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Do financial constraints threat the innovation process? Evidence from Portuguese firms

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Abstract:

This paper broadly addresses the financing problems of the innovation process, by analysing the extent to which financial constraints hinder firms' investment in R&D and innovation, as well as investigating the role of public financial support in alleviating such constraints. In order to overcome the problems associated with measuring financial constraints, we make use of both indirect and direct measures of constraints. Our findings suggest that while financial constraints have a perverse effect upon R&D investment and innovation, there is no evidence that subsidies mitigate such constraints. Accordingly, we raise a number of questions regarding the efficiency and effectiveness of subsidies in alleviating firms' financial constraints.

Keywords: innovation; R&D investment; financial constraints; subsidies; Portugal.

JEL Classification: O30; D92; G32; L00; L20.

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1. Introduction

The recent shortage of financial resources has raised new interest on the role of financial constraints in firm dynamics. As a consequence, it is crucial to verify and quantify the extent to which R&D investment and ultimately innovation is affected by these constraints. If innovation is to be one of the main drivers of economic growth and if indeed such constraints are present, hindering firms' ability to work as main drivers of innovation and distorting the selection process, then financial constraints and policies to mitigate them, must be a priority in microeconomic research.

Accordingly, the goal of this paper is to broadly analyse the financing problems of the innovation process. In particular, we investigate the impact of financial constraints upon R&D investment and innovation, as well as the role of public financial support in alleviating such constraints. In order to provide robust findings, we use different approaches and both direct and indirect measures of constraints. For this purpose, we construct an unique dataset that contains firms' characteristics, balance sheets, information on innovation activity and a direct (self-assessed) measure of financial constraints. Upon this data, we first estimate the cash-flow sensitivity of cash (CCFS), by distinguishing different subsamples of firms that either or not innovate, invest in R&D and receive public financial support. Secondly, to investigate the impact of financial constraints upon R&D investment, we test different specifications, controlling for selection and endogeneity. Thirdly, in order to account for endogeneity of financial constraints on innovation, we specify a simultaneous equations probit model that we further extend to the ordered probit case. Finally, we explore the impact of public financial support (subsidies) upon firms' perception of constraints, through both a probit and a simultaneous equations probit (and ordered probit) specifications.

Our findings suggest that firms that do not innovate (but are potential innovators), those that do not invest in R&D, and those that do not receive public funding are financially constrained. Moreover, controlling for endogeneity, we find that financial constraints severely reduce the amounts invested in R&D and seriously hamper innovation. Finally, we question the extent to which subsidies effectively alleviate firms' financial constraints.

This paper is the first, as far as we know, to combine different methodologies to evaluate the role of financial constraints on the innovation activity of firms. More importantly, it contributes to the extant innovation literature by being the first, to our knowledge, to explicitly analyse the nexus between financial constraints and public financial support, bridging two closely related lines of research within innovation studies. Finally, we make use of an unique dataset that covers the period 1996-2004 and combines firms' characteristics with both balance sheet data and information on the innovation activities of firms, drawn from three different waves of Community Innovation Surveys (CISs II, III and IV). This has barely been done and is a novelty with respect to Portugal.

The paper is organized as follows. Section 2 makes a brief incursion on the empirical literature concerning financial constraints, innovation and public financial support, as well as it puts forward the main hypothesis to be tested. In Section 3 we briefly discuss the dataset used, while Section 4 describes the empirical methodology followed. Section 5 presents the main results, that are followed by a discussion in Section 6. Finally Section 7 pulls the pieces together and concludes.

2. Financing problems of the innovation process

2.1. Measuring financial constraints

The abstract nature of the concept of financial constraints—albeit for subjective firm self-evaluation, it is not directly measurable—has challenged researchers, mostly on empirical grounds, to consistently measure constraints and to provide robust estimates of its impact upon R&D investment and innovation. In fact, even on theoretical grounds, it is difficult to come up with a clear-cut definition of financial constraints. For the purpose of this paper, we define financial constraints as the inability of a firm to raise the necessary amounts (usually due to external finance shortage) to finance its innovation activity.

Despite theoretical literature identifies difficulties in the access of firms to external funds, empirically there is no consensus on how to measure financial constraints (see Hubbard, 1998 or Carreira and Silva, 2010 for a discussion). Most of the empirical studies resort to the primordial Fazzari, Hubbard and Petersen (1988) measure of Investment-Cash Flow Sensitivities (ICFS), by adapting it to R&D investment and innovation (e.g. Bond et al., 2003, Magri, 2010). Another approach is to check if parameter restrictions of a derived reduced form Euler equation for R&D investment, based on Whited (1992), are satisfied (e.g. Harhoff, 1998). Recently, within a perspective of demand for cash, Almeida et al. (2004) suggested that financial constraints might be measured through the sensitivity of cash to cash-flows (CCFS). The rationale is that only financially constrained firms will need to optimize their cash stocks over time in order to maximize their profits and hedge future shocks by holding cash. In fact, for R&D investment, but using an approach in line with Bond et al. (2003), Brown and Petersen (2011) suggest that financially constrained firms manage liquidity to smooth their R&D spending. Other strategies include the construction of indexes of variables that are generally agreed to be good proxies of constraints (e.g. Musso and Schiavo, 2008; Hovakimien and Hovakimien, 2009) or, if data is available, resort to firms' self-evaluation of constraints (e.g. Angelini and Generale, 2005; Savignac, 2008).

2.2. Financial constraints, R&D investment and innovation

When it comes to R&D investment and innovation, assuming that the effort to innovate draws from the capacity that firms have to invest in R&D (input for innovation), then this type of investment is expected to be more financially constrained than investment in physical capital. This results from the fact that R&D, in opposition to physical capital is not only harder to use as collateral (possible credit multiplier effects), but is also of a riskier nature and entails significant information asymmetry problems (Hall and Lerner, 2010). In particular, these information asymmetries may be further amplified if firms try to conceal their R&D projects, fearing any leak of information to competitors, that could prove to be fatal in their attempt to innovate.[1]

Notwithstanding, empirical literature on the impact of financial constraints upon innovation has mostly relied on datasets composed mainly of firms' financial information, patents and R&D expenses (e.g. Harhoff, 1998, Scellato, 2007 or Brown and Petersen, 2011) that are not as specific as for example (for the European case) the Community Innovations Surveys (CISs), that are particularly designed to evaluate the innovation activity of firms—see Mairesse and Mohnen, 2010 for a survey of findings using CIS. Additionally, they also include extremely useful information on firms' perception of financial constraints.

To our knowledge, only a reduced number of tests have been performed with a combined dataset of CIS (or other specific innovation survey) and financial information, of which Mueller and Zimmermann (2006), Savignac (2008), Gorodnichenko and Schnitzer (2010) and Czarnitzki and Hottenrott (2011a) are examples.

While initial results using CISs found that the impact of obstacles on the innovation activity of firms was positive, subsequent literature has found that, after controlling for endogenous variables, such as financial constraints, the reported estimates on the impact of obstacles were found to be negative, as expected (e.g. Savignac, 2008, Tiwari et al., 2008).

[1] We should note, however, that besides the usual, but distinct, forms to raise external finance (see Majumdar, 2011 for heterogeneous impacts of different debt types in R&D investment)—such as bank lending, issuing debt and equity in capital markets or even trade credit—business angels and, notoriously, venture capital play a central role when it comes to innovation (see Hall and Lerner, 2010 for an overview). Nevertheless, an analysis of the role of venture capital on the financing of innovation is not in the scope of this paper. Effectively, we do not have information on start-ups and very young firms due to the CIS sample design.

This endogeneity, for the specific case of financial constraints, results from unobservables that correlate both with financial constraints and innovation\R&D investment. This is the case of firm-specific R&D investment project uncertainty, duration and confidentiality (see Savignac, 2008). We should also note that innovators might be expected to face lower constraints due to a better financial position associated with a possibly better economic performance, which further adds to the endogeneity problem. Moreover, the decision to apply for credit and the probability of credit approval, may well depend upon firms' R&D intensity (Guiso, 1998; Azteni and Piga, 2005).[2] Therefore, once endogeneity is taken into account, we expect that:[3]

H1) Financial constraints reduce the amounts invested in R&D

H2) The probability that a firm innovates is negatively affected by financial constraints

2.3. Pubic financial support

Financial constraints and subsidies are two closely related lines of research within innovation studies. On one hand, as previously discussed, researchers have strived to measure the impact of financial constraints upon R&D investment and innovation. On the other hand, the effects of public policy, and specifically subsidies, on R&D spending and innovation performance, have been given particular attention in recent years (e.g. Bloom et al., 2002; Almus and Czarnitzki, 2003; Aerts and Schmidt, 2008; Schneider and Veugelers, 2010). However, as far as we know, the role of public financial support to R&D investment and innovation (hereafter subsidies for simplicity purposes) in alleviating firms' financial constraints has never been analysed explicitly.[4]

Subsidising private R&D and innovation activities is generally agreed by researchers to be desirable in order to foster economic growth, as well as it is in the agenda of several policymakers. The main theoretical argument for public support of R&D and innovation activities resides in higher social than private returns to R&D investment, due to incomplete

[2] Not to mention the possible endogeneity stemming from the survey-based financial constraints variable we use, since the probability that a firm reports as constrained might well increase as it is committed to more innovation projects. Additionally, more innovative firms are also more aware of such constraints (e.g. Tiwari et al., 2008; Savignac, 2008).

[3] Even though it is not the purpose of this paper to explore such effects, we should note that innovation may also be hampered by other constraints that relate to the ability of firms to absorb new technology (Cohen and Levinthal, 1990) and enhance competitiveness (e.g. Teece et al., 1997). Namely, a set of resources and capabilities at the human, organizational, networking and legislatory levels, as argued by the resource-based literature, may significantly constrain innovation (e.g. Hewitt-Dundas, 2006).

[4] We should note that the impact of public intervention upon financial constraints, that are not specific to the innovation process, has been previously analysed, even though with different methodologies (e.g. Zecchini and Ventura, 2009).

appropriability and knowledge spillovers (Hall and Lerner, 2010). In this line, the main empirical issue is whether subsidies stimulate or replace R&D spending (David et al., 2000). Recent empirical literature suggests that the former hypothesis holds—subsidies have a significant additionality effect on R&D spending (e.g. Aerts and Schmidt, 2008; Czarnitzki and Bento, 2011). This effect seems to be particularly relevant for research activity in comparison to development, where subsidies appear to have a "crowding out" effect (Clausen, 2009). This distinction—in line with the findings that point that the former is more prone to financial constraints than the latter (Czarnitzki et al., 2011)—suggests that subsidies may prove to be particularly efficient when aimed at financially constrained firms.

Accordingly, besides the market inefficiencies argument, associated with the "public good" nature of knowledge, the existence of financial market frictions (financial constraints) might also be ground for public intervention. Therefore, the question of interest is whether public financial support effectively reduces financial constraints? It is apparent that subsidies directly increase firms' financial capacity. However, when it comes to information asymmetries and firm access to external funds, the effect is not as clear—except for other public intervention forms such as special credit lines and backed debt policies. Nevertheless, provided that subsidies are specifically designed and correctly allocated to financially constrained firms, they signal favourable growth (innovation, in this particular context) prospects to investors. Additionally, such subsidies in the current period, may enhance current economic performance and therefore reduce financial constraints in the future. As a consequence, we expect that:

H3) Subsidies reduce the extent to which R&D investment\innovation is financially constrained

Overall, the analysis of the impact of financial constraints upon the innovation process usually relies on either subjective self-assessed measures or on methodologies that can be questionable on theoretical and empirical grounds. In fact, there appears to be no consistent measure of financial constraints, even though strong policy implications are drawn from investigations using a sole measure of such constraints with strong underlying assumptions (Coad, 2010). Keeping this caveat in mind, and resorting to different measures, we attempt to contribute to the clarification of the financing problems (and possible remedies) of the innovation process.

3. Data

We construct an unique dataset from the combination of three different data sources through a code number provided by the Portuguese National Statistical Office (INE). The first, is formed by the successive Portuguese CIS, referring to the periods 1995-1997 (CIS2), 1998-2000 (CIS3) and 2002-2004 (CIS4). Secondly, by resorting to *Inquérito às Empresas Harmonizado* (IEH), we have access to the balance sheets (though at a relatively low level of disaggregation), on an early basis, of the universe of Portuguese firms with more than 100 employees and a random sample of firms with less than 100 employees. Finally, we have detailed information of firms' generic characteristics, as well as we are able to track firms through time, by resorting to *Ficheiro de Unidades Estatísticas* (FUE)—is conducted every year and includes the universe of Portuguese firms. As a result, we are able to construct a panel, for variables on firms' financial status and generic characteristics, that covers the period 1996-2004 and is representative of the Portuguese economic sector disaggregation, further enriching the information on CISs surveyed firms. Therefore, our final dataset is composed by 8,132 CIS observations (CIS 2, 3 and 4) appended by an unbalanced panel of the respective 7,079 firms for the period 1996-2004, corresponding to 30,177 observations.

