CRENoS
Centro Ricerche Economiche Nord Sud
*Università di Cagliari*
*Università di Sassari*

# CREDIT RATIONING IN HIGH-TECH FIRMS AND SAMPLE SELECTION

Gianfranco Atzeni
Claudio Piga

CONTRIBUTI DI RICERCA
03/04

**Gianfranco Atzeni**
*University of Sassari and CRENoS*
atzeni@uniss.it

**Claudio Piga***
*Nottingham University Business School and CRENoS*
Claudio.piga@nottingham.ac.uk

# CREDIT RATIONING IN HIGH-TECH FIRMS AND SAMPLE SELECTION

**Abstract**
We argue that it may be inappropriate to study whether high-tech firms are liquidity-constrained, without first modeling their antecedent decision to apply for credit. This sample selection issue is relevant when studying a borrower-lender relationship, as the same factors can influence both the demand and the supply side. E.g., we find firms engaged in R&D to be less likely to request extra funds. When they do we observe a higher probability of being denied credit. Thus, our findings lend support to the notion of credit constraints being severe for innovative firms, although we suggest that other measures of innovative activity, in addition to total R&D expenditures, should be used to understand the occurrence of credit constraints in the high-tech sector.

JEL: D45, G21, G32, E51
*Keywords:* Bivariate Probit; Innovation; selectivity; in-house R&D.

*Contact Author.
Address for correspondence:
Nottingham University Business School
Wollaton Road,
Nottingham NG8 1BB
Tel: (++44)-(+)115-9515484
Fax: (++44)-(+)115-8466667

June 2003

## 1. Introduction

Credit rationing occurs when a firm demands but is refused credit, even if it is willing to pay a higher interest rate (Freixas and Rochet, 1997). Indeed, an interest rate increment has four effects on the lender's return to debt. First, an obvious positive price effect. Second, an adverse selection effect because best firms drop out of the market. Third, a positive selection effect due to the fact that some low-return high-risk entrepreneurs leave the market. Fourth, an adverse selection effect as some high-return low-risk switch to the equity market (Hellmann and Stiglitz, 2000). When the adverse selection effects dominate the positive effects, the result is an inverse relationship between interest rate increments and return to the bank. The efficient allocation of resources is not reached, and the result is insufficient lending (De Meza and Webb, 2000). Conversely de Meza and Webb (1990) present a model where the equilibrium outcome within an asymmetric information environment is overlending.

However, for firms in High-Tech sectors, on which this paper focuses, the overlending outcome is unlikely to occur. Carpenter and Petersen (2002) present the reasons why underlending best describes the relationship between innovative firms and lenders (see also Hall, 2002). First, information is not perfect for the very nature of innovation processes. The R&D process is uncertain because of the difficulties, even for the best-informed agent, to forecast output given the inputs employed (Arrow, 1962). R&D returns are, therefore, more unpredictable and uncertain, giving rise to moral hazard and adverse selection problems on the borrower's part. A second aspect is related to the strategic need for secrecy, which causes firms not to share information with the lenders (Himmelberg and Petersen, 1994). Furthermore, because R&D processes involve accumulation of capital, which has typically an intangible nature, investment has a low collateral value, thereby limiting the access to credit. Finally, marginal cost of financial distress is likely to rise rapidly with leverage. Firms facing severe financial restrictions may have to abandon critical innovative projects, which crucially determine a firm's growth opportunities. Financial markets usually anticipate this behaviour lowering a firms' market value (Carpenter and Petersen, 2002). Therefore, internal financing is crucial for innovation.

This paper pursues two main objectives. First, following Guiso (1998), an investigation of the factors affecting a firm's probability of having its credit application turned down is carried out. We focus in particular on different measures of R&D expenditures. Indeed, it turns out that using measures of, respectively, Self-Financed R&D outlays and R&D expenditures in internal facilities yields results that are different from those obtained in a regression including total R&D expenditures. Second, we extend Guiso's approach by using a sample selection methodology that enables the distinction between the determinants of extra credit demand and those influencing the success of a credit application. This is an important difference because only the sub-sample of firms needing extra credit should be considered in the analysis of whether a firm's credit application was subsequently rejected. However, such a consideration is not found in the existing literature, to which this paper contributes by trying to answer, from an empirical viewpoint and with particular reference to innovative firms, questions regarding the occurrence of credit rationing, the extent of the phenomenon, the role played by internal finance and different forms of innovative strategies.

