NOTES D'ÉTUDES

ET DE RECHERCHE

FINANCING CONSTRAINTS AND A FIRM'S DECISION AND ABILITY TO INNOVATE: ESTABLISHING DIRECT AND REVERSE EFFECTS

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Financing Constraints and a Firm's Decision and Ability to Innovate: Establishing Direct and Reverse Effects

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Abstract

The paper analyzes the existence and impact of financing constraints as a possibly serious obstacle to innovation by firms. The econometric framework we employ in our study is the simultaneous bivariate probit with mutual endogeneity of direct indicators of financial constraints and innovation decisions by firms. A novel method for establishing coherency conditions is used. It allows us for the first time to estimate models hitherto classified as incoherent through the use of prior sign restrictions on model parameters. We are thus able to quantify the interaction between financing constraints and a firm's decision and ability to innovate without forcing the econometric models to be recursive. Hence, we obtain direct as well as reverse interaction effects, leading us to conclude that binding financing constraints discourage innovation and at the same time innovative firms are more likely to face binding financing constraints.

Keywords: Limited Dependent Variable Models, Coherency Conditions

JEL Classifications: C51, C52, C15

Résumé

Cet article s'intéresse à l'existence et au rôle des contraintes financières en tant que facteur d'entrave à l'innovation technologique des entreprises. L'analyse économétrique est menée à partir d'un modèle probit bivarié tenant compte de l'endogénéité mutuelle des indicateurs directs de contraintes financières et d'innovation. Notre approche est fondée sur une nouvelle méthode pour établir les conditions de cohérence du modèle. Celle-ci permet d'estimer pour la première fois des modèles qualifiés jusqu'à présent «incohérents» grâce à la prise en compte de restrictions de signes a priori sur les paramètres du modèle. Nous sommes ainsi en mesure d'évaluer les interactions entre innovation et contraintes financières sans contraindre le modèle à être récursif. Les estimations mettent en évidence des effets directs et inversés, ce qui nous amène à conclure que les difficultés de financement entravent l'innovation des entreprises et que dans le même temps, les entreprises innovantes sont plus enclines à rencontrer des contraintes financières.

Mots clés: Modèles à variable dépendante limitée, Condition de cohérence

Classification JEL : C51, C52, C15

Non technical summary

Many authors have emphasized the likely importance of binding financing constraints can have on firm behaviour, especially on investment (e.g. Fazzari et al. (1988), Hennessy and Whited (2007)). In this paper, we analyze the existence and impact of financing constraints as a possibly debilitating obstacle to innovation by firms. More precisely, it aims at studying the interactions between financing constraints and innovation by examining direct as well as reverse effects.

As in Savignac (2006), direct measures of financing constraints are employed which overcomes the problems with the traditional approach of trying to deduce indirectly the existence and impact of financing constraints through the significance of firm wealth variables. The importance of using direct as opposed to indirect measures of financing constraints has been illustrated recently by Moyen (2004) using a synthetic sample methodology, and Hennessy and Whited (2007) through the method of simulated moments.

The econometric framework we employ in our study is the simultaneous bivariate probit with mutual endogeneity of direct indicators of financial constraints and innovation decisions by firms with one equation characterizing whether or not a firm chooses to be innovative, and the other the (endogenous) probability that a firm will face a binding financing constraint.

The paper discusses the important identification issue of *coherency conditions* in such limited dependent variable models with endogeneity and flexible temporal and contemporaneous correlations in the unobservable error terms. The usual way to guarantee "coherency" is to work only with recursive models. For instance, if binding financing constraints are allowed to affect the probability that a firm innovates in the innovation equation, the innovation indicator is not allowed to be included in the financing constraint equations and vice versa.

We derive the necessary econometric methodology to allow us to investigate a simultaneous role for the two cross effects using *a priori* sign restrictions on the model coefficients. Our novel methods for establishing coherency conditions allow us for the first time to estimate models hitherto classified as incoherent through the use of prior sign restrictions on model parameters. We are thus able to quantify the interaction between financing constraints and a firm's decision and ability to innovate without forcing the econometric models to be recursive. Hence, we obtain direct as well as reverse interaction effects, leading us to conclude that binding financing constraints discourage innovation and at the same time innovative firms are more likely to face binding financing constraints.

Moreover, we investigate the importance of state-dependence in dynamic versions of our models. We confirm the importance of dynamics in the joint analysis of binding financing constraints and firm innovation. Such issues are critical if direct and reverse interactions between innovation and financing constraints are to be quantified reliably.

Résumé non technique

De nombreux auteurs ont souligné l'importance des contraintes de financement pour expliquer le comportement des entreprises, en particulier, en matière d'investissement (Fazzari et al. (1988), Hennessy and Whited (2007)). Dans cet article, nous analysons le rôle des contraintes financières en tant que facteur d'entrave à l'innovation des entreprises. Notre objectif est d'étudier les interactions entre innovation et contraintes financières.

Comme dans Savignac (2006), des mesures directes de l'existence de contraintes de financement sont utilisées. Ceci permet de surmonter les problèmes liés à l'approche qui consiste à examiner l'effet des contraintes de financement via les variables de richesse de l'entreprise. La nécessité de s'appuyer sur des mesures directes plutôt que sur des mesures indirectes de contraintes de financement a été récemment illustrée par Moyen (2004) ou encore Hennessy et Whited (2007).

Le modèle estimé est un probit simultané qui tient compte de l'endogénéité des indicateurs directs de contraintes financières et d'innovation : une première équation caractérise la décision d'innover de la firme et une seconde définit la probabilité que le firme rencontre des contraintes financières.

Le papier expose le problème de *coherency conditions* dans ces modèles à variables dépendantes limitées avec endogénéité et corrélations contemporaine et inter temporelle des termes d'erreur. Habituellement, la cohérence de ces modèles est garantie par l'estimation d'une forme triangulaire (récursive) : par exemple, si la variable de contraintes financières est introduite dans l'équation d'innovation, la variable d'innovation doit être exclue de l'équation de contraintes financières et vice-versa.

Nous obtenons un cadre méthodologique qui permet d'étudier simultanément le rôle des effets croisés en s'appuyant sur des restrictions de signe *a priori* des coefficients du modèle. Cette nouvelle méthode nous permet d'estimer des modèles qualifiés jusqu'à présent d'«incohérents».

Nous sommes ainsi en mesure d'évaluer les interactions entre contraintes financières et comportement innovant des entreprises sans imposer la récursivité du modèle économétrique. Nos estimations des effets directs et inversés montrent que des contraintes financières entravent l'innovation et que dans le même temps, les entreprises innovantes sont plus enclines à rencontrer des contraintes financières.

En outre, dans une version dynamique du modèle, l'effet de la dépendance d'état est examiné. Ceci confirme l'importance de la dynamique des interactions dont on doit tenir compte pour évaluer correctement les effets directs et inversés entre l'innovation et les contraintes financières.

1 Introduction

The paper analyzes the existence and impact of financing constraints as a possibly serious obstacle to innovation by firms. Direct measures of financing constraints are employed using survey data collected by the Banque de France, which overcomes the problems with the traditional approach in the past literature of trying to deduce the existence and impact of financing constraints through the significance of firm wealth variables. The main economic issues are discussed in Section 2. The econometric framework employed for this study is presented in Section 3. In the same section we introduce the important identification issue of *coherency conditions* in such LDV models with endogeneity and flexible temporal and contemporaneous correlations in the unobservable errors, and discuss how our novel methods, explained in detail in a Technical Appendix, allow us for the first time to estimate models hitherto classified as incoherent through the use of prior sign restrictions on model parameters. The Technical Appendix also overviews how we evaluated the novel methods through a set of Monte-Carlo experiments. We then present in Section 4 preliminary estimation results using standard methods considered in the literature, and explain how such methods are expected to lead to very unreliable findings. In Section 5, we apply our novel Restricted ML Estimation approach conditioned on prior sign restrictions on model parameters and thus are able to quantify, for the first time in the literature, the interaction between financing constraints and a firm's decision and ability to innovate without forcing the model to be recursive. Thus, direct as well as reverse interaction effects are obtained. Data sources, construction of variables, and other major data issues are discussed in a Data Appendix. Section 6 explains how we exploit the nature of the available datasets to study whether, ceteris paribus, past financial distress or innovation failures can affect a firm's current experiences in these two dimensions. Section 7 describes our plan for future extensions of this research, while Section 8 concludes.

2 Overview of Economic Issues

Many past authors have recognized the likely importance of binding financing constraints can have on firm behaviour. Examples include Fazzari et al. (1988) who investigate the impact of financing constraints on investment, while Hennessy and Whited (2007) attempt to quantify how costly constrained external financing is by the use of simulated moments methodology. In this paper, we analyze the existence and impact of financing constraints as a possibly debilitating obstacle to innovation by firms. According to the data employed, nearly one quarter of firms wishing to innovate report that their efforts towards innovation are hindered in a major way by financing constraints they encounter, leading them sometimes to delay the development and adoption of innovations, and sometimes even to abandon their innovative efforts.

We identify the following leading causes of encountering financing constraints by innovative firms[1] specifically because they attempt to be innovative:

First, two problems caused by asymmetric information between a firm and its prospective external financiers are highlighted, implying that the celebrated Modigliani and Miller theorem (1958, 1963) does not apply in such cases. The first such problem is that of "adverse selection", which justifies the earlier idea of Stiglitz and Weiss (1982) and may lead to quantity rationing in preference to allocation of funds through interest rates. More modern theories generate a hierarchy of sources of finance, namely (a) internal financing, (b) bank loans, and (c) equity financing through venture capital financiers, the three modes ranked in terms of increasing cost to innovative firms.

The second important informational asymmetry problem is "moral hazard" identified by Jensen and Meckling (1976), which is most serious for "start-up" firms, since for such newly established entities the usual dichotomy between owners' and managers' interests becomes even more pronounced.

The next leading cause identified in the paper is due to the fact that innovative firms typically have a higher fraction of intangible assets, implying they are not as able to raise the necessary collateral for low-cost financing. For example, special human expertise and other specific human capital may not be readily marketable outside a specific firm and hence bankers may be unwilling to grant loans based on such assets.

