and factors of production respond to these shocks.[54] We can model such dynamics by assuming a first order autoregressive process for μ_{it}:

[53] In these key R&D performing industries, the average share of observations with positive R&D investment is 76.2% compared to 61.4% for other industries. The average R&D intensity among the key industries is almost double that of the other industries (0.626 vs. 0.328). In addition, the top 5% of R&D performers in these industries perform more R&D both in absolute terms and relative to value added than their counterparts in other industries.
[54] Later, we show that this is indeed the case in our data.

$$(11)\ \ y_{it} = \alpha c_{it} + \beta l_{it} + \gamma k_{it} + \varphi s_{it} + \eta_i + \omega_t + \mu_{it} + m_{it}$$

$$(12)\ \mu_{it} = \rho\mu_{it-1} + v_{it} |\rho| < 1; v_{it}, m_{it} \sim MA(0)$$

where m_{it} represent measurement errors (assumed to be serially uncorrelated).
Equations 11 and 12 lead to the dynamic autoregressive distributed lag regression model that includes lagged values of the dependent and independent variables as regressors:

$$(13)\ \ y_{it} = \alpha c_{it} - \rho\alpha c_{it-1} + \beta l_{it} - \rho\beta l_{it-1} + \gamma k_{it} - \rho\gamma k_{it-1} + \varphi s_{it} - \rho\varphi s_{it-1}$$
$$+\rho y_{it-1} + \omega_t - \rho\omega_t + \eta_i(1-\rho) + v_{it} + m_{it} - \rho m_{it-1}$$

or

$$(13')\ \ y_{it} = \pi_1 y_{it-1} + \pi_2 c_{it} - \pi_3 c_{it-1} + \pi_4 l_{it} + \pi_5 l_{it-1}$$
$$+ \pi_6 k_{it} + \pi_7 k_{it-1} + \pi_8 s_{it} + \pi_9 s_{it-1} + \omega_t^* + \eta_i^* + e_{it}$$

$$(14)\ \ e_{it} = v_{it} + m_{it} - \rho m_{it-1}$$

where $\omega_t^* = (\omega_t - \rho\omega_{t-1})$ and $\eta_i^* = (1-\rho)\eta_i$.

If there are no measurement errors $e_{it} \sim MA(0)$ and $e_{it} \sim MA(1)$ otherwise.[55]

In equation 13,the coefficients on lagged inputs are expected to be nonlinear combinations of the coefficients on the lagged dependent variable (ρ) and the respective contemporaneous input ($\alpha, \beta, \gamma, \varphi$).These "common factor" restrictions are$\pi_3 = -\pi_1\pi_2$;$\pi_5 = -\pi_1\pi_4$; $\pi_7 = -\pi_1\pi_6$; and $\pi_9 = -\pi_1\pi_8$. We can test Equation 13 for the implied nonlinear restrictions; if they are not rejected, the associated coefficients can be computed by the minimum distance procedure. If common factor restrictions are rejected, the long-run solution of the model can be computed as nonlinear combinations of the estimated coefficients as follows:[56]

$$(15)\ \ y = \frac{\eta_i^*}{1-\widehat{\pi_1}} + (\frac{\widehat{\pi_2}+\widehat{\pi_3}}{1-\widehat{\pi_1}})c + + \left(\frac{\widehat{\pi_4}+\widehat{\pi_5}}{1-\widehat{\pi_1}}\right) l + (\frac{\widehat{\pi_6}+\widehat{\pi_7}}{1-\widehat{\pi_1}})k + (\frac{\widehat{\pi_8}+\widehat{\pi_9}}{1-\widehat{\pi_1}})s + \frac{\widehat{w^*}}{1-\widehat{\pi_1}}$$

2-2. Empirical implementation

We estimate both the unrestricted and restricted models as shown in Equations 6 and 6'. The coefficients implied by the common factor restrictions are obtained by first estimating (unrestricted) equation 6 and then computing the restricted coefficients by a Chamberlain-type minimum distance procedure (Chamberlain, 1984; Wooldridge, 2002). We adopt the two-step procedure using the optimal weight matrix and correcting for potential small sample bias (downward) following the approach suggested in Windmeijer (2005). In theory, the procedure is asymptotically more efficient than the one-step procedure.

[55]To derive Equation 10, rewrite Equation 8 lagged one-period for μ_{it-1}, and substitute into Equation 9. Next, Equation 9 is substituted for μ_{it} in Equation 8.
[56]We use the Delta method to compute the standard errors of the calculated coefficients.

In this paper, we transform our equation by forward orthogonal deviation (FOD) instead of first differencing (FD) to eliminate fixed effects without introducing all realizations of disturbances in the equation.[57] Since our data set is unbalanced, first differencing would introduce many gaps, causing many observations to be lost. In contrast to the FD transformation which subtracts the previous value from the current value, the FOD transformation subtracts the average of all available future observations from the current value. Therefore, the FOD transformation minimizes the loss of observations.

The lagged dependent variable is endogenous by construction. In all specifications, we assume that labour, tangible capital, own R&D, and the dummy indicating zero R&D are endogenous while the spillover pool is exogenous. Our assumptions imply that we can use lagged t-2 and earlier values in levels and lagged t-1 first differences as valid instruments. In order to increase the precision of the estimator, we include the whole set of suitably lagged values implied by the adopted lag-structure.[58] Note that the presence of measurement errors in the factor inputs and value added may lead to violation of the exogeneity assumptions for the instruments requiring us to adopt alternative lag structures for the instruments.[59] We formally test for serial correlation in the errors using the Arellano and Bond (1991) test (henceforth, AB test).

2-3. Results

In theory, the FE estimator suffers from dynamic panel bias (*i.e.* Nickell bias) since the transformed lagged dependent variable is correlated with the transformed error term. Specifically, the transformed regressor is negatively correlated with the transformed error term because the within-transformation introduces past and future realizations of the errors with a negative sign (see Nickell, 1981 for details). This is the opposite of OLS where regressors and errors are positively correlated.[60] Therefore, we expect an unbiased estimate to be within the bounds set by OLS (upper bound) and FE estimates (lower bound).

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[57] We also tried FD transformation for all the following estimations. In general, the estimates based on FD transformation tend have larger standard errors relative to the ones based on FOD transformation. Moreover, the coefficients for factor inputs tend to be closer to the coefficients that are known to be biased (*i.e.* OLS and FE). This appears to be consistent with Hayakawa (2009) in which the author shows (by simulation studies) that the GMM estimator of the model transformed by the FOD transformation tends to perform better than that transformed by FD.

