FILIPE SILVA & CARLOS CARREIRA

Do financial constraints threat the innovation process?

Evidence from Portuguese firms

ESTUDOS DO GEMF

N.º 10 2011

PUBLICAÇÃO CO-FINANCIADA PELA FUNDAÇÃO PARA A CIÊNCIA E TECNOLOGIA

Impresso na Secção de Textos da FEUC COIMBRA 2011
Do financial constraints threaten the innovation process? Evidence from Portuguese firms

Filipe Silva* and Carlos Carreira
Faculdade de Economia/GEMF, Universidade de Coimbra

(This version: May 2011)

Abstract:
This paper investigates the extent to which R&D investment and innovation are financially constrained. For that purpose, we resort to the estimation of a selection model of R&D investment, a simultaneous equations probit model of innovation and constraints and cash to cash-flow sensitivities upon an unique and newly assembled 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. 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.

* Corresponding author:
GEMF–Grupo de Estudos Monetários e Financeiros
Faculdade de Economia, Universidade de Coimbra
Av. Dias da Silva, 165
3004-512 Coimbra, Portugal
Email: filipeourico@gmail.com
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 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. 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 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. Upon this data, we fist 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 finance. Secondly, to investigate the impact of financial constraints upon R&D investment, we test different specifications, controlling for selection and endogeneity. Finally, 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.

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 drawn 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 and, when it comes to R&D and innovation, it is novel.

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 and innovation (e.g. Bond et al., 2003, Magri, 2010), 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). 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. 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. 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.\textsuperscript{1}

We should also note that there is a significant heterogeneity with respect to the types of R&D investment, namely investment for cutting-edge R&D purposes is expected to be financially constrained while those for routine R&D purposes is not (Czarnitzki and Hottenrott, 2011b), as well as research activities are more prone to financial constraints than are development ones (Czarnitzki et al., 2011). However, in this paper, we do not make such distinctions.

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 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). 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, which further adds to the endogeneity problem.\textsuperscript{2} Again, for the case of financial

\textsuperscript{1} We should note, however, that besides the usual, but heterogeneous, forms to raise external finance (see Majumdar, 2011 for heterogeneous impact of different debt types in R&D investment)—such as bank lending, issuing debt and equity in capital markets or even trade credit—venture capital and business angels play a central role for the case of innovation projects (e.g. Caselli et al., 2009, Kortum and Lerner, 2010). Still, an analysis of the role of venture capital on the financing of innovation is not in the scope of this paper.

\textsuperscript{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.
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), Tiwari et al. (2008) for the Netherlands, Savignac, 2008 for French established firms and Czarnitzki and Hottenrott (2011a) for German manufacturing 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 (2009), Gorodnichenko and Schnitzer (2010) and Czarnitzki and Hottenrott (2011) are examples.  

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 legislative 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 increases R&D investment (e.g. Bloom et al., 2002; Almus and Czarnitzki, 2003, Aerts and Schmidt, 2008). 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 (David et al., 2000; Clausen, 2009).

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

3 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
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. 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.

---

4 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 there exist potential biases resulting from individuals perception. As an extreme example, while for some changing the colour of a product might be a significant improvement of the product (accounted for 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.

Finally, the inclusion of the partially qualitative, subjective and censored CIS databases, in our panel of balance sheets and firms' characteristics, raises an additional 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

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. However, constrained firms may use cash to reduce debt if hedging needs are low (Acharya et al, 2007), which we try to control through debt issuances and sales growth (proxying investment opportunities). Additionally, as pointed by Almeida et al. (2009) in a subsequent paper, investment in relatively liquid assets, other than cash, may be used to transfer resources across time (we
include financial investments). Keeping these caveats in mind, we have the following empirical specification:

\[
\Delta CS_{i,t} = \beta_1 CF_{i,t} + \beta_2 \Delta y_{i,t} + \beta_3 S_{i,t} + \beta_4 I_{i,t} + \beta_5 \Delta NW C_{i,t} + \beta_6 ISS_{i,t} + \beta_7 \Delta INT_{i,t} + \beta_8 FinI_{i,t} + \varepsilon_{i,t} \tag{A1}
\]

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, \( \Delta NW C_{i,t} \) 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. Furthermore, we also control for financial investments (\( FinI_{i,t} \)), not only a demand for cash but may also work as an alternative way to transfer resources across time. In both specifications, all variables are scaled by total assets (except the control for firm size). 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

---

5 In the original model they assumed that firms transfer resources only through cash.
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.\footnote{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.}

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.

