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ABSTRACT

What do we know about the relationship between innovation and productivity among firms? The workhorse model of this relationship is presented and the implications of analysis using this model and the usually available data on product and process innovation are derived. The recent empirical evidence on the relationship between innovation and productivity in firms is then surveyed. The conclusion is that there are substantial positive impacts of product innovation on revenue productivity, but that the impact of process innovation is more ambiguous, suggesting some market power on the part of the firms being analyzed.

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Innovation and Productivity

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Early work on the sources of productivity growth revealed that growth in capital and labor explained less than half of such growth in the United States and many other countries. The remainder (the 'residual') was ascribed to technical change and a large literature grew up that attempted to find measures for technical change (improvements in capital and labor quality, R&D activities, and so forth) and use these measures to try to explain the residual growth in productivity (Griliches 1996, 1998, among others). Considerable success has been achieved by this approach, to the extent that many countries are now moving to incorporate measures of R&D capital stock in their systems of national income accounts, and therefore to directly attribute some of economic growth to its contribution as well as adding the creation of knowledge capital to output itself.

Driven by interest in the unexplained portion of productivity growth and partly in response to various economic slowdowns and productivity gaps among nations, a large body of research on innovative activity and productivity in firms has accumulated. For reasons of data availability, this work has mostly used two measures of innovative activity: R&D spending and patent counts.[2] As measures of innovation, each of these has both positive and negative attributes. Both pertain primarily to technological innovation and are more suited to measuring innovation in manufacturing firms than in other areas such as services. R&D spending has the advantage that it is denominated in comparable units (currency) and represents a (costly) decision variable on the part of the firm about its appropriate level of innovative activity. For the same reason, it is only an input to innovation and cannot tell us about innovation success. Patent counts are a measure of invention success, and can be considered at least a partial measure of innovation output, but they are inherently very noisy (a few are associated with very valuable inventions and most describe inventions of little value) and the extent of their innovation coverage varies by sector, with sectors like pharmaceuticals and instruments making heavy use of patents while other sectors use them very little.

As the industrial structure of advanced economies has shifted away from manufacturing and towards services, economists and others have gradually become aware that concepts

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[2] A recent survey of results for the R&D-productivity relationship is Hall, Mairesse, and Mohnen (2010).

like "technical change" and "R&D" describe only some of the sources of increased productivity in the economy, and recent research has begun to look at innovation more broadly as a source of growth. This research has been greatly helped by the introduction of the Oslo Manual (Tanaka *et al.* 2005) with guidelines for the definition of various kinds of innovation and by the surveys of innovative activity in business firms that have been conducted in a large number of countries around the world, mostly using this manual as a guide (Mairesse and Mohnen 2010). Several non-R&D kinds of innovative expenditure have been identified: the later phases of development and testing that are not included in R&D, capital expenditures related to the introduction of new processes, marketing expenditures related to new products, certain kinds of employee training, expenditures on design and technical specifications, etc.

Figure 1, which is based on data from these kinds of surveys, shows the distribution of the share of firms that report either product or process innovation during the three year period 2004-2006 by country and size of firm.[3] The figure is instructive: it shows that in most countries, between 30 and 50 per cent of firms introduce a product or process innovation during a three year period, and that the rate of introduction is much higher and also more even across countries among large firms, as we might have expected. The number for the United States does seem abnormally low, which may reflect the experimental nature of the new BRDIS survey, but it is so low that the true number is unlikely to place the US among the most innovative countries.

Figure 2 shows the same thing, broken down by product and process innovation. The two types of innovation are equally likely, with some differences across countries. It is however, worth noting that Italy is among the most innovative countries, and the US among the least, which raises some questions about the quality of the innovation variables when examined across countries. However, Figure 3 provides a different look at the data, splitting the firms by whether or not they report performing R&D. Here the U.S. share of process innovators is 66 per cent for R&D-doing firms, and only 8 per cent for non-R&D-doers. So the suspicion is that because the BRDIS survey is primarily designed to collect R&D information from firms, the data may be inadequately reported for non-R&D-doers, leading to the low overall numbers for the US.[4]

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[3] The data for this and the subsequent figure comes for the most part from the European Community Innovation Survey combined with data from OECD for non-European countries. These statisical offices have tried to make the numbers as comparable across countries as possible. Data for the United States comes from the new 2008 Business R&D and Innovation Survey (BRDIS), conducted by the National Science Foundation and may not be exactly comparable to the European data.

[4] Although the sampling frame for the BRDIS was the population of U.S. firms with 5 or more employees, this survey was the successor to the longrunning RD-1 survey which was only filled out by RD-doing firms, and

How does the aggregate innovation picture compare with aggregate productivity measures? To answer this question, I compared the process and product innovation rates at the country level with overall labor productivity (GDP per hours worked, also from OECD). The results are shown in Figures 5 and 6. With the exception of a couple of outliers (Norway and possibly the Netherlands), the share of both SMEs and large firms that innovate appears to be positively related to labor productivity at the country level. Simple univariate regressions for the relationship were significant, and even more so when robust methods such as Least Absolute Deviations or Least Median of Squares were used. The relationship is clearly stronger for the large firms, probably because they are subject to better measurement and less imputation, and because they are more indicative of the whole economy performance.

Although the correlation displayed should not be taken too seriously, given the number of confounding influences and differences in industrial structure across countries, even at the aggregate level there does seem to be a relationship between innovative activity by firms and productivity, albeit one that leaves room for many other influences. It is natural to ask how this relationship comes about – what actions by individual firms lead to aggregate productivity improvements? One can think of two main channels by which the presence of more innovative firms can translate into productivity improvements: first, innovation in existing firms can both increase their efficiency and improve the goods and services they offer, thus increasing demand as well as reducing costs of production. Second, innovating firms are likely to grow more than others and new entrants with better products to offer are likely to displace existing inefficient firms, with a concomitant increase in aggregate productivity levels. In both cases the relationship between innovation and productivity is influenced by the institutional and macroeconomic environment in which the firms operate, possibly leading to substantial differences across countries in the relationship between them.

The present paper will review the ways in which economists have analyzed the relationship between productivity and innovation, focusing on the use of such innovation survey data as well as other data on innovative output such as patents. The differing measures of innovation (dummy variables, innovative sales, and innovation expenditure) that the various surveys yield will be reviewed and their drawbacks and advantages discussed. The distinction between innovation input (expenditures and choices under the control of the firm) and innovation output (depending on inputs but also with a large element of chance) is important and there are rationales for using both concepts.

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the innovation questions were at the end of a long survey, most of which concerned R&D. So there is some suspicion that they may not always have been accurately answered by non-R&D-doers. This suggestion has been informally confirmed by conversations with the NSF.

After discussing measures of innovation, the paper will review two approaches to measuring the relationship between productivity and innovation: the econometric or regression approach and the growth accounting approach. Both are in their relative infancy due to the fact that the appropriate data has been lacking until quite recently (and is still not widely available).

Innovation – the concept and its measurement

There were two early empirical efforts which generated datasets on innovation that have been used in some studies (regrettably few studies, in fact). They are the SPRU study of UK firms begun in 1970, and conducted over a period 15 years through 1984 (Freeman and Soete 1997) and the study by Acs and Audretsch during the 1980s that looked at US firm innovations. The SPRU study asked almost 400 experts in industry to identify significant technical innovations that were commercialized in the UK sometime between 1945 and 1983 and then surveyed the firms that had introduced the innovations. The database contains over 4000 innovations, almost all of which are in the manufacturing sector. It has been used to show that the relationship between innovative activity and firm size is largely U-shaped, and that smaller firms show greater innovative activity than they do formal R&D activity (Pavitt *et al.* 1987). A couple of the papers surveyed below (Geroski 1989 and Sterlacchini 1989) make use of this database, but it has not been exploited extensively in the analysis of innovation and productivity.

The 1990 Acs and Audretsch study for the US Small Business Administration (SBA) was based on a survey of over 100 trade journals in 1982 that looked for announcement of the market introduction of inventions. The definition used by the SBA was the following:

> "a process that begins with an invention, proceeds with the development of the invention and results in introduction of a new product, process or service to the marketplace"

This survey yielded over 8000 US innovations, most if which probably dated to 1978-1982, but all of which were introduced in 1982. Acs and Audretsch use these data to analyze the role of small firms in innovation, the growth of firms, and the evolution of market structure. Unfortunately they do not provide any analysis of the relationship between these invention introductions and firm productivity.

