FONDAZIONE ENI ENRICO MATTEI

NOTA DI LAVORO

44.2016

Firm Employment Growth, R&D Expenditures and Exports

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Economic Theory
Series Editor: Carlo Carraro

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Summary

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Keywords: Exports, R&D, Firm Growth, Quantile Regression

JEL Classification: J63, M51, O31, F14

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Abstract

This paper studies firms' decisions to export and invest in R&D and their effects on employment growth and labor flows for a sample of Italian SMEs operating in the manufacturing industry. After accounting for the under-reporting of R&D in SMEs, our quantile regressions reveal that (i) R&D is associated with higher employment growth rates, higher hiring rates and lower separation rates; (ii) R&D-induced exports are negatively related to employment growth and accessions and positively related to separations; and (iii) pure exports are not a driver of employment growth and labor flows.

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1. Introduction

There is a large and growing body of literature that investigates the relationship between firms' growth and innovation amongst small and medium-size enterprises (SMEs) with vast, yet inconclusive, empirical evidence on the role of innovation for firms' growth in employment (Lachenmaier and Rottmann, 2011; Hall, Lotti and Mairesse, 2008; Dachs and Peters, 2014; Hall et al., 2008). Surprisingly, amongst these studies, the degree of openness of an SME to foreign markets has so far received little systematic attention even though the literature recognizes that international trade is a key determinant of firm size since trade expands a firm's market size. For example, exports of goods and services from the European Union supports around 25 million jobs in Europe, suggesting the importance of international trade for job creation and, thus, firm growth (Sousa, Rueda-Cantouche, Arto, and Andreoni, 2012). Classical trade theory based on the Ricardian principle of comparative advantage predicts that trade leads to workers moving between industries while the new heterogeneous trade theory (Melitz, 2003; Bernard et al. 2003) focuses on the reallocation of factors of production within industries from domestic firms to the more productive export-oriented firms. Whether we use classical trade theory or heterogeneous trade theory, economists agree about the long-run gains from trade as resources are used more efficiently. However, economists also recognize the fact that there are short-run adjustment costs as labor markets adjust to growing international trade. While the literature discusses the impact of innovation on firm growth, our study takes an in-depth look at labor market dynamics at the firm-level and provides insight into how export oriented firms may exhibit different employment growth patterns compared to non-exporting firms.

Along with the vast literature on firm growth and innovation there is also a large body of theoretical and empirical research that examines the relationship between innovation and firms' exports. In open economy growth models, innovation is a key driver of exports (Grossman and Helpman, 1990, 1991). The intuition behind this is that firms that innovate are more likely to export because they can charge lower prices and thus obtain higher returns from foreign sales than non-innovating firms. Firms that innovate by upgrading their products or introducing completely new ones are more likely to export (Caldera, 2010). The importance of innovation for productivity and firms' exports has been studied in several empirical studies with the conclusion that both endogenous and exogenous innovation increases exports (Wakelin 1998; Lachenmaier and Wößmann, 2006; Becker and Egger, 2013).

This study, thus, bridges the innovation-firm growth literature and the innovation-export literature and, to the best of our knowledge, is amongst the first papers to span this gap. Using a rich micro-level firm dataset, this paper investigates firms' decisions to export and invest in research and development (R&D) and studies its effect on firm employment growth and labor flows for a sample of SMEs belonging to the Italian manufacturing industry. Our study contributes to the literature by, first, exploring the nature of the export-innovation relationship for the case of Italian SMEs and, second, by examining the implications of export and R&D choices for firms' growth and labor flows. Our empirical analysis differs from related research in several ways. The first departure from previous literature is that we use R&D intensity and export intensity, while previous research have mainly focused on binary indicators of R&D and export status. Our approach therefore has the advantage of exploiting information on firms' behavior at the micro-level. Second, to the best of our knowledge, the findings of this study are the first to incorporate export activities into an empirical model of firm growth. Third, unlike previous research, we shed light on the impact of export and innovation activities on labor flows at the firm level. An important part of understanding employment growth at the firm level is learning about its layoff and recruiting behavior. Our empirical strategy tests whether firms' innovation activities and export activities can be associated with changes in hires, changes in separations or both.

After accounting for the under-reporting of R&D in SMEs and potential endogeneity, our quantile regressions reveal that R&D is associated with higher growth rates, higher hiring rates and lower separation rates. We also find that R&D-induced exports are negatively related to firm growth and accessions and positively related to separations. However, pure exports are not a driver of growth and labor flows. The rest of the paper is organized as follows. Section 2 reviews the literature. Section 3 provides a brief description of research methods. Data are presented in section 4 and section 5 discusses the results. Section 6 concludes.

2. Nexus between R&D Expenditures, Exports and Firm Growth

This paper relates to two branches of the literature. The first branch investigates the impact of innovation on firm growth, while the second branch explores the interrelationship between exports and firm-level R&D decisions. We briefly provide the background behind both these branches of literature.

Innovation and Firm Growth

Theoretical contributions suggest that both the kind and strength of innovation strategies are likely to produce different outcomes in firm size and labor flows, with the net effect of innovation on employment being unclear (Van Reenen, 1997). Studies based on output measures of innovation investigate the impact of two kinds of innovation, product innovation and process innovation, both of which can have an ambiguous impact on firm employment. Product innovation can increase employment as more labor is needed to produce new goods or improve the quality of existing goods. On the other hand, product innovation in the form of firms' introduction of new and/or more differentiated products in an attempt to strengthen their market power and set higher prices, could lead to output and employment contractions. Process innovation modifies the relative productivity of production factors and, to the extent that such innovation is of a labor-saving kind, it could reduce employment. However, when process innovation is associated with lower production costs, firms tend to increase production and their workforce via price reductions and increased demand.

While product innovation is often found to have a positive impact on growth (Lachenmaier and Rottmann, 2011; Hall, Lotti and Mairesse, 2008; Dachs and Peters, 2014), process innovation has been associated not only to employment growth (Lachenmaier and Rottmann, 2011) but also to employment reductions (Dachs & Peters, 2014) and employment stability (Hall et al., 2008). Some studies have focused on the effects of input measures of innovations, which are typically R&D activities, on employment changes. From this standpoint, both Yasuda (2005) and Falk (2012) find that R&D expenditures have a positive impact on growth, while Brouwer, Kleinknecht, and Reijnen (1993) report a negative relationship between R&D expenditures and employment. However, after the authors refine their R&D measure as the percentage of R&D dedicated to product development they find a positive impact on employment growth. On the other hand, Klette & Førre, (1998) do not find any clear-cut relationship between job creation and R&D intensity.

