The Long Good-Bye: 
A Longitudinal Analysis of Barriers to Innovation

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*Financing R&D and innovation for corporate growth in the EU: Strategies, drivers and barriers*

- R&D and innovation: Sources and constraints at company level

**VERY PRELIMINARY DRAFT**

**PLEASE DO NOT QUOTE WITHOUT AUTHORS’ PERMISSION**
Abstract

The paper adds to the literature on barriers to innovation by disentangling the effect of different barriers on each phase of the innovation cycle, and their indirect effect on firms’ economic performance. The empirical test is based on an unbalanced panel of firm data from four waves of the UK Community Innovation Survey (UKIS) between 2002 and 2010 merged with the UK Business Structure Database. We employ a modified version of the CDM approach, by estimating different equations according to each of the phases of the innovation cycle. The preliminary results focus on the direct and indirect effects of different obstacles on the final phase of the innovation cycle, the productivity returns on innovation. This allows for a fine-grained analysis and discussion of the implications in terms of potential tools and – most crucially - timing of innovation policy specifically aimed at increasing the productivity returns of innovation.

Key words: Barriers to innovation; financial constraints; innovation cycle; Productivity returns to innovation; Panel data; Quantile regressions

JEL classification: C23 031 032 033
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1 - Introduction

The scant literature on the topic of barriers to innovation is mostly based on empirical and theoretical approaches on the effects of financial constraints on firms' innovative behavior (see Hall, 2002 for a review). Although the availability of both internal and external financial resources is essential in order to engage in innovation activities and successfully introduce a new product or service, other important factors have recently been shown to exert a significant hindrance effect on the firm's innovative process (see for example D'Este et al., 2008; 2012 and Blanchard et al., 2012, Pellegrino and Savona, 2013). Among these, particular attention has to be given to factors such as the lack of appropriate information on technologies and market, the shortage of adequate skills and the lack of sufficient demand.

Crucially, each of these different factors might exert a different deterring effect at different phases of the innovation process. For instance, the lack of financial resources might deter the initial decision to invest in innovation activities, while the lack of sufficient demand might lower incentives to launch a new product even though adequate financial resources are available. Providing evidence about which of these factors mostly affect each of the different phases of the firms' innovative process has therefore very relevant policy implications.

To our knowledge, none of the empirical contributions on barriers to innovation has so far disentangled the hampering effect of different barriers on each phase of the innovation cycle. This work aims at contributing to this recent stream of literature by empirically assessing the relevance of different kinds of hindrances that a firm can encounter during the innovation cycle, and their indirect effect on the firm’s economic performance.

We use of a CDM\(^1\)-type approach in a panel data context, following Griffith et al. (2006) and Mairesse and Robin (2009), who enrich the basic CDM model considering as innovative outputs product as well as process innovation, we formalize our empirical model in five equations: (1) the firm’s decision as to whether engage in R&D activity; (2)
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the firm’s decision regarding the amount of resources to be invested in R&D activity; (3) - (4) the knowledge production function, in which we consider two different innovative outputs (product and process innovation); (5) the productivity equation.

The five equations of the model are estimated recursively by applying different econometric specifications (in a panel context) according to the nature of each dependent variable: 1) a generalized tobit model for the first two equations; 2) a biprobit for equation 3 and 4; 3) a quantile regression for the last equation.

The empirical test is based on an unbalanced panel of firm data from four waves of the UK Community Innovation Survey (UKIS) between 2002 and 2010 merged with the UK Business Structure Database. The dataset includes a set of general information (main industry of affiliation, turnover, employment, founding year) and a (much larger) set of innovation variables measuring the firms’ engagement in innovation activity, economic and non-economic measures of the effects of innovation, subjective evaluations of factors hampering or fostering innovation, participation in cooperative innovation activities and some complementary innovation activities such as organisational change and marketing.

The main novelty of our approach is that, unlike the vast majority of the CDM model-type studies, we specifically focus on the role of different types of obstacles to innovation as a potential cause of failure, exit and low level of productivity and growth. We consider as main regressors four dummies variables that identify the presence of obstacle to innovation related to finance, market, knowledge and regulations factors. In line with some of the most recent contributions (D’Este et al., 2008 and 2012; Savignac, 2008; Pellegrino and Savona, 2013), we use an approach that allows us to overcome the usual selection bias which has led to the counterintuitive evidence of a positive impact of the obstacles to innovation to the firm’s propensity to innovate (both at the input and output level). We properly identify the relevant sample of potential innovators by filtering out those firms which are not willing to innovate and therefore do not engage in any innovation activity for reasons others than obstacles.