## 2. Data set and model

The data used in this paper comes from the Survey of Manufacturing Firms (SMF), which was carried out by an Italian investment bank, Mediocredito Centrale (see www.mcc.it), in 1998. The SFM considers a stratified sample of Italian firms with at least 11 and up to 500 employees: the stratification was made according to the number of employees, sectors composition and location, taking as benchmark the Census of Italian Firms. It also includes all the Italian manufacturing firms with more than 500 employees.

The SFM contains both questionnaire information about a firm's structure, its behaviour in 1997 and balance sheet data for up to nine years (1989-1997). The wealth of data contained in this and the previous releases of the SMF have been used extensively in the literature (Atzeni and Carboni, 2003; Bagella et al. 2000; Filatotchev et al., 2002; Piga, 2002; Piga and Vivarelli, 2003).

When testing for the existence of credit rationing, it is crucial to find a proper measure of the firm's access to the credit market. As pointed out by Guiso (1998) the large majority of the empirical studies employ indirect indicators (see among the others: Fazzari et al. (1988), Hoshi et al. (1991), Petersen and Rajan (1994), Gertler and Gilchrist (1994)), which are likely to catch other effects not related to liquidity constraints and to the access to the market for loans. As in Guiso (1998) we employ a direct measure of access to credit.

In the SMF there are three questions that can be used to directly evaluate the firm's access to credit market: 1) whether at the current market interest rate the firm wants an additional quantity of credit; 2) whether the firm is willing to pay a higher interest rate to obtain that additional quantity; 3) whether the firm applied but the credit has been denied. These are used to construct the two dependent variables under study. The first one, MORECRED, is equal to 1 if the firm declares it wanted more credit and was willing to pay either the current or a higher interest rate (see Guiso, 1998, for discussion). The second dependent variable is denoted as DENIED: it is equal to 1 if the firm declares to have applied for credit and this was denied. Therefore, credit rationing occurs when both MORECREDIT and DENIED are equal to 1.

Note that credit constrained firms are identified in an exactly identical manner in Guiso (1998), where another dataset collected in 1993 by the Bank of Italy was used. However, in this study we extend Guiso's single equation Probit approach by adopting a methodology that explicitly takes into account that the analysis of the determinants of a bank's decision to deny credit is made on a sample of firms which is not randomly selected. Indeed only if MORECRED is equal to 1, the firm may have applied to the bank for additional credit. In other words, a sample selectivity bias may arise if the probability of being short of financial resources is not distinguished from the that of being turned down when applying for credit.

To address the sample selectivity issue, a bivariate probit model with censoring setting is employed (Greene, 2003, pp.713-714). Formally the model can be represented as follows:

(1) $y^*_{i1} = b'_{i1} x_{i1} + e_{i1}$, $y_{i1} = 1$ if $y^*_{i1} > 0$, 0 otherwise

$y^*_{i2} = b'_{i2} x_{i2} + e_{i2}$, $y_{i2} = 1$ if $y^*_{i2} > 0$, 0 otherwise

$(e_1, e_2) \sim \text{BVN}(0,0,1,1, r)$

$(y_{i1}, x_{i1})$ is observed only when $y_{i2} = 1$

The likelihood function is:

(2)

$$L_{ss} = \prod_{y_1=1, y_2=1} \Phi_2 \left[ b'_{i1} x_{i1}, b'_2 x_{i2}, r \right] \prod_{y_1=0, y_2=1} \Phi_2 \left[ b'_{i1} x_{i1}, b'_{i2} x_{i2}, -r \right] \prod_{yi_2=0} \Phi \left[ b'_{i2} x_{i2} \right]$$

where $\Phi_2$ denotes the bivariate normal cumulative distribution function with $\rho = \text{Cov}[\varepsilon_{i1}, \varepsilon_{i2}]$. Eq. (2) is maximized with respect to parameters $\beta_1$, $\beta_2$ and $\rho$. Thus, the methodology does not use the two-stage Heckit procedure due to Heckman (1979) but, instead, a maximum likelihood estimation (MLE) approach where the robust Huber/White estimator of the variance is used in place of the conventional MLE variance estimator. For more about this methodology and its applications, the reader is referred to Piga and Vivarelli (2003) and Montmarquette et al. (2001). Here we limit to recall that when $\rho = 0$, it is possible to estimate the model using indipendent probit equations.

