Cash is King: Financing the Innovation-Productivity Link at Firm Level

Cecil Y. Ang[1]
University of Virginia

Abstract

Recent models of firm level innovation have provided more insights into the process than traditional indicators of innovative activities such as R&D. Based on the three-step Crépon, Duguet and Mairesse (CDM) model, empirical studies have incorporated micro data from several national innovation surveys alongside traditional R&D and productivity measures to produce reasonable results. Despite extensive application of the CDM model to describe the innovation-productivity link, the effects of financing variations on the process have not been explored. Using micro-data on Italian firms from 2001-03 (similar to Hall et al), I find that the ability to self-finance has a strong influence on the likelihood of process innovation success, and consequently firm productivity. In addition, committing more labor, and not capital, to formal R&D networks will increase the odds of innovation success and higher productivity, contrary to prevailing thought. Lastly, I find that the effects of debtor-in-possession, management autonomy, education, trade, and customer types on the innovation-productivity link are more mixed for firms at different technology levels.

1 Cecil Ang is a 2005 Singapore Airlines Scholar who graduated in 2009 with a Bachelor of Science in Commerce (Finance) and Economics at McIntire School of Commerce, University of Virginia, USA. He would like to thank Professor Bronwyn Hall of UC Berkeley for her invaluable advice, Fransceca Lotti of Bank of Italy for her help in securing the dataset used in this paper, and Attilio Pasetto of UniCredit Group for his kindness and generosity in granting him access to the survey data. Lastly, he would like to thank Professor Hernan Moscoso Boedo for his patience and guidance as his adviser. Comments are welcome at cecilang@virginia.edu.

I. Introduction

Long run economic productivity has been an area of active research and policy debate for decades since Robert Solow posited that long run equilibrium growth is determined by the Solow Residual more than 50 years ago (Solow, 1956). In a confession of ignorance, Solow conceded that this variable is exogenous to his model and "may have no apparent explanation at all" (Solow, 1994). To Solow, innovation is a black-box event.

Since then, a copious amount of theoretical and empirical studies have attempted to construct an endogenous model of growth centered around innovation and to measure the effects innovation has on productivity at both aggregate and firm levels. Arguably, aggregate innovation as a function of firm activities and models developed at the micro-level will provide us with better insights into the innovation-productivity link. Recent firm-level studies include Lichtenberg and Siegel (1991) on the U.S., Hall and Mairesse (1995) on France, Harhoff (1998) and Bönte (2003) on Germany, Klette and Johansen (1996) on Norway, Janz et al (2004) on Germany and Sweden, Lööf and Heshmati (2002) on Sweden, Lotti and Santarelli (2001) on Italy. These authors find that R&D expenses positively impact productivity, although some have suggested that their impact has declined over time (Klette and Kortum, 2004). However, the existing literature still does not provide a unique answer in terms of both the structure and impact of innovation, largely because extensive assumptions were made to remove uncertainty inherent in the process. These studies adopted an input approach, assuming a production function framework with R&D as an input and productivity as a direct outcome.

This input approach overlooked two key aspects of innovation. First, R&D does not capture all aspects of innovation which can and often do take place through other channels. Indeed, Dyer and Nobeoka (2000) documented that innovation frequently occurred outside former research labs through their study of Toyota's knowledge sharing network. Second, and a follow-up issue, is that the input approach does not sufficiently address the effects of financing on firms' willingness to innovate and the probability of their success. As discussed by Stiglitz and Weiss (1981) and Bester (1987), raising the interest rate can decrease borrowers' level of risk aversion and increase their willingness to engage in riskier projects such as R&D. To avoid this adverse selection problem, the average lender rations credit to borrowers and/or requires higher collaterals, regardless of their willingness to pay higher interest rates, to attract safer borrowers. Therefore, an average borrower's ability to finance profitable projects is reduced, resulting in lower innovation efforts. Although the above two aspects are arguably more salient for smaller firms with fewer assets for collateralization purposes, the fact that the input approach does not capture the complete innovation story will result in an underestimation of innovation's impact on productivity.

To address problems inherent in input models, recent studies adopted an output approach which treats the innovation outcomes of R&D as a subsequent input in a traditional production function. In an influential paper, Crépon, Duguet and Mairesse (1998) proposed and estimated a model (CDM model hereinafter) which decomposed the innovation-productivity relationship into three steps based on firms' logic to conduct innovation. In the first step, firms decide whether or not to employ innovative inputs and the amount of resources to invest. Conditional on firms' decisions in the first step, the second step replicates a knowledge production function (Pakes et al. 1984) in which earlier inputs produce innovation outputs such as a new product or production process. Finally, an innovation augmented Cobb-Douglas production function is used to measure the effect of innovation outputs on productivity. The CDM model is designed to utilize new micro-data from national innovation surveys conducted according to guidelines from the Oslo Manual (OECD, 2005). These surveys are gaining popularity in the U.K., European Union and Canada, giving scholars insights into the various impacts of innovation on firm-level productivity. Recent work using this approach includes Griffith et al (2006) on four European countries.

In particular, Parisi et al (2006) and Hall et al (2008) applied modified versions of the CDM model to a sample of Italian firms based on the Mediocredito-Capitalia survey data from 1995 to 2003. Although Parisi et al focused more on large and medium firms and Hall et al dealt with small and medium enterprises (SMEs), both studies show that process innovation has a large and significant impact on productivity. In addition, R&D is more positively related to product innovation, and capital expenditure appears to matter more for process innovation. Overall, Hall et al finds that firm size is negatively related to R&D intensity but positively related to the likelihood of success in product and process innovation, contrary to conventional wisdom. These two studies are significant because (i) panel data is introduced and (ii) juxtaposing their results helps us understand the impact variation in firm size has on innovation and productivity.

Despite reasonable results, empirical studies that explored the innovation-productivity link using the output approach have ignored financing effects. Therefore, this paper aims to bridge the gap by expanding the CDM model to allow for variation in financing sources in each step within the innovation-productivity link. The remainder of this paper is organized as follows: Section II summarizes previous theoretical and empirical studies on financing the innovation-productivity link; Section III describes the data and econometric model used, and Section IV concludes with a discussion of results.

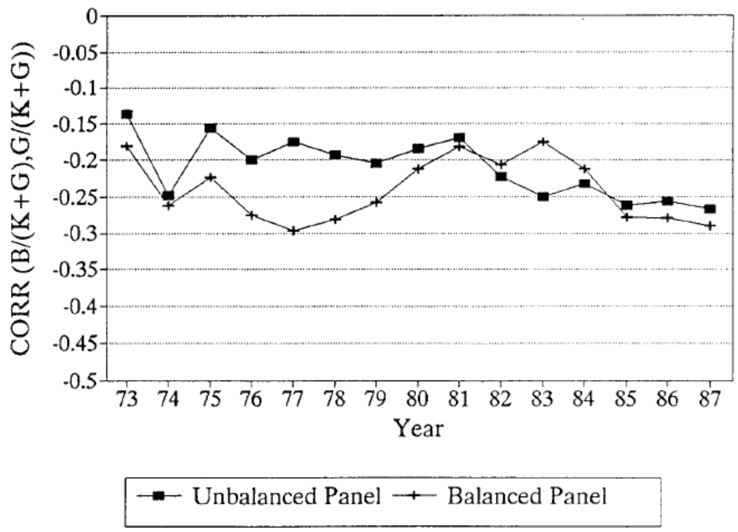
II. Previous Studies of Financing Effects on Firm Level Innovation and Productivity

Broadly speaking, a firm has two ways of financing their production and innovation activities. One, it can raise debt and/or equity from external parties such as public or private financiers. Two, a firm can tap its internal cash reserves as a quicker and less costly alternative. Input models such as Romer (1990) and Grossman and Helpman (1991 & 1994) proposed an innovation structure in which R&D is funded by external markets under perfect information: i.e. lenders are willing to provide credit when innovative outcomes are known. It is therefore not surprising that relaxing the assumption of perfect information will frustrate these models, especially since innovative projects yield highly uncertain outcomes with dubious benefits.

Due to asymmetric information, the average lender will practice credit rationing to borrowers with insufficient tangible collaterals. As noted by Stiglitz and Weiss (1981) and Bester (1987), credit rationing allows lenders to address adverse selection problems created by higher interest rates and to attract safer loan applicants looking to finance projects with more certain outcomes. Therefore, it is conceivably difficult for firms to tap external debt as a source of funding for R&D expenditure. Hall (1992) provides affirming evidence by exploring the relationship between debt and R&D, and finds that the R&D intensity of a firm, or the ratio of the economic value of a manufacturing firm's stock of R&D assets (G) to net physical and knowledge capital (K+G), is negatively correlated with the ratio of debt it currently owes (B) to net physical and knowledge capital (Figure 1)[2] . This means that an increase in debt to net assets will serve to increase physical and not knowledge assets.

