# Endogenous financial constraints and innovation 

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#### Abstract

We investigate which indicators of a firm's innovation activities are associated with financial constraints and analyze the nature and direction of causal links between innovation and financial constraints. By estimating simultaneous bivariate probit models on data from the UK Innovation Surveys, we show that among innovation inputs, research and development (R\&D) activity increases the likelihood that firms face financial constraints. Among innovation outputs, only new-to-market products generate financial constraints. Reverse effects on innovation appear limited to external R\&D.


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## 1. Introduction

Innovation is widely recognized as a fundamental driver of economic growth, but the pathways to innovation are complex and often hindered by the fundamentally uncertain nature of research and development ( $R \& D$ ) processes and their market outcomes (Rosenberg, 1994). Access to capital can be a significant barrier to innovation because it reduces investments in its core inputs (e.g. $\mathrm{R} \& D$ ) which in turn may result in fewer new products and lower growth rates relative to the optimal case of frictionless capital markets (Hall and Lerner, 2010). By inducing risk and informational asymmetries into the relation between firms and investors, innovation can restrict the availability of finance when internal funds are not sufficient to sponsor R\&D projects (Cosh et al., 2009). This problem acquired special relevance in the aftermath of the 2008 financial crisis, during which the more innovative firms (and young and small firms in particular) might have been hit especially hard by reduced availability or rising external cost of capital (OECD, 2009), a likely consequence of higher product market uncertainty and the stronger information asymmetries associated with it. However, Kahle and Stulz's (2013) study of a large sample of public US firms during the postLehman period casts doubt on the link between a shock in the supply of credit and firms' capital expenditures.

Despite a number of studies on the cash-flow sensitivity of R\&D investments (see, e.g. Hall, 1992; Himmelberg and Petersen, 1994; Harhoff, 1998; Mulkay et al., 2000; Bond et al., 2005), the extent to and the way in which innovation activities of firms may exacerbate financial constraints are not sufficiently understood (Hall, 2010). The literature on financial constraints discusses the identification and nature of financial constraints (Kaplan and Zingales, 1997, 2000; Carpenter et al., 1998; Fazzari et al., 1988, 2000; Cleary, 1999; Cleary et al., 2007; Hadlock and Pierce, 2010; Farre-Mensa and Ljungqvist, 2016) but tends to neglect the study of their determinants, particularly in the innovation domain: financial constraints are typically difficult to observe, and this often prevents their use as an
outcome variable. Increasing recognition of the multi-dimensional nature of innovation calls for analytical approaches that focus not only on the role of innovation inputs (e.g. R\&D) but also on the relationship between innovation outputs (e.g. new products or new production processes) and financial constraints. Some of these innovation outcomes have recently been related to financial constraints in cross-sectional studies (Hottenrott and Peters, 2012; Audretsch et al., 2014; Mancusi and Vezzulli, 2014; Lee et al., 2015). However, a comprehensive study of their relative importance of innovation inputs and outputs in determining and being determined by financial constraints is missing.

More importantly, the potential feedback loop between financial constraints and innovation must be taken into account. On the one hand, financial constraints can limit firms' engagement in risky R\&D activities (Hall and Lerner, 2010); on the other hand, innovation can generate financial constraints through associated asymmetric information caused by the high costs and uncertainties generated in lengthy processes of R\&D, testing, distribution and marketing (Scherer, 1999; Brown et al., 2009). The existing literature either assumes exogeneity of financial constraints or employs indirect procedures, such as Heckman-type corrections or regression discontinuity designs, to estimate the treatment effect of financial constraints on innovation (Acharya and $\mathrm{Xu}, 2017$ ). However, a modeling approach that directly addresses the fundamental endogeneity problem in the relationship between firm financing and innovation is preferable, as endogeneity can have serious implications for the validity of empirical findings and consequently for the lessons that can be drawn from this body of evidence to inform policy.

In this paper, we investigate the link between financial constraints and innovation through multivariate longitudinal analyses of direct measures of a firm's financial constraints and innovation characteristics. We model firms' innovation-financing behaviors comprehensively and simultaneously along different dimensions of innovation, including inputs, processes and outputs, and not simply R\&D. Our strategy is to treat financial constraints and innovation as a simultaneous dynamic system while accounting for unobserved firm-specific effects. We develop a set of simultaneous equations models, suited to the treatment of endogeneity, and apply them to UK Innovation Survey panel data available through the UK Office of National Statistics (ONS). These data contain a wealth of information on firm innovation activities that have not been used to date to address the problem of firm financing in a simultaneous setting. We also consider in our analysis small and non-listed firms. These are usually missing from studies of cash-flow sensitivities of investment, even though small and medium-sized enterprises (SMEs) play a fundamental role in the dynamics of Schumpeterian creative destruction that characterize modern competitive processes (Schumpeter, 1942; Acs and Audretsch, 1990; Breschi et al., 2000; Aghion et al., 2013).

Our results suggest that innovating firms are more likely to experience financial constraints. By considering a broad range of innovation indicators, we show that only some innovation inputs and outputs increase the likelihood that firms experience financial constraints. We further show that innovation outputs in the form of products that are new to the market cause financial constraints. In line with theory, effects of innovation on financial constraints are strongest where informationally opaque activities and uncertain market outcomes create a potential for severe agency conflicts. The reverse effect of financial constraints on the likelihood of innovation appears limited to external R\&D activity that is not captured by formal R\&D spending. Although the literature has traditionally emphasized that financial constraints may prevent firms from innovating, we stress that the resource requirements of firms increase when they innovate. This implies that from a policy viewpoint attention should be paid not only to the costs of technological search, but also to the capital outlays required by the exploitation of innovation, which are often underestimated.

Our study contributes to the literature on the effects of financial constraints on innovation (e.g. Canepa and Stoneman, 2007; Hoegl et al., 2008; D'Este et al., 2012; Hottenrott and Peters, 2012; Audretsch et al., 2014; Acharya and Xu, 2017; Howell, 2016; Pellegrino and Savona, 2017) and to the study of financial constraints more broadly (e.g. Fazzari et al., 1988, 2000; Hall, 1992; Himmelberg and Petersen, 1994; Kaplan and Zingales, 1997, 2000; Carpenter et al., 1998; Cleary, 1999; Bond et al., 2005; Cleary et al., 2007; Brown et al., 2009; Hadlock and Pierce, 2010; Brown et al., 2012; Lee et al., 2015; Farre-Mensa and Ljungqvist, 2016). First, we investigate the relative importance of a broad range of indicators of a firm's innovation profile as determinants of financial constraints, including measures of R\&D and the firm's innovation outcomes. Second, we employ a structural model to account for endogeneity in the relationship between financial constraints and innovation and are thus able to study the bivariate and dynamic interaction of both variables and to resolve previous conflicting evidence. Third, we contribute to the literature on the identification of financial constraints based on survey data.

The article is organized as follows. Section 2 reviews the relevant literature and frames our research design. Section 3 presents our data, models, and estimation approach. Section 4 presents the results of our main analyses. Section 5 extends the results by showing alternative model configurations and estimation methods. It further discusses and tests the validity of our measure of financial constraints. In Section 6, we draw the study to a close by reflecting on its contribution to the literature and by commenting on its policy implications.

## 2. Financial constraints and investments in innovation

We begin the literature review by discussing the problems of identification and evaluation of the drivers of financial constraints. We then reflect on the specific role of innovation and focus on the bidirectional relationship between innovation and financial constraints.

### 2.1 Measurement and determinants of financial constraints

Empirical studies of firms' financing behaviors reflect the existence of constraints on raising external finance (e.g. Fazzari et al., 1988, 2000; Whited, 1992; Bond and Meghir, 1994; Carpenter et al., 1998; Bond et al., 2003; Mulier et al., 2016). Authors typically measure the degree of financial constraint by screening a firm's financial reports for evidence of firms identifying themselves as financially constrained or by comparing the cash-flow sensitivity of investment between subsamples constructed from a measure that proxies for constraints. Among the first of these studies, Kaplan and Zingales (1997; KZ) examine the management's discussion of the firm's liquidity (i.e. future needs for funds and sources of liquidity, as well as demand for funds) and classify the firm into five categories according to the degree of financial constraint, using quantitative information to augment the qualitative data (e.g. information on dividends and share repurchases). Hadlock and Pierce (2010) expand the method of KZ to include more firms, carefully rate statements in the firm's $10-\mathrm{K}$ that pertains to a firm's ability to raise funds or finance its operations and aggregate these ratings to arrive at a 5-point scale similar to the one developed by KZ. Hoberg and Maksimovic (2015) automate the reading process and machine-read the "Management's Discussion and Analysis" in $10-\mathrm{K}$ text for all electronically filed 10-Ks from 1997 to 2009.

These measures of financial constraints can then be used as outcome variables to find determinants of financial constraints. Kaplan and Zingales (1997) estimate an ordered logit model using their classification and find that a firm's cash flow, market-book ratio, leverage, dividends, and cash holdings explain whether a firm can be classified as financially constrained. These variables have themselves become a common proxy for financial constraints in the literature (the first ones to define the KZ index as a linear combination of regressors of constraints are Lamont et al., 2001). Subsequent studies have found that cash flow, Q, leverage, dividends, cash, size and age explain constraints (Whited and Wu, 2006; Hadlock and Pierce, 2010). Hoberg and Maksimovic (2015) find that constraints are more severe for R\&D-intensive firms, supporting earlier findings by Brown et al. (2009).

If dynamic investment models of the firm (Bond and Meghir, 1994) are correct, the presence of financial constraints in firms that self-report or exhibit signs of being constrained can be confirmed by estimating the sensitivity of investment to changes in cash flow for subsamples of a priori constrained and unconstrained firms. Differences in the sensitivity to cash flow between these groups indicate that the variable used to split the sample (e.g. dividends, KZ index, Hadlock-Pierce index) reflects financial constraints. Historically, studies of firm's cash-flow sensitivity of investment have mostly used investment in tangible assets to test for financing frictions. Models with R\&D investments rather than physical investment as an outcome variable were developed much later because of the limited availability of long R\&D time series and methodological difficulties such as those encountered in measuring the R\&D capital stock. ${ }^{1}$

The analytical framework of regressing investment on cash flow and average Q (approximating marginal Q )including the very identification of financial constraint and financial distress-has, however, been challenged in subsequent studies on methodological and theoretical grounds (Schiantarelli, 1996; Kaplan and Zingales, 1997, 2000; Cleary, 1999; Cleary et al., 2007; Chen and Chen, 2012). The use of conventional regressions of investment on cash

1 For extensive discussions of this literature see the reviews by Schiantarelli (1996), Hubbard (1998), Bond and Van Reenen (2007), and Coad (2010). See Brown and Petersen (2009) for a comparison of cash flow sensitivities of physical investment and R\&D.
flow has been criticized for neglecting the potential endogeneity of cash flow and for not controlling for external financing (Brown and Petersen, 2009). Hu and Schiantarelli (1998) recognize the methodological limitation of preclassifying firms into constrained and unconstrained subpopulations and then estimating cash-flow sensitivities for each. They estimate instead a switching regression model in the traditional $Q$ investment model framework. In line with early studies, this approach mostly confirms findings of financial constraints to investment (Almeida and Campello, 2007). Riddick and Whited (2009) argue that the positive correlation between investment and cash flow is better explained by a productivity shock that simultaneously affects cash flow and the marginal product of capital, inducing firms to invest in additional productive capacity. Most recently, Farre-Mensa and Ljungqvist (2016) called into question the ability of conventional measures of financial constraints to distinguish constrained from unconstrained firms. They use exogenous shocks to firm's demand for external finance and show that firms classified as constrained by five measures (dividends, credit ratings, and indices developed by Kaplan and Zingales, 1997; Hadlock and Pierce, 2010; Whited and Wu, 2006) are equally or better able to adjust their leverage in response to changes in the local tax regime.

In addition to these theoretical and methodological difficulties, the scope of potential determinants of financial frictions has largely been limited to readily available accounting information. However, a firm's financial statements do not always accurately capture its business activities to a degree that can easily be related to its ability to raise finance. For example, a firm's supply schedule of capital varies with its projects and is likely to depend on availability of collateral and information asymmetries 231caused by R\&D activities (Farre-Mensa and Ljungqvist, 2016). Proponents of the "wedge" model of financial constraints, which assumes a higher cost of capital for external than for internal finance, maintain that such a wedge can be due to the opaqueness of a firm's projects and private information that cannot easily be communicated to external parties (Myers and Majluf, 1984; Krasker, 1986; Brown et al., 2009, 2012). It can be argued that a firm's efforts to innovate, a main cause of financing constraints, has received relatively little attention, partly as a result of limited data availability, although there are hardly any activities within firms that create a greater potential for moral hazard and similar agency problems related to asymmetric information.

### 2.2 Endogeneity and the multifaceted nature of innovation

Another reason for the lack of conclusive evidence on firms' innovation characteristics in relation to their financing behavior is the bidirectional causality between the two constructs. Although innovation is likely to affect a firm's ability to raise finance, the availability of funding can also constrain its ability to carry out research and innovation projects. Existing studies address this fundamental methodological problem in various ways. A number of studies concerned with technical change exploit the deregulation of intrastate and interstate branch banking in the USA in the 1970s until the mid1990s as a natural experiment that relaxes financing constraints. Although increased competition among banks as a result of interstate banking deregulation in the 1980 s increases the number and quality of patents (Amore et al., 2013; Chava et al., 2013), increased market power of banks due to intrastate deregulation seems to reduce patenting (Chava et al., 2013). Banking deregulation mainly benefits private firms, which previously had limited access to credit from local banks (Cornaggia et al., 2015). Within the cash-flow sensitivity framework, there also is some evidence of binding financial constraints for R\&D investment, which nonetheless appear to vary considerably across time periods and countries (Hall, 1992; Himmelberg and Petersen, 1994; Harhoff, 1998; Mulkay et al., 2000; Bond et al., 2005; Cincera and Ravet, 2010; Brown et al., 2012), often not unlike physical investment (Carpenter et al., 1998).

In addition to the problem of endogeneity of financial constraints as a determinant of innovation, this stream of contributions has a narrow focus on traditional indicators of innovation (predominantly audited R\&D expenditures and to a lesser extent patents). Following Schumpeter (1934), several authors have instead highlighted that innovation processes are multi-dimensional (see, e.g. Kline and Rosenberg, 1986; Dosi, 1988; Crepon et al., 1998; Jaffe and Trajtenberg, 2002). Innovation inputs (e.g. R\&D, associated with the highest level of investment risk and information asymmetries) can be distinguished from intermediate outputs (e.g. inventions measured by patents) as well as from final outputs (innovated products, processes, and services, which may be new to the firm or new the market). Moreover, each of these dimensions can be significantly affected by a range of practices and strategic choices about the sourcing of external knowledge, the acquisition of technologies and access to other complementary assets (Teece,

1992, 2010; Stoneman, 2001). The use of a broader and more precise range of innovation indicators has great potential to refine our understanding of firms' financing behaviors (Canepa and Stoneman, 2007).