[58] However, since moment conditions rise quadratically in number with T employing all suitably lagged values as instruments may cause 'overfitting-bias'. A tell-tale sign of 'overfitting' is a high p-value (close to unity) for the test of joint validity of the instruments (Bowsher, 2002). Since we do not have a particularly large T and we do not find any sign of overfitting-bias, we always employ all possible moment conditions implied by the adopted lag structure for the instruments. We tried reducing the set of moment conditions by restricting instruments to more recent lags (*e.g.* using t-2 to t-6). However, we find that improvement in the overall validity of moment conditions is marginal. Moreover, the estimated coefficients do not change to any meaningful extent. We also tried 'collapsing' the matrix of instruments (see Roodmand, 2009). However, collapsing leads not only to much larger standard errors but also to coefficients that are outside a reasonable range.

[59] The estimation strategy allows for higher-order (but finite) autoregressive models given that we have a minimum number of time series of observations available for identification. If there are (serially uncorrelated) measurement errors, then $e_{it} \sim MA(1)$ in Equation (10'). In this case, we need to use lagged t-3 and earlier values in levels for the transformed equation and lagged t-2 in first differences for the levels equation.

[60] For instance, consider a negative productivity shock in year t-1 for firm i. The fixed effect for firm i for the sample period would appear to be lower due to the deviation from the sample average by the extent of the unexplained productivity shock. Hence, in year t, lagged output and the fixed effect (embedded in the error term) would both be lower (positive correlation).

Columns 1 and 2 in Table 8 summarize some key results based on OLS and FE. We reject the common factor restrictions in both specifications (p-value: 0.000) so the long-run coefficients are reported for the factor inputs. First, note that the OLS coefficients on labour and own-R&D are quite large, compared to our FE estimates from the static model. Adding firm fixed effects to the dynamic model changes the magnitude of the estimates substantially except for the long-run spillover coefficient. The coefficients for the lagged value added, labour, and own R&D experience downward shifts (relative to the OLS estimates), presumably induced by the 'Nickell-bias' as a result of within-transformation.[61] This is consistent with our theoretical predictions. We use the OLS and FE results as rough upper and lower bounds respectively to assess the relevant estimates we obtain from the subsequent estimation strategies used to mitigate the endogeneity bias.

Columns 3 – 5 report the estimates based on AB GMM and system GMM across different lag structures adopted for the instruments.[62] For all specifications, we report the long-run coefficients for the factor inputs calculated using equation 15 since we reject the common factor restrictions (p-value: 0.000). The qualitative results based on the coefficients implied by the common factor restriction are the same.

We started with using the lagged t-2 and earlier levels as instruments for the transformed equation but the lagged dependent variable is quite close to that based on FE and the long-run coefficients for the input variables are outside the bounds set by OLS and FE. Also, we reject the null of the validity of this lag structure in the Hansen test of overidentifying restrictions and find evidence of serially correlated errors as indicated by the AB test. Hence, we adopt the lagged t-3 and earlier levels as the instruments for the transformed equation in column 3 but there remain diagnostic issues. However, the coefficient for the lagged dependent variable is higher than that based on using the instruments lagged t-2 and earlier, indicating that we are mitigating the bias to some extent. The coefficients for labour and own R&D are still outside the bounds. The coefficient for tangible capital appears to be too large given our prior knowledge. Also, we reject the constant returns to scale. Employing alternative lag structures (*e.g.* using lagged t-4 and earlier values) does not improve the validity of our specification.

Table 8: Production function, Dynamic specifications, Mahalanobis distance measure

Dependent: $\ln(\text{value added})_t$	(1) OLS	(2) FE	(3) AB GMM	(4) System GMM	(5) System GMM
Lag order of inst. for diff. eqn.	-	-	t-3 and earlier	t-2 and earlier	t-4 and earlier

[61] For the FE results (column 2), we do not report the test results for AB tests since AB test is not appropriate for fixed effect regressions in a dynamic panel data context. The AB tests assume the right-hand-side variables are not correlated with future errors (see Arellano-Bond, 1991). Such assumption is not valid with the mean-deviations transformation.

[62] We also experimented with a simpler approach following Anderson and Hsiao (1972) and its extended version based on Holtz-Eakin, Newey, and Rosen (1988) using 'GMM-style' instruments. However, the coefficients tended to be smaller than the FE estimate and their standard errors were larger than that based on OLS and FE.

Lag order of inst. for levels eqn.	-	-	-	t-1	t-3
$\ln(\text{Value added})_{t-1}$	0.744***	0.382***	0.501***	0.578***	0.846***
	(0.001)	(0.002)	(0.017)	(0.006)	(0.014)
$\ln(\text{Labour})_{t}$	0.611***	0.571***	0.514***	0.815***	0.946***
	(0.003)	(0.003)	(0.059)	(0.026)	(0.063)
$\ln(\text{Labour})_{t-1}$	-0.411***	-0.209***	-0.251***	-0.532***	-0.862***
	(0.003)	(0.003)	(0.047)	(0.019)	(0.055)
$\ln(\text{Tangible capital})_{t}$	0.255***	0.272***	0.474***	0.399***	0.421***
	(0.001)	(0.001)	(0.009)	(0.009)	(0.012)
$\ln(\text{Tangible capital})_{t-1}$	-0.221***	-0.128***	-0.231***	-0.289***	-0.376***
	(0.001)	(0.002)	(0.010)	(0.007)	(0.012)
$\ln(\text{R\&D capital})_{t}$	0.104***	0.068***	-0.178***	0.032***	-0.022
	(0.002)	(0.003)	(0.027)	(0.010)	(0.028)
$\ln(\text{R\&D capital})_{t-1}$	-0.050***	-0.042***	0.120***	0.002	0.049*
	(0.002)	(0.002)	(0.022)	(0.008)	(0.026)
$\text{lnln}(\text{Spillover pool})_{t}$	0.118***	-0.128**	-0.266***	0.419***	-0.033
	(0.035)	(0.051)	(0.064)	(0.063)	(0.050)
$\ln(\text{Spillover pool})_{t-1}$	-0.109***	0.163***	0.282***	-0.392***	0.041
	(0.035)	(0.051)	(0.063)	(0.062)	(0.050)
No. Observations (firm x year)	243,040	243,040	213,757	243,040	243,040
No. Instruments	N/A	N/A	290	401	286
Hansen Overid. Test	-	-	0.000	0.000	0.000
Diff. Hansen for level eqn.	-	-	-	0.000	0.000
A-B AR(1) test	0.000	-	0.000	0.000	0.000
A-B AR(2) test	0.000	-	0.000	0.000	0.375
			Long-run (equilibrium) coefficients		
ln(Labour)	0.782***	0.586***	0.526***	0.670***	0.548***
	(0.004)	(0.004)	(0.039)	(0.018)	(0.074)
ln(Tangible capital)	0.133***	0.234***	0.488***	0.260***	0.294***
	(0.002)	(0.002)	(0.014)	(0.009)	(0.036)
ln(R&D capital)	0.211***	0.043***	-0.116***	0.082***	0.177***
	(0.003)	(0.003)	(0.016)	(0.009)	(0.032)
ln(Spillover pool)	0.036***	0.056**	0.032	0.064***	0.052***
	(0.003)	(0.019)	(0.033)	(0.005)	(0.011)
sum of β's	1.126	0.863	0.897	1.012	1.019
CRS test	0.000	0.000	0.021	0.350	0.638

