Learning by Exporting and Research, Innovation and Productivity Relationship: Evidence from French food industry

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Abstract

This paper studies whether exporting induces productivity gains for producers. It argue that exporting affects productivity both directly and indirectly through higher incentives to invest in R&D. The latter is know in the literature as the learning by exporting (`LBE`) machanism. We develop a model in which both effects can be assess simultaneously. This model consists of four nonlinear dynamic simultaneous equations models that include individual effects and idiosyncratic errors correlated across equations. Using firm-level accounting data and detailed new product launched data from the french dairy industry for the period 2010-2017, we estimate our model by full information maximum likelihood (`FIML`), to empirically address the concerns of endogeneity. The results suggest a static productivity gains due to exporting (direct effect). Concerning the `LBE` process, we find that firms that operate in international markets are more likely to invest in R&D, which in turn affect their productivity through innovation. Furthermore, the results provide evidence of robust unidirectional causality from exporting to R&D investment, from R&D investment to innovation, and from innovation to productivity.

Keywords: Exports; R&D; Innovation; Productivity; Dynamics; Simultaneous equations

1 Introduction

The relationship between firm's performance and exports has been largely explored in the literature. Since the seminal work of Andrew B. Bernard, Jensen, and Lawrence (1995), many studies have shown the higher performance characteristics (e.g. higher wage, higher productivity, greater capital intensity, more workers, etc...) of exporting firms relative to non-exporters. According to these studies, two mechanisms can explain the strong positive correlation between firms' exports status and their performance. The first is related to self-selection; this mechanism is closely related to the hypothesis of sunk cost in entering in the export market (Dixit 1989; Krugman 1989; Baldwin 1990; Roberts and Tybout 1997). In accordance with these findings, Melitz (2003) provides a theoretical framework for modeling firms' export decisions, in which heterogeneous firms face sunk costs of entry and uncertainty concerning their productivity. The model shows that only the most productive firms enter the export market. The self-selection hypothesis induces that the causality link is tied to the productivity to exporting.[1]

The second mechanism is learning by exporting (hereafter, LBE).[2] According to De Loecker (2013), LBE simply refers to the mechanism whereby firms improve their productivity after entering export markets. In a similar way, Castellani (2002) refers to LBE as a change in the stochastic process governing firms' productivity that is induced by export behaviour. However, not all exporting effects on productivity refer to LBE mechanism. For example, the exploitation of economies of scale from the largest markets may induces static efficiency gains (Castellani 2002; Silva et al. 2012). Hence, LBE is not simply the outcome of the presence in the export market. Some authors, such as Serti and Tomasi (2008), Andersson and Lööf (2009) and De Loecker (2013), mention that experience and commitment of exporters or buyer-seller relationships are key drivers of LBE mechanism. Silva et al. (2012) suggest that, LBE process is based on fierce competition, contacts with foreigner buyers, and new problems that challenge technological development and can produce dynamic efficiency gains. The detection of LBE effects is important for the design of economic policy. Indeed, if LBE really exists, then governmental support to encourage firms to export is justified as an attempt to internalize positive externalities (Silva et al. 2012).

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[1] See Greenaway and Kneller (2007) and Wagner (2007) for theoretical and empirical reviews on the self-selection, respectively.

[2] Greenaway and Kneller (2007), Wagner (2007) and Silva et al. (2012) provide extensive reviews of this empirical litterature.

Empirical studies about LBE mechanism provided mixed results. While some studies tend to show evidence of LBE effect (Biesebroeck 2005; De Loecker 2007, 2013; Crespi, Criscuolo, and Haskel 2008; Lileeva and Trefler 2010), other studies fail to find evidence of such a mechanism (Clerides, Lach, and Tybout 1998; Andrew B. Bernard and Jensen 1999; B. Aw, Chung, and Roberts 2000; Delgado, Ruano, and Farinas 2002; Castellani 2002; Wagner 2002). To identify the learning mechanism, the literature has developed many empirical approaches. However, a common feature of these approaches is that they analyze the causal effect of exports on productivity. A drawback with these approaches is that they analyze LBE in a reduced way. As suggested by Silva et al. (2012), LBE should be measured using information on the specific mechanisms through which firms acquire knowledge in order to become more productive. Indeed, if exporting does affect learning, and learning then affects productivity, it would be valuable to test this relationship directly using data on exports, learning, and productivity (Crespi, Criscuolo, and Haskel 2008).[3] According to De Loecker (2013), investment in marketing, upgrading in product quality, innovation activities, or dealing with foreign buyers can be channels through which LBE mechanism operates. This paper focuses on firms' innovation activities as a learning-by-exporting mecanism's channel.

