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Keskusteluaiheita – Discussion papers

No. 1085

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DO STOCK OPTION SCHEMES AFFECT FIRM TECHNICAL INEFFICIENCY? EVIDENCE FROM FINLAND

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* This study is part of the author's PhD dissertation. I am extremely grateful to William Greene, Pekka Ilmakunnas, Otto Toivanen and Hung-Jen Wang for their helpful comments and suggestions. I thank Seppo Ikäheimo from the Helsinki School of Economics and Alexander Corporate Finance Ltd for the data on stock option schemes in publicly traded Finnish companies, as well to Balance Consulting for the financial statement data. In addition, I thank the LIIKE program of the Academy of Finland, the Foundation of Kluuvi, the Marcus Wallenberg Foundation and the Helsinki School of Economics Research Foundation for financial support. All support from the Research Institute of the Finnish Economy (ETLA) is gratefully acknowledged. An earlier version of this paper has benefited from comments by participants at the XXVIII Annual Meeting of the Finnish Society for Economic Research in Helsinki, February 2-3, 2006, and at the Productivity session of 33rd conference of the EARIE in Amsterdam, August 25-27, 2006. As usually, all remaining errors are my own.

ISSN 0781-6847 30.03.2007

MÄKINEN, Mikko, **DO STOCK OPTION SCHEMES AFFECT FIRM TECHNICAL INEFFICIENCY? EVIDENCE FROM FINLAND.** Helsinki: ETLA, Elinkeinoelämän Tutkimuslaitos, The Research Institute of the Finnish Economy, 2007, 26 p. (Keskustelu-aiheita, Discussion Papers, ISSN 0781-6847; No. 1085).

ABSTRACT: In this paper we study whether stock option schemes affect firm technical inefficiency. We estimate Cobb-Douglas stochastic production frontier models using a novel panel data set on the publicly listed Finnish firms in the manufacturing and ICT sectors over the period from 1992 to 2002. We find evidence that the mean inefficiency estimates in the ICT sector are clearly higher than in the manufacturing sector. Furthermore, our empirical findings suggest that broad-based option firms may have higher mean inefficiency than selective and non-option firms in the manufacturing sector. The quantitative assessments of the marginal effects on the inefficiency support the view that especially broad-based schemes affect the mean and the variance of the inefficiency term u_{it} in the manufacturing sector, but not in the ICT sector. Our findings do not provide empirical support for the view that stock option schemes reduce firm technical inefficiency.

KEYWORDS: stochastic frontier, technical inefficiency, production function, stock options

JEL-codes: C3, J3, M5

1. Introduction

During the 1990s, stock options became an increasingly popular compensation method in many countries (e.g. Murphy, 1999). Initially, stock options were typically allocated only to executives[1], but the association of stock options mainly with managerial compensation changed rapidly after companies worldwide started to issue options to the workforce more broadly (e.g. Weeden, Carberry and Rodrick, 1998; Lebow et al., 1998; and Blasi, Kruse and Bernstein, 2003). The growing use of stock options has generated heated public discussion with some viewing stock options as a device by which managers transfer excessive benefits to themselves, while others see options as a major innovation in managerial and personnel compensation.

The growth of option adoptions has accompanied a mushrooming of theoretical and empirical literature on stock options (e.g. Ittner et al., 2003). Whereas sharp disagreements exist among theorists on the economic impact of different types of option schemes, an existing empirical work in economics has typically focused on the link between options and firm productivity. For example, Jones, Kalmi and Mäkinen (2006b) argue: *"For selective option schemes, the baseline fixed effects estimator suggests a 2.1-2.4% positive and statistically significant effect of the option program indicator on firm productivity. However, in empirical models in which endogeneity and dynamics are taken into account, no evidence is found of a link with firm productivity."* This evidence of a non-significant link raises a question whether, instead of firm productivity, stock options affect firm technical inefficiency, as inefficiency is defined in the stochastic production frontier literature. For example, the proponents of options typically argue that option plans may motivate managers and employees to make better decisions, work harder and share information within a firm in a way that decreases firm inefficiency. Other examples of exogenous factors that may affect inefficiency are the degree of competitive pressures, input and output quality indicators, network characteristics, ownership form, and various managerial characteristics etc. (Kumbhakar and Lovell, 2000).[2] To the best of our knowledge, we provide the first empirical evidence in the literature on the link between stock option schemes and firm technical inefficiency.

The key research questions are: (i) whether firm-level technical inefficiency is higher in non-option than in option firms; (ii) whether the impact of options on firm technical inefficiency is dependent upon whether a plan is broad-based or selective. We estimate simultaneously stochastic production frontier parameters, inefficiency scores and marginal effects by using novel panel data on Finnish publicly listed firms[3] in the manufacturing and ICT sectors in 1992-2002. Our data enable a careful investigation of the inefficiency effects of different types of option plans, i.e. whether options are allocated selectively to a specific group of employees (i.e. a selective option scheme) or whether all employees are eligible to participate (i.e. a broad-based option scheme). Since a possibility to obtain firm-level inefficiency estimates is the main reason to use stochastic frontier models, we follow a common procedure in the literature and treat all explanatory variables as exogenous.

We find evidence that the shape of the inefficiency distribution differ notably between the manufacturing and the ICT sectors. For example, mean inefficiency estimates in the ICT sector are substantially higher than in the manufacturing sector, though naturally efficient and inefficient firms exist in both sectors. Also, in the ICT sector mean conditional inefficiency estimates indicate that there is no mean inefficiency difference between option and non-option firms. However, in the manufacturing sector our findings suggest that broad-based firms may have higher mean inefficiency than selective and non-option firms.

The quantitative assessment of the average marginal effects on the inefficiency term supports the view that especially broad-based schemes affect the mean and the variance of the inefficiency term in the manufacturing sector. The findings on the mean of inefficiency suggest that broad-based schemes may increase technical inefficiency. Respectively, the marginal effect of broad-based schemes on the variance of the inefficiency term is significant, implying an increase in production uncertainty. In sum, these findings would indicate, other things equal, that broad-based scheme firms in the manufacturing sector may achieve lower and more uncertain productivity growth as time goes by. For selective schemes, we find no evidence of a link with technical inefficiency. Finally, our findings do not support the hypothesis that option schemes reduce firm technical inefficiency.