Note: Standard errors are in parentheses. For column 3 – 5, standard errors are computed based on the two-step procedure correcting for potential small sample bias following Windmeijer (2005). Lagged value added is endogenous by construction. We assume that labour, capital, own R&D, and the dummy for zero R&D are endogenous - their suitably lagged values (in levels for the FOD equation and in first differences for the levels equations) are included as GMM-style instruments. The spillover pool is assumed to be exogenous and therefore, included as IV-style instruments. All the test results are reported with p-values. *** p<0.01, ** p<0.05, * p<0.10

As discussed in section 2-1, the instruments used in column 3 are likely to be weak due to the persistence in the factor inputs and real value added.[63] Indeed, most of the estimates for the factor

[63] Real value added and all (potentially endogenous) factor inputs are quite persistent in our data. We estimated a simple AR(1) specification on real value added and on each of the factor inputs. Based on our preferred

inputs based on AB GMM are closer to the Nickell-biased FE estimates than to the upwardly biased OLS estimates, suggesting that the weak instrument biases are potentially important in our case.[64] Therefore, in Columns 4 and 5, we report the estimates from employing additional moment conditions for the equation in levels (*i.e.* system GMM).

In column 4, we adopt lagged levels dated t-2 and earlier as instruments for the transformed equation, combined with lagged first differences dated t-1 as instruments for the levels equation. The coefficients for lagged value added, labour, and own R&D are within the bounds set by OLS and FE. These coefficients are larger than their AB GMM counterparts, which are in turn closer to the Nickell-bias-tainted estimate. This relationship among the coefficients indicates that employing additional moment conditions for the equation in levels does mitigate finite sample bias to some extent. Moreover, adopting the additional moment conditions appear to improve efficiency as indicated by the smaller the standard errors for the coefficients compared to those based on the AB GMM in column 3. We also find statistical evidence of constant returns to scale (p-value: 0.350).

However, the AB test suggests there is second-order serial correlation in the first-differenced residuals. With the lag structure adopted in column 5, the AB test indicates that we do not have second-order correlation (*i.e.* no MA(1) structure in the error terms in levels). Although we still reject the overall validity of our moment conditions, the own R&D and the spillover coefficients remain positive and statistically significant.

One puzzle is that, despite no evidence of an MA(1) structure in the error terms (in levels), we still reject the validity of using lagged levels dated t-4 and earlier and lagged first differences dated t-3 as instruments. This may indicate that *both* measurement errors (m_{it}) and productivity shocks (v_{it}) are serially correlated but in the opposite direction offsetting the appearances of serial correlation stemming from m_{it} and v_{it}in the error term (e_{it}).[65] Further adjusting the lag structure of the instruments (*e.g.* t-5 and earlier levels for the transformed equation and t-4 first differences for the equation in levels) leads to slight improvement in the validity of the moment conditions but the coefficients tend to be outside the bounds and the standard errors increase.

Although we find some signs that adopting additional moment conditions for the levels equation appears to mitigate finite sample bias and improve efficiency, we do not necessarily prefer the system-GMM estimates to our FE estimates based on the static model. The rejection of the overall validity of the moment restrictions we impose and its discrepancy with the AB test on the residuals suggest that it is quite challenging to find an ideal specification in our data. However, our estimates broadly support our previous findings that there are positive and statistically significant 'pure technological' spillovers among Canadian firms.[66]

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specification with system-GMM, the coefficients on the lagged dependent variables in all AR(1) specifications are close to unity (ranging from 0.859 to 0.959). OLS tends to result in larger coefficients but we believe that these are likely to be biased upward.

[64] Weak instruments are likely to bias the AB estimates in the direction of FE estimates. See Blundell and Bond (2002) for more detail.

[65]A similar situation is observed in Blundell and Bond (2002).

[66] We also estimated the dynamic model for 6-year rolling sub-periods from 2000 to 2012. The system-GMM estimates for the spillover pool remained positive and statistically significant throughout all sub-periods except for

VI. Analysis by size of firm

In Section IV, we reported positive and statistically significant output elasticities for own-R&D and the spillover pool. In this section, we investigate whether these elasticities vary by size of firm by estimating variants of equation 2, using a static specification. We first split the sample into large and small firms; however, the coefficients on labour and tangible capital were not statistically different for large and small firms, so the analysis proceeded using equations for all firms. The analysis of the spillover pool considers both the generation and receipt of knowledge. To accomplish this goal, we calculate separate spillover pools generated by small and large firms and include interaction effects in the regressions to identify spillover effects between firms of different sizes.

The LEAP database has a potential weakness when assessing R&D impacts by size of firm. As discussed earlier, when two firms merge or when one firm is acquired by another, adjustments are made to create the new entity in the historical data.[67] Of particular interest here are the changes arising from mergers of two small firms to create a larger entity and the takeover of a smaller firm by a large firm. These changes reduce the number of small firm observations and artificially reduce the small firm spillover pool while increasing the large firm pool. Further, if the return to R&D differs by size of firm, the synthetic mergers could affect the estimated R&D output elasticity of larger firms.

Fortunately, the number of firms affected by these adjustments is small. Baldwin, Leung, and Landry (2016) report that the aggregate business entry rate for 2011 falls from 13.2% to 13% after adjustments for mergers, acquisitions, divestitures and other legal restructurings that occurred in 2012. While this result is not specific to changes in the number of small firms, it does suggest that the treatment of mergers and acquisitions in LEAP is unlikely to be having a substantial impact on our parameter estimates.

As noted earlier, we define small firms as the firms receiving the enhanced SRED tax credits and large firms as those receiving the regular credit. Firms are required to report the amount of R&D spending that is eligible for the enhanced credit, which is known as the "expenditure limit". Unfortunately, the treatment of mergers and acquisitions in T2-LEAP prevents us from using the reported expenditure limit to identify recipients of the enhanced credit. When a firm eligible for the enhanced credit is taken over by a large firm that is not, then the synthetically merged entity retains a positive expenditure limit, erroneously indicating that it is eligible for the enhanced credit.