We expect innovation characteristics of a firm that are related to intangible assets and uncertain market prospects to affect its perceived financing constraints to a greater extent than investment in externally observable and examinable new products and services with a well-known market. Expenses for R\&D) and advertising, which can be seen as proxies for asset intangibility, shape a firm's capital structure and are associated with smaller degrees of leverage (Bah and Dumontier, 2001; Carpenter and Petersen, 2002; Kayo and Kimura, 2011). The large information asymmetries and agency costs associated with new product development-especially in the high-tech industry-require complex and thus costly financing solutions, which often involve equity in the form of venture capital (Gompers, 1995). Czarnitzki and Hottenrott (2011) report evidence that cutting-edge R\&D projects may cause credit constraints more often than routine R\&D investments. Lee et al. (2015) find that new-to-the-market innovations make it more difficult to access external capital. We thus expect that innovation activities and investment in early product development and opaque internal $\mathrm{R} \& \mathrm{D}$ projects will more likely generate financing difficulties than innovation outcomes such as new products in established markets or new business processes.

The introduction and continued implementation of Community Innovation Surveys (CISs) in Europe has enabled the measurement of different stages and dimensions of innovations on a large scale. The CIS also contains two specific questions on firms' perceived financial constraints (namely the extent to which "access to finance" and "cost of finance" constitute barriers to innovation). Systematic research into the links between environmental constraints and the inputs, processes and outputs of innovation has only begun relatively recently (Canepa and Stoneman, 2007; Mohnen et al., 2008; Savignac, 2008; Müller and Zimmermann, 2009; D’Este et al., 2012; Hottenrott and Peters, 2012; Audretsch et al., 2014; Acharya and Xu, 2017). ${ }^{2}$

Despite the quality of these contributions, there are considerable margins for progress on theoretical, methodological and empirical grounds. For example, the predominantly cross-sectional nature of the innovation output data used in the literature does not capture dynamic effects and state dependence in innovation activities. It also makes it difficult to identify the potential reverse causality between financial constraints and innovation. Prior art on this topic typically models either constraints or innovation as exogenous or introduces simultaneity by adding contemporaneous error correlation without allowing for two-way causality. One rare exception is a study of French firms by Hajivassiliou and Savignac (2016), who use bivariate probit modeling with state dependency in both financial constraints and innovation variables. This analysis is limited by the use of only two CIS waves, but the findings suggest the possibility that innovation outcomes increase financial constraints, while financial constraints may reduce the likelihood of innovation. Hottenrott and Peters (2012) instead exploit a speculative question only contained in one wave of the Mannheim Innovation Panel to explore the determinants of financial constraints. Results obtained from cross-sectional estimations suggest that financial constraints do not depend solely on the availability of internal finance but can be driven by the increased financial needs of innovating firms. Even though external investors might be able to observe the successful outcome of firms' $\& \& D$ investments, the effect of greater resources requirements or of market uncertainty appear to outweigh the reduction of information asymmetries. These insights deserve further investigation in a broader longitudinal setting that fully accounts for dynamic effects and reverse causality.

## 3. Data and methodology

### 3.1 Data

The CISs provide a rich direct source of information on firms' innovation activities and the economic environment in which these take place. In the UK, the data are collected at enterprise level by the ONS. The CIS-UK 2011 sampled over 28,000 UK enterprises. ${ }^{3}$ The sampling frame included all enterprises with 10 or more employees in sections C-K

2 Czarnitzki and Hottenrott (2011) analyze panel data on German firms that include different indicators inputs (research vs. development), but exclude indicators of innovative output. Interestingly, different R\&D indictors produce different effects on financial constraints.
3 Department for Business, Innovation and Skills, Office for National Statistics and Northern Ireland. Department of Enterprise, Trade and Investment, UK Innovation Survey, 1994-2010: Secure Data Service Access [computer file], 2nd edn. Essex: UK Data Archive [distributor]: Colchester, October 2012. SN: 6699, http://dx.doi.org/10.5255/UKDA-SN-6699-2.
of the Standard Industrial Classification (SIC) 2003 or 2007 in the official business register, which include both manufacturing and service sectors. The underlying sample is stratified by region, industry sector and size, and weights are attached to responses according to the firm's weight relative to the number of firms in the stratum. For all enterprises with 250 or more employees, a census was used. SMEs were sampled at random within each stratum.

We use four CIS-UK waves (CIS4-CIS7, covering the periods 2002-2004, 2004-2006, 2006-2008, and 20082010) to assess British firms' perceived constraints in accessing capital markets and their impact on innovation input and output. Later waves cannot be used for our purpose because, unfortunately, the questionnaire was changed for the period 2010-2012, which broke the continuity of our dependent variables. Individual cross sections contain about 15,000 observations each. After linking all four waves and excluding firms with incomplete time series (gaps) in all dependent variables, we obtain an unbalanced panel dataset with 3218 firms. Due to missing variables in some dependent variables, some of our analyses may have slightly fewer firms. For independent variables, there are 2659 two-period panels ( 2628 for CIS5-6 and 31 for CIS6-7) and 559 three-period panels, which yields 6995 firm-year observations in total for our bivariate models. Because lagged dependent variables consume one observation per firm, dependent variables in our bivariate models have up to $6995+3218=10,213$ observations. Single-variable models have slightly more observations because observations for which the second dependent variable in our bivariate model would be missing remain in the sample. We match the CIS dataset with the Business Structure Database ${ }^{4}$ (BSD) to obtain additional variables on firm age and legal form, as well as for our analysis of firm death.

One feature of the data that needs special attention is a 1-year overlap between consecutive surveys: each survey asks firms every 2 years about their activities over the previous 3 years. The potential serial correlation induced in the variables that are affected by this overlap has at least three implications for our modeling strategy. First, we use a dynamic model structure with lagged dependent variables to formally capture autocorrelation. Second, we choose lagged independent variables to construct economically meaningful models. Third, we test the robustness of our findings by incorporating a number of alternative measures of innovation inputs and outputs: the survey question about R\&D activities refers to a three-year period, whereas a similar question about R\&D expenditures asks for the firm's expenditures only in the last year of the survey period and is thus unaffected by overlapping observation periods. ${ }^{5}$

The distribution of firms in our sample is roughly comparable with the overall distribution of firms with 10 or more employees in the UK. We use SIC 2003 top-level classifications to construct industry dummy variables, which are presented in Table 1. To add a finer level of detail to our study of R\&D and innovation activities, we split the manufacturing sector into high- and low-tech firms according to the OECD (2005) Science, Technology and Industry Scoreboard. Along the same line of reasoning, we separate R\&D service firms from "other services." Manufacturing firms are overrepresented compared with the UK population of firms with more than nine employees $(32.7 \%$ vs. $19.3 \%$ ) at the expense of other sectors, most notably hotels and restaurants ( $5.5 \%$ vs. $12.5 \%$ ), trade ( $17.7 \%$ vs. $23.0 \%$ ), and construction ( $7.6 \%$ vs. $11.2 \%$ ).

### 3.2 Variables

Because we aim to simultaneously predict the presence of innovation activities and financial constraints in firms, all our dependent variables are binary indicator variables based on firms' self-reported measures of financial constraints and innovation. This choice of variables is further motivated by the observation that many firms report no R\&D expenditures but say they engage in R\&D activities. There is evidence that firms do not report R\&D expenses in their financial statements but still file patents (Koh and Reeb, 2015) or achieve product innovations (Santamaría et al., 2009). The reporting of R\&D activities, if not the decision processes within firms, may follow a two-step process, in which firms first decide whether to engage in R\&D (i.e. a binary decision) and then decide whether and how much audited R\&D expenditures to report. For all our dependent variables on financial constraints and innovation, we either use survey items directly or construct binary variables from them.

4 Office for National Statistics, Business Structure Database, 1997-2011: Secure Data Service Access [computer file]. 3rd edn. Essex: UK Data Archive [distributor]: Colchester, October 2012. SN: 6697, http://dx.doi.org/10.5255/UKDA-SN-6697-3.
5 The respondents' tendency to answer survey questions with the most recent year in mind (Tversky and Kahneman, 1973) is likely to help mitigate correlations across time periods. The availability heuristic will favor data that are more readily available in the respondent's memory and will underweight earlier years, thus attenuating possible autocorrelation effects that are not due to underlying economic processes but to survey design.
Table 1. Descriptive statistics

| Panel A. summary statistics |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Variable | $N$ | Min | Max | Mean | SD | Panel ( $p$ ), cross-sec tion ( $i$ ), or time $(t)$ |
| R\&D internal (expenditure) | 10,402 | 0 | 1 | 0.279 | 0.448 | $p$ |
| R\&D external (expenditure) | 10,402 | 0 | 1 | 0.104 | 0.305 | $p$ |
| R\&D any (expenditure) | 10,402 | 0 | 1 | 0.296 | 0.456 | $p$ |
| R\&D internal (activity) | 10,266 | 0 | 1 | 0.345 | 0.475 | $p$ |
| R\&D external (activity) | 10,253 | 0 | 1 | 0.136 | 0.343 | $p$ |
| R\&D any (activity) | 10,259 | 0 | 1 | 0.363 | 0.481 | $p$ |
| Innovation (any) | 10,377 | 0 | 1 | 0.343 | 0.475 | $p$ |
| Innovation new to market | 10,251 | 0 | 1 | 0.134 | 0.340 | $p$ |
| Innovation new to firm | 10,249 | 0 | 1 | 0.128 | 0.334 | $p$ |
| Innovation (good) | 10,382 | 0 | 1 | 0.190 | 0.392 | $p$ |
| Innovation (process) | 10,385 | 0 | 1 | 0.186 | 0.389 | $p$ |
| Innovation (service) | 10,379 | 0 | 1 | 0.179 | 0.384 | $p$ |
| Financial constraint | 10,258 | 0 | 1 | 0.245 | 0.430 | $p$ |
| Turnover (log) | 6995 | (0, 7.5] | (9.5,17.5] | 8.668 | 1.881 | $p$ |
| Observations in interval |  | 2159 | 2185 |  |  |  |
| Market scope | 6995 | 1 | 4 | 2.337 | 1.135 | $p$ |
| Human capital | 6995 | [0] | $(0.5,2]$ | 0.137 | 0.237 | $p$ |
| Observations in interval |  | 2260 | 562 |  |  |  |
| Operating margin | 6995 | (-1.1,0] | $(0.15,1]$ | 0.105 | 0.136 | $p$ |
| Observations in interval |  | 797 | 1842 |  |  |  |
| Market share (log) | 6995 | $(-13.5,-8]$ | $(-6,0]$ | $-6.728$ | 2.191 | $p$ |
| Observations in interval |  | 2182 | 2460 |  |  |  |
| Age (log) | 6995 | (0, 2.5] | (3.9, 4.1] | 3.234 | 0.558 | $i$ |
| in interval |  | 796 | 1728 |  |  |  |
| Group member | 6995 | 0 | 1 | 0.352 | 0.478 | $i$ |
| Company | 6995 | 0 | 1 | 0.864 | 0.343 | $i$ |
| Foreign ownership | 6995 | 0 | 1 | 0.121 | 0.326 | $i$ |
| Sector: construction | 6995 | 0 | 1 | 0.076 | 0.265 | $i$ |
| sector: financial | 6995 | 0 | 1 | 0.031 | 0.172 | $i$ |
| Sector: hotels, restaurants | 6995 | 0 | 1 | 0.055 | 0.228 | $i$ |
| Sector: R\&D services | 6995 | 0 | 1 | 0.031 | 0.173 | $i$ |
| Sector: medium/high-tech manufacturing | 6995 | 0 | 1 | 0.106 | 0.308 | $i$ |
| Sector: medium/low-tech manufacturing | 6995 | 0 | 1 | 0.221 | 0.415 | $i$ |

Table 1. Continued

| Panel A. summary statistics |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Variable | $N$ | Min | Max | Mean | SD | Panel ( $p$ ), cross-section (i), or time ( $t$ ) |
| Sector: other services | 6995 | 0 | 1 | 0.199 | 0.399 | $i$ |
| Sector: trade | 6995 | 0 | 1 | 0.177 | 0.382 | $i$ |
| Sector: transport | 6995 | 0 | 1 | 0.082 | 0.275 | $i$ |
| Sector: other | 6995 | 0 | 1 | 0.021 | 0.145 | $i$ |
| Time effect CIS5 | 6995 | 0 | 1 | 0.456 | 0.498 | $t$ |
| Time effect CIS6 | 6995 | 0 | 1 | 0.460 | 0.498 | $t$ |
| Time effect CIS7 | 6995 | 0 | 1 | 0.084 | 0.278 | $t$ |
| Panel B. variable definitions |  |  |  |  |  |  |
| Variable | Definition |  |  |  |  |  |
| $\mathrm{R} \& \mathrm{D}$ internal (expenditure) | The firm's stated amount of internal R\&D expenditures is positive in the last year of the survey period (e.g. in 2008 for the period 2006-2008); dummy variable |  |  |  |  |  |
| R\&D external (expenditure) | The firm's stated amount of external R\&D expenditures is positive in the last year of the survey period (e.g. in 2008 for the period 2006-2008); dummy variable |  |  |  |  |  |
| R\&D any (expenditure) | The firm states positive internal or external R\&D expenditures |  |  |  |  |  |
| R\&D internal (activity) | The firm engaged in creative work on an occasional or regular basis to increase the stock of knowledge or used it to devise new and improved goods, services, and processes; dummy variable |  |  |  |  |  |
| R\&D external (activity) | The firm engaged in external R\&D activities; same as internal R\&D, but purchased by the firm and performed by other companies (including other businesses within its group) or by public or private research organizations; dummy variable |  |  |  |  |  |
| R\&D any (activity) | The firm engaged in internal or external R\&D activities |  |  |  |  |  |
| Innovation (any) | The firm introduced any kind of innovation as defined below |  |  |  |  |  |
| Innovation new to market | The firm introduced a new good or service onto the market before its competitors; dummy variable |  |  |  |  |  |
| Innovation new to firm | The firm introduced a new good or service that was essentially the same as a product already available from its competitors; dummy variableThe firm introduced new or significantly improved goods |  |  |  |  |  |
| Innovation (good) |  |  |  |  |  |  |
| Innovation (process) | The firm introduced any new or significantly improved processes for producing or supplying products |  |  |  |  |  |
| Innovation (service) | The firm introduced new or significantly improved services |  |  |  |  |  |
| Financial constraint | The firm faced constraints in the availability of finance. This dummy variable is derived from the corresponding survey question <br> "How important were the following factors as constraints on innovation activities in influencing a decision not to innovate?" |  |  |  |  |  |