This paper is organised as follows. Section 2 briefly describes the evolution of stock option programs in Finland. In section 3 we describe our data and empirical strategy. Section 4 reports the empirical findings. Finally, section 5 concludes.

2. The development of option schemes in Finland

In this section, we briefly review the option schemes' adoption pattern in Finland.[4] Table 1 describes the evolution of option plans in the publicly traded firms on the Helsinki Stock Exchange (HEX) between 1987 (when the first employee stock option scheme was launched in Finland) and 2002. We have information on the presence of option schemes on the main list throughout the period and on the minor lists, i.e. NM-list (New Market) and I-list (Investor), since 1997.

Column 1 gives the number of firms on the HEX main list. Column 2 shows the total number of listed firms, including the two minor lists (from 1997). It appears that the number of listed firms fluctuates a lot with the business cycle. The first period of growth was the economic boom years 1987-1989, when the number of firms increased from 52 to

Table 1. Development of stock option plans in Finland

Year	(1) No. of firms on the main list	(2) No. of firms in total	(3) No. of first option plan in this year	(4) No. of new option plans in this year	(5) No. of main list firms having option plans	(6) No. of firms having option plan	(7) HEX portfolio index, yearly changes(1
1987	52	-	1	1	1 (1.9%)	1	-
1988	70	-	2	2	3 (4.3%)	3	-
1989	82	-	4	6	6 (8.5%)	7	-
1990	77	-	2	3	7 (9.1%)	8	-0.380
1991	66	-	3	4	9 (13.6%)	10	-0.113
1992	65	-	1	1	8 (12.3%)	11	0.077
1993	60	-	4	6	12 (20.0%)	15	0.657
1994	68	-	20	21	27 (39.7%)	34	0.164
1995	74	-	5	7	34 (45.9%)	38	-0.062
1996	73	-	3	9	34 (46.6%)	36	0.322
1997	82	115	12	22	40 (48.8%)	46 (40.0%)	0.273
1998	92	119	24	47	60 (65.2%)	69 (58.0%)	0.138
1999	102	137	21	41	77 (75.5%)	91 (66.4%)	0.541
2000	107	150	20	59	88 (82.2%)	113 (75.3%)	-0.242
2001	103	145	4	32	87 (84.5%)	112 (77.2%)	-0.191
2002	99	137	1	29	82 (82.8%)	101 (73.7%)	-0.150
Total			127	290			

1) The portfolio index in trade-weighted average share returns, where a maximum weight assigned to one company is 10%. For years 1990-1995 we have used the general index, since the portfolio index is calculated only since 1996. Changes are in logarithmic scale.

82. From 1989 onwards the number of firms fell, reaching a low point of 60 firms in 1993. The main reason for this was the Great Finnish Depression in 1990-1993, when many Finnish firms had financial problems.[5] After 1993 the number of listed firms started to rise, and the 1989 level was reached again in 1997. The increase continued until 2000, but thereafter the number fell again. From 1997 onwards we also include firms on the two

minor lists. In some cases, firms switched from the minor to the major list. At the same time, however, there are new firms entering the minor lists, especially in 2000 when relatively many small ICT firms entered the NM-list.

Column 3 indicates how many firms have adopted their first option scheme in a given year. Altogether, 127 firms have adopted a stock option plan. While seven pioneering firms implemented their option plans as early as the 1980s, very few plans were launched during the economic depression years of 1990-1993. The renewed interest in option plans began in 1994, when 20 firms (almost 40% of listed firms) adopted option schemes. Relatively few firms adopted schemes during 1995-1996 (possibly because the taxation of option gains changed from a moderate capital tax into a substantially higher marginal income tax), but since 1997 options have became widely popular. The rise of option schemes during 1999-2000 was fuelled by new listings. When new listings stopped after 2000, so did the introduction of new option schemes. Firms often launch new schemes once the previous schemes are close to expiring, or they may operate many schemes simultaneously: 84 of the 127 firms (66%) that have ever adopted a scheme have implemented more than one scheme (three firms have reached 7 successive schemes).[6]

Column 4 shows the number of firms that adopted new option schemes in a given year. The total number of option adoptions we are aware of is 290. The early peak year was 1994 (21 firms adopted). From 1997 (22 firms adopted) the adoption increased further, but after 59 plans in 2000 the adoptions started to decline, with 32 new schemes in 2001 and 28 in 2002.

In Column 5 we use the information on timing and launching of a scheme. A firm is treated as having a scheme in year t, if it has at least one scheme that has started in year t or earlier and if the final date for exercising options in this scheme is in year t+1 or later. Column 5 indicates that the proportion of firms with an option scheme increased until

1993, by which time 20% of the main list firms had an option scheme. This proportion jumped to around 40% in 1994, after which it increased slowly for three years, until it jumped again to 65% in 1998. The temporary maximum was reached in 2001, when almost 85% of the main list firms had a stock option scheme.

Column 6 shows the development for all firms, also for those outside the main list. The proportion of firms with stock option schemes is somewhat lower for all firms, due to many non-option firms at the I-list.

More generally, the extensive growth of stock option schemes reflects a deep change in the Finnish corporate governance system. In the end of the 1980s, the Finnish corporate governance system in listed firms was very much bank-centred and resembled the German system (see e.g. Hyytinen, Kuosa and Takalo, 2003). The stock market started its recovery after the depression in 1993, and the importance of the equity market in financial intermediation grew throughout the 1990s. Both the turnover and market value of firms listed on the stock exchange increased dramatically throughout the decade, with Nokia leading this development.

Now Finnish stock markets are much deeper, more transparent and arguably provide more reliable information than in the past. At the same time, both monitoring of insider trading and legal punishments have become stricter. During the last 10-15 years Finland has shifted from a bank-based financial intermediation towards a market-based system. As discussed above, the most active period of stock option adoptions coincided with the height of the stock market boom in the late 1990s. However, as market prices started to fall after May 2000, accelerating further in 2001 and 2002, the rate of stock option adoption decreased markedly (see e.g. Jones, Kalmi and Mäkinen, 2006a).