1 From Crepon, Duguet, Mairesse (1998).
The preliminary results presented here focus on the direct and indirect effects of different obstacles on the final phase of the innovation cycle, the productivity returns on innovation. This allows a fine-grained analysis and discussion of the implications in terms of potential tools and – most crucially - timing of innovation policy specifically aimed at increasing the productivity returns of innovation.

2 - Background literature

2.1 Barriers in the innovation literature and policy discourse

The economic literature has traditionally considered innovation, and in particular R&D, as a major source of economic growth. Inspired to a large extent by the seminal contribution by Griliches (1979) and, subsequently, by the well-known Crépon-Duguet-Mairesse model (Crépon et al., 1998), numerous studies have provided evidence about the leading role played by innovation in promoting competiveness and productivity growth.

In general, the large majority of these studies has mainly focused on the drivers and sources of innovation, devoting particular attention to those firm and market characteristics that increase firms’ probability to become successful innovators (both at input and output level). However, this literature has systematically neglected the factors that might hinder and slow down firms’ decision and effort to engage in innovation activity as well as the translation of innovation investments into new products and services.

Surprisingly, and interestingly, the (lack of) empirical support to the role of barriers to innovation within the innovation literature is not in line with the interest in barriers to innovation, which had characterized the policy discourse in the UK in the 1980s. In a very recent paper, Perren and Sapsed (2013) conduct a discourse analysis on the use of the term ‘innovation' in the English parliamentary discourse over the past forty-five years, based on the archive of the UK’s parliamentary records. They find that the use of the term ‘innovation' in the UK policy debates has increased over time and spread over a variety of policy domains, with an increasingly positive tone.
This latter aspect is particularly interesting for the purpose of this paper, as it helps locating the interest in barriers to innovation in historical perspective within the policy domain. Also, it allows highlighting the contribution of this paper with respect to the provision of empirical evidence on barriers towards the implementation of ‘evidence based policy’.

Perren and Sapsed (2013), following Lundvall and Borrás (2005), interpret the increasing shift to positive tones over the term ‘innovation’ – that is, an increasing shift in focus from barriers to drivers of innovation – as a result of a shift in the innovation policy models. These scholars' view is that the initial substantial presence of the words ‘barriers to innovation’ in the 1970s and beginning of the 1980s with respect to ‘drivers of innovation’, was consistent with the dominance of the laissez faire (innovation) policy model, which confined the role of the government to the corrections of market failures. The removal of barriers to innovation was included in these types of interventions, whereas the provision of incentives and subsidies to incentive innovation was labeled at the time as automatically distorting market efficiency.

The discourse shifted again in the beginning of the 1990s toward more a systemic model, which implied a re-orientation of the interest on the drivers rather than the barriers to innovation. The government has in this case a more active role than the mere removal of barriers or market failures that might hamper firms’ innovative efforts (see also Rothwell, 1982, as quoted in Perren and Sapsed, 2013).

Interestingly, the parliamentary and policy interest over barriers to innovation has been ‘countercyclical’ with respect to the academic interest of and contributions from the innovation literature. In this respect, as put forward in other occasions by one of us (lammarino et al., 2009; D'Este et al., 2012; Pellegrino and Savona, 2013) we consider the release of barriers to innovation as a necessary (though not sufficient) condition to ensure that decision to invest in innovation, amount of resources devoted to it, successful translation of invention into innovation and (socially) profitable launch of a new product all lead to higher and job-friendly growth.

Within this perspective, we have contributed to the literature on obstacles to innovation, which has had a recent upsurge among innovation scholars.
In particular, innovation scholars have devoted an increasing attention to the perception of (mainly financial) obstacles to innovation and their deterring impact on firms’ decisions to engage in innovation activity, the intensity of this engagement and the propensity to innovate (among others, Baldwin and Lin, 2002; Galia and Legros, 2004; Canepa and Stoneman, 2007; Segarra Blasco et al., 2008; Tiwari et al., 2008; Savignac, 2008; Iammarino et al., 2009; Mancusi and Vezzulli, 2010; Pellegrino and Savona, 2013).