The main caveat of this dataset is the great loss of observations when we try to make use of both the panel structure and the CIS waves (with 1997, 2000 and 2004 as reference years) simultaneously, since not all firms in the CIS data are present in the panel data—note that the panel, for firms with less than 100 employees, is composed by a random sample. Moreover, the 3 different CISs surveys are not exactly identical, so we had to abandon some variables in order to homogenise the CISs information (e.g. the use of information technologies).

Additionally, the waves of CIS refer to a certain time span (1995-97, 1998-2000 and 2000-04) meaning that—only for the case of CCFS estimation—we must either assign a reference year for each wave, or assume that the reported information represents the average during the time span. Initially we opted for the former, however, the greatly reduced number of observations forced us to implement the later, so to have consistent estimates and to be able to use more appropriate estimation techniques.[5] Still, we expect that access to the corresponding datasets for 2004 onwards, once available, will allow us to improve these results.

[5] The assumption on average values during the corresponding wave period is fairly strong, however, it is a necessary evil in order to achieve consistent estimation when we split the sample to estimate CCFS in a GMM style. For robustness checks we also calculate the wave period averages of the variables in IEH and FUE, when applicable, and construct a panel of the 3 corresponding waves.

Furthermore, the subjective nature of the self-assessed variables means that potential biases, resulting from individuals perception, may exist. As an extreme example, while for some changing the colour of a product might be a significant improvement of the product (accounted as product innovation), for others it is not the case. This will also apply to variables such as reported financial constraints, where we might have respondents that feel that their firm is highly financially constrained, when it actually is much less constrained than another firm reporting low constraints.[6]

Finally, the inclusion of the partially qualitative, subjective and censored CIS data, in our panel of balance sheets and firms' characteristics, raises an additional number of methodological issues that must be carefully dealt with (Mairesse and Mohnen, 2010). Examples can be found in the binary variables that identify if a firm has introduced innovations, in the ordinal categorical and subjective nature of the variable that identifies the availability of external finance as a factor hampering innovation, or in the censored variable of R&D expenses (only reported for those firms that decide to invest). For detailed description of the variables used and their construction, please see the Appendix.

4. Methodology

4.1. Model A: Measuring financial constraints using CCFS

Almeida et al. (2004) construct a model of liquidity demand and derive an empirical equation to estimate the sensitivity of cash to cash-flows. Briefly, the rationale is that a constrained firm will save cash out of cash flows in order to take advantage of future investment opportunities and hedge against future shocks, incurring in opportunity costs of present foregone investments. Conversely, unconstrained firms will not need to optimize their cash stocks over time since they have access to external funds. Therefore CCFS should be positive and significant for the former while no such relation should be found for the latter. The financial nature of the cash stock variable is a shield against miss-measurements in Q (sales growth in our case) and investment opportunities hidden in cash-flow. The reason being that it is not expected that firms will increase their cash stocks if cash-flow signals a new\better investment opportunity, unless they are financially constrained. However, constrained firms may use cash to reduce debt if hedging needs are low (Acharya et al, 2007), which we try to control trough debt issuances and sales growth (proxying investment opportunities).

[6] Some studies overcome this problem by using data on the credit requested and effectively granted (e.g. Russo and Rossi, 2001; Angelini and Generale, 2005). We do not have such information.

Additionally, as pointed by Almeida et al. (2011) in a subsequent paper, investment in relatively liquid assets, other than cash, may be used to transfer resources across time (we include financial investments).[7] Keeping these caveats in mind, we have the following empirical specification:

$$\Delta CS_{i,t} = \beta_1 CF_{i,t} + \beta_2 \Delta y_{i,t} + \beta_3 S_{i,t} + \beta_4 I_{i,t} + \beta_5 \Delta NWC_{i,t} + \beta_6 ISS_{i,t} + \\ + \beta_7 \Delta INT_{i,t} + \beta_8 FinI_{i,t} + \varepsilon_{i,t} \quad \text{(A1)}$$

where $\Delta CS_{i,t}$ is the variation in cash stocks for firm i in year t, $CF_{i,t}$ is cash-flow, $S_{i,t}$ is a control for firm size (log of total assets), $I_{i,t}$ is investment, $\Delta NWC_{i,t}$ is the variation of noncash net working capital and $\varepsilon_{i,t}$ the error term. We shall use sales growth ($\Delta y_{i,t}$) instead of Q as a proxy for investment opportunities (please see the Appendix). Additionally, we implement a slight modification to the original model. In the spirit of Lin (2007), we substitute the variation of short term-debt by the sum of net debt and equity issuances ($ISS_{i,t}$) and changes in interest paid ($\Delta INT_{i,t}$). The former modification is due to the fact that debt and equity issuances, while being a signal of easier access to external funds, might have a significant impact upon cash stocks (by accounting procedures), so we control for such effect. With respect to the latter, firms may decide to reduce their borrowings or pay back debt according to expected interest expenses. However, instead of benchmark interest rate variations, we use variations of interest paid, which allows for firm variation and thus can also be seen as a form of credit rating. Furthermore, we also control for financial investments ($FinI_{i,t}$), that not only are a demand for cash but may also work as an alternative way to transfer resources across time.[8] The above mentioned variables (except *S*) are scaled by total assets.

The financial and investment covariates are endogenous, so there is a need to estimate the model using instrumental variables, along with fixed effects to take account of unobserved firm-level heterogeneity and panel-robust standard errors. The cross-sectional nature of the different CIS waves (1997, 2000 and 2004) entails significant problems for the estimation of CCFS. The endogeneity of the financial covariates recommends the use of

[7] In the original model they assumed that firms transfer resources only through cash.

[8] We test the different specifications departing from Almeida et a. (2004). CCFS estimates range from 0.1 to 0.26, where major differences are driven by the replacement of short-term debt by equity and debt issuances and interest payments. The inclusion of financial investments (always strongly significant) leads to a slight reduction of CCFS estimates, possibly capturing the effect (for financially constrained firms) of the use of these investments to allocate present resources (cash-flows) to future states as an alternative to cash holdings (see Table A1 in Appendix).

instrumental variables. However, the most appropriate instruments would be lagged—in some cases twice and further lagged because of the exogeneity condition, in order to provide consistent estimates—values of these variables. Unfortunately, the use of lagged values—particularly those of variables built upon differenced values—will require at least 2 periods of data to be lost, meaning that the first wave of CIS (1997) would not be taken into account.[9] Therefore, for this model, we assume that the CIS information represents averages for the corresponding wave span and make use of the full length of the panel.

In order to compare financial constraints across different types of firms, we split our sample into subsamples of firms that: (i) innovated (*INNOV*=1) and those that did not (*INNOV*=1); (ii) decided to invest in R&D (*RD*=1) and those that did not (*RD*=0); (iii) received public financial support (*SUB*=1) and those that did not (*SUB*=1). For the case of investment in R&D, we additionally estimate an interaction of total R&D expenditures (I_RD) with cash-flow of the form:

$$\Delta CS_{i,t} = \beta_1 CF_{i,t} + \alpha_0 I\_RD_{i,t} + \alpha_1 CF_{i,t} * I\_RD_{i,t} + \beta_2 \Delta y_{i,t} + \beta_4 I_{i,t} + \beta_5 \Delta NWC_{i,t} + \beta_6 ISS_{i,t} + \\ + \beta_7 \Delta INT_{i,t} + \beta_8 FinI_{i,t} + \varepsilon_{i,t} \quad \text{(A2)}$$

4.2.Model B: Sample selection in R&D investment, with endogenous financial constraints

In addition to the possible endogeneity of FC for reasons presented in Section 2.2, our R&D investment variable has an excess of zeroes and is highly skewed.[10] Accordingly, we assume that the R&D investment process encompasses two decisions. While the first is firms' decision either to invest or not in R&D, the second is the decision of the amounts that should be invested. However, these are not independent (the errors from two-step equations are correlated, which we confirm further on) and therefore a joint specification is needed. Consequently, this setup falls into the selection models category.[11]

As a result, to evaluate the impact of financial constraints, as well as other firms' characteristics, on the amounts spent in R&D we build up a model that takes into account both selection and the endogenous nature of the financial constraint variable. The model is described as:

[9] The set of instruments includes profitability, percentage of sales of innovated products, lagged net working capital two-digit industry indicators, lagged bond issuance, leverage and self assessed financial constraints.
[10] While we have 71% of zeroes, the mean (904324) is much higher than the median (163549).
[11] We recognize the possibility of an alternative specification that relates to the Poisson distribution, usually associated with count data (GLM with a log-link that extends to the GMM version for instrumenting FC). See Nichols (2010) for a reference.

$$RD\_I = Z_1\beta_1 + \alpha FC + \varepsilon \tag{B1}$$

$$FC^* = X\beta_2 + u \tag{B2}$$

$$RD = 1(Z\beta_3 + v > 0) \quad , \qquad v \sim N(0,1) \tag{B3}$$

where (B3) describes the selection process, since we only observe the amount invested in R&D (RD_I)—measured in logarithms—when firms decide to invest in R&D ($RD = 1$). This decision is based on a latent variable that can be seen as the propensity to invest ($RD^* = Z\beta_3 + v$). Both Z and RD are always observed. Additionally, self-assessed financial constraints (FC) is also always observed (note that the latent variable FC^* is not), but is an endogenous variable in (B1). Finally, we allow for arbitrary correlation among v, u and ε.

The estimation procedure takes two steps: (a) we estimate a probit model for equation (B3) upon the full sample and obtain the estimated inverse Mills ratios ($\hat{\lambda}_{i3} =$); (b) using that information, we estimate

$$RD\_I_i = Z_{i1}\beta_1 + \alpha FC_i + \gamma\hat{\lambda}_{i3} + e_i \tag{B4}$$

upon the selection sample. So far, this is similar to the traditional Heckit estimator (after Heckman, 1976, 1979). However, the suspected endogeneity of the ordinal FC requires that we take into account (B2) (see Wooldridge, 2002 pp. 567-570).[12] Note that at least one covariate in Z must be excluded (Z_i) in the estimating equation (B4) in order to guarantee identification.

In order to obtain correct standard errors we use the bootstrap pairs method, instead of a more complex derivation of the necessary correction of the standard errors. Accordingly, we bootstrap following procedure: 1) estimate a probit of the R&D investment decision; 2) construct the inverse Mills ratio; 3) estimate the volume of R&D investment, taking into account the inverse mills and the endogeneity of financial constraints.

To take into account the endogeneity of financial constraints we use different consistent approaches in the last step, namely: 3.1) Ignore the ordinal nature of FC and estimate a regular optimal GMM; 3.2) Obtain fitted values of FC by resorting to the

[12] This equation explains financial constraints through the combination of both firms' characteristics and financial variables: firm size (SIZE); firm age (AGE); 2-digit industry dummies (CAE rev 2.1); percentage of public and foreign capital (PUB_K and FOR_K, respectively); investment opportunities *(ΔY);* cash stocks (CS); cash-flow (CF); leverage (LEV); debt and equity issuances (ISS); changes in interest paid (ΔINT); returns on financial investments (R_FIN); exports (EXP); market share (MKTS) and a dummy for firms that received subsidies (SUB). With the exception of PUB_K, FOR_K, ΔY, ISS and ΔNWC, we use the year lag values to account for the wave span.

appropriate ordered probit estimation and then use these as instrument for FC —see Cameron and Trivedi, 2005 pp. 193.

Once again, the data imposes us some constraints in estimating the selection model. Not only the same problem with the inclusion of covariates persists, but there is an additional issue with our dependent variable (expenditures in R&D). If we opt to scale those expenses by either total assets or sales, there is a significant loss of observations (approximately half of initial number of observations). As a result we will work with non-scaled logarithm of total expenditures in R&D. Our full set of variables Z includes: firm size; age; industry dummies; exports *(EXP)*; labour productivity ($LPROD$); investment opportunities to R&D investment (Y_IN); investment opportunities (ΔY); percentage of R&D employees (RD_WORK), public funding (SUB); cooperation with other firms and institutions ($COOP$); leverage; market share (MKTS) and other barriers to innovate (B_TRAB, B_TECH and B_MARK). In the estimating equation (B4) we exclude $MKTS$, $LPROD$, leverage and other barriers to innovate in order to guarantee identification.[13]

We compare the estimates with those of a simple OLS, a "hurdle" model and a selection model with no endogeneity, where we should note that, in these cases, non-linear FC can not be used directly in the estimating equation. Accordingly we collapse it into a binary indicator of whether or not a firm reported any financial constraints (FC^c).[14]

4.3.Model C: Impact of financial constraints directly upon innovation

Following Savignac (2008), we estimate the impact of financial constraints directly upon innovation. This is achieved by estimating a simultaneous equations model (specifically a bivariate normal specification of errors within a simultaneous equations probit model) of underlying latent variables—propensity to innovate ($INNOV^*$) and level of financial constraints (FC^{c*})—of the following form:

$$\begin{cases} INNOV^* = X_1\beta_1 + \alpha_1 FC^c + \varepsilon_1 \\ FC^{c*} = X_2\beta_2 + \alpha_2 INNOV + \varepsilon_2 \end{cases}, \tag{C1}$$

[13] If Z_1=Z, then β_1 is only identified because of the nonlinearity of the inverse mills ratio. This can lead to multicollinearity problems. As a rule of thumb, at least two variables should not appear in the selected regression.