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, there are situations where this will not be the case: a) firms, regardless of being or not financially constrained, might just not be interested in innovating in the first step. For example, this might well be the case in industries where the pace of technological change is rather slow (Marsili and Verspagen, 2002; Castellacci, 2007); b) non-financially constrained firms may try to innovate, even though they are unsuccessful and therefore will belong to the non-innovators group; c) reasonably financially constrained firms, even without putting too much effort, might be able to innovate, since innovation is measured in a rather broad sense. As an example, if we would be able to distinguish between "radical" from "routine" or "incremental" innovations then we could expect significant differences in the impact of financial constraints (e.g. Czarnitzki and Hottenrott, 2011b). 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). However, Magri (2010) finds statistically significant ICFS differences for Italian firms.\footnote{Note that her interpretation is quite different and based on firm size (small innovative firms)} On the contrary, we expect distinct results when we compare CCFS for firms that invested in R&D (effort to innovate) with those that did not (this is in line with Bond et al. 2003 findings for ICFS). 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 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: 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. 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.

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:

\[ RD_{-I} = Z_1 \beta_1 + \alpha FC + \varepsilon \]  \hspace{1cm} (B1)

\[ FC^* = X \beta_2 + u \]  \hspace{1cm} (B2)

8 While we have 71% of zeroes, the mean (904324) is much higher than the median (163549).

9 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.
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. Additionally, self-assessed financial constraints \((FC)\) is always observed (note that the latent variable \(FC^*\) is not), but is an endogenous variable in (B1), the covariates \(Z\) and \(RD\) are always observed. Finally, we allow for arbitrary correlation among \(v, u\) and \(\varepsilon\).

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

\[
RD_I = Z_i \beta_1 + \alpha FC_i + \gamma \hat{\lambda}_{i3} + e_i
\]

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). 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 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

\[ RD = 1(Z\beta_3 + v > 0), \quad v \sim N(0,1) \]  

(B3)

---

10 This equation explains financial constraints through the 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).
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 (AY); 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.\(^{11}\)

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, 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.

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:

\[
\begin{align*}
FC^c &= 1(X\beta_2 + u > 0) \\
RD &= 1(Z\beta_3 + FC + v > 0),
\end{align*}
\]

\[
\begin{pmatrix}
u \\ v
\end{pmatrix} \sim \Phi_2 \begin{bmatrix} 1 & \rho \\ 0 & 1 \end{bmatrix} \quad (B5)
\]

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

4.3. Model C: 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 simultaneous equations model (specifically a bivariate normal specification of errors within a simultaneous probit model) of underlying latent variables (propensity to innovate and level of financial constraints) of the following form:

\[\quad\]

\(^{11}\) If $Z_1 = Z$, then $\beta_1$ 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.
\[
\begin{align*}
\{ \text{INNOV} &= X_1 \beta_1 + \alpha_1 \text{FC}^c + \varepsilon_1, \\
\text{FC}^c &= X_2 \beta_2 + \alpha_2 \text{INNOV} + \varepsilon_2 \}
\end{align*}
\]  
(C1)

where \( \text{FC}^c \) 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:

\[
\begin{align*}
\{ \text{INNOV} &= X_1 \beta_1 + \alpha_1 \text{FC}^c + \varepsilon_1, \\
\text{FC}^c &= X_2 \beta_2 + \varepsilon_2 \}
\end{align*}
\]  
\( \varepsilon_2 \sim \Phi_2 \begin{bmatrix} 0 \\ 1 \\ \rho \\ 1 \end{bmatrix} \)  
(C2)

where \( X_1 \) includes the investment in R&D (\( \text{RD}_I \)), firm size, age, other barriers to innovate (\( \text{B}_{\text{TRAB}}, \text{B}_{\text{TECH}} \) and \( \text{B}_{\text{MARK}} \)), cooperation with other firms and institutions (\( \text{COOP} \)); percentage of R&D employees (\( \text{RD}_\text{WORK} \)); investment opportunities (\( \Delta Y \)) and market share (\( \text{MKTS} \)). In the vector \( X_2 \) we include the usual determinants of FC, in accordance to (B2) in 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).\(^{12} \) 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

Table 1 reports the summary statistics for model (A), by the different subsamples of firms. We should point that mean cash-flow (\( \text{CF} \)) 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 (\( S \): total assets) and sales growth (\( \Delta Y \)). Additionally, Table 2 reports the same statistics for the remaining models.