Innovation and Firm Exports

Both international trade theories and endogenous growth models stress the importance of R&D for firms. The product life cycle theory of international trade argues that innovations can provide a comparative advantage to firms to compete internationally (Vernon, 1966; Krugman, 1979; Dollar, 1996). Endogenous growth models consider innovation to be endogenous and thus suggest that the effect of innovation on exports can run two-way (Grossman and Helpman, 1989, 1990, 1991). Thus, in the literature that examines the linkages between a firm's export activities and innovation, a major concern is to fully understand the direction of causality between exports and innovation. A firm's decision to invest in R&D and to innovate may yield a productivity premium that (partially) explains firm export behavior, i.e., the self-selection hypothesis (Clerides, Lach, & Tybout, 1998). Stemming from the idea that only the more productive firm enters foreign markets since they can bear the fixed costs of trade barriers (Melitz, 2003), innovation is regarded as an explanatory factor of productivity premiums. In the opposite direction, being engaged in export activities increases the firms' ability to assimilate knowledge more effectively, which drives firms to intensify their innovative efforts. This is the learning-by-exporting hypothesis. The literature until now has assessed the importance of the learning-by-exporting mechanism for export starters (i.e. firms that enter foreign markets for the first time) and for firms in low-income countries selling their goods in high-income countries where buyers demand higher quality products (Atkin, Khandelwal, & Osman, 2014). In other words, firms either start producing high-quality products when they first enter a new market and develop steeper learning curves, or they benefit from the transfer of knowledge when dealing with foreign buyers. Empirical results so far are in favor of the first argument, although some papers find evidence in favor of the learning-by-exporting hypothesis. For instance, Damijan et al. (2010) find that participation in trade may stimulate process innovations, but the effect is limited to a group of medium and large first-time exporters because export volumes of small first-time exporters are too small to achieve immediate efficiency gains through process innovations. Also, Günther and Norber (1999) find that export activities do not enforce innovation activities in the German service sector. Finally, Girma et al. (2008) find evidence for such direct effects of previous exporting on R&D for Irish firms but not for British firms.

Studies also look at the linkages between innovation and firms' *desire* to export which can be grouped into studies that look at innovation effort (R&D expenditures) and innovation product measures (i.e. product and process innovation). Aw et al (2007) using firm-level data for Taiwan does not find a significant relation between firm-level R&D and the probability of firms to begin exporting. However, using Spanish manufacturing SMEs, Cassiman et al (2010) find that product innovation, but not process innovation, drives firm-level exports propensity while Caldera (2009) finds that both product and process innovation impacts exports with the impact of product innovation being higher than process innovation. Similarly, Becker and Egger (2007), using German firm data, find that firms introducing a product and process innovation simultaneously increase their propensity to export by about 10 percentage points. However, Damijan et al (2010), using data on the Slovenian manufacturing, finds no evidence that product or process innovation drives export propensity at the firm level. Finally, Beveren and Vandenbussche (2010) using innovation survey data for Belgium look at innovative effort (R&D) and innovative output (product and process innovation). Their study finds that firms anticipating their entry into export markets self-select into innovation, rather than product and process innovation being the reason behind entry into the export market.

In spite of the interest in the role of innovation-driven firm growth, very little attention has been paid to study export activities and their linkages to R&D expenditures. To the best of our knowledge, export indicators have been only used as simple control variables in growth equations. Goedhuys and Sleuwaegen (2010) discuss the growth performance of a sample of Sub-Saharan African entrepreneurial firms. To account for export activities, the authors include a dummy for exporters and find that it is not statistically relevant. Also Czarnitzki & Delanote (2012) use a dichotomous indicator for export status in a study of young innovative companies in Flanders, and they find a negative and statistically significant impact of export on firm growth. Hölzl (2009) uses the export to sales ratio and concludes that exports are important for high-growth firms. This paper suggests that exports and R&D expenditures are interconnected in a more complex way and explores this relationship further to disentangle the effects on firm growth.

3. Empirical Model

The empirical model is constructed in three stages. In the first stage, we take into account the issue of under-reporting of R&D in SMEs and estimate an R&D intensity equation. Predicted values are then used in the second stage to estimate export intensity due to R&D. The third stage is aimed at answering our research questions and, thus, includes the core regressions that show the impact of export activities and R&D activities on firm growth and labor flows.

As suggested by Kleinknecht (1987) and confirmed by Santarelli & Sterlacchini (1990), official R&D measures for SMEs may severely underestimate their innovation activities. The presence of informal activities, the type of R&D being undertaken, or the absence of structured R&D departments are all likely to be factors influencing the declared R&D effort (Roper, 1999) and are likely to be more relevant when focusing on SMEs (Klette and Kortum, 2004). Thus, self-reported R&D expenditure often fails to adequately describe the innovative effort of SMEs. The estimates of the R&D intensity equation are thus a necessary step to obtain a better proxy of the innovative activities carried out by firms in our sample.[1]

To account for under-reporting of R&D in SMEs, we assume that a latent variable $\widetilde{R\&D}$ is related to a set of independent variables, x_i, and to the observed R&D intensity according to the following standard type I Tobit model:

$$\widetilde{R\&D} = \alpha + \beta x_i + \varepsilon_i$$
$$R\&D = \begin{cases} \widetilde{R\&D}, & \widetilde{R\&D} > c \\ 0, & \widetilde{R\&D} \le c \end{cases}.$$

It is worth noting that in this step, we also control for self-selection of firms into R&D through a Two-stage Least Square (2SLS) model and, similar to Hall, Lotti, & Mairesse (2009) *on the same data*, we reject the hypothesis of self-selection. Consequently, we estimate the R&D equation by a Tobit regression without the inclusion of a correction term for selectivity. From this step, we take the predicted values as a firm level proxy of actual R&D intensity.

In the second stage we delve into the relationship between R&D intensity and export intensity. First, we run a Tobit model in which we regress export intensity on the estimated R&D. Thus, we use these estimates to obtain predicted values and residuals, which describe, respectively, the amount of export intensity due to the R&D effort and the residual amount of export intensity that is not explained by R&D. Predicted values and residuals are included in the last stage of the estimation procedure.

The third stage of the empirical model is devoted to study the impact of export activities and R&D activities on firm growth and its components, specifically the hiring and separation rates. To capture the direct effect of R&D we include the estimated R&D values from the first stage, while the indirect effect of R&D through exports is captured by the estimated export intensity. The residual obtained from the second stage captures the direct impact of exports. We will refer to this effect as the pure export effect.

In this study, we adopt quantile regressions to identify the impact of R&D and exports on a firm's employment growth, hiring rate and separation rate. Quantile regressions have increasingly gained the attention of scholars in the literature based on the growth-innovation relationship, allowing numerous authors to find that, at a micro level, the effects of innovation vary substantially along the conditional distribution of the employment growth[2]. In particular, we follow Koenker & Bassett Jr (1978), Koenker & Hallock (2001) and Buchinsky (1998) to estimate a model specified as:

[1] A similar approach can be found in Crépon et al. (1998) and Hall et al. (2009).
[2] See, among others, Goedhuys & Sleuwaegen (2010) and Falk (2012).

$$y_i = x_i'\beta_\theta + u_{\theta i} \quad with \ Quant_\theta(y_i|x_i) = x_i'\beta_\theta \qquad \text{(i=1,...,n)}, \qquad (1)$$

where $Quant_\theta(y_i|x_i)$ denotes the quantile of y_i, conditional on the set of regressors x_i, θ indicates the quantiles, n is the sample size, β_θ is the vector of coefficient to be estimated and $u_{\theta i}$ is the error component. In particular, the estimator for β_θ solves the problem:

$$\min_\beta \frac{1}{n}\left\{\sum_{i:y_i \geq x_i'\beta_\theta} \theta|y_i - x_i'\beta_\theta| + \sum_{i:y_i < x_i'\beta_\theta}(1-\theta)|y_i - x_i'\beta_\theta|\right\}. \qquad (2)$$

This methodology has several advantages over alternative strategies. First, it can be used to characterize the overall distribution of a dependent variable given a set of regressors. This allows us to quantify the effects of a variable more accurately than standard linear regression techniques based on conditional mean functions. Second, quantile regression techniques have been proved to be robust in the presence of heteroskedastic and non-normally distributed errors. Finally, the quantile regression objective function is a weighted sum of absolute deviations, so the estimated coefficients are less sensitive to outliers.