In order to identify enhanced credit recipients, we apply a simplified version of the eligibility criteria for taxable income and assets discussed in footnote 41 to the firms in our sample.[68] This simple solution appears to be quite satisfactory as the annual number of enhanced and regular credit recipients are consistent with the numbers reported in Jenkins et al. (2011).

The rest of this section reviews of output elasticities and then discusses rates of return on the spillover pool and the stock of own-R&D.

2005-2010 and 2006-2011 (negative but insignificant). The output elasticity with respect to own R&D is positive and statistically significant in all 6-year periods.

[67] Note that if a firm merges with or is acquired by a foreign firm and leaves Canada, an exit is recorded in the data.

[68]The eligibility criteria for taxable income and assets vary over time.

1. Output elasticities

Results are reported in Table 9 for own-R&D and spillover pool output elasticities. The first column shows the own-R&D output elasticity; the entry in the first row is the base model result for all firms that was reported in Table 5. The next two rows in column one show the own-R&D output elasticity by size of firm. A key result is that the output elasticity for large firms is almost a third larger than for small firms. The difference is statistically significant and robust to several changes to the sample.

The elasticities do not change substantially when rolling six-year regressions are performed over the 2000-12 period or when the 13-year estimation period is successively shortened to five years ending in 2012. The estimates are also robust to changes in the data trimming criteria employed. We performed regressions with the full sample and with additional trimming by employment, tangible capital, R&D capital and value added without observing any substantial changes in the own-R&D output elasticities.[69] Similarly, the large difference in the productivity of R&D is robust to the exclusion of startups, which are characterized by lower productivity than established firms. Excluding firms less than three or five years old has only a minor impact on the R&D output elasticity of large firms and virtually no impact on the small firm elasticity. We also examined whether this is driven by our definition of small firms. Adopting a more conventional definition that small firms have less than 100 or 500 employees,[70] we find an even larger gap in the output elasticity of own R&D capital between small and large firms. We also estimated a dynamic production function allowing the own R&D coefficient to differ by firm size. Our preferred system-GMM estimates indicate that the output elasticity of own R&D is larger for large firms than for small firms and the difference between the two is statistically significant (p-value = 0.000).[71] Finally, we obtain a similar result for the key R&D performing industries that were discussed in section V.

Output elasticities for Mahalanobis spillovers are shown in columns 2-4 in Table 9. The entry in row one, column two (spillovers sent by all firms and received by all firms) is the base model result reported in Table 5. Rows two and three of the second column indicate how spillovers generated by small and large firms benefit all firms. The point estimates of the coefficients indicate that spillovers generated rise with firm size,[72] and we reject the hypothesis that the two coefficients have the same value (p-value: 0.000).

The finding that spillovers rise with firm size is robust to changes in the trimming criteria for our sample. We carried out our regression analysis using the full sample and samples with additional trimming by value added, employment, tangible capital stock, R&D capital, and value added to R&D capital ratio as described in the data cleaning section, respectively. In all samples, we continued to find smaller spillovers from small firms. Excluding firms that are less than three or five years old (*i.e.* start-ups) did not change our qualitative result that spillovers from small firms are smaller than those from large firms. Further, based on conventional definitions of small firms, spillovers generated by small firms are not statistically significant while those generated by large firms continue to be positive and significant. Finally, we estimated the dynamic equation using system-GMM with separate spillover pools for small

[69] We also repeated the tests described in the "data cleaning" section using an equation with own-R&D disaggregated by firm size. Recall that data trimming also affects the ratio of value added to R&D capital, which is used to transform elasticities to rates of return.

[70] In terms of the average labour unit (ALU), these definitions translate into ALU<81 and ALU<517 based on firm size distributions in T2-LEAP and in the overall business register.

[71] Using our preferred system-GMM estimates, we compute the long-run coefficients for employment, tangible capital, small firm R&D capital, large firm R&D capital, and the spillover pool as: 0.698 (0.017); 0.224 (0.009); 0.081 (0.009); 0.126 (0.010); 0.057 (0.005) respectively – all significant at 1% (standard errors are in parentheses).

[72] Note that the aggregate spillover pool is the sum of the pool generated by small and large firms.

and large firms, confirming the finding that spillovers rise with firm size. We reject the null hypothesis that the two coefficients are the same in magnitude with a p-value of 0.080.[73]

Table 9: Estimated output elasticities by size of firm, Static specifications, Fixed Effects

	Own-R&D	Mahalanobis Spillovers Received by		
		All firms	Small firms	Large firms
All firms	0.040***	0.040**	0.039**	0.032
	(0.002)	(0.020)	(0.020)	(0.023)
Small firms	0.038***	0.023***	0.021***	0.048***
	(0.002)	(0.008)	(0.008)	(0.017)
Large firms	0.050***	0.062***	0.061***	0.025
	(0.003)	(0.008)	(0.008)	(0.019)

Note: Standard errors clustered by firm are in parentheses. See footnotes to Table 5 for a description of the base model and the indicators of statistical significance. The entries in row 1, columns 1 and 2 are from Table 5. The coefficients in column (3) and (4) are obtained from estimating the baseline specification as in Table 5 but with own R&D and the aggregate and size-specific spillover pool interacted with a variable indicating small and large firms, respectively. *** p<0.01, ** p<0.05, * p<0.10

The results summarized in Table 9 also indicate that spillovers are greater between than within firm size groups. That is, knowledge transfers from small (large) firms to large (small) firms are greater than transfers among small (large) firms. These differences are statistically significant. Further, we find no statistical evidence for spillovers among large firms. The coefficient is positive but not statistically different from zero. It appears that the insignificance of the spillovers received by large firms (row 1, column 4) is mainly driven by the statistically insignificant spillovers among large firms.

2. Rates of Return

The private rate of return is defined as the marginal increase in the output of firm i induced by a marginal increase in firm i's R&D stock. The external rate of return is the marginal increase in the output of all the other firms induced by a marginal increase in firm i's R&D stock. The social rate of return is the sum of the private and external rates of return.

We make several simplifying assumptions to allow us to calculate the rate of return as the product of the estimated output elasticities and the ratio of value added to R&D capital stock. In particular, we abstract from what Bloom, Schankerman, and Van Reenen (2013) describe as the amplification effects of R&D. That is, we do not take into account the effect of an increase in the R&D stock of firm i on the return to the R&D of other firms and hence their decision to perform R&D or own returns in the subsequent periods.[74] We also assume that all firms are fully symmetric in output, R&D, and technological linkages. In other words, we assume all firms have the same size of output and R&D stock and the same technological linkages (*i.e.* $p_{ij} = p_{ik} = p \;\forall\; i, j, k$).