3. The data and estimation strategy

3.1 The data

In this section we describe the data and our estimation strategy. To examine the impact of option schemes on firm technical inefficiency, we use new panel data for the publicly listed Finnish firms in the manufacturing and ICT sectors in 1992-2002. Our firm-level data include information on firms' stock option programs and financial statements. Moreover, our option data enable a distinction between selective and broad-based schemes allowing an investigation of the inefficiency effects of different types of option plans. In the option data set, we have combined four different option data sources: firms' annual statements and general meeting reports, firms' press releases on the adoption of a scheme, the option data gathered by Professor Seppo Ikäheimo from the Helsinki School of Economics, and the option data provided by Alexander Corporate Finance Ltd, an investment bank that designs option programs in Finland. We then cross-checked the option information several times, and in a few cases when it did not match, we have trusted the firms' own public announcements. Thereafter we matched option data with firm-level accounting data, obtained from Balance Consulting Ltd, a firm specialised in accounting information.

Our data include *all* listed Finnish companies for a minimum of four consecutive years in the manufacturing and ICT sectors. It is an unbalanced panel, i.e. we do not observe the same cross-section units in each year. Apparently, some of the yearly variation is due to the entry and exit (attrition) of listed firms at the Helsinki Stock Exchange (HEX). Also, a few firms merged in the period, and in these cases we included only new merged firms after the merger. In addition, concerning mainly recently listed firms in a few cases, we added a firm's financial statement information prior to the listing, if that information was available in the accounting data.[7]

Table 2. Summary statistics for the manufacturing sector

Variable	Name	Firm-year obs	Mean	Std. Dev.	Min	Max
ln(va)	Natural logarithm of value-added	571	18.27	1.79	14.95	22.37
ln(l)	Natural logarithm of employees	571	7.38	1.67	4.32	10.74
ln(k)	Natural logarithm of fixed capital	571	18.37	2.16	13.94	23.58
dilu*	Potential dilution in the range of (0,1); a proxy of option program size	298	0.0482	0.0462	0.0031	0.3069
diluss*	Potential dilution for selective stock option programs	228	0.0322	0.0227	0.0031	0.1109
dilubb*	Potential dilution for broad-based stock option programs	70	0.1003	0.0624	0.0369	0.3069
opt	Option program dummy	571	0.522	0.500	0	1
ssopt	Selective option program dummy	571	0.399	0.490	0	1
bbsopt	Broad-based option program dummy	571	0.123	0.328	0	1

All value measures are deflated using an industry-specific gross output deflator at 2000 constant Euros obtained from Statistics Finland. * Summary statistics for dilu, diluss and dilubb variables are only for those firms that have a stock option program. The data contains 571 firm-year observations regarding 62 firms.

Table 3. Summary statistics for the ICT sector

Variable	Name	Firm-year obs	Mean	Std. Dev.	Min	Max
ln(va)	Natural logarithm of value-added	243	17.13	1.50	13.56	22.16
ln(l)	Natural logarithm of employees	243	6.35	1.38	3.95	10.62
ln(k)	Natural logarithm of fixed capital	243	16.62	1.78	13.87	21.17
dilu*	Potential dilution in the range of (0,1); a proxy of option program size	139	0.0703	0.0452	0.0018	0.2138
diluss*	Potential dilution for selective stock option programs	64	0.0580	0.0377	0.0018	0.1872
dilubb*	Potential dilution for broad-based stock option programs	75	0.0807	0.0486	0.0184	0.2138
opt	Option program dummy	243	0.572	0.496	0	1
ssopt	Selective option program dummy	243	0.263	0.441	0	1
bbsopt	Broad-based option program dummy	243	0.309	0.463	0	1

All value measures are deflated using an industry-specific gross output deflator at 2000 constant Euros obtained from Statistics Finland. * Summary statistics for dilu, diluss and dilubb variables are only for those firms that have a stock option program. The data contains 243 firm-year observations regarding 32 firms.

To control for potential bias of very small and very large firms, we have excluded potential outlier observations, i.e. an observation if employment was less than 50 persons, if fixed capital was less than €1,000,000, and if employment was more than 50,000 persons. We also deflated all nominal monetary variables by an industry based gross-output deflator at constant 2000 Euros, obtained from Statistics Finland. The final data set contains 571 firm-year observations regarding 62 firms in the manufacturing sector and 243 firm-year observations covering 32 firms in the ICT sector, so that the number of observations of a firm *i*, i.e. T_i, is $4 \leq T_i \leq 11$.[8] Tables 2 and 3 present summary statistics for our key variables in the manufacturing and the ICT sectors.

In the analysis that follows, we distinguish between broad-based and selective option schemes. The latter are mostly managerial schemes, although they can also include other key personnel (e.g. R&D employees). However, in order to qualify as a broad-based scheme, all employees (or at least a great majority) should be eligible to participate. The classification on broad-based and selective option schemes is based on firms' public stock exchange reports.[9] The Finnish Law on Joint Stock Companies requires listed firms to report all relevant terms of stock option schemes to shareholders prior to adoption. While a high rate of eligibility does not automatically guarantee a high participation rate, there are good reasons to believe that these are closely connected. For one thing, employees usually face only small costs when they subscribe to options—e.g. by providing a zero-interest loan to the company, with the company repaying the loan at face value after a certain period, usually 1-3 years. Thus, while employees face a cost in terms of foregone interest and liquidity, typically this cost is far below the real value of the options. Moreover, not all companies use this procedure, as they essentially give options for free to their employees.[10]

We use different indicators for the presence or absence of an option scheme, the size of the scheme and whether the scheme is selective or broad-based. Two of the indicators are binary variables and one is a continuous variable. Our *first binary indicator* is *opt* measuring the presence of a scheme in a firm in a given year t. It equals one for option firms and zero otherwise. Thus, the indicator distinguishes option and non-option firms and allows us to compare inefficiency differences between option and non-option firms.

Our *second binary indicator* measures also the presence or absence of a plan, but it distinguishes between selective *(ssopt)* and broad-based *(bbsopt)* plans. By a selective plan we mean a scheme that is targeted to a selected group of employees including managerial programs, but also schemes that are targeted to key personnel. Broad-based plans are all encompassing, including managers, but they do not have to be egalitarian in the sense of all participants having the same number of options. By using these distinct dummy variables, we can examine whether inefficiency differs between selective and broad-based schemes.