5.2 Results for Model A

\(^{12} \) 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.
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 (Table 3), we do not find statistically significant differences in constraints (CCFS of 0.102 against 0.111, respectively). 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 3 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.

It may be possible to argue that public finance has a positive effect in reducing financial constraints (columns 6 and 7 of Table 3), 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).

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 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.

5.3. Results of Model B

In Table 4 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 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

---

13 Confidence intervals are available from authors on request
14 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
selection but not endogeneity (Heckman) and finally, columns (7-8) report the estimates of the model that accounts for both selection and endogeneity.\(^{15}\)

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 $\hat{\lambda}_{13}$ 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.\(^{16}\)

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, or alternatively it might suggest that investment in physical capital is warranted.\(^{17}\) Conversely, a reduction of sales might signal that the firm needs to be innovative and change. 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.

5.3. Results of Model C

When it comes to innovation, Table 5 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

\(^{15}\) Since the derivation of the appropriate correction terms for the asymptotic variance is rather complex, we resort to paired bootstrap estimation.

\(^{16}\) As a check for robustness, we constructed a panel of the 3 wave periods by calculating the averages, over wave period, of financial variables. In this case, fixed effects or independents estimations by wave also report negative impacts of FC on R&D investment, even though these are not statistically significant, except for the case of the first wave (CIS2), where we obtain significant negative impacts (in line with overall results). Additionally, results obtained fitting a Tobit to log(1+R&D investment)—e.g. Czarnitzki and Hottenrott (2011b)— also leads to a negative (but not significant) impact of FC upon R&D investment. Statistics not reported but available from authors on request.

\(^{17}\) Note that the correlation of sales growth is positive and negative with respect to physical capital investment and R&D investment, respectively. Not reported, but available from authors on request.
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. 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 specifications) for the remaining variables of interest.

[insert Table 5 about here]

6. Conclusion

In this paper we explore the impact of financial constraints to R&D investment and innovation by estimating a selection model, a simultaneous equations probit model, 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 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, which 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. Finally, also resorting to the same direct self-asses 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.

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 as well as different measures of financial constraints (direct and indirect), we are able to provide compelling evidence that constraints to innovation, particularly to R&D investment, are binding. Therefore, if innovation is to be regarded as a key driver of economic growth, policy actions should be considered in order to alleviate such constraints.
References


Clausen, T. (2009) 'Do subsidies have positive impacts on R&D and innovation activities at the firm level?' Structural Change and Economic Dynamics 20(4): 239-253.


Heckman, J. (1976) 'The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models.' *Annals of Economic and Social Measurement* 5(4): 120-137.


Majumdar, S. (2011) 'Retentions, relations and innovation the financing of R&D in India' *Economics of Innovation and New Technology* 20(3): 233–257


**Appendix:** 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 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.