[14] The "hurdle" model is set as a pair of independent equations: a) decision equation, estimated through a probit; b) volume equation, estimated by OLS. We additionally estimate the corresponding two parts model taking into account the endogeneity of FC. For that purpose we estimate the corresponding simultaneous equations and IV regressions that allow us to test for endogeneity, since such tests are rather difficult to compute for the full Model B.

For logical consistency purposes we set ($\alpha_2 = 0$) and additionally normalize the variance of the errors:

$$\begin{cases} INNOV^* = X_1\beta_1 + \alpha_1 FC^c + \varepsilon_1 \\ FC^{c*} = X_2\beta_2 + \varepsilon_2 \end{cases}, \quad \begin{pmatrix}\varepsilon_1 \\ \varepsilon_2\end{pmatrix} \sim \Phi_2 \begin{bmatrix}0 \\ 0\end{bmatrix} \begin{bmatrix}1 & \rho \\ \rho & 1\end{bmatrix} \tag{C2}$$

where X_1 includes the investment in R&D (*RD_I*), firm size, age, other barriers to innovate (B_TRAB, B_TECH and B_MARK), subsidies (*SUB*), cooperation with other firms and institutions *(COOP)*, percentage of R&D employees (*RD_WORK*), investment opportunities *(ΔY)* and market share (*MKTS*). In the vector X_2 we include the usual determinants of FC, in accordance to (B2) in Model B. If there are no omitted or unobservable variables that affect simultaneously the probabilities of a firm reporting financial constraints and innovating ($\rho = 0$), these equations can be estimated separately, meaning that FC can be treated as exogenous.

We further extend the model to allow FC outcomes to be ordinal and estimate the corresponding ordered probit model (see Greene and Hensher, 2010 pp. 222 for details and Sajaia, 2008 for STATA implementation).[15] Finally, we discriminate between product and process innovation in order to provide robust results.

4.4. Model D: Subsidies and financial constraints

The last group of estimations in this paper attempts to clarify the link between public financial support and financial constraints. Specifically, we estimate the impact of subsidies upon the reported levels of constraints.

There are some reasons to believe that subsidies are endogenous. Firstly, if a firm is financially constrained, there in an higher probability that it applies for subsidies (we do not have data on subsidy requests), as well as it might be seen as a potentially more appropriate target for public policy. Secondly, the possibility of artificial survey positive correlation being present may require that we use balance sheet variables as instruments. Finally, potential correlated unobservables, such as public policy goals and budgets, firms' applications for subsidy programs and the quality of the underlying project (Jaffe, 2002; Schneider and Veugelers, 2010) imply that treating SUB as endogenous should be considered.

[15] Note that since the estimation of marginal effects in this case are of rather hard computation and above all interpretation we refrain from estimating them.

Accordingly, as in the previous section, we specify a simultaneous equations probit model (with the corresponding latent variables specification), that we further extend to the ordered probit case in order to fully explore the FC variable. The same logical consistency constraint applies and we also normalize the variance of the errors. Therefore, we simultaneously estimate the following model:

$$\begin{cases} FC^{c*} = X_1\beta_1 + \alpha_1 SUB + u \\ SUB^* = X_2\beta_2 + v \end{cases}, \qquad \binom{u}{v} \sim \Phi_2 \begin{bmatrix} 0 \\ 0 \end{bmatrix} \begin{bmatrix} 1 & \varrho \\ \varrho & 1 \end{bmatrix} \tag{D1}$$

where X_1 includes the following controls: firm size (SIZE); firm age (AGE); 2-digit industry dummies (CAE rev 2.1); percentage of public and foreign capital (PUB_K and FOR_K, respectively); investment opportunities *(ΔY);* cash stocks (CS); cash-flow (CF); leverage (LEV); debt and equity issuances (ISS); changes in interest paid (ΔINT); returns on financial investments (R_FIN); exports (EXP); market share (MKTS). All these variables, are obtained from balance sheets. Therefore, we use the first lag of these variables to account for the CIS wave span and reduce artificial survey correlation. Exceptions are PUB_K, FOR_K, ΔY, ISS and ΔNWC, since they either do not have sufficient annual variation, or their construction is based on the previous period (would imply the loss of all CIS2 observations). When it comes to X_2, we include size (SIZE), age (AGE), percentage of R&D employees (*RD_WORK*), market share (*MKTS*), intangibles (INTANG), exports (EXP), percentage of public (PUB_K) and foreign capital and (FOR_K), cooperation with other firms and institutions (COOP) and share of subsidies by industry (SUB%I) and region (SUB%R). Again, if there are no omitted or unobservable variables that affect simultaneously FC and SUB ($\varrho = 0$), we can estimate the equations separately.

5. Empirical Results

5.1. Summary Statistics

Table 1 reports the means and standard deviations of the main variables used in model (A), by the different subsamples of firms. We should point that mean cash-flow is larger (and less volatile) for firms that innovate, invest in R&D and those that receive subsidies. The same appears to be true with respect to size (total assets) and sales growth.[16]

[insert Table 1 about here]

[16] For each variable of interest, the differences between groups are formally tested through both Mann–Whitney and Fligner-Policello tests, as well as also confirmed by quantile-quantile plots. This applies to all results in this section. The statistics are available from authors on request.

Table 2 reports the same statistics for the remaining models. As it is clear from columns (2) and (3), firms that invest in R&D are larger (number of employees), older, have a larger percentage of R&D workers and export more. Additionally, while they have higher innovation investment opportunities (percentage sales of new products), they have lower physical capital investment opportunites (sales growth). Moreover, within this group, there is a larger number of firms that report higher financial constraints, receive subsidies and cooperate.

With respect to firms that innovate (columns 5-6), these are found to be larger (number of employees), older, have an higher percentage of R&D workers and higher market shares, but have lower investment opportunities (sales growth). These firms also spend remarkably larger amounts in R&D investment. Furthermore, there is a larger number of firms that innovate and receive subsidies, cooperate, report higher levels of financial constraints as well as other barriers to innovate (except for the case of market barriers).

Finally, firms that receive subsidies (columns 8-9) are larger (number of employees), older, have larger (lower) percentage of public (foreign) capital, lower cash stocks but higher cash-flow, are less leveraged, issue less debt, have larger variation of non-cash working capital, export more and have larger market shares.

[insert Table 2 about here]

5.2 Results for Model A

Analysing the results on financial constraints to innovation using the CCFS methodology (Table 3), we do not find statistically significant differences in constraints between innovators and non-innovators—the cash-flow coefficients are 0.100 and 0.112, respectively (columns 2-3). However, if we distinguish between non-innovators that are willing to innovate (hampered firms) and those that do not desire to innovate (unwilling to innovate), the figures are different—CCFS of 0.215 against 0.123, respectively (columns 5-6). Please see the Appendix for definition details.[17]

Evidence on different levels of constraints is clearer if instead of comparing innovators with non-innovators, we distinguish between firms that invested in R&D and

[17] Nevertheless, the former estimate is quite imprecise due to a reduced number of observations and the latter is still statistically significant—possibly capturing firms that are financially constrained with respect to other activities, rather than innovation. We should also note that "hampered firms" include those that either faced financial constraints or any other sort of obstacles to innovate. If we restrict the sample to "hampered firms" that report financial constraints, we obtain 34 firms with the corresponding 75 observations and a CCFS estimate of 0.339** (0.148). Conversely, for the remaining firms (hampered by other obstacles) the CCFS estimate is found to be negative but not statistically different from zero.

those that did not. In fact, as we can see from Table 4, there is a striking difference in CCFS (columns 1-2). While for firms that invested in R&D, the estimated CCFS is not statistically different from zero, firms that did not invest in R&D save, on average, a remarkable amount of 20 cents out of each euro of cash flow.[18] With respect to total R&D expenditures (column 5), the cash-flow interaction term is negative and statically significant (only at 0.1 level), further adding to a potential inverse relationship between financial constraints and R&D investment.

[insert Table 3 about here]

[insert Table 4 about here]

From the estimates in columns 3 and 4, it may be possible to argue that public finance has a positive effect in reducing financial constraints. Firms that do not have public financial support save, on average, 12 cents out of each euro of cash-flow, which contrasts with the group of firms that received funding (the coefficient is not statistically different from zero).[19]

With respect to other variables, we should note that investment and non-cash net working capital are demands for cash. Accordingly, the negative sign is not unexpected. Conversely, the positive impact found for equity and debt issuances reflects the importance of these sources of cash, even though there is an associated cost (interest payments) that reduce cash savings. Finally, financial investments are a demand for cash, but may also be used to transfer resources across time. Therefore, while we find a negative impact for those firms that are not expected to be financially constrained, the same is not true when it comes to constrained ones.[20]

Even though CCFS appear to be able to provide useful insights on the level of financial constraints, this methodology suffers from the fact that it is unable to explore the causality flow between financial constraints (an estimated mean for a given subsample) and R&D investment, innovation or subsidies. Consequently, bearing in mind the subjective

[18] The findings obtained using interactions (for the full sample) of cash-flow with dummies indicating if a firm either or not innovated, invested in R&D and received subsidies are not different. These results can be obtained from the authors on request

[19] However, a test on the difference between estimates is not able to reject the equality of coefficients, even though this is due to the lack of precision stemming from the low number of observations for the SUB=1 subsample.

[20] Financially constrained firms may redirect cash-flows and present liquidity (cash stocks) to future states, in the form of financial investment (relatively liquid assets) to be used as a source of liquidity in the future. However, we should note that a decrease of financial investments may not necessarily mean an increase in cash stocks. The reason is that since both can be used to finance investment (e.g. R&D investment and innovation investment in general) or face financial distress (e.g. service debt, cover operational losses), it may occur a contemporaneous decrease in cash stocks and financial investments

nature of such variable, we resort to the reported levels of financial constraints to innovate, as an explanatory variable for these activities in the following sections.

5.3. Results of Model B

In Table 5 we report the estimation results of the selection model with endogenous financial constraints. It can be compared with the Heckman-style estimation of the corresponding model, with an additional treatment of endogeneity. While in column (1) we report the estimates of a simple OLS, columns (2-5) report the estimates of a two-parts specification, where we assume that the amount invested in R&D is independent of the decision to invest in R&D (no selection). In column (6) we estimate a model that accounts for selection but not endogeneity (Heckman) and finally, columns (7-8) report the estimates of the model that accounts for both selection and endogeneity.[21]

[insert Table 5 about here]

While on one hand the results from columns (2-5) point that endogeneity must be taken into account (statistically significant $\hat{\rho}$ coefficient on the decision equation and a formal endogeneity test on the volume equation), on the other hand, the necessity to account for selection is confirmed by the statistically significant coefficient on $\hat{\lambda}_{i3}$ in columns (6-8). Once both selection and endogeneity are taken into account, we show that an increase in financial constraints leads to a decrease in the amounts invested in R&D.[22] Accordingly, we do not reject *H1*. Additionally, our results suggest that subsidies stimulate R&D investment since, in all specifications, there is a strong positive impact of subsidies upon both the decision to invest and the amounts spent in R&D.

With respect to other variables of interest, we should note the positive impact of size, R&D investment opportunities, percentage of R&D employees and cooperation, which is not unexpected. On the other hand, investment opportunities (sales growth) reduce R&D investment, most probably due to the fact that higher sales growth signal that no innovation efforts are needed since the firm is performing rather well, or alternatively it might suggest

[21] Since the derivation of the appropriate correction terms for the asymptotic variance is rather complex, we resort to paired bootstrap estimation with 999 replications.

[22] As a check for robustness, we constructed a panel of the 3 wave periods by calculating the averages, over wave period, of financial variables (Table A2, appendix). In this case, there appears to be a reduction in the negative effect of financial constraints on R&D investment along the 3 waves. Additionally, results obtained fitting a Tobit to log(1+R&D investment)—e.g. Czarnitzki and Hottenrott (2011b)—also lead to a negative (but not significant) impact of FC upon R&D investment. Statistics not reported but available from authors on request.

that investment in physical capital is warranted.[23] Conversely, a reduction of sales might signal that the firm needs to be innovative and change. Finally, the estimates on firm age are quite unstable. On one hand, the negative signs may indicate that, as firms grow older, they tend to accommodate and invest less in R&D. This can also be related to life cycle of a certain industry and the strength of the selection pressure. On the other hand, the positive signs suggest that as firms age, they increase their knowledge stock and are better suited to pursue R&D activities.