Our *third program indicator* is potential dilution *(dilu)*. This indicator measures the potential size of effective schemes in a firm in a given year.[11] This is a continuous variable, i.e. the ratio of the number of shares that may be awarded through effective option plans in a given year divided by the sum of the total number of shares and the number of new shares that may be awarded through options at the end of a year. If a program ends in the middle of a year *t*, then year *t-1* is the last year used in assessing a potential dilution. The indicator allows us to explore whether option schemes can be simultaneously associated with the mean and the variance of the inefficiency term. We also use dilution indicators for selective (*diluss*) and broad-based (*dilubb*) schemes to examine whether there is a difference between the schemes.

3.2 Estimation strategy

In their pioneering work Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977) proposed independently stochastic production frontier models. Since then the literature has proposed several specifications and estimation techniques.[12] Early specifications focused on estimating technical inefficiency with cross-section data, but access to panel data allowed a richer modelling approach in the form of the fixed effects (e.g. Schmidt and Sickles, 1984) and the random effects (e.g. Pitt and Lee, 1981) estimators enabling us to relax some relatively strong distributional assumptions needed in cross-section models.[13] A stochastic production frontier panel data model can be written as

(1) $y_{it} = \alpha + \beta' x_{it} + v_{it} - u_{it}$, $u_{it} \geq 0$, i=1,...,N and t=1,...,T,

where firm output y_{it} is a scalar, and x_{it} is a vector of explanatory variables, such as inputs used in a production process. As proposed by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977), a composed error term $\varepsilon_{it} = v_{it} - u_{it}$ is the difference between a normally distributed two-sided noise component v_{it} and a normally distributed nonnegative inefficiency component u_{it} with the following assumptions:[14]

(2) $v_{it} \sim \mathrm{N}\left(0, \sigma_v^2\right)$, $u_{it} \sim \left|U_{it}\right|$ where $U_{it} \sim \mathrm{N}\left(0, \sigma_u^2\right)$ and independent of v_{it}.

A research interest may be in production technology parameters β, but one of the main reasons to estimate stochastic frontier models lies in obtaining inefficiency estimates $\hat{u}_{it}$. Unfortunately, these cannot be obtained directly from Equation (1), since only composed residuals $\hat{\varepsilon}_{it}$ are observed. Jondrow, Materov, Lovell, and Schmidt (1982) proposed the mean of the conditional distribution of u_{it} given ε_{it} as a point estimator for inefficiency term under the distributional assumptions presented in Equation (2):

(3) $$\mathrm{E}\left[u_{it} \left| \varepsilon_{it} \right.\right] = \frac{\sigma\lambda}{1+\lambda^2}\left[\frac{\phi\left(\frac{\varepsilon_{it}\lambda}{\sigma}\right)}{1-\Phi\left(\frac{\varepsilon_{it}\lambda}{\sigma}\right)} - \left(\frac{\varepsilon_{it}\lambda}{\sigma}\right)\right]$$, where

$\sigma = \left(\sigma_u^2 + \sigma_v^2\right)^{1/2}$, $\lambda = \frac{\sigma_u}{\sigma_v}$, and $\Phi(\cdot)$ and $\phi(\cdot)$ are standard normal cumulative distribution and density functions, respectively. Although Equation (3) gives point estimates for conditional technical inefficiencies[15], a major drawback is that it does not assess what may drive these inefficiencies.[16]

Greene (2002a; 2005) and Wang (2002) have recently proposed new maximum likelihood estimators that provide parameterizations of the exogenous influences on inefficiency. For example, Greene (2002a; 2005) suggests several estimators to account for heterogeneity among firms and to estimate simultaneously both technology parameters and technical inefficiency.[17] Wang (2002) proposes a model where heteroscedasticity and non-monotonic efficiency effects can be modelled. In addition, the model allows one to accommodate unconditional marginal effects of exogenous variables on the mean and the variance of u_{it} and to examine statistical significance of marginal effects by bootstrapping.[18]

We denote a firm's production function by $f(.)$, which relates firm value added[19] at time t, i.e. va_{it}, to inputs used in a production process:

(4) $$va_{it} = f(k_{it}, l_{it}, x_t; \beta)$$, where i=1,2, ..., N and t=1,2,...,T.

In Equation (4), subscripts *i* and *t* index firm and time, respectively. Firm deflated fixed capital is k_{it}, the sum of a firm's tangible and intangible assets at the end of the year, labour input l_{it} is the mean number of employees in a given year, and x_t is a time trend to account for technological change. We assume a Cobb-Douglas stochastic production frontier[20] as follows:

(5)
$$\ln va_{it} = \beta_k \ln k_{it} + \beta_l \ln l_{it} + \beta_x x_t + \varepsilon_{it},\ \text{where i=1,2,..., N; t=1,...,T,}$$
$$\varepsilon_{it} = v_{it} - u_{it}, v_{it} \sim \mathrm{N}\left(0, \sigma_v^2\right),\ u_{it} \sim \left|U_{it}\right|,\ U_{it} \sim \mathrm{N}\left(0, \sigma_u^2\right).$$

In Equation (5) all variables are the same as in Equation (4): a firm's inputs in the production process are capital k_{it} and labour l_{it}, and x_t is a linear time trend. We estimate separate industry-level models for the ICT and manufacturing sectors, since the sectors may differ in several ways. For example, a firm may need more capital in the manufacturing sector than in the ICT sector, whereas labour may be a more important production factor in the ICT than in manufacturing.