Much of this literature is exclusively based on the use of the Community Innovation Survey, which is one of the largest-scale survey gathering information on innovation behavior and outcomes. Section 3 describes in detail the survey and Table A1 in the appendix reports the specific question of interest here. Here it is worth mentioning the methodological issues linked to the qualitative nature of the variables and the cross-sectional nature of the data, which has driven estimation choices, results and interpretations (for an exhaustive review, see Mohnen and Mairesse, 2010).

In the case of the econometric treatment of research questions revolving around the perception and effects of barriers to innovation, there has been a methodological and interpretative turning point in this literature, started by Savignac (2008) and D’Este et al. (2008, 2012) and followed by others more recently (Blanchard et al., 2013; Pellegrino and Savona, 2013), related to the identification of the relevant sample and the consequent treatment of endogeneity of the relationship between experience of barriers and innovation performance, as well as the interpretation of the estimated coefficients.

The role of barriers to innovation has therefore been considered as having a ‘deterrent’ or ‘revealed’ effect (D’Este et al., 2012) depending on whether firms perceived obstacles when they engaged in no or more than one innovation activities.

In this paper we aim to add to this latter contribution by fine-graining the different role that both deterring and revealed barriers have in affecting the different phases of the innovation cycle. The effect of financial, demand, and knowledge barriers on one of the phases of the innovation cycle, namely the propensity to introduce a product or process innovation, has already been undertaken in Pellegrino and Savona (2013). Here, as
mentioned in the introduction, we would like to extend this analysis to the ‘upstream’ phases of the cycle – i.e. the decision to invest in innovation inputs and the amount of financial effort devoted to innovation – and the ‘downstream’ phases – i.e. the labour productivity returns of the introduction of a new product/process. We encompass this in a complex five-equations model a la CDM. Here we focus on the (direct and indirect) effects of market, financial and knowledge barriers on the latest phase of the cycle, the productivity returns to innovation. We put forward our conjectures in the next section.

2.2 Direct and indirect effects of barriers to innovation on firms’ productivity: a conceptual typology – (To be completed)

This section offers a speculative conceptual typology of the potential direct and indirect effects of the experience of obstacles on productivity – and the associated expected coefficients.

Financial obstacles

Knowledge obstacles

Market-related obstacles

3 - Empirical Analysis

3.1 Econometric Strategy

3.1.1 Model and estimation strategy

As mentioned, while Pellegrino and Savona (2013) have looked at the ‘upstream phases’ of the effect of barriers on the propensity to innovate, the preliminary analysis conducted in this paper focuses instead on the estimation of the direct and indirect effects of barriers on firms’ productivity levels.
Firms have persistent differences in their productivity levels, even at the level of finely disaggregated industries (Metcalfe, 1994; Dosi and Grazzi, 2006; Syverson, 2011). Heterogeneity in productivity levels is due to a number of factors, which include innovative activity. For some successful innovators, persistently high productivity may be due to their innovation efforts. For low productivity firms, however, there may be a multiplicity of factors holding back their productivity levels – innovation barriers, or the liability of small size, or factors related to their sector of activity, etc.

We therefore consider there to be two key econometric issues worth pursuing. First of all, firms differ considerably in their productivity levels, and a focus on the 'average effect for the average firm' will neglect this heterogeneity across firms. Second, we can expect that the determinants of productivity vary across the productivity distribution – that is, that the factors associated with the success of high productivity firms might not be the same as those factors affecting the outcomes of low productivity firms. Indeed, in our context of innovation barriers, it makes sense to suppose that barriers have different effects for high and low productivity firms. For example, as mentioned in the previous section, low productivity firms may face barriers that prevent them from getting their innovation efforts off the ground – such as cost barriers that prevent them from undertaking innovation in the first place. In contrast, it may be the case that high productivity firms face a different set of barriers, such as knowledge barriers that hinder how effectively they can exploit their innovation outputs in an unfamiliar marketplace.