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

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

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 and C

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Model B</th>
<th>VARIABLES</th>
<th>Model C</th>
</tr>
</thead>
<tbody>
<tr>
<td>RD_I</td>
<td>12.148</td>
<td>INNOV</td>
<td>0.961</td>
</tr>
<tr>
<td></td>
<td>(2.000)</td>
<td></td>
<td>(0.193)</td>
</tr>
<tr>
<td>FC</td>
<td>1.062</td>
<td>FC*</td>
<td>0.470</td>
</tr>
<tr>
<td></td>
<td>(1.206)</td>
<td></td>
<td>(0.499)</td>
</tr>
<tr>
<td>SIZE</td>
<td>5.124</td>
<td>RD_I</td>
<td>10.057</td>
</tr>
<tr>
<td></td>
<td>(1.169)</td>
<td></td>
<td>(4.910)</td>
</tr>
<tr>
<td>AGE</td>
<td>3.107</td>
<td>SIZE</td>
<td>383.157</td>
</tr>
<tr>
<td></td>
<td>(0.713)</td>
<td></td>
<td>(1.049,444)</td>
</tr>
<tr>
<td>EXP</td>
<td>0.320</td>
<td>AGE</td>
<td>27.983</td>
</tr>
<tr>
<td></td>
<td>(0.508)</td>
<td></td>
<td>(20.342)</td>
</tr>
<tr>
<td>Y_IN</td>
<td>0.199</td>
<td>COOP</td>
<td>0.322</td>
</tr>
<tr>
<td></td>
<td>(0.317)</td>
<td></td>
<td>(0.467)</td>
</tr>
<tr>
<td>ΔY</td>
<td>-0.051</td>
<td>B_TRAB</td>
<td>0.526</td>
</tr>
<tr>
<td></td>
<td>(0.266)</td>
<td></td>
<td>(0.500)</td>
</tr>
<tr>
<td>RD_WORK</td>
<td>0.009</td>
<td>B_TECH</td>
<td>0.487</td>
</tr>
<tr>
<td></td>
<td>(0.042)</td>
<td></td>
<td>(0.500)</td>
</tr>
<tr>
<td>SUB</td>
<td>0.282</td>
<td>B_MARK</td>
<td>0.561</td>
</tr>
<tr>
<td></td>
<td>(0.450)</td>
<td></td>
<td>(0.496)</td>
</tr>
<tr>
<td>COOP</td>
<td>0.356</td>
<td>ΔY</td>
<td>-0.048</td>
</tr>
<tr>
<td></td>
<td>(0.479)</td>
<td></td>
<td>(0.261)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>RD_WORK</td>
<td>0.008</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.038)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MKTS</td>
<td>0.232</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.272)</td>
</tr>
</tbody>
</table>

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>
<thead>
<tr>
<th>VARIABLES</th>
<th>Overall</th>
<th>Innovators</th>
<th>Non-Innovators</th>
<th>RD=1</th>
<th>RD=0</th>
<th>&quot;Subsidised&quot;</th>
<th>Non-&quot;Subsidised&quot;</th>
</tr>
</thead>
</table>
| CF
| 0.115*** | 0.102**   | 0.111*        | 0.073 | 0.168*** | 0.080       | 0.119***        |
|          | (0.038)  | (0.049)    | (0.058)       | (0.049) | (0.062) | (0.123)     | (0.039)         |
| Δy
| 0.023*** | 0.014      | 0.024**       | 0.018* | 0.028*** | -0.003      | 0.023***        |
|          | (0.008)  | (0.011)    | (0.011)       | (0.010) | (0.012) | (0.019)     | (0.008)         |
| S
| 0.022*** | 0.021**    | 0.024*        | 0.034*** | 0.016   | 0.045       | 0.021***        |
|          | (0.008)  | (0.009)    | (0.014)       | (0.010) | (0.016) | (0.029)     | (0.008)         |
| I
| -0.135*** | -0.126***  | -0.144***     | -0.112*** | -0.139*** | -0.057      | -0.143***       |
|          | (0.021)  | (0.029)    | (0.029)       | (0.027) | (0.034) | (0.055)     | (0.022)         |
| ΔNWg
| -0.139*** | -0.115***  | -0.161***     | -0.107*** | -0.168*** | -0.105**    | -0.139***       |
|          | (0.015)  | (0.018)    | (0.022)       | (0.019) | (0.023) | (0.042)     | (0.016)         |
| ISS
| 0.035*** | 0.052***   | 0.019         | 0.038** | 0.029   | 0.010       | 0.035***        |
|          | (0.012)  | (0.016)    | (0.017)       | (0.017) | (0.018) | (0.039)     | (0.013)         |
| ΔNT
| -0.236   | -0.089     | -0.368        | -0.193   | -0.244  | 0.844       | -0.252          |
|          | (0.210)  | (0.264)    | (0.300)       | (0.273) | (0.310) | (0.710)     | (0.215)         |
| FIN
| -0.101*** | -0.110***  | -0.100        | -0.137*** | 0.006   | -0.330***  | -0.073**        |
|          | (0.032)  | (0.031)    | (0.091)       | (0.034) | (0.100) | (0.122)     | (0.031)         |