2 Figure 1, Hall 1992.

Figure 1: Correlation of Leverage and R&D Capital

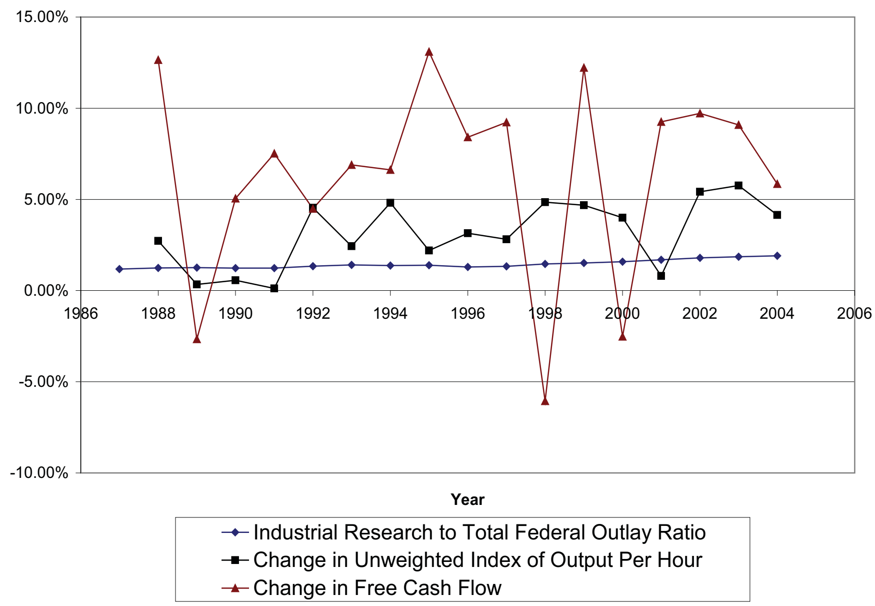


Nevertheless, firms can still tap external equity and internal cash as potential funding sources for R&D. Indeed, Brown et al (2009) finds that the R&D activities in young, publicly traded U.S. high-tech firms are almost entirely funded by issuing equity and tapping cash reserves. However, there appears to be no direct evidence that variation in the supply of such financing sources has effects on aggregate R&D. In addition, Hall (2002) surveyed existing literature on the financing of R&D and concluded that there is sufficient evidence of a market failure in financing R&D since R&D intensive firms face a higher cost of capital than firms in other industries. Even the presence of a venture capital industry is limited in filling this funding gap because of (i) a lack of support for small start-ups in some fields and (ii) the requirement of a thick market in small and new firm stocks (such as NASDAQ or EASDAQ) to facilitate exit strategies. Therefore, Hall's results provide preliminary support that external financing is mainly used to fund capital expenditure and not R&D because of asymmetric information and moral hazard problems associated with the latter. It is noteworthy that Brown et al and the literature that Hall surveyed adopted the input approach as opposed to the output approach based on the CDM model. Because the former approach potentially underestimates the impact innovation has on productivity, we can therefore say very little about the true effects financing has on the innovation-productivity link up to this point.

The last external source of financing for firm-level innovation is public funding—either direct (tax-funded) or indirect (public contribution). Ang

(2009) finds that consistent, though small, growth in federal industrial research expenditures (consisting of research spending on General Science, Energy, Agriculture, Labor, and Health) can hardly explain the variations in average annual productivity growth across 138 NAICS industries, which share a closer relationship with the free cash flow of profit-seeking US firms (Figure 2)[3]. Noticing a one-year lag between changes in internally-generated cash flow and productivity growth, Ang proposed that innovation, and hence productivity, is largely financed by internal cash. However, a lack of data robustness in this theoretical paper dilutes the strength of its assertion.

Figure 2: Industrial Research to Federal Outlays Ratio and Productivity in NAICS industries



In contrast, Hall et al (2008) used data from Italian small and medium enterprises (the same source is used in this paper) and found that the reception of subsidies has a substantial impact on innovation efforts or, at least, the likelihood of reporting a positive R&D. However, the impact of internal funding was not analyzed there, leaving a gap that this paper aims to fill.

3 U.S. Office of Management and Budget, Budget of the United States Government, Historical Tables, annual; U.S. Bureau of Labor Statistics; U.S. Bureau of Economic Analysis.

To address the impact of financing on the innovation-productivity link, I believe a good empirical paper should strive to answer the following questions:

(1) Do firms finance R&D by tapping external or internal financing sources?

(2) Does having access to various financing sources improve the level of innovative effort? In other words, are subsidies and a firm's capital structure (i.e. debt to equity ratio) relevant in its innovation decision-making process?

(3) Does variation in financing affect the odds of success for different types of innovation?

(4) Recent studies applying the CDM model to micro-data have shown that capital expenditure has a large and significant impact on process innovation, which affects productivity more than product innovation does. Does this mean that access to external financing has a greater impact on productivity since debt and equity are mostly used to finance capital expenditure according to prior studies?

III. Data and Methodology

To answer the four topic-framing questions raised above, I constructed a modified CDM model using micro-data from the 9th wave of the Mediocredito-Capitalia Survey (MCS) on Italian manufacturing firms conducted by UniCredit Group (an Italian commercial bank). This survey's questionnaire was constructed according to guidelines from the Oslo Manual (OECD, 2005) and covered three consecutive years prior to its creation (2001-2003). The MCS consists of firms with more than 500 employees, and smaller firms were selected using a sampling design characterized by geographical area, industry, and firm size. It is noteworthy that this survey is exactly identical to the one used by Parisi et al and Hall et al.

Following the methodology of Hall et al for the benefit of direct comparison, I first excluded firms with missing values or with extreme observations for tested variables[4]. The sample was divided based on the following categories: small and large firms, high-tech and low-tech firms, firm age, whether or not a firm declares a formal innovation structure, whether or not a firm is single or part of an umbrella of companies, etc[5]. For large firms, a lower threshold of

4 Requirements: (i) sales per employee between 2000 and 10 million local dollars, (ii) growth rates of employment and sales of old and new products between -150 percent and 150 percent, and (iii) R&D employment share less than 100 percent. R&D to sales ratio was used where R&D employment share information was missing. In addition, I restricted the sample by excluding a few observations with zero or missing investment. For further details, see Hall, Lotti and Mairesse (2008).

5 See Appendix A for definitions of variables that describe firm characteristics.

250 employees was applied, in line with the definition of the European Commission. This yielded an unbalanced panel of 3,452 firms and a balanced panel of 700 firms. Table 1 contains some descriptive statistics for both panels which include firm size, R&D investment, innovation type and success, competition, and changes to corporate structures due to acquisitions or divestment.

Firm size distributions for high- and low-tech firms are skewed to the right for both panels and high-tech firms tend to be larger. On average, 45% of firms in the unbalanced panel invest in R&D as compared to 100% of firms in the balanced panel. With regards to the types of innovation, about 24% of firms in the unbalanced panel reported success with both product and process innovations and around 18% of them developed new processes only. In contrast, about 44% of firms in the balanced panel reported success with both product and process innovations and around 17% of them developed new processes only, slightly lower than the unbalanced panel. Also, firms from the unbalanced panel are less successful since 59% reported process and/or product innovation as compared to 85.43% of firms in the balanced panel.

Concerning competition, 99% of firms in the unbalanced panel exported products during the survey period as compared to 89% of firms in the balanced panel. However, only 13% and 11% of firms established distribution networks abroad for the unbalanced and balanced panel, respectively. Firms appear to rely on third party distribution within Italy as well, since 19% and 14% of firms maintain national distribution networks for the unbalanced and balanced panel, respectively. For the unbalanced panel, 12% of firms made acquisitions and 4% made divestments during the survey period while none of the firms in the balanced panel had similar activities.

Table 2 shows indicators of firm control, management autonomy, financing and capital structures[6]. Regarding firm control and management autonomy, one third of firms from the unbalanced panel and one quarter of firms from the balanced panel are majority owned by banks, which is surprising and suggests debtor-in-possession scenarios for these firms. About 80% of firms have full autonomy in various aspects of management, such as administration, financing, marketing and R&D, while most firms are managed by executives from outside of the owner family. Regarding financing sources and capital structure, all firms from my sample have access to bank credit and almost all have access to both public and private equity funding. Perhaps the most surprising findings lie in how R&D and capital expenditure (purchasing of plant, property and equipment) are financed. About 80% of R&D expenditure is financed by internal funds, lending preliminary support to Ang's (2009) hypothesis that innovation is financed by firms' cash reserves. On average, capital expendi-

6 See Appendix B for financing variable definitions

ture is about 45% financed by internal funds, 16% financed by debt (short term and long term) and 15% financed through leasing. Apparently, internal funding is a vital source of financing for various firm activities within the sample.