Quantile regression is an appropriate technique in our context, because it allows us to investigate the effects of barriers on productivity, allowing for heterogeneous effects across the (conditional) productivity distribution.

Our regression equation is the following linear model:

\[
\text{Prod}_{i,t} = \alpha_0 + \alpha_1 \text{Barriers}_{i,t} + \alpha_2 \text{InnovationControls}_{i,t} + \alpha_3 \text{FirmControls}_{i,t} + \epsilon_{it}
\]

(1)

where \(\alpha_i\) are the regression coefficients and \(\epsilon_{it}\) is the usual error term for firm \(i\) at time \(t\).
Estimating equation (1) using quantile regression yields a set of coefficient estimates that are associated with a specific quantile \( \theta \) – and we expect there to be variation in the coefficients across the quantiles.

Next section describes the database and specifies the proxies we use to estimate equation (1) in terms of regressors and dependent variable. We then discuss the preliminary results in the following section.

### 3.1.2 Data base and variables

The empirical analysis is based on firm-level data from four waves of the UK Community Innovation Survey (UKIS) for the period 2002 -2004 (UKIS 4); 2004-2006 (UKIS 5); 2006-2008 (UKIS 6) and 2008-2010 (UKIS 7). The UKIS is traditionally based on a stratified random sample (namely sector, region and size-band) drawn from the ONS (Office for National Statistics) Inter-Departmental Business Register (IDBR), and is representative at both the sector and the firm size level of the entire population of UK firms with more than 10 employees.

The dataset comprises a set of general information (main industry of affiliation, turnover, employment, founding year\(^2\)) and a (much larger) set of innovation variables measuring the firms’ engagement in innovation activity, economic and non-economic measures of the effects of innovation, subjective evaluations of factors hampering or fostering innovation\(^3\), participation in cooperative innovation activities and some complementary innovation activities such as organisational change and marketing\(^4\).

The survey sampled 28,000 UK enterprises in each wave with a relatively high response rate (58% for UKIS 4, 53% for UKIS 5, 51% for UKIS 6 and 50% for UKIS 7) that leads to a whole sample of 59,940 observations (40,709 firms observed for 1 up to

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\(^2\) This additional information was drawn from the UK Business Structure Database.

\(^3\) The appendix reports the section of the UKIS questionnaire on barriers to innovation. These include cost, knowledge, market and regulation barriers.

\(^4\) The information on group belongings and on public financial support for innovation are not available due to slightly changes in the questionnaire designs through the four surveys.
Unfortunately, the high presence of missing values combined with the relatively short time series dimension of the panel leads to many variables being observed either never or just once for a considerable number of firms. Moreover, filtering out the firms that are not willing to innovate and focusing on the “relevant sample” (i.e. the cohort of the so called ‘potential innovators’, see Pellegrino and Savona, 2013 for a detailed explanation of the empirical identification of the relevant sample), leads to a further reduction of the sample size.

Thus, the trade-off here is between applying panel econometric techniques that allow us to perform more precise estimations, though leading to a significant reduction of the sample size, or wiping out the time series dimension in favour of a higher level of representativeness of the sample used for the analyses. We choose to opt for the first option, as we prefer to prioritise taking into account the unobservable firm heterogeneity. Accordingly, after dropping those firms - pertaining to both the total sample and the relevant sample - that are observed for just one year (31,577); those operating in the primary and construction sectors (2,767 observations); those with missing values in all the variables used for our analysis (9,280 observations) we ended up with an unbalanced panel of 16,316 firms-year observations.

Table A2 provides an overview of our dataset by presenting the summary statistics. The dependent variable is labour revenue productivity, calculated as the ratio between sales and number of employees (LAB_prod). Among the firm-level variables that are not directly related to innovation, we have information on firm size (Log_SIZE) and firm age (Log_AGE), a dummy variable for exporting activity (EXPORT_d). Our firm-level innovation variables include R&D expenditures (both in amount and as a proportion of sales; RDT and RDTint respectively), sources of information (INFO_INT and INFO_EXT), cooperative activity (COOP), method of protection of innovative activity (PROT_FOR) and EDU_HIGH, that is the share of employees with (hard or soft science) tertiary education.

