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

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Abstract:

This paper investigates the extent to which R&D investment and innovation are financially constrained, as well as it identifies the main determinants of financial constraints. For that purpose, we resort to the estimation of a selection model, a bivariate model of innovation and constraints, an ordered response model and cash to cash-flow sensitivities upon an unique dataset that comprises information on firms' characteristics, balance sheet information and data on firms' innovation activity. Our findings suggest that firms that do not invest in R&D and those that do not receive public funding are financially constrained. Additionally, whereas both size and cash flow seem to be determinant in explaining financial constraints, firm age appears not to have an impact upon firms' perception of such constraints. Finally, controlling for endogeneity, financial constraints severely reduce the amounts invested in R&D and seriously hamper innovation.

Keywords: Innovation; R&D investment; Financial constraints; Firm-level studies; Portugal.

JEL Classification: O30; D92; G32; L00; L2.

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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 hinder firms' ability to work as main drivers of innovation and distort the selection process, then financial constraints must be a priority in microeconomic research.

Accordingly, the goal of this paper is to investigate the extent to which R&D investment and innovation are financially constrained. Additionally, we seek to identify the main determinants of financial constraints. In order to provide robust findings, we use different approaches and measures of constraints.

For this purpose, we construct an unique dataset from the combination of three different data sources that contain firms' characteristics, balance sheets and information on innovation activity, respectively. This dataset is particularly advantageous since it contains both specific information on innovation and a direct, self-assessed measure of financial constraints. We estimate an ordered probit model to evaluate the impact that firms' characteristics have on the probability that they report a certain level of financial constraints, while we also resort to the estimation of the cash-flow sensitivity of cash (CCFS) on the different subsamples of firms that either or not innovate, invest in R&D, receive public finance and report different degrees of financial constraints. Finally, to account for the impact of financial constraints upon R&D investment and innovation, we estimate a selection model and a bivariate probit model to control for the endogeneity of such constraints.

This paper is original in the sense that it 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. Moreover, 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 from three different waves of Community Innovation Surveys (CISs II, III and IV), which has barely been done and is a novelty with respect to Portugal. Finally, it explores a recent methodology to measure financial constraints (CCFS) that, although appearing intuitive, useful and appealing, to our knowledge has scarcely been used, particularly since this is the first application concerning innovation.

The paper is organized as follows. Section 2 will make a brief incursion on the empirical literature concerning financial constraints and innovation, with a particular focus on analysis based on CISs. In Section 3 we will discuss the dataset used. Section 4 describes the empirical methodology followed and some preliminary hypothesis, while Section 5 presents the main results. Finally Section 7 pulls the pieces together and concludes.

2. Financial constraints and innovation

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. If on one hand, we can broadly say that financial constraints exist whenever there is a wedge between the costs of obtaining internal and external funds—following Kaplan and Zingales's (1997) definition that virtually covers every firm—, on the other, we prefer to define financial constraints as the inability of a firm to raise the necessary amounts (usually due to external finance shortage) to finance their investment and growth.

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). While some authors may resort to the primordial Fazzari, Hubbard and Petersen (1988) measure of Investment-Cash Flow Sensitivities, by adapting it to R&D investment (e.g. Bond et al., 2003), others 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). Within the Evolutionary perspective, tests on the existence of financial constraints, that do not dissociate current financial performance from current investment opportunities, are rather scarce (Coad, 2010). 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), since only financially constrained firms will need to optimize their cash stocks over time in order to maximize their profits and hedge future socks by holding cash. Finally, other strategies include the construction of indexes of variables that are generally agreed to be good proxies of constraints or, if data is available, resort to the subjective firms' self-evaluation of constraints.

When it comes to R&D 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, 2002). 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.

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, 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 the empirical literature on innovation that resorted to the CISs. Additionally, they also include extremely useful information on firms' perception of financial constraints.

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, Blanchard et al., 2008). This endogeneity, for the specific case of financial constraints, results from unobservables that correlate both with financial constraints and innovation\R&D investment such as firm-specific R&D investment project uncertainty, duration and confidentiality (see Savignac, 2008). We should also note that firms that innovate might be expected to face lower constraints due to a better financial position stemming from possibly better economic performance. Again, for the case of financial constraints, Canepa and Stoneman (2008) find that not only financial constraints seem to be higher for smaller firms and in high-tech industries in the UK, but also that either the cost or availability of finance are major barriers to innovate. These results were also found by Mohnen et al. (2008) and Tiwari et al. (2008) for the Netherlands and Savignac, 2008 for French established firms.

However, 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 info, of which Mueller and Zimmermann (2006), Savignac (2008), Clausen (2008) and Gorodnichenko and Schnitzer (2010) are examples.[1]

[1] Clausen (2008) does not specifically analyses financial constraints, instead he uses a combination of these types of datasets to investigate the impact of different types of subsidies on R&D spending

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).