As discussed earlier, the relationship between financing and the innovation-productivity link will be explored using the CDM model. This model is well-designed for innovation survey data and follows the logic of an average firm's decision to invest in innovation and the subsequent outcomes. The CDM model works in three steps. In the first step, I will model the process that leads a firm to decide whether to invest in innovative projects or not, and given its propensity to invest, how much to spend on innovation per employee. To this step I will add independent variables measuring the firm's ability to finance its decisions. In the second step, I will model direct innovation expenditure as an input in a knowledge production function together with other firm characteristics which also include variables used to measure financing abilities. As output, firms can "produce" process and/or product innovation in this step. In the third and final step, I will model the innovation outputs as independent variables in a Cobb-Douglas production function to measure the impacts financing and innovation have on productivity.

R&D Decision

This first step follows a firm's decision of whether or not to conduct R&D, and given the decision to do so, the firm will choose its R&D intensity (R&D expenditure per employee). This step can be summarized in the following selection model:

$$RD_i = \begin{cases} 1 \; if \; RD_i^* = w_i\alpha + \varepsilon_i > \bar{c} \\ 0 \; if \; RD_i^* = w_i\alpha + \varepsilon_i \leq \bar{c} \end{cases} \tag{1}$$

$$RDInt_i = \begin{cases} RDInt_i^* = Bz_i + e_i \; if \; RD_i = 1 \\ 0 \qquad\qquad\qquad\qquad if \; RD_i^* = 0 \end{cases} \tag{2}$$

RD_i is observable and represented by an indicator function that takes the value 1 if firm *i* declares positive R&Ds; RD_{i*} is a latent indicator variable of value 1 when firm *i* decides to perform R&D if they are above a given threshold $\bar{c}$, w_i is a set of independent variables affecting R&D and ε_i is the error term. $RDInt_i$ is firm *i*'s R&D intensity and $RDInt_{i*}$ is the latent variable accounting for the firm's innovative effort. z_i is a set of determinants of R&D. Assuming that the error terms in the selection model are bivariate normal with mean zero and variance unity, the model can be estimated by maximum likelihood or Heckman selection model (Heckman, 1979).

Before estimating the selection model, I conducted a non-parametric test for the presence of selection bias (see Das et al, 2003 and Hall et al, 2008). First, I estimated a probit model in which the presence of positive R&D is regressed on a set of firm characteristics as shown in Table A1. These include the traditional indicators such as firm size, firm age and their squares, family control over management, as well as dummies[7] for:

(a) Management autonomy (in administration, financing, marketing, R&D)

(b) Banks' ownership of firm (minority vs. majority)

(c) Firms' declaration that they are part of an umbrella of companies (old, large umbrella and its age)

(d) Exporting firms

(e) Customer type (retail/households, business and others)

(f) Main product type and associated manufacturing technology (high-tech vs. low-tech)

(g) Acquisition(s) or divestment(s) made during survey period.

In addition, I added financing indicators (i) cash to asset ratio, (ii) cash to asset ratio lagged one period, and (iii) firm's debt to equity ratio to capture the effects financing has on a firm's innovative decision, and (iv) tax and/or financial incentives that the firm can receive for innovating. It is noteworthy that all firms in the balanced panel have access to at least one form of external financing (either debt or equity). The above variables are chosen as a list of probable factors of consideration for an executive before he starts budgeting for R&D activities.

Next, I extracted the predicted probabilities of investing in R&D from the probit regression and the corresponding inverse Mill's ratio. I then estimated for R&D intensity using a simple linear regression model (OLS), adding in the predicted probabilities, the inverse Mill's ratio, their squares, and interaction terms. The presence of selection bias is then indicated by the significance of the coefficients of "probability terms"[8]. The results from this OLS regression are also reported in Table A1. As shown, the probability terms are never significant singly or jointly, implying that a simple OLS model can be used to estimate R&D intensity since there appears to be no selection bias. The results of this linear estimation are shown in Table 3.

7 See Appendix A and B for variable definitions.

8 As noted in Hall et al (2008), this is a generalization of the Heckman two-step procedure for estimation when the error terms in the two equations are jointly normally distributed. The test here is valid even if the distribution is not normal.

I find that the presence of bank(s) as a majority owner of the firm and the firm's age class are strongly negatively related to the R&D intensity of the firm while its internal funding ability and the amount of incentives it receives for innovating strongly influence its innovative efforts. These findings are not surprising since:

(a) Debtors possess the firm's assets precisely because it engaged in too many risky projects in the past, leading to defaults on loan covenants. Therefore, it is not surprising that the first thing debtors-in-possession will do is to cut down on R&D expenses to reduce the firm's risk profile.

(b) The older the firm is, the more hierarchical and bureaucratic its operations become, leading to tedious budgeting processes, especially for risky projects such as R&D.

(c) As mentioned in Section II, access to internal funds to finance R&D is a cheaper and quicker alternative to taking up a loan from a bank or issuing claims against the firm's assets. Therefore, it is not surprising that the willingness to innovate increases as internal funds grow.

(d) Apparently, incentives to innovate, either tax- or financial-related, significantly increase an average firm's R&D engagement.

The above effects are especially strong for low-tech firms.

The surprises are due to the fact that exporting goods and selling to retail and/or other businesses do not have strong effects on a firm's willingness to innovate, contrary to Hall et al (2008). Also, the size of the firm and the umbrella group that it belongs to do not have significant effects on its willingness to engage in R&D, another contradiction to Hall et al. Nevertheless, my results agree that firm and group sizes do have slightly significant and negative effects on R&D intensity for both technology classes although the large firm effect (bureaucracy and hierarchy) is stronger for low-tech firms than high-tech firms.

Knowledge Production

In the second step of the CDM model, I will estimate the probability of product and process innovation success using a knowledge production function to account for informal activities. This step is represented by a bivariate probit model, assuming that the set of firm characteristics affecting both types of innovation are similar, as follows:

$$\begin{cases} Prodinnov_i &= RD_i^*\gamma + x_i\delta + \mu_{1i} \\ Prodinnov_i &= RD_i^*\gamma + x_i\delta + \mu_{2i} \end{cases} \quad (3)$$

where RD_{i*} is the latent innovation effort chosen by the firm as predicted in step 1, x_i is a set of covariates and u_{1i} and u_{2i} are the error terms such that $Cov(u_{1i}, u_{2i}) = \rho$. To avoid potential endogeneity problems, predicted R&D intensity values are used in lieu of observed values from the sample as an instrument for innovative effort in the knowledge production function.

However, the set of variables used for x_i is not the same as the one in step 1. Most notably, customer types are replaced by firm control factors, distribution channels, interactions with outsiders through exports or outsourcing, R&D structures, presence of strategic integration or reshuffling activities, employees' levels of education, and dedication of human resources to the innovation process. These changes are made because information on what customers want is already gathered in step 1. Treating this set of information as given, an average firm will then return to the drawing board independent of customers to develop new products or processes with the aim of catering to the latter's needs eventually. Therefore, the management's educational background, its dedication and the degree of control it has over this second stage ought to exert stronger influence. One can also see this step as the missing link in the copious endogenous growth literature since it opens up the innovation "blackbox" that "might have no apparent explanation" according to Solow.

Table 4 shows the results of this bivariate probit model. The estimated correlation coefficient is positive and significant overall, implying that product and process innovation are both influenced by the same variable set. The same can be said for high-tech firms but not low-tech ones since the coefficient for the latter sample is positive but not significant. Nevertheless, we can still make overall inferences.

Regarding innovation success, it is interesting to note that predicted R&D intensity exerts a strong influence over process innovation but not over product innovation, which is mostly influenced by the amount of staff dedicated to the R&D process as measured by the R&D labor intensity coefficient. Also surprising was the fact that capital expenditure (capex) and information technology expenditure (ITexp) intensities exert mixed effects on innovation success, contrary to Hall et al. Specifically, capex intensity significantly influences product innovation but not process innovation, and ITexp intensity does otherwise.

In addition, the effects that predicted R&D intensity, capex intensity and ITexp intensity have on both innovation types vary greatly for high-tech and low-tech firms. For high-tech firms, R&D intensity has a large negative but slightly significant impact on product innovation as compared to the significantly positive impact it has on product innovation for low-tech firms. Also, capex intensity has a small but significant impact on product innovation in low-tech firms only. Lastly, ITexp intensity exerts small but significant positive effects on process innovation only for high-tech firms and product innovation only for low-tech firms. The most surprising finding here is that committing capital to conduct R&D will increase a firm's odds of inventing a new product only if it is a low-tech firm. In addition, buying machines and/or spending capital on an IT infrastructure matters little for product or process innovation regardless of firm type.