Using a two-equation methodology is important as it enables to discriminate between a variable's effects on credit demand and supply. Consider, for instance, the role of internal financial resources. It reduces the probability that a firm needs credit but it also enhances the chances of a successful application. Thus, the effect on the former does not have to be confounded with that on the latter.

Table 1 reports the descriptive statistics of the dependent and independent variables used. The linear correlation is not reported to save on space, but no pair of regressors shows a linear correlation value above 0.365. To avoid simultaneity problems, all regressors are lagged. After having dropped missing values, the original sample size of 4495 observations, reduces to 3106. Most of the control variables employed are widely used in the literature (Guiso, 1998; Piga, 2002; Showalter, 1999). To evaluate the relationship between credit rationing and innovation, we consider total R&D, Self financed R&D and internal R&D outlays, all normalized by total assets. The two latter regressors have not been used before, although understanding how the R&D investment is financed or whether it is carried out purely internally or with external partners can shed some light on a lender's decision to grant credit. Indeed, a greater share of self-financed R&D is associated with a "signalling effect" (Leland and Pyle, 1977), which may induce banks to be more confident in lending to the firm. Conversely, a purely internal R&D strategy may reinforce the need for secrecy, thereby exacerbating the information asymmetry between borrower and lender. Furthermore, external R&D entails both an increase in a firm's cost flexibility, as external projects may be more easily cancelled, and a reduction in the amount of "intangible assets": it should therefore enhance a lender's propensity to grant credit.

Table 2 reports the regressors' means for the four sub-groups created by the dependent variables. In the first column are included the firms that do not need extra credit (86% of the sample), which are more profitable (EBIT around 9%), less indebted, bigger in size and mainly belonging to the North of the country. In the third column there are firms to whom credit was granted (78%), while the fourth column contain data about the remaining 22%, those turned down by the bank. Therefore credit rationed firms are 3.1% of the total sample (see Tab. 1), which is similar to what previously reported by Guiso (1998) for a different firm's sample. Rationed firms are less profitable (5.1%), more indebted, smaller in size and more likely belongs to the South of the country.

## 3. Results

Table 3 reports the results of the Bivariate Probit with sample selection estimation from three models, which differ only in the measure of R&D used. The three regressors are not jointly used to avoid obvious collinearity problems. The last two rows, reporting tests on the significance of ? and the comparison between the sample selection and the standard Probit technique, both indicate the appropriateness of the approach used.

Generally, our estimates reveal that firms with a positive R&D budget in 1995-1996 tended not to require additional financing in 1997. Such an effect is statistically significant when we include Self-financed or internal R&D budgets. Because in practice a great proportion of R&D spending corresponds to wages to R&D personnel, and firms want to avoid having to lay off knowledge workers, firms will set up R&D facilities only when they have secured sufficient financial funds (Hall, 2002). Hence, the negative signs in the selection equation for all the R&D variables.

However, our findings reveal that when innovative firms applied for credit, their applications were more likely to be rejected. Indeed the estimates show that the probability of being denied credit is positively associated with R&D spending. More importantly, the statistical significance varies depending on the measure used. Total R&D expenditure is only weakly significant, thereby providing some support to the notion of a positive relationship between High-Tech firms and credit constraint. However, such a relationship disappears when we consider Self-Financed R&D, which is not statistically significant at any conventional level. This suggests that self-financing of risky activities works as a credible signal used by lenders to separate good from bad borrowers. Furthermore, having a higher proportion of in-house R&D activities increases the likelihood of being denied credit. This indicates the need, when investigating the factors leading to credit constraint in innovative firms, to differentiate between different types of R&D strategies, as total R&D may not reflect accurately the nature of the problems responsible for credit constraint. Indeed, a firm spending its entire R&D budget in extramural activities is unlikely to exhibit those characteristics which may lead to the failure of the lender-borrower relationship. Finally, note how the absolute values of the R&D variables' coefficients in both equations behave in accordance with our foregoing arguments.

We now briefly comment on the estimates of the other explanatory variables. EBIT and Inventories have opposite impacts on MORECRED: profitability reduces the need of external finances while these may be requested to finance shortages in liquidity when a great proportion of working capital is immobilized in inventories. Neither of these regressors is significant in the DENIED equation. Conversely, Net Hiring reduces the probability of rejection, but it does not significantly increase the need of extra credit. Because a firm's decision to hire is forward looking, given the associated adjustment costs, banks seem to consider an increase in the number of employees as "good news" because it signals about a firm' s future profitability (Guiso, 1998).