A key question we attempt to answer econometrically involves the incidence of financing constraints, and in particular whether innovative firms encounter more significant such constraints ceteris paribus when they attempt to innovate. It is explained how accumulated wealth and ploughed-back past profits can play an important role in alleviating constraints, since they make internal financing more readily available to the firm. A near consensus in the literature accepts a significantly positive correlation between firm wealth and innovation, and takes this as evidence that firm wealth relaxes financing constraints. Instead, this paper aims at establishing a role of financing constraints based by innovating firms *specifically because* they are innovating, other things equal. Towards this end, the existence of constraints is not deduced indirectly through the common argument above, but is directly measured by employing real data on the encountering of binding financing constraints as reported by firms in surveys by the European Union, carried out in 4 waves since 1990 (CIS1-CIS4), as well as in a French survey about the financing of innovation (FIT). Firms with 20+ employees were surveyed with a response rate of 85%, while every firm with 500+ employees is included in the datasets. The financing constraint variables we employ are described in detail in the Data Appendix. An important shortcoming of our data is that firms were asked to respond as to whether their *plans to innovate* were thwarted

[1] Applying the definition of the Oslo manual of the OECD and following Savignac (2006), we characterize as innovative a firm that introduces or develops a product or process innovation, or is in process of doing so.

by the presence of financing constraints, and not whether their *overall investment* plans were thus seriously hindered. We are currently investigating the availability of such direct measures of overall financing constraints from other sources, notably the Banque de France and the French National Institute of Statistical and Economic Studies (INSEE). Such direct measures will allow us to answer whether innovative firms encounter more significant financing constraints pertaining to all their plans, not just for funding innovation.[2]

The key question we pose in this paper is whether binding financing constraints have a seriously adverse impact on innovation by firms. The approach here is innovative in several respects: firstly, unlike earlier literature direct measures of binding constraints are employed, instead of using traditional indirect proxy variables like firm wealth, accumulated profits, etc. Secondly, the econometric approach allows explicitly the existence of binding financing constraint to be endogenously determined. Our main finding is that there is a very significantly negative effect on innovation due to the presence of financing constraints, ceteris paribus. We also show that ignoring the endogeneity of the constraint indicator together with the endogenous decision of whether a firm wishes to innovate or not, induces very serious upward biases in the estimated coefficient. Consequently, a satisfactory resolution to an existing paradox is produced: not taking correct account of the endogeneity of financing constraints, leads one to incorrectly conclude that presence of financing constraints and innovation are positively correlated. We now give a simple illustration of the nature of this paradox:

Suppose one half of the firms do not wish to innovate, and hence do not face binding financing constraints by banks. The other half of firms who wish to innovate, approach the banks for a loan. For simplicity, let us say that half of them face a binding constraint and are denied their request for loan by the bank, while the other half are granted their request. Consequently, three quarters of firms end up *not* innovating (1/2 who did not wish to and did not face finance constraints (group A), plus 1/4 who wished to innovate but were refused the loan (group B)), while only 1/4 end up innovating (wished to and were granted their loan request (group C)). Group A of size 1/2 exhibits positive correlation between constraints and innovation (did not innovate, did not face constraints), while groups B of size 1/4 and C of size 1/4 exhibit negative correlation (B: did not innovate because of high financing constraints, C: innovated because of low constraints). If we select only the potentially innovating firms (B+C) the correlation is very negative. If we average also group A, the overall correlation will be significantly higher, namely 0 in this example.

It should be self-evident that the traditional approaches of testing for presence of binding financing constraints indirectly by checking for the importance of firm

[2] Savignac (2006) finds that innovative firms appear to face significantly reduced probabilities of bank loans specifically because of their innovative activities. In addtion, she finds that the bank loans for the innovative firms that were successful in securing them are in fact at a significantly lower interest rate on the average.

wealth, past profits, etc., can be seriously misleading. For example, it could be that richer firms may *wish* to invest more and hence need more funds simply because they anticipate future profits, not just because they are *able* to borrow more because they face lower constraints. A simple analogy with studying the intertemporal consumption decision is quite illuminating: the Euler equation framework with rational expectations implies that current consumption decisions should be unaffected by current income. The traditional financial constraints empirical analyses are akin to concluding that economic agents face binding liquidity constraints by observing econometrically that current consumption decisions are significantly affected by the level of current income, which of course does not necessarily follow. This line of objection forms the basis of the Kaplan and Zingales (1997) critique. The main findings of Moyen (2004) are also particularly relevant in this respect: using a synthetic sample methodology, she illustrates that the magnitude and the *sign* of the impact of cash flow on investment change drastically depending on which indirect method is used for inferring the presence of financial constraints on a firm. The pitfalls in using indirect measures of external finance constraints are also highlighted by Hennessy and Whited (2007).

To overcome such shortcomings, our econometric analysis here follows Savignac (2006) and proceeds to employ three *direct measures of financing constraints*, obtained from the FIT ("Financement de l'Innovation Technologique") database collected by SESSI: (i) unavailability of new financing; (ii) searching and waiting for new financing; and (iii) too high a cost of new financing. The sample consists of 3710 firms corresponding to an overall response rate of about 70% (and 60% for large firms). See the Data Appendix for an extensive discussion of our data sources, and of the variables we employ as best proxies for the theoretical economic quantities and their characteristics.[3]

The dataset is rich enough to allow us to focus econometrically on the impact of financial constraints as such on limiting innovation, while considering directly important economic factors which may limit innovation, such as: market risk, unavailability of suitable personnel, too high costs, excessive costs for abandoning innovation, and not sufficient knowledge of available financing.[4]

These databases are merged with the "Centrale de Bilans" (CdB) of the Banque de France, which contains full balance sheet data on the firms in the sample thus giving us direct data on bank loans, tangible and intangible assets, as well as sources of finance.[5]

A bivariate probit model is estimated with these data, with one equation characterizing whether or not a firm chooses to be innovative, and the other the (endogenous) probability that a firm will face a binding financing constraint, i.e.,

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[3] For further details, we refer the reader to Savignac (2006), Annexes A-C.

[4] Using the standard terminology of the existing literature, this is the distinction between *financial* and *economic* distress factors.

[5] The response rate for CdB is just above 50%.

$$\begin{aligned} Prob(\text{Innovate?}) \quad = \quad & f(\text{Binding Financial Constraint Indicator, Size, Market Power,} \\ & \text{"Push" Technological Opportunities,} \\ & \text{Latent Consumer Demand for New Products, ...}) \end{aligned}$$

$$\begin{aligned} Prob(\text{Binding Financing Constraint?}) \quad = \quad & f(\text{Innovation Indicator, Size,} \\ & \text{Guarantees/Collateral/Corporate Bonds, ...}) \end{aligned}$$

We explain carefully the need to work only with recursive versions of the bivariate probits to guarantee "coherency". Our preferred version is to drop Innovation from the second equation and keep "Financing Constraints" in the first, though in the "Robustness Checks" of Savignac (2006), she also presents results from dropping "Financing Constraints" from the first equation while keeping Innovation in the second. Four versions of the estimated models are explored in Section 4: version (i) excludes measures of financing constraints as well as the "Financing Constraints" incidence indicator itself; version (ii) includes proxy measures of financing constraints (like collateral amount, profit margin, debt ratio, etc.) but not the "Financing Constraints" incidence indicator itself; version (iii) employs the reported indicator dummy of "Financing Constraints" treating it as exogenous; while version (iv) allows the reported indicator dummy of "Financing Constraints" to be included as endogenous.

In the Technical Appendix we derive the necessary econometric methodology to allow us to investigate a simultaneous role for the two cross effects using *a priori* sign restrictions on the model coefficients.

A key finding confirms the importance of allowing for endogeneity of "Financing Constraints": the impact of the "Financing Constraints" indicator has an extremely significant statistically *negative* effect on innovation, with the size of the effect almost tripled once endogeneity is introduced.

Another key finding is that repeating the estimations on the full sample as opposed to just the potentially innovating firms reinforces the impact of endogeneity and the role of sample selection described earlier: treating "Financing Constraints" as exogenous gives a positive (though insignificant) coefficient, while estimating with endogeneity confirm the very significantly negative effect found in the subsample estimations.

We are in the process of investigating other versions of the simultaneous bivariate probit models presented above:

- Additional "liquidity" measures should be included in order to distinguish better between financial and *economic* distress. In particular, available cash stock is likely to be an important conditioning factor.

- Surprisingly, belonging to a holding group does not seem to help innovation nor lead to less financial distress. Perhaps this is because we did not allow for the possibility that the critical factor may be the *size of the holding group*.

- The likely endogeneity of the profitability and asset tangibility measures needs to be addressed.

3 The Econometric Problem of "Coherency" in LDV Models

We now turn to the fundamental identification issue of *coherency conditions* in LDV models with endogeneity and flexible temporal and contemporaneous correlations in the unobservable errors. The methods we develop here, explained in greater detail in the Technical Appendix, allow us to achieve coherency in models traditionally classified as incoherent through the use of prior restrictions on model parameters.

Consider the bivariate probit model outlined in the previous section:

$$\begin{aligned} Prob(\text{Innovate?}) \;=\;& f(\text{Binding Financial Constraint Indicator, Size, Market Power,} \\ & \text{"Push" Technological Opportunities,} \\ & \text{Latent Consumer Demand for New Products, ...}) \end{aligned}$$

$$\begin{aligned} Prob(\text{Binding Financing Constraint?}) \;=\;& f(\text{Innovation Indicator, Size,} \\ & \text{Guarantees/Collateral/Corporate Bonds, ...}) \end{aligned}$$

To formalize this representation of this system, define two latent dependent variables I^*_{it} and F^*_{it} and two binary limited dependent variables I_{it} and F_{it} as follows:

$$I_{it} = \begin{cases} 1 & if \quad I^*_{it} \equiv x^I_{it}\beta^I + \gamma F_{it} + \epsilon^I_{it} > 0 \\ 0 & if \quad I^*_{it} \equiv x^I_{it}\beta^I + \gamma F_{it} + \epsilon^I_{it} \leq 0 \end{cases} \tag{1}$$

$$F_{it} = \begin{cases} 1 & if \quad F^*_{it} \equiv x^F_{it}\beta^F + \delta I_{it} + \epsilon^F_{it} > 0 \\ 0 & if \quad F^*_{it} \equiv x^F_{it}\beta^F + \delta I_{it} + \epsilon^F_{it} \leq 0 \end{cases} \tag{2}$$

The formal condition for the econometric "coherency" of this model obtained in the existing literature is that $\gamma \cdot \delta = 0$, which of course corresponds to no reverse interaction terms to exist between the innovation and financing constraint side: if $\gamma \neq 0$ and binding financing constraints are allowed to affect the probability that a firm innovates in the innovation equation, the innovation indicator is not allowed to be included in the financing constraint equations and vice versa (if $\delta \neq 0$, γ must be 0).

Novel econometric developments in Hajivassiliou (2007), which are discussed in detail in the Technical Appendix below, prove that this condition is not necessary, however. The new results establish that our bivariate binary probit model can be estimated efficiently through the Conditional Maximum Likelihood Method, conditional on the prior sign restriction that γ and δ must not have the same sign. On a priori economic reasoning grounds, we expect this sign restriction to be satisfied in our case, since we believe that $\gamma \geq 0$ (a binding finance constraint lowers the likelihood that a firm will afford to innovate ceteris paribus), while $\delta \leq 0$ (innovative firms are more likely to face binding financing constraints ceteris paribus).

4 The Importance of Simultaneity and Sample Selection

We take as our starting point the results obtained by Savignac (2006) who studied the impact of financial constraints on the decision to innovate by assuming recursivity. The propensity to innovate is explained by the traditional determinants of innovation (firm size and market power, technology push, latent consumer demand) and by a qualitative indicator reflecting the financial difficulties encountered by firms to conduct their innovative projects. Simultaneously, the probability that a firm faces a binding financing constraint is explained by firm ex ante economic performances and financing structure. The results of these regressions are reported in tables 1 and 2 below. Without taking into account the endogeneity of the financial constraint, a surprising significant positive effect of this variable on the propensity to innovate is obtained (third column of tables 1a and 1b).[6]

In sharp contrast, when endogeneity is accounted for, the estimated coefficient of the financial constraints becomes negative, as expected, while all other estimates remain largely unchanged (second column of tables 2a and 2b). Furthermore, a strong correlation between the errors of both equations is found when both equations are simultaneously estimated.