4. Data Description

4.1 Survey Data

We use establishment-level, cross-sectional data drawn from three waves of the "Survey of Italian Manufacturing Firms" (SIMF) which is conducted by Mediocredito-Capitalia in 2001, 2004 and 2007 and provides information on the three years prior to the interview. Firms are asked to complete a questionnaire eliciting information on the labor force, innovation activities, export involvement and financial characteristics. Each wave includes both a stratified sample of firms with more than 10 workers and up to 500 workers and a sample of all firms above this threshold.[3] Even if each wave contains around 9000 records, exploiting the panel dimension of the data is arguable, since the sample overlapping across waves is extremely small.[4] There are several advantages in using this data. First, firm-level data provide a better representation of the process of job creation and destruction compared to aggregate data. In particular, we use annual hires and separations, as well as employment stocks, to recover measures of firm growth and labor flows. Second, since the survey includes R&D and non-R&D companies, we are able to control for self-selection into R&D. Third, the survey simultaneously delivers information on employment, R&D and export for a sufficiently large number of private firms in the manufacturing sector, allowing us to fully conduct our econometric analysis.

Despite these advantages, the SIMF poses some limitations as well. First, data on hires and separations are not as accurate as one would wish to relate them to specific positions or skill levels. The data contain the number of hires and

[3] Stratification is based on industry, geographic area and firm size.

[4] By merging the second and third waves, (Piva & Vivarelli, 2005) are able to build a panel of 575 manufacturing firms.

separations for each year, but it is not possible to verify if these changes also reflect a change in the skill composition of each firm.[5] Second, the data do not describe the process of entry and exit of firms in the manufacturing sector. For instance, when firms are no longer included in the survey, it is not possible to discern whether those firms also did not survive in the market. Third, we cannot distinguish between voluntary quits and layoffs, rather we only observe separations between workers and firms.

We merge the data from the three waves and exclude firms with inconsistent or missing information. Since our focus is confined to SMEs, we use a threshold of 250 employees to select the estimation sample. For our estimation procedure which consists of three stages, we include all firms with exploitable information in the first and second stage to ensure the highest sample size and representativeness in each stage. Thus, when we deal with the problem of under-reporting of R&D, we have valid information on 18,222 observations. In the second stage, export intensity was available only for the last year of each survey, which reduced the sample to 8762 firms. Finally, as it will be clarified in the next section, the net employment change computed from flow variables does not always match the net employment change computed from stock variables. We decided to drop these observations and run the quantile regressions on a final sample of 6328 observations.

4.2 *Data Variables*

To depict employment dynamics, we implement the empirical model on three key dependent variables, i.e. the growth rate, hiring rate and separation rate. Specifically, the growth rate is defined as the yearly net employment change over initial employment. There are some discrepancies in the way data have been reported. The net employment change computed from flow variables (i.e. the difference between the yearly number of hires and separations) does not always match the net employment change computed from stock variables (i.e. the difference between employment at the end of the year and employment at the beginning of the year). To ensure consistency of the firm growth rates, we compute and compare the net employment change both ways and keep all the observations with coherence between stock and flow variables.

Hiring and separation rates are defined, respectively, as the yearly number of hires and separations divided by total employment. Here we stress the fact that our focus on hiring and separation rates is new in this literature. Up to now, scholars have thoroughly devoted their attention on various measures of firm growth, but no research has been yet conducted on the components of the growth rate. We believe it is worth investigating whether it is possible to associate firms' R&D to variations in the rates at which firms hire new workers, separates from existing ones or both, because it improves our understanding of the factors behind the hiring and separation processes. Firms grow and contract by changing the number of hires, the number of separations, or both. These choices cannot be thought of as non-random and, at least in principle, can be affected by R&D and export strategies. Indeed, since in R&D companies knowledge is intensively used, an increase in the number of hires

[5] To be precise, firms were also asked to report the composition of their workforce in terms of managers, blue collars and white collars, but the response rate to this questions is extremely low.

could reflect the need to enrich or replace the endowment of skills. Lower separations could depend upon the need to retain skills and knowledge belonging to existing employees. Exporting firms might also shape their personnel policies differently from non-exporting firms. Thus, observed hiring and separations can eventually be interpreted as the result of optimal personnel policies that take into account the commitment to innovation and internationalization pursued by firms.

The explanatory variables that are of main interest are those related to exports and R&D. In our data, while R&D expenditure has been reported on a yearly basis, both export status and export intensity have been reported only for the last year of each survey. This data limitation leads us to focus only on available information. We first compute R&D intensity as the ratio between R&D expenditure and turnover. Due to the high skewness of the R&D intensity, the standard practice is to take a logarithmic transformation. Nevertheless, transforming to log-space implies a cost. Since the logarithm is defined only for strictly positive values, all zeroes must be dealt with a discretionary assignment, either one or, as found in similar studies, with the minimum strictly positive value. Yet, this is an arbitrary data imputation that, in some cases, can lead to very different estimations, especially when there is a large number of zeroes. Instead, one can use the inverse hyperbolic sine transformation (IHS). The IHS is defined as the $ln\left(y_i + (y_i^2 + 1)^{\frac{1}{2}}\right)$ and, therefore, it can be interpreted in the same way as a standard logarithmic variable but, unlike a log variable, the IHS is also defined at zero.

4.3 ***Summary Statistics***

Based on the sample of 6328 observations, Tables 1 to 3 shows summary statistics of growth, hiring and separation rates by export and R&D status. According to these unconditional figures, firms that engage in R&D activities, but do not trade internationally, have the highest growth rates. It seems that innovating firms are able to grow faster if they choose to sell their goods in national markets. This could be in line with the idea of a limited competitive pressure in national markets compared to the competitive pressure faced in international markets. R&D can be the source of market power, which becomes stronger when the size of the market is limited. The same tables reveal that the growth and labor flow rates of non-innovative firms do not differ substantially when comparing exporters and non-exporters. In contrast, the growth and labor flow rates of exporters tend to be higher for non-innovating firms. Another interesting fact is that the standard deviations of the growth, hiring and separation rates of exporting firms are about twice as much as those of non-exporters. This large variability, however, might be related to differences in other firm dimensions, such as industry or regional characteristics that will be accounted for in our multivariate analysis.