The impact of Debt is particularly interesting, especially if compared with the simple Probit model. Guiso (1998) reports a positive and significant coefficient for this variable, i.e., debt has a very significant effect on the probability of being liquidity-constrained. Our results reveal that short term debt has a very significant positive effect on the demand of additional credit - maybe because firms want funds to service existing debts - but not on a bank's decision to deny credit. Similar arguments can be applied to the effect of geographical location on credit rationing. Firms in the North are less likely to need extra funds, but when they do, the probability of being denied credit is significantly higher than that of firms in other areas. This is consistent with banks in the North being more skilled at screening. Firm's size is not significant in the lending decision, while it has a negative impact on the probability of requiring additional funds, suggesting that small firms find it more difficult to access the credit market. The hypothesis that an ISO9000 quality certification should reduce the probability of rejection is only partly supported by the data. A firm owned by a bank is less likely to need extra credit; the opposite result holds for exporting firms.

According to Jensen and Meckling (1976), the agency cost of debt increases with the concentration of insider ownership, due to the managers/owners incentive to "go for broke", i.e., invest in very risky projects with very high returns. If the investment fails, because of limited liability, lenders bear the consequence. Indeed, we find a positive relationship between concentration of insider ownership and the demand for more funds, although we should also expect such a concentration to be a major reason for denying credit. However, this regressor was highly insignificant in the DENIED equation, and was then omitted. Finally, our measure of non-debt Tax Shield reduces the probability of demanding more credit.

## 4. Conclusions

While the reasons why financing constraints may be more widespread in the high-tech sector have been extensively discussed in the literature (Hall, 2002), very few articles have attempted to investigate such an issue from an empirical viewpoint (Carpenter and Petersen, 2002; Himmelberg and Petersen, 1994; Guiso, 1998). This paper uses an extensive dataset of Italian manufacturing firms to investigate the factors affecting a firm's probability of being credit-constrained, after controlling for the determinants of its antecedent decision to apply for credit. Firms with a positive R&D budget are less likely to request extra funds but when they do we observe a higher probability of their application being rejected. Thus, our findings lend support to the arguments of credit constraints being particularly severe for innovative firms. However, this outcome is partly mitigated when firms have a high proportion of Self-Financed R&D investments and/or when a significant amount of their R&D budget is spent in extramural activities. Thus, our findings reveal that total R&D expenditures may not accurately reflect the nature of the problems leading to potential credit market failure, and that more differentiated measures of R&D activity should be used to assess the presence of credit constraints in the high-tech sector.

## References


Arrow, K.J. (1962), Economic Welfare and the Allocation of Resources for Invention, in R.R. Nelson (ed.), *The Rate and Direction of Inventive Activity: Economic and Social Factors*, Princeton University Press, 609-625.

Atzeni, G. E., Carboni, O. A. (2003), ICT productivity and human capital: the Italian North-South duality, *International Review of Economic and Business*, forthcoming.

Bagella, M., Becchetti, L., Caggese, A. (2000), Financial constraints on investment: A three-pillar approach, *Research in Economics*, 55, 219-254.

Carpenter, R. E., Petersen, B.C. (2002), Capital market imperfections, high-tech investment, and new equity financing, *The Economic Journal*, 112, F54-F72.

de Meza, D., Webb, D. (2000), Does credit rationing imply insufficient lending ?, *Journal of Public Economics*, 78, 215-234.

de Meza, D., Webb, D. (1990), Risk, adverse selection and capital market failure, *The Economic Journal*, 100, 206-14.

Fazzari, S., Hubbard, R.G., Petersen, H. B. (1988), Investment and Finance Reconsidered, *Brookings Paper on Economic Activity*, 141-195.

Filatotchev, I., Piga, C., and Dyomina, N. (2003), Network positioning and R&D activity: a study of Italian groups, *R&D Management*, 33, 37–48.

Freixas, X., and Rochet, J. (1997), *Microeconomics of Banking*, Mit Press, Cambridge, MA.

Gertler, M., Gilchrist, S., (1994), Monetary policy, business cycles and the behaviour of small manufacturing firms, *The Quarterly Journal of Economic*, 3, 309-334.

Greene, W. H. (2003). *Econometric Analysis*. Prentice Hall, Upper Saddle River, NJ, 5th edition.

Guiso, L. (1998). High-tech firms and credit rationing. *Journal of Economic Behaviour and Organization,* 35, 39–59.