IPROD is a dummy indicating whether firms have introduced a product innovation while IPROC a process innovation. IORG is also a dummy for firms that have gone through

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5 Since CIS data are collected retrospectively (innovating over the past three years), the 9 years
organisational innovation. The estimation includes usual dummy variables for region and industry to control for region- and sector-specific factors affecting productivity levels.

### 3.2 Preliminary econometric results

#### 3.2.1 What Limits the Productivity Returns to Innovation?

Table A3 included in the appendix reports the results of the quantile estimation of the labour productivity equation (equation 1 in Section 3.1.1)\(^6\).

Table A3 reports the results of more a conservative specification, which includes obstacles dummies that take value 1 only for those firms that have not only experienced, but considered each of these set of obstacles as relevantly affecting their innovation activities.

The quantile regression employed here turns out to be the most appropriate econometric specification for the topic at hand. The different quantile coefficients associated to the different barriers obstacles show substantial variation across different quantiles, when significant.

This is the case of financial and, partly market-related barriers. Financial obstacles show a strongly negative impact on productivity, which substantially worsen for higher quantiles. Market-related obstacles are instead positively and not significantly associated to the different quantiles, though it turns (weakly) significant for the q90.

While the effect of the other obstacles is not significant, we suspect that these results are not really representative of an indirect effect of the barriers on productivity via the innovation process. Rather, they might be the outcome of a pure cash-flow effect: the more constrained is the finance, the less liquidity they get, which might affect in turn the period pertaining to the four different surveys allows us to have data just for four time periods.

\(^6\) We have estimated also different specifications of equation 1. Equation 1 has been estimated using OLS (pooled, fixed and random effects) and using two quantile regression specifications. The first one include as regressors dummies for each set of obstacles (financial, knowledge-, market- and regulation-related) which take value 1 if firms have experienced and 0 if they did not.
level of sales, explaining the negative coefficient across the distribution of productivity levels.

The other innovation and economic variables also show interestingly differentiated effects along the quantile distribution. The introduction of product innovation has a surprisingly more significant effect on productivity, as we would expect the introduction of process innovation to have an equally important positive effect on productivity. This suggests that productivity performance is here very much related to demand effects rather than cost-cutting activities.

Given this evidence, we would have expected market-related barriers to have a negative effect on labour productivity, which is not the case in any of our specifications, except for the highest quantile (and a positive coefficient). This might be a symptom of how firms react to markets dominated by large incumbents, i.e. by putting the effort in innovating more and perform better in terms of sales per employee.

Traditional economic variables show the expected coefficients, although with substantial differences along the sample distribution. For instance, age, size, internationalisation and share of tertiary educated employees all have a strong significant and positive effect on labour productivity, which increases along the distribution. This is very much in line with innovation theory and turns out to be largely confirmed by our results.

4 - Discussion and Conclusions

The paper contributes to the literature on barriers to innovation and builds upon the results of a recent paper (Pellegrino and Savona, 2013) by looking at the effects of barriers on economic performance of firms in terms of labour productivity.

We build a model extending the widely used CDM model to disentangle the effects of different barriers to innovation – among which financial, market-related, lack of knowledge and the need to meet national and international regulations – on the different phases of the innovation cycle – that is the decisions to invest, the amount of innovation
investments, the actual launch of an innovative product or the occurrence of process or organisational innovation and, finally, the labour productivity returns of innovation.

In this paper we focus on the results of the latest phase of the cycle, namely the effect of barriers on labour productivity returns of innovation and we present our preliminary results.

While in our previous work we have highlighted that most of the barriers, i.e. financial, market related and partly knowledge barriers affect the propensity to innovate, here the effect of these on labour productivity seem to be confined to the financial obstacles only, which turn out to be negatively affecting labour productivity and increasingly so along the sample quantile distribution.