These findings seemingly contradict our prevailing notion that "spending more equals doing more" in terms of innovation, although actually, this notion is not entirely wrong. The right question we should ask is, "What resource do we spend and for what?" From my analysis, it appears that labor is the resource we should spend, not capital, and more of it should be committed to maintaining an innovation network within and outside the firm. This is because R&D labor intensity has a significantly large and positive influence on product innovation for high-tech firms and both product and process innovation for low-tech firms. Additionally, maintaining both internal and external innovation networks has similar beneficial effects on product and process innovation regardless of firm type. Therefore, the new notion should read: "Mobilizing more labor to maintain innovation networks equals doing more" in terms of innovation.

Regarding autonomy, control over administration appears to have strong positive influence over product innovation while autonomy in financing exerts strong positive effects over process innovation overall. Upon further analysis, administrative autonomy's effect on product innovation applies to low-tech firms only and financing autonomy's effect on process innovation applies to high-tech firms only. For the former, the finding makes sense since mobilizing labor to innovate requires administrative speed and independence. In the latter case however, it is interesting to note that administration autonomy has a strong negative effect on process innovation in high-tech firms while financing autonomy has taken its logical position with a strong positive effect on the same innovation and firm type. This is especially surprising since we have established earlier that spending capital does not result in innovation, but committing labor does. Therefore, speed and independence in mobilizing funds should not matter. However, further examination revealed that R&D labor intensity does not matter for process innovation in high-tech firms anyway, while IT expenditure intensity and the existence of distribution networks abroad do. Therefore, it makes sense that administrative autonomy does not matter. However, further analysis is needed to determine why it reduces the odds of process innovation. Perhaps an Italian specific effect is at work here. Furthermore, financing autonomy does not equate to innovation per se; its influence must work through one or several other expenditure related variables. My analysis suggests that this independence is exercised to build IT infrastructure and grow distribution networks abroad, but once again I would not venture to assert that the above findings about financing autonomy represent all firms since I suspect that they describe a more Italian phenomenon instead of a global occurrence.

Concerning interactions with outsiders and competition, exporters have higher odds of product innovation but lower odds of process innovation, which was surprising because Hall et al provided prior evidence that exporting and both product and process innovation share a positive relationship. Also, outsourcing has small and insignificant effects on both innovation types. Here, my results suffer from a lack of historical data and inferences about firms' business cycles and trading trends might not be meaningful.

With regards to financing, the availability of internal funding (measured by cash to asset ratio) appears to exert strong negative influence over process innovation only for both current and lagged terms. However, effects of cash on hand are mixed at different technology levels. For high-tech firms, the availability of internal funding exerts strong positive influence over product innovation while the effects are strongly negative for low-tech firms, indicating that high-tech firms rely extensively on their internal funds while an inference about low-tech firms cannot be made due to a lack of significant correlation in this sub-sample. Another interesting finding is that debtor-in-possession results in a significantly higher probability of success in process innovation, in line with Nini, Smith and Sufi (2009) who find that firms experiencing new capital expenditure restrictions from creditors markedly improved their operating performance. Also, it is surprising to note that incentives to innovate significantly, and negatively, affect the likelihood of success for both product and process innovation, with the latter exhibiting a stronger relationship. This interesting finding makes one wonder if policy makers ought to continue to use taxpayers' money to encourage innovation. Results from Table 4 are once again strongly influenced by the low-tech sub-sample and further research in this area of public policy may be rewarding. Lastly, an average firm's capital structure is significant for process innovation only but its impact is small.

Productivity Function

In the final step of the CDM model, I will use a simple regression model (OLS) to represent a Cobb-Douglas production function with constant returns to scale together with labor, capital and innovation inputs as follows:

$$y_i = \pi_1 k_1 + \pi_2 \, Prodinnov_i + \pi_3 \, Pocinnov_i + \pi_3 L_i + \pi_4 F_i + v_i \quad (4)$$

where yi is labor productivity (sales per employee, in log), ki is capex intensity (capex per employee, in log), a proxy for physical capital as per Hall et al (2008), Prodinnovi and Procinnovi are innovation inputs, proxied by their respective predicted probabilities from step 2 to address potential endogeneity problems. Li is a set of firm characteristics including autonomy, debtor-in-possession scenarios, firm and group size and age, customer types, interactions with outsiders, distribution channels, family executives and R&D labor intensity (to implement innovation). Fi is a set of financing characteristics including internal funding abilities, capital structure and R&D incentives. Results are displayed in Table 5.

Contrary to results in Hall et al (2008), predicted product innovation is never significant, with or without the inclusion of capex intensity in the set Li. However, predicted process innovation does have a strong positive impact on productivity in the overall sample, in line with evidence from Hall et al. Interestingly, both predicted process and product innovation are robust to the inclusion or exclusion of capex intensity in the overall sample. In fact, capex intensity has a weak and insignificant effect on productivity and the overall R-sqr of the model barely changes when it is removed from equation 4. Additionally, the strong overall positive impact of predicted process innovation on productivity seems to fizzle out at different technology levels. Also, firm size has a strong positive impact on productivity overall, driven mostly by high-tech firms. Again, this finding contrasts sharply with Hall et al, although my results do agree that firm size enhances the odds of succeeding in product innovation.

Strong drivers of productivity across the overall sample and technology sub-samples are dominated by foreign interactions (export and distribution channel abroad), financing sources (cash to asset ratio and R&D incentive) and dedication of human resources to R&D (R&D labor intensity). Of the five main drivers, R&D incentives exhibit the smallest effect across all samples, once again calling into question the efficiency of public subsidies. In addition to the five main drivers, autonomy over administration and marketing and firm size have strong impacts on productivity for high-tech firms while customer types and distribution channels enhance productivity the most for low-tech firms. However, administrative autonomy's large and significantly negative effects on productivity for high-tech firms only once again perplex me as per step 2. This is because I expected administrative autonomy to help with mobilizing labor to focus on R&D and certainly did not expect it to weaken the beneficial link between R&D labor intensity and productivity. More research is certainly required in this area to solve this mystery.

To address the possibility that the financing variable set Fi might introduce endogeneity problems in the production function (since sales and profit can affect cash and equity level and vice-versa), Fi was removed from equation 4 and the results are shown in Table 6. The effects variables exert on productivity are similar to a model with financing variables with the exception of product innovation having a slightly significant but largely positive impact on productivity, in line with Hall et al. Nevertheless, process innovation's impact on productivity is still stronger and larger than product innovation. It is also interesting to note that firm age and autonomy over administration and marketing became more significant, although coefficient magnitudes are still small.

Putting results from steps 1, 2 and 3 together, it appears that internal funding has a positive impact on productivity while R&D incentives have a net negative effect on productivity as shown in column 7, Figure 3. This chart is, of course, a very crude analysis and serves only as a first-pass result about financing effects. Although the magnitudes shown in the chart are not accurate (magnitudes can be found from the interaction of coefficients with the predicted probabilities extracted from a step 2 bivariate probit model after adjusting for correlation in the low-tech sub-sample), the chart is still useful because it provides us with an indication of directions. Since financing is removed from the production function to avoid co-linearity problems, direct effects (column 6) will disappear and the effects of internal funds, R&D incentives and capital structure can be found from column 8 in the chart. To the extent of my sample's accuracy, it appears that the innovation-productivity link is not dependent of an average firm's capital structure and the use of R&D incentives is counter-productive in enhancing productivity. These incentives might be more effective if they are granted to firms after the innovation stage rather than before it. In contrast, the adage "cash is king" will apply here since internal funding abilities appears to be the most efficient way to increase innovation success and boost productivity at firm level. It is also noteworthy that these findings support the hypothesis about relationships among internal funding, subsidies and labor productivity in Ang (2009).

Figure 3: Multiplier Effects of Financing Sources and Capital Structure on Productivity

INDIRECT EFFECTS

Product innovation

	(1)	(2)	(3)
	Coefficients (All firms)		Productivity Multiplier
Variable	Step 1	Step 2	(1*Pr. Rdint +2)
Cash to asset ratio	0.613	0.000	0.000
R&D incentives	0.443	-0.605	-0.605
Debt to equity ratio	0.000	0.000	0.000
Predicted R&D intensity		*0.000*	

Process innovation

	(1)	(2)	(4)
	Coefficients (All firms)		Productivity Multiplier
Variable	Step 1	Step 2	(1*Pr. Rdint +2)
Cash to asset ratio	0.613	-1.213	0.133
R&D incentives	0.443	-1.242	-0.269
Debt to equity ratio	0.000	0.009	0.009
Predicted R&D intensity		*2.196*	

TOTAL EFFECTS

Labor Producitivity

	(5)	(6)	(7)	(8)
	Coefficients (All firms)		Total (with financing)	Total (without financing)
Variable	Productivity Multiplier (3+4)	Step 3: Direct effects	(5*Pr. Prodinnov + 5* Pr. Procinnov +6)	(5*Pr. Prodinnov + 5* Pr. Procinnov)
Cash to asset ratio	0.133	0.215	0.291	0.135
R&D incentives	-0.874	0.092	-0.411	-0.253
Debt to equity ratio	0.009	0.000	0.005	0.003
Predicted Prodinnov (with financing)		*0.000*		
Predicted Procinnov (with financing)		*0.575*		
Predicted Prodinnov (without financing)		*0.289*		
Predicted Procinnov (without financing)		*0.729*		

IV. Discussion

In this paper, I have proposed and estimated a three-step model to analyze the effects variation in financing sources have on an average firm's (i) willingness and ability to engage in innovative activities, (ii) odds of succeeding in product and/or process innovation, and (iii) ability to enhance its productivity through the innovation-production link. Based on the CDM model, my results accounted for informal innovative efforts at micro-level, and I have shown that innovation does occur through various channels alongside traditional R&D as measured by R&D expenditure.