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 0.829 0.851 0.517 0.566 0.883 0.977 0.847
R-squared 0.149 0.126 0.172 0.122 0.194 0.184 0.151

Notes: Regression of equation (A1). 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 4: Investment in R&D

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>OLS</th>
<th>Bivariate Probit</th>
<th>Bivariate Ordered Probit</th>
<th>Linear after Probit</th>
<th>Linear after Ordered Probit</th>
<th>Selection Heckman</th>
<th>Selection by steps last step 3.1</th>
<th>Selection by steps last step 3.2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Selection</td>
<td>NO</td>
<td>NO</td>
<td>NO</td>
<td>NO</td>
<td>NO</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Endogeneity</td>
<td>NO</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>NO</td>
<td>NO</td>
<td>YES</td>
</tr>
<tr>
<td>Dependent Var.</td>
<td>(1) RD_I</td>
<td>(2) RD decision</td>
<td>(3) RD decision</td>
<td>(4) RD_I</td>
<td>(5) RD_I</td>
<td>(6) RD_I</td>
<td>(7) RD_I</td>
<td>(8) RD_I</td>
</tr>
<tr>
<td>FC</td>
<td>0.162</td>
<td>-0.824***</td>
<td>-0.393***</td>
<td>-2.095***</td>
<td>-0.976***</td>
<td>-0.165</td>
<td>-0.750**</td>
<td>-0.813**</td>
</tr>
<tr>
<td></td>
<td>(0.243)</td>
<td>(0.275)</td>
<td>(0.138)</td>
<td>(0.476)</td>
<td>(0.171)</td>
<td>(0.120)</td>
<td>(0.369)</td>
<td>(0.408)</td>
</tr>
<tr>
<td>SIZE</td>
<td>0.646***</td>
<td>0.028</td>
<td>0.053</td>
<td>0.653***</td>
<td>0.711***</td>
<td>0.715***</td>
<td>0.640***</td>
<td>0.633***</td>
</tr>
<tr>
<td></td>
<td>(0.121)</td>
<td>(0.021)</td>
<td>(0.033)</td>
<td>(0.053)</td>
<td>(0.050)</td>
<td>(0.051)</td>
<td>(0.083)</td>
<td>(0.077)</td>
</tr>
<tr>
<td>AGE</td>
<td>-0.155</td>
<td>-0.006</td>
<td>0.021</td>
<td>-0.162**</td>
<td>-0.185**</td>
<td>-0.188**</td>
<td>-0.166</td>
<td>-0.152**</td>
</tr>
<tr>
<td></td>
<td>(0.182)</td>
<td>(0.048)</td>
<td>(0.042)</td>
<td>(0.077)</td>
<td>(0.079)</td>
<td>(0.081)</td>
<td>(0.109)</td>
<td>(0.085)</td>
</tr>
<tr>
<td>EXP</td>
<td>-0.114</td>
<td>-0.087</td>
<td>-0.079</td>
<td>-0.272**</td>
<td>-0.009</td>
<td>-0.130</td>
<td>-0.131</td>
<td>-0.138</td>
</tr>
<tr>
<td></td>
<td>(0.266)</td>
<td>(0.059)</td>
<td>(0.059)</td>
<td>(0.119)</td>
<td>(0.122)</td>
<td>(0.118)</td>
<td>(0.154)</td>
<td>(0.121)</td>
</tr>
<tr>
<td>Y_IN</td>
<td>1.038***</td>
<td>1.563***</td>
<td>1.550***</td>
<td>0.633***</td>
<td>0.651***</td>
<td>0.492***</td>
<td>0.471*</td>
<td>0.470**</td>
</tr>
<tr>
<td></td>
<td>(0.383)</td>
<td>(0.227)</td>
<td>(0.246)</td>
<td>(0.173)</td>
<td>(0.177)</td>
<td>(0.186)</td>
<td>(0.255)</td>
<td>(0.188)</td>
</tr>
<tr>
<td>∆Y</td>
<td>-0.532</td>
<td>-0.168*</td>
<td>-0.186**</td>
<td>-0.562***</td>
<td>-0.460**</td>
<td>-0.502**</td>
<td>-0.497*</td>
<td>-0.511**</td>
</tr>
<tr>
<td></td>
<td>(0.461)</td>
<td>(0.090)</td>
<td>(0.090)</td>
<td>(0.190)</td>
<td>(0.190)</td>
<td>(0.208)</td>
<td>(0.294)</td>
<td>(0.228)</td>
</tr>
<tr>
<td>RD_WORK</td>
<td>6.163***</td>
<td>2.643</td>
<td>2.569</td>
<td>3.896***</td>
<td>3.688***</td>
<td>3.167**</td>
<td>2.636</td>
<td>2.659**</td>
</tr>
<tr>
<td></td>
<td>(1.548)</td>
<td>(1.707)</td>
<td>(1.609)</td>
<td>(0.873)</td>
<td>(1.103)</td>
<td>(1.441)</td>
<td>(1.671)</td>
<td>(1.430)</td>
</tr>
<tr>
<td>SUB</td>
<td>1.587***</td>
<td>0.986***</td>
<td>0.949***</td>
<td>0.715***</td>
<td>0.820***</td>
<td>0.190</td>
<td>-0.065</td>
<td>-0.098</td>
</tr>
<tr>
<td></td>
<td>(0.249)</td>
<td>(0.137)</td>
<td>(0.151)</td>
<td>(0.137)</td>
<td>(0.150)</td>
<td>(0.183)</td>
<td>(0.277)</td>
<td>(0.233)</td>
</tr>
<tr>
<td>COOP</td>
<td>1.175***</td>
<td>0.995***</td>
<td>0.950***</td>
<td>0.180*</td>
<td>0.342***</td>
<td>-0.150</td>
<td>-0.342</td>
<td>-0.362</td>
</tr>
<tr>
<td></td>
<td>(0.255)</td>
<td>(0.119)</td>
<td>(0.132)</td>
<td>(0.108)</td>
<td>(0.115)</td>
<td>(0.196)</td>
<td>(0.243)</td>
<td>(1.775)</td>
</tr>
<tr>
<td>Industry dummies</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Other controls</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>β or λ coef.:</td>
<td>0.630*(β)</td>
<td>0.628**(β)</td>
<td>0.702****(β)</td>
<td>0.689**(β)</td>
<td>-2.518**(λ)</td>
<td>-4.368**(λ)</td>
<td>-4.600****(λ)</td>
<td></td>
</tr>
<tr>
<td>endog. or select.</td>
<td>(0.255)</td>
<td>(0.282)</td>
<td>(0.190)</td>
<td>(0.129)</td>
<td>(1.029)</td>
<td>(1.734)</td>
<td>(1.618)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>2,608</td>
<td>2,572</td>
<td>2,572</td>
<td>1,284</td>
<td>1,284</td>
<td>1,541</td>
<td>1,541</td>
<td>1,541</td>
</tr>
<tr>
<td>Chi-squared</td>
<td>0.825 (R2)</td>
<td>783.6</td>
<td>77.09</td>
<td>202.4</td>
<td>57780</td>
<td>11906</td>
<td>0.976 (R2)</td>
<td>0.977 (R2)</td>
</tr>
</tbody>
</table>