For this purpose, we assess two relationships. The first relationship goes from exports to innovation activities (e.g. R&D investment). The relationship between export and R&D investment can be explained by endogenous growth theories. Grossman and Helpman (1991) show that trade reveals information to exporters and give them access to the knowledge stocks of their trading partners. Exporters are more likely to invest in R&D than domestic firms because they are exposed to knowledge inputs not available to incumbent firms serving the domestic market. According to Salomon and Shaver (2005), export provides at least two types of knowledge: markets and technological knowledge. First, consumer preferences in international markets (market knowledge) may differ from those of their domestic counterparts. Thus, exposure to foreign markets can provide additional information to exporters not available in domestic market. In addition, Clerides, Lach, and Tybout (1998) argue that, exposure to export markets forces firms to alter and customize their product range to the needs of different international markets. More investments are needed to understand and assimilate these additional informations. Second, for the technological knowledge, the idea is that being exposed to a richer source of technology on export markets could lead firms to improve their knowledge base. Empirical studies show positive effect of firm's export decisions on R&D investment. For

[3]The difficulty in accessing learning data hinders that procedure. In our knowledge, only Crespi, Criscuolo, and Haskel (2008) use a direct measure of learning (from Community Innovation Survey data) to analyze LBE mechanism.

instance, Bee Yan Aw, Roberts, and Winston (2007) use Taiwanese data to analyze a firm's decisions to export and invest in R&D. They find that exporters need to produce effective R&D in order to generate efficiency gains. Additionally, Girma, Gorg, and Hanley (2008) find that previous export experience enhances the innovative capability of Irish firms. Such results are also found in Blind and Jungmittag (2004), Salomon and Shaver (2005), Salomon and Jin (2008), Salomon and Jin (2010).

The second relationship goes from innovation activities to firm's productivity. Estimating the return to R&D has been a major focus of empirical research for decades; most of these studies used the knowledge production function framework developed by Griliches (1979). In this framework, firm investment in R&D creates a stock of knowledge that enters into the firm's production function as an additional input along with physical capital, labor, and materials (Peters et al. 2017). An interesting point in this framework is the partial derivative of output with respect to the knowledge stock. Numerous studies have documented a positive relationship between R&D and productivity. Surveys by Mairesse and Sassenou (1991) and Griliches (1998) provide a useful overview of these studies. However, few of these studies corrected for potential selection bias, accounting for non-R&D performers and for simultaneity bias, because of the stochastic nature of R&D. Moreover, these studies generally did not into account theinformation on the innovation output. Indeed, the Griliches's framework neglect the link which Pakes and Griliches (1984) label as "the knowledge production function" i.e. production of commercially valuable knowledge or innovation output (Lööf and Heshmati 2006). Pakes and Griliches (1984) accounted for the fact that it is not innovation input (R&D) but innovation output that increases productivity. Crepon, Duguet, and Mairesse (1998) addressed these problems and proposed a model, which describes the relationship between R&D investment, innovation output, and productivity. The structural approach developed by Crepon, Duguet, and Mairesse (1998) –hereafter, CDM model – is a three-step model consisting of four equations. In the first step, firms decide whether to engage in R&D activities or not and on the amount of money to invest in R&D. Given the firm's decision to invest in R&D, the second step defines the knowledge production function, in which innovation output results from R&D investment and other factors. In a third step, the augmented Cobb-Douglas production function describes the effect of innovation output on productivity. Crepon, Duguet, and Mairesse (1998) estimated their model for French manufacturing firms, and a growing number of studies followed this line of research (See for instance, Mairesse, Mohnen, and Kremp 2005; Lööf and Heshmati 2006; B. H. Hall, Lotti, and Mairesse 2009; Acosta, Coronado, and Romero 2015; Peters et al. 2018).

To investigate firms' innovation activities as a learning-by-exporting mechanism's channel, we ask the following research questions: are exporters are more likely to invest in innovation? Does higher investment in innovation lead to higher innovation output? Is higher innovation output linked to higher productivity? This paper investigate these questions based on a firm-level panel data set for the Dairy industry in France. This is an interesting case to take for several reasons. First, the global demand for dairy products is growing. The dairy sector enjoys a sustained increase in aggregate demand especially in Asian countries where population growth combines with a gradual change in diets associated with an overall increase in purchasing power. Second, it is a mature exporting industry. Third, it is one of the most (labor) productive manufacturing industries. Fourth, although it is one of the least technology intensive industries, the dairy industry is one of the most innovative; especially in terms of product innovation. Finally, by focusing on a specific industry in a given country, we can avoid the potential for cross-industry effects to complicate causality links.