Table 1. Continued

| Panel B. variable definitions |  |
| :---: | :---: |
| Variable | Definition |
|  | Firms answering "not experienced" or "low" are treated as not being financially constrained, while those answering "medium" or "high" are defined as financially constrained |
| Turnover (log) | The firm's turnover in GBP (thousands, natural logarithm) for the last year of the survey period. This variable is lagged by one period. For a small number of firm, turnover was missing, but could be recovered from the corresponding entries in the BSD. Reading example: There are 2159 observation in the interval [0, 7.5] |
| Market scope | The largest geographic market in which a firm sells goods or services. Possible answers are $1=$ "Local/regional within the UK," $2=$ "UK," $3=$ "Other Europe," and $4=$ "All other countries" |
| Human capital | The proportion of a firm's employees in the last year of the survey period that was educated to degree level or above. The maximum value is 2 , since this variable adds the survey items "science or engineering subjects" and "other subjects." This variable is lagged by one period |
| Operating margin | Operating margin, defined as gross value added at factor cost minus total labor cost, divided by turnover. A firm's operating margin is calculated for the first year of the relevant CIS wave. For example, the operating margin used to predict dependent variables in CIS7 (2008-2010) is from 2008. About $59 \%$ of all observations for this variable have been imputed using regression imputation |
| Market share (log) | Market share (natural logarithm) of the firm, defined as the firm's turnover divided by concurrent total market turnover. A market is defined based on five-digit SIC2007 codes, using the full sample and sampling weights of the Annual Respondents Database. About $2 \%$ of all observations for this variable have been imputed using regression imputation |
| Age (log) | Firm age (natural logarithm) calculated as (2010 minus birth year). Firm birth is censored at 1973 in the BSD. In order to avoid potential biases due to censored right-hand variables, we impute censored values using predicted values from a tobit regression of birth year on all other independent variables. This places many observations in the interval (3.8, 4.1] |
| Group member | The firm is part of an enterprise group in the first period (CIS4); dummy variable |
| Company | The firm has status "company" as opposed to sole proprietorship etc. in the BSD; dummy variable |
| Foreign ownership | The firm is under foreign ownership (ultimately) in CIS5 (2004-2006); dummy variable |
| Sector: construction | SIC (1992, UK) codes beginning with: 45 |
| Sector: financial | SIC (1992, UK) codes beginning with: $35,24,30,32,33,31,34,29$ |
| Sector: Hotels, Restaurants | SIC (1992, UK) codes beginning with: $25,23,26,27,28,36,37,20,21,22,15,16,17,18,19$ |
| Sector: R\&D services | SIC (1992, UK) codes beginning with: 55 |
| Sector: medium/high-tech manufacturing SIC (1992, UK) codes beginning with: 65, 67 |  |
| Sector: medium/low-tech manufacturing | SIC (1992, UK) codes beginning with: 72, 73 |
| Sector: other services | SIC (1992, UK) codes beginning with: 70, 71, 74, 90-99 |
| Sector: Trade | SIC (1992, UK) codes beginning with: 50-52 |

Table 1. Continued

| Panel B. variable definitions |  |
| :--- | :--- |
| Variable | Definition |
| Sector: Transport | SIC (1992, UK) codes beginning with: $60-63$ |
| Sector: Other | SIC (1992, UK) codes beginning with: 10-14, 75, 80, 85 (mining, utilities, education, public administration, and health) |
| Time effect CIS5 | Time dummy for CIS5 (period 2004-2006) |
| Time effect CIS6 | Time dummy for CIS6 (period 2006-2008) |
| Time effect CIS7 | Time dummy for CIS7 (period 2008-2010) |




 have more observations, since the first observation for each firm is used up for lagged dependent variables.

Our six binary measures for R\&D activities are based on two survey questions. First, the questionnaire asks firms, "During the 3-year period (survey period, e.g. 2006-2008), did this business invest in any of the following, for the purposes of current or future innovation?" with answers "Internal Research and Development" and "Acquisition of external Research and Development," which translate into our dependent variables "R\&D internal (activity)" and "R\&D external (activity)." The binary variable "R\&D any (activity)" equals one whenever any of these two variables is answered positively by the firm. The second question is, "for each of the main innovation related investments in question (previous question), please ESTIMATE the amount of expenditure for the year (last year of survey period, e.g. 2008)." We treat positive amounts as indicators for internal and external R\&D expenditures, which yields our dependent variables "R\&D internal (expenditure)," "R\&D external (expenditure)," and "R\&D any (expenditure)."

Dependent variables for innovation outputs correspond to survey items for the development of new goods, services or processes. The questionnaire asks, "During the 3-year period [survey period], did this business introduce (i) new or significantly improved goods? [...] (ii) new or significantly improved services?" and "did this business introduce any new or significantly improved processes for producing or supplying goods or services?" Additionally, we distinguish new goods and services that are new to the market from those that have been introduced by a competitor and are merely new to the firm. Finally, the variable "Innovation (any)" measures whether the firm introduced any type of innovation-good, service, or process.

Our goal in the regressions of R\&D and innovation outcomes is to investigate the relationship between financial constraints and a range of measures of a firm's innovation activities. Because not all R\&D and innovation outcomes are present in our models at all times, the reference category for $R \& D$ and innovation outcomes in each regression is different. For example, when using new-to-the-firm innovation as an outcome, the reference category (i.e. firms that do not produce such an innovation) is composed of firms that may still produce innovation, albeit not of the new-to-the-firm kind.

To assess financial constraints, firms answer the question, "how important were the following factors in constraining innovation activities: [...] availability of finance." "Cost of finance" was another possible constraint in this block of items. We focus on the availability of finance, however, to stay close to the meaning of financial constraints as an unobserved differential between internal and external cost of finance that limits the availability of external finance. One important advantage of using a self-response measure over cash-flow sensitivities is that we can directly observe changes over time. In other words, instead of searching for latent financial constraints in different groups of firms, we can directly investigate their determinants and impact on innovation. Whenever firms answer this item with "high" or "medium," we code this answer as "experiencing financial constraints" and treat the firm as unconstrained if the answer is "low" or "not experienced." About one quarter of the sample's firms report financial constraints, a proportion that is largely driven by the two CIS waves in 2008 and 2010, as one might expect from the general economic climate at the time. An econometric advantage of the UK Innovation Survey relative to the innovation surveys of other European countries is that all sample firms were asked whether they experienced financial constraints rather than only those that report innovation activities. We find a substantial proportion of firms in all innovation and constraint regimes, including financially constrained non-innovating firms. Potential selection biases within our sample are therefore greatly reduced.

Independent variables in our analyses relate to a firms' innovative capacity and the likelihood of financial constraints. The range of variables is limited by their availability in official—and linkable—ONS datasets. We measure a firm's size as the natural logarithm of its turnover in the last year of each survey period. Firm age is calculated as (2010—birth year), where birth year is obtained from the BSD dataset and thus does not vary over time. Since age changes in much the same way for all firms over time, the likelihood of detecting a time series effect in addition to the cross-sectional one is quite small given the short panel. However, treating age as firm-year specific would introduce four additional parameters (Wooldridge terms, see Wooldridge, 2005), which remain insignificant in our tests. Whether a firm is a member of a group, is a subsidiary of a foreign firm and whether it has the legal status "company" can proxy for the availability of external finance and the availability of information about the firm to investors. Similarly, the market scope of a firm can be related to information production, but also to competitiveness in the market and the constant need to be ahead of the competition by innovating. Human capital is expected to have a positive impact not only on the likelihood to innovate, but also on the likelihood of financial constraints due to information asymmetries in firms with substantial intangible assets.

We augment this set of explanatory variables by adding the firm's market share to the $\mathrm{R} \& \mathrm{D}$ and innovation equations and the gross profit margin as a regressor for financial constraints, such that each variable appears in only one
of the two equations of our model. Market share has long been hypothesized to affect firm innovation activities (Scherer, 1984 ; Blundell et al., 1999; Aghion et al., 2005; Cohen, 2010). A firm's gross operating margin is correlated with cash flow and hence with financial constraints (as discussed in Section 2.1) but not directly related to the firm's innovation output unless very long lags are considered (Geroski et al., 1993). ${ }^{6}$ These exclusion restrictions improve the identification of the coefficients of interest, since identification would otherwise rely only on the model's functional form (one exclusion restriction would be sufficient in our model design to remove the reliance on the form of the likelihood function).

### 3.3 Model specification and estimation

We model the interaction between financing constraints and innovation as two simultaneous dynamic equations with concurrent error correlation between equations. This design formally captures the mutual endogeneity of financial constraints and innovation in a structural model that does not prioritize one or the other variable. It also makes it possible to cleanly accommodate two endogenous binary dependent variables in a regression framework. ${ }^{7}$

The UK Innovation Survey's structure enables us to specify a dynamic panel structure, combining several past waves to form a proper panel $(T>2) .{ }^{8}$ Linking four-survey waves allows us, in addition to incorporating first-order dynamics, to use Wooldridge's (2005) approach to address the initial conditions problem in dynamic panels. This modeling approach, in combination with the panel dataset, has the advantage that we can directly address the effects of unobserved firm characteristics. As a result, we can model the entire population of firms regardless of their ex-ante innovation characteristics, such as being a potential innovator, rather than having to exclude non-innovators from the sample that may otherwise induce a spurious positive correlation between innovation and financial constraints that can be observed in cross-sectional studies (Savignac, 2008; Mancusi and Vezzulli, 2014; Pellegrino and Savona, 2017).

The system of equations for observed innovation activities $\left(y_{i t}^{A}\right)$ and financial constraints $\left(y_{i t}^{B}\right)$ is:

$$
\begin{align*}
& y_{i t}^{A}=I\left(X_{i t}^{A} \beta^{A}+\lambda_{A}^{A} y_{i, t-1}^{A}+\lambda_{B}^{A} y_{i, t-1}^{B}+c_{i}^{A}+\sigma_{i t}^{A}>0\right) \\
& y_{i t}^{B}=I\left(X_{i t}^{B} \beta^{B}+\lambda_{B}^{B} y_{i, t-1}^{B}+\lambda_{A}^{B} y_{i, t-1}^{B}+c_{i}^{B}+\sigma_{i t}^{B}>0\right) \tag{1}
\end{align*}
$$

where

$$
\binom{\sigma_{i t}^{A}}{\sigma_{i t}^{B}} \sim N\left[0,\left(\begin{array}{cc}
1 & \rho_{i t}  \tag{2}\\
\rho_{i t} & 1
\end{array}\right)\right]
$$

and $I(\cdot)$ is the indicator function. Exogenous variables $X_{i t}^{A}$ and $X_{i t}^{B}$ could have the same content, since the model would be identified by the assumption that errors are normally distributed. However, we impose exclusion restrictions on both equations to improve identification, using the firm's market share in the first equation that explains innovation activities and the gross operating margin in the financial constraints equation. Coefficients can only be identified up to scale, since error variances need to be normalized to unity as in univariate probit models. Analogous

6 These are also the results obtained from cross-sectional models estimated on our sample (available upon request).
7 We include lagged dependent variables and not contemporaneous ones because the modeling of a simultaneous system of two binary variables is not possible without imposing further restrictions (Lewbel, 2007). In general, for certain values of the error terms the model can have multiple or no solutions. Restricting the support of the errors by ruling out these regions by assumption or imposing constraints on the system that effectively convert it to a recursive (triangular) system does not address the underlying economics of the situation we are trying to model. Furthermore, it seems unlikely that a model with concurrent bidirectional effects will describe an economic process. Tamer (2003) mentions that games with two players that have no Nash equilibrium in pure strategies or multiple equilibria correspond to econometric models with coherency or completeness problems. If the process generating financial constraints and innovation can be described as a game between two players (e.g. firms and investors), there may not be a unique solution to this game (i.e. the actions of the players would not be well defined). However, our model converges to a contemporaneous one if progressively shorter time periods are used for the analysis.
8 Prior studies often lose observations in their attempts to incorporate lagged dependent variables by merging several cross-sections and therefore have to restrict the scope of their analysis to cross-sections (Silva and Carreira, 2012; Hajivassiliou and Savignac, 2016).
to Wooldridge's (2005) panel probit estimator, we add random effects conditional on exogenous variables and initial values of both dependent variables.

These random effects can be written as

$$
\begin{align*}
& c_{i}^{A}=\alpha_{0}^{\mathrm{A}}+\alpha_{1 \mathrm{~A}}^{\mathrm{A}} y_{i 0}^{A}+\alpha_{1 B}^{A} y_{i 0}^{B}+\mathbf{x}_{i}^{A} \boldsymbol{\alpha}_{2}^{\mathrm{A}}+\mathrm{a}_{\mathrm{i}}^{\mathrm{A}} \\
& c_{\mathrm{i}}^{\mathrm{B}}=\alpha_{0}^{\mathrm{B}}+\alpha_{1 \mathrm{~A}}^{\mathrm{B}} \mathrm{y}_{\mathrm{i} 0}^{\mathrm{A}}+\alpha_{1 \mathrm{~B}}^{\mathrm{B}} \mathrm{y}_{\mathrm{i} 0}^{\mathrm{B}}+\mathbf{x}_{\mathrm{i}}^{\mathrm{B}} \boldsymbol{\alpha}_{2}^{\mathrm{B}}+\mathrm{a}_{\mathrm{i}}^{\mathrm{B}}, \tag{3}
\end{align*}
$$

where the row vectors $\mathbf{x}_{i}^{A}$ and $\mathbf{x}_{i}^{B}$ contain past, present and future observations for exogenous variables, as well as time-constant variables. ${ }^{9}$ This implies that the effects of constant firm-specific variables cannot be separately identified, because they would appear in the model both as a main effect and in the conditional mean of the random effects. Random effects are assumed to be independent from the idiosyncratic firm-year error component in equation (1). Their unobserved components are modeled as

$$
\binom{a_{i}^{A}}{a_{i}^{B}} \sim N\left[0,\left(\begin{array}{cc}
\sigma_{a^{A}}^{2} & \sigma_{a^{A}, a^{B}}  \tag{4}\\
\sigma_{a^{A}, a^{B}} & \sigma_{a^{B}}^{2}
\end{array}\right)\right] .
$$

Since the likelihood function for both equations is analytically intractable, we use a maximum simulated likelihood (MSL) method to estimate this system of equations. ${ }^{10}$ The error terms in all estimations are derived from 100 random draws. We tested smaller and larger sets of random errors and found that the added precision in larger samples is tiny compared with the increased computational costs of estimation, which are of the order of several hours per estimation. Standard errors shown in our results are based on the outer product of the gradient method.