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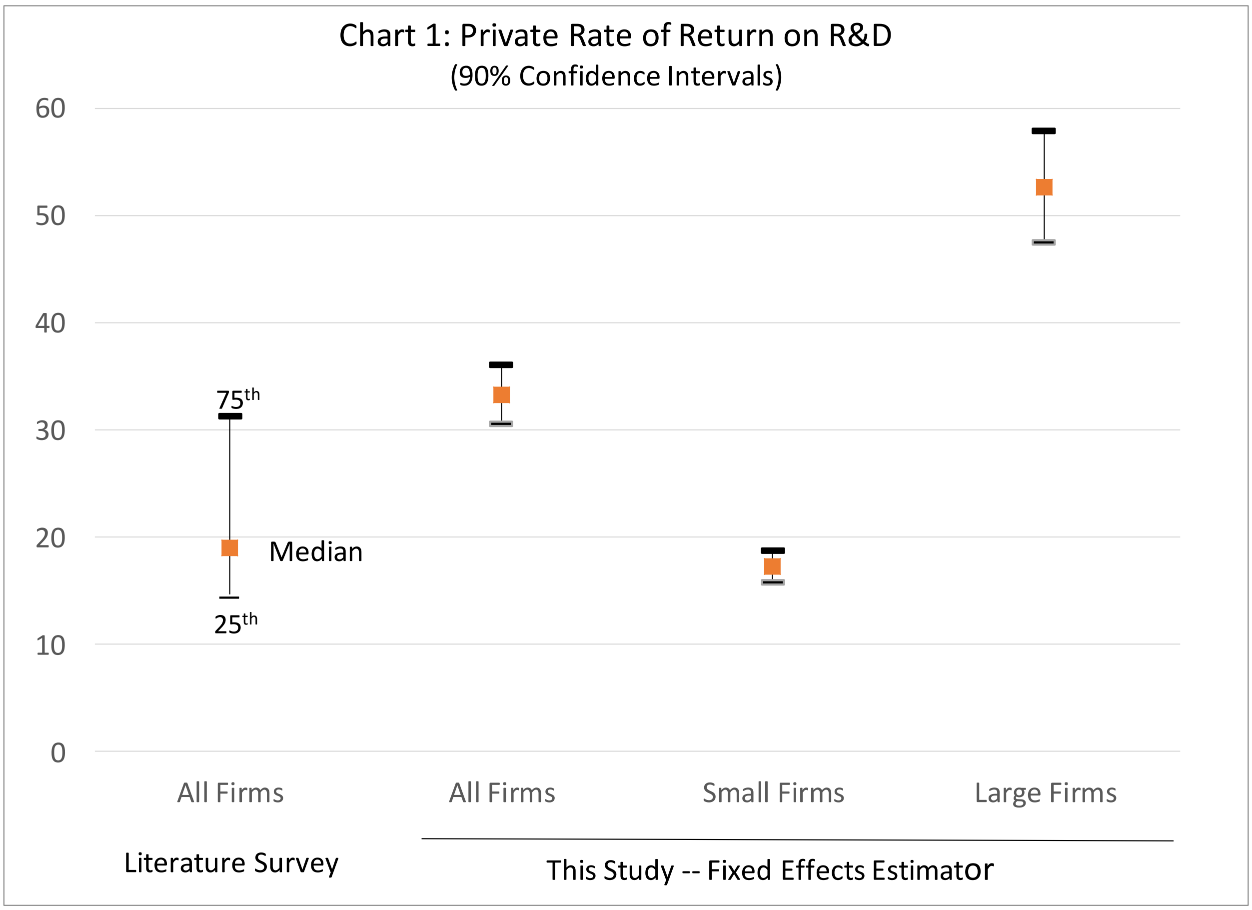
[73] Based on our preferred system-GMM estimates, we calculate that the long-run coefficients for employment, tangible capital, R&D capital, the small firm spillover pool , and the large firm spillover pool are: 0.661 (0.018); 0.271 (0.009); 0.079 (0.009); 0.050 (0.017); 0.080 (0.014) respectively – all significant at 1% (standard errors are in parentheses).

[74] Also, we do not capture in our analysis the transfer of rents among firms operating in the same or similar product markets.

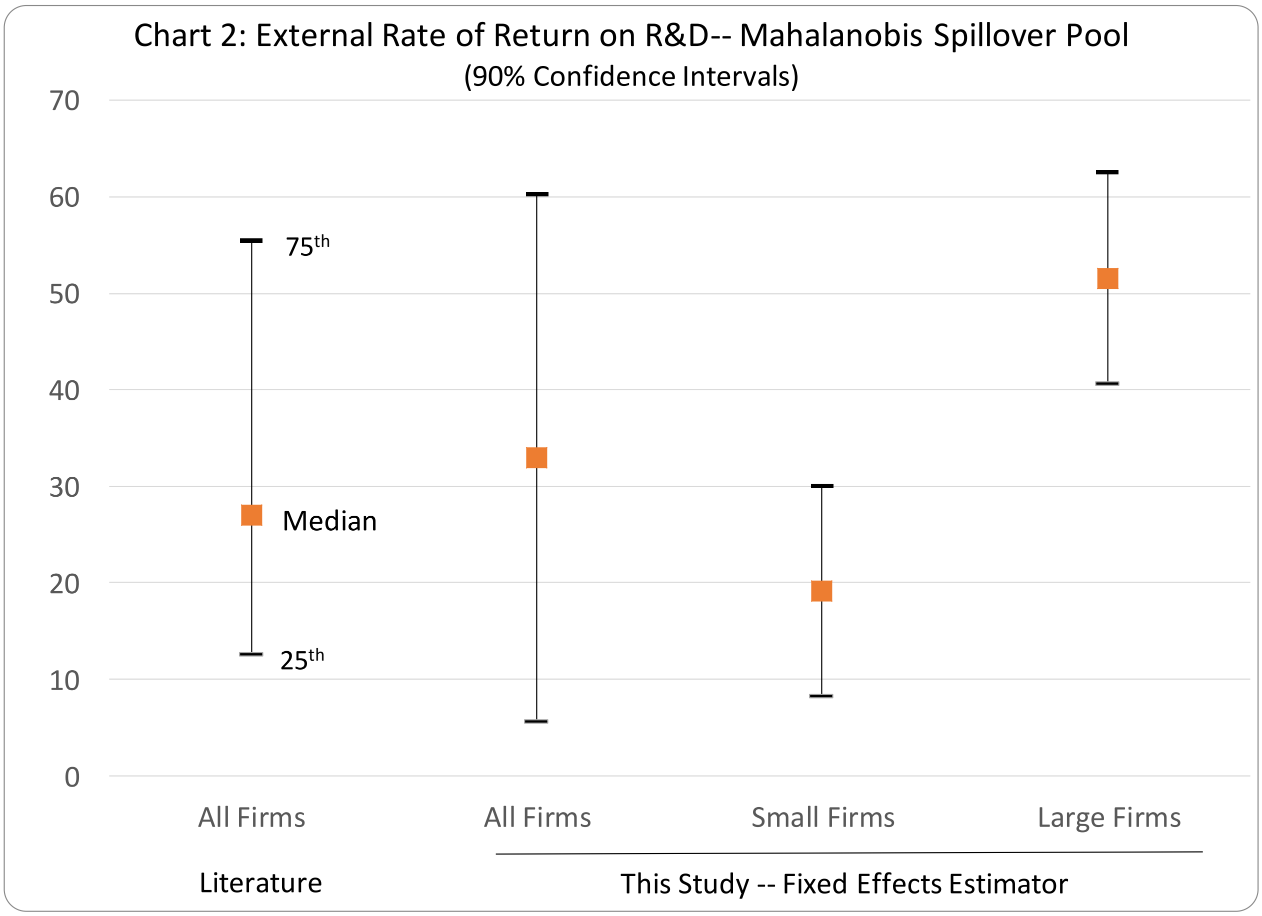
With these assumptions, we can write the private rate of return as $\gamma\frac{Y}{K}$ and the external rate of return as $\varphi\frac{Y}{K}$. Hence, the social rate of return can be written as $\frac{Y}{K}(\gamma+\varphi)$. The size-specific private and external rates of return can be obtained by multiplying the size-specific own R&D and spillover coefficients by the Y to K ratio.[75] In Appendix 3, we provide the detailed derivation of the private and external rates of return (both aggregate and by size) based on our estimating equation.