Further econometric refinements of this work will take into account the whole CDM-like sequence of mechanisms – which will allow us to disentangle indirect mechanisms at work.
ANNEXES

References


Annex 1 – Acknowledgments and Disclaimer

This work was based on data from UK CIS data, produced by the Office for National Statistics (ONS) and supplied by the Secure Data Service at the UK Data Archive. The data are Crown Copyright and reproduced with the permission of the controller of HMSO and Queen's Printer for Scotland. The use of the data in this work does not imply the endorsement of ONS or the Secure Data Service at the UK Data Archive in relation to the interpretation or analysis of the data. This work uses research datasets which may not exactly reproduce National Statistics aggregates.
### Annex 2 – Tables and Figures

#### Table A1. CIS questionnaire: barriers to innovation

*During the three years period ---- how important were the following factors as constraints to your innovation activities or influencing a decision to innovate?*

<table>
<thead>
<tr>
<th>Barrier factors</th>
<th>Barrier items</th>
<th>Factors not experienced</th>
<th>Degree of importance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Low</td>
</tr>
<tr>
<td>Cost factors</td>
<td>Excessive perceived economic risks</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td></td>
<td>Direct innovation costs too high</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td></td>
<td>Cost of finance</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td></td>
<td>Availability for finance</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Knowledge factors</td>
<td>Lack of qualified personnel</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td></td>
<td>Lack of information on technology</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td></td>
<td>Lack of information on markets</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Market factors</td>
<td>Market dominated by established enterprises</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td></td>
<td>Uncertain demand for innovative goods or services</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td>Regulation factors</td>
<td>Need to meet UK Government regulations</td>
<td>☐</td>
<td>☐</td>
</tr>
<tr>
<td></td>
<td>Need to meet EU regulations</td>
<td>☐</td>
<td>☐</td>
</tr>
</tbody>
</table>
Table A2. – Main variables - Descriptive statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>(count)</th>
<th>(mean)</th>
<th>(Var)</th>
<th>(sd)</th>
<th>(skewness)</th>
<th>(kurtosis)</th>
<th>(p5)</th>
<th>(p10)</th>
<th>(p25)</th>
<th>(p50)</th>
<th>(p75)</th>
<th>(p90)</th>
<th>(p95)</th>
</tr>
</thead>
<tbody>
<tr>
<td>IPROC</td>
<td>13563</td>
<td>0.274</td>
<td>0.199</td>
<td>0.446</td>
<td>1.014</td>
<td>2.027</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>IPROD</td>
<td>13558</td>
<td>0.434</td>
<td>0.246</td>
<td>0.496</td>
<td>0.267</td>
<td>1.071</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>AGE</td>
<td>13565</td>
<td>21.605</td>
<td>98.952</td>
<td>9.947</td>
<td>-0.107</td>
<td>1.782</td>
<td>5.000</td>
<td>8.000</td>
<td>14.000</td>
<td>21.000</td>
<td>32.000</td>
<td>34.000</td>
<td>36.000</td>
</tr>
<tr>
<td>EXPORT_d</td>
<td>13565</td>
<td>0.459</td>
<td>0.248</td>
<td>0.498</td>
<td>0.163</td>
<td>1.026</td>
<td>0.000</td>
<td>0.000</td>
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<td>0.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>EDU_HIGH</td>
<td>13565</td>
<td>17.189</td>
<td>676.932</td>
<td>26.018</td>
<td>1.974</td>
<td>5.974</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>6.000</td>
<td>20.000</td>
<td>60.000</td>
<td>89.000</td>
</tr>
<tr>
<td>IORG</td>
<td>13565</td>
<td>0.321</td>
<td>0.218</td>
<td>0.467</td>
<td>0.769</td>
<td>1.591</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>HIN_COST_H_qr</td>
<td>13565</td>
<td>0.360</td>
<td>0.230</td>
<td>0.480</td>
<td>0.584</td>
<td>1.342</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>1.000</td>
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<tr>
<td>HIN_KNOW_H_qr</td>
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<td>0.125</td>
<td>0.109</td>
<td>0.330</td>
<td>2.273</td>
<td>6.164</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
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Table A5 Labor productivity - Quantile: obstacles vars. (firms perceiving obstacles as highly important)

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<td>(0.94)</td>
<td>(1.38)</td>
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<td>(1.72)</td>
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<td>(17.64)</td>
<td>(17.63)</td>
<td>(9.09)</td>
<td>(8.14)</td>
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<td>(7.99)</td>
<td>(10.48)</td>
<td>(14.24)</td>
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<td>(3.83)</td>
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The Long Good-Bye: A longitudinal Analysis of Barriers to Innovation

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_t_ statistics in parentheses

* _p_ < 0.1, ** _p_ < 0.05, *** _p_ < 0.01