## 4. Results

If we want to identify the dynamic effect of financial constraints on innovation and the reverse effect, we need to observe firms that switch from being constrained to unconstrained and from innovation-active to inactive or in the opposite direction. Table 2 shows the pattern of state transitions we observe in the data. A large number of firms remain inactive and unconstrained ("no/no" in the upper left corner in both panels). A plausible island of stability can also be identified for financially unconstrained R\&D performers and innovators (i.e. the "Yes/No" cell). As expected, the most unusual state transitions are firms that are financially constrained but start performing $\mathrm{R} \& \mathrm{D}$ in the next period $(1.4 \%+1.2 \%=2.6 \%)$. However, there are also relatively few firms that perform $R \& D$ in one period and who are constrained and stop their $R \& D$ efforts in the next period $(1.6 \%+1.2 \%=$ $2.8 \%)$. Many firms switch between the constrained and unconstrained states or remain constrained while not performing R\&D or innovating. R\&D and innovation show similar transition probabilities. About $12.9 \%$ of all firm-year transitions are from not performing $R \& D$ to performing, while $12.4 \%$ switch from non-innovating to innovating. When we look at the opposite direction, $11.8 \%$ of $\mathrm{R} \& \mathrm{D}$ performers stop investing in $\mathrm{R} \& \mathrm{D}$, while $14.5 \%$ of innovators stop innovating. Similar magnitudes can be observed for financial constraints, where $15.1 \%$ of firm-year transitions switch into the constrained state, but only $11.5 \%$ become unconstrained. This finding mirrors the economic climate during the sample period, in which credit became more difficult to obtain. Since all cells are occupied by a considerable number of firms, we are confident that a simultaneous bivariate binary model can produce meaningful results.

9 A limitation of our specification of random effects is that the time-varying variables are required to be strictly exogenous, which may not be the case because they may depend on previous realizations of our dependent variables. It is likely that over the medium or long-term innovation and financial constraints will have an impact on, say, turnover. As a result, coefficients for these terms may be subject to bias, the size of which depends on how strongly the timevarying covariates are determined by our dependent variables. Our main focus, however, is on the cross-equation terms (e.g. financial constraints in the innovation equation), which are affected less by endogeneity because they are econometrically further removed from the sources of the endogeneity (through their correlation with the potentially endogenous time-varying variable).
10 Gouriéroux and Monfort (1996) and Train (2009) provide descriptions of estimation techniques and applications.

Table 2. Transition matrices for dependent variables

| Panel A: R\&D <br> R\&D (any)/financial constraints in $t$ | $\mathrm{R} \& \mathrm{D}($ any )/financial constraints in $t+1$ |  |  |  |  |  |  |  | Total | \% |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | No/No | \% | No/Yes | \% | Yes/No | \% | Yes/Yes | \% |  |  |
| No/No | 2514 | 36.2 | 459 | 6.6 | 537 | 7.7 | 179 | 2.6 | 3689 | 53.1 |
| No/Yes | 352 | 5.1 | 237 | 3.4 | 96 | 1.4 | 82 | 1.2 | 767 | 11.0 |
| Yes/No | 476 | 6.8 | 111 | 1.6 | 880 | 12.7 | 303 | 4.4 | 1770 | 25.5 |
| Yes/Yes | 150 | 2.2 | 85 | 1.2 | 193 | 2.8 | 296 | 4.3 | 724 | 10.4 |
| Total | 3492 | 50.2 | 892 | 12.8 | 1706 | 24.5 | 860 | 12.4 | 6950 | 100.0 |

Panel B: Innovation
Innovation (any)/financial constraints in $t+1$


Notes: This table shows the number of transitions between R\&D and financial constraints states during the whole sample period. Each firm has two state variables that correspond to our dependent variables: whether it performs any R\&D (or produces an innovation) and whether it experiences financial constraints in a given CIS round. For example, a firm can perform R\&D and not experience financial constraint in period $t$ ("Yes/No" in leftmost column) and transition to no R\&D, but financial constraints in period $t+1$ (column "No/Yes"). This state transition would add one observation to the cell ("Yes/No" and "No/Yes"). Cells represent the sum of all such transitions over all CIS rounds. The lower panel shows state transitions for the innovation variable that measures whether a firm produces any kind of innovation in period $t$.

### 4.1 R\&D models

Results from the estimation of simultaneous equation models with R\&D and financial constraints (Table 3) reveal high persistence in both indicators over time. Financial constraints do not affect R\&D with the sole exception of a negative effect in our model for external R\&D activities. This finding suggests that external R\&D is more sensitive to changes in the availability of finance than internal R\&D. It is also plausible from the firm's point of view to reduce risky external procurement of R\&D when resources become scarce in favor of more informationally transparent and vital internal R\&D. Firms have been found to smooth their R\&D expenditures by varying their cash holdings (Brown and Petersen, 2011), which explains the limited effect of financial constraints on R\&D in our sample. Because internal R\&D investments have large adjustment costs (Himmelberg and Petersen, 1994; Hall, 2002), as they tend to involve long-term investment in human capital or specialized equipment that cannot easily be sold, external R\&D contracts may be easier to terminate in the event of a liquidity shock. The long-term nature and costsmoothing of most R\&D projects also explains the seeming disparity between firms' positive answer to the survey question on financial constraints (i.e. they admit that financial constraints are important in constraining their innovation activities) and our finding that there is no relationship with most R\&D variables: firms feel constrained in their activities, but they do not stop them altogether. They may, however, curtail expenses for non-vital projects, which tend to be external research projects more often than internal ones.

In line with earlier cross-sectional findings of increased financial constraints in technology firms with high R\&D expenditures (Westhead and Storey, 1997), R\&D increases financial constraints, but only in models using indicators of R\&D activity (models 2 and 6 ), as opposed to R\&D expenditures (models 1, 3, and 5). This suggests that firms engaging in informal ${ }^{11} \mathrm{R} \& D$ activities have greater difficulties in attracting external finance relative to firms that engage in formal R\&D that is, recorded in financial accounts and thus more readily observable by investors than unreported activities. From a theoretical viewpoint, this result supports the interpretation on innovation variables as

11 We refer to"formal" and "informal" R\&D activities as instances of research and development that take place within a firm with or without a specific R\&D budget, respectively. Although "formal" R\&D activities are associated with some expenditures, "informal" activities are not, but the firm may still answer "yes" to the survey question on whether it has performed any R\&D activity in the given period.
Table 3. R\&D: simultaneous equations

| Dependent variable in <br> R\&D equation | R\&D any <br> $($ expenditure $)$ | R\&D any <br> $($ activity $)$ | R\&D external <br> (expenditure) | R\&D external <br> (activity) | R\&D internal <br> $($ expenditure $)$ |
| :--- | :---: | :---: | :---: | ---: | ---: | ---: |
| (activity) |  |  |  |  |  |

Table 3. Continued

| Dependent variable in R\&D equation | $\begin{gathered} \mathrm{R} \& \mathrm{D} \text { any } \\ \text { (expenditure) } \end{gathered}$ | R\&D any (activity) | R\&D external (expenditure) | R\&D external (activity) | R\&D internal (expenditure) | R\&D internal (activity) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Operating margin | $-0.246(0.088) * * *$ | $-0.249(0.088)^{* * *}$ | $-0.246(0.089)^{* * *}$ | $-0.251(0.090) * * *$ | $-0.242(0.088) * * *$ | $-0.253(0.089)^{* * *}$ |
| Age (log) | -0.108 (0.035)*** | $-0.105(0.035)^{* * *}$ | $-0.111(0.036)^{* * *}$ | -0.111 (0.036) ** * | $-0.108(0.035)^{* * *}$ | -0.111 (0.038)*** |
| Group member | $-0.096(0.045)^{* *}$ | -0.101 (0.045)** | -0.099 (0.046)** | $-0.101(0.047)^{* *}$ | -0.099 (0.046)** | -0.111 (0.048)** |
| Company | 0.078 (0.064) | 0.091 (0.065) | 0.084 (0.064) | 0.103 (0.065) | 0.075 (0.064) | 0.084 (0.068) |
| Foreign ownership | -0.007 (0.065) | 0.003 (0.065) | -0.003 (0.066) | 0.003 (0.067) | -0.005 (0.065) | -0.005 (0.069) |
| Time effect CIS6 | $0.551(0.040) * * *$ | $0.555(0.041) * * *$ | $0.551(0.040) * * *$ | $0.551(0.040) * * *$ | $0.551(0.040) * * *$ | $0.560(0.041)^{* * *}$ |
| Time effect CIS7 | 0.445 (0.077)*** | $0.451(0.079) * * *$ | $0.446(0.078) * * *$ | 0.450 (0.078)*** | 0.446 (0.077)*** | 0.466 (0.080)*** |
| Industry effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Wooldridge terms |  |  |  |  |  |  |
| R\&D in CIS4 | 0.115 (0.064)* | 0.060 (0.061) | 0.002 (0.080) | 0.011 (0.074) | $0.154(0.066) * *$ | 0.124 (0.065)* |
| Financial constraints in CIS4 | 0.474 (0.067)*** | $0.455(0.066) * * *$ | $0.494(0.070) * * *$ | $0.500(0.070)^{* * *}$ | $0.473(0.067) * * *$ | 0.515 (0.072)*** |
| Turnover (log), CIS4 | -0.003 (0.015) | -0.001 (0.015) | -0.003 (0.015) | -0.002 (0.015) | -0.003 (0.015) | -0.002 (0.016) |
| Turnover (log), CIS5 | 0.017 (0.039) | 0.020 (0.040) | 0.017 (0.039) | 0.022 (0.039) | 0.017 (0.039) | 0.025 (0.042) |
| Turnover (log), CIS6 | $-0.069(0.030) * *$ | $-0.073(0.031) * *$ | $-0.070(0.031) * *$ | $-0.075(0.031) * *$ | $-0.067(0.030) * *$ | $-0.074(0.032) * *$ |
| Market scope, CIS5 | 0.019 (0.037) | 0.012 (0.038) | 0.023 (0.037) | 0.023 (0.038) | 0.019 (0.037) | 0.016 (0.038) |
| Market scope, CIS6 | -0.095 (0.044)** | -0.102 (0.044)** | $-0.089(0.044) * *$ | -0.085 (0.045)* | -0.095 (0.044)** | $-0.104(0.046)^{* *}$ |
| Market scope, CIS7 | -0.026 (0.018) | -0.028 (0.018) | -0.027 (0.019) | -0.027 (0.019) | -0.026 (0.018) | -0.030 (0.019) |
| Human capital, CIS4 | 0.059 (0.127) | 0.050 (0.128) | 0.083 (0.129) | 0.086 (0.130) | 0.055 (0.126) | 0.064 (0.130) |
| Human capital, CIS5 | 0.248 (0.120)** | 0.264 (0.121)** | 0.257 (0.121)** | 0.268 (0.123)** | 0.249 (0.120)** | $0.263(0.125)^{* *}$ |
| Human capital, CIS6 | 0.083 (0.132) | 0.051 (0.135) | 0.089 (0.134) | 0.090 (0.136) | 0.080 (0.132) | 0.083 (0.140) |
| Operating margin, CIS4 | 0.097 (0.130) | 0.095 (0.133) | 0.076 (0.125) | 0.075 (0.130) | 0.097 (0.129) | 0.100 (0.138) |
| Operating margin, CIS5 | 0.113 (0.124) | 0.117 (0.125) | 0.125 (0.126) | 0.137 (0.128) | 0.111 (0.124) | 0.108 (0.131) |
| Operating margin, CIS6 | 0.030 (0.140) | 0.033 (0.140) | 0.038 (0.140) | 0.029 (0.141) | 0.015 (0.142) | 0.021 (0.149) |
| Error correlation $i, t$ | 0.085 (0.045)** | $0.223(0.044) * * *$ | $0.094(0.046)^{* *}$ | 0.120 (0.049)** | 0.091 (0.047)* | $0.201(0.045)^{* * *}$ |
| Error correlation $i$ | 0.413 (0.240)** | -0.175 (0.347) | 0.442 (0.226)** | 0.506 (0.208)** | 0.365 (0.234) | 0.006 (0.192) |
| SD random effect equation (A) | $0.692(0.083) * * *$ | $0.712(0.079) * * *$ | $0.325(0.114)^{* * *}$ | 0.540 (0.100)*** | $0.735(0.085) * * *$ | $0.760(0.081)^{* * *}$ |
| SD random effect equation (B) | $0.266(0.025)^{* * *}$ | $0.204(0.023) * * *$ | $0.289(0.028) * * *$ | $0.304(0.027)^{* * *}$ | $0.270(0.026) * * *$ | 0.338 (0.030)*** |
| Observations | 6995 | 6930 | 6932 | 6921 | 6995 | 6945 |
| Log-likelihood | -6643 | -6905 | -5414 | -5721 | -6517 | -6839 |
| Wald statistic | 1857 | 1805 | 1474 | 1513 | 1787 | 1742 |
| Wald $P$-value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

[^0]measuring the potential for asymmetric information in a firm's innovation activities because informal R\&D activities may be even harder for external investors to evaluate than those reported in audited financial statements.

There are no regular and systematically strong effects across R\&D indicators for other time-varying variables. In two instances (models 2 and 6), turnover seems to exert a negative effect on the likelihood of a subsequent internal R\&D activity-a possible sign that growing firms slow down R\&D in the following survey period. ${ }^{12}$ Interestingly, time effects in the R\&D equations reflect external macroeconomic conditions. Firms report R\&D activities more frequently for CIS6 (2006-2008) relative to CIS5 (2004-2006), while engagement in R\&D deteriorates significantly during the financial crisis (CIS7 in 2008-2010). This can be explained in the light of the adverse climate in product markets characterizing the last years of our sample period compared with the relatively more favorable climate of 2006 and the best part of 2007. Market demand fluctuations are a more appropriate explanation of these effects relative to the financial environment because we already control for the firms' financing conditions. Foreign ownership is negatively associated with $R \& D$ in 4 (models 1, 2, 5, and 6) out of 6 models, which implies that R\&D investments may be overall closer to the firms' overseas headquarters. ${ }^{13}$ Finally, time-varying market share is positive and weakly significant in only one model, which mirrors the diverse theoretical predictions on the effect of market structure on innovation (Cohen, 2010), although we note that market share as a Wooldridge term positively predicts $\mathrm{R} \& \mathrm{D}$ in most models, as well as in single-variable regressions (see Section 5.1).

Among the determinants of firm financial constraints, besides the role of R\&D, results show negative and significant effects for human capital, operating margin and age-that is, these firm characteristics mitigate financial constraints. The effect of firm age is to be expected because information about older firms is more readily available than for younger firms, thus reducing information asymmetries and consequently the cost of external relative to internal capital. ${ }^{14}$ Firms with higher operating margins tend to have more free cash flow, while belonging to a group may enable firms to access an internal capital market, both of which reduces their dependency on external finance. The apparent negative effect of human capital is instead more difficult to interpret: intangible assets, such as human capital, should in theory aggravate information asymmetries in the market for external capital, and prior cross-sectional evidence points toward an increased likelihood of financial constraints for firms with a high level of human capital (Hottenrott and Peters, 2012). On the one hand, variations in human capital over time seem unable to explain the likelihood of observing R\&D. On the other hand, human capital is positively related to $R \& D$ through unobserved firm effects (Wooldridge terms in the R\&D equation), which explains why we do not find a positive effect for timevarying human capital. Turning to the relationship between human capital and financial constraints, we find that firms with a larger share of employees with a degree are more likely to face financial constraints, but only through unobservable firm characteristics related to human capital. Over time, instead, human capital mitigates financial constraints. A negative effect can be explained if we assume that increasing human capital can lead to higher productivity, which in turn-ceteris paribus-should be associated with growth and therefore more favorable financial prospects. It is also possible that after controlling for the adverse effect of $\mathrm{R} \& \mathrm{D}$ on constraints, human capital, as measured by the ratio of staff with a degree, exerts a residual beneficial effect by helping to overcome information gaps between the firm and potential investors.