Both the SPRU and the SBA surveys used the innovation as the unit of observation, and any firm-level analysis using these data is therefore based only on innovative firms. In contrast, the innovation surveys described below are conducted at the firm level and sometimes collect data on non-innovative firms as well. Thanks to work by the OECD and others, we now have a definition of innovation done by firms that is fairly standard across a wide range of countries and surveys:

> "An innovation is the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organisational method in business practices, workplace organisation or external relations."[5]

Most of the work on innovation described in this paper has been based on surveys that use a version of this definition. Thus there has been consistency in the definition of the innovation variables across study, although perhaps not consistency in the interviewees' understanding of the definition. However, note that there is at least one slightly ambiguous feature of the definition, in that it does not define "new" very precisely. Some of the surveys have made a distinction between "new to the firm" innovations and "new to the market" innovations, which can be a way of distinguishing more radical innovation from imitation. But in general, the interpretation of "new" is left to the survey respondent.

In spite of the apparent clarity of the definition of innovation in the Oslo Manual, measuring innovation in a form that is useful for statistical analysis has proved challenging. The central problem is that no two innovations are alike. Some innovations (e. g., the invention of the telephone or perhaps the telegraph) create a whole new market sector whereas others are useful but trivial, and there is a wide range in between. In general we can say that smaller innovations are more numerous than game-changing ones. As shown in Table 1, this fact is very visible in the data collected by Acs and Audretsch. During the year 1982, over 85 per cent of the innovations they identified were modest improvements to existing products, and none created entire new markets. Fewer than 2 per cent were considered even the first of its type on the market in existing market categories.[6]

The innovation surveys have typically measured innovation in two ways: first, by asking whether the firm introduced an innovation of a certain type (product, process, organisational, marketing, etc.) during a preceding period (usually the past three years) and second, by asking what share of the firm's sales are due to products introduced during the same preceding period. The first measure has a number of drawbacks, which have become quite evident as it has been used in many empirical studies. When examined across a range of firm sizes, it produces the misleading results that larger firms are more likely to be innovative, whereas in truth larger firms are involved in a wider range of activities and

[5] *Oslo Manual* (OECD 2005), third edition, p. 46.

[6] Note that by using the 1982 date, Acs and Audretsch did miss two major innovations: the IBM personal computer and Microsoft DOS, both of which were introduced in 1981 and which arguably meet the definition of "created entire new market".

therefore more likely to have an innovation in at least one of them. So this variable cannot be used to make the kind of statements that one sometimes hears, such as "large firms are more innovative than small firms."

Another problem is the previously mentioned unequal size of innovations and the failure in some surveys to distinguish between "new to the market" and "new to the firm." Based on the Acs and Audretsch results we know that many more of the innovative firms will have introduced improvements to existing products rather than entirely new goods and services, but the latter may be more important than the former. This view of the "skewness" of innovation values is supported by a large amount of research on the valuation of patented inventions (Harhoff *et al.* 1999; Scherer and Harhoff 2000; Hall *et al.* 2005). Although patented inventions are not precisely the same as innovations, they are similar and share some of their distributional properties, with the majority worth very little, and a few that are quite valuable to their owners.

Because of the imprecision and noisiness of the innovation dummies, many researchers prefer to use the second measure, the share of sales of innovative products, which does give a good indication of how important the innovation(s) were overall for the firm in question. Unfortunately, this measure is useful only for goods and services and cannot be used to capture process or organisational innovation. Nevertheless, it is the one relied on by more than half of the papers discussed in the following sections, often accompanied by a dummy for process innovation. Only one example exists where firms were asked to quantify the impact of process innovation on cost reduction (Peters 2006, for Germany).

Productivity – the concept and its measurement

What we mean by the term "productivity" is fairly easy to understand although difficult to measure: it is the quantity of output that can be produced using a given level of inputs. At this level of the definition, there is not even a presumption of optimality or efficiency in production. However, normally we assume that the entity whose productivity we wish to measure is "efficient" in the sense that it is using the minimum necessary level of inputs to produce a certain level of output, given its level of technological knowledge, its organization, its size, and other endowments, as well as the environment in which it operates.

Economists generally describe the relationship between output and the level of inputs using a production function, of which the most convenient for analysis is the following:[7]

$$Q = AC^{\alpha}L^{\beta} \tag{1}$$

[7] I ask the well-informed reader for patience with the elementary review provided here, which is primarily for the purpose of setting notation for the subsequent discussion.

Where Q is output, C is the level of capital stock, and L is labor (and potentially other non-capital inputs).[8] A is the overall level of productivity which may vary across entities. That is, because of organizational differences, frictions, or other constraints, entities with identical levels of C and L may not be able to achieve the same level of output Q.

For measurement purposes, the logarithm of equation (1) is taken:

$$q_{it} = a_{it} + \alpha c_{it} + \beta l_{it} \qquad i = entity, t = time \tag{2}$$

where the added subscripts denote the fact that productivity levels are usually measured for a number of entities over several time periods. Equation (2) yields an expression for total factor productivity (usually denoted TFP):

$$TFP \equiv a_{it} = q_{it} - \alpha c_{it} - \beta l_{it} \tag{3}$$

All well and good, but measuring TFP therefore requires measures of real output Q, real capital stock C, and labor input L (as well as possible other inputs, such as energy and materials), to say nothing of the coefficients α and β. I discuss the latter problem first.

There are two widely used approaches to estimating the weights α and β to be applied to the inputs in the productivity measure: 1) assume that input markets are competitive, which implies that the coefficients are the shares of revenue received by each of the factors;[9] and 2) assume the coefficients are (roughly) constant across entities and estimate them via regression. Solution (1) is favored by statistical agencies and others who simply need a measure of TFP for an individual entity and may not have a sample available for estimation, and solution (2) is the one typically used by econometricians and the main one employed in the literature discussed later in this paper, although there are some exceptions.[10]

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[8] The treatment here has been greatly simplified by omitting purchased inputs (such as materials, energy, etc.). In practice these inputs are more important on a share basis than either capital or labor and need to be included in estimation (typically accounting for about 0.7 of the inputs). Alternatively, one can measure output as value added, which is usually defined as output less purchased inputs. The precise choice of what to include or exclude depends to some extent on data availability, and several variations have been pursued in the literature discussed here. In particular, many of the available datasets do not include measures of the firm's capital stock and researchers are forced to resort to proxies such as current investment spending.

[9] This approach can be modified to account for scale economies and market power as in R. Hall (1988), or indeed almost anything that implies homogeneity of some degree in the production function. See below for a modification that allows the firms to have some degree of market power.

[10] A large literature has developed on the methodologies for estimating the production function in the presence of simulateneity between input and output choice and errors of measurement. Some key papers are Blundell and Bond (2000), Griliches and Mairesse (1984), and Olley and Pakes (1996).

The second problem, how to measure the inputs and outputs themselves, is subject to a multitude of solutions. Unfortunately, the choices can have considerable impact not only on the measurement of TFP but also on the relation of that measure to innovation. The difficulty lies in the measurement of real inputs and outputs, holding constant the unit of measure over time. To take a concrete and well-known example, computers, which are a component of capital, have changed considerably over time. If we measure their contribution to the inputs simply as expenditure on computers, it is likely to be roughly constant over time, and TFP will grow as the computers become more productive. However, if instead we deflate the computer expenditure by an index of the effective price of computing power, which has fallen dramatically over the past 30 years, the real quantity of computers will grow substantially during the same period, and TFP growth will be correspondingly less. In essence, some technical change or innovation has been transferred from TFP to its inputs.[11] The same argument applies to the labor input, where quality has probably generally increased over time so that a person-hour 30 years ago is not the same as one today. All this means that TFP measures need to be used carefully, with an understanding of the approach used to deflation and quality adjustment.[12] That is, much of the effects of innovation may show up as higher quality inputs if they are quality adjusted, and will not appear in output.

For the output measure, the problem is even more striking when we look at the level of the firm or enterprise, because of the potential for variations in market power across firms, and for the role that innovation plays in creating and/or increasing that market power. The easiest way to see this is to rewrite the TFP equation in terms of revenue rather than real output, under the assumption of an iso-elastic demand equation. The idea behind this approach is that each firm produces differentiated products and therefore faces its own downward sloping demand curve. Firms have idiosyncratic output prices, so that deflation of revenue by an overall deflator simply yields real revenue rather than an actual output measure. I denote the log of real revenue by r_{it} and the log of the firm's output price by p_{it},

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[11] Of course, if the analysis is done at the aggregate level, the production of computers will be in the output measure, and their share of TFP will increase. See Denison (1966) and Jorgenson and Griliches(1967) for discussion of this point.