Overall, financial constraints severely affect the amounts invested in R&D once FC are treated as endogenous.

5.4. Results of Model C

When it comes to innovation, Table 6 reports our estimates of the simultaneous equations probit and ordered probit models (columns 2 and 3, respectively), as well as those of a simple univariate probit model (column 1) that does not account for the possibility of endogenous financial constraints. As expected, the rejection of the hypothesis of independent equations (Wald test of whether $\rho = 0$) confirms that FC must be treated endogenously. Once this endogeneity is taken into account, the impact of FC upon innovation becomes negative and statistically significant for both binary and ordinal specifications. Therefore, we are not able to reject *H2*. Additionally, as naturally expected, the amounts spent in R&D positively affect innovation, even though there is no significant impact of subsidies upon the probability that a firm innovates. Nevertheless, if we observe this effect for each wave, we find that while in the first two waves, there is a strong positive impact of subsidies upon innovation, this is not the case when we analyse the last wave (see table A3 in appendix).

With respect to other variables, cooperation and size (for the ordered specification) are found to significantly increase innovation, which is not unexpected—in contrast with the odd positive coefficient for market barriers. We do not find statistically significant coefficients, within the simultaneous equations specifications, for the remaining variables of interest.[24] Finally, we do not find any statistically significant difference (at 0.1 level) between the impact of financial constraints on product and process innovation (see Table A4 in Appendix). Nevertheless, significant differences are found with respect to investment opportunities, that have a significant positive (negative) impact on product (process)

[23] Note that the spearman correlation coefficient of sales growth is positive (0.2411*) and negative (-0.0591*) with respect to physical capital investment (I) and total R&D investment (I_RD), respectively.

[24] As for the case of R&D expenditure, when we divide the sample by CIS wave periods (Table A3, appendix) we find that financial constraints decrease in importance as we move along the CIS waves.

innovation, as well as concerning the impact of subsidies—that appears to be only relevant for product innovation.

[insert Table 6 about here]

5.5. Results of Model D

The results on the impact of subsidies on financial constraints (Table 7) are quite puzzling. While for regressions that use contemporaneous and lagged balance sheet variables (columns 1, 3 and 4) we find a positive and statistically significant impact of subsidies on financial constraints (regardless of whether we control for endogeneity or not), when we use lagged subsidies and CIS wave variables (columns 2, 5 and 6), the estimated coefficients are not statistically different from zero. Interestingly (but not surprising) when lagged variables are used, one can not reject the null hypothesis that subsidies can be treated as exogenous. With respect to other potential determinants of financial constraints, when significant, they are found to carry the expected sign.

[insert Table 7 about here]

This rather puzzling rejection of *H3*, that contrasts with the expectations of an inverse relationship, as suggested by the findings in Section 5.2, deserves a detailed inspection of both survey variables. Specifically, in Table 8, we report the frequencies of FC and SUB. As expected, the majority of firms do not receive subsidies (88.1%), as well as there is a relatively large percentage of firms that face difficulties in obtaining external funds to finance innovation (43.3%, but increasing in the level of constraints). Additionally, for firms that report financial constraints and receive financial support (6.3%), the percentage of subsidies for those that report minor difficulties (12.5%) is lower than those that report high and very high levels of constraints (21% and 19.1%, respectively).

However, there is a remarkably large number of firms, among those that receive subsidies (11.9%), that reported not to be financially constrained (47.4%). This can either indicate that firms that receive subsidies *ex-ante* do not face significant constraints, or that there is a misallocation of subsidies. We are more inclined towards the second explanation since this value increases to 62.5% if instead of FC_wwe compute the relative frequencies for FC_{w-1}—i.e. 62.5% of firms that received subsidies during one CIS wave, have reported no constraints in the previous wave (Table A5, appendix).[25] Furthermore, if instead of SUB_w we

[25] The subscript w stands for CIS wave. Additionally, the impact of financial constraints on the probability that a firm receives subsidies—either in the current or subsequent period—is never statistically significant. Available from authors on request.

use SUB_{w-1}, one can observe that only 39.3% of firms that received subsidies in one period, report no constraints on the subsequent period. Still, these results may well reflect the idea of "subsidy persistence" (e.g. Hussinger, 2008). In fact, the transition probability of a firm continuing as subsidized is 39.5%, being 40% for firms that report as unconstrained.

[insert Table 8 about here]

These results need further testing, preferably using treatment effects estimation techniques. However, our CIS panel is not sufficiently long and the financial constraints variable is not linear (despite we can do a linear projection), not to mention possible problems associated with the subjective nature of this particular survey variable. In fact, we do not exclude the possibility that there are problems associated with the subjective nature of the FC self-assessed variable.

6. Discussion

Overall, our results suggest that the innovation process is negatively affected by financial constraints. On one hand, for the case of R&D investment, both our indirect and direct measures point towards a strong negative impact of financial constraints. Indeed, CCFS estimates are much larger for firms that do not invest in R&D (Model A, Section 5.2)—in line with the findings of Bond et al. (2003) for ICFS. This result meets the expectation that only firms that are not financially constrained are able to invest in R&D. Additionally, once endogeneity is taken into account, higher reported levels of constraints reduce the probability that a firm invests in R&D, as well as the R&D investment volume (Model B, Section 5.3). Accordingly, as stated in our hypothesis *H1*, financial constraints reduce the amounts invested in R&D.

When it comes to innovation, even though the CCFS estimates do not allow a straightforward conclusion (Model A), the analysis of Model C (Section 5.4) reveals that, once we take into account endogeneity, financial constraints significantly reduce the probability that a firm innovates, as stated in *H2*. Yet, we should spend some time in trying to understand why we do not find clear-cut results using CCFS. In particular, the extent to which the non-innovators (innovators) group will include some firms that are, a-priori, not constrained (constrained)—one would expect significantly lower (higher) CCFS for firms that do (do not) innovate.

Firstly, this methodology is time-invariant and relies on an *a priori* assignment of firms into distinct groups. Therefore, some lag effects may not be totally captured by the methodology and, notoriously, it does not account for endogeneity. Secondly, regardless of being or not financially constrained, firms might just not be interested in innovating in the first step. For example, it might well be the case in industries where the pace of technological change is rather slow (Marsili and Verspagen, 2002; Castellacci, 2007). This is particularly relevant for our CCFS estimation because the question on self-assessed constraints (FC) is answered by all firms in all CIS waves, whether they innovated or not. Using this information, we identify potential innovators (within non-innovators) that, according to our estimates, seem to be more financially constrained than those firms not willing to innovate. Notwithstanding, the question is asked specifically with respect to innovation barriers. As a result, while it is not expected that firms that do not want to innovate report constraints to innovation (FC), the CCFS measure may also capture the extent to which firms—unwilling to innovate—are financially constrained with respect to their operational and physical capital investment activities (other than innovation). This is probably the reason why we still find significant CCFS for firms unwilling to innovate. Thirdly, non-financially constrained firms may try to innovate, even though they are unsuccessful and therefore will belong to the non-innovators group. Finally, since innovation is measured in a rather broad sense, reasonably financially constrained firms, even without putting too much effort, might be able to innovate. As an example, if we would be able to distinguish between "radical" from "routine" types of investment in R&D and innovations, then we could expect significant differences in the impact of financial constraints (Czarnitzki and Hottenrott, 2011b).

Nevertheless, the combination of both survey and balance sheet information—that allows us to instrument the self-assessed constraints variable—certainly helps to clarify the negative impact that financial constraints have upon R&D investment and ultimately innovation. Consequently, the perverse effect of financial constraints upon the innovation process, calls for policies that help to mitigate such constraints. Accordingly, we evaluate the extent to which public financial support (subsidies) effectively alleviates financial constraints to innovate.

Our first results, using CCFS, suggest an inverse relationship between subsidies and constraints (Section 5.2.). The immediate interpretation is that firms receiving subsidies are not constrained. In this case, even though we would expect the difference to the subsidised group to be significant, there certainly also exist some firms in the non-subsidised group that are not financially constrained. However, this analysis is static. Accordingly, it neither clarifies if there is a causality flowing from subsidized to unconstrained, nor whether subsidies are actually being allocated to financially constrained firms. In fact, even though the results from the CCFS analysis would suggest an inverse relationship between subsidies and constraints, the findings obtained using Model D (Section 5.5) point towards the rejection of the hypothesis that subsidies alleviate financial constraints (*H3*). This rather puzzling result requires further clarification and some explanations, that we summarize as follows:

a) Subsidies are not being allocated correctly. This is one of the two worrisome possible explanations, that is based on our analysis of relative frequencies. In fact, we report a large number of firms that receive subsidies, despite not reporting as financially constrained in current or previous periods. If this is the case, then policymakers should be more cautious in designing incentives and, notoriously, in scrutinizing firms as potential targets. Nevertheless, this hypothesis needs further testing, in particular with information on the specific incentive schemes.

b) Learning and self-selection in applying for subsidies. This is related to point a). We do not know which firms apply for subsidies. However, if certain firms are more engaged in innovation activities and have a better procedural knowledge, it is possible that they obtain subsidies, even if not financially constrained. Therefore, such subsidies will not affect the levels of constraints faced by such firms. We argue that there is a "learning by applying" effect, in which firms—along the time and consecutive applications for funds—learn own to best satisfy the requirements of subsidies programs, as well as they gain insights on the institutional setup behind subsidy allocation. This is in line with the "subsidy persistence" found in our data. If this is the case, firms that regularly apply for subsidies dominate the application process, regardless of the effectiveness of the subsidy (either from a "constraints alleviating" or "innovation enhancing" perspective). Moreover, firms that already have an "application know-how", may discourage applications from firms that apply for the first time, since the latter know in advance that they lack the expertise and therefore have a lower probability of obtaining the subsidy. Consequently, regular applicants will self-select into subsidies. This self-selection effect may also explain the results of Section 5.2., where we do not find significant CCFS for subsidized firms. However, we should note that the extent to which firms learn how to apply for subsidies, may not signify that they also learn how to elaborate a successful project at the eyes of private lenders. This is due to different goals of private (maximize returns with minimal risk of default) and public lenders (deal with market failures by alleviating financial constraints, fostering innovation, or both). Accordingly, we may have constrained firms that will continue to receive subsidies with their levels of financial constraints remaining unchanged.

c) Subsidies do not alleviate financial constraints. In other words, the wedge between external and internal forms of finance remains unchanged after a firm receives a subsidy. This case also requires a serious rethinking of public policy programs. In fact, in addition to our estimation results, the analysis of frequencies using lagged values suggests that there is a significant percentage of firms that, even after receiving subsidies, report high levels of constraints. This may occur mainly for two reasons. On the one hand, such subsidies are strictly designed to foster innovation, regardless of firms' difficulties in raising external funds. This means that there is no "signalling" effect to investors and that ultimately funds are not being allocated to those firms that most need them. On the other hand, subsidies have a "crowding out" effect that does not alter economic performance and subsequent reduction in constraints. However, for a more appropriate causality testing, we would need a dependent variable of financial constraints that is firm-specific (not estimated means), objective, continuous (and not scores) and, most importantly, time varying (in order to allow treatment effects estimation). Unfortunately, to our knowledge, there is no such measure. Moreover, different forms of public incentives (such as special credit lines and backed debt policies), may prove to be more effective in reducing constraints. Regrettably, we do not have sufficient information to distinguish these forms of intervention from subsidies *strictu sensu* (e.g. grants and tax credit).

d) The subjective nature of the survey FC variable. In this particular case, the possible bias would be towards higher reported levels of constraints, since firms would tend to over-report as financially constrained. This would not be a major concern if the bias is transversal and equal to all firms (would only imply a scaling of the effect), which is already a quite strong assumption. However, if this bias is associated with a "subsidy persistence" phenomena, then it is natural to expect that a significant number of firms, that continuously receive subsidies, will still perceive themselves as financially constrained. Nevertheless, this respondent perception problem is not as serious for the other models, since for such cases financial constraints is an explanatory variable that is instrumented with balance sheet data. However interesting, the extent to which firms' self-evaluation of constraints deviates from reality is not in the scope of this paper, but is certainly a topic that deserves detailed investigation in the future.