In my opinion, the CDM model is a reasonable way to open up the "black box" of innovation. However, we need to clearly spell out the relevant variables at each step to better describe the decision process of a manager who is budgeting for innovative projects. Therefore, I have modified earlier methodologies in this paper as follows:

(1) Step one (R&D decision) included firm ownership, customer types and available funding sources on top of traditional firm characteristics since:

a. Owners might have mandates that managers need to follow, such as reduction in risk profile in the case of debtor-in-possession.

b. Customers' needs influence managers' willingness to innovate.

c. Managers' ability to innovate is restricted by how much resources they have at their disposal.

(2) Step two (knowledge production) accounted for various means through which innovation can occur, along with the resources and conditions required to attain success. These include:

a. Various traditional business expenditures such as R&D, machinery, equipment and IT

b. Autonomy over various business functions such as administrative, financing, marketing and R&D, as well as ownership.

c. Traditional firm characteristics such as firm size and age, etc.

d. Types of distribution channels

e. R&D networks and affiliations

f. Available funding sources

g. Structural activities such as integration, divestment and production outsourcing

h. Labor related issues such as education and staff commitment to innovation

Using this modified approach, I found that foreign interactions, financing sources and dedication of human resources have strong direct and indirect impacts on productivity through innovation while management autonomy, debtor-in-possession, education and other traditional firm characteristics display mixed effects on (i) product and process innovation and (ii) firms with different levels of production technology. In addition, results show that administration autonomy reduces the odds of innovation success and productivity, which I find perplexing. Therefore, this issue should be taken up for further research and I suspect that it will reveal even more interesting results. Overall, I have shown that process innovation has the greatest impact on productivity overall, in line with Hall et al.

Despite several intriguing findings in this paper, the following four outcomes stood out as issues that corporate stakeholders and policy makers should immediately address and keep in mind:

(1) Subsidies are not the most optimal financing source in fostering innovation. Policy makers should think twice before using taxpayers' money as carrots to induce corporate innovation because the whole exercise is self-defeating.

(2) The capital structure of a firm is irrelevant to innovation. It does not matter if a company is leveraged to the hilt or has no debt on its balance sheet. How assets are financed has no effect on a company's innovative abilities and productivity. The only time when debt aids innovation is when a company defaults and its banker is in charge, since process improvements are more likely to occur then. However, I am sure most would rather self-innovate than to relinquish autonomy to the banker.

(3) Mobilizing more labor to maintain innovation networks will induce innovation. Throwing more money at capital assets will not make ideas work but throwing more people at an innovation network just might. R&D labor intensity is a strong predictor of innovation success, especially when a lot of brainpower comes together in a structured manner regularly.

(4) Cash is indeed king. Cash to innovation is like fuel to an engine; we need more of it to comfortably invest in and implement ideas. However, a caveat applies here: cash helps in the decision making process, but there is still uncertainty as to its effects on innovation production, especially for a low-tech firm since cash hoarding has a negative effect on product innovation success.

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Appendix A: Firm Characteristics Variable Definitions

Innovator: dummy variable that takes value 1 if the firm declares to have process or product innovation during the three years of the survey.

Process innovation (procinnov): dummy variable that takes value 1 if the firm declares to have introduced a process innovation during the three years of the survey.

Product innovation (prodinnov): dummy variable that takes value 1 if the firm declares to have introduced a product innovation during the three years of the survey.

External R&D structure (extRDstruct): dummy variable that takes value 1 if the firm declares that it maintains an external innovation network during the three years of the survey.

Internal R&D structure (intRDstruct): dummy variable that takes value 1 if the firm declares that it maintains an internal innovation network during the three years of the survey.

Employees (avgemp): number of employees at start of survey, headcount.

Firm size classes: [0-250], [>250] employees.

Large firms (largefirm): dummy variable that takes value 1 if firm has more than 250 full time employees.

Group size classes: [0-250], [>250] employees.

Large group (largegrp): dummy variable that takes value 1 if the umbrella group hires more than 250 full time employees in total.

Part of an umbrella of companies (partumb): dummy variable that takes value 1 if the firm declares to be part of a group of companies during the three years of the survey.

Single firm: dummy variable that takes value 0 if firm declares not to be part of a group of companies during the three years of the survey.

Part of research consortium (partcons): dummy variable that takes value 1 if the firm declares to be part of a research consortium during the three years of the survey.

Firm age (age): firm's age (in years).

Group age (grpage): umbrella group's age (in years).

Firm age classes: [1-25], [>25] years.

Old firm (oldfirm): dummy variable that takes value 1 if firm is established more than 25 years ago.

Group age classes: [1-25], [>25] years.

Old group (oldgroup): dummy variable that takes value 1 if umbrella group is established more than 25 years ago.

Customer Type: types of customer that firm sells its main product to directly or indirectly.

Customer classes: [Retail/households], [Companies], [Others]

Retail customers (custretail): dummy variable that takes the value 1 if firm sells to households directly (e-commerce) or indirectly (through retailers).

Business to business customers(custb2b): dummy variable that takes value 1 if firm sells to other businesses directly (e-commerce) or indirectly (through a distributor).

Exported main products: dummy variable that takes value 1 if the firm has declares to have exported products over the survey period.

Maintains overseas distribution network (distabroad): dummy variable that takes value 1 if the firm has declares own >50% of a distribution network abroad over the survey period.

Maintains national distribution network (distnational): dummy variable that takes value 1 if the firm has declares own >50% of a national distribution network over the survey period.

Outsourced part of production (outsource): dummy variable that takes value 1 if the firm has declares to have outsourced part of their production process over the survey period.

High-tech firms (high-tech): dummy variable representing high and medium-high technology industries that takes value 1 if firm produces the following main products : chemicals; office accounting & computer machinery; radio, TV & telecommunication instruments; medical, precision & optical instruments; electrical machinery and apparatus; machinery & equipment; railroad & train equipment.

Low-tech firms: encompasses low and medium-low technology industries (rubber & plastic products; coke, refined petroleum products; other non-metallic mineral products; basic metals and fabricated metal products; manufacturing; wood, pulp & paper; food, beverages & tobacco products; textile, textile products, leather & footwear).

Invested in capital expenditure (capex): dummy variable that takes value 1 if the firm has declares positive plant, property and equipment expenditures over the survey period.

Invested in information technology (ITexp): dummy variable that takes value 1 if the firm has declares positive expenditures on computer, internet services etc. over the survey period.

Invested in R&D (RDexp): dummy variable that takes value 1 if the firm has declares positive R&Ds over the survey period.

Capital intensity (logcapexint): Capital expenditure per employee, in logs.

IT expenditure intensity (logITexpint): IT expenditure per employee, in logs.

R&D intensity (logRDexpint): R&Ds per 2002 full time employee, in real terms and in logs.

Labor productivity: real sales per employee, in logs.

Labor productivity from new product: real sales per employee, in logs.

R&D labor intensity: ratio of R&D workers to average employees.

Share of sales with new products: percentage of the sales in the last year of the survey coming from new or significantly improved products (in percentage).

Appendix B: Firm Control, Management, Financing and Capital Structure Variables Definitions

Bank ownership classes: measures presence of bankruptcy: [no ownership, 0%], [minority interest, 1-10%], [non-controlling, <50%], [majority owned by bank, >=50%].

Bank has majority ownership (bankmajor): dummy variable that takes value one if firm is majority owned by bank. This variable measures the likelihood of debtor-in-possession situations when the borrower (firm) defaults on loan payments of contracted covenants.

Full autonomy (auto~): dummy variable that takes value 1 if firm declares to have full autonomy over the following aspects of management: [administration (admin)], [financing(fin)], [marketing(mktg)], [R&D(RD)].

Executive positions held by family (pctfamexecs): percentage of executive positions held by founding family during survey period.

Executive positions held outside family: percentage of executive positions not held by founding family during survey period.

Has relationship(s) with bank: dummy variable that takes value 1 if firm declares to maintain relationship with at least one bank during survey period.