The own-R&D output elasticity implies a gross of depreciation private rate of return on all R&D of about 33% (Chart 1). This rate of return is substantially higher than the median value of estimates obtained from our literature survey.



[75] For the private rate of return, we multiply the size-specific own R&D coefficient by the size-specific Y to K ratio. For the external rate of return, we multiply the size-specific spillover coefficient by the aggregate Y to K ratio. See Appendix 3.

The private rate of return on R&D is much higher for large than for small firms, about 53% compared to 17% (Chart 2). A key contributing factor to this gap is more generous R&D subsidies for small than for large firms, which has different impacts on the required net of subsidy rate of return on R&D by firm size. In Canada, the combined federal-provincial tax-based effective subsidy rate for small firms averaged about 23 percentage points more than its large firm counterpart over the 2010-2012 period (Table 10). A more generous subsidy rate could therefore account for about two-thirds of the 35-percentage point gap in private rates of return. When expressed gross of subsidies and net of depreciation, the private rate of return on R&D capital is approximately 60% for large firms and 48% for small firms.



As discussed in the preceding section, the low profitability of startups could in principle be affecting the relative rate of return on R&D, but our analysis does not support this proposition. Another possibility is that barriers to entry erected by larger firms put downward pressure on the productivity of the R&D capital of small firms. Finally, R&D capital may benefit from economies of scale or scope in the same way as tangible capital, causing R&D productivity to rise with firm size.[76]

[76] When tangible capital is disaggregated by firm size in our production function, we obtain a higher rate of return on tangible capital used by large firms than on tangible capital used by small firms.

The implied external rate of return on all R&D is also approximately 33%, which is just over the 60th percentile of the results from our literature survey (Chart 2).[77] The external rate of return on R&D performed by small firms is about 19%, while the rate calculated for large firms is approximately 52%

As discussed in Section II.4, theoretical considerations do not provide firm guidance on whether and in what direction spillovers should be expected to vary by size of firm. The two other analyses of spillovers by firm size obtain conflicting results. Bloom, Schankerman, and Van Reenen (2013), report that small firms operate in "technological niches" that limit the applicability of their research to other firms, causing a statistically-significant rise in spillovers with firm size. Ornaghi (2006), working with Spanish data, concluded that small firms generated more substantial spillovers than large firms.

Our analysis also provides some evidence on factors affecting spillovers by size of firm. First, our dataset does not support the finding by Bloom, Schankerman, and Van Reenen (2013) that small firms undertake R&D in a narrower range of technological fields: the technological proximity indexes we calculated do not vary substantially by size of firm.[78] Second, there is some empirical support for the proposition that small firms perform less basic research and more experimental development than larger firms.[79] Third, net of depreciation and subsidies the private rate of return on R&D performed by small firms is just over 2% compared to almost 38% for large firms. While a low net 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.

Table 10: Federal and Provincial
SR&ED Effective[1] Investment Tax Credit Rates
(2010-12 in percentage)

	Federal	Provincial[2]	Combined[3]
Small firms	37.0	14.0	45.8
Large firms	18.0	5.7	22.7
Small less large	19.0	8.3	23.2

1. See Lester (2012) for additional information on effective credit rates
2. Expenditure-weighted sum of provincial statutory rates.

3. The base for the federal credit is reduced by the amount of provincial assistance provided.

VII. 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 only other estimates available were prepared 31 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

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[77] 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.
[78] Recall from Table 4 that the mean spillover pool (both aggregate and by size) is greater for small firms than for larger firms.
[79]We can only calculate the share of firms performing basic research by size of firm with the current data set.

performers to be included in the analysis. Third, we calculate separate spillover pools by size of firm, which allows us to assess whether spillovers vary with the size of the firm performing the R&D.

Our preferred measure of the spillover pool indicates that the rate of return on external R&D is about 33 per cent, which is higher than typically found in the literature. We find evidence that spillovers rise with the size of the firm performing the R&D. This result 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. We also find much lower private rate of return on R&D performed by small firms than by large firms. Subsidies appear to be playing a key role in this result.

Our preferred coefficients are obtained by estimating a static production function with fixed effects. Our analysis with system generalized method of moments estimators based on a dynamic model provides broad support for the results from the static model.

Appendix 1: Sample Selection Process

Our sample selection is determined by the availability of information for each firm's technology position. This information is reported in schedules 60 and 32 in the CRA (Canada Revenue Agency) form T661 - Scientific Research and Experimental Development (SR&ED) Expenditures Claim.[80]In the form, firms are required to report spending on each R&D project along with a technology field code for the project. CRA provides firms with a set of codes assigned to 28 technology fields (3-digit code) which are further disaggregated into 147 detailed fields (5-digit code).