Hall, B. H. (2002), The Financing of Research and Development, *Oxford Review of Economic Policy*, 18(1), 35-51.

Heckman, J. (1979), Sample Selection Bias as a Specification Error, *Econometrica,* 47:153–161.

Hellmann, T., Stiglitz, J. (2000), Credit and equity rationing in markets with adverse selection, *European Economic Review*, 44, 281-304.

Himmelberg, C., Petersen, B. (1994), R&D and Internal Finance: a panel study of small firms in high-tech industries, *Review of Economics and Statistics*, 76, 38-51.

Hoshi, T., Kashyap, A., Scharfstein, D., (1991), Corporate structure, liquidity and investment: evidence from japanese industrial groups, *The Quarterly Journal of Economics*, 56, 33-60.

Jensen, M.C., Meckling, W. H. (1976), Theory of the firm: Managerial Behaviour, Agency Costs and Ownership Structure, *Journal of Financial Economics*, 3, 305-360.

Leland, H.E., Pyle, D.H. (1977), Information Asymmetries, Financial Structure and Financial Intermediaries, *Journal of Finance*, 32, 371-387.

Montmarquette, C., Mahseredjian, S., Houle, R. (2001). The determinants of university dropouts: a bivariate probability model with sample selection, *Economics of Education Review*, 20, 475–484.

Piga, C.A. (2002), Debt and Firms' Relationship: the Italian Evidence, *Review of Industrial Organization,* 20, 267—282.

Piga, C.A., Vivarelli, M. (2003), Sample Selection in estimating the determinants of cooperative R&D, *Applied Economics Letters,* 10, 243-246.

Petersen, M.A., Rajan, R.G., (1994), The benefits of lending relationships: evidence from small business data, *The Journal of Finance*, 1, 3-37.

Showalter, D. M. (1999), Strategic Debt: Evidence in Manufacturing, *International Journal of Industrial Organization*, 17, 319-333.

**Tab. 1 – Dependent variables and regressors**

| Dependent variables | Description | Mean N=3106 | Min N=3106 | Max N=3106 |
|---|---|---|---|---|
| MORECRED | dummy=1 if firm wanted more credit or was willing to pay a higher interest rate in 1997 | 0.140 | 0 | 1 |
| DENIED | dummy=1 if firm applied for credit but it has been denied in 1997 | 0.031 | 0 | 1 |
| Independent variables | | | | |
| EBITTA | EBIT on total assets (mean 1995-96) | 0.088 | -0.089 | 0.685 |
| INVENTCA | inventories on current assets (mean 1995-96) | 0.266 | 0.000 | 0.719 |
| NETHIRINGS | % of net hirings over total employees (mean 1995-96) | 0.019 | -0.197 | 0.505 |
| R&DTA | R&D on total assets (mean 1995-96) | 0.003 | 0.000 | 0.035 |
| SFR&DTA | % of Self Financed R&D on total assets (mean 1995-96) | 0.002 | 0.000 | 0.035 |
| INTR&DTA | Internal R&D outlays on total assets (mean 1995-96) | 0.002 | 0.000 | 0.035 |
| STDTA | Short term debt on total assets (mean 1995-96) | 0.144 | 0.000 | 0.597 |
| BANKOWN | dummy=1 if a firm is owned by a bank | 0.051 | 0.000 | 1.000 |
| EXPORT | dummy=1 if firm has exported | 0.722 | 0.000 | 1.000 |
| HERFOWNCONTR | Herfindhal index of share of control | 59.505 | 0.000 | 100.00 |
| ISO9000 | dummy=1 if firm has obtained ISO 9000 certification | 0.292 | 0.000 | 1.000 |
| NORTH | dummy=1 if firms is located in the North of Italy | 0.830 | 0.000 | 1.000 |
| TAXSHIELD | depreciation of tangible assets over tangible assets | 0.118 | 0.000 | 0.396 |
| SIZE | Nat. Log of total Sales (mean 1995-96) | 9.482 | 6.577 | 14.815 |