While on one hand it appears that subsidies promote innovation (during the first two waves of our data) and particularly foster R&D investment (Sections 5.4. and 5.3., respectively), on the other our results do not support the idea that this is done *via* a reduction of financial constraints (Section 5.5.). In other words, the rationale for subsidies appears to be solely on the grounds of innovation as a "public good". Accordingly, the allocation of funds to firms that do not suffer financial constraints (if this is the case), may well create inefficiencies, possibly even within a social welfare perspective, since it may reinforce the dominant position of certain firms against other firms (or profitable net present value projects) that either are unable to obtain external finance or do not have the necessary expertise to obtain public financial support—provided explanation c) holds.

On the whole, even though this paper lacks a simultaneous analysis of the different dimensions (which is econometrically extremely complex), it provides a broad view of the effects of financial constraints upon the innovation process. Furthermore, the paper raises a number of questions and provides ground for debate regarding the allocation and effectiveness of subsidies in alleviating firms' financial constraints.

7. Conclusion

In this paper we broadly analyse the financing problems of the innovation process. Specifically, we explore the impact of financial constraints to R&D investment and innovation, as well as the role of public financial support in alleviating such constraints. Accordingly, we estimate a selection model, simultaneous equations probit models, as well as the sensitivity of cash to cash-flow upon an unique, newly assembled, sample of Portuguese firms.

Using the CCFS methodology to assess the mean level of financial constraints by subsamples of firms, we find that CCFS are larger for firms that do not innovate (but are potential innovators), for those that do not invest in R&D and for firms that do not receive subsidies. This indicates that R&D investment may be financially constrained and subsidies may help in reducing financial constraints. On the other hand, by analysing the impact of a self-assessed measure of constraints upon R&D investment, we show that only when the endogeneity problem associated with this variable is taken into account, do financial constraints significantly decrease the amounts invested in R&D. Furthermore, also resorting to the same direct measure, innovation (in a broad sense) is only found to be significantly hampered by financial constraints once we allow for a joint specification of errors of both equations. However, when we focus on the effect of subsidies upon the reported levels of financial constraints, we do not find evidence supporting the constraints alleviating effect of subsidies. On the contrary, our evidence raises serious concerns regarding the extent to which subsidies reduce financial constraints.

Overall, even though financial constraints analysis usually relies on rather fragile relationships to identify and measure constraints, by adopting different strategies to assess the impact of financial constraints upon the innovation process, we are able to provide compelling evidence that constraints to R&D investment and innovation are binding. Nevertheless, we raise a number of questions regarding the efficiency and effectiveness of policy actions to reduce such constraints—despite they seem to increase innovation activity and, most notoriously, R&D investment. Although such relationship needs further testing, this paper opens ground for academic debate on the topic and points towards a reconsideration of corresponding future policy actions.

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Apendix 1. Construction of variables

From the data at our disposal we were able to create the following variables:

Balance sheets variables

Size (SIZE): Measured as log of the number of employees;

Size (S): Computed as log of inflation-adjusted assets;

Age (AGE): Computed as the difference between the current year and the year of establishment of the firm plus one, in logs;

Public capital (PUB_K): Percentage of capital owned by the public sector;

Foreign capital (FOR_K): Percentage of capital owned by non-nationals;

Investment (I): Measured as additions to plant, property and equipment- gross investment, scaled by total assets;

Output (Y): Measured as total sales and services, scaled by total assets. We use the sum of both sales and services as total output and distinguish firms only by their sector of activity legal classification. If distinction was to be made on an output basis, it would be impossible to discern most firms between manufacturing and services. As an example, some manufacturing firms also provide post-sales services;

Cash- flow (CF): Computed as net income before taxes plus depreciation, scaled by total assets;

Cash stock (CS): Measured as total cash holdings, scaled by total assets;

Investment Opportunities (ΔY): In most empirical studies, investment opportunities are measured using average Tobin's Q (the ratio between the total market value and asset value of a firm). However, we refrain from using this measure for two different reasons. The first is due to the fact that we are not able to calculate it since we do not have information on financial markets. Even if it was possible, we would obtain a biased sample with respect to financial constraints, not only because it is generally agreed that smaller and younger firms face severer constraints—only a few are publicly traded—, but also due to the fact that information on quoted firms is legally required and so, information asymmetry problems are diluted for such firms, potentially reducing financing problems. The second reason is more of a theoretical one. Firstly, marginal Q is unobservable, so researchers use average Q as a proxy—see Hayashi, 1981, for the derivation of average Q. Secondly, the introduction of Q directly into the estimation of investment models for the purpose of analysing financial constraints may cause the sensitivities to cash-flows to be overestimated, as they might contain information about investment opportunities that were not captured by Q—Alti, 2003, in a model where financial frictions are absent, shows that, even after Q correction, firms exhibit sensitivities to cash-flow.

Debt and equity issuances (ISS): Sum of debt and equity issuances, scaled by total assets. For the year 2001 equity issuances are reported as missing. The reason lies in legal changes that took place with the introduction of Euro (most firms adjusted their equity, not necessarily meaning issuing equity);

Non-cash net working capital (NWK): Difference between non-cash current assets and current liabilities, scaled by total assets;
Interest payments (*INT*): Interest payments of a firm, scaled by total assets. It can be argued to proxy for the credit rating of the firms;
Leverage (LEV): Measured as the ration of liabilities to the total value of a firm;
Financial investments (*FinI*): Financial investments of firms, scaled by assets. It can be seen as relatively liquid assets that allow firms to transfer resources across time;
Returns on financial investments (*R_FinI*): Returns on financial investments of firms, scaled by assets;
Intangible assets (INTANG): Computed as intangible assets, scaled by total assets. In the absence of a better alternative, this variable is intended to proxy the knowledge stock, through R&D stock and the patent stock of firms (we do not have detailed information neither on patents, nor on highly disaggregated firm accounts);
Labour productivity (LPROD): We compute a standard ratio of value-add to number of employees;
Exports (EXP): Firm exports, scaled by assets;
Market share (MKTS): This variable is constructed as a firm's sales over total sales of the corresponding firm's industry (at maximum level of industry classification disaggregation).

CIS wave variables

Decision to invest in R&D (RD): Binary variable for firms that engaged in innovation activities and those that did not;
R&D investment (I_RD): Total expenditure in R&D activities in logs. The logarithm is computed as (1+investment) because of zero expenditures;
R&D investment (RD_I): Volume of expenditure in R&D activities in logs;
Innovation (INNOV): Binary variable that indicates if a firm has innovated or not. It is measured in the broad sense and encompasses both product and process innovation;
Public Finance (SUB): Binary variable for firms that received public funding and those that did not. For the sake of this paper and simplicity we will refer it as "subsidies";
Share of subsidized firms-Industry (SUB%I): Computed as the ratio of number of subsidized firms in each industry (2-digit, CAE rev 2.1) to the total number of subsidized firms;
Share of subsidized firms-Region (SUB%R): Computed as *SUB%I* but for each region (NUT2). Both of these variables serve as instruments for subsidies. The rationale is that, in the absence of information on public policy budgets, the share of subsidies by industry and region will reflect policy targets that favour certain industries or regions (see Schneider and Veugelers, 2010);
Cooperation (*COOP*): Binary variable that indicates if a firms cooperated with other firms or institutions for the purpose of innovation activities;
Investment opportunities—innovation (Y_IN): Percentage of innovated products in total sales (Y);
R&D workers (RD_WORK): Percentage of employers in the firm that work on R&D;

Financial constraints (FC): Ordinal variable that measures the degree to which firms reported that the lack of external finance hampered innovation activity (self-evaluation). We do not include in this variable the "perception of excessive economic risks" and "high costs of innovation" information reported in CIS. The former can not objectively be seen as financial constraints, while the latter might carry a significant size effect ("high costs" should be normalized by a firm's assets but this is not possible since this the variable of interest is ordinal);

Financial constraints (FC^c): FC is collapsed into a binary variable of whether or not firms report financial constraints;

Other barriers to innovate, namely: *Employees qualification* (*B_TRAB*): Binary variable that indicates lack of qualified personnel as a barrier to innovate; *Technology information* (*B_TECH*): Binary variable that indicates lack of technological information as a barrier to innovate; *Market information* (*B_MARK*): Binary variable that indicates lack of market information or other market-related barriers as a barrier to innovate.

Potential innovators: For the estimation of Model A, we identify potential innovators, in order to distinguish firms that do not innovate (even though they are willing to so) from firms that have no intentions to innovate. *Potential innovators* are those firms that innovated (*INNOV=1*), or attempted to innovate (either with an abandoned or ongoing project), or reported some kind of obstacle to innovate (either *FC* or other barriers). Conversely, firms that did not innovate and did not attempt to do so and reported no obstacles to innovation are classified as *firms unwilling to innovate*. Finally, of the non-innovating firms (*INNOV=0*), potential innovators are classified as *hampered firms*.

All continuous variables of interest were winsorized at 1% level in order to avoid problems with outliers in the estimation procedures. Deflators used include the Industrial Production Price Index and Labour Cost Index, both drawn from INE, and the GDP deflator, drawn from the Portuguese Central Bank (BdP). Nevertheless, no deflators were used when a variable was constructed as a ratio of two nominal values (normalized). In such cases we assume that the price growth rates are homogeneous.

Apendix 2. Additional results

Table A1. Different specifications of Model A.

	Specifications			
VARIABLES	(1)	(2)	(3)	(4)
$CF_{i,t}$	0.101**	0.126***	0.100**	0.117***
	(0.050)	(0.043)	(0.050)	(0.043)
$\Delta y_{i,t}$	0.030***	0.024**	0.030***	0.024**
	(0.010)	(0.010)	(0.010)	(0.010)
$S_{i,t}$	0.033***	0.015*	0.038***	0.018**
	(0.009)	(0.008)	(0.009)	(0.009)
$I_{i,t}$	-0.128***	-0.138***	-0.132***	-0.143***
	(0.022)	(0.023)	(0.022)	(0.023)
$\Delta NWC_{i,t}$	-0.183***	-0.154***	-0.186***	-0.154***
	(0.021)	(0.018)	(0.022)	(0.018)
$\Delta STDEBT_{i,t}$	-0.058***		-0.060***	
	(0.016)		(0.016)	
$ISS_{i,t}$		0.035**		0.035**
		(0.014)		(0.014)
$\Delta INT_{i,t}$		-0.082		-0.090
		(0.279)		(0.280)
$FinI_{i,t}$			-0.108***	-0.097***
			(0.034)	(0.034)
Observations	3,320	3,320	3,320	3,320
Number of firms	1,458	1,458	1,458	1,458
Hansen p-value	0.142	0.697	0.162	0.650
R-squared	0.181	0.164	0.185	0.167

Notes: Regression of different specifications for the estimation of CCFS upon the full sample. Column (1) reports the results using Almeida et al. (2004) specification. In column (2) the variation of short-term debt ($\Delta STDEBT_{i,t}$) is replaced by the sum of net debt and equity issuances ($ISS_{i,t}$) and changes in interest paid ($\Delta INT_{i,t}$). Column (3) adds financial investments to the baseline specification of column (1), while column (4) reports the results from the specification used throughout the paper—equation (A1). See Section 4.1 for further explanation. Robust standard errors in parenthesis. ***, **, and * denote statistical significance at the .01, .05, and .10 levels, respectively. Further test statistics and confidence intervals available from the authors on request.

Table A2. Investment in R&D: CIS waves.

VARIABLES	Wave dummies (1)	By wave (2) CIS2	(3) CIS3	(4) CIS4
FC	-0.937***	-2.789**	-0.708***	-0.436
	(0.329)	(1.244)	(0.29)	(0.579)
SIZE	0.981***	1.634***	1.054***	1.072***
	(0.072)	(0.153)	(0.141)	(0.073)
AGE	0.326***	0.683**	0.15	0.312*
	(0.104)	(0.328)	(0.186)	(0.195)
EXP	-0.006	0.095	-0.146	0.197
	(0.132)	(0.431)	(0.246)	(0.188)
Y_IN	1.165***	1.409*	0.697***	2.713***
	(0.266)	(0.903)	(0.273)	(0.497)
ΔY	-0.709***	[a]	-2.499*	0.139
	(0.26)		(1.603)	(0.640)
RD_WORK	4.952***	26.712	2.335*	6.259***
	(1.388)	(22.231)	(1.524)	(1.250)
SUB	0.693***	[a]	0.281	1.52***
	(0.188)		(0.228)	(0.300)
COOP	0.336**	1.173**	0.294	1.424***
	(0.204)	(0.622)	(0.243)	(0.388)
WAVE2	1.128***			
	(0.463)			
WAVE3	0.988**			
	(0.453)			
γ	0.553*	4.957***	-0.205	2.505***
	(0.383)	(1.416)	(0.324)	(0.655)
Observations	1,270	176	307	767
Chi-squared	339.5	0.949 (R2)	0.980 (R2)	0.970 (R2)

Notes: Estimates for Model B. In these estimations we compute the mean of balance sheet variables for each corresponding CIS wave period Bootstrapped standard errors (999 replications) in parenthesis. ***, **, and * denote statistical significance at the .01, .05, and .10 levels, respectively. All regressions include industry dummies. The estimates of the selection variable RD, the dummy variable that represents firms' decision to invest, as well as further test statistics, are available from the authors on request. In all estimations we use the procedure 3.2) of Section 4.2 to take into account FC endogeneity. Statistically significant $\hat{\gamma}$ coefficients indicate the presence of selection.