Notes: Estimates for Model B. 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. Statistically significant β (columns 2-5) and λ (columns 6-8) coefficients indicate the presence of endogeneity and selection, respectively.
<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Exogenous FC</th>
<th>Endogenous FC</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Probit</td>
<td>Probit</td>
</tr>
<tr>
<td>FC</td>
<td>-0.186</td>
<td>-1.840***</td>
</tr>
<tr>
<td></td>
<td>(0.136)</td>
<td>(0.288)</td>
</tr>
<tr>
<td>RD_I</td>
<td>0.073***</td>
<td>0.018**</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>SIZE</td>
<td>0.001**</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>AGE</td>
<td>0.013***</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>COOP</td>
<td>0.134</td>
<td>0.061</td>
</tr>
<tr>
<td></td>
<td>(0.144)</td>
<td>(0.089)</td>
</tr>
<tr>
<td>B_TRAB</td>
<td>0.110</td>
<td>-0.125</td>
</tr>
<tr>
<td></td>
<td>(0.221)</td>
<td>(0.144)</td>
</tr>
<tr>
<td>B_TECH</td>
<td>-0.035</td>
<td>0.068</td>
</tr>
<tr>
<td></td>
<td>(0.215)</td>
<td>(0.131)</td>
</tr>
<tr>
<td>B_MARK</td>
<td>0.519***</td>
<td>0.130</td>
</tr>
<tr>
<td></td>
<td>(0.158)</td>
<td>(0.117)</td>
</tr>
<tr>
<td>ΔY</td>
<td>-0.456*</td>
<td>-0.312*</td>
</tr>
<tr>
<td></td>
<td>(0.250)</td>
<td>(0.180)</td>
</tr>
<tr>
<td>RD_WORK</td>
<td>2.100</td>
<td>2.405</td>
</tr>
<tr>
<td></td>
<td>(2.424)</td>
<td>(1.936)</td>
</tr>
<tr>
<td>MKTS</td>
<td>1.197***</td>
<td>0.269*</td>
</tr>
<tr>
<td></td>
<td>(0.334)</td>
<td>(0.151)</td>
</tr>
<tr>
<td>Industry dummies</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Observations</td>
<td>1,644</td>
<td>1,627</td>
</tr>
<tr>
<td>Chi-squared</td>
<td>570.2</td>
<td>346.7</td>
</tr>
<tr>
<td>P-value of independent eq. test</td>
<td>0.004</td>
<td>0.018</td>
</tr>
</tbody>
</table>