Table 4 clearly shows that there are sharp differences in firms' characteristics associated to R&D and export status that must be taken into account in a multivariate setting. Exporting firms are on average three years older than non-exporting firms, while R&D companies are only one year older than non-R&D firms. Exporting firms are also substantially larger than non-exporters, especially if they also invest in R&D. Overall, firms involved both in export and innovative activities are on average larger and older. It is also interesting to highlight that exporters usually report foreign companies as their main competitors. Finally, from the geographic indicators, we also find that, among all SMEs that simultaneously report to be active both as exporters and innovators, only 9% belong to the South of Italy.

5. Empirical Results

5.1. Accounting for the under-reporting of R&D in SMEs

Before running the regressions, we check whether firms self-select into R&D with a 2SLS model. The first step is a selection equation estimated via Probit. Then we compute the inverse Mills ratio, which is then included in the Tobit equation. We find that the estimated coefficient of the selectivity term is not significant at conventional levels, which is similar to what was found by Hall et al. (2008) for the same data. We therefore conclude that self-selection is not relevant in our data.[6] Thus, we decided to focus on a type-I Tobit model and use a rich set of variables aimed at capturing observable differences in R&D intensity. We include the log of turnover, initial size and age indicators. We also add geographical dummies to capture disparities in local markets. Furthermore, we include a dummy variable, which is equal to one when firms report that their main competitors are from abroad and a dummy equals to one when the firm belongs to a group of firms. We also add 29 industry dummies, year dummies and wave dummies. Estimates are carried out on a sample of 18222 observations, while standard errors are bootstrapped with 399 replications.

For convenience, Table 5 reports only a subset of the estimated coefficients for the R&D equation (stage 1). Industry, year and wave dummies have not been included in the table, but they are highly significant, both individually and jointly, with F-values equal to 535.80, 31.82 and 26.88, respectively. We find that even if the coefficients on size and squared size are statistically significant, both effects are very small in magnitude. This is in line with the idea that R&D intensity is independent of firm size (see Klette and Kortum, 2004). Being part of a business group and dealing with foreign competition are both positively associated to R&D. We also find positive and highly significant effects of the geographical indicators (with the reference region being the South of Italy). Overall, our model produces a good fit to the data with a pseudo-R squared of 80.15%.

We use the predicted values from this first stage to proxy the R&D intensity of firms in our sample. This R&D intensity is used to study the export-innovation relationship as well as the impact of R&D and export activities on growth, hiring and separation rates.

5.2 Estimating the export-innovation relationship

We now turn to the estimation of the export-innovation relationship.[7] Estimates are reported in Table 6 and show that R&D intensity has a positive and

[6] All tables are available upon request.

[7] As before, we first assess self-selection into export with a two-stage procedure. We first estimate a selection into an export equation and recover the inverse Mills ratio. Then, we include this ratio in a second stage Tobit

significant impact on the export intensity. This result is not surprising, since most of the literature has already highlighted the importance of innovation as a driver for international trade. Successful exporters are often innovators because innovation helps firms facing the more intense competition in international markets.

Table 6 reports marginal effects on the latent variable, while the marginal effects on the actual export intensity can be obtained by multiplying the estimated coefficients by the probability that an observation is different from zero.[8] In our case, the marginal effect of R&D on exports turns out to be 3.63. To evaluate the magnitude of this effect, we start from a reasonable change in our regressor, say 5%. By multiplying this percentage change by 3.63, we obtain 18.15%, which is the percentage increase in our dependent variable.[9] In our estimation sample, the average export intensity is 23%, thus we can conclude that a 5% increase in R&D intensity for the average firm would lead to an export intensity of about 27% (= 23% + (23% * 0.1815)).

As far as the other regressors are concerned, we find that size and age are not good predictors of exports, while the dummy for foreign competitors is positively associated to export intensity. Being part of a group is negatively associated with export intensity. Also geographic dummies indicate large disparities among Italian regions. Most of the coefficients on industry, year and wave dummies are again highly significant.

From the main Tobit estimation, we compute predicted values and residuals that are later used to understand the impact of exports on growth and labor flows. Predicted values tell us the share of export intensity which is explained by R&D intensity and other control variables. Thus we use them in the next estimation step to account for any indirect effect of R&D on our dependent variables. Instead, we use residuals as the component of export intensity that is not explained by R&D. Although we control for many factors, interpreting the estimated coefficients in the second stage as causal effects should be done with cautiousness. In particular, the variability of the R&D intensity could partly be endogenous. Section 5.4 will deal with the problem of potential endogeneity both with the Smith & Blundell (1986) two-stage procedure and an instrumental variable approach.

5.3 Effect of export and innovation on firm growth and labor flows

Quantile regression results for the growth, hiring and separation rates are reported in Table 7. The main variables of interest are the R&D intensity, the R&D-induced export intensity and the export intensity not explained by R&D. In this way, we aim at capturing separately the direct impact of R&D, the indirect impact of R&D (through exports) and a pure export effect on growth and labor flows.

Focusing first on the growth rate (Table 7, Panel *a*), we see that an increase in R&D intensity has a large positive impact on almost all the quantiles of the growth distribution. Moreover, the magnitude of the estimated coefficients is more

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regression and control the significance of the selection term. Since the Mills ratio is not significant at conventional levels, we do not correct for selection in our estimates of export intensity.

[8] See Vrabeck (2000) for more details.

[9] Since the dependent variable is measured in logarithmic form, a change in a regressor can be read as the growth rate in the export intensity.

pronounced when moving to the tails of the distribution. Since we have estimated a log-log model the coefficients can be interpreted as elasticities. In particular, at the tails of the distribution, a one percent increase in R&D intensity is associated with a 4.9 and 3.9 percent increase at the 0.1 and 0.9 quantiles, respectively. The coefficient values become less pronounced when moving to the center of the distribution, thus R&D affects the shape of the conditional growth distribution especially along the tails.

As far as the share of export intensity explained by R&D is concerned, i.e., the indirect effect of R&D, we find that it is negatively associated to growth, with greater effects when placed further from the median. Nevertheless, the direct effect of R&D largely compensates the indirect effect, thus the R&D intensity produces an overall improvement in the growth performance of SMEs. This is in line with most of the existing results on this topic, and thus, our findings support the idea that R&D improves the growth performance of SMEs. However, we further refine the existing results in the literature by showing that the shape of the conditional firm growth distribution is negatively affected by the indirect impact of R&D through exports, even if this impact is small in magnitude. In other words, changes of the conditional firm growth distribution driven by firms' R&D activities are slightly more pronounced if firms are not active in international markets. Perhaps, a cautious interpretation would be that firms are able to extract a higher rent from R&D investments when facing domestic rather than international competition. As Italian firms are often considered to be soft innovators, competition among Italian firms is largely driven by expanding the existing variety of products, especially in the manufacturing sector.

Turning our attention to the coefficients related to the pure export effect, we see that they are also negative, small in magnitude but never significant at conventional levels. As pointed out in section 2, previous research has only marginally tackled the export-innovation relationship when estimating equations of firm growth. Our results suggest that there is no clear evidence in favor of a pure export effect on firm growth, while we find that R&D-driven exports negatively affects the growth distribution of firms.