[6] Versions (a) of each table present results based from the full sample of 1940 firms, while in versions (b) we restrict the estimations to the subsample of 1082 potentially innovative firms only.

Table 1.a
Propensity to Innovate Probit Ignoring Endogeneity
(full sample, nobs=1940)

	Model 1		Model 2		Model 3	
Variable	Coeff.	Std.	Coeff.	Std.	Coeff.	Std.
Constant	-2.51***	0.21	-2.73***	0.26	-2.61***	0.21
Size	0.32***	0.03	0.23***	0.06	0.33***	0.03
Market share	-0.01	0.06	-0.03	0.06	-0.01	0.06
TP4	1.76***	0.15	1.74***	0.15	1.66***	0.16
TP3	1.25***	0.12	1.22***	0.12	1.19***	0.12
TP2	0.82***	0.12	0.80***	0.12	0.77***	0.12
Financial constraints	-	-	-	-	0.55***	0.09
Collateral amount	-	-	0.08*	0.041	-	-
Banking debt	-	-	-0.001	0.001	-	-
Own financing	-	-	0.001	0.001	-	-
Profit margin	-	-	0.004**	0.002	-	-
Industry dummies	misc		misc		misc	
Log lik	-1080.5		-1073.2		-1060.3	

Table 1.b
Propensity to Innovate Probit Ignoring Endogeneity
(Potentially innovative firms, nobs=1082)

	Model 1		Model 2		Model 3	
Variable	Coeff.	Std.	Coeff.	Std.	Coeff.	Std.
Constant	-1.22***	0.34	-1.11**	0.51	-1.07***	0.35
Size	0.27***	0.06	0.27***	0.06	0.27***	0.06
Market share	0.76***	0.30	0.60**	0.29	0.72**	0.30
TP4	1.20***	0.24	1.18***	0.24	1.33***	0.24
TP3	0.81***	0.20	0.76***	0.20	0.88***	0.20
TP2	0.39***	0.19	0.33*	0.19	0.44**	0.19
Financial constraints	-	-	-	-	-0.52***	0.10
Collateral amount	-	-	-0.002	0.002	-	-
Banking debt	-	-	-0.007	0.004	-	-
Own financing	-	-	0.002	0.004	-	-
Profit margin	-	-	0.007***	0.002	-	-
Industry dummies	misc	misc	misc	misc	misc	misc
Log lik	-516.2		-504.8		-501.9	

Table 2.a
Innovation and Financing Constraints Joint Probit Without Reverse Interaction Effects (full sample, nobs=1940)

	Single Equations		Bivariate Probits	
	Coeff.	Std.	Coeff.	Std.
Innovation equation				
Constant	-2.731***	0.225	-2.408***	0.290
Size	0.304***	0.034	0.293***	0.034
Market share	0.025	0.063	0.022	0.058
TP4	1.646***	0.165	1.572***	0.180
TP3	1.086***	0.132	1.030***	0.142
TP2	0.684***	0.128	0.647***	0.133
Financial Constraints	0.127	0.105	-0.653**	0.311
Excessive economic risk	0.649***	0.090	0.610***	0.090
Lack of qualified employees	0.571***	0.093	0.541***	0.092
Innovation costs too high	0.358***	0.089	0.340***	0.086
Excessive get-out clause	-1.117***	0.265	-1.056***	0.244
Lack of knowledge about financing	0.370*	0.221	0.334	0.212
11 Industry dummies	misc		misc	
Financial Constraint Equation				
Constant	-0.868***	0.243	-0.814***	0.241
Size	-0.054	0.067	-0.013	0.073
Collateral amount	0.067	0.047	0.035	0.050
Banking debt ratio	0.010***	0.002	0.010***	0.002
Own financing ratio	-0.003**	0.001	-0.003***	0.001
Profit margin	-0.007***	0.002	-0.008***	0.002
11 industry dummies	misc		misc	
$corr_{12}$			-0.448***	0.171
Log lik Innovation	-965.4			
Log lik Fin Constraint	-803.7			
Log lik Bivariate			-1766	

Table 2.b
Innovation and Financing Constraints Joint Probit
Without Reverse Interaction Effects
(Potentially innovative firms, nobs=1082)

	Single Equations		Bivariate Probits	
	Coeff.	Std.	Coeff.	Std.
Innovation Equation				
Constant	-0.879**	0.356	-0.292	0.388
Size	0.283***	0.058	0.232***	0.060
Market share	0.698**	0.295	0.643***	0.240
TP4	1.343***	0.249	1.210***	0.238
TP3	0.871***	0.203	0.766***	0.188
TP2	0.431**	0.197	0.363**	0.179
Financial Constraints	-0.415***	0.109	-1.290***	0.269
Excessive economic risk	-0.130	0.099	-0.127	0.094
Lack of qualified employees	-0.070	0.100	-0.060	0.095
Innovation costs too high	-0.417***	0.098	-0.381***	0.095
Excessive get-out clause	-0.268	0.259	-0.246	0.243
Lack of knowledge about financing	0.356	0.220	0.315	0.192
11 Industry dummies	misc		misc	
Financial Constraint Equation				
Constant	0.458	0.417	0.457	0.410
Size	-0.150*	0.081	-0.102	0.084
Collateral amount	0.069	0.058	0.033	0.059
Banking debt ratio	0.007	0.004	0.007*	0.004
Own financing ratio	-0.007*	0.004	-0.007**	0.003
Profit margin	-0.012***	0.002	-0.012***	0.002
11 industry dummies	misc		misc	
$corr_{12}$			0.574***	0.170
Log lik Innovation	-488.8			
Log lik Fin Constraint	-599.2			
Log lik Bivariate			-1083.0	

5 Empirical Results Establishing Reverse Interaction Effects

Using the econometric machinery we develop in the Technical Appendix that allows us to estimate joint binary probit equations with interaction terms on both sides, we present in Tables 3a and 3b the application of those methods to the key issue of Being Innovative vs. Binding Financing Constraints interactions. Our final estimates in the second columns of each table confirm our expectations on *a priori grounds*, as well as the Monte Carlo findings summarized in the Technical Appendix: a firm undertaking actively innovative activities raises significantly the probably of it encountering a binding financing constraint, possibly because potential lenders are particularly wary of granting loans to firms of such type because of the extra riskiness involved. The effect is stronger for the full sample of firms, presumably because the greater homogeneity of the potentially innovative firms subsample dampens the impact of this interaction. The inclusion of interaction terms in both sides results in a lowering of the significance of the estimated correlation coefficients in the unobservables of the two sides, which is reassuring. Our findings should act as a strong warning to researchers in this field who employ traditional methods that either ignore or incorporate inappropriately the model coherency issue: the resulting estimation biases from such practices appear very serious indeed.

Furthermore, our results confirm that attempting to apply Linear Probability methods to the Innovation-Financing Constraint interaction leads to very significant biases also. These results are in line with the theoretical and Monte Carlo results of Hajivassiliou (2007) that are summarized in the Technical Appendix below.

Table 3.a
Innovation and Financing Constraints Joint Probit
With Reverse Interaction Effects **(full sample, nobs=1940)**

	Single Equations		Bivariate Probits	
	Coeff.	Std.	Coeff.	Std.
Innovation equation				
Constant	-2.731***	0.225	-7.235***	0.118
Size	0.304***	0.034	0.183***	0.020
Market share	0.025	0.063	0.020	0.045
TP4	1.646***	0.165	1.822***	0.183
TP3	1.086***	0.132	1.0110***	0.199
TP2	0.684***	0.128	0.437***	0.176
Financial Constraints	0.127	0.105	-0.324**	0.255
Excessive economic risk	0.649***	0.090	0.550***	0.070
Lack of qualified employees	0.571***	0.093	0.431***	0.081
Innovation costs too high	0.358***	0.089	0.233***	0.072
Excessive get-out clause	-1.117***	0.265	-1.022***	0.145
Lack of knowledge about financing	0.370*	0.221	0.221	0.133
11 Industry dummies	misc		misc	
Financial Constraint Equation				
Constant	-0.868***	0.243	-1.221***	0.241
Firm Innovates			0.647***	0.032
Size	-0.054	0.067	-0.016	0.073
Collateral amount	0.067	0.047	0.030	0.050
Banking debt ratio	0.010***	0.002	0.015***	0.002
Own financing ratio	-0.003**	0.001	-0.001***	0.001
Profit margin	-0.007***	0.002	-0.002***	0.002
11 industry dummies	misc		misc	
$corr_{12}$			-0.132***	0.013
Log lik Innovation	-965.4			
Log lik Fin Constraint	-803.7			
Log lik Bivariate			-1712	

Table 3.b
Innovation and Financing Constraints Joint Probit
With Reverse Interaction Effects
(Potentially innovative firms, nobs=1082)

	Single Equations		Bivariate Probits	
	Coeff.	Std.	Coeff.	Std.
Innovation Equation				
Constant	-0.879**	0.356	-0.292	0.388
Size	0.283***	0.058	0.232***	0.060
Market share	0.698**	0.295	0.643***	0.240
TP4	1.343***	0.249	1.210***	0.238
TP3	0.871***	0.203	0.766***	0.188
TP2	0.431**	0.197	0.363**	0.179
Financial Constraints	-0.415***	0.109	-1.290***	0.269
Excessive economic risk	-0.130	0.099	-0.127	0.094
Lack of qualified employees	-0.070	0.100	-0.060	0.095
Innovation costs too high	-0.417***	0.098	-0.381***	0.095
Excessive get-out clause	-0.268	0.259	-0.246	0.243
Lack of knowledge about financing	0.356	0.220	0.315	0.192
11 Industry dummies	misc		misc	
Financial Constraint Equation				
Constant	0.458	0.417	0.467	0.410
Firm Innovates			0.324***	0.133
Size	-0.150*	0.081	-0.099	0.084
Collateral amount	0.069	0.058	0.030	0.059
Banking debt ratio	0.007	0.004	0.004*	0.004
Own financing ratio	-0.007*	0.004	-0.003**	0.003
Profit margin	-0.012***	0.002	-0.077***	0.002
11 industry dummies	misc		misc	
$corr_{12}$			0.254***	0.150
Log lik Innovation	-488.8			
Log lik Fin Constraint	-599.2			
Log lik Bivariate			-1067.9	

Table 4.a

Innovation and Financing Constraints Joint Probit

With Reverse Interaction Effects and Dynamics

(full sample, nobs=1940)

	Single Equations		Bivariate Probits	
	Coeff.	Std.	Coeff.	Std.
Innovation equation				
Constant	-2.731***	0.225	-7.235***	0.118
Size	0.304***	0.034	0.183***	0.020
Market share	0.025	0.063	0.020	0.045
TP4	1.646***	0.165	1.822***	0.183
TP3	1.086***	0.132	1.0110***	0.199
TP2	0.684***	0.128	0.437***	0.176
Financial Constraints	0.127	0.105	-0.324**	0.255
Excessive economic risk	0.649***	0.090	0.550***	0.070
Lack of qualified employees	0.571***	0.093	0.431***	0.081
Innovation costs too high	0.358***	0.089	0.233***	0.072
Excessive get-out clause	-1.117***	0.265	-1.022***	0.145
Lack of knowledge about financing	0.370*	0.221	0.221	0.133
11 Industry dummies	misc		misc	
Financial Constraint Equation				
Constant	-0.868***	0.243	-1.221***	0.241
Firm Innovates			0.647***	0.032
Size	-0.054	0.067	-0.016	0.073
Collateral amount	0.067	0.047	0.030	0.050
Banking debt ratio	0.010***	0.002	0.015***	0.002
Own financing ratio	-0.003**	0.001	-0.001***	0.001
Profit margin	-0.007***	0.002	-0.002***	0.002
11 industry dummies	misc		misc	
$corr_{12}$			-0.132***	0.013
Log lik Innovation	-965.4			
Log lik Fin Constraint	-803.7			
Log lik Bivariate			-1712	