Main R&D financing source: percentage of R&D financed by the following sources as declared by firm:

[venture capital], [internal funds], [long term bonds], [long term bank credit], [public contributions], [tax funded], [other].

Main Capex financing source: percentage of capex financed by the following sources as declared by firm:

[venture capital], [internal funds], [short term bank credit], [long term bonds], [long term bank credit], [public contributions], [tax funded], [leasing], [from groups within umbrella], [from other companies], [other].

Debt/equity (debteq): ratio of debt funding to equity funding on firm's balance sheet, average 2001-2003

Cash/asset (cashass): ratio of cash reserves to total assets (book value) on firm's balance sheet, average 2001-2003

Cash/asset lagged one year (cashasslag): ratio of cash reserves to total assets (book value) on firm's balance sheet, lagged one year.

Receives R&D incentives (RDince): Receives financial or tax incentives to innovate.

Made acquisition (acquis): made acquisition(s) during survey period.

Made divestment (divest): divested part of business during survey period.

Appendix C: Tables

Table 1: Firm Characteristics

Period: 2001-2003	Unbalanced	Balanced
Number of observations (firms)	3,452	700
	In %	
Innovator (process and/or product)	58.86	85.43
Process innovation	42.29	60.86
Product innovation	40.61	68.57
Process innovation and Product innovation	24.04	44.00
Process innovation only	18.25	16.86
Innovation Structure		
External and/or Internal	100.00	100.00
Internal	96.67	92.57
External	76.30	46.14
Internal only	72.97	53.86
Small firm (1-250 employees)	83.46	87.00
Large firm (>=250)	16.54	13.00
Single firm	68.02	64.00
Part of an umbrella of companies	31.98	36.00
Part of research consortium	11.94	15.14
Firm Age		
1-25 years	49.25	50.86
> 25 years	50.75	49.14
Customer Type		
Retail	13.93	7.86
Companies	57.56	88.00
Government	26.16	0.00
Others	2.35	4.14
Exported main products	99.04	88.71
Maintains overseas distribution network	13.15	11.14
Maintains national distribution network	19.32	13.57
Outsourced part of production	17.53	22.29
Invested in capital expenditure (Capex)	85.66	100.00
Invested in information technology (IT)	68.48	87.86
Invested in R&D	45.08	100.00
Made acquisition(s)	12.37	0.00
Made divestment(s)	4.46	0.00
High Tech	46.06	55.71
No. of employees, Mean (Median)	150.88(59)	144.04(83)
Low Tech	53.94	44.29
No. of employees, Mean (Median)	140.06(51)	119.67(65)

Table 2: Firm control, management, financing and capital structure

Period: 2001-2003	Unbalanced	Balanced
Number of observations (firms)	3,452	700
	In %	
Bank ownership		
No ownership (0%)	18.86	19.43
Minority (1-10%)	1.16	21.00
Non-controlling (11-50%)	44.76	33.71
Majority (>=50%)	35.23	25.86
Full autonomy		
Administration	85.52	82.29
Financing	83.95	79.43
Marketing	84.97	81.57
R&D	85.11	82.00
Executive positions held by family	6.34	14.57
Executive positions outisde family	93.66	85.43
Has relationship(s) with bank	100.00	100.00
Main R&D financing source:		
Venture capital (VC)	0.67	0.57
Internal funds	80.58	81.43
Long term bonds	4.38	4.00
Long term bank credit	2.49	2.29
Public contributions	3.51	3.29
Tax funded	1.35	1.14
Other	0.81	7.28
Main Capex financing source:		
Venture capital (VC)	0.64	0.57
Internal funds	43.17	44.71
Short term bank credit	4.25	4.43
Long term bonds	7.87	7.29
Long term bank credit	4.64	4.71
Public contributions	1.06	1.14
Tax funded	1.59	1.14
Leasing	14.65	13.57
From within umbrella	0.92	1.14
From other companies	0.04	0.00
Other	0.25	21.30
Access to public and/or private equity	99.80	100.00
Has financial or tax incentives to innovate	49.42	64.71
Debt/Equity (average 01-03)	311.72	262.87

Table 3: STEP 1 - R&D decision: OLS, dependent variable - R&D intensity (R&D expenditure per employee, in log)

All firms (n=2100)

R&D exp per employee (in log)	Coef.	Std. Err.	P>|t|
bankmajor	-0.123**	0.063	0.050
largefirm	0.143	0.089	0.108
largegrp	-0.007	0.103	0.943
oldfirm	-0.234**	0.095	0.013
oldgrp	-0.098	0.103	0.343
age	0.008	0.005	0.125
agesqr	0.000	0.000	0.601
grpage	-0.004	0.007	0.522
grpagesqr	0.000	0.000	0.580
export	0.017	0.089	0.852
custretail	-0.240	0.169	0.155
custb2b	-0.197	0.140	0.161
pctfamexecs	0.080	0.133	0.548
cashass	0.613***	0.153	0.000
cashasslag	0.310*	0.171	0.069
debteq	-0.004	0.003	0.143
RDince	0.443***	0.056	0.000
year	-0.017	0.036	0.643
costant	36.865	71.878	0.608
Adjusted R-sqr	0.047		

High Tech firms (n=1170)

R&D exp per employee (in log)	Coef.	Std. Err.	P>|t|
bankmajor	0.147*	0.080	0.066
largefirm	0.013	0.106	0.901
largegrp	-0.242*	0.128	0.060
oldfirm	-0.220*	0.121	0.070
oldgrp	0.059	0.122	0.627
age	-0.005	0.007	0.479
agesqr	0.000	0.000	0.245
grpage	-0.017**	0.008	0.035
grpagesqr	0.000*	0.000	0.074
export	0.114	0.115	0.320
custretail	0.014	0.259	0.957
custb2b	-0.141	0.184	0.445
pctfamexecs	0.025	0.184	0.892
cashass	0.586***	0.163	0.000
cashasslag	0.318*	0.179	0.076
debteq	-0.004	0.003	0.218
RDince	0.341***	0.071	0.000
year	-0.020	0.045	0.665
constant	43.108	90.487	0.634
Adjusted R-sqr	0.055		

Low Tech firms (n=930)

R&D exp per employee (in log)	Coef.	Std. Err.	P>|t|
bankmajor	-0.464***	0.100	0.000
largefirm	0.279*	0.159	0.079
largegrp	0.269	0.169	0.111
oldfirm	-0.273*	0.156	0.081
oldgrp	-0.304*	0.183	0.096
age	0.029***	0.011	0.007
agesqr	-0.000**	0.000	0.048
grpage	0.010	0.011	0.371
grpagesqr	0.000	0.000	0.439
export	-0.064	0.137	0.642
custretail	-0.326	0.242	0.178
custb2b	-0.265	0.217	0.223
pctfamexecs	0.175	0.194	0.366
cashass	0.725**	0.363	0.046
cashasslag	0.171	0.424	0.687
debteq	-0.005	0.005	0.349
RDince	0.540***	0.092	0.000
year	-0.006	0.058	0.918
constant	15.085	116.098	0.897
Adjusted R-sqr	0.079		

Table 4: STEP 2 - Knowledge production: Bivariate probit, dependent variable - declared product innovation and process innovation

All firms (n=2100)