With respect to public financial support, while it has been shown to effectively reduce financial constraints (see Carreira and Silva, 2010 for a survey), it enhances innovation and stimulates R&D investment (e.g. Bloom et al., 2002; Aerts and Schmidt, 2008; Bérubé and Mohnen, 2009). However, this may depend on the type of subsidy, since subsidies to different stages of the innovation process may either stimulate or replace R&D spending (Clausen, 2010; Arundel et al., 2008).

Finally, 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 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), which 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.[2] 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. Still, we expect that access to the corresponding datasets for 2004 onwards, once available, will allow us to improve these results.

Finally, the inclusion of the partially qualitative, subjective and censored CIS databases, in our panel of balance sheets and firms' characteristics, raises a number of methodological issues that must be carefully dealt with (see 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

[2] 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, especially when we split the sample to estimate CCFS in a GMM style.

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. On the other hand, 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 because 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. As a result, we have the following empirical specification:

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

where $\Delta CS_{i,t}$ is the variation in cash stocks for firm i in period 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, $\Delta STDEBT_{i,t}$ is the variation of short-term debt 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 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 rates variations, we use variations of interest paid, which allows for firm variation and thus can also be seen as a form of credit rating. 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 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, if lagged values, and 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. Alternatively, we focus mainly on contemporaneous or once lagged variables to instrument the endogenous variables.[3]

In order to compare financial constraints across different types of firms, we split our sample into subsamples of firms that: (i) innovated and those that did not; (ii) decided to invest in R&D (*RD*=1) and those that did not (*RD*=0); (iii) received public financial support and those that did not. Finally, as a robustness check of our CCFS measure of financial constraints, we estimate these sensitivities for the subsamples of groups that either reported financial constraints (*FC*) to be "high" (3), "medium" (2), "low" (1) and "not relevant" (0).

We expect that firms that innovate will present lower CCFS than non-innovators because the latter, by being constrained, are not able to invest in R&D. However, we must be cautious in our analysis since there might be some cases in which firms do not innovate because they simply do not need or want to do so. In such cases we can no longer say that innovation is constrained by financial constraints if we observe differences in CCFS between the two groups. Additionally, if a firm wants to innovate, is not financially constrained and takes the efforts to do so but is not successful, then, even though not financially constrained, it will be part of the non-innovators group (a-priori constrained). Furthermore, there might be some cases within the innovators group, because innovation is measured in a rather broad sense, that did not have to do—or were unable to do so due to constraints—significant efforts and investments to innovate, but eventually managed innovate. For these reasons, we can not expect that the differences between innovators and non-innovators in terms of CCFS will be conclusive, since the non-innovators(innovators) group will include some firms that are, a-priori, not constrained (constrained). On the contrary, we expect distinct results when we compare firms that invested in R&D (effort to innovate) with those that did not. With respect to public funding, we naturally expect that firms that received financial support will not be constrained. In this case, even though there might also exist some firms in the non-"subsidised" group that are not financially constrained, the difference to the "subsidised" group is expected to be considerable. Finally we should note that the question on FC is

[3] 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

answered by all firms in all CIS waves, whether they innovated or not. Still, the question is asked specifically with respect to innovation barriers. As a result, the estimates on CCFS for firms that reported to be "non-constrained" may be upward biased since such firms may have no desires to innovate (do not face such barriers) but may still be financially constrained with respect to their operational and physical capital investment activities.

We may be able to argue that, for the sake of a robust and consistent analysis we should focus mainly on the efforts to innovate, namely R&D investment. It is not the knowledge production function (or innovation as a function of the innovation efforts and other explanatory variables) that is affected directly, but rather in an indirect way, through the efforts to innovate.

Finally, we should note that this methodology has some pitfalls. In fact, while some empirical studies found that CCFS can be highly significant even for unconstrained firms (e.g. Lin, 2007, Pál and Ferrando, 2010), Almeida et al. (2009) point out that since holding cash is not the only form of inter-temporal allocation of capital (in Almeida et al., 2004 they assumed that all fixed investment is illiquid), CCFS may actually be negative for constrained firms (Riddick and Whited, 2009) since firms may invest in liquid assets (other than cash).

4.2. Model B: Ordered probit of reported financial constraints outcomes

This dataset is particularly useful since it includes firms' self-evaluation of the degree to which they are financially constrained. The combination of such variable with firms' financial information is thus of great interest, since it allows us to check the validity of certain variables as good proxies for financial constraints.