Table 4.b

Innovation and Financing Constraints Joint Probit

With Reverse Interaction Effects and Dynamics

(Potentially innovative firms, nobs=1082)

	Single Equations		Bivariate Probits	
	Coeff.	Std.	Coeff.	Std.
Innovation Equation				
Constant	-0.879**	0.356	-0.292	0.388
Size	0.283***	0.058	0.232***	0.060
Market share	0.698**	0.295	0.643***	0.240
TP4	1.343***	0.249	1.210***	0.238
TP3	0.871***	0.203	0.766***	0.188
TP2	0.431**	0.197	0.363**	0.179
Financial Constraints	-0.415***	0.109	-1.290***	0.269
Excessive economic risk	-0.130	0.099	-0.127	0.094
Lack of qualified employees	-0.070	0.100	-0.060	0.095
Innovation costs too high	-0.417***	0.098	-0.381***	0.095
Excessive get-out clause	-0.268	0.259	-0.246	0.243
Lack of knowledge about financing	0.356	0.220	0.315	0.192
11 Industry dummies	misc		misc	
Financial Constraint Equation				
Constant	0.458	0.417	0.467	0.410
Firm Innovates			0.324***	0.133
Size	-0.150*	0.081	-0.099	0.084
Collateral amount	0.069	0.058	0.030	0.059
Banking debt ratio	0.007	0.004	0.004*	0.004
Own financing ratio	-0.007*	0.004	-0.003**	0.003
Profit margin	-0.012***	0.002	-0.077***	0.002
11 industry dummies	misc		misc	
$corr_{12}$			0.254***	0.150
Log lik Innovation	-488.8			
Log lik Fin Constraint	-599.2			
Log lik Bivariate			-1067.9	

6 State Dependence in Financing and Innovation Experiences of Firms

We now explain how the nature of the available datasets can be exploited to study whether, ceteris paribus, past financial distress or innovation failures can affect a firm's current experiences in these two dimensions.

Though the datasets we use are not truly longitudinal, "panel" sets, the CIS part of the information we use was collected in four biennial waves. Hence, we know whether a particular firm i has reported binding financing constraints in the past. Similarly, we can also tell whether a firm has failed in the past in its efforts to be innovative. Consequently, though our dataset is not a true panel, we can extend our econometric equations modelling the probabilities of being innovative and of encountering binding financing constraints at the end of the sample period to condition also on past experiences in these two dimensions. The table that follows gives the transition matrix between the four regimes $(I_{it}, F_{it}) = \{(1,1),(1,0),(0,1),(0,0)\}$ from the early period covered by the CIS (1994-6) to the later one covered by the FIT (1997-9). These transitions confirm the importance of dynamics in the joint analysis of binding financing constraints and firm innovation. Detailed econometric estimations that include state dependence terms on both sides of our model have been obtained, but for the sake of brevity, we do not present them here. The interested reader can contact the corresponding author for the set of tables documenting these results. In summary, our findings confirm the very strong importance of such dynamic terms and establish very significant positive state dependency in our models.

Table 5.a
Innov Transitions 1994-6 –> 1997-9

		1997-1999 (FIT)		
		$I_{it} = 1$	$I_{it} = 0$	Total
1994-1996 (CIS2)	$I_{i,t-1} = 1$	84.45 543 60.54	40.74 354 39.46	42.53 897 100
	$I_{i,t-1} = 0$	15.55 100 16.26	59.26 515 83.74	57.47 615 100
	Total	100 643 42.53	100 869 57.47	100 1512 100

Table 5.b
FinCons Transitions 1994-6 –> 1997-9

		1997-1999 (FIT)		
		$F_{it} = 1$	$F_{it} = 0$	Total
1994-1996 (CIS2)	$F_{i,t-1} = 1$	41.32 100 33.00	15.98 203 67.00	20.04 303 100
	$F_{i,t-1} = 0$	58.68 142 67.00	84.02 1067 88.25	76.96 1209 100
	Total	100 242 16.01	100 1072 83.99	100 1512 100

Legend:

col % Cell Count row %

:

Table 5.c

1994-6 –> 1997-9 Transitions

		1997-1999 (FIT)				
		$I_{it}=1$ *and* $F_{it}=1$	$I_{it}=1$ *and* $F_{it}=0$	$I_{it}=0$ *and* $F_{it}=1$	$I_{it}=0$ *and* $F_{it}=0$	Total
1994-1996 (CIS2)	$I_{i,t-1}=1$ *and* $F_{i,t-1}=1$	15.8 77 37.6	37.7 58 28.3	14.8 13 6.3	7.3 57 27.8	13.6 205 100
	$I_{i,t-1}=1$ *and* $F_{i,t-1}=0$	68.9 337 48.7	46.1 71 10.3	30.7 27 3.9	32.9 257 37.1	45.8 692 100
	$I_{i,t-1}=0$ *and* $F_{i,t-1}=1$	1.4 7 7.1	7.8 12 12.2	19.3 17 17.3	7.9 62 63.3	6.5 98 100
	$I_{i,t-1}=0$ *and* $F_{i,t-1}=0$	13.9 68 13.2	8.4 13 2.5	35.2 31 6.0	51.9 405 78.3	34.2 517 100
	Total	100 489 32.3	100 154 10.2	100 88 5.8	100 781 51.7	100 1512 100

Legend:

col % Cell Count row %

7 Avenues for Future Research

In this section we outline our plans for extending the analysis of the paper in several directions.

Several ideas that we leave for future extensions of this research are the following:

First, there might exist useful additional information in the ranking of the different types of financing constraints over and above the simple binary indicator used here. For example, an ordered 3-value financing indicator might have been used instead, with the second equation being a 3-way ordered probit instead of a binary one.

Second, perhaps the size variable should enter non-linearly, e.g., through a simple quadratic or similar forms, to allow for the U-curve style of relations predicted by some theoretical models in the literature.

Thirdly, we could consider splitting the sample of innovative firms into ones who are *real innovators* from the ones who are merely *adopters* of innovative technologies and/or processes. This information will be in available in the forthcoming CIS4 survey. On a priori grounds, it appears that financiers are likely to treat these two sub-types of innovative firms as quite distinct, with concomitant differences in funding riskiness. Unfortunately, the sub-category of "potentially innovative" firms who have attempted to introduce innovations but *failed* may need to be dropped altogether and the consequences of doing so to be investigated, since it appears impossible to identify the *reasons* for such failures, in particular whether it was due to binding financial constraints or due to the innovation idea being inherently bad.

A related hypothesis we plan to analyze, which is studied preliminarily in Corres et al (2001), is that of *hierarchical financing* in terms of effective cost: first proceed with internal financing, and only continue with external one if the granted interest rate is low enough. The first alternative explanation explored is that the structure of types of debt are different, which would explain partially the differences in average interest rates observed. The second alternative is that innovating firms are in general of bigger size and established for longer so that they can be granted loans at lower interest rates. The third alternative explanation, which our preferred one, goes as follows: the findings are driven by a very serious selection bias, since observing a zero interest rate could mean one of three things: (a) the firm did not want any new loan; (b) the firm requested a loan but did not take one because the interest terms of the loan were too expensive; or (c) the firm requested a loan but the bank did not grant one. Along similar lines, it appears worthwhile to study explicitly the alternative mode of financing of issuing new shares for publicly quoted firms.

A further refinement we consider elsewhere is to build more detailed sequential models whereby a firm chooses whether or not to request a loan and given it decides yes, whether or not the bank grants the loan. In addition, it seems interesting to model also the final possibility that a firm may apply for a loan, the bank might grant it, *but the firm might reject the offer as too costly.* Assuming all the necessary data exists for building such an econometric framework, one could learn quite a lot about the mechanisms of these markets.

Finally, it should be noted that our econometric approach developed in this paper can be applied to the related problem of investment decisions by firms being directly affected by binding financing constraints.

8 Conclusions

In this paper we analyzed the existence and impact of financing constraints as a possibly serious obstacle to innovation by firms. Direct measures of financing constraints were employed using survey data collected by the Banque de France, which helped us overcome the problems with the traditional approach in the past literature of trying to deduce the existence and impact of financing constraints through the significance of firm wealth variables.

We used as the main econometric framework for our empirical analyses the simultaneous bivariate probit with mutual endogeneity. We discussed the important identification issue of *coherency conditions* in such LDV models with endogeneity and flexible temporal and contemporaneous correlations in the unobservables. We presented novel methods for establishing coherency conditions that allowed us for the first time to estimate models hitherto classified as incoherent through the use of prior sign restrictions on model parameters. We were thus able to quantify the interaction between financing constraints and a firm's decision and ability to innovate without forcing the econometric models to be recursive. Hence, we obtained direct as well as reverse interaction effects, leading us to conclude that binding financing constraints discourage innovation and at the same time innovative firms are more likely to face binding financing constraints. Finally, we investigated the importance of state-dependence in dynamic versions of our models and concluded that such issues are critical if direct and reverse interactions between innovation and financing constraints are to be quantified reliably.

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9 Data Appendix

We use data from two sources: a survey about the financing conditions of innovative projects for established manufacturing firms and the Banque de France Balance Sheet Data.

9.1 The FIT survey

We use the survey "Financement de l'Innovation Technologique" (FIT) that was conducted in 2000 by the French Ministry of Industry. Its aim was to obtain statistical information about the financing conditions of innovative projects of manufacturing firms in France. This survey allows to identify the firms which undertook innovative projects between 1997 and 1999 and it gives qualitative information about the financial constraints that firms may have experienced when planning and conducting those projects. A sample of 5500 industrial companies was surveyed. It is composed by manufacturing firms with 20 employees and more (excluding agricultural-food and building sectors). It is important to notice that start-ups and new established firms are not in the field of this survey. Globally, the rate of response amounts to 70% (Sessi 2002) so that about 3700 firms are present in the available FIT sample.

As the Community Innovation Surveys (CIS), the FIT survey is based upon the technological innovation concept exposed in the Oslo manual (OECD 1997).[7] This measure of innovative activities is less restrictive than R&D expenditures or patents data. Indeed, innovative activities are not systematically associated with R&D investments and patents are also strategic tools that are not necessarily used by firms to protect innovation.

In this paper, we are interested in identifying firms with innovative activities (and not only those that succeeded in introducing their innovation on the market).

- We qualified as "innovative" a firm that have introduced or develop a product or process innovation or that have been in process of doing so during the surveyed period. This identification of innovative firms is made thanks to their answers to the three following questions:

1) In 1997, 1998 or 1999, did Your enterprise introduce onto the market any new or significantly improved products for Your enterprise?

2) In 1997, 1998 or 1999, did Your enterprise introduce onto the market any new or significantly improved process for Your enterprise?