To study whether stock option schemes affect firm technical inefficiency, we utilize the recent developments in the literature that allows parameterizing the composite error term $\varepsilon_{it} = v_{it} - u_{it}$.[21] By doing this we can account for heteroscedasticity in the inefficiency component u_{it} (e.g. Caudill and Ford, 1993) and in the noise component v_{it} (e.g. Hadri, 1999).[22] But more importantly, by modelling the mean and the variance of inefficiency term u_{it}[23] as a function of stock option schemes, we can examine our two research hypotheses, namely (i) that firm-level technical inefficiency is expected to be higher in non-option than option firms; (ii) that the impact of options on firm technical inefficiency is expected to be dependent upon whether the plan is broad-based or selective. Thus, the variance of u_{it} is parameterized as an exponential function of firm size (measured by $\ln(l_{it})$) and stock option variables as follows[24]:

(6) $$\sigma_u^2 = \sigma_{uit}^2 = \exp(\delta' z_{it}) = \exp(\alpha + \delta_L \ln(l_{it}) + \delta_{opt} opt_{it})$$

(7) $$\sigma_u^2 = \sigma_{uit}^2 = \exp(\delta' z_{it}) = \exp(\alpha + \delta_L \ln(l_{it}) + \delta_{ssopt} ssopt_{it} + \delta_{bbsopt} bbsopt_{it}).$$

Besides the variance of the inefficiency component, the symmetric noise component can be heteroscedastic with respect to the size of firms. Thus, we model v_{it} as an exponential function of firm size as follows:

(8) $\sigma_v^2 = \sigma_{vit}^2 = \exp(\gamma' z_{it})$ =$\exp(\alpha + \gamma_L \ln(l_{it}))$.

To model flexible parameterizations of exogenous influences on the mean (e.g. Kumbhakar, Ghosh and McGuckin, 1991) and the variance of the inefficiency term u_{it} (e.g. Caudill and Ford, 1993), we use a model suggested by Wang (2002).[25] Contrary to Equations (6)-(8), now the effects on the inefficiency term are measured by the unconditional statistics of $\mathrm{E}[u_{it}]$ and $\mathrm{Var}[u_{it}]$.[26] The first two moments of u_{it} are

(9) $$m_1 = \mathrm{E}[u_{it}] = \sigma_{it}\left[\Lambda + \frac{\phi(\Lambda)}{\Phi(\Lambda)}\right]$$

(10) $$m_2 = \mathrm{Var}[u_{it}] = \sigma_{it}^2\left[1 - \Lambda\left[\frac{\phi(\Lambda)}{\Phi(\Lambda)}\right] - \left[\frac{\phi(\Lambda)}{\Phi(\Lambda)}\right]^2\right],$$ where

$\Lambda = \frac{\mu_{it}}{\sigma_{it}}$, and $\Phi(\cdot)$ and $\phi(\cdot)$ are standard normal cumulative distribution and density functions, respectively. The marginal effect of an exogenous variable *z* on $\mathrm{E}[u_{it}]$ can be calculated as follows:

(11) $$\frac{\partial \mathrm{E}[u_{it}]}{\partial \mathrm{z}} = \delta_z\left[1 - \Lambda\left[\frac{\phi(\Lambda)}{\Phi(\Lambda)}\right] - \left[\frac{\phi(\Lambda)}{\Phi(\Lambda)}\right]^2\right]$$

$$+\gamma_z \frac{\sigma_{it}}{2}\left[(1+\Lambda)^2\left[\frac{\phi(\Lambda)}{\Phi(\Lambda)}\right] + \Lambda\left[\frac{\phi(\Lambda)}{\Phi(\Lambda)}\right]^2\right],$$ where

δ_z and γ_z are the estimated coefficients of an exogenous variable *z* in Equations (6)-(8). Thus, the marginal effect is the sum of adjusted slope coefficients. Respectively, the marginal effect of an exogenous variable *z* on $\mathrm{Var}[u_{it}]$ is

(12) $$\frac{\partial \mathrm{Var}[u_{it}]}{\partial \mathrm{z}} = \frac{\delta_z}{\sigma_{it}}\left[\frac{\phi(\Lambda)}{\Phi(\Lambda)}\right](m_1^2 - m_2) +$$

$$+\gamma_z \sigma_{it}^2 \left[1 - \frac{1}{2} \left[\frac{\phi(\Lambda)}{\Phi(\Lambda)} \right] \left(\Lambda + \Lambda^3 + \left(2 + 3\Lambda^2\right) \left[\frac{\phi(\Lambda)}{\Phi(\Lambda)} \right] + 2\Lambda \left[\frac{\phi(\Lambda)}{\Phi(\Lambda)} \right]^2 \right) \right], \text{ where}$$

m_1 and m_2 are the first two moments of u_{it}, represented in (9) and (10).[27]

4. Estimation results

Table 4 presents the stochastic production frontier estimates for the manufacturing and ICT sectors. As can be seen from Table 4, production technology parameter estimates are in line with our prior expectations, i.e. capital input elasticities are higher in manufacturing than in the ICT sector, whereas labour input elasticity estimates are higher in the ICT sector than in manufacturing. In the manufacturing sector, estimated elasticities for capital are 0.29 (0.16 in the ICT sector) and for labour 0.71 (0.85 in the ICT sector), indicating that a production process in the manufacturing sector is more capital and less labour intensive than in the ICT sector. In both sectors, Wald tests support constant returns to scale hypothesis. The constant rate of technical change estimate is about 2.5 % per year in the manufacturing sector, but we find no evidence of that in the ICT sector. The estimates of λ are statistically significant and higher than one, indicating the existence of inefficiency in both sectors. When comparing the estimates of σ_u between the sectors, the variance of technical production inefficiency appears to be clearly higher in the ICT sector (0.68) than in the manufacturing sector (0.18). In addition, especially the presence of broad-based schemes seems to affect the variance of σ_u. The choice of parameterizing the error term v_{it} as a function of firm size seems to be an adequate approach in the manufacturing sector, but the size of the firm is statistically insignificant in the ICT sector.