The availability of self-assessed levels of constraints reported by firms allows us to derive the following empirical model:

$$FC^* = X\beta + \varepsilon, \qquad \varepsilon \sim N(0,1) \tag{B1}$$

$$FC = \begin{cases} 0\,, & if\ FC^* \leq \alpha_1 \\ 1\,, & if\ \alpha_1 < FC^* \leq \alpha_2 \\ 2\,, & if\ \alpha_2 < FC^* \leq \alpha_3 \\ 3\,, & if\ FC^* > \alpha_3 \end{cases} \tag{B2}$$

$$P(FC = j|X) = \begin{cases} \Phi(\alpha_1 - X\beta) & , \quad if\ \ j = 0 \\ \Phi(\alpha_2 - X\beta) - \Phi(\alpha_1 - X\beta) & , \quad if\ \ j = 1 \\ \Phi(\alpha_3 - X\beta) - \Phi(\alpha_2 - X\beta) & , \quad if\ \ j = 2 \\ 1 - \Phi(\alpha_3 - X\beta) & , \quad if\ \ j = 3 \end{cases} \tag{B3}$$

where α_j are unknown threshold points of a latent financial constraints function (FC*) that depends on covariates included in X. The choice of variables in X is somewhat constrained by the nature of our dataset. In particular, the inclusion of CISs variables greatly reduces the set of observations upon which the model is estimated. As a result, we estimate $P(FC = j|X)$ by including in the X vector of explanatory variables a combination of both firms' characteristics and financial variables: firm size (*SIZE*); firm age (AGE); industry dummies (CAE); cash stocks (CS); cash-flow (*CF*), debt and equity issuances (*ISS*); leverage (*LEV*); returns on financial investments (R_FIN); exports (*EXP*); changes in interest paid (ΔINT); and a dummy for firms that received subsidies (*SUB*). Finally, we compute the marginal effects $\partial P(FC = j|X)/\partial x_k$ to obtain the impact of x_k on the estimated probability that firms report constraints at the j level.

We expect that, a number of explanatory variables will have a significant impact upon reported levels of financial constraints (FC). These include variables that are generally agreed to work as good proxies for financial constraints (see Carreira and Silva, 2010). Namely, we expect to verify a negative relationship between *FC* and *SIZE, AGE, CS, CF*, R_FIN, ISS and SUB, while a positive relationship between *FC* and both *LEV* and ΔINT

4.3.Model C: Sample selection in R&D investment, with endogenous financial constraints

In addition to the possible endogeneity of FC for reasons presented in Section 2, our R&D investment variable has an excess of zeroes and is highly skewed.[4] 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-steps equations are correlated, which we confirm further on) and therefore a joint specification is needed. Consequently, this setup falls into the selection models category.[5]

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:

[4] While we have 71% of zeroes, the mean (904324) is much higher than the median (163549).
[5] We are currently exploring 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.

$$RD\_I = Z_1\beta_1 + \alpha FC + \varepsilon \quad \text{(C1)}$$

$$FC^* = X\beta_2 + u \quad \text{(C2)}$$

$$RD = 1(Z\beta_3 + v > 0) \quad , \qquad v \sim N(0,1) \quad \text{(C3)}$$

where (C3) 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. Additionally, self-assessed financial constraints (FC) is always observed (note that the latent variable FC^* is not), but is an endogenous variable in (C1), the covariates Z and RD are always observed. 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 (C3) upon the full sample and obtain the estimated inverse Mills ratios ($\hat{\lambda}_{i3}$); (b) using that information, we estimate

$$RD\_I_i = Z_{i1}\beta_1 + \alpha FC_i + \gamma\hat{\lambda}_{i3} + e_i \quad \text{(C4)}$$

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 (C2) (see Wooldridge, 2002 pp. 567-570). Note that at least one covariate in Z must be excluded (Z_i) in the estimating equation (C4) 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 appropriate ordered probit estimation and then use these as instrument for FC —see Cameron and Trivedi, 2005 pp. 193.

Once again, the dataset 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; 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 (C4) we exclude *MKTS, LPROD,* leverage and other barriers to innovate in order to guarantee identification.[6] 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 this latter case, 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.

Finally, since FC is not a continuous variable, usual tests of endogeneity are unfeasible. Accordingly we focus on the probability that a firm invests in R&D, estimate a bivariate probit model of the following form and perform a test of independent equations:

$$\begin{cases} FC^c = 1(X\beta_2 + u > 0) \\ RD = 1(Z\beta_3 + FC + v > 0) \end{cases}, \qquad \begin{pmatrix} u \\ v \end{pmatrix} \sim \Phi_2 \begin{bmatrix} 0 \\ 0 \end{bmatrix} \begin{bmatrix} 1 & \varrho \\ \varrho & 1 \end{bmatrix} \tag{C5}$$

If there are no omitted or unobservable variables that affect simultaneously the probabilities of a firm reporting financial constraints and investing in R&D ($\varrho = 0$), these equations can be estimated separately, meaning that FC can be treated as exogenous.