[12] On the output side, Hall (1996), Mairesse and Hall (1996), and Griliches (1994) present R&D-productivity regressions that illustrate the effect a properly measured computing sector deflator can have on the measured returns to R&D via its impact on the measurement of TFP. Those authors show that using a hedonic price deflator for computing rather than an overall GDP deflator more than triples the elasticity of output with respect to R&D, from 0.03 to 0.11. That is, most of the returns to R&D during the period estimated (1980s) went to price reduction and real output increase, and very little was received by the firms in the form of increased revenues. See also OECD (2003), pp. 43-44 for a discussion of this issue.

with $r_{it} = p_{it} + q_{it}$. Write the iso-elastic demand equation facing the firm in logarithmic form as follows:[13]

$$q_{it} = \eta p_{it} \tag{4}$$

where η is the (negative) demand elasticity. Combining equations (2) and (4) yields the following expression for the (observable) revenue as a function of the inputs and TFP:

$$r_{it} = \frac{\eta + 1}{\eta}(a_{it} + \alpha c_{it} + \beta l_{it}) \tag{5}$$

The above equation implies that the estimated coefficients of capital and labor in the productivity equation will be negative if demand is inelastic ($0>\eta>-1$) and biased downward if demand is elastic ($\eta<-1$). As η approaches -∞ (perfectly elastic, or price-taking), the bias disappears and the equation is identical to equation(2), but with revenue in place of output.

The conclusion is that if a regression based on equation (5) is used to estimate TFP (a_{it}), the estimate will typically be biased downward over a reasonable range of demand elasticities. Note also that for a profit-maximizing firm, the bias is equal to $1-m$, where m is the markup. The further we are from perfect competition ($m=1$) and the higher the markup, the greater is the downward bias. After I present the basic model that relates innovation and productivity in the next section, I will derive the implications of equation (5) for the measurement of that relationship.

Modeling the relationship

When looking at the contribution of innovative activity to productivity, the usual starting point is to add a measure of the knowledge or intangible capital created by innovative activity to the production function:

$$Q = AC^{\alpha} L^{\beta} K^{\gamma} \tag{6}$$

Here K is some kind of proxy for the knowledge stock of the firm. K can stand for a number of aspects of the entity's innovative capability: its technological knowledge obtained via R&D, its competency at transforming research results into useful products and processes, and so forth. It can even be based on innovative success rather than capability. Traditionally K has been measured as a stock of past R&D spending but as other kinds of

[13] This treatment of the problem is drawn from Griliches and Mairesse (1984). Also see Mairesse and Jaumandreu (2005) and Foster et al. 2008 for discussions of the differences between revenue productivity estimation and true productivity estimation.

data have become available, other measures involving patents or innovation indicators have been used.

As before, the logarithm of equation (1) is taken:

$$q_{it} = a_{it} + \alpha c_{it} + \beta l_{it} + \gamma k_{it} \qquad i = entity, t = time \tag{7}$$

Because much of innovative activity is directed towards new products and product improvement, it is useful to rewrite the demand equation to allow the knowledge stock to shift the demand curve facing the firm:

$$q_{it} = \eta p_{it} + \varphi k_{it} \qquad \varphi > 0 \tag{8}$$

Assuming that the knowledge stock has a positive coefficient implies that the effect of increased knowledge or innovative activity is to shift the demand curve out by making the firm's products more attractive to its customers, at a given price.

Combining equations (7) and (8) as before, we obtain the following equation for revenue:

$$r_{it} = \left(\frac{\eta + 1}{\eta}\right)\left(a_{it} + \alpha c_{it} + \beta l_{it}\right) + \left(\frac{\gamma(\eta + 1) - \varphi}{\eta}\right) k_{it} \tag{9}$$

This equation shows that knowledge stock K is likely to contribute to revenue and therefore to measured productivity growth via two channels: directly by increasing the efficiency of production and indirectly by shifting the demand curve for the firm's products outward (note that η is negative so that $-\varphi/\eta$ is positive). It is usual to think of these two channels as process and product innovation.

For full identification of the system implied by equation (9), it would be desirable either to have data on individual firm output prices to allow separate estimation of η and φ or to have some information on the components of K that might be directed toward processes and/or products.[14] At the simplest level, one can gain some idea of the relative importance of the two types of innovation for productivity using the innovation dummy variables available from the various innovation surveys. One implication of the foregoing model is that process innovation will have ambiguous effects on revenue productivity, effects that depend on the firm's market power, whereas the effect of product innovation is likely to be positive.

[14] Mairesse and Jaumandreu (2005) compare productivity estimates using revenue and output deflated at the firm level for France and Spain. They do not find significant differences in the estimates, but they did not include R&D in the equation nor do they have true quality-adjusted price deflators. These two facts may account for the difference between their finding and that of Mairesse and Hall (1996) for the US.

In the studies reviewed here, the estimation of equation (9) is generally performed by regressing a measure of log revenue per employee (r_{it}-l_{it}) on the logs of capital or investment, firm size measured in terms of employment, and various proxies for innovative activity. Industry dummies at the two-digit level are almost always included, to control for things such as omitted inputs (in cases where value added is not available), differences in vertical integration, the omission of capital stocks (in cases where only current investment is available), and the overall level of technological knowledge. Although the model is in terms of the stock of knowledge or innovative capability, the usual proxies for this variable are the current level of innovative activity, measured as a dummy for some innovation during the past three years, or as the share of products sold that were introduced during the past three years. Because the estimation is almost always cross sectional, the fact that a flow of innovation rather than a stock is used will make little difference to the interpretation of the estimates, provided that innovation is persistent within firms. See Peters (2009) for evidence that this is the case.

The empirical evidence

Appendix Tables 1 and 2 summarize the studies which have attempted to estimate a quantitative relationship between firm-level productivity and innovation measures explicitly.[15] 25 papers are listed, of which all but two use data from the Community Innovation Survey (CIS) or its imitators in other countries. Of those using CIS-type data, 18 use some variant of the well-known CDM (Crepon, Duguet, and Mairesse) model for the analysis. One of these papers used both levels and growth rates to measure productivity (Loof and Heshmati 2006), but most have chosen either levels (14 papers) or growth rates (10 papers) exclusively.

Use of the CDM model implies that most of the estimates are essentially cross-sectional ones that ignore issues of the timing of innovation and its contribution to productivity (exceptions are Masso and Vahter 2008, Belderbos et al 2004, Peters 2006). This is a reflection of the nature of the innovation surveys, which ask about innovative behavior during the past three years and contain or are matched to other firm information that is contemporary with the innovation data. The data available are usually not sufficient to construct a time series (panel) for the firms involved since the samples are redrawn for each survey and there is little overlap.[16] Thus the analysis usually relates productivity in

[15] The table ignores the large literature which studies R&D and productivity; see Hall, Mairesse, and Mohnen 2010 for a recent survey of this topic.

[16] For example, Criscuolo and Haskell (2003) report that there are 1596 manufacturing firms in their CIS2 sample and 4567 in their CIS3 sample, but only 509 appear in both surveys. Hall, Lotti, and Mairesse (2008) have 9,462 firms in their sample drawn from three MCC surveys, but only 608 of these firms appear in all three surveys.

one period to innovation in the same period or slightly before that period but does not trace out any dynamic response. It is noteworthy that the results for the papers that do use lagged measures of innovation are not notably different from those using contemporary measures, reinforcing the cross-sectional and long run nature of these results.

The CDM model has been described by many others in detail (see the references in appendix Tables 1 and 2) and I will only summarize it here. It generally consists of three sets of relationships, the first two of which can involve more than one equation. The first set of equations describes whether a firm undertakes R&D and if so, how much, as a function of firm and industry characteristics. The second set describes the various types of innovation outcomes as a function of R&D intensity and other firm/industry characteristics. In many cases, the R&D variable in the innovation equations is computed as the expected R&D intensity given the firm's characteristics. This procedure is grounded on the idea that many firms do informal R&D but do not report their spending separately to the statistical agency performing the survey. In a sense, the model fills in their R&D values with what might have been expected given their size, industry, nature of competition, etc. Looked at another way, including the fitted value of R&D intensity for firms that actually report R&D is a form of instrumental variable estimation of the innovation equations, which helps to correct for the simultaneity that might be present due to the fact that innovation is measured over the past three years, whereas frequently R&D is a current year measure.