The rest of this paper is organized as follows. Section 2 discusses the literature reviews. Section 3 discusses the empirical methodology that we use. Section 4 describes the data, variables used in the empirical analysis and summary statistics. Section 5 presents the empirical results. Finally, Section 6 summarises the key findings

2 Econometric model and estimation procedure

This paper aims to show how firms' export participation affect productivity through the innovation process.

exporting provides a channel for knowledge acquisition by the firm which allow it.

However, assimilation of this expertise from its export markets contacts requires R&D investment. This new expertise thus materializes in innovation output, which in turn may contribute to the firms' productivity. To model this, we extend the CDM modelby adding one new equation corresponding to export participation. It also describes our estimation approach.

2.1 Framework

2.1.1 Investment in export markets

To identify and quantify factors that increase the probability to export, we estimate a reduced linear version of the export participation choice following a similar approach to Roberts and Tybout (1997) and Andrew B. Bernard and Jensen (2004). More precisely, Roberts and Tybout (1997) develop a dynamic discrete choice model of exporting behavior that separates the roles of profit heterogeneity and sunk entry costs in explaining firms' exporting status. Following these authors, we assume that a firm will decide to export if the discounted expected future profits from exporting, $E_t[V_{t+1}(\cdot)|e_{it} = 1]$, net of relevant cost are greater than the expected future profits from not exporting, $E_t[V_{t+1}(\cdot)|e_{it} = 0]$; ie,

$$e_{it} = \begin{cases} 1, & \text{if } \Delta E_t[V_{t+1}(\cdot)] > C^e(e_{i,t-1}, I_t) \\ 0, & \text{otherwise,} \end{cases} \tag{1}$$

$\Delta E_t[V_{t+1}(\cdot)] = E_t[V_{t+1}(\cdot)|e_{it} = 1] - E_t[V_{t+1}(\cdot)|e_{it} = 0]$ is the marginal benefit from exporting; where e_{it} is a discrete variable identifying the firm's export status in period t; where $C^e(e_{i,t-1}, I_t)$ are the trade costs. To parameterize this equation, we assume that the marginal benefit from exporting arise from foreign demand condition and from the differences in firm-level characteristics to control for production process. To capture the heterogeneity in firms' trade cost, we assume that firm i's cost depends on the firm's prior export experience, $e_{i,t-1}$, and other characteristics, I_t. The indicator variable for whether or not the firm invested in export in the previous year, $e_{i,t-1}$, takes the value 1 if the firm export in *t-1* and 0 otherwise. This captures sunk start-up costs of establishing distribution channels, learning bureaucratic procedures, and adapting their products and packaging for foreign markets (see for instance Das, Roberts, and Tybout 2007; Roberts and Tybout 1997). I_t include foreign markets condition, local geographic characteristics (see for instance Koenig, Mayneris, and Poncet 2010; Koenig 2009) and firm-level characteristics to control for fixed cost of exporting. Then, we estimate Eq.(1) using a dynamic binary-choice nonstructural approach of the form,

$$e_{it} = \begin{cases} 1, & \text{if } \mu_{1,t} + \beta_1' x_{1,it} + \gamma_1 e_{i,t-1} + \eta_{1,i} + \varepsilon_{1,it} > 0 \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

where $x_{1,it}$ collect information on firm-level and regional characteristics; $\mu_{1,t}$ is the industry-year dummies variables to control for foreign demand and market conditions (e.g. demand elasticity in foreign market and the costs of monitoring foreign customs procedures and product standards); $\eta_{1,i}$ is the time-invariant unobserved firm heterogeneity, e.g. managerial ability, that affect marginal benefit from exporting and trade costs; $\varepsilon_{1,it}$ is the error term. The scalar γ_1 and the vector β_1 capture, respectively, the effects of past exporting decision, and firm (and regional) characteristics on current export decision and are to be estimated.

In accordance with the trade literature (see for instance, Andrew B. Bernard and Jensen 2004; Roberts and Tybout 1997), Firm-level characteristics include size, age, wage, market share and Ownership structure. To control for regional characteristics, we include export-spillover and regional dummies variables. Table 1 provides more information on these characteristics.