12 We acknowledge that there might also be a risk of minor collinearity in this result and in the result we obtain for the human capital variable due to the inclusion of the cross-sectional Wooldridge term in this estimation.
13 It is important to note that the presence of $x_{i}$ in equation (3) prevents us from identifying time-constant variables, because we cannot separate the effect of these variables on both outcome variables from their correlation with the random effects in equation (3). For example, firms owned by a foreign parent seem to perform less internal R\&D. Because the indicator for UK subsidiaries of foreign firms would also enter the conditional distribution of the random effects, including this variable in $X_{i t}$ would cause perfect collinearity with the one in $x_{i}$. Hence, instead of foreign ownership directly causing less R\&D, it might be related to some unobserved quality which in turn is associated with less R\&D without any implication of causality. It might even be the case that less research-intensive businesses are acquired by foreign firms more often.
14 This result must however be interpreted with caution since age is constant across time periods and might also be correlated with unobserved random effects that reduce financial constraints.
Table 4. Innovation: simultaneous equations

| Dependent variable in innovation eqn. | Innovation any | Innovation new to market | Innovation new to firm | Innovation (good) | Innovation (process) | Innovation (service) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Dependent: innovation |  |  |  |  |  |  |
| Innovation (lag) | $0.522(0.075)^{* * *}$ | 0.640 (0.110) *** | $0.450(0.095)^{* * *}$ | 0.546 (0.103)*** | $0.519(0.085)^{* * *}$ | 0.444 (0.092) *** |
| Financial constraints (lag) | 0.007 (0.073) | 0.058 (0.098) | 0.011 (0.079) | 0.003 (0.085) | 0.076 (0.082) | 0.041 (0.080) |
| Turnover (log) (lag) | -0.028 (0.037) | -0.019 (0.065) | 0.000 (0.051) | -0.039 (0.046) | 0.017 (0.040) | -0.060 (0.046) |
| Market scope | 0.115 (0.048)** | 0.130 (0.070)* | 0.009 (0.062) | 0.044 (0.062) | 0.089 (0.057) | 0.068 (0.054) |
| Human capital (lag) | -0.059 (0.144) | 0.064 (0.222) | -0.068 (0.170) | 0.005 (0.178) | -0.055 (0.178) | 0.019 (0.170) |
| Market share (log) (lag) | 0.021 (0.026) | -0.004 (0.034) | 0.000 (0.031) | 0.007 (0.038) | 0.032 (0.030) | -0.025 (0.029) |
| Age (log) | -0.036 (0.039) | -0.058 (0.054) | -0.014 (0.042) | -0.082 (0.048)* | -0.040 (0.046) | -0.033 (0.046) |
| Group member | -0.085 (0.050)* | -0.089 (0.066) | 0.003 (0.053) | -0.019 (0.060) | $-0.107(0.058) *$ | $-0.166(0.056)^{* * *}$ |
| Company | 0.007 (0.064) | 0.105 (0.099) | 0.060 (0.079) | 0.132 (0.091) | -0.060 (0.078) | 0.126 (0.075)* |
| Foreign ownership | 0.012 (0.071) | 0.027 (0.082) | -0.005 (0.074) | -0.007 (0.076) | 0.009 (0.077) | -0.028 (0.080) |
| Time effect CIS6 | $0.103(0.039)^{* * *}$ | $0.351(0.056)^{* * *}$ | -0.048 (0.046) | 0.050 (0.047) | 0.032 (0.047) | -0.017 (0.044) |
| Time effect CIS7 | 0.203 (0.079)** | 0.318 (0.107)*** | 0.016 (0.090) | 0.095 (0.104) | 0.093 (0.088) | 0.032 (0.089) |
| Industry effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Wooldridge terms |  |  |  |  |  |  |
| Innovation in CIS4 | $0.483(0.079)^{* * *}$ | $0.732(0.121)^{* * *}$ | 0.245 (0.089)*** | 0.697 (0.115)*** | $0.386(0.086)^{* * *}$ | $0.591(0.099)^{* * *}$ |
| Financial constraints in CIS4 | 0.098 (0.067) | -0.014 (0.083) | 0.092 (0.072) | 0.052 (0.077) | 0.133 (0.074)* | 0.075 (0.074) |
| Turnover (log), CIS4 | -0.007 (0.018) | 0.006 (0.021) | -0.022 (0.020) | 0.031 (0.023) | -0.007 (0.019) | 0.016 (0.023) |
| Turnover (log), CIS5 | 0.001 (0.049) | -0.036 (0.078) | -0.006 (0.060) | -0.031 (0.061) | -0.072 (0.056) | -0.013 (0.059) |
| Turnover (log), CIS6 | 0.060 (0.040) | 0.066 (0.061) | 0.025 (0.045) | 0.040 (0.052) | $0.136(0.049) * * *$ | 0.103 (0.048)** |
| Market scope, CIS5 | 0.077 (0.040)* | -0.001 (0.056) | 0.087 (0.045)** | 0.051 (0.052) | 0.020 (0.043) | 0.067 (0.046) |
| Market scope, CIS6 | -0.002 (0.042) | 0.047 (0.059) | 0.005 (0.050) | 0.057 (0.054) | 0.025 (0.052) | -0.002 (0.046) |
| Market scope, CIS7 | 0.013 (0.026) | 0.031 (0.032) | 0.003 (0.028) | 0.044 (0.030) | 0.009 (0.029) | 0.003 (0.029) |
| Human capital, CIS4 | 0.095 (0.143) | 0.023 (0.178) | 0.208 (0.157) | 0.194 (0.173) | -0.038 (0.158) | 0.068 (0.159) |
| Human capital, CIS5 | -0.019 (0.126) | -0.088 (0.196) | -0.103 (0.142) | -0.062 (0.149) | 0.164 (0.149) | -0.063 (0.146) |
| Human capital, CIS6 | $0.376(0.143)^{* * *}$ | $0.522(0.184) * * *$ | 0.071 (0.155) | 0.218 (0.170) | 0.216 (0.163) | 0.490 (0.157)*** |
| Market share (log), CIS4 | 0.031 (0.031) | 0.050 (0.042) | 0.022 (0.035) | 0.044 (0.043) | 0.057 (0.037) | 0.038 (0.035) |
| Market share (log), CIS5 | -0.015 (0.030) | -0.004 (0.039) | 0.014 (0.032) | -0.003 (0.037) | -0.072 (0.039)* | -0.003 (0.033) |
| Market share (log), CIS6 | 0.027 (0.012)** | 0.040 (0.017)** | 0.011 (0.013) | $0.047(0.015)^{* * *}$ | 0.014 (0.014) | $0.027(0.013)^{* *}$ |
| Dependent: financial constraints |  |  |  |  |  |  |
| Innovation (lag) | 0.051 (0.069) | $0.202(0.092)^{* *}$ | -0.042 (0.083) | 0.060 (0.086) | 0.128 (0.075)* | 0.063 (0.076) |
| Financial constraints (lag) | $0.500(0.069)^{* * *}$ | $0.459(0.075) * * *$ | 0.473 (0.075)*** | $0.484(0.073) * * *$ | $0.512(0.067) * * *$ | 0.498 (0.066)*** |
| Turnover (log) (lag) | 0.052 (0.037) | 0.047 (0.037) | 0.046 (0.038) | 0.050 (0.038) | 0.052 (0.037) | 0.057 (0.037) |
| Market scope | 0.110 (0.050)** | 0.105 (0.050)** | 0.108 (0.051)** | 0.110 (0.051)** | 0.105 (0.050)** | 0.111 (0.051)** |
| Human capital (lag) | -0.270 (0.142)* | -0.281 (0.141)** | -0.276 (0.142)* | -0.263 (0.141)* | $-0.276(0.141)^{* *}$ | -0.270 (0.143)* |
| Operating margin | -0.234 (0.089)*** | $-0.244(0.090)^{* * *}$ | $-0.241(0.089)^{* * *}$ | -0.245 (0.088)*** | $-0.231(0.087)^{\text {**** }}$ | $-0.237(0.087)^{* * *}$ |

Table 4. Continued

| Dependent variable in innovation eqn. | Innovation any | Innovation new to market | Innovation new to firm | Innovation (good) | Innovation (process) | Innovation (service) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Age (log) | $-0.102(0.035)^{* * *}$ | $-0.107(0.036)^{* * *}$ | -0.113 (0.037)*** | -0.106 (0.036) *** | $-0.108(0.035)^{\text {\%***}}$ | -0.110 (0.035) *** |
| Group member | $-0.101(0.045)^{* *}$ | -0.105 (0.046)** | -0.104 (0.047)** | $-0.106(0.046)^{* *}$ | $-0.095(0.045)^{* *}$ | $-0.097(0.045)^{* *}$ |
| Company | 0.097 (0.064) | 0.102 (0.066) | 0.103 (0.067) | 0.087 (0.065) | 0.093 (0.063) | 0.087 (0.064) |
| Foreign ownership | 0.002 (0.065) | 0.008 (0.067) | -0.003 (0.067) | -0.001 (0.066) | 0.000 (0.064) | 0.000 (0.065) |
| Time effect CIS6 | $0.554(0.040)^{* * *}$ | $0.569(0.041)^{* * *}$ | $0.560(0.040)^{* * *}$ | $0.557(0.040$ )*** | $0.555(0.040) * * *$ | 0.549 (0.039)*** |
| Time effect CIS7 | $0.451(0.078)$ *** | 0.460 (0.079)*** | 0.457 (0.079)*** | 0.448 (0.079)*** | $0.450(0.078) * * *$ | 0.446 (0.077)*** |
| Industry effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Wooldridge terms |  |  |  |  |  |  |
| Innovation in CIS4 | 0.090 (0.057) | 0.017 (0.076) | 0.033 (0.071) | 0.118 (0.073) | 0.027 (0.060) | 0.056 (0.066) |
| Financial constraints in CIS4 | 0.460 (0.065) *** | $0.497(0.073) * * *$ | $0.499(0.073)$ *** | $0.485(0.071)^{* * *}$ | $0.455(0.066)^{* * *}$ | $0.466(0.065)^{* * *}$ |
| Turnover (log), CIS4 | -0.006 (0.015) | -0.006 (0.015) | -0.007 (0.015) | -0.005 (0.015) | -0.005 (0.015) | -0.002 (0.015) |
| Turnover (log), CIS5 | 0.017 (0.038) | 0.018 (0.039) | 0.020 (0.040) | 0.021 (0.039) | 0.018 (0.039) | 0.016 (0.038) |
| Turnover (log), CIS6 | -0.072 (0.030)** | -0.064 (0.031)** | $-0.062(0.031)^{* *}$ | $-0.072(0.031) * *$ | $-0.074(0.030)^{* *}$ | $-0.073(0.030) * *$ |
| Market scope, CIS5 | 0.014 (0.037) | 0.019 (0.038) | 0.025 (0.038) | 0.017 (0.037) | 0.017 (0.036) | 0.017 (0.037) |
| Market scope, CIS6 | -0.091 (0.044)** | $-0.096(0.044) * *$ | $-0.089(0.045)^{* *}$ | $-0.096(0.044) * *$ | -0.085 (0.043)* | -0.090 (0.044)** |
| Market scope, CIS7 | -0.028 (0.018) | -0.030 (0.019) | -0.031 (0.019)* | -0.027 (0.019) | -0.028 (0.018) | -0.029 (0.018) |
| Human capital, CIS4 | 0.057 (0.125) | 0.068 (0.129) | 0.081 (0.129) | 0.079 (0.127) | 0.075 (0.124) | 0.071 (0.125) |
| Human capital, CIS5 | 0.244 (0.119)** | 0.249 (0.121)** | 0.256 (0.122)** | 0.239 (0.120)** | 0.253 (0.118)** | 0.248 (0.119)** |
| Human capital, CIS6 | 0.086 (0.130) | 0.040 (0.136) | 0.059 (0.137) | 0.088 (0.132) | 0.079 (0.129) | 0.074 (0.132) |
| Operating margin, CIS4 | 0.088 (0.136) | 0.106 (0.142) | 0.090 (0.126) | 0.096 (0.138) | 0.084 (0.130) | 0.089 (0.133) |
| Operating margin, CIS5 | 0.101 (0.123) | 0.125 (0.129) | 0.125 (0.127) | 0.111 (0.122) | 0.114 (0.123) | 0.102 (0.120) |
| Operating margin, CIS6 | -0.008 (0.141) | 0.014 (0.146) | 0.015 (0.144) | 0.006 (0.147) | 0.004 (0.140) | 0.000 (0.141) |
| Error correlation $i, t$ | $0.145(0.041)^{* * *}$ | 0.079 (0.052) | $0.149(0.043)^{* * *}$ | $0.161(0.048)$ *** | $0.141(0.045)^{* * *}$ | $0.119(0.045)^{* * *}$ |
| Error correlation $i$ | 0.461 (0.303) | 0.138 (0.297) | 0.150 (0.329) | 0.249 (0.316) | 0.250 (0.373) | 0.512 (0.345) |
| SD random effect equation (A) | 0.510 (0.077)*** | $0.504(0.110)^{* * *}$ | 0.334 (0.101)*** | $-0.497(0.101)^{* * *}$ | $0.538(0.087)^{* * *}$ | $-0.540(0.085)^{* * *}$ |
| SD random effect equation (B) | $0.238(0.024)^{* * *}$ | $0.309(0.030)^{* * *}$ | $0.313(0.030)^{* * *}$ | 0.283 (0.029)*** | $0.211(0.023) * * *$ | 0.249 (0.024)*** |
| Observations | 6973 | 6910 | 6906 | 6982 | 6986 | 6975 |
| Log-likelihood | -7100 | -5353 | -5911 | -5926 | -6195 | -6354 |
| Wald statistic | 1863 | 1421 | 1003 | 1846 | 1435 | 1439 |
| Wald $P$-value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

[^1]
### 4.2 Innovation models

The results generated by models with innovation measures (Table 4) reveal that not only R\&D but also innovation is highly persistent through time and across indicators. The introduction of new goods, new services, and new processes as well as products that are new to the firm or new to the market is strongly related to past success at innovating.