The innovation equations in the CDM model can be probit equations for the probability of product, process, or organizational innovation or they can also include an equation for the share of innovative sales (typically the sales share of products introduced during the past three years). In the latter case, the variable is sometimes transformed using logit transform which allows for infinite rather than finite support. That is, if z is the share, ranging from 0 to 1, the logit transform $log(z/(1-z)) \in (-\infty, +\infty)$ is used.[17] Following the logic used above, the predicted innovation probabilities or shares are then included in a productivity equation. The resulting estimates give the contribution of expected innovation conditional on R&D and other firm characteristics to productivity.

Tables 2a (levels, using innovative sales share), 2b (levels, using the product innovation dummy), and 3 (growth rates) summarize the results of estimating the productivity-innovation relationship from the papers listed in the appendix tables. I discuss each of these tables in turn. It should be noted that although I am treating the estimates as comparable, the precise regressions used in any particular paper will differ from those in

[17] The alert reader will note that this expression is undefined for $z=0$ and $z=1$. Normally this problem is solved by setting $z=0.01$ and $z=0.99$ respectively.

other papers, as will the data construction itself. In addition, most researchers have included innovation variables that are predicted values from earlier regressions, as in the CDM model, while a few have included the actual innovation variables from the survey.

In spite of these variations, the results for the elasticity of output with respect to the innovative sales share (shown in Table 2a) are reasonably consistent across countries and time periods. The highest elasticities (0.23-0.29) are for knowledge-intensive or high technology sectors. Most of the elasticities for Western Europe lie between 0.09 and 0.13, and less-developed countries, the service sector, and the low technology sectors have elasticities less than 0.09, with the exception of the insignificant estimate for Chilean data. Thus we can conclude that innovative sales are associated with revenue productivity, and that the association is stronger for higher technology sectors. For a typical Western European manufacturing firm, doubling the share of innovative sales will increase revenue productivity by about 11 per cent.

Table 2b presents the results of the productivity regression that uses a 0/1 measure of product innovation instead of the innovative sales share. For reasons mentioned earlier, this measure will vary by size of firm purely for measurement reasons and should be considered a much weaker proxy for innovative output. We do see that the results are more variable, although still positive for the most part. For manufacturing sectors in Western Europe, typical values are around 0.05-0.10, implying that product innovating firms have an average productivity that is about 8 per cent higher than non-innovators, but there is a wide dispersion.

The results for process innovation in both Tables 2a and 2b are even more variable, with some negative, some zero, and some positive. Note that the few positive estimates in Table 2a are for the two cases where the authors included this variable alone in the productivity regression, without the innovative sales variable (Mairesse *et al.* 2005 for France and Siedschlag *et al.* 2010 for Ireland). The other positive estimates occur when product innovation is measured by a dummy rather than by the share of innovative sales, which suggests that they are partly due to the measurement error implicit in using a dummy to proxy for innovation. That is, we know from many of the surveys that process and product innovation go together. Therefore if we have a weak measure of product innovation, we might expect that the process innovation dummy would pick up more of the overall innovative activity. Recalling the discussion of equation (9), one could argue that the estimates in Table 2a, which are mostly negative for process innovation and positive for product innovation, suggest that firms are operating in the inelastic portion of their demand curves and that revenue productivity is enhanced mainly by the introduction of new and improved products, and not by efficiency improvements in the production process.[18]

Table 3 presents results for a productivity regression where the left hand side is productivity growth, rather than its level. This relationship is not precisely the growth rate version of the regressions that lie behind Table 2, since it relates growth to the level of innovative activity, not to its growth rate. In general, the results are similar to but slightly lower than the level version of the equation, with an innovative sales elasticity focused on the range 0.04-0.08, and a product innovation dummy of about 0.02. As before, process innovation is negative when included with product innovation in the equation, although positive on its own. It is noteworthy that the only study with a true estimate of the cost savings due to process innovation rather than a dummy (Peters 2006) yields a large and marginally significant elasticity of 0.14, implying that if we had better measures of process innovation, we might be able to improve the measure of its impact considerably.

From this summary of the empirical relationship between the various innovation measures and firm-level revenue productivity we can conclude the following: first, there is a positive relationship, albeit somewhat noisy, between innovation in firms and their productivity both the level and its growth. Second, the positive relationship is primarily due to product innovation. The impact of process innovation is more variable, and often negative. This can be interpreted in one of two ways: the typical firm enjoys some market power and operates in the inelastic portion of its demand curve so that revenue productivity falls when it becomes more efficient. Alternatively, it is possible that there is so much measurement error in the innovation variables that only one of the two is positive and significant when entered in the productivity equation. Without instruments that are better targeted to predicting the two different kinds of innovation, this possibility cannot be ruled out.

Conclusions

The foregoing survey of empirical evidence on the relationship between innovation and productivity finds an economically significant impact of product innovation on revenue productivity and a somewhat more ambiguous impact of process innovation. As I have argued, the latter result is primarily due to the fact that we are not able to measure the real quantity effect of process innovation, which is the relevant quantity for social welfare. We can only measure the real revenue effect, which combines the impact of innovation on both quantity and price. So overall we can conclude that in spite of the fact that innovative

[18] The results surveyed here do not generally include the effects of organizational innovation, which has been shown to be associated with revenue productivity improvement, especially when accompanied by IT investment. However, in many cases the data available on organizational innovation (a simple dummy variable) do not allow researchers to include this variable along with the other innovation variables in productivity regressions, due to the collinearity of the various innovation variables previously referred to.

activity is not very well measured in many cases, it does generally increase an individual firm's ability to derive revenue from its inputs.

Of course, this conclusion leads to new questions. What are the factors in the firm's environment that encourage such innovative activity? And how is aggregate productivity influenced by the innovative activities of individual firms? Although it is beyond the scope of this paper to answer these questions, some promising avenues to explore have been suggested recently in the literature. Taking the second question first, the approach of Foster, Haltiwanger, and Syverson (2008), although intensive in its data requirements, has yielded interesting insights on the relative importance of productivity growth in existing firms and net entry in aggregate productivity growth. In addition these authors perform a detailed analysis of the differences between revenue productivity growth and "physical" productivity growth, making the same distinction between efficiency and demand effects that I have made in this survey. They find that the use of revenue productivity will tend to understate the contribution of entrants to productivity growth, and that demand variation is a more important determinant of firm survival than efficiency in production.

A very interesting line of work would be to understand the extent to which innovative activity on the part of entrants and the existing firms is behind the results in Foster *et al.* (2008). That is, the paper provides evidence on the composition of aggregate productivity growth but not on its sources. Aghion *et al.* 2009 find that foreign firm entry in technologically advanced UK sectors spurs both innovation (measured as patents) and productivity growth, whereas entry by such firms in lagging sectors reduces innovation and productivity growth by domestic firms in those sectors, arguing that this is due to the fact that firms are discouraged by the cost of catching up. On the other hand, Gorodnichenko *et al.* 2010, using data from emerging market countries in Eastern Europe and the former Soviet Union, find a robust relationship between foreign competition (self-reported by the firms) and innovation in all sectors, including the service sector. Thus we have evidence that at least some kinds of entry encourage innovative activity, although relatively little that traces the path from entry to innovation and then to productivity.

As to the regulatory and financial environment that encourages innovation on the part of firms, following important efforts led by the World Bank to collect data on entry regulation, the rule of law, and other country characteristics, a substantial cross country growth literature has developed that relates these characteristics to entry (Djankov *et al.* (2002); Aidis *et al.* 2009; Ciccone and Papaioannou 2006), investment (Alesina *et al.* 2003), productivity (Cole *et al.* 2005), and firm size and growth (Fisman and Sarria-Allende 2004; Klapper *et al.* 2006). Briefly summarized, stronger entry regulation and/or higher entry costs are associated with fewer new firms, greater existing firm size and growth, lower

TFP, less investment, and higher profits.[19] Most of the studies cited have made a serious attempt to find instruments or controls which allow them to argue that this relationship is causal. Thus far none of these studies explicitly looks at the impact on innovative activity and its relationship with productivity, although one can argue that the entry of new firms is a form of innovation. To get a full picture of the macro-economy that incorporates firm entry and exit, innovation, and the resulting productivity growth, a picture that would allow one to clearly understand the use of various policy levers, is a goal not yet achieved in the literature.