Table 4. Stochastic production frontier estimates

	(1)	(2)	(3)	(4)
	Manufacturing Pooled MLE		ICT Pooled MLE	
constant	7.705 *** (0.156)	7.707 *** (0.157)	9.502 *** (0.408)	9.496 *** (0.410)
ln (labour)	0.709 *** (0.019)	0.710 *** (0.019)	0.853 *** (0.060)	0.856 *** (0.061)
ln (capital)	0.293 *** (0.012)	0.293 *** (0.011)	0.161 *** (0.042)	0.160 *** (0.043)
year	0.026 *** (0.006)	0.025 *** (0.006)	0.007 (0.010)	0.007 (0.010)
Parameters in the variance of v				
constant	-2.185 *** (0.519)	-2.238 *** (0.505)	-2.687 (1.920)	-2.699 (2.095)
ln (labour)	-0.182 ** (0.074)	-0.174 *** (0.072)	-0.167 (0.324)	-0.170 (0.354)
Parameters in the variance of u				
constant	-3.466 *** (0.997)	-3.889 *** (1.104)	-0.590 (0.654)	-0.964 (0.843)
ln (labour)	0.125 (0.116)	0.197 (0.131)	-0.018 (0.108)	0.051 (0.144)
opt	0.344 * (0.183)	-	0.622 ** (0.174)	-
ssopt	-	0.039 (0.193)	-	0.397 (0.425)
bbsopt	-	0.791 ** (0.326)	-	0.773 *** (0.169)
year	-0.037 (0.045)	-0.052 (0.048)	-0.064 (0.064)	-0.073 (0.063)
σ_v	0.175	0.176	0.155	0.156
σ_u	0.279	0.276	0.677	0.677
σ	0.330	0.327	0.695	0.695
$\lambda=\sigma_u / \sigma_v$	1.59	1.57	4.37	4.34
Log likelihood function	6.585	10.211	-124.114	-123.307
Finite sample corrected AIC	7.223	2.050	269.176	269.757
Wald test for constant returns to scale (p-value) Ho: $\beta_k + \beta_l = 1$	0.88	0.85	0.96	0.69

The dependent variable is ln(value-added). Standard errors in parenthesis. ***, **, * statistically significant at 1%, 5% and 10% levels, respectively. We have 62 firms/571 observations in the manufacturing sector and 32 firms/243 observations in the ICT sector. SSOPT is a dummy variable for selective and BBSOPT is a dummy for broad-based option schemes, respectively. As a control group we use non-option firms.

Table 5. Conditional inefficiencies

Estimated inefficiencies $\hat{u}_{it}$	(1) Manufacturing Pooled MLE	(2)	(3) ICT Pooled MLE	(4)
Mean	0.217	0.213	0.451	0.449
Standard deviation	0.125	0.126	0.258	0.257
Minimum	0.040	0.041	0.050	0.051
Maximum	0.762	0.780	0.959	0.954

Conditional inefficiencies are based on the models presented in Table 4.

Table 6. Mean conditional inefficiencies by industry and the type of stock option scheme

	(1) Selective scheme firms	(2) Broad-based scheme firms	(3) Non-option firms	(4) Total
Manufacturing	0.218 (236 obs)	0.280 (70 obs)	0.190 (265 obs)	0.213 (571 obs)
ICT	0.445 (64 obs)	0.467 (75 obs)	0.438 (104 obs)	0.449 (243 obs)
Total	0.266 (300 obs)	0.377 (145 obs)	0.260 (369 obs)	0.283 (814 obs)

Conditional inefficiencies are based on the models presented in Table 4.

Based on stochastic production frontier models in Table 4, Tables 5-6 report conditional inefficiency estimates by industry and the type of option scheme. In Table 5, the mean inefficiency estimates are substantially higher in the ICT sector than in manufacturing. For example, the estimated mean inefficiency is 0.21 or 21% with a standard deviation of 0.13 in the manufacturing sector, whereas in the ICT sector it is 0.45 or 45% with a standard deviation of 0.26. It is, however, important to notice that efficient and inefficient firms exist in both sectors, e.g. minimum inefficiency is 4% in manufacturing and 5% in the ICT sector.

Table 6 shows the mean conditional inefficiencies by industry and the type of option schemes. As can be seen, in the ICT sector mean conditional inefficiencies vary in the range of 0.44-0.47 indicating that there is no clearly observable mean inefficiency difference between option and non-option firms. However, in the manufacturing sector our findings suggest that broad-based firms (0.28; 70 observations) may have higher mean inefficiency than selective (0.22; 236 observations) and non-option (0.21; 265 observations) firms, though the number of observations differs by the type of option scheme.

Table 7. Pooled stochastic production frontier ML estimates when parameterizing the variance and the mean of u

	Manufacturing	ICT
constant	7.791 (0.042) ***	9.570 (0.440) ***
ln (labour)	0.707 (0.042) ***	0.863 (0.052) ***
ln (capital)	0.286 (0.034) ***	0.150 (0.043) ***
year	0.023 (0.007) ***	0.003 (0.014)
Parameters in the mean of u		
constant	-17.634 (110.227)	-1.541 (2.786)
year	1.302 (8.040)	-0.423 (0.463)
diluss	-12.697 (68.423)	26.733 (25.529)
dilubb	-3.324 (33.001)	-10.269 (9.962)
ln (labour)	0.194 (1.006)	0.249 (0.288)
Parameters in the variance of u		
constant	0.873 (6.222)	0.573 (1.654)
year	-0.221 (0.062) ***	0.124 (0.077)
diluss	0.573 (11.964)	-5.838 (4.787)
dilubb	5.055 (1.722) ***	3.829 (4.233)
ln (labour)	0.065 (0.091)	-0.180 (0.190)
Parameters in the variance of v		
constant	-3.280 (0.194) ***	-3.494 (0.339) ***
Wald test for constant returns to scale (p-value) Ho: $\beta_k + \beta_l = 1$	0.64	0.45
Wald test for joint significance of variables in the mean of u (without constant, p-value) Ho: *year, diluss, dilubb, ln(labour)* =0	0.99	0.45
Wald test for joint significance of variables in the variance of u (without constant, p-value) Ho: *year, diluss, dilubb, ln(labour)* =0	0.00 ***	0.00 ***
Wald test for joint significance of *diluss* and *dilubb* variables in the mean and variance of u (without constant, p-value) Ho: *diluss, dilubb* =0	0.03 **	0.046 **
Log pseudolikelihood	13.595	-112.599

The dependent variable is ln(value-added). Diluss is a selective and dilubb is a broad-based option scheme proxy variable, respectively. Standard errors in parentheses in the stochastic production frontier are robust (adjusted for intragroup correlation).
***, **, * statistically significant at 1%, 5% and 10% levels, respectively. We have 62 firms/571 observations in the manufacturing sector and 32 firms/243 observations in the ICT sector.