[a] Dropped for collinearity reasons.

Table A3. Innovation: CIS waves.

	CIS2		CIS3		CIS4	
VARIABLES	Probit	Ordered Probit	Probit	Ordered Probit	Probit	Ordered Probit
	(1)	(2)	(3)	(4)	(5)	(6)
$FC^c \setminus \mathrm{FC}$	-2.858***	-1.205***	-1.217***	-0.722***	-0.898***	-0.566***
	(0.326)	(0.225)	(0.301)	(0.098)	(0.307)	(0.191)
RD_I	0.267***	0.272***	0.239***	0.172***	0.176***	0.208***
	(0.027)	(0.028)	(0.032)	(0.039)	(0.017)	(0.038)
SIZE	0.174**	0.229**	-0.140*	-0.058	0.024	0.047
	(0.075)	(0.105)	(0.078)	(0.093)	(0.035)	(0.050)
AGE	-0.011	-0.078	-0.098	0.046	0.050	0.105
	(0.114)	(0.146)	(0.105)	(0.132)	(0.068)	(0.081)
SUB	4.883***	7.064***	0.609**	0.505*	0.085	0.107
	(0.301)	(0.227)	(0.294)	(0.287)	(0.236)	(0.387)
COOP	-0.420	0.066	0.710	-0.411	0.797***	1.108***
	(0.257)	(0.344)	(0.451)	(0.272)	(0.228)	(0.357)
B_TRAB	0.160	0.109	-0.408*	-0.248*	0.185	-0.240
	(0.203)	(0.285)	(0.230)	(0.150)	(0.157)	(0.201)
B_TECH	0.271	0.591*	0.401**	0.030	-0.035	0.162
	(0.413)	(0.337)	(0.194)	(0.149)	(0.152)	(0.190)
B_MARK	-0.830**	-0.202	-0.161	-0.051	-0.270**	0.016
	(0.403)	(0.494)	(0.150)	(0.136)	(0.123)	(0.151)
ΔY	-6.242	-3.545	5.436	14.255*	0.880	2.528
	(4.685)	(5.696)	(4.853)	(7.667)	(2.317)	(2.394)
RD_WORK	-335.582	-336.592	1.281	0.459	0.527	0.794**
	(509.347)	(503.060)	(0.846)	(1.175)	(0.344)	(0.379)
MKTS	0.320	0.253	0.485*	-0.344	0.161	0.068
	(0.252)	(0.277)	(0.268)	(0.229)	(0.175)	(0.181)
ρ	0.545**	0.348*	0.545**	0.348*	0.545**	0.348*
	(0.261)	(0.209)	(0.261)	(0.209)	(0.261)	(0.209)
Observations	897	897	585	585	1,848	1,848
Chi-squared	2126	4870	3225	323.6	619.1	657.5

Notes: Estimates for equation (C2). In these estimations we compute the mean of balance sheet variables for each corresponding CIS wave period. Robust standard errors in parenthesis. ***, **, and * denote statistical significance at the .01, .05, and .10 levels, respectively. All regressions include industry dummies. Further test statistics are available from the authors on request.

Table A4. Innovation: Product vs Process.

	Product		Process	
VARIABLES	Probit	Ordered Probit	Probit	Ordered Probit
	(1)	(2)	(3)	(4)
$FC^c \setminus \mathrm{FC}$	-0.974***	-0.517***	-0.919***	-0.395**
	(0.163)	(0.141)	(0.203)	(0.178)
RD_I	0.103***	0.123***	0.135***	0.146***
	(0.007)	(0.020)	(0.009)	(0.016)
SIZE	-0.037	-0.064	0.037	0.121*
	(0.026)	(0.053)	(0.029)	(0.071)
AGE	-0.011	0.168**	-0.040	0.143*
	(0.043)	(0.074)	(0.049)	(0.080)
SUB	0.354***	0.100	0.107	-0.002
	(0.097)	(0.191)	(0.122)	(0.211)
COOP	0.345***	0.424***	0.481***	0.708***
	(0.089)	(0.146)	(0.102)	(0.182)
B_TRAB	-0.060	-0.201	0.070	0.255
	(0.102)	(0.197)	(0.112)	(0.232)
B_TECH	-0.040	-0.044	0.284**	0.298
	(0.102)	(0.209)	(0.115)	(0.240)
B_MARK	0.093	0.162	0.005	0.060
	(0.079)	(0.157)	(0.090)	(0.210)
ΔY	1.892*	0.312	-2.677**	-3.379*
	(1.092)	(1.117)	(1.109)	(1.875)
RD_WORK	-0.113	0.037	-0.308**	-0.183
	(0.115)	(0.280)	(0.126)	(0.335)
MKTS	-0.080	-0.352	-0.097	-0.114
	(0.122)	(0.217)	(0.119)	(0.236)
ρ	0.723***	0.897**	0.645***	0.522*
	(0.160)	(0.409)	(0.185)	(0.311)
Observations	3,206	3,206	3,206	3,206
Chi-squared	1227	360.2	1221	356.3

Notes: Estimates for equation (C2) using either product (columns 1-2) or process (columns 3-4) innovation as dependent variable. Robust standard errors in parenthesis. ***, **, and * denote statistical significance at the .01, .05, and .10 levels, respectively. All regressions include industry dummies. Further test statistics are available from the authors on request.

Table A5. Frequencies of FC and SUB: Lagged values

	FC_w	SUB_{w-1}		Total
		0	1	
Frequency	0	214	53	267
SUB %		80.15	19.85	100.00
FC %		48.09	39.26	46.03
Total%		36.90	9.14	46.03
Frequency	1	56	24	80
SUB %		70.00	30.00	100.00
FC %		12.58	17.78	13.79
Total%		9.66	4.14	13.79
Frequency	2	73	31	104
SUB %		70.19	29.81	100.00
FC %		16.40	22.96	17.93
Total%		12.59	5.34	17.93
Frequency	3	102	27	129
SUB %		79.07	20.93	100.00
FC %		22.92	20.00	22.24
Total%		17.59	4.66	22.24
Frequency	YES	231	82	313
SUB %		73.80	26.20	100.00
FC %		51.91	60.74	53.97
Total%		39.83	14.14	53.97
Frequency	Total	455	135	580
SUB %		76.72	23.28	100.00
FC %		100.00	100.00	100.00
Total%		76.72	23.28	100.00

FC_{w-1}	SUB_w		Total
	0	1	
0	213	65	278
	76.62	23.38	100.00
	63.96	62.50	63.62
	48.74	14.87	63.62
1	35	9	44
	79.55	20.45	100.00
	10.51	8.65	10.07
	8.01	2.06	10.07
2	41	10	51
	80.39	19.61	100.00
	12.31	9.62	11.67
	9.38	2.29	11.67
3	44	20	64
	68.75	31.25	100.00
	13.21	19.23	14.65
	10.07	4.58	14.65
YES	120	39	159
	75.47	24.53	100.00
	36.04	37.50	36.38
	27.46	8.92	36.38
Total	333	104	437
	76.20	23.80	100.00
	100.00	100.00	100.00
	76.20	23.80	100.00

Notes: Frequencies of financial constraints (rows) and subsidies (columns). SUB % (FC %) are relative frequencies within rows (columns) of each cell. For the ordinal FC variable, higher values correspond to higher reported constraints (zero for absence of constraints). We compare current (w) values of FC and SUB with the corresponding CIS wave lagged values (w-1).

Table A6. Spearman's rank correlation matrix: Models A and B.

VARIABLES MODEL A	$\Delta CS_{i,t}$	$CF_{i,t}$	$\Delta y_{i,t}$	$S_{i,t}$	$I_{i,t}$	$\Delta NWC_{i,t}$	$ISS_{i,t}$	$\Delta INT_{i,t}$	$FinI_{i,t}$	FC	SUB	$INNOV$	RD
$\Delta CS_{i,t}$	1.0000												
$CF_{i,t}$	0.0620	1.0000											
$\Delta y_{i,t}$	0.1435*	0.1900*	1.0000										
$S_{i,t}$	0.0300	-0.0312	0.0473	1.0000									
$I_{i,t}$	-0.0001	0.1987*	0.2170*	0.0449	1.0000								
$\Delta NWC_{i,t}$	-0.2171*	0.0080	-0.0108	-0.0110	-0.3578*	1.0000							
$ISS_{i,t}$	0.1021*	-0.1067*	0.2313*	0.0027	0.2261*	-0.1203*	1.0000						
$\Delta INT_{i,t}$	-0.0035	-0.0689*	0.0791*	-0.0267	-0.0470	0.0101	0.2056*	1.0000					
$FinI_{i,t}$	0.0023	-0.0828*	-0.0481	0.4019*	-0.0157	-0.0125	-0.0155	-0.0377	1.0000				
FC	-0.0037	-0.0890*	0.0353	-0.0413	0.2043*	-0.0862*	0.0614	-0.0557	0.0151	1.0000			
SUB	-0.0074	0.0571	0.0540	0.1222*	0.1096*	-0.0256	0.0412	-0.0198	0.0457	0.0703*	1.0000		
INNOV	-0.0063	0.0811*	0.0812*	0.2069*	0.1321*	-0.0321	0.0417	-0.0129	0.0939*	0.0359	0.3024*	1.0000	
RD	-0.0025	0.1017*	0.0598	0.2558*	0.1230*	-0.0472	0.0344	-0.0441	0.1345*	0.0758*	0.2675*	0.6426*	1.0000

MODEL B	RD_I	FC	SIZE	AGE	*EXP*	Y_IN	ΔY	RD_WK	SUB	COOP
RD_I	1.0000									
FC	-0.0764	1.0000								
SIZE	0.4384*	-0.1282*	1.0000							
AGE	0.0260	0.0230	0.1493*	1.0000						
EXP	0.1465*	-0.0254	0.2506*	0.0872	1.0000					
Y_IN	0.1492*	0.0550	0.0716	0.0213	0.1774*	1.0000				
ΔY	-0.0240	-0.0590	0.0528	0.1248*	0.0580	-0.0512	1.0000			
RD_WORK	0.1377*	-0.0211	0.1360*	0.0840	0.2034*	0.1733*	0.0133	1.0000		
SUB	0.2116*	0.0399	0.1371*	0.0446	0.1082	0.1261*	-0.0049	0.1640*	1.0000	
COOP	0.1800*	0.0119	0.1906*	0.0204	0.0290	0.1191*	0.0054	0.1582*	0.2491*	1.0000

Notes: Rank correlation coefficients were calculated using Sidak's adjustment. * denotes statistical significance at the .01 level.