4.4. Model D: Impact of financial constraints directly upon innovation

In a last step, following Savignac (2008) we estimate the impact of financial constraints directly upon innovation. This is achieved by estimating a bivariate probit model of underlying latent variables (propensity to innovate and level of financial constraints) of the following form:

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

[6] 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.

where FC^c is the collapsed FC ordinal variable into a binary variable of whether a firm reports financial constraints or not. For logical consistency purposes we set ($\alpha_2 = 0$) and additionally normalize the variance of the errors:

$$\begin{cases} INNOV = X_1\beta_1 + \alpha_1 FC^c + \varepsilon_1 \\ FC^c = X_2\beta_2 + \varepsilon_2 \end{cases}, \qquad \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \end{pmatrix} \sim \Phi_2 \begin{bmatrix} 0 \\ 0 \end{bmatrix} \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \tag{D1}$$

where X_1 includes the investment in R&D (*RD_I*), firm size, age, other barriers to innovate, cooperation; percentage of R&D employees; investment opportunities *(ΔY)* and market share (*MKTS*). In the vector X_2 we include the usual determinants of FC, in accordance to Model B. Finally, we further extend the model to allow FC outcomes to be ordinal and estimate the corresponding bivariate ordered probit model (see Greene and Hensher, 2010 pp. 222 for details and Sajaia, 2008 for STATA implementation).[7] Finally, 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.

5. Empirical Results

5.1. Summary Statistics

[insert Table 1 about here]

Table 1 reports the summary statistics for model (A), by the different subsamples of firms. We should point that mean cash-flow (*CF*) is larger (and less volatile) for firms that innovate, invest in R&D, receive subsidies, as well as for those that report as not financially constrained. The same appears to be true with respect to size (*S*: total assets) and sales growth (ΔY).[8] Additionally, Table 2 reports the same statistics for the remaining models.

[insert Table 2 about here]

5.2 Results for Model A

The results on the financial constraints to innovation are rather unclear, as expected after the hypothesis raised in Section 4.1. If we compare firms that innovate with those that do not

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

[8] Note that for the case of sales growth, this pattern is not as clear when it comes to reported financial constraints, since severely constrained firms' sales growth is as large as non-constrained ones.

(Table 4), we do not find statistically significant differences in constraints (CCFS of 0.093 against 0.112, respectively)[9]. Evidence on different levels of constraints becomes much clear if instead of comparing innovators with non-innovators, we distinguish between firms that invested in R&D and those that did not. In fact, as we can see from Table 4 where there is a striking difference in CCFS (columns 4 and 5). 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 17 cents out of each euro of cash flow.

[insert Table 4 about here]

It may be possible to argue that public finance has a positive effect in reducing financial constraints (columns 6 and 7 of Table 4), since firms that do not have public financial support save, on average, 12 cents out of each euro of cash-flow, which is in clear contrast with the estimate for the group of firms that received funding (the coefficient is not statistically different from zero).

When we estimate CCFS by reported levels of financial constraints (Table 5) we find that even though all groups of firms reported positive and statistically significant cash-flows—recent empirical literature has argued that even non-constrained firms may report significant CCFS even though the estimates are always much lower than those of constrained firms—these are not totally unexpected results, since the significance of this estimates will also depend on how many financial explanatory variables we include, given that the estimating equation might approach an accounting identity (see Section 4.1). Additionally, even though we should expect CCFS not to be significant for firms that report as non constrained, we should notice that in the CIS survey, the question on FC is made with respect to factors hampering innovation. We may have selection issues since some firms may have reported no FC to innovate because they just did not wanted to innovate and so FC were not an hampering factor and yet, their operational and investment activities may be financially constrained (which is not asked). This means that in the (FC=0) group there might be firms that are financially constrained. Still, if instead we use a broader definition of FC that encompasses "high costs of innovation" (see appendix), the CCFS appears to perform much better.[10] Nevertheless, for those firms that reported constraints, the estimates are larger. While non-constrained firms saved, on average, 15 cents out of each euro of extra cash flow, firms

[9] Confidence intervals are available from authors on request

[10] Estimated CCFS for broadly defined FC are 0.111, 0.230*, 0.160* and 0.207*** for firms that report no, low, medium and high levels of constraints, respectively. Statistics not reported, but available from authors on request.

that reported as constrained saved, on average, between 17 and 20 cents. Note that the significance of the estimates increases as we move from non-constrained to higher levels of constraints.

Accordingly, CCFS appear to be able to provide useful insights on the level of financial constraints. However, 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 either R&D investment or innovation. Consequently, we resort to the reported levels of financial constraints to innovate as an explanatory variable for these activities in the following sections.

[insert Table 5 about here]

5.3. Results for Model B

Table 6 reports the marginal effects after the estimation of the determinants of financial constraints in the ordinal model for the different levels of FC. Firstly, cash-flow appears to have a significant impact in explaining constraints, since an extra euro of cash-flow increases, by 20%, the probability that a firm reports as not financially constrained, while it (increasingly) reduces the probability that a firm report higher levels of constraints. Secondly, in line with empirical literature (see Carreira and Silva, 2010), firm size, cash stocks, debt and equity issuances, and exports have a negative impact upon financial constraints. Expected results are also found with respect to the positive impact of leverage and interest payments and financial constraints. Conversely, firm age appears to have a negative impact upon reported constraints.[11]. Finally, the estimated probabilities for the outcomes of *FC* are very close to observed values.