Product innovation	Coef.	Std. Err.	P>|z|	Process innovation	Coef.	Std. Err.	P>|z|
predicted				predicted			
logRDexpint	0.960	0.792	0.225	logRDexpint	2.196***	0.745	0.003
logcapexint	0.058***	0.017	0.001	logcapexint	0.01	0.017	0.551
logITexpint	0.018	0.011	0.111	logITexpint	0.031***	0.011	0.004
autoadmin	0.600***	0.209	0.004	autoadmin	-0.21	0.189	0.277
autofin	-0.084	0.207	0.687	autofin	0.471***	0.182	0.010
automktg	-0.356	0.264	0.178	automktg	-0.486**	0.236	0.040
autoRD	0.383	0.255	0.134	autoRD	0.31	0.231	0.185
bankmajor	-0.034	0.120	0.778	bankmajor	0.342***	0.113	0.002
largefirm	0.551***	0.180	0.002	largefirm	-0.18	0.159	0.253
largegrp	0.106	0.123	0.388	largegrp	-0.369***	0.123	0.003
oldfirm	0.387*	0.220	0.078	oldfirm	0.626***	0.204	0.002
oldgrp	0.043	0.144	0.764	oldgrp	0.308**	0.138	0.025
age	-0.037***	0.011	0.001	age	-0.024***	0.009	0.009
agesqr	0.000***	0.000	0.000	agesqr	0.000**	0.000	0.019
grpage	0.018**	0.008	0.033	grpage	-0.01	0.008	0.524
grpagesqr	0.000*	0.000	0.077	grpagesqr	0.00	0.000	0.856
export	0.227**	0.095	0.017	export	-0.200**	0.095	0.035
distnational	-0.016	0.136	0.909	distnational	0.06	0.124	0.657
distabroad	0.270*	0.153	0.078	distabroad	0.02	0.137	0.892
partcons	-0.205**	0.090	0.023	partcons	0.143*	0.083	0.084
extRDstruct	0.264***	0.068	0.000	extRDstruct	0.113*	0.064	0.076
intRDstruct	0.441***	0.120	0.000	intRDstruct	0.252**	0.119	0.034
pctfamexecs	0.502***	0.175	0.004	pctfamexecs	-0.335**	0.157	0.032
cashass	-0.442	0.522	0.397	cashass	-1.213**	0.489	0.013
cashasslag	-0.369	0.311	0.236	cashasslag	-0.602**	0.294	0.040
debteq	0.005	0.004	0.287	debteq	0.009**	0.004	0.033
RDince	-0.605*	0.358	0.091	RDince	-1.242***	0.337	0.000
acquis	0.018	0.091	0.842	acquis	-0.303***	0.088	0.001
divest	-0.257*	0.145	0.076	divest	0.10	0.128	0.418
schooling	-0.001*	0.000	0.085	schooling	0.003***	0.001	0.000
diploma	-0.003***	0.001	0.001	diploma	-0.001*	0.001	0.080
degree	0.033***	0.005	0.000	degree	0.00	0.003	0.272
RDlabint	1.723***	0.421	0.000	RDlabint	0.46	0.316	0.149
outsource	-0.066	0.076	0.386	outsource	0.10	0.071	0.145
year	0.018	0.042	0.669	year	0.03	0.040	0.436
constant	-38.602	84.389	0.647	constant	-68.88	80.084	0.390
Rho	0.128***	0.038	0.001				
Chi-sqr (df=1)	10.890						
Prob>Chi-sqr	0.001						

Table 4 (cont.): STEP 2 - Knowledge production: Bivariate probit, dependent variable - declared product innovation and process innovation

High Tech firms (n=1170)

Product innovation	Coef.	Std. Err.	P>|z|	Process innovation	Coef.	Std. Err.	P>|z|
predicted				predicted			
logRDexpint	-2.112*	1.080	0.051	logRDexpint	1.017	1.069	0.341
logcapexint	0.015	0.025	0.565	logcapexint	-0.012	0.024	0.618
logITexpint	0.021	0.016	0.188	logITexpint	0.043***	0.015	0.005
autoadmin	0.385	0.300	0.200	autoadmin	-0.949***	0.283	0.001
autofin	-0.182	0.296	0.538	autofin	1.062***	0.261	0.000
automktg	-0.319	0.337	0.345	automktg	-0.483	0.305	0.114
autoRD	0.558*	0.334	0.095	autoRD	0.589*	0.308	0.056
bankmajor	0.071	0.183	0.697	bankmajor	0.001	0.179	0.997
largefirm	0.313*	0.179	0.080	largefirm	0.131	0.156	0.402
largegrp	-0.565*	0.306	0.065	largegrp	-0.486	0.304	0.111
oldfirm	0.093	0.286	0.745	oldfirm	0.402	0.281	0.152
oldgrp	0.159	0.171	0.353	oldgrp	0.047	0.164	0.772
age	-0.084***	0.017	0.000	age	-0.036**	0.014	0.011
agesqr	0.001***	0.000	0.000	agesqr	0.000***	0.000	0.010
grpage	-0.032	0.022	0.134	grpage	-0.014	0.021	0.505
grpagesqr	0.000	0.000	0.149	grpagesqr	0.000	0.000	0.618
export	0.492***	0.182	0.007	export	-0.342*	0.182	0.061
distnational	-0.021	0.258	0.934	distnational	-0.399*	0.235	0.089
distabroad	0.508*	0.294	0.084	distabroad	0.710***	0.262	0.007
partcons	-0.009	0.130	0.947	partcons	0.159	0.121	0.191
extRDstruct	0.344***	0.093	0.000	extRDstruct	0.194**	0.087	0.027
intRDstruct	0.375*	0.193	0.052	intRDstruct	0.147	0.190	0.440
pctfamexecs	-0.035	0.225	0.875	pctfamexecs	-0.080	0.206	0.697
cashass	1.351**	0.671	0.044	cashass	-0.348	0.660	0.598
cashasslag	0.597	0.414	0.149	cashasslag	-0.221	0.404	0.585
debteq	-0.009	0.006	0.127	debteq	0.008	0.006	0.193
RDince	0.472	0.383	0.217	RDince	-0.571	0.379	0.131
acquis	-0.157	0.130	0.229	acquis	-0.328***	0.123	0.007
divest	-0.155	0.211	0.463	divest	-0.157	0.181	0.384
schooling	0.001	0.001	0.286	schooling	0.004***	0.001	0.000
diploma	-0.002	0.001	0.132	diploma	-0.003***	0.001	0.001
degree	0.024***	0.006	0.000	degree	0.011***	0.004	0.007
RDlabint	1.923***	0.636	0.002	RDlabint	0.239	0.445	0.590
outsource	0.021	0.102	0.837	outsource	0.043	0.098	0.661
year	-0.036	0.059	0.542	year	0.013	0.056	0.815
constant	80.497**	119.310	0.500	constant	-28.451	113.421	0.802
Rho	0.192***	3.629	0.000				
Chi-sqr (df=1	12.693						
Prob>Chi-sqr	0.000						

Table 4 (cont.): STEP 2 - Knowledge production: Bivariate probit, dependent variable - declared product innovation and process innovation

Low Tech firms (n=930)

Product innovation	Coef.	Std. Err.	P>|z|	Process innovation	Coef.	Std. Err.	P>|z|
predicted				predicted			
logRDexpint	3.160***	0.992	0.001	logRDexpint	1.074	0.780	0.169
logcapexint	0.106***	0.027	0.000	logcapexint	0.039	0.025	0.120
logITexpint	0.029*	0.018	0.097	logITexpint	0.016	0.017	0.341
autoadmin	0.913***	0.349	0.009	autoadmin	0.220	0.308	0.475
autofin	0.474	0.386	0.219	autofin	-0.079	0.312	0.800
automktg	-0.521	0.571	0.361	automktg	0.109	0.446	0.807
autoRD	0.280	0.483	0.562	autoRD	-0.364	0.419	0.386
bankmajor	1.470***	0.472	0.002	bankmajor	0.514	0.375	0.170
largefirm	0.601	0.413	0.146	largefirm	-0.487	0.333	0.143
largegrp	-0.472	0.328	0.151	largegrp	-0.342	0.284	0.229
oldfirm	0.679**	0.328	0.038	oldfirm	0.463*	0.269	0.085
oldgrp	0.469	0.360	0.193	oldgrp	0.525*	0.299	0.079
age	-0.100***	0.033	0.002	age	-0.017	0.026	0.506
agesqr	0.001***	0.000	0.003	agesqr	0.000	0.000	0.549
grpage	-0.003	0.017	0.861	grpage	-0.001	0.016	0.941
grpagesqr	0.000	0.000	0.249	grpagesqr	0.000	0.000	0.418
export	0.326**	0.158	0.039	export	-0.088	0.147	0.552
distnational	-0.037	0.183	0.841	distnational	0.269*	0.162	0.096
distabroad	0.227	0.208	0.275	distabroad	-0.232	0.181	0.202
partcons	-0.240*	0.136	0.077	partcons	0.215*	0.124	0.082
extRDstruct	0.329***	0.115	0.004	extRDstruct	0.117	0.104	0.261
intRDstruct	0.492***	0.175	0.005	intRDstruct	0.315*	0.164	0.055
pctfamexecs	0.834***	0.320	0.009	pctfamexecs	-0.385	0.256	0.132
cashass	-1.875**	0.835	0.025	cashass	-0.911	0.676	0.178
cashasslag	-0.452	0.485	0.352	cashasslag	-0.224	0.437	0.609
debteq	0.016**	0.008	0.032	debteq	0.003	0.006	0.586
RDince	-1.825***	0.550	0.001	RDince	-0.950**	0.438	0.030
acquis	0.153	0.148	0.300	acquis	-0.109	0.140	0.436
divest	-0.520**	0.238	0.029	divest	0.624***	0.225	0.005
schooling	-0.002**	0.001	0.017	schooling	0.004***	0.001	0.000
diploma	-0.005***	0.002	0.002	diploma	0.004**	0.002	0.014
degree	0.045***	0.013	0.000	degree	-0.025***	0.009	0.005
RDlabint	2.301***	0.680	0.001	RDlabint	1.128**	0.519	0.030
outsource	-0.267**	0.128	0.037	outsource	0.216*	0.114	0.058
year	0.007	0.062	0.910	year	0.006	0.059	0.914
constant	-23.070	124.700	0.853	constant	-17.885	117.831	0.879
Rho	0.462	0.763	0.446				
Chi-sqr (df=1)	0.580						
Prob>Chi-sqr	0.446						