2.1.2 Investment in innovation activities

To model firm decision to invest in R&D, we first make explicit assumptions about the timing of the firm's decision to export and undertake R&D. We assume that the firm first makes its discrete decision to export in period t. Following this, it makes the discrete decision to undertake R&D. This assumption implies that the firm decision to export affects the return to investing in R&D. Then, the valuation of R&D investment may differ for exporters and non-exporters. Following Bee Yan Aw, Roberts, and Winston (2007), an exporting (or non-exporting) firm will choose to invest in R&D if the marginal benefit of conducting R&D is greater than the costs of innovation:

$$d_{it} = \begin{cases} 1, & \text{if } \Delta E_t[V_{t+1}(\cdot)|e_{it}] > C(d_{i,t-1}; e_{it}; J_t) \\ 0, & \text{otherwise,} \end{cases} \tag{3}$$

where d_{it} is a discrete variable identifying the firm's R&D choice in period t, and $C(d_{i,t-1}; e_{it}; J_t)$ is the cost of innovation. To parameterize this equation, we assume that the marginal benefit from undertake R&D arise from demand condition, difference in market size (e.g. exporting firms have larger market size than non-exporting firms) and other firm-level characteristics. To capture the heterogeneity in firms' innovation cost, we assume that firm i's cost depends on the firm's prior R&D experience, $d_{i,t-1}$, export status, e_{it}, and other characteristics, J_t. The indicator variable for whether or not the firm invested in R&D in the previous year, $d_{i,t-1}$, takes the value 1 if the firm undertake R&D in *t-1* and 0 otherwise. This captures differences in the cost of innovation between maintaining ongoing R&D operations and starting new ones. Export participation, e_{it}, captures additional cost required to assimilate foreign knowledge. J_t include industrial and firm characteristics, controlling for fixed innovating costs. We estimate Eq.(3) using a dynamic binary-choice nonstructural approach of the form,

$$d_{it} = \begin{cases} 1, & \text{if } \mu_{2,t} + \alpha_2 e_{it} + \gamma_2 d_{i,t-1} + \beta_2' x_{2,it} + \eta_{2,i} + \varepsilon_{2,it} > 0 \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

where $x_{2,it}$ collect information on firm-level characteristics; $\mu_{2,t}$ is the industry-year dummies variables to control for foreign demand and market conditions (e.g. elasticity of demand, technological opportunity, market structure and appropriability); $\eta_{2,i}$ capture the time-invariant unobserved firm heterogeneity relevant for R&D investment; $\varepsilon_{2,it}$ is the error term. The scalars α_2, γ_2 and the vector β_2 capture, respectively, the effects of export participation, past R&D achievement and firm characteristics on current R&D achievement. Firm-level characteristics include, size, age, wage, ownership structure and public support.

2.1.3 Innovation output

This third stage of the model explains the innovation outcomes given by the following innovation production function,

$$z_{it} = \mathbb{1}[z_{it}^* \geq 0] \tag{5}$$

$$z_{it}^* = \mu_{3,t} + \alpha_3 d_{it} + \gamma_3 z_{i,t-1} + \beta_3' x_{3,it} + \eta_{3,i} + \varepsilon_{3,it} \tag{6}$$

where $t = 1, \ldots T_i$, $i = 1, \ldots N$ and $\mathbf{1}[\ldots]$ is an indicator function that takes on the value 1 if the expression between square brackets is true and 0 otherwise; where z_{it} is the innovation output variable taking the value one when the firm introduce new product and 0 otherwise. Eqs.(5) and (6) model the innovation output decision as a latent function of its investment in R&D (d_{it}), its past innovation achievement ($z_{i,t-1}$), its observable characteristics ($x_{3,it}$), time-invariant unobserved individual effects ($\eta_{3,i}$) and other time-variant unobserved variables ($\varepsilon_{3,it}$). z_{it}^* represents the incentive to innovate. If the incentive is sufficiently high, firm is an innovator in which case z_{it} is observed to be 1. We include in $x_{3,it}$, firm and industry characteristics. Firm characteristics include size, age, R&D spillover, wage, market share and ownership structure. As industrial characteristics, we include industry-year fixed effects to account for technology-push and demand-pull. The scalars α_3 and γ_3 and the vector β_3 capture, respectively, the effects of

R&D, past innovation output and firm characteristics on current innovation output and are to be estimated.