[insert Table 6 about here]

5.4. Results of Model C

In Table 7 we report the estimation results of the selection model with the endogenous treatment of financial constraints. It can be compared with the Heckman-style estimation of the corresponding model, with an additional control for endogeneity. While in column (1) we report the estimates of a simple OLS, columns (2-5) report the estimates of a Hurdle

[11] Note that age and size may not be monotonically related to constraints (e.g. Silva and Carreira, 2010 for differences between manufacturing and services). We test the inclusion of squared age and size, but the coefficients are not significant.

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.[12]

While on one hand the results from columns (2-5) point that equations are not independent and therefore endogeneity must be taken into account (statistically significant $\hat{\rho}$ coefficients), 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.

With respect to other variables of interest, we should note the positive impact of size, labour productivity, R&D investment opportunities, percentage of R&D employees and subsidies. 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, even though it might signal that investment in physical capital is warranted.[13] Conversely, a reduction of sales might signal that the firm needs to change and be innovative. Finally, the negative sign of firm age 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.

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

[insert Table 7 about here]

5.4. Results of Model D

When it comes to innovation, Table 8 reports our estimates of the bivariate probit and bivariate ordered probit model, as well as those of a simple univariate probit model that does not account for the possibility of endogenous financial constraints. As expected, the rejection of the hypothesis of independent equations (Walt 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

[12] Since the derivation of the appropriate correction terms for the asymptotic variance is rather complex, we resort to paired bootstrap estimation.
[13] Note that while the correlation of sales growth is positive and negative with respect to physical capital investment and R&D investment.

specifications. Additionally, as naturally expected, the amounts spent in R&D positively affect innovation. With respect to other variables, while investment opportunities and market share have, respectively, a negative and positive impact upon the probability that a firm innovates, we do not find significant impacts (within the bivariate models) for the remaining variables of interest.

[insert Table 8 about here]

6. Conclusion

In this paper we explore the impact of financial constraints upon R&D investment and innovation. Additionally, we analyse the determinants of financial constraints and evaluate the soundness of commonly accepted proxies, as well as of the sensitivity of cash stocks to cash-flow, as measures of financial constraints.

Our main findings suggest that: (a) CCFS appear to be able to provide useful insights on the level of financial constraints while, apart from age, we were able to corroborate the validity of the commonly accepted proxies for financial constraints; (b) while the results opposing innovators and non-innovators are rather unclear, CCFS are larger for firms that do not invest in R&D and for those that do not receive subsidies; (c) financial constraints severely reduce the amounts invested in R&D; (d) once endogenity is taken into account, innovation is significantly hampered by financial constraints.

Overall, this paper contributes not only to a better understanding of the determinants of firms' financial constraints but it also adds to the literature on innovation barriers by measuring the degree to which innovators are financially constrained and the impact of these constraints in hindering R&D investment and innovation.

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Apendix: Construction of variables

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

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

Size (S): Computed as log 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;

Economic activity (CAE): Codified variable concerning the economic activity classification, fully disaggregated;

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

R&D investment (RD_I): Total 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;

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 would only be able to calculate it for a relatively small subsample of firms (only those that are publicly traded), thus losing significant information, in particular, observations of smaller and younger firms. Consequently, 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.

Investment opportunities—innovation (Y_IN): Percentage of innovated products in total sales (Y);

Exports (EXP): Firm exports, scaled by assets;

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 Euros (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;

Labour productivity (LPROD): We compute a standard ratio of value-add to number of employees;

Returns on financial investments (*R_FIN*): Returns on financial investments of firms, scaled by assets;

Dividends (DIV): Since, we do not have direct access to this variable, we have to calculate it based on other variables, of which, unfortunately one of them is relatively unreliable. As a consequence, we prefer to transform the information into a binary variable that indicates whether or not the firm paid dividends;

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).

Decision to invest in R&D (RD): Binary variable for firms that engaged in innovation activities and those that did not;

Innovation (INNOV): Binary variable for firms that innovated and those that did not;

Public Finance (SUB): Binary variable for firms that received public funding and those that did not;

Cooperation (*COOP*): Binary variable that indicates if a firms cooperated with other firms or institutions for the purpose of innovation activities;

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);

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.

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.