To explore the results more in-depth, we investigate whether the higher growth rates induced by R&D activities are compatible with the responses of accession and separation rates to R&D. To the best of our knowledge, scholars have not yet assessed the impact of exports and innovation activities on labor flows at the firm level, though we believe that an understanding of how innovation (and exports) affects accession and separations can be of great interest for policy makers.

The estimated coefficients in panels *(b)* and *(c)* of Table 7 are clearly coherent with those presented in panel *(a)*. As R&D intensity rises, both the conditional distribution of hires and separations react in a way that is compatible with the positive effect of R&D on growth. In other words, R&D companies grow faster because of both increasing hiring and decreasing separations. SMEs that choose to invest in R&D tend to stabilize their workforce (lower separations) and are able to create opportunities for new jobs (higher hiring). Quantitatively, a one percent increase in R&D intensity is able to explain around a 0.7 percent increase in the hiring rate up to the median. The effect becomes even stronger at the right tail of the distribution, where estimated coefficients sharply increase up to 4.089 at the 0.9 quantile. At the same time, we observe that from the 0.7 to 0.9 quantiles, a unit percentage change in R&D intensity is followed by a 2 percent decrease in separations. Together, these findings suggest that innovation is a key element for reshaping firms' hiring and firing strategies. At the firm level, workers inflows and outflows can be thought of as the result of optimal personnel policies, which in turn can be affected by innovation strategies. Innovation strategies clearly modify the future skill composition of firms, which cannot be ignored when setting up optimal personnel policies. In particular, our results seems to support both the idea of human capital retention through lower separation rates and the need for new competences and skills in firms characterized by an innovative environment.

We also find compatibility between the negative effect of the R&D-induced exports on growth and the signs of the effects on accessions and separations. Indeed, results show that the lower growth rates associated with the fraction of export intensity explained by R&D are the result of lower hiring rates and higher separation rates. Finally, in line with the results in panel (*a*), we find that there is no evidence of a pure export effect on both hiring and separation rates.

5.4 Robustness

To check the robustness of our results, we rerun the quantile regressions after excluding the pure export effect. Results are shown in Table 8 and confirm what was previously found. The exclusion of the export effect does not alter the point estimates and their statistical significance. Again, the results for the hiring and separation rates corroborate both the positive impact of R&D and the negative effect of the R&D-induced export on growth. This suggests that companies that actively engage in R&D activities outperform non-innovating companies in terms of employment growth, but this effect is slightly mitigated by the increased propensity to export once R&D is conducted.

Up to now, we have ignored the fact that most Italian companies export inside the EU. Since our data allows us to identify intra-EU exports we restrict the analysis by excluding those companies that trade outside the EU. We then look at purely domestic companies that do not export at all and companies that trade inside the EU only. Results are reported in Table 9. Once again, the signs and the magnitude of the estimated coefficients point toward a positive impact of R&D intensity on employment growth and a negative impact of R&D-induced exports on growth. Also the components of the growth rate react in the expected way to increasing R&D and R&D-induced exports. Finally, exports *per se* do not seem to play a specific role for firms' growth. In particular, we find that at the right tail of the growth and hiring distributions, the impact of R&D is even stronger.

We further check the robustness of our results running the quantile regressions for a sub-sample of data. In particular, in Table 10, which is based on the last and most recent observation available for each firm in the sample the estimations continue to corroborate our results.

5.5 Endogeneity

As pointed out in section 3, the coefficients estimated from the second stage of the empirical model could suffer from potential endogeneity bias. In particular, there is a problem of endogeneity of the R&D intensity due to the potential correlation between this measure and the error term in the export intensity equation. Indeed, exogeneity of R&D would require that firms' R&D efforts took place independently from export decisions.[10] Despite controlling for several factors, in the absence of an exogenous variation in the R&D behavior, our estimates should be interpreted with cautiousness. To this end, we first test for potential endogeneity of the R&D intensity with the Smith & Blundell (1986) two-stage procedure. Then, even if this approach fails to reject exogeneity, we adopt an instrumental variable approach to check the robustness of the results.

When conducting the Smith & Blundell test, we first regress the R&D intensity over the same regressors of the R&D equation in stage 1. The residuals from this stage are plugged into the Tobit estimation of the export intensity equation. Exogeneity is then evaluated by means of t-statistics on the coefficient of the first stage residuals. In particular, if we cannot reject the null hypothesis, the R&D intensity is an endogenous regressor and the standard errors for the R&D equation are not valid. Instead, if the t-test confirms exogeneity, then the second stage coefficients should not differ in magnitude and significance levels from those obtained in the Tobit regression that does not include the first stage residuals among its regressors. The procedure delivers a large p-value (0.364) for the residuals and the estimated coefficients are in line with those presented in Table 6. Thus, we conclude that exogeneity is not rejected (complete tables are available upon request).

Even if this procedure is heavily used in applied work and makes us confident that our results do not suffer from endogeneity bias, we still assess the robustness of our results through the estimation of an IV Tobit model. The use of IV regressions is not new to the export-innovation literature (e.g. Lachenmaier and Wößmann, 2006; Czarnitzki and Wastyn, 2010) and is based on the need to find variation in innovation activities that is exogenous to export performance. In this study, we use the yearly average amount of government financial incentives to firms' R&D expenditure as the instrument. In the survey, firms were asked to report the percentage of R&D financed through direct subsidies and tax incentives, and the number of laws to which they applied in order to benefit from public financial incentives. We divide the amount of financial incentives by the number of laws to obtain the yearly average amount of public financial incentives received by firms. We test the relevance of the chosen instrument by looking at the F-value of the instrumental variable which, according to Staiger and Stock (1997), should exceed the value of 10.

From the first stage regression, R^2 and adjusted-R^2 are around 0.72, so there will not be a considerable loss of precision in our IV estimation. Results indicate that the instrument has a positive and significant effect on R&D intensity and the F-statistic is 34.19, which is considerably larger than the rule of thumb of 10. Therefore

[10] A possible rational for this assumption could be found in the irreversibility nature of R&D investments (Pindyck, 1991; Abel et al., 1996).

we conclude that the instrument is relevant, and the IV regressions will not suffer from a possible weak instrument bias.

At the second stage, we find that the instrument has a positive and significant impact on export intensity. Moreover, the minimum chi-square statistic (Amemiya, 1978; Newey, 1987; Lee 1992) shows a p-value of 0.1849, implying that our instrument is indeed an exogenous regressor. The IV Tobit coefficients are then used, as before, to obtain predicted values and residuals, which describe, respectively, the export intensity due to the R&D effort and the export intensity which is not explained by R&D. Then, we study the impact of exports and R&D on firm growth, hiring and separation rates in order to confirm our previous results.

Quantile regression results for the growth rate and its components are reported in Table 11. Once again an increase in R&D intensity has a significant and large positive impact on the growth distribution. We notice that the magnitude of the estimated coefficients is slightly more pronounced. Also, the negative effect of the R&D-induced exports on growth is confirmed and, with the exception of some cases, export *per se* does not play a specific role for firms' growth. As in previous estimates, these results are fully compatible with the effects found for the hiring and separation rates.