Financial constraints do not appear to affect the likelihood of innovating. Coefficients for all types of innovation are far from being significant. As is the case in R\&D models, this finding suggests that firms do not abandon their innovation programs altogether in response to potentially short-lived difficulties in raising finance. Among the variables that exert a significant effect on innovation, market scope has a positive effect, which suggests that operations on a larger market favor innovation, and in particular new-to-market innovation. Being part of a group seems instead to impede service innovation (model 6), a possible sign that service innovation is highly concentrated within few units in large service firms or that being part of a group constrains firms' interaction with final users and their ability to change the process of service delivery. Finally, firms seem to have been relatively more innovative during the period 2006-2010. Both time effects are positive for new-to-market innovations (models 1 and 2). This could indicate an effect of the time lag between R\&D and innovation: adverse financial market conditions affect the firms' financial situation immediately, as reflected in time effects, but have a delayed impact on $\mathrm{R} \& \mathrm{D}$ investment, which in turn is translated into innovation with a time lag. ${ }^{15}$

Although financial constraints do not affect innovation, inspection of the results for the financial constraints equation in Table 4 reveals that some types of innovation aggravate financial constraints. We find positive coefficients for new-to-market innovation (model 2)—in line with Hottenrott and Peters' (2012) cross-sectional evidence—and for new processes (model 5). All coefficients for innovations are positive with the exception of new products that are only new to the firm, which suggests that only the introduction of tried and tested products may be welcomed by external investors and by the market as well. From an agency perspective, this makes sense: it seems unlikely that new products and services, which are readily available for inspection by investors, should introduce asymmetries in financing relations that could lead to financial constraints. ${ }^{16}$

These findings can be interpreted as an indication of financing needs not met by external sources of capital. It is indeed interesting to see that the indicators of innovation that affect financial constraints correspond to the riskiest and most capital-intensive innovations: new-to-market innovations. This is compatible with the view that financial pressures increase in firms facing the costs associated with the scaling-up of production, the expansion of logistics operations and the early market diffusion of their new products. It is also possible that given the high variability in the quality of innovations, financial pressures increase because the market does not always respond positively to the introduction of new products. It is important to stress, however, that models in Table 4 employ innovation outputs as indicators for general innovative activities and thus might capture aspects of informationally opaque R\&D projects that cause financial constraints. From an investor's point of view, innovation-by-imitation (innovation new only to the firm) should be more transparent than less readily inspected types of innovations. The interpretation that R\&D projects feed into new products which are then correlated with financial constraints is also compatible with our results.

### 4.3 Unobserved heterogeneity in R\&D and innovation

The inclusion of cross-sectional variables in our specifications of random effects provides some estimation benefits and offers insights into unobserved firm characteristics. Controlling for initial conditions through Wooldridge (2005)

15 An alternative explanation is that firms had to introduce new products to adapt to changes in demand.
16 It is possible that the innovation survey design allows for the presence of some noise in the default category of the new-to-firm innovation indicator. A product that is new to the market could be considered by default also new to the firm. There could be the case of a new release of a product that the firm is already producing, while other firms are not. Finally, a respondent can answer affirmatively to both the new-to-the-firm and new-to-market questions for the same innovation or for two different innovations. It is very difficult to disentangle from one another these different scenarios on the basis of the standard questionnaire, but it remains true that new-to-market innovations are always a minority relative to new-to-firm innovation in the population of innovation-active firms and the presence of some noise in the measurement of this variable is unlikely to jeopardize the estimation results, as confirmed by the test on the 'any innovation' indicator in column 1, which is insignificant despite the significant result for new-to-market innovations in column 2.

Table 5. Financial constraints predict firm death

|  | 1 | 2 | 3 | 4 |
| :--- | :---: | :---: | :---: | ---: |
| Financial constraints (lag) | $0.266(0.065)^{* * *}$ | $0.294(0.065)^{* * *}$ | $0.290(0.065)^{* * *}$ | $0.288(0.065)^{* * *}$ |
| R\&D any (activity) |  | $-0.205(0.074)^{* *}$ |  |  |
| R\&D any (expenditure) |  | $-0.203(0.081)^{* *}$ | $-0.158(0.073)^{*}$ |  |
| Innovation (any) |  |  |  | $-0.157(0.030)^{* * *}$ |
| Turnover (log) (lag) | $-0.160(0.030)^{* * *}$ | $-0.155(0.030)^{* * *}$ | $-0.156(0.030)^{* * *}$ | $-0.042(0.034)$ |
| Market scope | $-0.058(0.033)$ | $-0.041(0.034)$ | $-0.049(0.033)$ |  |
| Human capital (lag) | $-0.033(0.139)$ | $0.013(0.138)$ | $-0.001(0.138)$ | $-0.020(0.138)$ |
| Market share (log) (lag) | $0.051(0.258)$ | $0.054(0.257)$ | $0.050(0.258)$ | $0.059(0.257)$ |
| Operating margin | $-0.011(0.023)$ | $-0.010(0.023)$ | $-0.010(0.023)$ | $-0.011(0.023)$ |
| Age (log) | $-0.292(0.053)^{* * *}$ | $-0.294(0.053)^{* * * *}$ | $-0.294(0.053)^{* * *}$ | $-0.294(0.054)^{* * *}$ |
| Group member | $0.012(0.074)$ | $0.011(0.074)$ | $0.013(0.074)$ | $0.007(0.074)$ |
| Company | $-0.005(0.085)$ | $-0.007(0.085)$ | $-0.005(0.085)$ | $-0.010(0.085)$ |
| Foreign ownership | $0.079(0.129)$ | $0.071(0.130)$ | $0.069(0.130)$ | $0.083(0.130)$ |
| Time effect CIS6 | $0.027(0.063)$ | $0.032(0.063)$ | $0.028(0.063)$ | $0.026(0.063)$ |
| Time effect CIS7 | $-0.184(0.180)$ | $-0.209(0.181)$ | $-0.203(0.181)$ | $-0.190(0.181)$ |
| Industry effects | Yes | Yes | Yes | Yes |
| Observations | 9978 | 9978 | 9978 | 9978 |
| McFadden Pseudo- $R^{2}$ (adjusted) | 0.072 | 0.075 | 0.075 | 0.074 |
| Log-likelihood | -990.646 | -986.678 | -987.348 | -988.185 |

Notes: This table presents pooled probit regressions predicting whether a firm exits the BSD. Standard errors are shown in parentheses. Significance levels: ***P<0.01, **P<0.05, and *P<0.1.
terms in both equations contributes to the identification of sensible and stable coefficients but reduces many significant coefficients found in univariate models (see Tables 7 and 8 in Section 5.1). Our modeling strategy thus reduces the likelihood of spurious results that are due to unobserved heterogeneity. For example, initial conditions of R\&D, innovation and financial constraints (i.e. in CIS4, corresponding to the first two lines under Wooldridge terms in Tables 3 and 4), which enter the conditional distribution of random effects in equation (3), turn out to be highly significant and positive in the R\&D and financial constraints equations. This finding also suggests that future research might benefit from investigating the unobservables that link a firm's financial environment and its innovation capabilities.

The inclusion of initial states for both outcomes in both equations, while retaining first-order dynamics, offers further insights into unobservable firm characteristics. Consider the positive coefficients for initial R\&D conditions ("R\&D in CIS4") in the financial constraints equation in Table 3 (models 1 , 5 , and 6). Initial R\&D activities are positively correlated with unobservables related to financial constraints, while time-varying R\&D itself ("R\&D [lag]") is also significant two models (2 and 6). This suggests that both current R\&D activities and being a latent R\&D performer-interpreted as a firm effect-could lead to financial constraints. For firms that do not show any R\&D activity in a period, nothing may have changed in the underlying characteristics of the firm, although it temporarily does not seem to perform any R\&D activities. Capital market participants may thus be able to distinguish R\&D performers, including those in a latent R\&D-performing state without visible activities, from non-performers.

Similarly, success at innovating as a firm effect does not affect financial constraints ("Innovation in CIS4" in the financial constraints equation in Table 4), as would be expected under standard agency theory, because innovation in itself does not cause information asymmetries. Another interpretation is that there is no such thing as a latent innovation state that is, there is no firm effect for innovation that adds to the overall firm random effect in the financial constraints equation. Innovations might be entirely random conditional on our observed variables. These interpretations are available under the normal interpretation of the financial constraints variable, that is to say a differential between external and internal financing costs and therefore a shortage of external funds. New-to-market innovations increase financial constraints, because these are more fundamental innovations that carry a greater risk of information asymmetries. In addition to this conventional explanation, we can interpret the survey question on constraints in more general terms as a signal of the demand for finance that usually follows successful innovations. Firms

Table 6. Comparison of financially constrained and unconstrained firms

| Variable |  |  |  |  |
| :--- | :--- | :--- | :--- | :--- |
|  |  |  | Mean |  |

This table shows mean comparisons for financially constrained and unconstrained firms using the full set of observations from CIS4 to CIS7. We use a two-sided two-sample t-test assuming unequal variances for turnover, market scope, human capital, operating margin, market share and age. Tests of differences in proportions for all other variables are two-sided tests using the large-sample normal approximation to the binomial test.
Significance: ${ }^{* * *} P<0.01,{ }^{* *} P<0.05$, and ${ }^{*} P<0.1$.
introducing novel products may find it necessary to approach external capital markets for expansion financing (ramping up production and marketing). This increase in the demand for finance, if unmet, produces a higher likelihood of financial constraints as detected in the Innovation Survey data.

Overall, innovation success in the previous period is more important for future innovation success than past R\&D is for future R\&D when compared with the importance of initial conditions. In other words, coefficients for lagged innovation are about as large as coefficients for initial innovation conditions ("Innovation at CIS4"), while initial R\&D conditions have a much stronger effect on future R\&D activities than lagged R\&D. This again suggests that there are unobserved firm characteristics that predispose firms to constantly perform R\&D. Innovation, on the
other hand, depends less on constant firm characteristics, but rather on past success in innovating. In general, the link between innovation outcomes and financial constraints appears weaker than the one between R\&D and financial constraints. Although both indicators for inputs or outputs in the innovation process explain financial constraints, the relationship through cross-equation correlation and random effects is considerably weaker. Initial conditions of innovation and financial constraints in one equation are not significant in the other in Table $4 .{ }^{17}$ Hence, unobserved firm heterogeneity in one variable seems to be unrelated to the other. The substantial correlation in unobserved firm effects nevertheless suggests the presence of unobserved firm characteristics that explain both innovation and financial constraints.

### 4.4 Financial constraints and firm exit

Our classification of firms into financially constrained and unconstrained is based on firms' answers to a question in the CIS about whether "availability of finance" constitutes a barrier to innovation. Because of the nature of the survey, this variable is self-reported and may be seen as subjective. The design of our financial constraints measure reflects the qualitative approach of Hoberg and Maksimovic (2015), who employ content analysis to extract information about financial constraints from 10-K statements and find that their index based on disclosures about capitalization and liquidity predicts R\&D and capital expenditures. In line with this approach, and consistently with other studies of financial constraints that use qualitative measures (Kaplan and Zingales, 1997; Whited and Wu, 2006; Hadlock and Pierce, 2010), our results show that financial constraints are more severe in firms that are young, small, and have relatively little cash flow.

A stronger confirmation of the external validity of our financial constraint indicator would be its ability to predict outcomes associated with financial constraints external to the survey. Firms that report constraints are expected to face bankruptcy or cease paying dividends more often than those that do not report constraints (Kaplan and Zingales, 2000). Therefore, a good measure of financial constraints should predict a firm's death. The BSD of the ONS includes demographic events, unlike the CISs, and we can match these data to our main dataset. Firm death is defined within the BSD as the year in which a firm leaves the Inter-Departmental Business Register, a database which is used by UK government for tax and statistical purposes and provides the main sampling frame for surveys carried out by the Office for National Statistics. We construct an indicator for firm death from the BSD year of death for the three-year period following each CIS wave (e.g. we register firm death for the period 2008-2010 and relate it to variables measured in the CIS wave 2006-2008). To estimate the likelihood of firm death, we employ pooled-sample probit models using the full set of CIS firms for which all dependent variables are observed. Out of 5984 enterprises in a sample of 9987 firm-years spanning three CIS waves (death predicted for CIS6-CIS8), 229 firms can be verified as leaving the sample.

Results of these probit models shown in Table 5 suggest a strong effect of self-reported financial constraints on firm death, despite the loss of demographic events in the matching process. Turnover and firm age are negatively related to firm death, which is expected if informational asymmetries or financial distress indeed drive survey responses to the question about the availability of finance. When we include measures of R\&D and innovation in models $2-4$, results reveal a positive effect of $R \& D$ activities, $R \& D$ expenditures and innovation on firm survival. Interestingly, informal R\&D activities predict firm death better than innovation outcomes. Correlation among R\&D and innovation variables prevents them from becoming significant if all measures are included simultaneously, but a top-down approach starting with a full model and removing insignificant measures of $\mathrm{R} \& \mathrm{D}$ and innovation one by one (results not reported here) suggests that informal internal R\&D activities contribute most to firm survival.

Although we choose the indicator for financial constraints based on the theoretical argument that the availability of external finance will differ if agency costs drive a wedge between internal and external financing costs, in practice firms that are financially constrained often look like financially distressed firms. Distress firms may have access to finance, albeit at a high cost reflecting its business and balance sheet. It is likely that our measure of financial constraints picks up aspects of both financial constraint and financial distress.