One avenue that looks promising is the work of Bartelsman, Haltiwanger, and Scarpetta (2009), who extended Foster *et al.* (2008) to look at the allocative efficiency of entry and exit by firms to data on firms in the US and seven European countries. They develop a relative diagnostic measure of inefficient allocation of resources across firms based on the covariance of firm size and productivity within industry. The idea of this measure is that economies that are subject to inefficient regulation that prevents firms from growing or shrinking to their optimal size will display a lower correlation between firm size and productivity, since more productive firms will not be able to grow and displace less productive firms. They show that this measure changed in the way one would expect in three East European countries between the early 1990s and the 2000s. However, in spite of its promise for analyzing the sources of aggregate productivity growth, this kind of work has formidable data requirements. It also does not yet incorporate any measure of innovation as a causal measure, but it seems that extending this approach might be useful for exploring the simultaneous relationship between innovation, regulation, and productivity.

[19] See Djankov (2009) for a recent survey of this literature.

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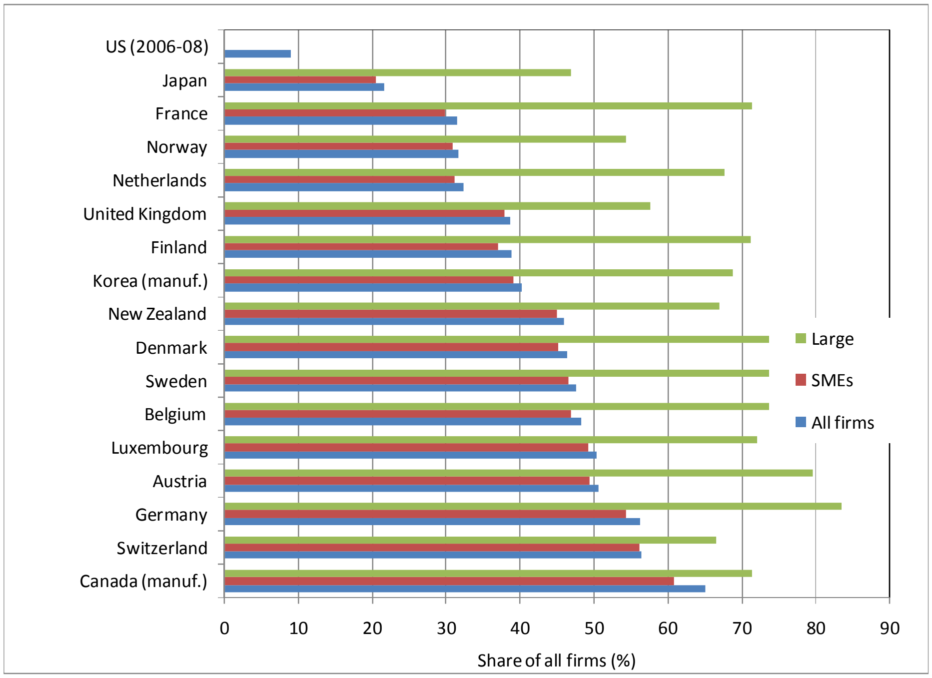
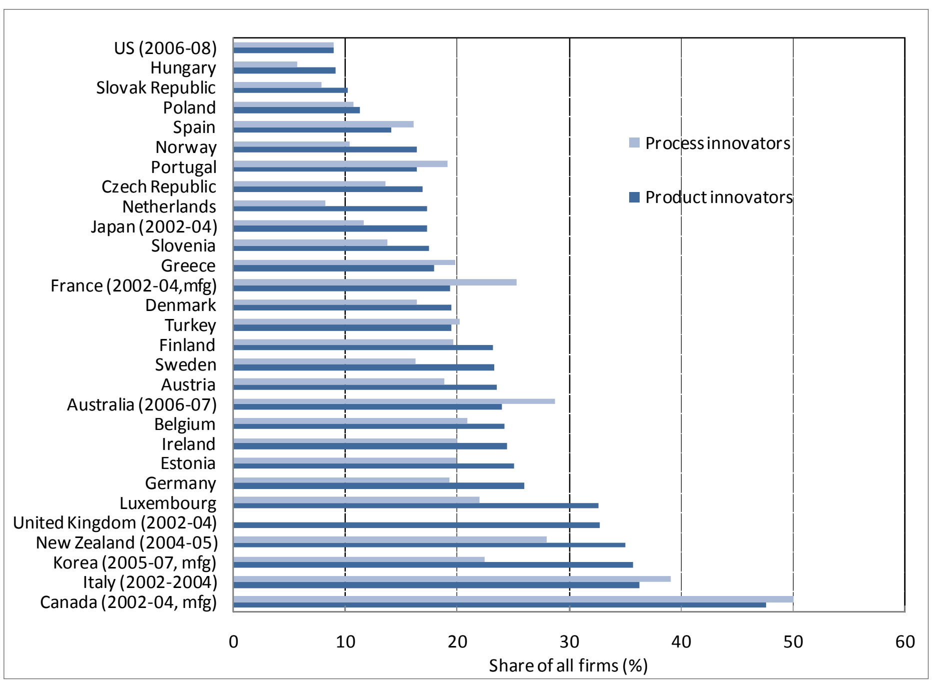
Figure 1: Innovating firms by size, as a share of all firms, 2004-06



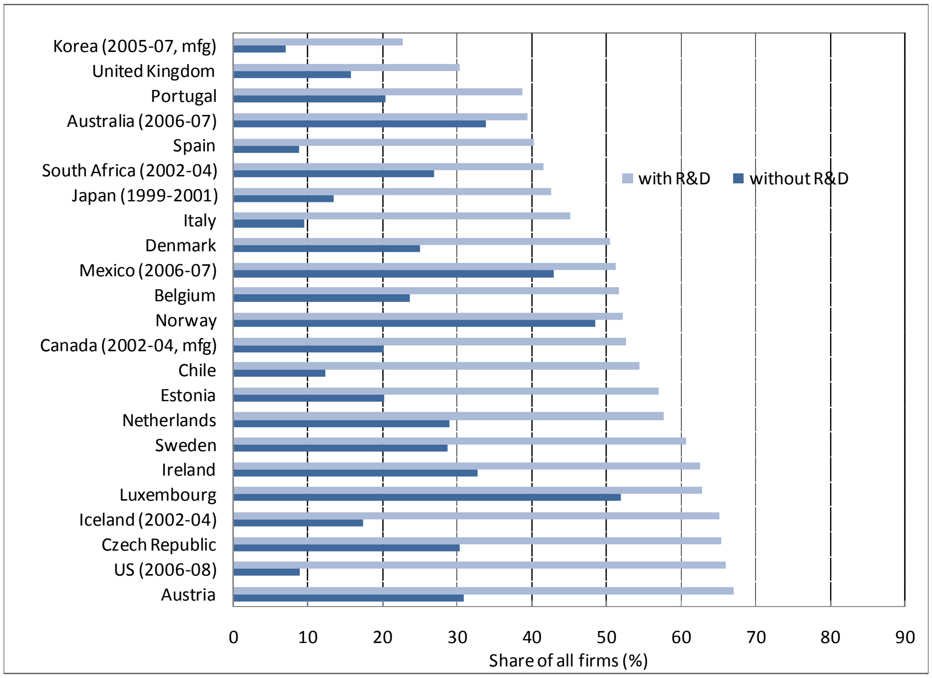
Source: Eurostat, CIS-2006, May 2009; NSF InfoBrief 11-300, October 2010; OECD.