6. Conclusion

Innovation, firm growth and exports have an inter-connected relationship which has been explored extensively in the literature. We investigate how employment growth and labor flows are related to firms' R&D activities and export involvement. While previous studies have investigated the impact of export and innovation activities on firm growth, to the best of our knowledge, their impact on the components of the firms' employment growth rate at the firm-level have not been studied in the literature. It is important to understand how firms' R&D and export activities affect their hiring of new workers, their separations from existing firms, or both, since it improves our understanding of the factors behind the hiring and separation processes. After all, firms grow and contract by changing the number of hires, the number of separations, or both and these choices can be affected by R&D and export strategies.

We use establishment-level, cross-section data drawn from three waves of the "Survey of Italian Manufacturing Firms." After controlling for self-selection and endogeneity, our quantile regressions reveal that R&D is associated with higher growth rates, higher hiring rates and lower separation rates; R&D-induced exports are negatively related to firm growth and accessions and positively related to separations; and pure exports are not a driver of growth and labor flows. As reported earlier, a cautious interpretation for the case of Italian SMEs would be that firms are able to extract a higher rent from R&D investments when they face domestic rather than international competition. Since Italian firms are often considered to be soft innovators, competition among Italian firms is largely driven by expanding the existing variety of products, especially in the manufacturing sector.

The major findings of this article have also interesting policy and managerial implications. Our results supports the idea that, while there is no market failure argument to justify public interventions to firms that are already growing fast (Hölzl, 2009), R&D public policies could be effective to foster export activities. Public interventions can serve as a policy tool for stimulating R&D spending and, through their positive effect on exports, have both welfare and growth implications. The welfare implications stem from customer needs improving through international trade and the growth implications arise from the positive effects on firms' employment (Hall et al., 2008). In this respect, however, our results indicate that pure exports do not affect growth and labor flows, while the negative effect of R&D-induced exports on firms' growth is small in magnitude. Therefore, to stimulate firms' employment growth, our results indicate that R&D-oriented policies should be preferred to export-oriented policies. Thus the main challenge for policy makers is to stimulate a creative environment for business development where firms grow and enter foreign markets as successful innovators. These policy implications turn out to be particularly relevant in the context of SMEs, where investment decisions, as pointed out in Esteves-Pérez and Rodriguez (2013), are often constrained by limited access to financial resources.

From a managerial point of view, firms that engage in R&D activities pursue different optimal personnel policies compared to non R&D firms. In particular, the need to increase the endowment of skills pushes the hiring rate upwards as knowledge is largely embodied in workers. At the same time, knowledge retention appears to be essential for innovative companies, as the separation rate is lower compared to that of non-innovative companies. When combined, these effects allow innovative firms to protect their intellectual property more effectively and, at the same time, allow workers to enjoy greater job stability. As pointed out by Buch et al. (2009), companies active in international markets may be able to balance demand risks or, as noted by Baumgarten (2015), labor exiting exporting firms could be lower to the extent that wages are higher in these companies. Furthermore, SMEs planning to increase their presence in foreign markets should accept the challenge to increase their R&D effort by availing of national and international funding opportunities.

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Table 1: Growth rates by R&D and export status

		Growth rate		
		Non exporters	Exporters	Total
Non-R&D companies	Mean	0.0334	0.0378	0.0358
	SD	0.3766	0.6865	0.5626
	Frequencies	1829	2068	3897
R&D companies	Mean	0.0472	0.0259	0.0307
	SD	0.2069	0.4527	0.4103
	Frequencies	549	1882	2431
Total	Mean	0.0366	0.0321	0.0338
	SD	0.3449	0.5868	0.5095
	Frequencies	2378	3950	6328

Table 2: Hiring rates by R&D and export status

		Hiring rate		
		Non exporters	Exporters	Total
Non-R&D	Mean	0.1298	0.1320	0.1310
	SD	0.4132	0.7638	0.6242
	Frequencies	1829	2068	3897
R&D companies	Mean	0.1291	0.1036	0.1094
	SD	0.2099	0.4820	0.4357
	Frequencies	549	1882	2431
Total	Mean	0.1296	0.1185	0.1227
	SD	0.3761	0.6451	0.5594
	Frequencies	2378	3950	6328

Table 3: Separation rates by R&D and export status

		Separation rate		
		Non exporters	Exporters	Total
Non-R&D	Mean	0.0964	0.0941	0.0952
	SD	0.1944	0.3090	0.2615
	Frequencies	1829	2068	3897
R&D companies	Mean	0.0819	0.0778	0.0787
	SD	0.0875	0.1144	0.1089
	Frequencies	549	1882	2431
Total	Mean	0.0931	0.0863	0.0889
	SD	0.1756	0.2372	0.2161
	Frequencies	2378	3950	6328

Table 4: Summary statistics by R&D and export status

	R&D companies				Non-R&D companies			
	Non-exporters		Exporters		Non-exporters		Exporters	
N	549		1882		1829		2068	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Size	39.091	35.402	69.455	56.522	33.132	31.781	49.707	44.322
Age	24.237	15.903	27.665	18.465	23.216	15.818	26.057	17.518
Foreign competitors	0.100	0.301	0.399	0.490	0.080	0.271	0.290	0.454
North-west	0.332	0.471	0.412	0.492	0.329	0.470	0.357	0.479
North-East	0.270	0.444	0.323	0.468	0.255	0.436	0.297	0.457
Centre	0.228	0.420	0.173	0.378	0.197	0.398	0.196	0.397
South	0.171	0.377	0.093	0.290	0.220	0.414	0.149	0.357

Table 5: Accounting for under-reporting of R&D in SMEs

Dependent variable: log R&D intensity	
log turnover	-0.0184**
	(0.00778)
Size	0.00127***
	(0.000341)
Size (squared)	-0.00000345***
	(0.000000966)
Age (0 - 15)	-0.00145
	(0.00248)
Age (16-25)	0.00220
	(0.00258)
NW	0.0159***
	(0.00505)
NE	0.0259***
	(0.00739)
C	0.0272***
	(0.00670)
Foreign competitors	0.0382***
	(0.00762)
Belonging to a Group	0.0179***
	(0.00505)
Pseudo R-squared	0.8015

Notes: The model includes industry dummies, year dummies and wave dummies. Standard errors are in parentheses and are bootstrapped with 399 replications. N=18222.

Table 6: Export-innovation relationship

Dependent variable: log export intensity	
log R&D intensity	5.627***
	(0.724)
log turnover	0.0994***
	(0.00929)
Size	-0.000885*
	(0.000458)
Size (squared)	0.00000154
	(0.00000154)
Age (0 - 15)	-0.0116
	(0.0107)
Age (16-25)	0.0120
	(0.00890)
NW	0.0928***
	(0.0138)
NE	0.0628***
	(0.0143)
C	0.0611***
	(0.0154)
Foreign competitors	0.182***
	(0.0131)
Belonging to a Group	-0.0543***
	(0.0121)
Pseudo R-squared	0.2557

Notes: The model includes industry dummies, year dummies, and wave dummies. Standard errors are in parentheses and are bootstrapped with 399 replications. N=8762.