[7] The Community Innovation Surveys (CIS) are conducted in each country by the national statistical entities in order to collect information about the innovative activities of firms. In each country, they are based on the same questionnaire that may be completed by additional questions. The survey used here (Financement de l'Innovation Technologique, FIT) is different because it is focused on the financing of innovation. However, its methodological framework is the same as the well-known CIS' one, in particular concerning the definition of innovation and the structure of the questionnaire.

3) In 1997, 1998 or 1999, did Your enterprise have projects of new or significantly improved products or processes:
- Which are not yet completed or not yet introduce to the market?
- Which were failures?

In other words, a firm is innovative when it answered positively to at least one of these three questions.

- The qualitative information about the obstacles to innovation is given in the last part of the questionnaire. **All surveyed firms** have to answer the following question:

In 1997, 1998 or 1999, what are the obstacles that have prevented your firm to conduct or to start innovative projects (multiple answers possible)?
- Excessive perceived economic risk
- Lack of qualified personnel
- Innovation costs too high
- Lack of sources of finance
- Slowness in the setting up of the financing
- Too high interest rates of the financing
- Excessive get out clause in the shareholder agreement
- Lack of knowledge about ad hoc financial networks
- No obstacle

In addition, the firm has to tick the effect of each listed hampering factors on their innovative projects: (seriously delayed, abandoned or prevented to be started). As a firm may have several innovative projects, it can mention several consequences of obstacles (for instance, both delayed and non started projects).

- We consider that a firm faced **financial constraints** when it answered that it has seriously delayed, abandoned or non-started projects because of:

- Too high interest rates of the financing
- Lack of sources of finance
- Slowness in the setting up of the financing

A significant part of the firms in our initial sample (44%) answered simultaneously that they have not completed nor are in process of implementing innovative projects, and that they do not encounter any obstacle to innovation. Consequently, it could be assessed that this group of firms does not **wish** to innovate and thus, that those firms are not concerned by obstacles to innovation in general and by financial obstacles in particular. To try to identify the firms that wished to innovate, we define two groups of firms:

- The **potentially innovative firms** are the firms that positively answered to the first three questions (*i.e.*. firms that introduced or developed a product or process innovation or that were in process of doing so during the surveyed period) **or** the non innovative firms that faced obstacles to innovation. Thus, some of those firms are innovative as defined above (they succeeded in starting, even in completing their projects) while the other ones were not able to start none of their innovative projects.

- The second type of firms (the **"others")** are the non innovative ones that ticked they did not face any obstacle to innovation. Consequently, it may be assessed that these firms did not wish to innovate.

9.2 The Banque de France Balance Sheet Dataset

In order to have more information about the surveyed firms (their size, economic performance and financing structure) we use the Banque de France Balance Sheet Dataset.[8] This is a database containing essentially very detailed accounting data of French companies, obtained from their fiscal forms plus some complementary questionnaires. The database includes all businesses with more than 500 employees and a fraction of smaller firms so that the member firms amount to around 34,000 companies. It achieves an overall coverage rate of 57% in industry (in terms of number of employees). This rich database is used by the Banque de France to update knowledge of the structure and performance of the French productive system. In addition, it makes it possible for example, to pinpoint sources of financing, to isolate group financing or to identify expenditures in intangible goods and services.

10 Our sample

Our sample results from the matching of these two sources. We were able to recover about 60% of the FIT sample companies. After some necessary cleaning, our sample contains 1940 firms.[9]. The distribution of the firms in our sample according to their innovative behavior and financing obstacles is given in the table below:

[8] The "Centrale de bilans" dataset.

[9] The manufacture of coke, refined petroleum products and nuclear fuel has been deleted because only two firms were present in the merged dataset. In addition, the firms with negative value added or with abnormally high investment rates have been excluded. This concerns only two firms.

Table. Number of firms in the sample

Potentially innovative firms				Others
with innovative activities		without innovative activities		
financially constrained	financially unconstrained	financially constrained	financially unconstrained	
198	613	112	159	858

Sources : Centrale de Bilans (Banque de France), FIT (Sessi)

Table. Definition of the variables

Name	Definition
Dependent variable : y_{1_i}	=1 if the firm was innovative, =0 otherwise
Explanatory : x_{1i}	
Size	log (number of employees)
Market share	$\frac{\text{sales of the firm}}{\text{sales of the sector}} \times 100$
TP1	=1 if the firm's market is technologically not innovative (mode of reference)
TP2	=1 if the firm's market is weakly innovative,
TP3	=1 if the firm's market is moderately innovative
TP4	=1 if the firm's market is strongly innovative
Financial constraints	=1 if the firm faced financial constraints, =0 otherwise
Other obstacles to innovation:	
Excessive economic risk	=1 if the firm ticked this obstacle, =0 otherwise
Lack of qualified employees	=1 if the firm ticked this obstacle, =0 otherwise
Innovation costs too high	=1 if the firm ticked this obstacle, =0 otherwise
Excessive get-out clause	=1 if the firm ticked this obstacle, =0 otherwise
Lack of knowledge about financing	=1 if the firm ticked this obstacle, =0 otherwise
Financial constraints equation	
Dependent variable : y_{2_i}	=1 if the firm faced financial constraints, =0 otherwise
Explanatory : x_{2i}	
Size	log (number of employees)
Collateral	log(tangible assets)
Banking debt ratio	$\frac{\text{Banking debt}}{\text{(Own financing+Market Financing+Financial debt)}} \times 100$
Own financing ratio	$\frac{\text{Own financing}}{\text{(Own financing+Market Financing+Financial debt)}} \times 100$
Gross operating profit margin	$\frac{\text{EBDIT}}{\text{Value added}} \times 100$

Sources : Centrale de Bilans (Banque de France), FIT (Sessi) and EAE (INSEE)

Table. Descriptive statistics (full sample)

	Mean	Std	Min	Max
Innovation	0.418	0.493	0	1
Size	4.783	1.107	2.890	9.716
Market share	0.177	0.566	0.001	16.15
TP1				
TP2	0.416	0.493	0	1
TP3	0.348	0.476	0	1
TP4	0.097	0.297	0	1
Financial constraints	0.160	0.366	0	1
Excessive economic risk	0.228	0.420	0	1
Lack of qualified employees	0.206	0.404	0	1
Innovation costs too high	0.261	0.439	0	1
Excessive get-out clause	0.031	0.176	0	1
Lack of knowledge about financing	0.044	0.207	0	1
Collateral	71.048	22.698	4.241	302.444
Banking debt ratio	17.678	15.758	0	92.307
Own financing ratio	31.827	24.195	-609.459	90.136
Gross operating profit margin	18.248	19.416	-197.600	76.850

Sources : Centrale de Bilans (Banque de France), FIT (Sessi) and EAE (INSEE)

11 Technical Appendix: Novel Approaches to Coherency without Recursivity

We now consider formally the coherency problem in LDV models using the Simultaneous LDV Model with Two Binary Responses:

$$y_{1it} = \tau_1 \left(y^*_{1it} \equiv [h_1(x'_{1it}\beta_1, y_{2it}\gamma) + \epsilon_{1it}]\right)$$

$$y_{2it} = \tau_2 \left(y^*_{2it} \equiv [h_2(x'_{2it}\beta_2, y_{1it}\delta) + \epsilon_{2it}]\right)$$

The existing econometric literature has established as the typical coherency condition to be: $\gamma \cdot \delta = 0$, i.e., no reverse interaction terms are allowed among the two endogenous variables.

Gourieroux, Laffont, and Monfort (1981) explain condition in terms of there being a valid function from $(\epsilon_{1it}, \epsilon_{2it})$ to the observable endogenous variables (y_{1it}, y_{2it}).

Lewbel (2005) establishes necessary and sufficient for coherency by approaching problem as requiring a valid reduced form system for (y_{1it}, y_{2it}).

To give an illustration of the reduced form approach, we proceed as follows:

If $\delta = 0$ then the reduced form equation for y_{2it} is:

$$y_{2it} = \tau_2 \left(h_2(x'_{2it}\beta_2) + \epsilon_{2it}\right)$$

and hence the reduced form equation for y_{1it} is given by:

$$y_{1it} = \tau_1 \left(h_1(x'_{1it}\beta_2, \gamma \cdot \tau_2 \left(h_2(x'_{2it}\beta_2) + \epsilon_{2it}\right)) + \epsilon_{1it}\right)$$

11.1 Leading Case: Joint Binary Model

Leading case: the binary response threshold crossing model defined by:

$$\tau_j(z) \equiv \mathbf{1}(z > 0)$$

In this case, $(y_1, y_2) \in \{(1,1), (1,0), (0,1), (0,0)\}$ such that:

(y_1, y_2)	y^*_1	,	y^*_2
$(1,1)$	$x'_1\beta_1 + \gamma + \epsilon_1 > 0$	,	$x'_2\beta_2 + \delta + \epsilon_2 > 0$
$(1,0)$	$x'_1\beta_1 + \epsilon_1 > 0$	,	$x'_2\beta_2 + \delta + \epsilon_2 < 0$
$(0,1)$	$x'_1\beta_1 + \gamma + \epsilon_1 < 0$	,	$x'_2\beta_2 + \epsilon_2 > 0$
$(0,0)$	$x'_1\beta_1 + \epsilon_1 < 0$	,	$x'_2\beta_2 + \epsilon_2 < 0$

11.2 General Explanation and Illustrative Applications

In general, in the absence of coherency conditions, there will be *overlaps* and/or *gaps* in the domain of $(\epsilon_1 + x_1'\beta_1, \epsilon_2 + x_2'\beta_2)$.

We now develop a joint binary probit model to study the impact of financing constraints on a firm's decision and ability to innovate.

Define two latent dependent variables I_{it}^* and F_{it}^* and two binary limited dependent variables I_{it} and F_{it} as follows:

$$I_{it} = \begin{cases} 1 & if \quad I_{it}^* \equiv x_{it}^I \beta^I + \gamma F_{it} + \epsilon_{it}^I > 0 \\ 0 & if \quad I_{it}^* \equiv x_{it}^I \beta^I + \gamma F_{it} + \epsilon_{it}^I \leq 0 \end{cases} \tag{3}$$

$$F_{it} = \begin{cases} 1 & if \quad F_{it}^* \equiv x_{it}^F \beta^F + \delta I_{it} + \epsilon_{it}^F > 0 \\ 0 & if \quad F_{it}^* \equiv x_{it}^F \beta^F + \delta I_{it} + \epsilon_{it}^F \leq 0 \end{cases} \tag{4}$$

For a typical it observation, the probability $Prob(I_{it}, F_{it}|X, \theta)$ is characterized by the constraints on the unobservables:

$$(a^I, a^F)' < (\epsilon^I, \epsilon^F)' < (b^I, b^F)'$$

through the configuration:

I_{it}	F_{it}	a^I	b^I	a^F	b^F
1	1	$-x_{it}^I\beta^I - \gamma$	∞	$-x_{it}^F\beta^F - \delta$	∞
1	0	$-x_{it}^I\beta^I$	∞	$-\infty$	$-x_{it}^F\beta^F - \delta$
0	1	$-\infty$	$-x_{it}^I\beta^I - \gamma$	$-x_{it}^F\beta^F$	∞
0	0	$-\infty$	$-x_{it}^I\beta^I$	$-\infty$	$-x_{it}^F\beta^F$

12 The Traditional Approach to Coherency Conditions

To maintain the logical consistency of the model (known in the literature as "coherency") y_1^* should not depend on y_2^* if y_2^* depends on y_1^* and vice-versa.