To examine whether option programs affect the mean and the variance of the inefficiency term, we use the estimator proposed by Wang (2002). Table 7 presents stochastic production function estimation results (with standard errors adjusted for intragroup correlation), when the mean and the variance of the inefficiency term are modelled as a function of option plans and firm size. Contrary to Table 4, where our option program indicators measure the presence of a plan, now the variable is *potential dilution*, measuring the potential size of an effective scheme in firm *i* in year *t*.[28] The following key findings emerge from Table 7. First, stochastic production frontier parameter estimates are in line with those presented in Tables 4. In addition, Wald tests clearly indicate constant returns to scale in production. Second, in both sectors the assumption that all parameters (constant excluded) are jointly zero is rejected for the variance of the inefficiency term, but not for the mean. However, the Wald test for the hypothesis that selective (*diluss*) and broad-based (*dilubb*) option scheme parameters are jointly zero both in the mean and in the variance of the inefficiency term is rejected in both sectors.[29] In sum, the tests support the parameterization of the mean and the variance of the inefficiency term. While informative, Table 7 does not provide an estimate of the magnitude of the effects of selective (*diluss*) and broad-based (*dilubb*) schemes on the mean and the variance of the inefficiency term u_{it}.

Table 8. Marginal effects on inefficiency

	Manufacturing	ICT
Marginal effects on $E(u_{it})$		
year	-0.0025 (0.285)	-0.0124 (0.0177)
diluss	-0.1907 (0.7153)	1.4733 (1.7382)
dilubb	0.6155 (0.2976) **	-0.0262 (1.4776)
ln(labour)	0.0129 (0.0102)	-0.0291 (0.0375)
Marginal effects on $Var(u_{it})$		
year	-0.0012 (0.0021)	0.0003 (0.0137)
diluss	-0.0499 (0.1941)	0.4539 (1.671)
dilubb	0.1780 (0.0893) **	0.1966 (0.7991)
ln(labour)	0.0036 (0.0028)	-0.0252 (0.0273)

Table reports sample means of marginal effects. Standard errors of marginal effects are bootstrapped results of 1,000 replications, statistical significant levels are based on bias-corrected and accelerated confidence intervals. ***, **, * statistically significant at 1%, 5% and 10% levels, respectively.

To provide a quantitative assessment of the marginal effects, Table 8 reports the marginal effects of the variables on $E(u_{it})$ and $Var(u_{it})$. The standard errors are bootstrapped results of 1,000 replications and significance levels are based on bias-corrected and accelerated intervals. The overall results support the view that especially broad-based schemes may affect the mean and the variance of the inefficiency term u_{it}. The results on $E(u_{it})$ show that an increase in the potential dilution of broad-based schemes is likely to increase production inefficiency. The average marginal effect is estimated to be 0.62, i.e. a one percentage point increase in the potential dilution of broad-based schemes increases firm technical inefficiency by 0.62%. Since $\partial E(\ln(va))/\partial dilubb = -\partial E(u)/\partial dilubb,$ the marginal effect on productivity would be about -0.62%. The average marginal effect of the potential dilution of broad-based schemes on $Var(u_{it})$ is positive, implying an increase in production uncertainty. Together these results would suggest, other things equal, that as time goes by broad-based scheme firms in the manufacturing sector may achieve lower and more uncertain productivity growth. For selective option schemes, we find no evidence that they affect firm inefficiency. Finally, our findings do not provide any empirical support for the view that stock option schemes reduce firm technical inefficiency in the manufacturing or ICT sector.

5. Conclusions

In this paper we study whether (i) firm-level technical inefficiency is higher in non-option than in option firms and (ii) whether the impact of options on firm technical inefficiency is related to the type of plan, i.e. whether the plan is broad-based or selective. We estimated stochastic production frontier models using novel panel data of Finnish publicly listed firms in the manufacturing and ICT sectors over the period 1992-2002. Our data enabled a careful investigation of the inefficiency effects of different types of option plans.

The key findings can be summarized as follows. First, the mean inefficiency estimates in the ICT sector are clearly higher than in the manufacturing sector. Efficient and inefficient firms exist in both sectors, but on average, mean inefficiency is higher in the ICT sector than in the manufacturing sector.

Second, our findings suggest that broad-based stock option firms in the manufacturing sector may have higher mean inefficiency than selective and non-option firms. On the contrary, in the ICT sector the mean inefficiency estimates do not indicate any difference between option and non-option firms.

Third, the quantitative assessment of the marginal effects supports the view that especially broad-based schemes in the manufacturing sector may affect the mean and the variance of the inefficiency term u_{it}. The results on the mean of the inefficiency $E(u_{it})$ show that an increase in the potential dilution of broad-based schemes increases production inefficiency in the manufacturing sector. Respectively, the average marginal effect of the potential dilution of broad-based schemes on the variance of the inefficiency term $Var(u_{it})$ implies production uncertainty in the manufacturing sector. These findings suggest that, other things equal, broad-based scheme firms in the manufacturing sector might achieve lower and more uncertain productivity growth as time goes by. Finally, we find no evidence that selective schemes affect firm inefficiency or the mean and the variance of the inefficiency term u_{it}. In summary, our findings do not provide any empirical support for the view that stock option schemes reduce firm technical inefficiency in the manufacturing or ICT sector.