We classify firms into three different groups depending on the availability of information on their technology position. First, there are firms that provide full information for technology field and spending for all R&D projects undertaken for all years over the period 2008-2012 (90.1% of total observations). Second, there are firms that provide information for all R&D projects undertaken in some but not all years (roughly 9.0% of total observations). In this case, we use information in the years in which they provided full information for technology fields and spending to identify their technology position.[81]These two groups of firms are included in our sample (99.1% of total observations). Third, there are firms that do not provide full information for any of the years over 2008-2012. They provide full information for either a fraction or none of the projects over the sample period. In order to reduce the impact of this partial reporting, we identify firms that provide full information for at least half of their R&D projects in a given year and treat them as if they provided enough information.[82] Firms that provide less technological field information are not included in our sample.[83]

Based on spending and field information for each project conducted by a given firm over the sample period, we identify the firm's position in technology space consisting of 147 (at 5-digit code) fields.

These firms are merged with our main data set (T2-LEAP) using the longitudinal enterprise identifier so that we have value added, average labour unit, capital stock and R&D stock variables for them. We also transfer technology position information for each firm being merged with the main data set so that we can weight the external pool of R&D for each firm each year over the 2000-2012 period. The weighted pool of R&D stock defined differentially for each firm is our spillover variable.

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[80] Schedules 32 and 60 represent different parts of formT661. Schedule 60 corresponds to Part 2 of T661, which contains information for each project claimed in a given fiscal year. Schedule 32 corresponds to Part 5 of T661, which provides firm-level aggregate R&D spending.

[81] For some of these firms, spending information is missing for some or all projects. Therefore, we use information available in schedule 32 to augment their spending information. We do not have field information in schedule 32, but we can use the aggregate spending information reported in schedule 32 for firms that conducted R&D in a single field in a given year. The number of such firms is small.

[82] For example, if firm X undertook 4 projects in 2008 but provided technology field codes for 3 of them, then firm X is identified. For such firms, we drop projects without technology field codes in that year so that the firm becomes a full respondent for technology field. However, the number of affected firms is very small (less than 50), increasing our sample size by only a negligible extent. This adjustment affects both the second and third group but most of the affected firms are from the third group.

[83] The number of firms excluded from our sample on this basis is relatively small: 0.9% of total observations.

Appendix 2: 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 $F_{nk} = \frac{RD_{nk}}{RD_n}$.

We obtain the following matrix by stacking F_n for all n vertically:

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

Note that the Jaffe proximity measure is 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.

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

Finally, we compute a matrix of uncentered correlation coefficients as follows:

$$\tilde{F} = \tilde{f}\tilde{f}'$$

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

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.

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

We obtain the following matrix by stacking T_k for all k vertically:

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

*Note that $t = f'$

In the next step, we normalize each element by the standard deviation of the corresponding vector.

$$\tilde{t} = \begin{bmatrix} F_{11} \big/ (T_1 T_1')^{0.5} & \cdots & F_{1N} \big/ (T_1 T_1')^{0.5} \\ \vdots & \ddots & \vdots \\ F_{K1} \big/ (T_K T_K')^{0.5} & \cdots & F_{KN} \big/ (T_K T_K')^{0.5} \end{bmatrix}_{(KxN)}$$

Finally, we compute a matrix of uncentered correlation coefficients as follows:

$$\tilde{T} = \tilde{t}\tilde{t}'$$

$$\tilde{T} = \begin{bmatrix} 1 & \cdots & T_1 T_K \big/ [(T_1 T_1')(T_N T_N')]^{0.5} \\ \vdots & \ddots & \vdots \\ T_K T_1 \big/ [(T_N T_N')(T_1 T_1')]^{0.5} & \cdots & 1 \end{bmatrix}_{(KxK)}$$

$\widetilde{T}$can be interpreted as the standard Jaffe proximity measure defined for technology fields.Using $\widetilde{T}$ as a weighting matrix, we compute the Mahalanobis-normed technology proximity measures as follows:

$$\tilde{P} = \tilde{f}\tilde{T}\tilde{f}'$$

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.

Appendix 3: Calculating the rate of return to R&D

Bloom, Schankerman, and Van Reenen (2013) introduce a framework for calculating rates of return based on estimated elasticities. They rely on three models which characterize the effect of own R&D and R&D performed by other firms on a given firm's R&D, market value, and output (*i.e.* R&D equation, market value equation and production equation).[84]

For the external rate of return, in addition to the direct effect of one firm's R&D on the other firms' output, they build in indirect effects of a change in one firm's R&D on the other firms' output through induced changes in their R&D. For the private rate of return, they exploit the relationship between the market value of a given firm and other firms' R&D (weighted by the product market linkages) to incorporate output gains through the business stealing effect.[85] This effect is added to the direct effect of own R&D on output when one calculates the private rate of return to R&D. By computing the private and external rates of return at the firm level, they incorporate asymmetry stemming from different output sizes (relative to R&D stock) and linkages in the technology and product market space.

It is possible to implement a special case of their general framework based only on the production function. In the online appendix (Appendix G) to Bloom, Schankerman, and Van Reenen (2013), the authors discuss such special case in which they assume symmetric firms and "switch off" the indirect effects associated with induced changes in R&D and business stealing. Following the special case introduced in Bloom *et al.* (2013), we provide a brief technical description of the underlying algebra for deriving the private and external rate of return equation.

First, we re-introduce our production function (explicitly writing out logs):

$$(1)\ \ln Y_i = \gamma lnK_i + \varphi lnS_i + \beta X_i$$

$$(2)\ \ln Y_i = \gamma lnK_i + \varphi \ln\left(\sum_{j\neq i} p_{ij}K_j\right) + \beta X_i$$

where S_i is the technology-weighted sum of external R&D stock available to firm i and X_i is a vector of all the other variables and p_{ij} is our technological proximity measure defined between firm i and firm j.

Then, we take a first-order approximation of the nonlinear equation $ln\left(\sum_{j\neq i} p_{ij}K_j\right)$ around an arbitrary point called $lnRD^0$. Define $f_i = l\,\mathrm{n}[\sum_{j\neq i} p_{ij}K_j] = ln[\sum_{j\neq i} p_{ij}\exp(lnK_j)]$. Then, we can approximate f_i as follows:

$$(3)\ f_i \approx \left\{ln \sum_{j\neq i} p_{ij}K_j^0 - \sum_{j\neq i}\left(\frac{p_{ij}K_j^0}{\sum_{j\neq i} p_{ij}K_j^0}\right) ln\, K_j^0\right\} + \sum_{j\neq i}\left(\frac{p_{ij}K_j^0}{\sum_{k\neq i} p_{ik}K_k^0}\right) ln\, K_j$$

$$\equiv a_i + \sum_{j\neq i} b_{ij} lnK_j$$

[84]Their framework assumes that their reduced-form equations are correctly specified and have structural implications (*i.e.* all the relationships are causal).