Notes: Estimates for equation (C2). 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.
2011-10 Do financial constraints threat the innovation process? Evidence from Portuguese firms  
- Filipe Silva & Carlos Carreira

2011-09 The State of Collective Bargaining and Worker Representation in Germany: The Erosion Continues  
- John T. Addison, Alex Bryson, Paulino Teixeira, André Pahnke & Lutz Bellmann

2011-08 From Goal Orientations to Employee Creativity and Performance: Evidence from Frontline Service Employees  
- Filipe Coelho & Carlos Sousa

2011-07 The Portuguese Business Cycle: Chronology and Duration Dependence  
- Vitor Castro

2011-06 Growth Performance in Portugal Since the 1960’s: A Simultaneous Equation Approach with Cumulative Causation Characteristics  
- Elias Soukiazis & Micaela Antunes

2011-05 Heteroskedasticity Testing Through Comparison of Wald-Type Statistics  
- José Murteira, Esmeralda Ramalho & Joaquim Ramalho

2011-04 Accession to the European Union, Interest Rates and Indebtedness: Greece and Portugal  
- Pedro Bação & António Portugal Duarte

2011-03 Economic Voting in Portuguese Municipal Elections  
- Rodrigo Martins & Francisco José Veiga

2011-02 Application of a structural model to a wholesale electricity market: The Spanish market from January 1999 to June 2007  
- Vitor Marques, Adelino Fortunato & Isabel Soares

2011-01 A Smoothed-Distribution Form of Nadaraya-Watson Estimation  
- Ralph W. Bailey & John T. Addison

2010-22 Business Survival in Portuguese Regions  
- Alcina Nunes & Elsa de Morais Sarmento

2010-21 A Closer Look at the World Business Cycle Synchronization  
- Pedro André Cerqueira

2010-20 Does Schumpeterian Creative Destruction Lead to Higher Productivity? The effects of firms’ entry  
- Carlos Carreira & Paulino Teixeira

2010-19 How Do Central Banks React to Wealth Composition and Asset Prices?  
- Vitor Castro & Ricardo M. Sousa

2010-18 The duration of business cycle expansions and contractions: Are there change-points in duration dependence?  
- Vitor Castro

2010-17 Water Pricing and Social Equity in Portuguese Municipalities  
- Rita Martins, Carlota Quintal, Eduardo Barata & Luís Cruz

2010-16 Financial constraints: Are there differences between manufacturing and services?  
- Filipe Silva & Carlos Carreira

2010-15 Measuring firms’ financial constraints: Evidence for Portugal through different approaches  
- Filipe Silva & Carlos Carreira

2010-14 Exchange Rate Target Zones: A Survey of the Literature  
- António Portugal Duarte, João Sousa Andrade & Adelaide Duarte

2010-13 Is foreign trade important for regional growth? Empirical evidence from Portugal  
- Elias Soukiazis & Micaela Antunes