Let us use a slightly more complicated simultaneous LDV model to illustrate the issue of coherency, namely the *binary & trinomial ordered probit model* of Hajivassiliou and Ioannides (2007) that studies interactions between liquidity and employment constraints on individual households indexed by i at a given point in time indexed by t. Define two latent dependent variables y_{1it}^* and y_{2it}^* and drop the it subscripts:

$$S = \begin{cases} 1 & if \quad y_1^* > 0 \ \text{(liquidity constraint binding)}, \\ 0 & if \quad y_1^* \leq 0 \ \text{(liquidity constraint not binding)}. \end{cases}$$

$$E = \begin{cases} -1 & if \quad\quad y_2^* \le \lambda^- \quad \text{(overemployed)} \\ 0 & if \quad \lambda^- \le y_2^* < \lambda^+ \quad \text{(voluntarily employed)} \\ +1 & if \quad\quad \lambda^+ \le y_2^* \quad \text{(under-/unemployed).} \end{cases}$$

$$y_1^* = \mathbf{1}(y_2^* < \lambda^-)\gamma_{11} + \mathbf{1}(\lambda^- < y_2^* < \lambda^+)\gamma_{12} + x_1'\beta_1 + \epsilon_1$$

$$y_2^* = \mathbf{1}(y_1^* > 0)\delta + x_2\beta_2 + \epsilon_2$$

Since (S, E) lie in $\{0, 1\} \times \{-1, 0, 1\}$, the 6 possible configurations may be enumerated as follows:

S	E	y_1^*	y_2^*
0	-1	$\gamma_{11} + x_1\beta_1 + \epsilon_1 < 0,$	$x_2\beta_2 + \epsilon_2 < \lambda^-$
0	0	$x_1\beta_1 + \epsilon_1 < 0,$	$\lambda^- < x_2\beta_2 + \epsilon_2 < \lambda^+$
0	+1	$\gamma_{12} + x_1\beta_1 + \epsilon_1 < 0,$	$\lambda^+ < x_2\beta_2 + \epsilon_2$
1	-1	$\gamma_{11} + x_1\beta_1 + \epsilon_1 > 0,$	$\delta + x_2\beta_2 + \epsilon_2 < \lambda^-$
1	0	$x_1\beta_1 + \epsilon_1 > 0,$	$\lambda^- < \delta + x_2\beta_2 + \epsilon_2 < \lambda^+$
1	+1	$\gamma_{12} + x_1\beta_1 + \epsilon_1 > 0,$	$\lambda^+ < \delta + x_2\beta_2 + \epsilon_2$

In terms of the unobservables, the probability of a (y_1, y_2) observed pair is equivalent to the probability:

$$\begin{pmatrix} a_1 \\ a_2 \end{pmatrix} < \begin{pmatrix} \epsilon_1 \\ \epsilon_2 \end{pmatrix} < \begin{pmatrix} b_1 \\ b_2 \end{pmatrix}$$

where $(\epsilon_1, \epsilon_2)' \sim N(0, \Sigma_\epsilon)$, and a and b are given by:

S	E	a_1	a_2	b_1	b_2
0	-1	$-\infty$	$-\infty$	$-(\gamma_{11} + x_1\beta_1)$	$\lambda^- - x_2\beta_2$
0	0	$-\infty$	$\lambda^- - x_2\beta_2$	$-x_1\beta_1$	$\lambda^+ - x_2\beta_2$
0	+1	$-\infty$	$\lambda^+ - x_2\beta_2$	$-(\gamma_{12} + x_1\beta_1)$	$+\infty$
1	-1	$-(\gamma_{11} + x_1\beta_1)$	$-\infty$	$+\infty$	$\lambda^- - \delta - x_2\beta_2$
1	0	$-x_1\beta_1$	$\lambda^- - \delta - x_2\beta_2$	$+\infty$	$\lambda^+ - \delta - x_2\beta_2$
1	+1	$-(\gamma_{12} + x_1\beta_1)$	$\lambda^+ - \delta - x_2\beta_2$	$+\infty$	$+\infty$

Using traditional arguments, we obtain that a sufficient condition for coherency of the model is:

$$(\gamma_{11} + \gamma_{12})\delta = 0 \text{ and } \gamma_{11}\gamma_{12}\delta = 0.$$

- To verify this condition, suppose $(S, E) = (0, 0)$. This rules out $(S, E) = (0, -1)$ because $x_2\beta_2 + \epsilon_2 > \lambda^-$, and rules out $(S, E) = (1, 0)$ because $x_1\beta_1 + \epsilon_1 < 0$.
- But $(1, -1)$ is not ruled out if the coherency conditions do not hold, since γ_{11} could be sufficiently negative and δ sufficiently positive to imply the $(1, -1)$ conditions.

- Similarly, the $(1, 1)$ possibility cannot be ruled out in the absence of the coherency conditions, since γ_{12} and δ can be sufficiently positive.
- Such logical inconsistencies are prevented if either (a) $\delta = 0$ or (b) γ_{11} and γ_{12} are simultaneously 0.

Similar considerations can be employed to establish that the traditional coherency condition for our model of financing constraints and firm innovation is:

$$\gamma \cdot \delta = 0.$$

This, of course, translates to the model (3)-(4) being *recursive*.

12.1 Difficulties with the traditional approaches:

The first difficulty is that derivations of formal conditions lack intuition, are difficult to generalize, and are sufficient but not necessary.

The second one is that in practice, non-triangular or reverse triangular cases are the most interesting.

To overcome the first difficulty, alternative ways for establishing coherency are developed here, that are both intuitive and straightforward. In addition, we show that less strict conditions are possible that in fact are more interesting in practical applications.

Regarding the second fundamental difficulty with the existing approaches, it is shown in the next Section how to establish coherency without recursiveness through the use of (a) endogeneity in terms of latent variables and/or (b) sign restrictions on model parameters. The fact that our novel approach for the first time eliminates the need to assume recursivity is quite important: recursivity corresponds to the key identifying assumption that innovation does not affect financial distress directly ($\delta = 0$). On a priori grounds, this assumption seems particularly dubious since innovation may lead to more profits and thus relax financial constraints (corresponding to $\delta > 0$). An alternative possibility is that innovation may lead to higher investment in intangible assets thus reinforcing binding financial constraints (corresponding to $\delta < 0$). Both possibilities violate the traditional coherency condition.[10]

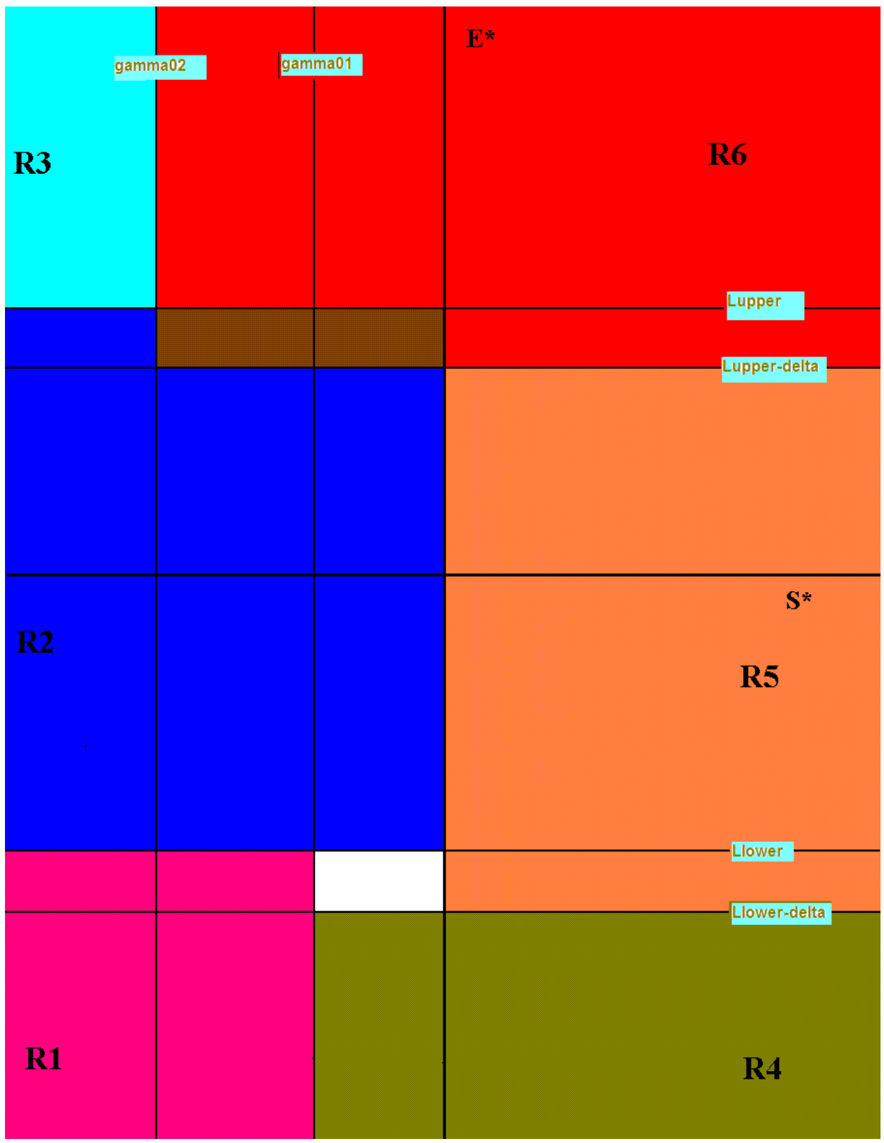
12.2 Novel Approach 1: Graphical

Let us illustrate the first approach using the Liquidity-Employment constraints application of Hajivassiliou and Ioannides (op.cit.). Figure overleaf 1 gives the 6 possible regimes $(S \times E) = \{1, 0\} \times \{-1, 0, 1\}$ in terms of the two latent variables y_1^* and y_2^*

[10] Note that throughout we expect $\gamma < 0$, i.e., the higher the probability that a firm faces a binding financial constraint, the less likely it is that it is able to innovate. So the two possibilities translate to: (a) $\gamma < 0$, $\delta > 0$ and (b) $\gamma < 0$, $\delta < 0$.

and the possible configurations in terms of parameters $\bar{\lambda}$, $\underline{\lambda}$, δ, γ_{11}, and γ_{12}. y_1^* is on the horizontal axis and y_2^* on the vertical.

The figure makes clear the role of the coherency condition (a) $\delta = 0$ or (b) $\gamma_{11} = \gamma_{12} = 0$: in general, regions $R2$ and $R6$ exhibit double-counting (cross-hatched area), as well as a white rectangle remains which makes the six regions not mutually exhaustive. These two logical incoherencies disappear when either $\delta = 0$ and/or $\gamma_{11} = \gamma_{12} = 0$ hold.