Table 1: Summary Statistics: Model A

VARIABLES	Overall	INNOV=1	INNOV=0	RD=1	RD=0	SUB=1	SUB=0	FC=0	FC=1	FC=2	FC=3
ΔCS	0.003	0.001	0.004	0.002	0.003	0.002	0.003	0.004	0.001	0.000	0.002
	(0.061)	(0.057)	(0.065)	(0.054)	(0.066)	(0.048)	(0.062)	(0.063)	(0.063)	(0.059)	(0.056)
CF	0.090	0.097	0.084	0.098	0.082	0.100	0.089	0.101	0.066	0.078	0.090
	(0.092)	(0.091)	(0.092)	(0.088)	(0.094)	(0.085)	(0.092)	(0.089)	(0.097)	(0.090)	(0.092)
ΔY	0.035	0.051	0.020	0.048	0.023	0.064	0.032	0.037	0.027	0.033	0.037
	(0.273)	(0.260)	(0.284)	(0.254)	(0.289)	(0.189)	(0.280)	(0.265)	(0.274)	(0.301)	(0.262)
S	16.048	16.409	15.710	16.499	15.644	16.674	15.988	16.243	15.570	15.864	16.061
	(1.645)	(1.646)	(1.570)	(1.603)	(1.575)	(1.568)	(1.640)	(1.675)	(1.474)	(1.705)	(1.521)
I	0.062	0.064	0.061	0.065	0.060	0.077	0.061	0.057	0.063	0.066	0.071
	(0.087)	(0.086)	(0.089)	(0.091)	(0.084)	(0.091)	(0.087)	(0.086)	(0.089)	(0.086)	(0.091)
ΔNWC	-0.046	-0.045	-0.047	-0.048	-0.044	-0.052	-0.046	-0.040	-0.055	-0.052	-0.052
	(0.159)	(0.146)	(0.171)	(0.144)	(0.172)	(0.131)	(0.162)	(0.155)	(0.171)	(0.162)	(0.160)
ISS	0.022	0.026	0.018	0.028	0.017	0.041	0.020	0.015	0.030	0.031	0.025
	(0.162)	(0.154)	(0.170)	(0.144)	(0.177)	(0.127)	(0.165)	(0.159)	(0.159)	(0.162)	(0.173)
ΔINT	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.002
	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.006)	(0.008)	(0.007)	(0.009)	(0.008)	(0.008)
Observations	4,145	2,003	2,142	1,955	2,190	357	3,788	2,042	549	801	753
	100%	48%	52%	47%	53%	9%	91%	49%	13%	19%	18%
Number of firms	1,458	697	761	649	815	116	1,342	705	199	303	266

Notes: Mean values and standard deviations, given in parenthesis, of the main variables used to estimate equation (A2). Both total sample and subsamples' statistics are reported.

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

VARIABLES	Model B	VARIABLES	Model C	VARIABLES	Model D
FC	0.904	RD_I	12.149	INNOV	0.961
	(1.174)		(2.000)		(0.193)
SIZE	297.120	FC^c	0.485	FC^c	0.470
	(807.273)		(0.500)		(0.499)
AGE	27.315	SIZE	373.936	RD_I	10.057
	(19.527)		(918.158)		(4.910)
CS	0.068	AGE	28.295	SIZE	383.157
	(0.101)		(20.498)		(1,049.444)
CF	0.091	EXP	0.308	AGE	27.983
	(0.096)		(0.507)		(20.342)
ISS	-0.031	LPROD	34,594.857	COOP	0.322
	(0.157)		(61,767.593)		(0.467)
ΔINT	0.001	Y_IN	0.190	B_TRAB	0.526
	(0.006)		(0.310)		(0.500)
LEV	0.663	ΔY	-0.050	B_TECH	0.487
	(0.258)		(0.267)		(0.500)
R_FIN	0.001	*B_TRAB*	0.550	B_MARK	0.561
	(0.003)		(0.498)		(0.496)
EXP	0.290	*B_TECH*	0.510	ΔY	-0.048
	(0.520)		(0.500)		(0.261)
		B_MARK	0.589	RD_WORK	0.008
			(0.492)		(0.038)
		RD_WORK	0.008	MKTS	0.232
			(0.039)		(0.272)
		SUB	0.250		
			(0.433)		
Observations	3,211	Observations	1,542	Observations	1,627