2.1.4 Productivity

The final part of the model explains the productivity as follow,

$$\omega_{it} = \mu_{4,t} + \alpha_4 z_{it} + \gamma_4 \omega_{i,t-1} + \beta_4' x_{4,it} + \eta_{4,i} + \varepsilon_{4,it} \tag{7}$$

where ω_{it} is the labor productivity (log. of value-added per employee). In Eq.(7), we parameterize the productivity evolution process as a function of lagged productivity ($\omega_{i,t-1}$), innovation output (z_{it}), other firms' characteristics ($x_{4,it}$), time-invariant unobserved individual effects ($\eta_{4,i}$) and time-variant unobserved variables ($\varepsilon_{4,it}$). The persistence in firm productivity over time is captured by the coefficients γ_4. The effect of innovation output on the firm productivity is captured by the coefficient α_4, and the vector β_4 captures the effect of other firms' characteristics. Firms' characteristics include the number of employees, the capital per employee and age. We also include export to control for static productivity gains from larger market size. Industry-year fixed effects take into account market structure.

Taking together, Eqs.(4), (5) and (7) constitute the well-know CDM model in which R&D investment is endogenous in the innovation output equation, and the innovation output is endogenous in the productivity equation.[4] Furthermore, due to the simultaneity, export participation is potentially endogenous in Eq.(4). Indeed, in order to participate in export market, firm may invest in R&D to upgrade the quality of their product, which induces a reverse causality problem. To take into account the fact that export participation, R&D investment and innovation output are respectively potentially endogenous in Eqs.(4), (6) and (7), the system formed by the Eqs. (2), (4), (6) and (7) are estimated simultaneously.

2.2 Estimation method

To consistently estimate parameters, the econometric literature on dynamic panel data shows that it's important to properly accounted for individual effects and the initial conditions. Estimation techniques that properly handle these problems in nonlinear dynamic panel data models are known in the literature.[5] In this study, we rely on the approach

[4]See B. H. Hall (2011) and Mohnen and Hall (2013) for a empirical review on CDM model and theoretical consideration.

[5]See for instance Heckman (1981), Honoré (1993), Honoré and Kyriazidou (2000) or Kyriazidou (2001) for different approaches.

propose by Wooldridge (2005) to deal with these problem.[6] Wooldridge (2005) proposed to specify the distribution of individual heterogeneity, conditional on the first observation in the sample. Following this approach, we assume the individual effects to be correlated with the initial conditions and the regressors,

$$\eta_{1,i} = b_{0,1} + b_1'\bar{x}_{1,i} + a_1 e_{i,0} + u_{1,i} \tag{8}$$

$$\eta_{2,i} = b_{0,2} + b_2'\bar{x}_{2,i} + a_2 d_{i,0} + u_{2,i} \tag{9}$$

$$\eta_{3,i} = b_{0,3} + b_3'\bar{x}_{3,i} + a_3 z_{i,0} + u_{3,i} \tag{10}$$

$$\eta_{4,i} = b_{0,4} + b_4'\bar{x}_{4,i} + a_4 \omega_{i,0} + u_{4,i} \tag{11}$$

where $\bar{x}_{1,i}$, $\bar{x}_{2,i}$, $\bar{x}_{3,i}$ and $\bar{x}_{4,i}$ denotes the time-average of $x_{1,it}$, $x_{2,it}$, $x_{3,it}$ and $x_{4,it}$ respectively; $d_{i,0}$, $z_{i,0}$, $w_{i,0}$ and $\omega_{i,0}$ pertain to the first available observation for each firm for dependent variables. The scalar a_1, a_2, a_3 and a_4 capture the dependence of the individual effects on the initial conditions. The individual effect $u_{1,i}$, $u_{2,i}$, $u_{3,i}$ and $u_{4,i}$ are quadrivariate normal with mean 0 and variance

$$\boldsymbol{\Sigma_u} = \begin{pmatrix} \sigma_{u_1}^2 & & & \\ \rho_{12}\sigma_{u_1}\sigma_{u_2} & \sigma_{u_2}^2 & & \\ \rho_{13}\sigma_{u_1}\sigma_{u_3} & \rho_{23}\sigma_{u_2}\sigma_{u_3} & \sigma_{u_3}^2 & \\ \rho_{14}\sigma_{u_1}\sigma_{u_4} & \rho_{24}\sigma_{u_2}\sigma_{u_4} & \rho_{34}\sigma_{u_3}\sigma_{u_4} & \sigma_{u_4}^2 \end{pmatrix} \tag{12}$$