Liquidity and Employment Constraints

12.3 Novel approach 2: DGP From First Principles

The second approach to incoherency consists of designing a data-generating algorithm (on a computer or hypothetical) to simulate random draws from an LDV model's structure. Again let us use the Liquidity-Employment Constraints application of Hajivassiliou and Ioannides (2006) to illustrate the method. We draw ϵ_1 and ϵ_2 under the joint bivariate normal distribution with zero mean vector and variance-covariance matrix Σ_ϵ, and given $x_1\beta_1$ and $x_2\beta_2$ attempt to generate y_1^* and y_2^*. But this is *impossible unless* the coherency condition holds. If (a) $\delta = 0$, then latent y_2^* can be drawn, then ldv y_2, which together with ϵ_1 and $x_1\beta_1$ determines the rhs of y_1^*, thus allowing y_1 to be drawn.

Similarly, if (b) $\gamma_{11} = \gamma_{12} = 0$, then y_1^* can be drawn from the first equation based on ϵ_1 and $x_1\beta_1$, which determines y_1, thus giving y_2^* and hence y_2.

This approach is related to the Gourieroux et al. (1981) condition that a function exist from ϵ_1, ϵ_2 to y_1, y_2. It is also related to Lewbel (2005) in that coherency translates to there being a valid reduced form for the endogenous variables.

13 Identification Under Additional Prior Sign Restrictions

The idea developed here is related to Uhlig (2005) whereby sign restrictions are used to achieve identification in vector autoregression macroeconomic models.

13.1 Latent Variable Endogeneity

$$y_{1it} = \tau_1 \left(y^*_{1it} \equiv [h_1(x'_{1it}\beta_1, y^*_{2it}\gamma) + \epsilon_{1it}] \right)$$
$$y_{2it} = \tau_2 \left(y^*_{2it} \equiv [h_2(x'_{2it}\beta_2, y^*_{1it}\delta) + \epsilon_{2it}] \right)$$

Then:

$$y^*_1 = x_1\beta_1 + y^*_2\gamma + \epsilon_1$$
$$y^*_2 = x_2\beta_2 + y^*_1\delta + \epsilon_2$$

and

$$y^*_1 = x_1\beta_1 + \gamma \cdot [x_2\beta_2 + y^*_1\delta + \epsilon_2] + \epsilon_1$$
$$y^*_2 = x_2\beta_2 + \delta \cdot [x_1\beta_1 + y^*_2\gamma + \epsilon_1] + \epsilon_2$$

Hence $y^*_1 = RF_1$ and $y^*_2 = RF_2$, allowing us to obtain $y_1 = \tau(RF_1)$ and $y_2 = \tau(RF_2)$.

13.2 Coherency through Sign Restrictions

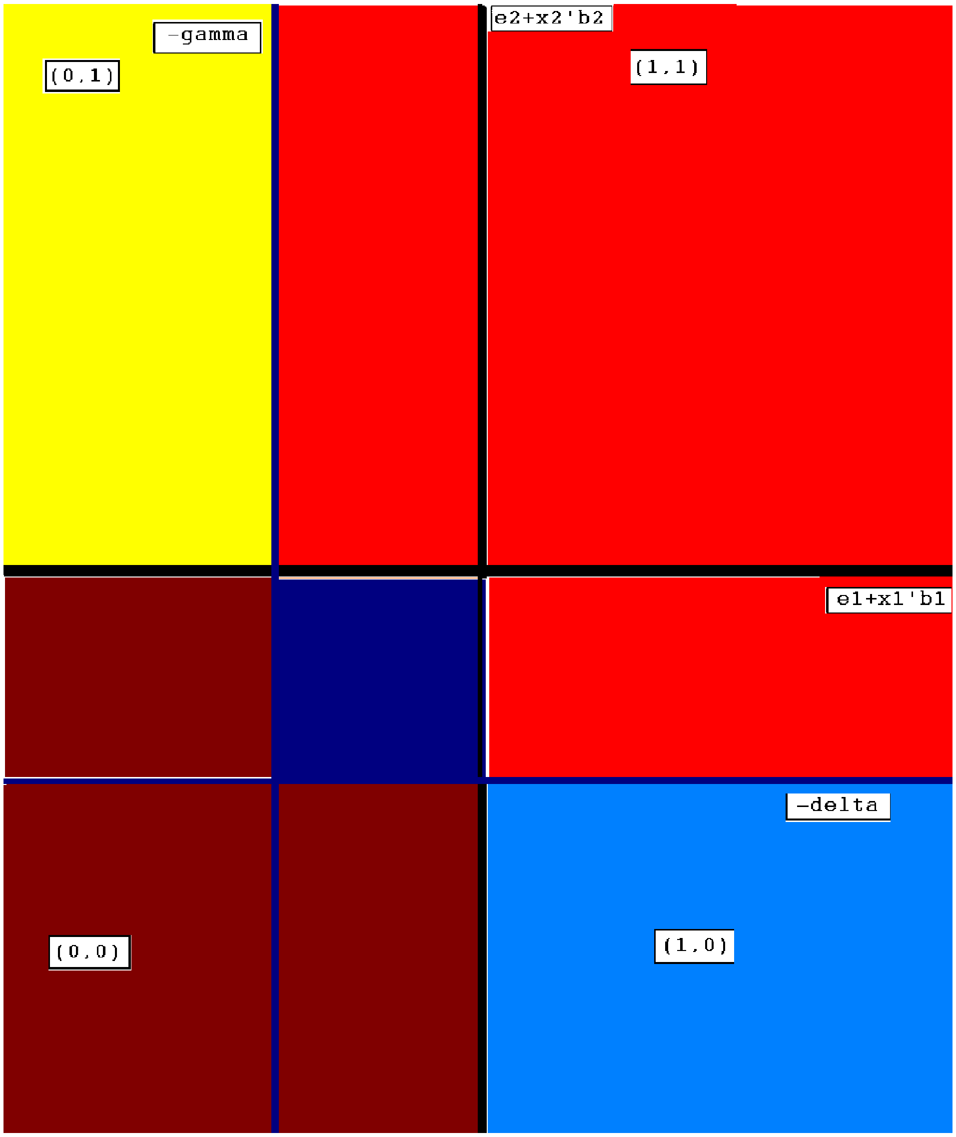
Illustrate with the Financing Constraints and Firm Innovation model:

$$I = \begin{cases} 1 & if \quad I^* \equiv x^I\beta^I + \gamma F + \epsilon^I > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$F = \begin{cases} 1 & if \quad F^* \equiv x^F\beta^F + \delta I + \epsilon^F > 0 \\ 0 & \text{otherwise} \end{cases}$$

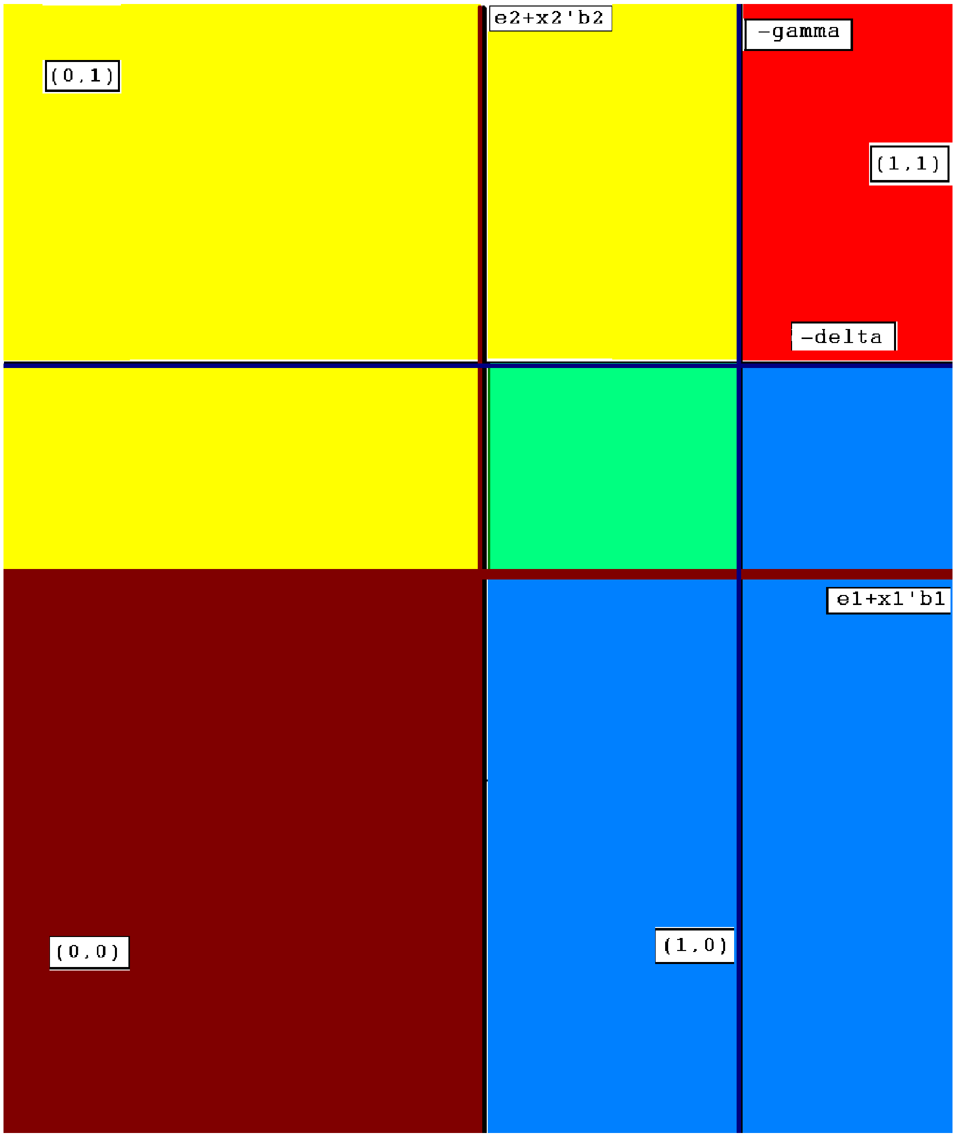
Four cases based on signs of γ, δ:

Case 1: $\gamma > 0, \delta > 0$ — overlapping regions, incoherency



Case 1: $\gamma > 0, \delta > 0$

Case 2: $\gamma < 0, \delta < 0$ — overlapping regions, incoherency

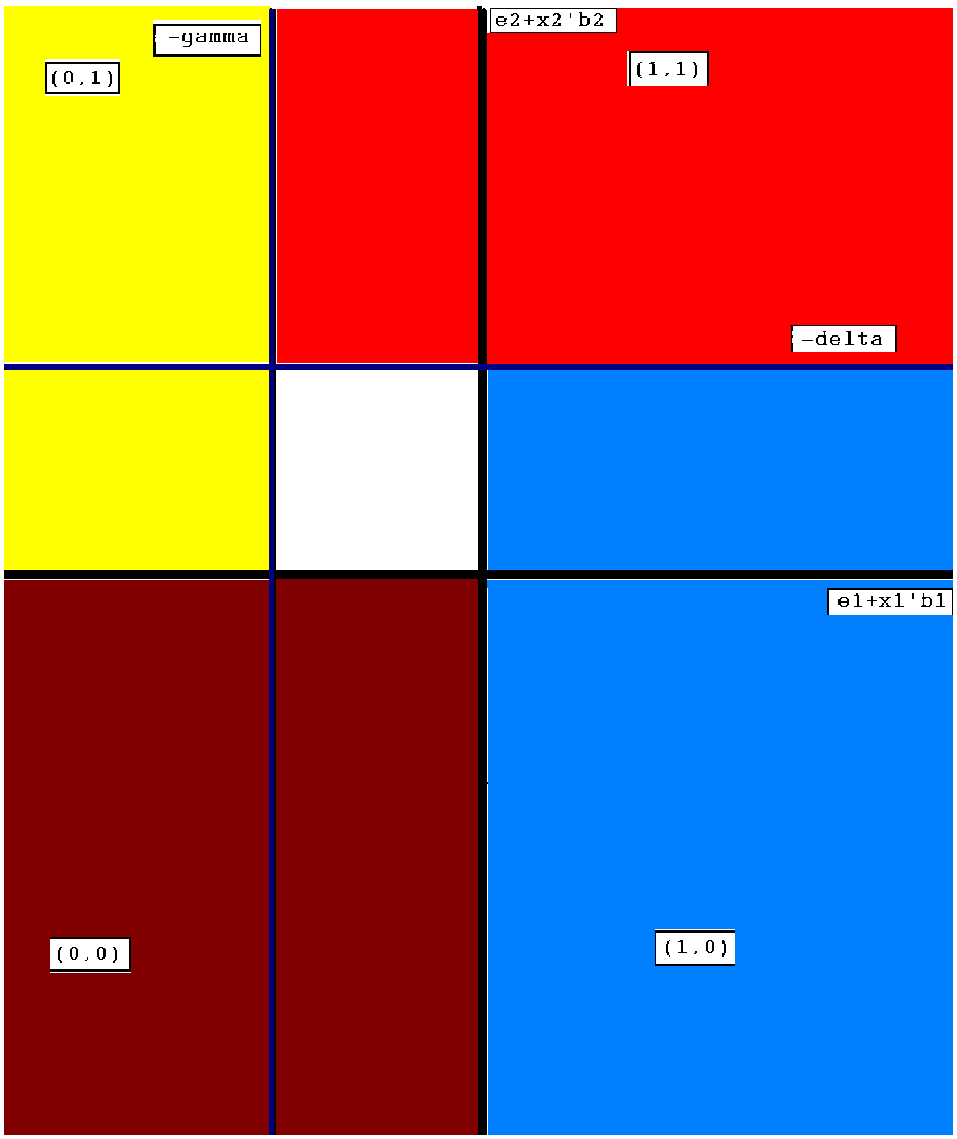


Case 2: $\gamma < 0, \delta < 0$

13.2.1 Case 3: $\gamma > 0, \delta < 0$ — empty regions, coherency through conditioning

For this case, coherency is achieved by conditioning to lie outside the "empty" region of figure 4, which has conditioning probability:

$$1 - Prob(-\gamma < \epsilon_1 + x_1\beta_1 < 0, 0 < \epsilon_2 + x_2\beta_2 < -\delta)$$

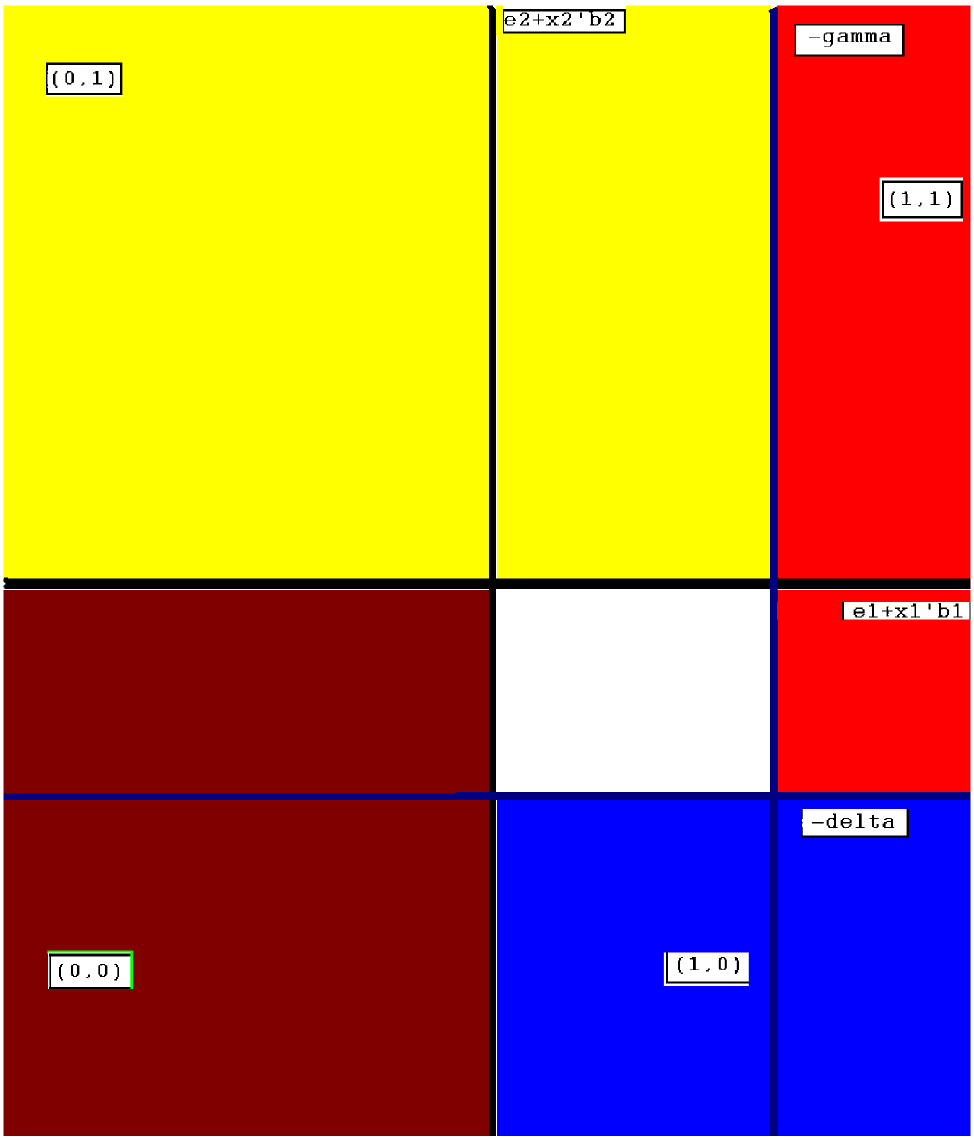


Case 3: $\gamma > 0, \delta < 0$

13.2.2 Case 4: $\gamma < 0, \delta > 0$ — empty regions, coherency through conditioning

For this case, coherency is achieved by conditioning to lie outside the "empty" region of figure 5, which has conditioning probability:

$1 - Prob(0 < \epsilon_1 + x_1\beta_1 < -\gamma, \delta < \epsilon_2 + x_2\beta_2 < 0)$



Case 4: $\gamma < 0, \delta > 0$

13.3 To Show Overlapping Regions Remain Incoherent Irrespective of LDV Definitions

At this point, a researcher might be tempted to suggest that the incoherency cases with overlapping regions (Cases 1 and 2 above) could be overcome by redefining one of the two limited dependent variables to their complement. According to this reasoning, since the incoherency is caused in these cases because γ and δ are of the same sign, and since changing y_2, say, to its complement $y_2^N \equiv (1 - y_2)$ would result in $\delta^N \equiv -\delta$, then coherency would be achieved since then $\gamma \cdot \delta^N < 0$.

Such reasoning would be incorrect, however. Section 7.7 in Hajivassiliou (2007) analyzes this idea and shows that such a redefinition would *maintain* the overlapping-region incoherency. This is because the $y_2^N \equiv (1 - y_2)$ redefinition would also switch the sign of γ and hence $\gamma^N \cdot \delta^N > 0$ just as $\gamma \cdot \delta > 0$.

14 Monte-Carlo Experiments

As we showed in the previous section, we obtain a coherent non-recursive model with interaction dummies included on both sides, provided we believe the feedback terms have opposite signs on the two sides. As explained already, note that it is sufficient to consider only the $\gamma \geq 0$, $\delta \leq 0$ case, since the reverse can always be subsumed by redefining the dependent binary variables to their complements $y'_{it} \equiv (1 - y_{it})$.

The Monte Carlo summarized in this Section illustrate the consequences of adopting the following *nine* estimation approaches:

(a) Incorrectly forcing the old coherency condition to hold, i.e., assuming recursivity when in fact both feedback terms are present (estimators `E-TRWN`=assuming $\delta = 0$ and `E-TRNW`=assuming $\gamma = 0$);[11]

(b) unrestricted likelihood estimation, which ignores the resulting incoherency due to the empty or overlap region(s) (estimator `E-INCO`);

(c) restricted likelihood estimation conditioning on the data lying outside the empty region(s) of incoherency (estimators `E-SQPM`=assuming $(\gamma \geq 0, \delta \leq 0)$ and `E-SQMP`=assuming $(\gamma \leq 0, \delta \geq 0)$)[12];

(d) restricted likelihood estimation conditioning on the data lying outside the overlap region(s) of incoherency (estimators `E-SQPM`=assuming $(\gamma \geq 0, \delta \geq 0)$ and `E-SQMP`=assuming $(\gamma \leq 0, \delta \leq 0)$); and

(e) LPOLS: (linear probability) ordinary least squares estimation of each binary probit equation ignoring the possible endogeneity of the interaction terms; and LP2SLS: applying two-stage least squares recognizing that the two interaction terms on the RHS of each probit equation can be endogenous.

[11] "`E-TRWN''`" stands for "Estimator-TRiangular system With interaction in first equation, No interaction in the second" and "`E-TRNW''`" analogously.

[12] "`E-SQMP`" corresponds to Estimator-Simultaneous Minus gamma, Plus delta and `E-SQPM` analogously.

We generate six "true" models:

- `DGP-TRWN` ($\delta = 0$);[13]
- `DGP-TRNW` ($\gamma = 0$);
- `DGP-SQPM` ($\gamma \geq 0, \delta \leq 0$);
- `DGP-SQMP` ($\gamma \leq 0, \delta \geq 0$);
- `DGP-SQPP` ($\gamma \geq 0, \delta \geq 0$); and
- `DGP-SQMM` ($\gamma \leq 0, \delta \leq 0$),

and in each case, calculate the seven estimators `E-TRWN`, `E-TRNW`, `E-INCO`, `E-SQPM`, `E-SQMP`, `E-SQPP` and., `E-SQMM.`[14]

The experiments performed confirm that our conditional likelihood approach under sign restrictions provides reliable, consistent and efficient estimates of the underlying parameters including the two interaction terms. In contrast, the existing traditional approaches (unrestricted MLE ignoring possible incoherency and MLE that incorrectly assumes recursivity of the system) give seriously misleading and inconsistent results. They also confirm that application of linear probability methods to the bivariate binary probit model typically leads to very unreliable findings, even if such methods attempt to take account of the endogeneity of the direct and reverse interaction effects. The reader is referred to Hajivassiliou (2007) for an extensive presentation of the Monte Carlos along the lines of this Section and their detailed analysis and findings.

[13] `DGP-xyz` as in `E-xyz`, except true Data-Generating-Process is `xyz` instead of Estimator assuming `xyz` data.

[14] The detailed methods for generating data from the each of the specified DGPs can be found in the Technical Appendix of Hajivassiliou (2007).

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