Table 5: STEP 3 - Production function: OLS, dependent variable - labor productivity (sales per employee, in log)

All firms (n=2100)

Sales per employee (in log)	Coef.	Std. Err.	P>|t|
predicted prodinnov probability	0.081	0.184	0.662
predicted procinnov probability	0.575***	0.213	0.007
logcapexint	0.000	0.006	0.985
autoadmin	-0.107*	0.057	0.059
automktg	0.100*	0.052	0.054
bankmajor	-0.004	0.025	0.875
largefirm	0.201***	0.045	0.000
largegrp	-0.079*	0.043	0.064
oldfirm	-0.010	0.037	0.781
oldgrp	0.042	0.040	0.296
age	-0.005**	0.002	0.018
agesqr	0.000	0.000	0.197
grpage	0.001	0.003	0.746
grpagesqr	0.000	0.000	0.390
export	0.208***	0.038	0.000
custretail	0.127*	0.069	0.067
custb2b	0.010	0.057	0.860
distnational	0.110**	0.046	0.018
distabroad	0.248***	0.051	0.000
pctfamexecs	0.031	0.057	0.578
cashass	0.215***	0.059	0.000
cashasslag	0.074	0.066	0.259
debteq	-0.001	0.001	0.291
RDince	0.092***	0.023	0.000
acquis	0.022	0.033	0.511
divest	-0.004	0.045	0.936
RDlabint	0.711***	0.116	0.000
outsource	-0.002	0.027	0.950
year	-0.015	0.014	0.266
constant	35.292	27.556	0.200
Adjusted-R-sqr	0.113		

Table 5 (cont.): STEP 3 - Production function: OLS, dependent variable - labor productivity (sales per employee, in log)

High Tech firms (n=1170)				*Low Tech firms (n=930)*			
Sales per employee (in log)	Coef.	Std. Err.	P>|t|	Sales per employee (in log)	Coef.	Std. Err.	P>|t|
predicted prodinnov probability	-0.157	0.166	0.342	predicted prodinnov probability	0.002	0.206	0.991
predicted procinnov probability	0.084	0.274	0.759	predicted procinnov probability	-0.368	0.227	0.105
logcapexint	-0.005	0.008	0.561	logcapexint	-0.010	0.009	0.285
autoadmin	-0.251***	0.067	0.000	autoadmin	-0.080	0.102	0.433
automktg	0.211***	0.062	0.001	automktg	-0.077	0.091	0.401
bankmajor	0.016	0.036	0.648	bankmajor	-0.045	0.038	0.234
largefirm	0.268***	0.049	0.000	largefirm	-0.054	0.068	0.423
largegrp	-0.057	0.055	0.299	largegrp	-0.066	0.066	0.318
oldfirm	0.069	0.049	0.159	oldfirm	-0.059	0.059	0.315
oldgrp	0.087*	0.048	0.069	oldgrp	-0.100	0.069	0.148
age	-0.008***	0.003	0.003	age	0.003	0.004	0.486
agesqr	0.000*	0.000	0.076	agesqr	0.000	0.000	0.167
grpage	0.000	0.003	0.917	grpage	-0.006	0.004	0.167
grpagesqr	0.000	0.000	0.947	grpagesqr	0.000	0.000	0.285
export	0.124**	0.053	0.019	export	0.245***	0.052	0.000
custretail	0.061	0.101	0.544	custretail	0.229**	0.096	0.017
custb2b	-0.113	0.075	0.136	custb2b	0.199**	0.085	0.019
distnational	-0.022	0.082	0.790	distnational	0.159***	0.060	0.008
distabroad	0.178**	0.088	0.043	distabroad	0.217***	0.065	0.001
pctfamexecs	0.036	0.071	0.611	pctfamexecs	-0.142*	0.082	0.084
cashass	0.174***	0.064	0.006	cashass	0.327**	0.137	0.017
cashasslag	0.055	0.070	0.426	cashasslag	0.181	0.158	0.251
debteq	-0.002*	0.001	0.062	debteq	0.001	0.002	0.527
RDince	0.052*	0.029	0.074	RDince	0.095**	0.038	0.012
acquis	0.038	0.040	0.339	acquis	-0.111**	0.054	0.040
divest	0.028	0.056	0.611	divest	0.030	0.075	0.686
RDlabint	0.509***	0.152	0.001	RDlabint	0.552***	0.173	0.001
outsource	0.035	0.032	0.274	outsource	0.021	0.044	0.630
year	-0.010	0.017	0.575	year	-0.026	0.021	0.223
constant	24.364	34.763	0.484	constant	57.473	43.016	0.182
Adjusted-R-sqr	0.101			Adjusted-R-sqr	0.171		

Table 6: STEP 3 - (No financing effects) - Production function: OLS, dependent variable - labor productivity (sales per employee)

All firms (n=2100)			
Sales per employee (in log)	Coef.	Std. Err.	P>|t|
predicted prodinnov probability	0.289*	0.174	0.096
predicted procinnov probability	0.729***	0.210	0.001
logcapexint	0.009	0.006	0.157
autoadmin	-0.108*	0.057	0.057
automktg	0.102**	0.052	0.049
bankmajor	0.006	0.025	0.822
largefirm	0.210***	0.045	0.000
largegrp	-0.067	0.043	0.119
oldfirm	0.000	0.037	0.993
oldgrp	0.042	0.040	0.297
age	-0.006***	0.002	0.007
agesqr	0.000*	0.000	0.085
grpage	0.001	0.003	0.773
grpagesqr	0.000	0.000	0.341
export	0.208***	0.039	0.000
custretail	0.073	0.069	0.290
custb2b	-0.032	0.057	0.573
distnational	0.089*	0.047	0.057
distabroad	0.256***	0.051	0.000
pctfamexecs	0.008	0.057	0.887
acquis	0.012	0.034	0.719
divest	0.000	0.046	0.993
RDlabint	0.715***	0.117	0.000
outsource	0.002	0.027	0.928
year	-0.012	0.013	0.362
constant	28.461	25.989	0.274
Adjusted-R-sqr	0.096		

Table 6 (cont.): STEP 3 - (No financing effects) - Production function: OLS, dependent variable - labor productivity (sales per employee)

High Tech firms (n=1170)				***Low Tech firms (n=930)***			
Sales per employee (in log)	Coef.	Std. Err.	P>|t|	Sales per employee (in log)	Coef.	Std. Err.	P>|t|
predicted prodinnov probability	-0.148	0.164	0.365	predicted prodinnov	0.241	0.193	0.212
predicted procinnov probability	0.330	0.259	0.203	predicted procinnov	-0.409*	0.226	0.071
logcapexint	0.003	0.008	0.720	logcapexint	-0.004	0.009	0.691
autoadmin	-0.257***	0.067	0.000	autoadmin	-0.085	0.102	0.406
automktg	0.235***	0.063	0.000	automktg	-0.104	0.091	0.256
bankmajor	0.006	0.036	0.876	bankmajor	-0.041	0.038	0.278
largefirm	0.274***	0.049	0.000	largefirm	-0.067	0.068	0.327
largegrp	-0.039	0.055	0.479	largegrp	-0.046	0.067	0.494
oldfirm	0.070*	0.048	0.064	oldfirm	-0.047	0.060	0.426
oldgrp	0.094*	0.048	0.051	oldgrp	-0.102	0.070	0.142
age	-0.009***	0.003	0.000	age	0.004	0.004	0.327
agesqr	0.000**	0.000	0.024	agesqr	0.000*	0.000	0.095
grpage	0.000	0.003	0.911	grpage	-0.006	0.004	0.158
grpagesqr	0.000	0.000	0.830	grpagesqr	0.000	0.000	0.328
export	0.145***	0.053	0.006	export	0.243***	0.053	0.000
custretail	0.015	0.101	0.884	custretail	0.231**	0.096	0.016
custb2b	-0.138*	0.075	0.067	custb2b	0.204**	0.084	0.016
distnational	-0.056	0.082	0.491	distnational	0.179***	0.060	0.003
distabroad	0.196**	0.088	0.027	distabroad	0.196***	0.065	0.003
pctfamexecs	0.030	0.071	0.674	pctfamexecs	-0.221	0.080	0.006
acquis	0.030	0.040	0.457	acquis	-0.117**	0.054	0.032
divest	0.019	0.056	0.739	divest	0.082	0.075	0.272
RDlabint	0.508***	0.152	0.001	RDlabint	0.615***	0.173	0.000
outsource	0.035	0.032	0.288	outsource	0.044	0.044	0.313
year	-0.007	0.016	0.657	year	-0.016	0.020	0.406
constant	19.448	32.687	0.552	constant	37.926	39.545	0.338
Adjusted-R-sqr	0.099			Adjusted-R-sqr	0.155		