The errors terms $\varepsilon_{1,it}$, $\varepsilon_{2,it}$, $\varepsilon_{3,it}$ and $\varepsilon_{4,it}$ are independent of the random effects and are also quadrivariate normal, with mean 0 and variance

$$\boldsymbol{\Sigma_\varepsilon} = \begin{pmatrix} 1 & & & \\ \tau_{12} & 1 & & \\ \tau_{13} & \tau_{23} & 1 & \\ \tau_{14}\sigma_4 & \tau_{24}\sigma_4 & \tau_{34}\sigma_4 & \sigma_4^2 \end{pmatrix} \tag{13}$$

When we condition on the individual effects $u_{1,i}$, $u_{2,i}$, $u_{3,i}$ and $u_{4,i}$, we can easily write the joint density of the ω_{it}, z_{it}, d_{it} and e_{it}. Define,

$$\begin{aligned} A_{it} =& \quad \mu_{1,t} + \gamma_1 e_{i,t-1} + \beta_1' x_{1,it} + b_{0,1} + b_1'\bar{x}_{1,i} + a_1 e_{i,0} + u_{1,i} \\ B_{it} =& \alpha_2 e_{it} + \mu_{2,t} + \gamma_2 d_{i,t-1} + \beta_2' x_{2,it} + b_{0,2} + b_2'\bar{x}_{2,i} + a_2 d_{i,0} + u_{2,i} \\ C_{it} =& \alpha_3 d_{it} + \mu_{3,t} + \gamma_3 z_{i,t-1} + \beta_3' x_{3,it} + b_{0,3} + b_3'\bar{x}_{3,i} + a_3 z_{i,0} + u_{3,i} \\ D_{it} =& \alpha_4 z_{it} + \mu_{4,t} + \gamma_4 \omega_{i,t-1} + \beta_4' x_{4,it} + b_{0,4} + b_4'\bar{x}_{4,i} + a_4 \omega_{i,0} + u_{4,i} \end{aligned}$$

[6] One limitation of this approach is that has been derived for balanced panels. However, using the sub-sample of balanced data still leads to consistent estimates if the dependent variables and attrition are independent. We are addressing this issue in the next section (dealt with this limitation on ddata section.)

The joint density, $\ell_{it|u}(\omega_{it},z_{it},d_{it},e_{it})$, of firm i at the period t conditional on the individual effects is written as[7]

$$\ell_{|u} = \frac{1}{\sigma_4}\phi\Big(\frac{\omega - D}{\sigma_4}\Big)\Phi_3\left(\frac{q_1\left(A + \frac{\tau_{14}}{\sigma_4}\varepsilon_4\right)}{\sqrt{1-\tau_{14}^2}}, \frac{q_2\left(B + \frac{\tau_{24}}{\sigma_4}\varepsilon_4\right)}{\sqrt{1-\tau_{24}^2}}, \frac{q_3\left(C + \frac{\tau_{34}}{\sigma_4}\varepsilon_4\right)}{\sqrt{1-\tau_{34}^2}}; q_1q_2\tau_1', q_1q_3\tau_2', q_2q_3\tau_3'\right) \quad (14)$$

where $q_{1,it} = 2e_{it} - 1$, $q_{2,it} = 2d_{it} - 1$ and $q_{3,it} = 2z_{it} - 1$; where $\Phi_3(\cdot)$ is the trivariate standard normal distribution function and,

$$\tau_1' = \frac{\tau_{12} - \tau_{14}\tau_{24}}{\sqrt{(1-\tau_{14}^2)(1-\tau_{24}^2)}},\ \tau_2' = \frac{\tau_{13} - \tau_{14}\tau_{34}}{\sqrt{(1-\tau_{14}^2)(1-\tau_{34}^2)}},\ \tau_3' = \frac{\tau_{23} - \tau_{24}\tau_{34}}{\sqrt{(1-\tau_{24}^2)(1-\tau_{34}^2)}}$$