Table A7. Spearman's rank correlation matrix: Models C.and D

VARIABLES MODEL C	INNOV	FC	RD_I	SIZE	AGE	SUB	COOP	B_TRB	B_TEC	B_MK	ΔY	RD_WK	MKTS
INNOV	1.0000												
FC	0.0739	1.0000											
RD_I	0.7713*	0.0711	1.0000										
SIZE	0.1717*	-0.0446	0.2451*	1.0000									
AGE	0.0174	0.0363	0.0225	0.1343*	1.0000								
SUB	0.3551*	0.0723	0.4299*	0.1542*	0.0374	1.0000							
COOP	0.4233*	0.0606	0.4561*	0.1881*	0.0171	0.3746*	1.0000						
B_TRAB	0.1117*	0.5557*	0.0874*	-0.0488	0.0261	0.0677	0.0850*	1.0000					
B_TECH	0.1272*	0.5489*	0.0965*	-0.0364	0.0215	0.0654	0.0776*	0.8064*	1.0000				
B_MARK	0.0572	0.4963*	0.0125	-0.0502	0.0130	0.0280	0.0376	0.6756*	0.6842*	1.0000			
ΔY	0.1994*	0.0131	0.2397*	0.1612*	0.0735	0.2105*	0.2216*	0.0168	0.0410	0.0056	1.0000		
RD_WORK	-0.1054*	-0.0352	-0.0789*	-0.0298	0.0945*	-0.0416	-0.0455	-0.0602	-0.0549	-0.0184	-0.0338	1.0000	
MKTS	0.0449	-0.0214	0.0490	-0.0694	0.0503	0.0474	0.0363	-0.0177	-0.0293	-0.0467	0.0735	-0.0031	1.00

MODEL D	FC	SUB	SIZE	AGE	PUB_K	FOR_K	ΔY	CS	CF	LEV	ISS	ΔNWC	R_FinI	EXP	MKTS
FC	1.0000														
SUB	0.0729	1.0000													
SIZE	-0.0403	0.1534*	1.0000												
AGE	0.0363	0.0386	0.1325*	1.0000											
PUB_K	-0.0285	0.0760	0.1719*	-0.1143*	1.0000										
FOR_K	-0.0898*	0.0104	0.1839*	0.0177	0.0195	1.0000									
ΔY	-0.0336	-0.0412	-0.0290	0.0965*	-0.0032	-0.0316	1.0000								
CS	-0.0622	-0.0545	-0.1410*	-0.0053	-0.0881*	0.0221	0.0069	1.0000							
CF	-0.0785*	0.0931*	0.0073	-0.0673	-0.0756	0.0721	-0.0532	0.2049*	1.0000						
LEV	0.0947*	-0.0969*	-0.0907*	-0.2132*	-0.0273	-0.0770	-0.0505	-0.1682*	-0.4140*	1.0000					
ISS	-0.0924*	-0.0479	0.0232	0.0497	0.0155	0.0556	0.2448*	-0.0334	-0.0156	0.0148	1.0000				
ΔNWC	0.1025*	0.0747	0.0337	0.0265	-0.0099	-0.0063	0.0710	-0.0636	0.0336	0.0212	0.1684*	1.0000			
R_FIN	-0.0532	0.0445	0.2101*	0.2374*	0.0662	-0.0183	0.0118	-0.0632	-0.0373	-0.1040*	0.0419	0.0186	1.0000		
EXP	-0.0140	0.1131*	0.2612*	0.0709	-0.0807*	0.2051*	0.0368	-0.0241	0.0855*	-0.1392*	0.0307	0.0366	-0.0349	1.0000	
MKTS	-0.0227	0.0477	-0.0733	0.0480	0.0199	0.0633	-0.0034	0.0286	0.0940*	-0.1318*	-0.0181	-0.0131	-0.0288	0.1384*	1.0000

Notes: Rank correlation coefficients were calculated using Sidak's adjustment. * denotes statistical significance at the 0.01 level.

TABLES

Table 1. Summary statistics: Model A.

VARIABLES	Overall	INNOV=1	INNOV=0	RD=1	RD=0	SUB=1	SUB=0
ΔCS	0.003	0.001	0.004	0.002	0.004	0.002	0.003
	(0.060)	(0.057)	(0.064)	(0.054)	(0.065)	(0.048)	(0.061)
CF	0.091	0.097	0.085	0.098	0.084	0.100	0.090
	(0.091)	(0.091)	(0.091)	(0.088)	(0.094)	(0.085)	(0.092)
ΔY	0.033	0.051	0.014	0.048	0.018	0.064	0.030
	(0.270)	(0.260)	(0.278)	(0.254)	(0.284)	(0.189)	(0.277)
S	16.080	16.409	15.740	16.499	15.670	16.670	16.021
	(1.644)	(1.646)	(1.570)	(1.605)	(1.577)	(1.569)	(1.639)
I	0.063	0.064	0.063	0.065	0.061	0.078	0.062
	(0.087)	(0.086)	(0.088)	(0.091)	(0.082)	(0.091)	(0.086)
ΔNWC	-0.048	-0.045	-0.050	-0.048	-0.047	-0.053	-0.047
	(0.157)	(0.146)	(0.167)	(0.145)	(0.168)	(0.131)	(0.159)
ISS	0.022	0.026	0.018	0.027	0.018	0.041	0.021
	(0.161)	(0.154)	(0.167)	(0.144)	(0.175)	(0.128)	(0.163)
ΔINT	-0.001	-0.001	-0.002	-0.001	-0.001	-0.001	-0.001
	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.006)	(0.008)
$FinI$	0.046	0.052	0.041	0.055	0.038	0.050	0.046
	(0.100)	(0.104)	(0.095)	(0.109)	(0.089)	(0.097)	(0.100)
Observations	3,941	2,003	1,938	1,947	1,994	356	3,585
	100%	51%	49%	49%	51%	9%	91%
Number of firms	1,355	697	658	645	711	116	1,239

Notes: Mean values and standard deviations, given in parenthesis, of the main variables used to estimate equation (A1). Both total sample and subsamples' statistics are reported.

Table 2. Summary statistics: Models B, C and D.

Model B	Total	RD=0	RD=1	Model C	Total	INNOV=0	INNOV=1	Model D	Total	SUB=0	SUB=1
	(1)	(2)	(3)		(4)	(5)	(6)		(7)	(8)	(9)
RD_I			12.139	INNOV	0.487			FC	0.903	0.872	1.122
			(2.012)		(0.500)				(1.175)	(1.166)	(1.214)
FC	1.055	1.046	1.064	FC	0.907	0.828	0.991	SUB	0.125		
	(1.195)	(1.185)	(1.206)		(1.175)	(1.153)	(1.191)		(0.331)		
SIZE	4.866	4.640	5.098	RD_I	5.127	0.417	10.091	SIZE	4.845	4.770	5.363
	(1.188)	(1.139)	(1.193)		(6.119)	(2.134)	(4.907)		(1.180)	(1.149)	(1.260)
AGE	3.083	3.061	3.105	SIZE	4.823	4.616	5.041	AGE	3.074	3.065	3.136
	(0.691)	(0.667)	(0.714)		(1.195)	(1.123)	(1.229)		(0.702)	(0.697)	(0.735)
EXP	0.279	0.242	0.317	AGE	3.072	3.057	3.089	PUB_K	4.580	4.064	8.184
	(0.502)	(0.496)	(0.506)		(0.702)	(0.695)	(0.710)		(19.683)	(18.566)	(25.933)
Y_IN	0.113	0.030	0.199	SUB	0.125	0.011	0.246	FOR_K	12.501	12.583	11.928
	(0.256)	(0.135)	(0.317)		(0.331)	(0.103)	(0.431)		(31.176)	(31.470)	(29.072)
ΔY	-0.032	-0.013	-0.052	COOP	0.164	0.011	0.325	ΔY	-0.026	-0.023	-0.049
	(0.289)	(0.307)	(0.268)		(0.370)	(0.106)	(0.469)		(0.259)	(0.263)	(0.227)
RD_WORK	0.006	0.002	0.010	B_TRAB	0.471	0.417	0.528	CS	0.069	0.070	0.055
	(0.032)	(0.015)	(0.043)		(0.499)	(0.493)	(0.499)		(0.101)	(0.103)	(0.083)
SUB	0.149	0.020	0.282	B_TECH	0.426	0.364	0.490	CF	0.091	0.088	0.110
	(0.356)	(0.141)	(0.450)		(0.495)	(0.481)	(0.500)		(0.096)	(0.096)	(0.092)
COOP	0.195	0.038	0.356	B_MARK	0.536	0.508	0.565	LEV	0.663	0.670	0.611
	(0.396)	(0.192)	(0.479)		(0.499)	(0.500)	(0.496)		(0.258)	(0.263)	(0.210)
				RD_WORK	0.005	0.002	0.008	ISS	-0.031	-0.029	-0.049
					(0.030)	(0.018)	(0.039)		(0.157)	(0.158)	(0.151)
				ΔY	-0.026	-0.003	-0.050	ΔNWC	0.001	0.001	0.002
					(0.259)	(0.258)	(0.258)		(0.006)	(0.007)	(0.006)
				MKTS	0.227	0.221	0.234	R_FinI	0.001	0.001	0.001
					(0.270)	(0.268)	(0.273)		(0.003)	(0.003)	(0.002)
								EXP	0.290	0.279	0.369
									(0.521)	(0.520)	(0.518)
								MKTS	0.227	0.225	0.245
									(0.270)	(0.269)	(0.275)
Observations	2,610	1,325	1,285	Observations	3,247	1,666	1,581	Observations	3,208	2,806	402

Notes: Mean values and standard deviations, given in parenthesis, of the main variables used to estimate models B, C and D.

Table 3. Cash-Cash Flow Sensitivity estimation: Innovators and potential innovators

VARIABLES	(1) Overall	(2) Innovators	(3) Non-Innovators	(4) Potential	(5) Hampered	(6) Unwilling
Potential innovators	Both	Yes	Both	Yes	Yes	No
Innovators	Both	Yes	No	Both	No	No
$CF_{i,t}$	0.117***	0.100*	0.112*	0.103**	0.215*	0.123*
	(0.043)	(0.055)	(0.064)	(0.052)	(0.117)	(0.068)
	[0.046 - 0.189]	[0.009 - 0.190]	[0.007 - 0.218]	[0.017 - 0.189]	[0.023 - 0.407]	[0.012 - 0.235]
$\Delta y_{i.t}$	0.024**	0.019	0.023*	0.018	0.010	0.026*
	(0.010)	(0.012)	(0.013)	(0.011)	(0.012)	(0.014)
	[0.008 - 0.040]	[-0.001 - 0.040]	[0.002 - 0.044]	[-0.000 - 0.036]	[-0.009 - 0.029]	[0.003 - 0.049]
$S_{i.t}$	0.018**	0.021**	0.015	0.019**	-0.004	0.023
	(0.009)	(0.010)	(0.016)	(0.009)	(0.020)	(0.018)
	[0.004 - 0.032]	[0.005 - 0.037]	[-0.012 - 0.042]	[0.004 - 0.033]	[-0.038 - 0.030]	[-0.006 - 0.053]
$I_{i.t}$	-0.143***	-0.152***	-0.131***	-0.162***	-0.188***	-0.112***
	(0.023)	(0.031)	(0.032)	(0.029)	(0.060)	(0.034)
	[-0.180 - -0.105]	[-0.203 - -0.101]	[-0.183 - -0.079]	[-0.209 - -0.115]	[-0.286 - -0.090]	[-0.167 - -0.057]
$\Delta NWC_{i.t}$	-0.154***	-0.123***	-0.178***	-0.124***	-0.073	-0.192***
	(0.018)	(0.020)	(0.026)	(0.019)	(0.045)	(0.027)
	[-0.184 - -0.125]	[-0.157 - -0.090]	[-0.220 - -0.136]	[-0.156 - -0.092]	[-0.147 - 0.000]	[-0.236 - -0.148]
$ISS_{i.t}$	0.035**	0.069***	0.010	0.065***	0.039	0.004
	(0.014)	(0.019)	(0.019)	(0.018)	(0.047)	(0.020)
	[0.011 - 0.058]	[0.038 - 0.100]	[-0.021 - 0.041]	[0.035 - 0.095]	[-0.039 - 0.117]	[-0.028 - 0.036]
$\Delta INT_{i.t}$	-0.090	-0.116	-0.186	-0.072	-0.172	-0.297
	(0.280)	(0.360)	(0.375)	(0.340)	(0.559)	(0.387)
	[-0.551 - 0.370]	[-0.709 - 0.477]	[-0.802 - 0.430]	[-0.631 - 0.487]	[-1.091 - 0.748]	[-0.934 - 0.339]
$FinI_{i.t}$	-0.097***	-0.120***	-0.074	-0.111***	0.527**	-0.092
	(0.034)	(0.032)	(0.090)	(0.032)	(0.266)	(0.093)
	[-0.152 - -0.041]	[-0.173 - -0.067]	[-0.223 - 0.074]	[-0.164 - -0.058]	[0.090 - 0.964]	[-0.245 - 0.060]
Observations	3,320	1,546	1,774	1,674	128	1646
Number of firms	1,458	677	781	727	50	731
Hansen p-value	0.650	0.510	0.194	0.538	0.304	0.218
R-squared	0.167	0.163	0.182	0.156	0.200	0.190

Notes: All regressions use the specification of equation (A1). In column (1) we report the results for the full sample, while columns (2) and (3) report the estimates for firms that innovated and that did not, respectively. Of the non-innovating firms, columns (5) and (6) report the results for potential innovators (hampered) and for those firms that were unwilling to innovate, respectively. Column (4) reports the results for all potential innovators (either effective innovators or not). Robust standard errors in parenthesis and 90% confidence intervals in brackets. ***, **, and * denote statistical significance at the .01, .05, and .10 levels, respectively. Further test statistics and confidence intervals available from the authors on request.

Table 4. Cash-Cash Flow Sensitivity estimation: R&D and Subsidies.