Figure 2: Innovating firms by type of innovation, as a share of all firms, 2004-06



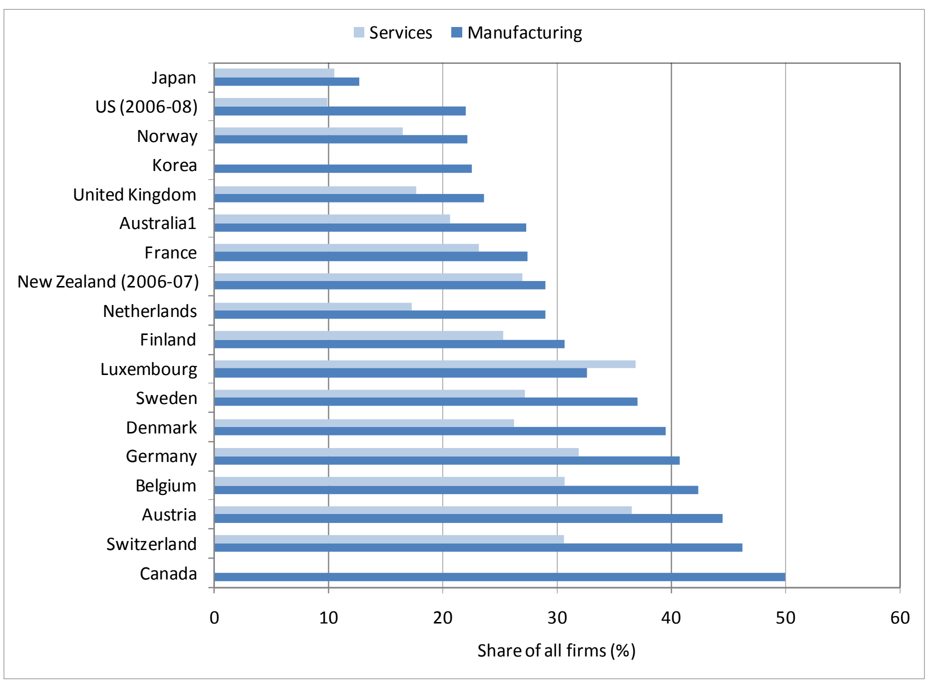
Source: Eurostat, CIS-2006, May 2009; NSF InfoBrief 11-300, October 2010.

Figure 3: In-house process innovators, as a share of all firms, 2004-06



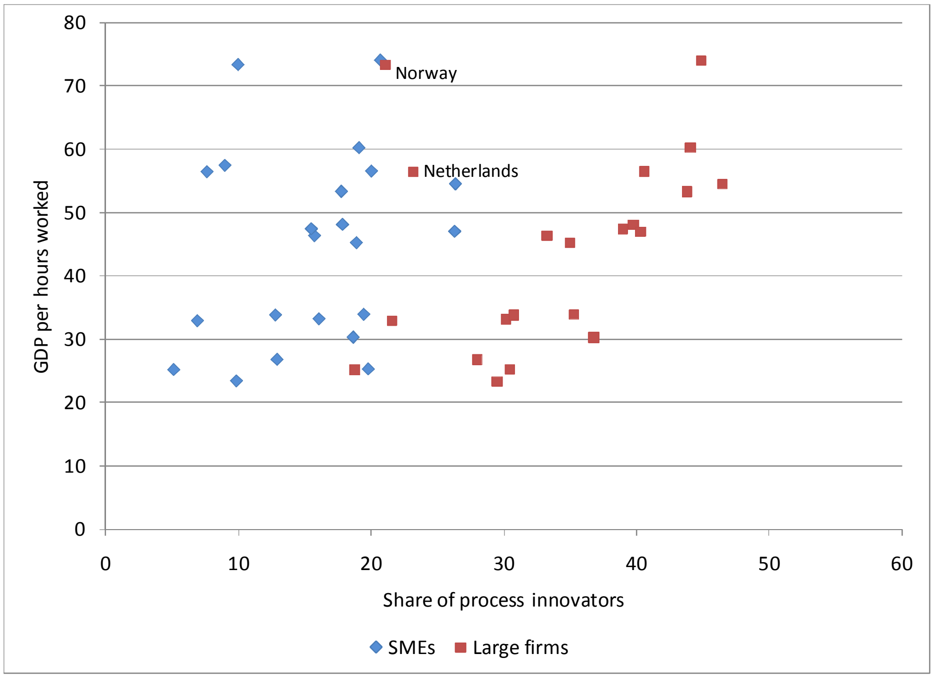
Source: Eurostat, CIS-2006, May 2009; NSF InfoBrief 11-300, October 2010; OECD.

Figure 4: In-house product innovators by sector, as a share of all firms, 2004-06



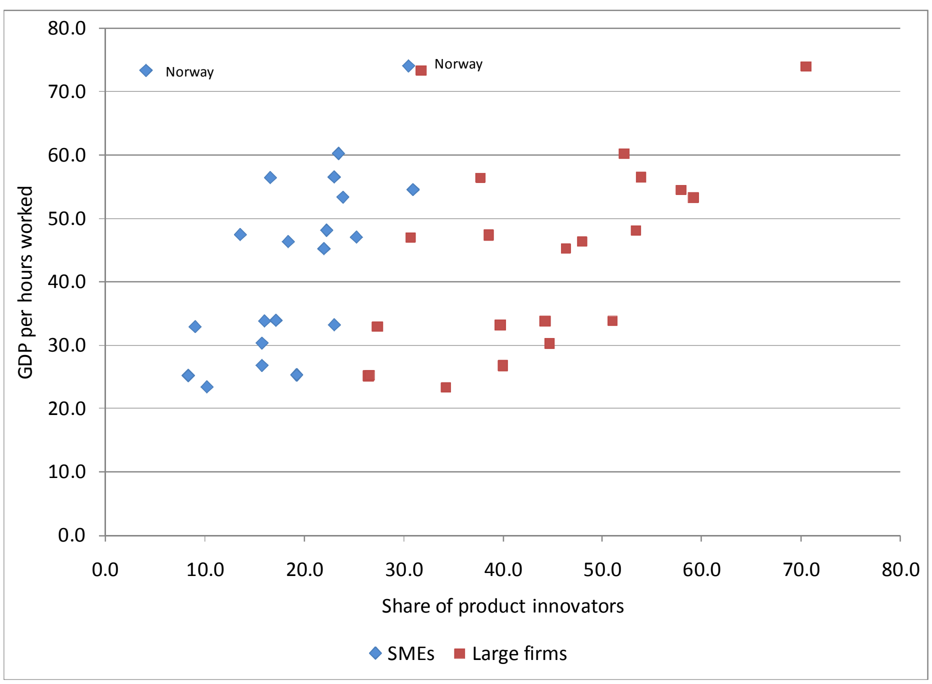
Source: Eurostat, CIS-2006, May 2009; NSF InfoBrief 11-300, October 2010.

Figure 5: Labor productivity levels and process innovation, by country



Source: OECD.stat and data from Figure 1.

Figure 6: Labor productivity levels and product innovation, by country



Source: OECD.stat and data from Figure 2.

Table 1: Manufacturing sector innovations by significance

	Number		*Share*	
	Large firms	*Small firms*	*Large firms*	*Small firms*
Establishes whole new categories	0	0	0.00%	0.00%
First of its type on the market in existing categories	50	30	1.76%	1.43%
A significant improvement on existing technology	360	216	12.70%	10.27%
Modest improvement designed to update existing products	2424	1858	85.53%	88.31%
Total	2834	2104		

Source: Acs and Audretsch (1990), Table 2.3

Table 2a: Results for the productivity-innovation relationship in TFP levels
(product innovation measured as innovative sales share)

Sample	*Time period*	*Elasticity with respect to innov sales share*	*Process innovation dummy*
Chilean mfg sector	1995-1998	0.18 (0.11)*	
Chinese R&D-doing mfg sector	1995-1999	0.035 (0.002)***	
Dutch mfg sector	1994-1996	0.13 (0.03)***	-1.3 (0.5)***
Finnish mfg sector	1994-1996	0.09 (0.06)	-0.03 (0.06)
French mfg sector	1986-1990	0.07 (0.02)***	
French Hi-tech mfg #	1998-2000	0.23 (0.15)*	0.06 (0.02)***
French Low-tech mfg #	1998-2000	0.05 (0.02)***	0.10 (0.04)***
German K-intensive mfg sector	1998-2000	0.27 (0.10)***	-0.14 (0.07)**
Irish firms #	2004-2008	0.11 (0.02)***	0.33 (0.08)***
Norwegian mfg sector	1995-1997	0.26 (0.06)***	0.01 (0.04)
Swedish K-intensive mfg sector	1998-2000	0.29 (0.08)***	-0.03 (0.12)
Swedish mfg sector	1994-1996	0.15 (0.04)***	-0.15 (0.04)***
Swedish mfg sector	1996-1998	0.12 (0.04)***	-0.07 (0.03)***
Swedish service sector	1996-1998	0.09 (0.05)*	-0.07 (0.05)

Source: author's summary from Appendix Table 1.

Innovative sales share and process innovation included separately in the production function.