Then, the likelihood function of one firm, starting from $t = 1$ is written as

$$L_i = \int_{\Re^4} \prod_{0_i+1}^{T_i} \ell_{it|u}(\omega_{it},z_{it},d_{it},e_{it}) \times \phi_4(u_{1,i}, u_{2,i}, u_{3,i}, u_{4,i})\, \mathrm{d}u_{1,i}\mathrm{d}u_{2,i}\mathrm{d}u_{3,i}\mathrm{d}u_{4,i} \quad (15)$$

where $\phi_4(\cdot)$ is the quadrivariate normal density function of $(u_{1,i}, u_{2,i}, u_{3,i}, u_{4,i})'$. This multivariate integral is generally not tractable and must be evaluated numerically. We use the adaptive Gauss-Hermite quadrature (for a detailed discussion on adaptive Gauss-Hermite quadrature, see, Skrondal and Rabe-Hesketh 2004). Let $\mathbf{L}$ be the Cholesky decomposition of $\mathbf{\Sigma}_u$; that is, $\mathbf{\Sigma}_\nu = \mathbf{LL}'$. It follows that $(u_{1,i}, u_{2,i}, u_{3,i}, u_{4,i})' = \mathbf{L}\psi_i$, where ψ_i is a vector of independent standard normal random variables. We can rewrite Eq.(15) as

$$L_i = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} \prod_{0_i+1}^{T_i} \ell_{it|u}(\omega_{it},z_{it},d_{it},e_{it}|\, (u_{1,i}, u_{2,i}, u_{3,i}, u_{4,i})' = \mathbf{L}\psi_i)\times$$
$$\phi(\psi_{1,i})\phi(\psi_{2,i})\phi(\psi_{3,i})\phi(\psi_{4,i})\, \mathrm{d}\psi_{1,i}\mathrm{d}\psi_{2,i}\mathrm{d}\psi_{3,i}\mathrm{d}\psi_{4,i} \quad (16)$$

Now the univariate integral can be approximated using Gauss–Hermite quadrature, which states that

$$\int_{-\infty}^{+\infty} e^{-z^2} f(z)dz \simeq \sum_{m=1}^{M} w_m f(a_m)$$

where w_m and a_m are, respectively, the weights and abscissas of the Gauss-Hermite integration, the tables of which are formulated in mathematical textbooks, and M is the total number of integration points. The larger M, the more accurate the Gauss-Hermite approximation. Consider a 4-dimensional quadrature grid containing M quadrature points in all the dimensions. Let the vector of abscissas $\mathbf{a}_m = (a_{m_1}, a_{m_2}, a_{m_4}, a_{m_4})'$ be a point in

[7]We drop the subscript "it" in the expression for writing convenience.

this grid, and let $\mathbf{w}_k = (w_{k_1}, w_{k_2}, w_{k_3}, w_{k_4})'$ be the vector of corresponding weights. The Gauss–Hermite quadrature approximation to the likelihood is

$$L_i \approx \sum_{m_1=1}^{M} \cdots \sum_{m_4=1}^{M} \left[\left\{ \prod_{0_i+1}^{T_i} \ell_{it|u}(\omega_{it}, z_{it}, d_{it}, e_{it} | \, (u_{1,i}, u_{2,i}, u_{3,i}, u_{4,i})' = \mathbf{L}\mathbf{a}_m) \right\} \left\{ \prod_{s=1}^{4} w_{m_s} \right\} \right] \tag{17}$$

3 Data and descriptive statistics

This section discusses the different data sources used in this study. We begin by focusing on Global New Products Database –hereafter `GNPD`–, a source of information on new product launches, and then present the procedure developed to match it with French databases. Finally, we present some descriptive statistics.

3.1 Data sources description

3.1.1 Global New Product Database

Innovation count consists in collecting information on innovations from various sources such as new product/process announcements, specialized journals, or databases (Becheikh, Landry, and Amara 2006). It is an object approach since it concentrates on the innovations themselves. This approach is often contrasted with the subject approach, which consists of collecting information on a particular firm (innovation surveys). Innovation count offers some advantage compared to the innovation surveys: First, it seems to be less subjective than the innovation outputs from the innovation surveys since it is based on published material and verifiable. Second, innovation count is recorded soon after their introduction and not two years after. Third, innovation count can cover small firms as well as large firms.

To measure innovation, we use an exhaustive list of new product launches. The product launch data come from `GNPD`. This product database reports new consumables product launched. In addition to secondary information sources (Trade Shows, Press Releases, Media, Corporate Intelligence, etc. . .), Mintel mainly uses primary information sources to enrich `GNPD`. The primary source of information comes from shoppers who receive a list of stores they need to visit weekly to target new products. Distribution channels monitored include supermarkets, the mass market, pharmacies, health food stores, mail order and Internet sales, and direct-to-consumer stores. When a new product is identified, it is cross-referenced with the Mintel Shopper website to limit duplication of products that have already been identified. The product is then purchased and sent to the Mintel offices. Mintel's data entry team records relevant information from the package, including launch type, EC identification, product claims, bar codes, ingredients, nutritional data, and product category information, etc. The products are then sent to be photographed. Each product sheet is subject to quality control by a team of editors before publication on the site. An editor reviews recording as an additional quality control measure. The products appear in `GNPD` within a delay of approximately one month after their launches or as close as possible to launch.