Table 6 shows a comparison between firms that perceive financial constraints and those that do not according to our measure. The comparison shows that financially constrained firms are typically less profitable, smaller, younger,

17 With the exception of process innovation, where we find a slightly significant cross-equation effect of initial conditions.
Table 7. R\&D: panel probit models

| Model | $\begin{gathered} \mathrm{R} \& \mathrm{D} \text { any } \\ \text { (expenditure) } \end{gathered}$ | R\&D any (activity) | R\&D external (expenditure) | R\&D external (activity) | R\&D internal (expenditure) | R\&D internal (activity) | Financial constraints |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| R\&D any (expenditure) (lag) | $1.071(0.038) * * *$ |  |  |  |  |  | $0.171(0.040)^{* * *}$ |
| R\&D any (activity) (lag) |  | $1.030(0.037)^{* * *}$ |  |  |  |  |  |
| R\&D external (expenditure) (lag) |  |  | $1.015(0.054) * * *$ |  |  |  |  |
| R\&D external (activity) (lag) |  |  |  | $0.974(0.049) * * *$ |  |  |  |
| R\&D internal (expenditure) (lag) |  |  |  |  | $1.103(0.039)^{* * *}$ |  |  |
| R\&D internal (activity) (lag) |  |  |  |  |  | $1.052(0.037)^{* * *}$ |  |
| Fin. constraints (lag) | 0.087 (0.043)** | 0.056 (0.042) | -0.002 (0.053) | -0.002 (0.049) | $0.097(0.044)^{* *}$ | 0.081 (0.042)* | $0.802(0.039)$ *** |
| Turnover (log) (lag) | 0.033 (0.015)** | 0.021 (0.015) | 0.040 (0.019)** | $0.056(0.018)^{* * *}$ | 0.026 (0.016) | 0.016 (0.015) | -0.002 (0.012) |
| Market scope | $0.192(0.019)$ *** | $0.184(0.018) * * *$ | $0.137(0.024)^{* * *}$ | 0.140 (0.022)*** | 0.197 (0.019)*** | 0.193 (0.018)*** | 0.034 (0.019)* |
| Human capital (lag) | 0.328 (0.080)*** | 0.291 (0.079)*** | 0.161 (0.098)** | 0.172 (0.091)** | $0.311(0.081)^{* * *}$ | 0.270 (0.079)*** | -0.012 (0.080) |
| Market share (log) (lag) | 0.042 (0.013)*** | $0.054(0.012)^{* * *}$ | $0.060(0.016)^{* * *}$ | $0.047(0.015)^{* * *}$ | 0.041 (0.013)*** | 0.051 (0.012)*** |  |
| Operating margin |  |  |  |  |  |  | $-0.441(0.141) * * *$ |
| Age (log) | -0.018 (0.034) | -0.024 (0.032) | -0.040 (0.043) | -0.074 (0.039)* | -0.021 (0.035) | -0.021 (0.033) | $-0.129(0.032) * * *$ |
| Group member | -0.019 (0.042) | -0.024 (0.041) | 0.087 (0.052)* | 0.044 (0.048) | -0.040 (0.043) | -0.046 (0.041) | $-0.106(0.042)^{* *}$ |
| Company | 0.089 (0.062) | 0.035 (0.057) | 0.042 (0.084) | -0.022 (0.075) | 0.102 (0.063) | 0.038 (0.058) | 0.001 (0.058) |
| Foreign ownership | -0.194 (0.059)*** | -0.091 (0.058) | -0.064 (0.067) | 0.013 (0.063) | $-0.187(0.060)^{* * *}$ | -0.111 (0.058)* | -0.011 (0.059) |
| Time effect CIS6 | $0.082(0.037)^{* *}$ | $0.106(0.036)^{* * *}$ | $-0.100(0.047)^{* *}$ | -0.024 (0.043) | 0.083 (0.038)** | 0.113 (0.036)*** | $0.537(0.037)^{* * *}$ |
| Time effect CIS7 | $-0.180(0.067)^{* * *}$ | -0.292 (0.065)*** | $-0.183(0.080)^{* *}$ | -0.170 (0.076)** | -0.196 (0.069)*** | -0.297 (0.066)*** | 0.339 (0.066)*** |
| Industry effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| SD ( $u_{i}$ ) | 0.002 | 0.003 | 0.001 | 0.002 | 0.002 | 0.003 | 0.001 |
| $P$-value for $u_{i}$ | 0.489 | 0.489 | 0.495 | 0.494 | 0.488 | 0.490 | 0.493 |
| Observations | 7074 | 7003 | 7074 | 6991 | 7074 | 7017 | 6995 |
| Log-likelihood | -3256 | -3554 | -1964 | -2335 | -3127 | -3483 | -3559 |
| $\chi^{2}$ test | 1769 | 1804 | 697 | 834 | 1786 | 1807 | 721 |
| $P$-value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

[^2]Table 8. Innovation: panel probit models

| Model | Innovation any | Innovation new to market | Innovation new to firm | Innovation (good) | Innovation (process) | Innovation (service) | Financial constraints |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Innovation (any) (lag) | $0.910(0.035)^{* * *}$ |  |  |  |  |  | $0.147(0.038)^{* * *}$ |
| Innovation new to market (lag) |  | $1.194(0.053)^{* * *}$ |  |  |  |  |  |
| Innovation new to firm (lag) |  |  | $0.648(0.063) * * *$ |  |  |  |  |
| Innovation (good) (lag) |  |  |  | $1.063(0.045)^{* * *}$ |  |  |  |
| Innovation (process) (lag) |  |  |  |  | $0.826(0.052) * * *$ |  |  |
| Innovation (service) (lag) |  |  |  |  |  | $0.909(0.043) * * *$ |  |
| Financial constraints (lag) | $0.106(0.041) * * *$ | 0.082 (0.052) | 0.087 (0.047)* | 0.059 (0.047) | $0.159(0.047)^{* * *}$ | $0.129(0.044)^{* * *}$ | $0.795(0.040)^{* * *}$ |
| Turnover (log) (lag) | 0.007 (0.015) | 0.006 (0.019) | 0.000 (0.017) | -0.007 (0.017) | 0.047 (0.017) *** | 0.015 (0.016) | -0.001 (0.012) |
| Market scope | 0.168 (0.018)*** | 0.169 (0.024)*** | $0.092(0.021)^{* * *}$ | $0.152(0.021)^{* * *}$ | 0.116 (0.022)*** | 0.120 (0.020)*** | 0.037 (0.019)** |
| Human capital (lag) | 0.166 (0.077)** | $0.267(0.096)^{* * *}$ | 0.049 (0.092) | 0.191 (0.092)** | $0.180(0.089)$ ** | $0.242(0.082) * * *$ | -0.007 (0.080) |
| Market share (log) (lag) | 0.043 (0.012)*** | $0.038(0.016)$ ** | $0.030(0.014)^{* *}$ | 0.043 (0.014)*** | $0.032(0.014)^{* *}$ | 0.017 (0.013) |  |
| Operating margin |  |  |  |  |  |  | $-0.447(0.142)^{* * *}$ |
| Age (log) | -0.055 (0.032)* | -0.062 (0.043) | -0.026 (0.038) | $-0.090(0.038) * *$ | -0.051 (0.038) | -0.046 (0.035) | $-0.122(0.032) * * *$ |
| Group member | -0.040 (0.040) | -0.041 (0.053) | 0.011 (0.048) | 0.013 (0.048) | -0.073 (0.048) | -0.103 (0.044)** | -0.107 (0.042)** |
| Company | -0.018 (0.056) | 0.074 (0.084) | 0.044 (0.069) | 0.080 (0.076) | -0.068 (0.069) | 0.088 (0.062) | 0.014 (0.058) |
| Foreign ownership | 0.019 (0.056) | 0.023 (0.068) | 0.007 (0.065) | 0.001 (0.063) | 0.020 (0.064) | -0.003 (0.062) | -0.017 (0.060) |
| Time effect CIS6 | $0.109(0.036)^{* * *}$ | $0.351(0.049)$ *** | -0.051 (0.042) | 0.035 (0.042) | 0.037 (0.042) | -0.040 (0.039) | 0.541 (0.037) *** |
| Time effect CIS7 | 0.129 (0.062)** | 0.230 (0.081)*** | -0.025 (0.074) | -0.018 (0.075) | 0.059 (0.071) | -0.065 (0.068) | 0.349 (0.066)*** |
| Industry effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| SD (u) | 0.005 | 0.001 | 0.105 | 0.001 | 0.260 | 0.003 | 0.002 |
| $P$-value for $u$ | 0.486 | 0.495 | 0.413 | 0.495 | 0.086 | 0.490 | 0.490 |
| Observations | 7052 | 6981 | 6977 | 7061 | 7064 | 7055 | 6975 |
| Log-likelihood | -3704 | -1960 | -2498 | -2502 | -2751 | -2948 | -3551 |
| $\chi^{2}$ test | 1386 | 1019 | 251 | 1515 | 817 | 757 | 715 |
| $P$-value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

[^3]Table 9. R\&D: simultaneous equations (Mundlak estimator)

| Model | R\&D any <br> $($ expenditure $)$ | R\&D any <br> (activity) | R\&D external <br> (expenditure) | R\&D external <br> (activity) | R\&D internal <br> (expenditure) |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| (activity) |  |  |  |  |  |

Table 9. Continued
$\left.\begin{array}{lccccc}\hline \text { Model } & \begin{array}{c}\text { R\&D any } \\ \text { (expenditure) }\end{array} & \begin{array}{c}\text { R\&D any } \\ \text { (activity) }\end{array} & \begin{array}{c}\text { R\&D external } \\ \text { (expenditure) }\end{array} & \begin{array}{c}\text { R\&D external } \\ \text { (activity) }\end{array} & \begin{array}{c}\text { R\&D internal } \\ \text { (expenditure) }\end{array} \\ \hline \text { Mundlak terms } & & & & & \\ \text { R\&D in CIS4 } & & & & \\ \text { (activity) }\end{array}\right]$

[^4]Table 10. Innovation: simultaneous equations (Mundlak estimator)

| Model | Innovation any | Innovation new to market | Innovation new to firm | Innovation (good) | Innovation (process) | Innovation (service) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Dependent: innovation |  |  |  |  |  |  |
| Innovation (lag) | 0.519 (0.075)*** | $0.636(0.110)^{* * *}$ | $0.453(0.093)^{* * *}$ | $0.600(0.097) * * *$ | 0.523 (0.084)*** | $0.518(0.088) * * *$ |
| Financial constraints (lag) | 0.004 (0.073) | 0.055 (0.097) | 0.012 (0.079) | 0.075 (0.084) | 0.054 (0.082) | -0.015 (0.073) |
| Turnover (log) (lag) | -0.017 (0.039) | -0.005 (0.067) | 0.005 (0.054) | -0.032 (0.050) | 0.019 (0.040) | -0.041 (0.048) |
| Market scope | 0.094 (0.049)* | 0.098 (0.073) | -0.005 (0.062) | 0.022 (0.061) | 0.084 (0.056) | 0.027 (0.053) |
| Human capital (lag) | -0.121 (0.141) | -0.072 (0.207) | -0.043 (0.162) | -0.011 (0.171) | -0.081 (0.166) | -0.068 (0.160) |
| Market share (log) (lag) | 0.016 (0.028) | 0.008 (0.036) | -0.010 (0.032) | 0.000 (0.037) | 0.015 (0.031) | -0.020 (0.029) |
| Age (log) | -0.042 (0.039) | -0.065 (0.054) | -0.018 (0.042) | -0.081 (0.046)* | -0.047 (0.046) | -0.035 (0.044) |
| Group member | -0.083 (0.050)* | -0.081 (0.067) | 0.006 (0.053) | -0.004 (0.057) | -0.104 (0.057)* | -0.149 (0.054) *** |
| Company | -0.011 (0.064) | 0.085 (0.098) | 0.049 (0.078) | 0.099 (0.087) | -0.072 (0.077) | 0.109 (0.071) |
| Foreign ownership | 0.019 (0.070) | 0.030 (0.082) | -0.007 (0.074) | -0.011 (0.072) | 0.017 (0.077) | -0.024 (0.074) |
| Time effect CIS6 | $0.103(0.039) * * *$ | $0.354(0.055)^{* * *}$ | -0.046 (0.046) | 0.053 (0.046) | 0.034 (0.046) | -0.020 (0.044) |
| Time effect CIS7 | 0.151 (0.072)** | 0.261 (0.098)*** | -0.001 (0.081) | 0.014 (0.092) | 0.079 (0.080) | -0.028 (0.080) |
| Industry effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Mundlak terms |  |  |  |  |  |  |
| R\&D in CIS4 | $0.484(0.079) * * *$ | $0.737(0.121)^{* * *}$ | 0.247 (0.088) *** | 0.633 (0.108)*** | $0.383(0.086)^{* * *}$ | $0.522(0.093)^{* * *}$ |
| Financial constraints in CIS4 | 0.095 (0.067) | -0.018 (0.083) | 0.091 (0.072) | -0.001 (0.074) | 0.142 (0.074)* | 0.098 (0.069) |
| Turnover (log) (lag), average | 0.021 (0.044) | 0.006 (0.071) | -0.020 (0.059) | 0.016 (0.057) | 0.038 (0.046) | 0.056 (0.053) |
| Market scope, average | 0.110 (0.055)** | 0.099 (0.081) | 0.114 (0.067)* | 0.147 (0.067)** | 0.053 (0.064) | 0.122 (0.059)** |
| Human capital (lag), average | 0.437 (0.192)** | 0.501 (0.270)* | 0.097 (0.216) | 0.279 (0.225) | 0.365 (0.217)* | 0.468 (0.212)** |
| Market share (log) (lag), average | 0.037 (0.033) | 0.042 (0.045) | 0.055 (0.037) | 0.056 (0.042) | 0.016 (0.038) | 0.045 (0.035) |
| Dependent: financial constraints |  |  |  |  |  |  |
| Innovation (lag) | 0.052 (0.068) | 0.201 (0.092)** | -0.038 (0.082) | 0.141 (0.086) | 0.106 (0.073) | 0.018 (0.071) |
| Financial constraints (lag) | $0.505(0.069) * * *$ | 0.468 (0.074)*** | $0.478(0.075) * * *$ | $0.492(0.073) * * *$ | $0.526(0.066)^{* * *}$ | $0.484(0.065)^{* * *}$ |
| Turnover (log) (lag) | 0.068 (0.040)* | 0.059 (0.040) | 0.058 (0.041) | 0.066 (0.041) | 0.068 (0.040)* | 0.069 (0.040)* |
| Market scope | 0.068 (0.051) | 0.062 (0.050) | 0.062 (0.051) | 0.066 (0.051) | 0.061 (0.050) | 0.071 (0.051) |
| Human capital (lag) | -0.246 (0.134)* | -0.247 (0.134)* | -0.245 (0.136)* | -0.252 (0.137)* | -0.252 (0.133)* | -0.239 (0.134)* |
| Operating margin | $-0.627(0.208) * * *$ | -0.645 (0.209)*** | -0.615 (0.209)*** | $-0.657(0.210)^{* * *}$ | -0.621 (0.208)*** | $-0.650(0.206)^{* * *}$ |
| Age (log) | $-0.098(0.035)^{* * *}$ | $-0.103(0.036)^{* * *}$ | -0.110 (0.037)*** | $-0.103(0.036)^{* * *}$ | $-0.106(0.034)^{* * *}$ | $-0.104(0.035)^{* * *}$ |
| Group member | $-0.113(0.045)^{* *}$ | -0.116 (0.046)** | -0.116 (0.047)** | $-0.120(0.046)^{* * *}$ | $-0.107(0.044)^{* *}$ | -0.110 (0.046)** |
| Company | 0.061 (0.065) | 0.072 (0.067) | 0.072 (0.068) | 0.050 (0.067) | 0.060 (0.064) | 0.057 (0.066) |