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Endnotes

[1] Mäkinen (2001) describes the evolution of stock option programs in Finland. Jones, Kalmi and Mäkinen (2006a) study the determinants of option schemes adoption in Finland. They also summarise in more detail the evolution of options and discuss the institutional background in Finland.
[2] See also Wang (2002) and Bottasso and Sembenelli (2004).
[3] Although the Finnish economy was only the 47th largest in the world in 2003, it is an extremely interesting case. First, The World Economic Forum (WEF) found Finland the most competitive in the survey of 104 economies in 2003-2004. More surprisingly, Finland has subsequently held the top position in three out of the last four years. Second, Transparency International ranks Finland as the world's least-corrupt country for the fifth consecutive year. Third, during the period 1992-2002 the great majority of publicly listed Finnish firms adopted their stock option plans. This enables us to study the effects of options in a place where their use was previously rare, such as in Finland.
[4] For a more detailed description see e.g. Jones, Kalmi and Mäkinen (2006a).
[5] For more detailed discussion about the Great Finnish Depression during 1990-1993 see e.g. Kiander and Vartia (1996), and Honkapohja and Koskela (1999).
[6] Firms may adopt schemes for different reasons. For example, the shareholders of a firm may prefer to broaden schemes to a larger set of employees, or there is a need to change the terms of a scheme for some reason.
[7] This is done to increase the number of observations in the data.
[8] We are aware that few unlisted Finnish firms have also adopted option schemes, at least during the bull market in the end of 1990s. Unfortunately, no information on these firms and option schemes was unavailable. We can only roughly conclude that it is perhaps more probable to find these programs within the ICT sector than within other sectors. We believe, however, that the number of these unlisted stock option firms is small, since option schemes works properly only in situations where the value of shares can be assessed in the stock market. Also, in order to study the impacts of stock option programs with public data, our data seem to be a reasonable choice.
[9] Our classification is different from Kroumova et al. (2006), who use a 50 % threshold as a criterion for broad-based schemes. Our data do not include this information, but they have the important advantage of being derived from publicly reported sources that must be externally verifiable, rather than from confidential surveys.
[10] We also interviewed Mr. Erkki Helaniemi, a partner at Alexander Corporate Finance, an investment bank, who has been personally involved in setting up dozens of option schemes. He confirmed that there are dramatic differences in the participation rates for option schemes, depending on eligibility.
[11] Unfortunately, we do not have information on stock option program details, such as exercise prices to calculate Black-Scholes values.
[12] Excellent literature surveys are Bauer (1990), Greene (1993; 1997), and Kumbhakar and Lovell (2000).
[13] For example, the linear fixed effects estimator captures all fixed effects between firms potentially making firm-specific inefficiency indecomposable from heterogeneity among firms. Moreover, at least one producer is assumed to be 100% technically efficient, and other firms' inefficiency is measured relative to this fully efficient producer. The random effects estimator suffers from the assumption that firm-specific inefficiency is the same in every year. For short panels this may be an appropriate assumption, but in longer panels this is likely to be problematic. Other drawbacks of the random effects estimator are that heterogeneity between firms is absorbed into the inefficiency term, and it is assumed that the inefficiency term is uncorrelated with other explanatory variables. Thus, as argued by Greene (2005), both traditional linear panel estimators previously used in the stochastic frontier literature may be seriously distorted due to blending of inefficiency and heterogeneity in the same term.
[14] The noise component v_{it} captures measurement errors and production function misspecification effects, whereas u_{it} is related to technical inefficiency.
[15] It is also possible to obtain confidence intervals for the point estimates of technical inefficiency, but we do not examine this issue here. For more details see Horrace and Schmidt (1996), and Bera and Sharma (1999).
[16] See Kumbhakar and Lovell (2000) for detailed discussion on how to account for exogenous influences in the one- and two-step approaches. Also, according to the Monte Carlo studies conducted by Schmidt and Wang (2002), the one-step modelling approach is more favourable than the two-step approach, where inefficiencies and exogenous effects are estimated sequentially.
[17] As a novel contribution to the stochastic frontier literature, Greene (2002a, 2005) greatly extends a simultaneous accounting of heteroskedasticity and inefficiency by proposing e.g. a new "true" fixed effects framework that more explicitly follows stochastic frontier modelling foundations applied frequently in cross-

section frontier models. See Prentice and Gloeckler (1978), Sueyoshi (1993), and Greene (2001, 2002a) for a formal derivation of the estimators. See also LIMDEP's manual and Greene (2002b, 2005).

[18] See Wang (2002).

[19] On theoretical grounds firm value added is a preferable measure to sales (i.e. as a proxy for firm output), since value added does not include intermediate inputs that are purchased from other firms.

[20] The following issues have influenced our empirical strategy. First, we assume a Cobb-Douglas form of technology, since it has been used frequently in the related productivity literature, such as the evaluation of the effects of ESOPs on firm productivity (e.g. Jones and Kato, 1995) and analysing the effects of stock options on firm productivity (e.g. Conyon and Freeman, 2004; Jones, Kalmi and Mäkinen, 2006b). Second, although the Cobb-Douglas functional form is more restrictive than other functional forms, such as the translog, we prefer the Cobb-Douglas production function, since the number of the translog production frontier model estimations worked poorly, i.e. the maximum likelihood estimators did not converge in the estimations. Third, since we do not have information on the detailed terms of option schemes, such as exercise prices, we must bypass some potentially important issue. For example, presumably the terms of option schemes differ among firms, which may affect performance effects. Thus, when an option scheme is substantially out of the money (i.e. a current stock price is substantially below an exercise price), options may not provide strong incentives for employees and managers to improve their performance.

[21] A priori we conducted several fixed effects estimations by LIMDEP where we modelled the mean and the variance of the inefficiency term. Unfortunately, all models behaved extremely poorly, even when we tried the stratification method. As noted in LIMDEP's manual pp. E24-27, fixed effects formulations, especially based on the Newton's method, can be "extremely problematic in all but the most favourable of cases". Therefore we can only report here results based on the pooled ML model.

[22] According to Bottasso and Sembenelli (2004), unaccounted heteroscedasticity in the u_{it} leads to biased estimates of the production frontier parameters and technical efficiency, whereas unaccounted heteroscedasticity in the v_{it} leads to biased estimates of technical efficiency.

[23] The mean measures the expected value of technical inefficiency, whereas the variance measures production uncertainty (Bera and Sharma, 1999).

[24] The estimation approach has a lot in common to Bottasso and Sembenelli (2004), who provide evidence on the relation between identity of ultimate owners and technical inefficiency by estimating stochastic production frontiers on Italian manufacturing firms.

[25] Note that we use here a different estimator. The reason is that the model, kindly provided by Hung-Jen Wang, utilises STATA's maximum likelihood routines and assumes that same the *z* affects both the mean and the variance of u_{it}.

[26] Wang (2002) underlines that the marginal effects on the conditional mean and variance of u_{it} are almost intractable, particularly when the variances of u_{it} and v_{it} are modelled.

[27] Based on a result from Barrow and Cohen (1954), $m_1^2-m_2>0$.

[28] The reason is that we had major problems in convergence of the ML estimator when using option program dummy indicators.

[29] We also specified models (not reported here) where the variance of v_{it} was modelled as a function of firm size. All estimated models and performed Wald tests indicated that v_{it} is not heteroskedastic with respect to firm size.

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