Table 2b: Results for the productivity-innovation relationship in TFP levels (product innovation measured as a dummy)

Sample	*Time period*	*Product innovation dummy*	*Process innovation dummy*
Argentinian mfg sector	1998-2000	-0.22 (0.15)	
Brazilian mfg sector	1998-2000	0.22 (0.04***	
Estonian mfg sector	1998-2000	0.17 (0.08)**	-0.03 (0.09)
Estonian mfg sector	2002-2004	0.03 (0.04)	0.18 (0.05)***
French mfg sector	1998-2000	0.08 (0.03)**	
French mfg sector	1998-2000	0.06 (0.02)***	0.07 (0.03)**
French mfg sector	1998-2000	0.05 (0.09)	0.41 (0.12)***
French mfg sector	2002-2004	-0.08 (0.13)	0.45 (0.16)***
French service sector	2002-2004	0.27 (0.52)	0.27 (0.45)
German mfg sector	1998-2000	-0.05 (0.03)	0.02 (0.05)
Irish firms #	2004-2008	0.45 (0.08)***	0.33 (0.08)***
Italian mfg sector	1995-2003	0.69 (0.15)***	-0.43 (0.13)***
Italian mfg sector SMEs	1995-2003	0.60 (0.09)***	0.19 (0.27)
Mexican mfg sector	1998-2000	0.31 (0.09)**	
Spanish mfg sector	2002-2004	0.16 (0.05)***	
Spanish mfg sector	1998-2000	0.18 (0.03)***	-0.04 (0.04)
Swiss mfg sector	1998-2000	0.06 (0.02)***	
UK mfg sector	1998-2000	0.06 (0.02)***	0.03 (0.04)

Source: author's summary from Appendix Table 1.

Table 3: Results for the productivity-innovation relationship in TFP growth rates

Sample	*Time period*	*Elasticity wrt Innov sales share*	*Product innovation dummy*	*Process innovation dummy*
Argentinian mfg sector	1992-2001		0.09 (0.08)	0.18 (0.08)**
Dutch mfg sector	1994-1998	0.009 (0.001)***		-1.2 (0.7)*
Dutch mfg sector	1996-1998	0.0002*** #		
French mfg sector	1986-1990		0.022 (0.004)***	
German mfg sector	2000-2003	0.04 (0.02)**		0.14 (0.08)* @
Italian mfg sector	1992-1997		0.12 (0.09)	0.04 (0.12)
Spanish mfg sector	1990-1998		0.015 (0.004)***	
Swedish mfg sector	1996-1998	0.07 (0.03)**		
Swedish service sector	1996-1998	0.08 (0.03)***		
UK mfg sector	1994-1996	-0.02 (0.02)		0.02 (0.01)*
UK mfg sector	1998-2000	0.07 (0.03)**		-0.04 (0.02)**

Source: author's summary from Appendix Table 1.

elasticity with respect to innovation expenditure per sales.

@ elasticity with respect to cost reduction per employee.

Appendix Table 1: Empirical studies of the productivity-innovation relationship using productivity levels

Authors (year)	*Country*	*Observations*	*Method**	*Output measure*	*Innov measure*	*Estimated impact of innovation*	*Comments*
Benavente (2006)	Chile	1995-98 438 mfg plants	CDM model: ALS	Log VA per emp	Log innov sales share	0.18 (0.11)*	SR prod not related to innovation or R&D, but related to engineers & admin (higher salaries); innovation due to capital, not in productivity
Crepon, Duguet, & Mairesse (1998)	France	SESSI 1986-90 ~5000 innov mfg firms	CDM model: ALS	Log VA per emp	Log innov sales share	0.065 (0.015)***	Positive impact of innovation sales share on productivity, as well as positive association of productivity with human capital in labor force
Griffith, Huergo, Harrison, & Mairesse (2006)	France, Germany, Spain, UK	CIS3 1998-2000 FR 3625 mfg firms DE 1123 mfg firms ES 3588 mfgfirms UK 1904 mfg firms	CDM model: sequential with IV	Log sales per emp	Product and process dummies	FR: 0.07 (0.03)** proc 0.06 (0.02)*** prod DE: 0.02 (0.05) proc -0.05 (0.03) prod ES: -0.04 (0.04) proc 0.18 (0.03)*** prod UK: 0.03 (0.04) proc 0.06 (0.02)*** prod	Estimation in 3 steps, no bivariate probit. Process innovation adds 0.07 in France, nothing in other countries; Product innovation positive except in Germany.
Hall, Lotti, & Mairesse (2011)	Italy	MCC 1992-2003 14294 mfg firms	CDM with 4 types of innovation: FIML for selection; quadrivariate probit; IV	Log sales per emp	4 innov dummies	prod: 0.69 (0.15)*** proc: -0.43 (0.13)***	innovation variables not separately well-identified in productivity equation; process appears to be negative and product positive for TFP.
Janz, Loof, & Peters (2003)	Germany Sweden	CIS3 1998-2000 1000 K-intensive mfg firms	CDM model: sequential with IV	Log sales per emp	Log innov sales per emp, process dummy	DE: 0.27 (0.10)*** prod -0.14 (0.07)** proc SE: 0.29 (0.08)*** prod -0.03 (0.12) proc	Allowed for feedback from productivity to innovation output. Elasticity of productivity wrt innov sales similar in both countries
Jefferson, Bai, et al (2006)	China	1995-99 5500 R&D-doing large/medium sized firms	CDM model: sequential with IV	Log sales per emp	Log innov sales share	0.035 (0.002)***	No correction for innovation selection bias
Loof & Heshmati (2006)	Sweden	CIS3 1996-98 1071 mfg firms 718 service firms 92 utility firms	CDM variation: FIML on selection submodel; 3SLS; sensitivity analysis	Log VA per emp	Log innov sales per emp, process dummy	prod: 0.12 (0.04)*** mfg 0.09 (0.05)** service proc: -0.07 (0.03)*** mfg -0.07 (0.05) service	survey data less reliable than register data; sales not as good as VA in productivity eq
Loof, Heshmati, Asplund, & Naas (2001)	Finland, Norway, Sweden	CIS2 1994-96 (95-97 in Norway) NO: 485 mfg firms FI: 323 mfg firms SE: 407 mfg firms	CDM variation: sequential with 3SLS	Log sales per emp	Log innov sales per emp, process dummy	FI: 0.090 (0.058) prod -0.029 (0.060) proc NO: 0.257 (0.062)*** prod 0.008 (0.044) proc SE: 0.148 (0.044)*** prod -0.148 (0.043)*** proc	Allows for simultaneity btwn innovation & output - feedback in NO but not FI and SE. Elasticity slightly higher for radical innovations.