Table 10. Continued

| Model | Innovation any | Innovation new to market | Innovation new to firm | Innovation (good) | Innovation (process) | Innovation (service) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Foreign ownership | 0.003 (0.065) | 0.008 (0.066) | -0.005 (0.067) | -0.001 (0.066) | 0.003 (0.063) | 0.000 (0.065) |
| Time effect CIS6 | $0.545(0.040)^{* * *}$ | $0.560(0.041)^{* * *}$ | $0.551(0.040) * * *$ | $0.555(0.041) * * *$ | 0.543 (0.039)*** | $0.542(0.039) * * *$ |
| Time effect CIS7 | 0.380 (0.072)*** | $0.387(0.073) * * *$ | $0.384(0.074) * * *$ | $0.381(0.074) * * *$ | $0.372(0.071)^{* * *}$ | 0.378 (0.071)*** |
| Industry effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Mundlak terms |  |  |  |  |  |  |
| R\&D in CIS4 | 0.083 (0.056) | 0.017 (0.076) | 0.029 (0.071) | 0.070 (0.073) | 0.032 (0.059) | $0.082(0.066)$ |
| Financial constraints in CIS4 | $0.453(0.065)^{* * *}$ | 0.488 (0.072)*** | $0.492(0.073) * * *$ | $0.483(0.072) * * *$ | $0.439(0.063) * * *$ | 0.473 (0.064)*** |
| Turnover (log) (lag), average | -0.078 (0.042)* | -0.067 (0.042) | -0.064 (0.043) | -0.073 (0.043)* | -0.078 (0.042)* | -0.075 (0.042)* |
| Market scope, average | -0.036 (0.055) | -0.036 (0.055) | -0.019 (0.055) | -0.038 (0.056) | -0.027 (0.054) | -0.033 (0.055) |
| Human capital (lag), average | 0.379 (0.182)** | 0.345 (0.185)* | 0.385 (0.187)** | $0.405(0.185)^{* *}$ | 0.395 (0.180)** | 0.376 (0.182)** |
| Market share (log) (lag), average | 0.293 (0.276) | 0.412 (0.281) | 0.367 (0.281) | 0.344 (0.281) | 0.317 (0.271) | 0.304 (0.276) |
| Error correlation $i$, $t$ | $0.144(0.041)^{* * *}$ | 0.078 (0.053) | $0.150(0.043) * * *$ | $0.207(0.047)$ *** | 0.125 (0.045)*** | 0.088 (0.040)** |
| Error correlation $i$ | 0.460 (0.296) | 0.135 (0.297) | 0.145 (0.332) | -0.076 (0.351) | 0.360 (0.397) | $0.653(0.147) * * *$ |
| SD random effect equation (A) | 0.517 (0.077)*** | 0.518 (0.109)*** | 0.331 (0.101)*** | 0.425 (0.102)*** | 0.540 (0.086)*** | $0.464(0.089)$ *** |
| SD random effect equation (B) | $0.241(0.025)^{* * *}$ | 0.304 (0.029)*** | $0.314(0.030)^{* * *}$ | 0.283 (0.029)*** | $0.194(0.022) * * *$ | 0.286 (0.023)*** |
| Observations | 6973 | 6910 | 6906 | 6982 | 6986 | 6975 |
| Log-likelihood | -7111 | -5365 | -5918 | -5942 | -6205 | -6371 |
| Wald statistic | 1853 | 1419 | 988 | 1863 | 1449 | 1578 |
| Wald $P$-value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

[^5]more internationally active and have a better educated workforce. They are also more innovative on all dimensions we measure, which again highlight the possibility that some firms are more innovative and more financially constrained due to the nature of their business (i.e. as a firm effect).

## 5. Additional estimations and robustness checks

In order to validate our results, we run a series of complementary and additional estimations. First, we compare the results obtained from simultaneous panel models with results generated by simpler models that do not control for reverse causality. We then perform robustness checks on the estimation technique by replacing the Wooldridge (2005) specification of the random effects' means by time averages of these terms as suggested by Mundlak (1978). Finally, we explore and contrast continuous and binary measures of R\&D.

### 5.1 Simultaneous versus independent equations

Tables 7 and 8 show the results of independent estimations of the effects of financial constraints on R\&D (Table 7, models 1-6) and of R\&D on financial constraints (Table 7, model 7); and financial constraints on innovation (Table 8, models 1-6) and of innovation on financial constraints (Table 8, model 7). To demonstrate how different these results are, let us consider as an illustrative example the results presented in Table 7. Some of these show positive effects of financial constraints on R\&D, a counter-intuitive result which can be explained by observing the structure of error correlations. Correlation coefficients for firm-year errors between both equations are substantial and significant in almost all our specifications, supporting our modeling strategy. This suggests that the curious positive effect of financial constraints on R\&D and innovation seen in these regressions is caused by unobserved heterogeneity that is correlated between equations.

We further explore the question of whether effects should be modeled as unidirectional or bidirectional in additional recursive bivariate probit models. If these models accurately reflect the data-generating process, this would allow us to estimate concurrent effects of innovation on financial constraints or vice versa. We test all possible combinations of concurrent effects within the constraints of the recursive bivariate probit model: we include one concurrent cross-equation effect in the equation for R\&D/innovation or financial constraints at a time and also test the effect of its lagged value. In unreported results, we find that these models either support our main findings or produce implausibly positive effects of financial constraints on innovation.

### 5.2 Time-average random effects

We aim to employ an estimation methodology that models random effects with as many degrees of freedom as possible. The Wooldridge (2005) specification of random effects; however, can lead to a proliferation of nuisance parameters, as each time-varying variable requires as many additional parameters as there are time periods in the data. These additional parameters may be close to redundant and may cause the model to fit the error terms rather than underlying economic relationships. To counter this potential problem, we estimate simpler models using time averages of panel variables (Mundlak, 1978).

Replacing Wooldridge (2005) terms with Mundlak (1978) terms in these alternative models produces results that are almost identical to our main results. Tables 9 and 10 show these robustness tests. All relationships between R\&D and financial constraints in our main results in Table 3 carry over to the robustness tests presented in Table 9. The negative effect of time-varying turnover on R\&D activities in Table 3 becomes slightly more significant, which is to be expected if degrees of freedom are removed from the model. Foreign ownership, turnover, market scope, and human capital remain significant cross-sectional predictors of R\&D. The only difference for the R\&D equation we find is a reduced effect of a firm's market share on external R\&D. Results for control variables in the financial constraints equation in Tables 3 and 9 are similarly robust to the alternative specification of random effects. A difference can only be observed in the effect of market scope, which is now insignificant where the more comprehensive model in Table 3 was able to distinguish time-varying effects from cross-sectional ones.

When testing our innovation models from Table 4 for robustness to an alternative random effect specification in Table 10, we find similarly stable results. All relationships between innovation indicators and financial constraints within and across equations remain the same, with the sole exception of process innovation, which loses its slightly significant effect on financial constraints. The substantial impact of new-to-the-market innovation, however, remains
in place. Time-varying market scope loses some of its significance in favor of its cross-sectional effect on innovation, in line with our findings in robustness tests for R\&D. Market scope also loses its effect on financial constraints, whereas all other control variables retain their effects. In sum, our findings are robust to a simpler specification using Mundlak (1978) random effects.

### 5.3 Continuous versus binary measures of R\&D

Our estimation design is driven by the observation that firms often do not perform any R\&D (Audretsch et al., 2014), while the intensity of R\&D may be a secondary decision once a firm engages in $R \& D$. In principle, a continuous measure of $\mathrm{R} \& \mathrm{D}$ expenditures is available from the CIS data and would enable a more precise estimation of bidirectional effects in models with financial constraints. However, data restrictions do not allow us to estimate feasible models of R\&D that incorporate the endogeneity of financial constraints while at the same time taking account of a two-stage decision process for whether or not to engage in R\&D and its volume.

However, we try a number of possible specifications to estimate the effect of financial constraints on continuous R\&D expenditures. First, we estimate a cross-sectional OLS model of the natural logarithm of R\&D expenditures using the R\&D equation from our main models above. Coefficients of financial constraints in this regression are similar to the results we obtain from binary single-equation models. Second, instrumenting financial constraints with gross operating profits yields an insignificant effect of financial constraints on R\&D. Third, to incorporate dynamics into the relationship between R\&D expenditures and financial constraints, we estimate the model for R\&D expenditures by system GMM (using all available lags of the dependent variables as GMM-style instruments and the firm's operating margin as IV-style instrument) but find no significant effect of financial constraints. All dynamic models of R\&D expenditures suffer from a lack of observations because observations where R\&D is zero drop out of the sample. This causes many holes in the panels ( $T=4$ for few firms, mostly $T=3$ ). Treating non-existent $\mathrm{R} \& \mathrm{D}$ as $£ 1$ when taking logs to retain these observations in the sample does not result in any model improvement.

In summary, running models for continuous $R \& D$ variables does not seem to be feasible with a sample of firms that sometimes start and stop spending on R\&D. A full treatment of this two-stage process with a binary R\&D indicator and continuous expenditures would need a third equation and a larger sample, even though the UK already runs a larger survey than most other European countries for which CISs are available. Adding future CIS waves would certainly be desirable given that we are trying to estimate models with first-order dynamics. This would not only increase the precision of coefficients for lagged variables, but also help us disentangle the direct effect of exogenous variables from their correlation with unobserved firm heterogeneity (in Wooldridge coefficients). ${ }^{18}$ Adding a third equation to the system would require the further development of custom estimation algorithms that can incorporate both binary and continuous dependent variables, as well as greater computing power than is currently available at the ONS's secure data service. However, because the first decision that firms need to make is whether or not to perform R\&D activities, and then decide on the depth of R\&D engagement, we believe our modeling strategy uncovers important and interesting dynamics and constitutes a novel point of departure for further studies with a potential focus on the intensity of R\&D investment as well as the volume of innovation outputs.

## 6. Conclusion

This article analyzes the nature and direction of the relationship between financial constraints and innovation and provides new evidence for a range of innovation inputs and outputs. To the best of our knowledge, this is the first study that compares a broad range of innovation characteristics and models their relationship with financial constraints as a dynamic bivariate process capable of addressing the initial conditions problem through Wooldridge's (2005) method in a panel setting. This allows us for the first time to test theoretical predictions on the effects of a set of innovation activities on firms' capital market access while taking account of reverse causality and dynamic effects. The CIS data cover small and non-listed firms, which are not included in existing studies on the cash-flow sensitivity of investment (e.g. Carpenter and Petersen, 2002), and they provide direct information on the perception of financial

18 An ONS decision to increase sample size seems unlikely at least in the short term, but new models could perhaps use the information contained in the ordinal measure for financial constraints to estimate panel version of ordered response models.
constraints combined with detailed information on the innovative profile of firms, covering R\&D expenditures and informal R\&D activities in its internal and external forms as well as several innovation outputs. Hence, our results highlight new aspects of the UK innovation-finance landscape that cannot be easily observed through a traditional cash-flow sensitivity approach, which is usually tested on samples of large listed firms. Our validation test of the financial constraints measure also shows that this measure is able to capture consequences of reduced access to external capital.

Our results contain few indications that past financial constraints affect R\&D programs or innovation output. Although businesses might be affected by difficulties in raising finance in the short term as reflected in their response to the survey question about financial constraints, financing problems do not induce firms to stop their innovative activities altogether. Our results still allow for the possibility that firms reduce the number or intensity of their R\&D projects without completely abandoning their $R \& D$ or innovation programs. The reverse effect of $R \& D$ on financial constraints, which is expected from theory, can be clearly identified in our results.

More surprisingly, there is evidence that innovation, and in particular new-to-market and product innovation, causes financial constraints. This finding has especially important implications for policy: it highlights the fact that the financing challenges of innovation do not stop when firms introduce a new product or service, but continue-and may in fact intensify-in the early stages of technology diffusion. This fact is systematically underestimated or-even more often-completely neglected in the literature. Although support for the generation of new products may be vital in many sectors of the economy, support for early firm growth may be at least as important, in particular for SMEs, to build capacity and enable the full exploitation of their innovation activities. Similarly, our results suggest that while specific measures can be useful to alleviate the financial constraints of younger firms, public support may be targeted not primarily at formal R\&D activities (typically covered by R\&D tax credit schemes), but also at informal R\&D activities that do not result in reported R\&D expenditures.

In relation to the broader macroeconomic environment in which this study is set, time effects reflect the impact of the recent financial crisis. Firms were significantly more often financially constrained during 2007/2008 than in the preceding period. Financial pressure fell slightly after 2008, but remained high compared with pre-crisis years. Although an effect of the crisis can be found in concurrent time effects on financial constraints, investment in R\&D lags the macroeconomic climate. Expenditures in R\&D kept increasing until 2008 and only dropped below pre-crisis levels towards the end of the sample period. This finding lends support to the theory that R\&D investment becomes pro-cyclical when firms face tightening credit constraints (Aghion et al., 2012).

The significant dynamic effects we find are of course only a part of the whole picture. R\&D activities can explain financial constraints, but other firm characteristics correlated with innovation might offer richer insights into the causes of constraints. Unobserved heterogeneity as well as firm-year errors appear to be correlated, which explains implausibly positive effects of financial constraints on innovation generated by simpler models. Future research could aim to address these hidden firm characteristics by collecting and merging additional information about firms' innovative capabilities and financial outlooks.

From a policy perspective, correlated unobserved firm characteristics that affect both innovation and financial constraints imply that deliberate efforts to reduce financial constraints at any given time may yield only limited results if temporary financial constraints do not affect long-term innovation activities (i.e. if the coefficient of financial constraints on R\&D or innovation is zero). However, the cross-sectional correlation of financial constraints and innovation through unobserved firm characteristics suggests that policy responses should be tailored to the idiosyncratic circumstances of firms and address those characteristics that make firms at the same time innovative and financially constrained.

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[^0]:    Notes: This table presents results for bivariate panel probit models with six R\&D measures and a financial constraints measure as dependent variables. All models are estimated using MSL with 100 random draws and standard errors (in parentheses) based on the outer product of the matrix of contributions to the gradient. Intercepts and industry effects are not shown. Wooldridge terms correspond to the coefficients in equation (3).
    Significance levels: *** $P<0.01, * * P<0.05$, and $* P<0.1$.

[^1]:    Notes: This table presents results for bivariate panel probit models with six innovation measures and a financial constraints measure as dependent variables. All models are estimated using MSL with 100 random draws and standard errors (in parentheses) based on the outer product of the matrix of contributions to the gradient. Intercepts and industry effects are not shown. Wooldridge terms correspond to the coefficients in equation (3).

[^2]:    Notes: This table presents random effects probit models for six R\&D measures and financial constraints as dependent variables. Heteroskedasticity-robust standard errors are in parentheses.
    Significance levels: *** $P<0.01, * * P<0.05$, and $* P<0.1$.

[^3]:    Notes: This table presents random effects probit models for six innovation measures and financial constraints as dependent variables. Heteroskedasticity-robust standard errors are in parentheses. Significance levels: *** $P<0.01$, ** $P<0.05$, and

[^4]:    Notes: This table presents results for bivariate panel probit models with six R\&D measures and a financial constraints measure as dependent variables. All models are estimated using MSL with 100 random draws and standard errors (in parentheses) based on the outer product of the matrix of contributions to the gradient. Intercepts and industry effects are not shown. All specifications in this table use Mundlak (1978) time averages rather than Wooldridge terms for the random effect's conditional mean. Significance levels: *** $P<0.01,{ }^{* *} P<0.05$, and ${ }^{*} P<0.1$.

[^5]:    Notes: This table presents results for bivariate panel probit models with six innovation measures and a financial constraints measure as dependent variables. All models are estimated using MSL with 100 random draws and standard errors (in parentheses) based on the outer product of the matrix of contributions to the gradient. Intercepts and industry effects are not shown. All specifications in this table use Mundlak (1978) time averages rather than Wooldridge terms for the random effect's conditional mean.
    Significance levels: ${ }^{* * *} P<0.01,{ }^{* *} P<0.05$, and ${ }^{*} P<0.1$.