Tab. 2 – Regressors means in the four possible outcomes

| | MORECRED | | DENIED (if MORECRED=1) | |
|---|---|---|---|---|
| | No (N=2671) | Yes (N=435) | No (N=339) | Yes (N=96) |
| EBIT on total assets | 0.091 | 0.071 | 0.076 | 0.051 |
| Inventories on current assets | 0.260 | 0.303 | 0.298 | 0.319 |
| % of net hirings over total employees | 0.018 | 0.022 | 0.025 | 0.010 |
| Total R&D on total assets | 0.003 | 0.002 | 0.002 | 0.002 |
| % of Self Financed R&D on total assets | 0.002 | 0.001 | 0.001 | 0.001 |
| Internal R&D outlays on total assets | 0.002 | 0.001 | 0.001 | 0.002 |
| Short term debt on total assets | 0.140 | 0.168 | 0.155 | 0.216 |
| Owned by a bank (0,1) | 0.055 | 0.030 | 0.029 | 0.031 |
| Export (0,1) | 0.725 | 0.708 | 0.699 | 0.740 |
| Herfindhal index of share of control | 0.594 | 0.604 | 0.600 | 0.620 |
| ISO 9000 (0,1) | 0.297 | 0.267 | 0.286 | 0.198 |
| North (0,1) | 0.853 | 0.690 | 0.696 | 0.667 |
| Tax shield | 0.120 | 0.103 | 0.107 | 0.088 |
| Log Sales | 9.520 | 9.247 | 9.257 | 9.211 |

**Tab. 3 – Bivariate Probit with Sample Selection estimation results.***

| | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| | DENIED N=435 | MORECRED N=3106 | DENIED N=435 | MORECRED N=3106 | DENIED N=435 | MORECRED N=3106 |
| Constant | 0.384 | 0.435 | 0.349 | 0.426 | 0.431 | 0.405 |
| | (0.397) | (0.090) | (0.438) | (0.096) | (0.344) | (0.115) |
| EBIT on total assets | -2.118 | -1.529 | -2.119 | -1.534 | -2.119 | -1.521 |
| | (0.213) | (0.001) | (0.217) | (0.001) | (0.201) | (0.001) |
| Inventories on current assets | -0.464 | 0.666 | -0.467 | 0.665 | -0.466 | 0.668 |
| | (0.157) | (0.000) | (0.152) | (0.000) | (0.150) | (0.000) |
| % of net hirings over total employees | -1.196 | 0.631 | -1.218 | 0.645 | -1.201 | 0.640 |
| | (0.084) | (0.146) | (0.080) | (0.138) | (0.081) | (0.140) |
| Total R&D on total assets | 15.653 | -6.991 | | | | |
| | (0.090) | (0.168) | | | | |
| % of Self Financed R&D on total assets | | | 15.065 | -11.869 | | |
| | | | (0.180) | (0.055) | | |
| Internal R&D outlays on total assets | | | | | 23.530 | -12.388 |
| | | | | | (0.043) | (0.043) |
| Short term debt on total assets | 0.413 | 0.747 | 0.436 | 0.740 | 0.408 | 0.743 |
| | (0.475) | (0.000) | (0.461) | (0.000) | (0.470) | (0.000) |
| North (0,1) | 0.351 | -0.504 | 0.355 | -0.504 | 0.353 | -0.504 |
| | (0.009) | (0.000) | (0.008) | (0.000) | (0.007) | (0.000) |
| Log Sales | 0.043 | -0.149 | 0.047 | -0.147 | 0.038 | -0.145 |
| | (0.509) | (0.000) | (0.467) | (0.000) | (0.555) | (0.000) |
| ISO 9000 (0,1) | -0.181 | | -0.171 | | -0.181 | |
| | (0.113) | | (0.127) | | (0.110) | |
| Owned by a bank (0,1) | | -0.237 | | -0.234 | | -0.235 |
| | | (0.091) | | (0.097) | | (0.090) |
| Export (0,1) | | 0.106 | | 0.107 | | 0.108 |
| | | (0.071) | | (0.068) | | (0.065) |
| Herfindhal index of share of control | | 0.002 | | 0.002 | | 0.002 |
| | | (0.014) | | (0.013) | | (0.013) |
| Tax shield | | -0.910 | | -0.892 | | -0.901 |
| | | (0.018) | | (0.021) | | (0.019) |
| Equations' residuals correlation ρ | -0.869 (0.026) | | -0.869 (0.029) | | -0.871 (0.021) | |
| Comparison Test [a] | $\chi^2(8)$= 30.38 (0.0002) | | $\chi^2(8)$= 29.04 (0.0003) | | $\chi^2(8)$= 31.69 (0.0001) | |

[*] Robust p-values in parentheses.
[a] Test of significance of the outcome equation of DENIED relative to the same model estimated using a standard Probit technique.