2010-12 MCMC, likelihood estimation and identifiability problems in DLM models  
- António Alberto Santos
2010-11 Regional growth in Portugal: assessing the contribution of earnings and education inequality
- Adelaide Duarte & Marta Simões

2010-10 Business Demography Dynamics in Portugal: A Semi-Parametric Survival Analysis
- Alcina Nunes & Elsa Sarmento

2010-09 Business Demography Dynamics in Portugal: A Non-Parametric Survival Analysis
- Alcina Nunes & Elsa Sarmento

2010-08 The impact of EU integration on the Portuguese distribution of employees’ earnings
- João A. S. Andrade, Adelaide P. S. Duarte & Marta C. N. Simões

2010-07 Fiscal sustainability and the accuracy of macroeconomic forecasts: do supranational forecasts rather than government forecasts make a difference?
- Carlos Fonseca Marinheiro

2010-06 Estimation of Risk-Neutral Density Surfaces
- A. M. Monteiro, R. H. Tütüncü & L. N. Vicente

2010-05 Productivity, wages, and the returns to firm-provided training: who is grabbing the biggest share?
- Ana Sofia Lopes & Paulino Teixeira

2010-04 Health Status Determinants in the OECD Countries. A Panel Data Approach with Endogenous Regressors
- Ana Poças & Elias Soukiazis

2010-03 Employment, exchange rates and labour market rigidity
- Fernando Alexandre, Pedro Bação, João Cerejeira & Miguel Portela

2010-02 Slip Sliding Away: Further Union Decline in Germany and Britain
- John T. Addison, Alex Bryson, Paulino Teixeira & André Pahnke

2010-01 The Demand for Excess Reserves in the Euro Area and the Impact of the Current Credit Crisis
- Fátima Teresa Sol Murta & Ana Margarida Garcia

2009-16 The performance of the European Stock Markets: a time-varying Sharpe ratio approach
- José A. Soares da Fonseca

2009-15 Exchange Rate Mean Reversion within a Target Zone: Evidence from a Country on the Periphery of the ERM
- António Portugal Duarte, João Sousa Andrade & Adelaide Duarte

2009-14 The Extent of Collective Bargaining and Workplace Representation: Transitions between States and their Determinants. A Comparative Analysis of Germany and Great Britain
- John T. Addison, Alex Bryson, Paulino Teixeira, André Pahnke & Lutz Bellmann

- Micaela Antunes & Elias Soukiazis

- John T. Addison, Chad Cotti & Christopher J. Surfield

2009-11 The PIGS, does the Group Exist? An empirical macroeconomic analysis based on the Okun Law
- João Sousa Andrade

2009-10 A Política Monetária do BCE. Uma estratégia original para a estabilidade nominal
- João Sousa Andrade

2009-09 Wage Dispersion in a Partially Unionized Labor Force
- John T. Addison, Ralph W. Bailey & W. Stanley Siebert

2009-08 Employment and exchange rates: the role of openness and technology
- Fernando Alexandre, Pedro Bação, João Cerejeira & Miguel Portela

2009-07 Channels of transmission of inequality to growth: A survey of the theory and evidence from a Portuguese perspective
- Adelaide Duarte & Marta Simões
2009-06  *No Deep Pockets: Some stylized results on firms’ financial constraints*  
- Filipe Silva & Carlos Carreira

2009-05  *Aggregate and sector-specific exchange rate indexes for the Portuguese economy*  
- Fernando Alexandre, Pedro Bação, João Cerejeira & Miguel Portela

2009-04  *Rent Seeking at Plant Level: An Application of the Card-De La Rica Tenure Model to Workers in German Works Councils*  
- John T. Addison, Paulino Teixeira & Thomas Zwick

2009-03  *Unobserved Worker Ability, Firm Heterogeneity, and the Returns to Schooling and Training*  
- Ana Sofia Lopes & Paulino Teixeira

2009-02  *Worker Directors: A German Product that Didn’t Export?*  
- John T. Addison & Claus Schnabel

2009-01  *Fiscal and Monetary Policies in a Keynesian Stock-flow Consistent Model*  
- Edwin Le Heron

*A série Estudos do GEMF foi iniciada em 1996.*