VARIABLES	RD=1	RD=0	SUB=1	SUB=0	I_RD
	(1)	(2)	(3)	(4)	(5)
$CF_{i\,t}$	0.051	0.204***	0.072	0.123***	0.135***
	(0.056)	(0.068)	(0.141)	(0.045)	(0.045)
	[-0.041 - 0.143]	[0.092 - 0.316]	[-0.160 - 0.304]	[0.049 - 0.196]	
$I\_RD_{i.t}$					0.000
					(0.001)
$CF_{i.t} * I\_RD_{i.t}$					-0.010*
					(0.006)
$\Delta y_{i.t}$	0.020*	0.030**	0.007	0.024**	0.024**
	(0.012)	(0.014)	(0.025)	(0.010)	(0.010)
	[0.001 - 0.039]	[0.006 - 0.053]	[-0.035 - 0.048]	[0.008 - 0.041]	
$S_{i.t}$	0.031***	0.012	0.041	0.017**	0.016*
	(0.012)	(0.018)	(0.031)	(0.009)	(0.009)
	[0.011 - 0.050]	[-0.019 - 0.042]	[-0.010 - 0.092]	[0.003 - 0.032]	
$I_{i.t}$	-0.131***	-0.114***	-0.081	-0.146***	-0.149***
	(0.028)	(0.039)	(0.056)	(0.025)	(0.023)
	[-0.178 - -0.085]	[-0.178 - -0.049]	[-0.174 - 0.011]	[-0.186 - -0.106]	
$\Delta NWC_{i.t}$	-0.110***	-0.194***	-0.089**	-0.158***	-0.154***
	(0.020)	(0.027)	(0.038)	(0.019)	(0.018)
	[-0.143 - -0.077]	[-0.239 - -0.150]	[-0.151 - -0.026]	[-0.189 - -0.127]	
$ISS_{i.t}$	0.048***	0.019	0.014	0.033**	0.038***
	(0.019)	(0.021)	(0.043)	(0.015)	(0.014)
	[0.018 - 0.079]	[-0.015 - 0.053]	[-0.056 - 0.084]	[0.008 - 0.058]	
$\Delta INT_{i.t}$	-0.343	-0.004	0.390	-0.079	-0.059
	(0.354)	(0.404)	(0.851)	(0.288)	(0.284)
	[-0.926 - 0.240]	[-0.670 - 0.661]	[-1.009 - 1.790]	[-0.553 - 0.395]	
$FinI_{i.t}$	-0.136***	-0.019	-0.268**	-0.073**	-0.098***
	(0.035)	(0.126)	(0.131)	(0.033)	(0.034)
	[-0.194 - -0.078]	[-0.227 - 0.189]	[-0.483 - -0.052]	[-0.128 - -0.017]	
Observations	1,500	1,718	255	3,065	3,065
Number of firms	649	815	116	1,342	1,342
Hansen p-value	0.319	0.830	0.637	0.763	0.763
R-squared	0.142	0.214	0.156	0.171	0.171

Notes: Regression of equation (A1) in columns (1-4) and of equation (A2) in column (5). Robust standard errors in parenthesis and 90% confidence intervals in brackets. ***, **, and * denote statistical significance at the .01, .05, and .10 levels, respectively. Further test statistics and confidence intervals available from the authors on request.

Table 5. Investment in R&D.

Estimation procedure	OLS	Two parts "hurdle" Decision	Volume	Two parts with endogeneity Decision	Volume	Selection Heckman	Full Model B last step 3.1)	last step 3.2)
Selection	NO	NO	NO	NO	NO	YES	YES	YES
Endogeneity	NO	NO	NO	YES	YES	NO	YES	YES
Dependent Var.	(1) I_RD	(2) RD	(3) RD_I	(4) RD	(5) RD_I	(6) RD_I	(7) RD_I	(8) RD_I
FC	0.073	0.046	0.395***	-0.505***	-0.561***	-0.150	-0.637***	-0.707***
	(0.303)	(0.086)	(0.152)	(0.055)	(0.142)	(0.115)	(0.238)	(0.271)
SIZE	0.758***	0.101***	1.527***	0.040	0.684***	0.995***	0.871***	0.976***
	(0.109)	(0.031)	(0.055)	(0.029)	(0.065)	(0.049)	(0.059)	(0.069)
AGE	-0.229	-0.045	1.022***	-0.007	-0.217**	0.191**	0.134*	0.273***
	(0.162)	(0.053)	(0.091)	(0.048)	(0.091)	(0.081)	(0.086)	(0.098)
EXP	0.014	-0.008	0.029	-0.045	0.016	0.007	0.021	0.028
	(0.273)	(0.074)	(0.166)	(0.065)	(0.146)	(0.129)	(0.116)	(0.124)
Y_IN	4.618***	1.321***	1.180***	1.076***	0.938***	1.501***	1.243***	1.735***
	(0.612)	(0.236)	(0.313)	(0.195)	(0.244)	(0.233)	(0.315)	(0.348)
ΔY	-1.100***	-0.255**	-1.658***	-0.215**	-0.504*	-0.829***	-0.701***	-0.923***
	(0.406)	(0.113)	(0.436)	(0.098)	(0.273)	(0.213)	(0.215)	(0.251)
RD_WORK	6.834***	2.972	8.122***	2.681	5.018***	5.198***	5.221***	5.579***
	(2.566)	(2.020)	(1.331)	(1.749)	(1.108)	(1.448)	(0.936)	(1.176)
SUB	3.577***	1.051***	0.301*	0.863***	0.593***	1.059***	0.876***	1.203***
	(0.347)	(0.145)	(0.176)	(0.128)	(0.151)	(0.171)	(0.209)	(0.228)
COOP	4.018***	1.120***	0.157	0.872***	0.091	0.874***	0.456**	0.886***
	(0.332)	(0.109)	(0.169)	(0.105)	(0.130)	(0.177)	(0.221)	(0.25)
Endogeneity &				0.935***($\hat{\rho}$)	13.439	1.597***($\hat{\gamma}$)	0.827**($\hat{\gamma}$)	1.685***($\hat{\gamma}$)
Selection tests				(0.151)	0.0002	(0.249)	(0.409)	(0.457)
Observations	2,608	2,608	1,285	2,567	1,270	2,608	1,270	1,270
Chi-squared	0.663 (R2)	339.5	0.966 (R2)	755.2	0.191 (R2)	18987	0.972 (R2)	0.973 (R2)

Notes: Estimates for Model B. Robust standard errors in parenthesis—bootstrapped (999 replications) for columns (7-8). ***, **, and * denote statistical significance at the .01, .05, and .10 levels, respectively. All regressions include industry dummies. The estimates of the selection variable RD, the dummy variable that represents firms' decision to invest, as well as further test statistics, are available from the authors on request. In this table we omit the controls LPROD, LEV, MKTS and other barriers to innovation (see section 4.2) in columns (1-2) and (4) for simplicity of presentation. In columns (1-3) and (6) the binary FC^c variable is used instead of ordinal FC. Estimation in columns (4-5) and (8) use the procedure 3.2) of Section 4.2 to take into account FC endogeneity, while in column (7) we use procedure 3.1). Statistically significant $\hat{\rho}$ (column 4) and $\hat{\gamma}$ (columns 6-8) coefficients indicate the presence of endogeneity and selection, respectively, while in column (5) we report a Chi-squared and corresponding p-value of the endogeneity test.

Table 6. Innovation.

VARIABLES	Exogenous FC	Endogenous FC	
	Probit	Probit	Ordered Probit
	(1)	(2)	(3)
FC^c \ FC	-0.066	-0.815***	-0.463***
	(0.092)	(0.303)	(0.125)
RD_I	0.209***	0.193***	0.239***
	(0.008)	(0.015)	(0.017)
SIZE	0.010	0.006	0.092*
	(0.034)	(0.032)	(0.051)
AGE	-0.094*	-0.032	0.037
	(0.052)	(0.059)	(0.073)
SUB	0.237	0.276	0.475
	(0.230)	(0.215)	(0.350)
COOP	0.836***	0.741***	0.547*
	(0.201)	(0.193)	(0.293)
B_TRAB	0.099	0.090	-0.245
	(0.142)	(0.134)	(0.183)
B_TECH	0.152	0.127	0.283
	(0.138)	(0.127)	(0.179)
B_MARK	-0.102	-0.080	0.467***
	(0.107)	(0.097)	(0.135)
ΔY	-0.982	-1.111	1.714
	(1.485)	(1.338)	(1.752)
RD_WORK	-0.166	-0.172	-0.164
	(0.147)	(0.142)	(0.212)
MKTS	-0.021	-0.039	-0.055
	(0.136)	(0.135)	(0.142)
ρ		0.545**	0.348*
		(0.261)	(0.209)
Observations	3,247	3,206	3,206
Chi-squared	852.2	1096	818.5

Notes: Estimates for equation (C2). Robust standard errors in parenthesis. ***, **, and * denote statistical significance at the .01, .05, and .10 levels, respectively. All regressions include industry dummies. Further test statistics are available from the authors on request.

Table 7. Financial constraints: The impact of subsidies.

			SUB treated as endogenous			
Dependent Var.	FC		FC^c	FC	FC^c	FC
CIS wave lag	(1) NO	(2) YES	(3) NO	(4) NO	(5) YES	(6) YES
SUB	0.174**	0.139	0.476***	0.769***	-0.628	-0.064
	(0.074)	(0.135)	(0.175)	(0.297)	(0.571)	(0.860)
SIZE	-0.050**	-0.022	-0.062**	-0.108***	0.037	-0.061
	(0.023)	(0.058)	(0.024)	(0.028)	(0.083)	(0.101)
AGE	0.051	-0.024	0.048	0.057	-0.037	-0.110
	(0.039)	(0.096)	(0.039)	(0.042)	(0.094)	(0.116)
PUB_K	-0.002	-0.003	-0.002	-0.002	-0.003	-0.003
	(0.001)	(0.003)	(0.001)	(0.001)	(0.003)	(0.003)
FOR_K	-0.003***	0.000	-0.003***	-0.004***	-0.000	-0.002
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
ΔY	-0.121	-0.121	-0.115	-0.115	-0.106	-0.260
	(0.102)	(0.225)	(0.102)	(0.116)	(0.224)	(0.274)
CS	-1.018***	-2.002***	-1.005***	-0.930***	-1.990***	-1.644**
	(0.283)	(0.689)	(0.283)	(0.300)	(0.664)	(0.737)
CF	-0.662**	-0.765	-0.639**	-1.059***	-0.720	-0.908
	(0.318)	(0.726)	(0.317)	(0.345)	(0.734)	(0.836)
LEV	0.226**	0.185	0.226**	0.493***	0.227	0.607*
	(0.108)	(0.259)	(0.107)	(0.123)	(0.254)	(0.311)
ISS	-0.375**	-0.130	-0.356**	-0.296	-0.101	0.101
	(0.170)	(0.356)	(0.169)	(0.200)	(0.350)	(0.445)
ΔINT	12.341***	13.252	12.542***	10.454**	15.049*	15.722
	(3.727)	(8.843)	(3.717)	(4.586)	(8.628)	(12.121)
R_FinI	-11.000	5.257	-10.751	-16.506	6.545	-1.368
	(12.050)	(22.711)	(11.981)	(11.969)	(21.959)	(22.696)
EXP	-0.049	-0.308***	-0.056	-0.065	-0.330***	-0.367***
	(0.060)	(0.105)	(0.060)	(0.065)	(0.106)	(0.131)
MKTS	-0.165	-0.033	-0.179*	-0.159	0.025	0.286
	(0.101)	(0.179)	(0.101)	(0.114)	(0.184)	(0.242)
ϱ			-0.227*	-0.203*	0.390	0.052
			(0.119)	(0.109)	(0.404)	(0.324)
Observations	3,208	556	3,180	3,180	549	549
Log-likelihood	-1701	-377.3	-2105	-1222	-509.9	-320.6

Notes: Columns (1-2) report estimates from an ordered probit regression, columns (3) and (5) those from an instrumental variables probit and columns (4) and (6) report the results for equation (D1). Robust standard errors in parenthesis. ***, **, and * denote statistical significance at the .01, .05, and .10 levels, respectively. All regressions include industry dummies.

Table 8. Frequencies of FC and SUB

	FC	SUB 0	SUB 1	Total
Frequency	0	1,781	201	1,982
SUB %		89.86	10.14	100
FC %		56.68	47.41	55.58
Total%		49.94	5.64	55.58
Frequency	1	393	53	446
SUB %		88.12	11.88	100.00
FC %		12.51	12.50	12.51
Total%		11.02	1.49	12.51
Frequency	2	462	89	551
SUB %		83.85	16.15	100.00
FC %		14.70	20.99	15.45
Total%		12.96	2.50	15.45
Frequency	3	506	81	587
SUB %		86.20	13.80	100.00
FC %		16.10	19.10	16.46
Total%		14.19	2.27	16.46
Frequency	YES	1,361	223	1,584
SUB %		85.92	14.08	100.00
FC %		43.32	52.59	16.46
Total%		38.17	6.25	16.46
Frequency	Total	3,142	424	3,566
SUB %		88.11	11.89	100.00
FC %		100.00	100.00	100.00
Total%		88.11	11.89	100.00

Notes: Frequencies of financial constraints (rows) and subsidies (columns). SUB % (FC %) are relative frequencies within rows (columns) of each cell. For the ordinal FC variable, higher values correspond to higher reported constraints (zero for absence of constraints).

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