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

Table 4: Cash-Cash Flow Sensitivity estimation by subsamples

VARIABLES	Overall	Innovators	Non-Innovators	RD=1	RD=0	"Subsidised"	Non-"Subsidised"
$CF_{i,t}$	0.114***	0.093*	0.112*	0.072	0.174***	0.061	0.118***
	(0.038)	(0.048)	(0.058)	(0.050)	(0.062)	(0.120)	(0.039)
$\Delta y_{i,t}$	0.023***	0.014	0.024**	0.018*	0.028**	0.008	0.023***
	(0.008)	(0.011)	(0.011)	(0.010)	(0.012)	(0.024)	(0.008)
$S_{i,t}$	0.017**	0.016*	0.023*	0.026**	0.014	-0.019	0.018**
	(0.008)	(0.009)	(0.014)	(0.010)	(0.015)	(0.035)	(0.008)
$I_{i,t}$	-0.130***	-0.117***	-0.141***	-0.103***	-0.139***	-0.014	-0.139***
	(0.021)	(0.030)	(0.029)	(0.027)	(0.034)	(0.058)	(0.022)
$\Delta NWC_{i,t}$	-0.138***	-0.114***	-0.161***	-0.106***	-0.169***	-0.092**	-0.139***
	(0.015)	(0.018)	(0.022)	(0.019)	(0.023)	(0.043)	(0.016)
$ISS_{i,t}$	0.033***	0.050***	0.017	0.036**	0.030*	0.021	0.034***
	(0.012)	(0.016)	(0.017)	(0.017)	(0.018)	(0.046)	(0.013)
$\Delta INT_{i,t}$	-0.240	-0.072	-0.397	-0.156	-0.246	0.552	-0.255
	(0.210)	(0.263)	(0.298)	(0.274)	(0.310)	(0.762)	(0.215)
Observations	3,320	1,595	1,725	1,500	1,718	255	3,065
Number of firms	1,458	697	761	649	815	116	1,342
Hansen chi2 p-value	0.671	0.754	0.514	0.557	0.772	0.967	0.670
R-squared	0.144	0.117	0.171	0.107	0.194	0.074	0.149

Notes: Regression of equation (A2). 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 5: Cash-Cash Flow Sensitivity estimation by levels of reported financial constraints

VARIABLES	FC=0	FC=1	FC=2	FC=3
$CF_{i,t}$	0.147*	0.178*	0.195**	0.174**
	(0.077)	(0.095)	(0.099)	(0.072)
$\Delta y_{i,t}$	0.032***	0.031**	-0.020	0.043**
	(0.012)	(0.014)	(0.013)	(0.018)
$S_{i,t}$	0.018	0.039	0.015	0.051
	(0.013)	(0.054)	(0.021)	(0.033)
$I_{i,t}$	-0.156***	-0.177***	-0.190***	-0.046
	(0.034)	(0.060)	(0.042)	(0.038)
$\Delta NWC_{i,t}$	-0.130***	-0.213***	-0.128***	-0.148***
	(0.023)	(0.047)	(0.030)	(0.039)
$ISS_{i,t}$	0.017	0.023	0.076***	0.019
	(0.018)	(0.040)	(0.027)	(0.026)
$\Delta INT_{i,t}$	-0.250	0.157	-0.406	0.191
	(0.387)	(0.572)	(0.428)	(0.416)
Observations	1,550	404	622	544
Number of firms	705	199	303	266
Hansen chi2 p-value	0.749	0.591	0.792	0.559
R-squared	0.143	0.242	0.173	0.220

Notes: Regression of equation (A2). 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 6: Determinants of financial constraints:

VARIABLES	FC=0	FC=1	FC=2	FC=3
Estimated Pr(FC=j)	0.579	0.114	0.147	0.159
% observations	57.6%	11.1%	14.7%	16.6%
SIZE	0.019**	-0.002**	-0.005**	-0.012**
	(0.007)	(0.001)	(0.002)	(0.005)
AGE	-0.022*	0.002*	0.006*	0.014*
	(0.013)	(0.001)	(0.004)	(0.008)
CS	0.258***	-0.026***	-0.072***	-0.160***
	(0.091)	(0.010)	(0.025)	(0.056)
CF	0.204**	-0.021**	-0.057**	-0.126**
	(0.097)	(0.010)	(0.027)	(0.060)
ISS	0.304***	-0.031***	-0.084***	-0.188***
	(0.054)	(0.006)	(0.016)	(0.033)
ΔINT	-5.399***	0.551***	1.498***	3.350***
	(1.220)	(0.132)	(0.347)	(0.760)
LEV	-0.017*	0.002	0.005*	0.011*
	(0.010)	(0.001)	(0.003)	(0.006)
R_FIN	12.003***	-1.225***	-3.330***	-7.449***
	(3.606)	(0.386)	(1.014)	(2.238)
EXP	0.050***	-0.005***	-0.014***	-0.031***
	(0.019)	(0.002)	(0.005)	(0.011)
Industry dummies		YES		
Observations	3,211	3,211	3,211	3,211
chi2	123.3	123.3	123.3	123.3

Notes:. Ordered Probit marginal effects resulting from the estimation of Model B. Robust standard errors in parenthesis. ***, **, and * denote statistical significance at the .01, .05, and .10 levels, respectively. Further statistics available from the authors on request.