Table 7: Direct and Indirect R&D Effects and Pure Export Effects

Main regressors	p10	p20	p30	p40	p50	p60	p70	p80	p90
Panel (a): Growth rate									
R&D intensity	4.903***	2.905***	1.031***	-2.39e-12	0.519***	1.657***	2.105***	2.453***	3.939***
	(0.542)	(0.313)	(0.152)	(0.0798)	(0.0971)	(0.224)	(0.279)	(0.566)	(0.651)
R&D indirect effect	-0.381***	-0.231***	-0.0782***	1.18e-13	-0.0295***	-0.105***	-0.128***	-0.158***	-0.286***
	(0.0516)	(0.0304)	(0.0130)	(0.00704)	(0.00733)	(0.0158)	(0.0238)	(0.0455)	(0.0604)
Pure export effect	-0.00363	-0.00529	0.000149	-3.18e-15	-0.000267	-0.000375	-0.00250	-0.00646	-0.00795
	(0.00871)	(0.00672)	(0.00176)	(0.00129)	(0.00124)	(0.00253)	(0.00445)	(0.00595)	(0.0106)
Panel (b): Hiring rate									
R&D intensity	9.85e-14	0.796***	0.743***	0.715***	0.760***	0.980***	1.983***	2.253***	4.089***
	(0.127)	(0.150)	(0.178)	(0.212)	(0.249)	(0.249)	(0.383)	(0.563)	(1.101)
R&D indirect effect	-4.75e-15	-0.0458***	-0.0382**	-0.0399**	-0.0364	-0.0315	-0.0966***	-0.134**	-0.191**
	(0.0117)	(0.0122)	(0.0163)	(0.0193)	(0.0224)	(0.0245)	(0.0366)	(0.0543)	(0.0852)
Pure export effect	3.57e-17	-0.00352	-0.00559	-0.00288	-0.00195	-0.00386	-0.00389	-0.00192	-0.000410
	(0.00224)	(0.00232)	(0.00362)	(0.00387)	(0.00437)	(0.00497)	(0.00753)	(0.00994)	(0.0235)
Panel (c): Separation rate									
R&D intensity	2.48e-12	-0.234**	-0.969***	-1.347***	-1.559***	-1.643***	-2.075***	-2.306***	-2.545***
	(0.109)	(0.108)	(0.159)	(0.159)	(0.172)	(0.266)	(0.255)	(0.414)	(0.885)
R&D indirect effect	-1.23e-13	0.0109	0.0756***	0.104***	0.138***	0.153***	0.191***	0.229***	0.252***
	(0.0105)	(0.0109)	(0.0165)	(0.0159)	(0.0196)	(0.0241)	(0.0271)	(0.0439)	(0.0723)
Pure export effect	7.95e-16	0.00198	0.00345	0.00194	0.00282	0.00196	0.00408	0.0167**	0.0171
	(0.00204)	(0.00213)	(0.00316)	(0.00351)	(0.00371)	(0.00456)	(0.00524)	(0.00801)	(0.0151)
N=6328.									

Table 8: Direct and Indirect R&D Effects

Main regressors	p10	p20	p30	p40	p50	p60	p70	p80	p90
Panel (a): Growth rate									
R&D intensity	4.877***	2.999***	1.031***	-2.77e-12	0.518***	1.660***	2.098***	2.500***	3.920***
	(0.471)	(0.300)	(0.153)	(0.0798)	(0.0968)	(0.227)	(0.283)	(0.571)	(0.606)
R&D indirect effect	-0.379***	-0.235***	-0.0781***	1.34e-13	-0.0295***	-0.106***	-0.127***	-0.160***	-0.279***
	(0.0480)	(0.0326)	(0.0131)	(0.00704)	(0.00732)	(0.0158)	(0.0242)	(0.0463)	(0.0562)
Panel (b): Hiring rate									
R&D intensity	1.07e-13	0.786***	0.734***	0.689***	0.704***	0.998***	1.919***	2.279***	4.087***
	(0.127)	(0.148)	(0.183)	(0.209)	(0.238)	(0.258)	(0.359)	(0.547)	(1.099)
R&D indirect effect	-4.91e-15	-0.0456***	-0.0389**	-0.0357*	-0.0316	-0.0338	-0.0895**	-0.136**	-0.190**
	(0.0117)	(0.0122)	(0.0166)	(0.0191)	(0.0223)	(0.0254)	(0.0348)	(0.0552)	(0.0835)
Panel (c): Separation rate									
R&D intensity	2.00e-12	-0.211*	-0.961***	-1.350***	-1.594***	-1.682***	-2.002***	-2.273***	-2.372***
	(0.109)	(0.110)	(0.160)	(0.159)	(0.176)	(0.258)	(0.248)	(0.448)	(0.522)
R&D indirect effect	-9.02e-14	0.00917	0.0750***	0.105***	0.139***	0.156***	0.185***	0.224***	0.247***
	(0.0105)	(0.0110)	(0.0162)	(0.0158)	(0.0194)	(0.0238)	(0.0268)	(0.0479)	(0.0642)
N=6328.									

Table 9: Direct and Indirect R&D effect and pure export effects (EU exporters and non-exporters)

Main regressors	p10	p20	p30	p40	p50	p60	p70	p80	p90
				Panel (a): **Growth rate (a)**					
R&D intensity	4.859***	3.066***	0.667**	-4.53e-15	-5.31e-14	2.101***	2.428***	4.018***	5.114***
	(0.792)	(0.734)	(0.293)	(0.197)	(0.206)	(0.577)	(0.781)	(1.533)	(1.582)
R&D indirect effect	-0.629***	-0.316***	-0.0888***	4.68e-16	4.13e-15	-0.134***	-0.155**	-0.280**	-0.374**
	(0.104)	(0.0772)	(0.0337)	(0.0219)	(0.0222)	(0.0396)	(0.0638)	(0.131)	(0.147)
Pure export effect	-0.101	-0.0675**	-0.0313	-8.89e-18	-1.59e-16	-0.0109	-0.0162	-0.0403*	-0.0952***
	(0.0777)	(0.0279)	(0.0256)	(0.00811)	(0.00824)	(0.0119)	(0.0150)	(0.0216)	(0.0240)
				Panel (b): **Hiring rate (b)**					
R&D intensity	6.12e-14	1.231***	1.718***	1.309***	1.033**	1.201	1.948**	4.216***	5.373***
	(0.343)	(0.297)	(0.313)	(0.422)	(0.409)	(0.806)	(0.859)	(1.564)	(2.030)
R&D indirect effect	-4.69e-15	-0.0660**	-0.0992***	-0.108***	-0.0750	-0.0465	-0.111	-0.170	-0.0748
	(0.0354)	(0.0279)	(0.0296)	(0.0395)	(0.0488)	(0.0768)	(0.0909)	(0.128)	(0.226)
Pure export effect	2.64e-16	0.00479	0.0123	-0.00224	-0.00801	-0.0143	-0.0242	-0.0121	-0.0537
	(0.0112)	(0.0105)	(0.00922)	(0.00995)	(0.0123)	(0.0175)	(0.0233)	(0.0430)	(0.0540)
				Panel (c): **Separation rate (c)**					
R&D intensity	1.39e-14	-0.0339	-0.921***	-1.466***	-1.550***	-1.729***	-1.972***	-1.958**	-1.819
	(0.297)	(0.283)	(0.339)	(0.366)	(0.392)	(0.465)	(0.497)	(0.903)	(1.467)
R&D indirect effect	-1.11e-15	0.00168	0.0780**	0.111**	0.187***	0.226***	0.312***	0.332***	0.416***
	(0.0351)	(0.0374)	(0.0385)	(0.0486)	(0.0497)	(0.0609)	(0.0671)	(0.106)	(0.161)
Pure export effect	-1.86e-16	0.000108	0.0213**	0.0203	0.0343	0.0592*	0.0627***	0.0619	0.164***
	(0.0126)	(0.0140)	(0.0105)	(0.0133)	(0.0252)	(0.0309)	(0.0157)	(0.0386)	(0.0380)
N = 2519									