[85]Such output gain is an increase in the level of labour and capital employed by the firm holding its productivity level constant.

Using the above approximation, we can re-write the production function as follows:

$$(4)\ \ln Y_i = \psi_i + \gamma lnK_i + \varphi \sum_{j\neq i} b_{ij} lnK_j + \beta' X_i$$

where $\psi_i = \varphi_2 a_i$.

From the above, one can write the external rate of return to R&D performed by firm i as $\varphi \frac{\sum_{j\neq i} b_{ji} Y_j}{K_i}$ which is equivalent to $\sum_{i\neq j} \frac{dY_i}{dK_j}$. If we allow the external rate of return to differ by size of firm, then the external rate of return to R&D performed by small firm i can be written as $\varphi^S \frac{\sum_{j\neq i}^{(N_S-1)} b_{ji} Y_j^S + \sum_{k\neq i}^{N_L} b_{ki} Y_k^L}{K_i^S}$ and that by large firm k as $\varphi^L \frac{\sum_{w\neq k}^{(N_L-1)} b_{wk} Y_w^L + \sum_{o\neq k}^{N_S} b_{ok} Y_o^S}{K_k^L}$ where φ^s and φ^l are size-specific spillover coefficients and N_S and N_L are the number of small and large firms respectively. The private of rate of return would simply be $\gamma \frac{Y_i}{K_i}$ or $\gamma^s \frac{Y_i}{K_i}$ and $\gamma^l \frac{Y_k}{K_k}$ by size.

At this point, we can assume that $Y_i = Y_j = Y$; $K_i = K_j = K$; and $p_{ij} = p_{ik} = p$ for all i, j, k. With this assumption, $\sum_{i\neq j} b_{ij}\, Y_i$ becomes:

$$(5)\ \sum_{i\neq j} b_{ij}\, Y_j = \sum_{i\neq j} \frac{pK}{p\sum_{k\neq j} K} Y = (N-1)\frac{K}{(N-1)K} Y = Y$$

where N is the number of firms in the economy.

Hence, we have that the external rate of return equals $\sum_{i\neq j} \frac{dY_i}{dK_j} = \varphi \frac{\sum_{i\neq j} b_{ij} Y_i}{K_j} = \varphi \frac{Y}{K}$ with the assumption of identical firms.

For the external rate by size, we first assume symmetry in technological linkages (*i.e.* $p_{ij} = p_{ik} = p$). For output and R&D stock, we can have either one of the following two assumptions:[86]

A. Assume symmetry in output and R&D stock across firms within the same size group (*i.e.* $Y_i^S = Y_j^S = Y^S$; $K_i^S = K_j^S = K^S$ and $Y_i^L = Y_j^L = Y^L$; $K_i^L = K_j^L = K^L$).

B. Assume symmetry in output and R&D stock across all firms (*i.e.* $Y_i^L = Y_j^L = Y$; $K_i^L = K_j^L = K$).

Assume symmetry in output and R&D stock across firms within the same size group

$$(6)\ b_{ji} = \frac{pK^S}{(N_s-1)pK^S + N_L pK^L} = \frac{K^S}{(N_s-1)K^S + N_L K^L}$$

[86] One can have similar assumptions for the technological linkages. However, we get the same results regardless since p cancels out in b.

$$(7)\ b_{ki} = \frac{pK^s}{N_s pK^s + (N_L - 1)pK^L} = \frac{K^s}{N_s K^s + (N_L - 1)K^L}$$

$$(8)\ MER^s = \varphi^s \frac{(N_s - 1)\frac{K^s Y^s}{(N_s - 1)K^s + N_L K^L} + N_L \frac{K^s Y^L}{N_s K^s + (N_L - 1)K^L}}{K^s}$$

$$= \varphi^s \left(\frac{(N_s - 1)Y^s}{(N_s - 1)K^s + N_L K^L} + \frac{N_L Y^L}{N_s K^s + (N_L - 1)K^L}\right)$$

$$(9)\ MER^L = \varphi^L \left(\frac{(N_L - 1)Y^L}{(N_L - 1)K^L + N_S K^S} + \frac{N_S Y^S}{N_L K^L + (N_S - 1)K^S}\right)$$

Then, we approximate $N_L K^L + N_S K^S \cong N_L K^L + N_S K^S - K^L$; $N_L K^L + N_S K^S \cong N_L K^L + N_S K^S - K^S$ and $N_L Y^L + N_S Y^S \cong N_L Y^L + N_S Y^S - Y^L$; $N_L Y^L + N_S Y^S \cong N_L Y^L + N_S Y^S - Y^S$.[87]

Using these approximations, we obtain the external rate of return by size as follows:

(10) $MER^s = \varphi^s \frac{N_s Y^s + N_L Y^L}{N_s K^S + N_L K^L}$ which is equivalent to $\varphi^s \frac{\bar{Y}}{\bar{K}}$

(11) $MER^L = \varphi^L \frac{N_s Y^s + N_L Y^L}{N_s K^S K^s + N_L K^L}$ which is equivalent to $\varphi^L \frac{\bar{Y}}{\bar{K}}$

Assume symmetry in output and R&D stock across all firms

$$(12)\quad b_{ji} = \frac{pK}{(N_s - 1)pK + N_L pK} = \frac{K}{(N_s - 1)K + N_L K}$$

$$(13)\quad b_{ki} = \frac{pK}{N_s pK + (N_L - 1)pK} = \frac{K}{N_s K + (N_L - 1)K}$$

$$(14)\quad MER^s = \varphi^s \frac{(N_s - 1)\frac{KY}{(N_s - 1)K + N_L K} + N_L \frac{KY}{N_s K + (N_L - 1)K}}{K}$$

$$= \varphi^s \left(\frac{(N_s - 1)Y}{(N_s - 1)K + N_L K} + \frac{N_L Y}{N_s K + (N_L - 1)K}\right)$$

[87] That is, the total R&D stock (output) minus R&D stock (output) of one firm is approximately equal to the total R&D stock (output).

$$= \varphi^s \left(\frac{NY - Y}{NK - K}\right) = \varphi^s \frac{(N-1)Y}{(N-1)K} = \varphi^s \frac{Y}{K}$$

where $N = N_s + N_L$.

Similarly,

(14) $MER^L = \varphi^L \frac{Y}{K}$

The private rate of return can be written as $\gamma \frac{Y}{K}$ or $\gamma^s \frac{Y^s}{K^s}$ and $\gamma^l \frac{Y^l}{K^l}$ by size based on the assumption A.

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