Table 7: Investment in R&D

VARIABLES	Estimation procedure							
	OLS	Bivariate Probit	Bivariate Ordered Probit	Linear after Probit	Linear after Orderd Probit	Selection Heckman	Selection by steps last step 3.1)	Selection by steps last step 3.2)
Selection	NO	NO	NO	NO	NO	YES	YES	YES
Endogeneity	NO	YES	YES	YES	YES	NO	YES	YES
Dependent Var.	(1) RD_I	(2) RD decision	(3) RD decision	(4) RD_I	(5) RD_I	(6) RD_I	(7) RD_I	(8) RD_I
FC	0.162	-0.824***	-0.393***	-2.095***	-0.976***	-0.165	-0.750**	-0.813**
	(0.243)	(0.275)	(0.138)	(0.476)	(0.171)	(0.120)	(0.369)	(0.408)
SIZE	0.646***	0.028	0.053	0.653***	0.711***	0.715***	0.640***	0.633***
	(0.121)	(0.021)	(0.033)	(0.053)	(0.050)	(0.051)	(0.083)	(0.077)
AGE	-0.155	-0.006	0.021	-0.162**	-0.185**	-0.188**	-0.166	-0.152*
	(0.182)	(0.048)	(0.042)	(0.077)	(0.079)	(0.081)	(0.109)	(0.085)
EXP	-0.114	-0.087	-0.079	-0.272**	-0.009	-0.130	-0.131	-0.138
	(0.266)	(0.059)	(0.059)	(0.119)	(0.122)	(0.118)	(0.154)	(0.121)
Y_IN	1.038***	1.563***	1.550***	0.633***	0.651***	0.492***	0.471*	0.470**
	(0.383)	(0.227)	(0.246)	(0.173)	(0.177)	(0.186)	(0.255)	(0.188)
ΔY	-0.532	-0.168*	-0.186**	-0.562***	-0.460**	-0.502**	-0.497*	-0.511**
	(0.461)	(0.090)	(0.090)	(0.190)	(0.190)	(0.208)	(0.294)	(0.228)
RD_WORK	6.163***	2.643	2.569	3.896***	3.688***	3.167**	2.636	2.659*
	(1.548)	(1.707)	(1.609)	(0.873)	(1.103)	(1.441)	(1.671)	(1.430)
SUB	1.587***	0.986***	0.949***	0.715***	0.820***	0.190	-0.065	-0.098
	(0.249)	(0.137)	(0.151)	(0.137)	(0.150)	(0.183)	(0.277)	(0.233)
COOP	1.175***	0.995***	0.950***	0.180*	0.342***	-0.150	-0.342	-0.362
	(0.255)	(0.119)	(0.132)	(0.108)	(0.115)	(0.196)	(0.243)	(1.775)
Industry dummies	YES	YES	YES	YES	YES	YES	YES	YES
Other controls		YES	YES					
$\hat{\rho}$ or $\hat{\lambda}$ coef.:		0.630**	0.628**	0.702***	0.689***	-2.518**	-4.368**	-4.600***
endog. or select.		(0.255)	(0.282)	(0.190)	(0.129)	(1.029)	(1.734)	(1.618)
Observations	2,608	2,572	2,572	1284	1284	1,541	1,541	1,541
Chi-squared	0.825 (R2)	783.6	77.09	202.4	57780	11906	0.976 (R2)	0.977 (R2)

Notes: Estimates for equation Model C. Robust standard errors in parenthesis (column 7 and 8 with bootstrapped se). ***, **, and * denote statistical significance at the .01, .05, and .10 levels, respectively. 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 some control variables for columns 3 and 4. In columns 1, 2 and 4 FC is collapsed into a binary variable of whether or not firms report financial constraints.

Table 8: Innovation

VARIABLES	Exogenous FC	Endogenous FC	
	Probit	Bivariate Probit	Bivariate Ordered Probit
FC	-0.186	-1.840***	-0.899***
	(0.136)	(0.288)	(0.259)
RD_I	0.073***	0.018**	0.021**
	(0.009)	(0.008)	(0.011)
SIZE	0.001**	0.000	0.000
	(0.000)	(0.000)	(0.000)
AGE	0.013***	-0.001	-0.001
	(0.004)	(0.002)	(0.003)
COOP	0.134	0.061	0.081
	(0.144)	(0.089)	(0.130)
B_TRAB	0.110	-0.125	-0.106
	(0.221)	(0.144)	(0.213)
B_TECH	-0.035	0.068	0.072
	(0.215)	(0.131)	(0.199)
B_MARK	0.519***	0.130	0.179
	(0.158)	(0.117)	(0.166)
ΔY	-0.456*	-0.312*	-0.368
	(0.250)	(0.180)	(0.276)
RD_WORK	2.100	2.405	1.878
	(2.424)	(1.936)	(2.310)
MKTS	1.197***	0.269*	0.404*
	(0.334)	(0.151)	(0.229)
Industry dummies	YES	YES	YES
Observations	1,644	1,627	1,627
Chi-squared	570.2	346.7	66.84
P-value of independent eq. test		0.004	0.018

Notes: Estimates for equation Model D. Robust standard errors in parenthesis. ***, **, and * denote statistical significance at the .01, .05, and .10 levels, respectively. The endogeneity test is based on a Wald test of independent equations for the case of the bivariate estimations. The estimates of FC equation, used as instruments, as well as further test statistics are available from the authors on request.