Mairesse & Robin (2010)	France	CIS3 1998-2000 3500 mfg firms CIS4 2002-2004 5000 mfg firms 3600 service firms	CDM model: FIML for selection eqs; bivariate probit; IV	Log VA per emp	Product and process dummies	mfg 98-00: 0.41 (0.12)*** proc 0.05 (0.09) prod mfg 02-04: 0.45 (0.16)*** proc -0.08 (0.13) prod service: 0.27 (0.45) proc 0.27 (0.52) prod	Estimation is in 3 steps, but also in 2 steps, with innov & labor productivity equations combined. Process innovation enters productivity, but not product. Explores using a single innovation indicator, which works just as well.
Mairesse, Mohnen, & Kremp (2005)	France	CIS3 1998-2000 2200 mfg firms	CDM & variations	Log VA per emp	Logit transform of innov sales share, process dummy, other dummies - all separately	HT: 0.23 (0.15)* 0.07 (0.03)*** radical 0.06 (0.02)*** process LT: 0.05 (0.02)*** -0.08 (0.05)* radical 0.10 (0.04)*** process	TFP using output ; going through innovation does not add much to estimates of return to R&D, after correcting for selectivity and endogeneity; endogeneity correction impt for innov variables
Masso & Vahter (2008)	Estonia	CIS3 1998-2000 1467 mfg firms CIS4 2002-2004 992 mfg firms	CDM variation: sequential with bivariate probit for innov	Log VA per emp	Product and process dummies (org dummies in 2nd period)	prod 98-00: 0.21 (0.08)*** 02-04: 0.00 (0.05) proc 98-00: -0.06 (0.10) 02-04: 0.15 (0.06)***	uses innov expenditure rather than R&D; proc & prod dummies; prod innovation increases productivity in recession; proc innovation in growth period. One and two year lag effects are roughly the same (cross sectional).
Masso & Vahter (2008)	Estonia	CIS3 1998-2000 1467 mfg firms CIS4 2002-2004 992 mfg firms	CDM variation: sequential with bivariate probit for innov	Log sales per emp	Product and process dummies (org dummies in 2nd period)	prod 98-00: 0.17 (0.08)** 02-04: 0.03 (0.04) proc 98-00: -0.03 (0.09) 02-04: 0.18 (0.05)***	uses innov expenditure rather than R&D; proc & prod dummies; prod innovation increases productivity in recession; proc innovation in growth period. One and two year lag effects are roughly the same (cross sectional).
Polder, Van Leeuwen et al (2009)	Nether-lands	CIS 3.5-4.5 2002-2006 ~1200 mfg & service firms	augmented CDM	Log VA per emp	3 innov dummies (proc prod org) in combo	mfg: 1.7 (0.4)*** org alone 1.0 (0.5)** org & proc 0.9 (0.2)*** all serv: 4.3 (0.5)*** org alone 17.1 (2.2)*** org & proc -8.3 (1.3)*** proc & prod 3.9 (0.5)*** all	Org innovation has strongest TFP effects. Process and product, only when combined with org innovation. However, signs of coefficient instability due to correlation of 8 combinations when predicted
Raffo, Lhuillery & Miotti (2008)	France, Spain, Switzerland, Argentina, Brazil, Mexico	CIS3 1998-2001 mfg AR 1308 firms BR 9452 firms MX 1515 firms FR 4618 firms CH 925 firms ES 3559 firms (2002-04)	CDM model: sequential with IV	Log sales per emp	product & organizational innov dummies	AR: -0.22 (0.15) BR: 0.22 (0.04)*** MX: 0.31 (0.09)*** FR: 0.08 (0.03)** ES: 0.16 (0.05)*** CH: 0.10 (0.06)*	Interaction of innovative activities with national systems weaker in developing countries. Foreign and domestic subs are uniformly more productive, but do more R&D only in France and Brazil.

van Leeuwen & Klomp (2006)	Nether-lands	CIS2 1994-96 1400 innov firms	CDM variation: 3SLS	Log sales per emp	Process dummy; innov sales share	prod: 0.13 (0.03)*** proc: -1.3 (0.5)***	Includes market share eq; feedback from sales to innovation; revenue function approach better than VA prod function framework (innov sales do not enter VA function in the presence of R&D and markup coefficients).
Siedschlag, Zhang, and Cahill (2010)	Ireland	CIS3 2004-2006 CIS4 2006-2008 723 firms (balanced panel)	CDM variation: sequential with IV	Log sales per emp	Product, process, and organizational dummies, innov sales share - all separately	innov sales: 0.11 (0.02)*** prod: 0.45 (0.08)*** proc: 0.33 (0.08)***	Uses innovation expenditure instead of R&D spending; includes FDI and foreign ownership characteristics.

* CDM = Crepon, Duguet, Mairesse model described in text. ALS = asymptotic least squares on multi-equation model. 3SLS = three stage least squares. FIML = full information maximum liklihood on multivariate normal model. OLS = ordinary least squares. IV = instrumental variable estimation.

Source: Author's collection, supplemented by Tabla A.1 (Chudnovsky et al 2006), Table 4.1 (Peters 2006).

Appendix Table 2: Empirical studies of the productivity-innovation relationship using productivity growth

Authors (year)	*Country*	*Observations*	*Method*	*Output measure*	*Innov measure*	*Estimated effect*	*Result*
Belderbos, Carree, & Lokshin (2004)	Nether-lands	CIS2, CIS3 1996-1998 2056 mfg firms	Productivity eq only	Log VA per emp	Innov exp per sales	elasticity ~ 0.0002 (0.00003)***	productivity and innov sales share on lagged innovative activity and various kinds of cooperation
Chudnovsky, Lopez, & Pupato (2006)	Argentina	INDEC-SECYT 1992-1996 INDEC-SECYT 1998-2001 718 mfg firms in a panel	CDM variation: sequential estimation with FE	Log sales per emp	product and process dummies; interactions	prod only: 0.09 (0.08) proc only: 0.18 (0.08)** both: 0.14 (0.06)** any: 0.13 (0.05)***	uses innov expend rather than R&D; fixed effect single eq estimation. Uses logit for prod/proc/both innovation dummies. R&D increases prob of prod innov; Tech acquisition increases prob of both
Criscuolo & Haskel (2003)	UK	CIS2, 3 1994-2000 5000 mfg firms	single eq regression for TFP growth: OLS	TFP growth (not clear if sales or VA)	Process dummy; share of innov sales	proc 94-96: 0.016 (0.009)* proc 98-00: -0.038 (0.019)** prod 94-96: -0.022 (0.017) prod 98-00: 0.065 (0.033)**	Process innovation lead to TFP growth but with substantial lag; novel process innovations negative at first
Duguet (2006)	France	SESSI 1986-90 ~5000 mfg firms	TFP growth reg with latent innov or dummies (GMM)	Log VA per hour	dummies for radical & incremental innovation	0.022 (0.004)*** radical -0.01 (0.01) incremental	only radical innovations affect TFP growth, with a coefficient of 0.02. latent innovation does not enter.
Geroski (1989)	UK	1976-79 79 industries	panel reg (CRS)	Log output per capital	# ind innov (flow) during past 3 yrs	0.025 (0.010)**	distributed lag of innovation counts more important than entry for TFP.
Huergo & Jaumandreu (2004)	Spain	1990-98 2300 mfg firms	semiparametric estimate of TFP	TFP growth	process innov dummy	0.015 (0.004)*** all 0 uncensored (innovators)	Process innovation lead to TFP growth immediately, then declines slowly over time. Primary interest is age distribution of investment returns.
Loof & Heshmati (2006)	Sweden	CIS3 1996-98 ~3000 mfg, service, + utility firms	sensitivity analysis using CDM model	Log VA per emp	Log innov sales per emp	0.07 (0.03)** mfg 0.08 (0.03)*** service	mfg, prod level - 0.12 elasticity with innov sales higher for profits, lower for services mfg, prod growth - elasticity 0.07 wrt innov sales higher for profits; and for services survey data less reliable than register data; sales not as good as VA
Parisi, Schiantarelli, & Sembenelli (2006)	Italy	MCC 1992-1997 465 mfg firms in both surveys	TFP growth regressions: IV	Log sales per emp	Product and process dummies	prod: 0.12 (0.09) proc: 0.04 (0.12)	Process innovations add to prod growth; product innovations do not enter. R&D elasticity is 0.04. R&D enters product innovation but not process.

Peters (2006)	Germany	MIP 2000-2003 522 mfg innov firms	CDM variation: sequential estimation	Log sales per emp	Log innov sales per emp; Log cost reduction per emp	prod: 0.04 (0.02)** proc: 0.14 (0.08)*	Uses survey estimates of cost savings due to procuess innovation as well as innovative sales share; lag between innovation and productivity growth
Sterlacchini (1989)	UK	1954-84 15 mfg inds	cross sections for 6-year periods	TFP growth averaged over 6 years	# ind innov produced; # ind innov used	0.08 (0.04)** inn produced 0.07-0.30 innov used	correlates R&D and SPRU innovations by industy of origin and use - ranking same. Prior to 73, ind of more impt for TFP. After, correlation btwn R&D growth and TFP, probably due to simultaneity. In 80s, relationship btwn R&D/innov & TFP breaks down
van Leeuwen (2002)	Nether-lands	CIS2,3 1994-1998 1929 mfg innov firms 510 mfg innov firms pooled	CDM variation: FIML on submodels for selection	Log sales per emp	share of innov sales; process dummy	prod dyn: 0.006 (0.004)* prod static: 0.009 (0.001)*** proc dyn: -1.2 (0.7)* proc static: -0.20 (0.50)	uses Griliches-Mairesse 1984 to connect revenue to knowledge stock via demand equation; also includes process innovation dummy. Estimation is both static (pooled across periods) and dynamic (second period only)

* CDM = Crepon, Duguet, Mairesse model described in text. ALS = asymptotic least squares on multi-equation model. 3SLS = three stage least squares. FIML = full information maximum liklihood on multivariate normal model. OLS = ordinary least squares. IV = instrumental variable estimation.

Source: Author's collection, supplemented by Tabla A.1 (Chudnovsky et al 2006), Table 4.1 (Peters 2006).