Table 10: Direct and indirect R&D effect and Pure export effects (last observation per firm)

Main regressors	p10	p20	p30	p40	p50	p60	p70	p80	p90
Panel (a): Growth rate									
R&D intensity	4.578***	2.704***	1.182***	-2.34e-12	-1.77e-12	1.369***	1.659***	1.781***	3.584***
	(0.729)	(0.343)	(0.215)	(0.0951)	(0.0945)	(0.239)	(0.336)	(0.433)	(1.072)
R&D indirect effect	-0.405***	-0.212***	-0.0887***	1.12e-13	8.51e-14	-0.0774***	-0.0846***	-0.0990**	-0.229***
	(0.0621)	(0.0381)	(0.0202)	(0.00851)	(0.00822)	(0.0171)	(0.0268)	(0.0432)	(0.0880)
Pure export effect	-0.0190	-0.0126*	-0.00290	-3.20e-15	-2.90e-15	-0.00108	-0.00396	-0.00575	-0.00977
	(0.0116)	(0.00731)	(0.00307)	(0.00165)	(0.00160)	(0.00287)	(0.00455)	(0.00676)	(0.0102)
Panel (b): Hiring rate									
R&D intensity	6.67e-14	0.688***	0.734***	0.650***	0.542**	0.726**	1.208***	1.808***	3.558***
	(0.154)	(0.136)	(0.194)	(0.220)	(0.259)	(0.323)	(0.459)	(0.603)	(1.273)
R&D indirect effect	-2.78e-15	-0.0352***	-0.0316*	-0.0317	-0.0130	-0.00336	-0.0208	-0.0697	-0.0949
	(0.0143)	(0.0126)	(0.0177)	(0.0209)	(0.0250)	(0.0307)	(0.0407)	(0.0574)	(0.113)
Pure export effect	1.03e-16	-0.00349	-0.00609	-0.00172	-0.000890	-0.00450	-0.00757	-0.00377	0.00917
	(0.00278)	(0.00249)	(0.00374)	(0.00450)	(0.00521)	(0.00540)	(0.00826)	(0.0138)	(0.0213)
Panel (c): Separation rate									
R&D intensity	1.17e-12	-0.154	-0.965***	-1.350***	-1.619***	-1.700***	-1.987***	-2.332***	-3.027***
	(0.126)	(0.129)	(0.182)	(0.168)	(0.192)	(0.264)	(0.250)	(0.464)	(0.803)
R&D indirect effect	-4.30e-14	0.00808	0.0744***	0.104***	0.150***	0.162***	0.198***	0.241***	0.303***
	(0.0127)	(0.0128)	(0.0202)	(0.0184)	(0.0242)	(0.0271)	(0.0300)	(0.0524)	(0.0865)
Pure export effect	1.59e-15	0.000991	0.00234	0.00275	0.00253	0.00340	0.00359	0.0143	0.0250*
	(0.00247)	(0.00247)	(0.00356)	(0.00367)	(0.00432)	(0.00527)	(0.00622)	(0.00896)	(0.0143)
N = 4625									

Table 11: Direct and indirect R&D effect and Pure export effects (IV Tobit model)

Main regressors	p10	p20	p30	p40	p50	p60	p70	p80	p90
Panel (a): Growth rate									
R&D intensity	4.850***	2.756***	0.813***	-2.14e-12	0.907***	2.204***	2.851***	3.732***	4.891***
	(0.494)	(0.259)	(0.126)	(0.0755)	(0.161)	(0.233)	(0.322)	(0.417)	(0.879)
R&D indirect effect	-0.345***	-0.185***	-0.0535***	5.30e-14	-0.0598***	-0.155***	-0.203***	-0.281***	-0.361***
	(0.0410)	(0.0213)	(0.00889)	(0.00623)	(0.0112)	(0.0177)	(0.0255)	(0.0394)	(0.0670)
Pure export effect	-0.0146*	-0.0119**	-0.00116	3.45e-16	-0.000436	-0.00106	-0.00333	-0.00520	-0.0123
	(0.00769)	(0.00604)	(0.00170)	(0.00127)	(0.00137)	(0.00254)	(0.00395)	(0.00721)	(0.0108)
Panel (b): Hiring rate									
R&D intensity	8.75e-14	0.970***	1.165***	1.071***	1.290***	1.712***	2.443***	3.108***	5.975***
	(0.126)	(0.141)	(0.188)	(0.219)	(0.246)	(0.291)	(0.319)	(0.506)	(1.175)
R&D indirect effect	-2.03e-15	-0.0640***	-0.0806***	-0.0777***	-0.0872***	-0.112***	-0.159***	-0.228***	-0.385***
	(0.0106)	(0.0114)	(0.0145)	(0.0179)	(0.0201)	(0.0245)	(0.0261)	(0.0448)	(0.102)
Pure export effect	-4.59e-17	-0.00272	-0.00441	-0.00311	-0.00181	-0.000599	-0.00261	0.00108	0.0102
	(0.00222)	(0.00230)	(0.00365)	(0.00390)	(0.00438)	(0.00498)	(0.00661)	(0.0119)	(0.0188)
Panel (c): Separation rate									
R&D intensity	1.97e-12	-0.204*	-0.805***	-1.175***	-1.286***	-1.328***	-1.755***	-2.023***	-2.160**
	(0.111)	(0.113)	(0.152)	(0.173)	(0.181)	(0.240)	(0.260)	(0.421)	(0.921)
R&D indirect effect	-5.38e-14	0.00696	0.0430***	0.0701***	0.0941***	0.108***	0.131***	0.175***	0.177***
	(0.00943)	(0.00969)	(0.0140)	(0.0145)	(0.0156)	(0.0190)	(0.0227)	(0.0403)	(0.0658)
Pure export effect	-6.92e-16	0.00268	0.00460	0.00465	0.00433	0.00600	0.00912*	0.0188**	0.0132
	(0.00202)	(0.00210)	(0.00312)	(0.00341)	(0.00372)	(0.00460)	(0.00545)	(0.00866)	(0.0151)
N = 6328									

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