Product innovation is recorded in `GNPD` under five types of launches:[8]

- "*New product*": This launch type is dependent on the Brand field. It is assigned when a new range, line, or family of products is encountered;
- "*New variety/range extension*": This launch type is dependent on the Brand field. It is used to document an extension to an existing range of products on the `GNPD`;
- "*New packaging*": This launch type is determined by visually inspecting the product for changes, and also when terms like New Look, New Packaging, or New Size are written on the pack;
- "*Reformulation*": This launch type is determined when terms such as New Formula, Even Better, Tastier, Now Lower in Fat, New and Improved, or Great New Taste are indicated on the pack;
- "*Relaunch*": This launch type is determined when specified on pack, via secondary source information (trade shows, PR, websites, and press) or when a product has been both significantly repackaged and also reformulated. If a product is reformulated and repackaged then this launch type is selected.

In this study, I focus on "*New product*," since the other types of launch refer more to product differentiation.[9] Then, we define as innovator a firm that has introduced a new product (according to `GNPD`).

Generally, `GNPD` is aimed at manufacturers, retailers and suppliers involved in the marketing, sale, research, or innovation of new products and who need to identify new trends (Solis 2016). However, `GNPD` is also used as a source of information in scientific studies: in food and nutrition (Mitchell 2008; D. J. Van Camp, Hooker, and Souza-Monteiro 2010; Roodenburg et al. 2011; Gallagher 2009; D. Van Camp, Hooker, and Chung-Tung 2012;

[8] A detailed description of these different types of launches is available here: `https://www.gnpd.com/gnpd/about/GNPD_Glossary_2016.1.pdf`

[9] See the third edition of the Oslo manual for detailed information: avalaible at `https://www.oecd-ilibrary.org/docserver/9789264013100-en.pdf?expires=1619780854&id=id&accname=guest&checksum=BA843C3F820A780AA5A7F8BA48A7474A`

Menard et al. 2012; Slining, Ng, and Popkin 2013; Martinez 2013; Yangui, Costa-Font, and Gil 2016; Souza-Monteiro and Hooker 2017; Gilham, Hall, and Woods 2018; Dickie, Woods, and Lawrence 2018; Tennant and Bruyninckx 2018), environment (Gouin et al. 2012; Zhang et al. 2015), biotechnology (Bouwmeester et al. 2009; Jankovic et al. 2010; Lucas et al. 2015), management (Anselmsson and Johansson 2009; Chrysochou 2010; Barcellos, Grunert, and Scholderer 2011; Krystallis and Chrysochou 2011; Stanton et al. 2015; Rubera, Chandrasekaran, and Ordanini 2016) and economics (Pofahl and Richards 2009; Li and Hooker 2009; Allender and Richards 2010). In economics, GNPD is generally used to understand consumer behavior; for example, Pofahl and Richards (2009) estimate the welfare effects on U.S. consumers resulting from the introduction of three bottled juice products. Allender and Richards (2010) estimate the potential change in California consumer surplus. To our knowledge, no study has focused on GNPD as a source of information on innovation activity at firm-level. In section 3.1.3, I present in detail the construction of an innovation database at firm-level using GNPD.

3.1.2 Other data sources

The second data source provides accounting data for French firms. This data source is called FARE. The corresponding data are drawn from compulsory reporting of firms and income statements to fiscal authorities in France. Since every firm need to report every year to the tax authorities, the coverage of the data is all French firms from 2010 to 2017 with no limiting threshold in terms of firm size or sales. This dataset provides us with information on employment, value-added, intangible asset, etc. To define industry, I use a detailed principal activity code, called APE.[10] This code is made up of 4-digits, the first two digits of which are common to both NACE (Statistical Classification of Economic Activities in the European Community) and ISIC (International Standard Industrial Classification of All Economic Activities). The French dairy industry is defined by the APE, 10.51, and is composed of four sub-industries: 10.51A (Manufacture of liquid milk and of fresh dairy products), 10.51B (Manufacture of butter), 10.51C (Manufacture of cheese), 10.51D (Manufacture of other dairy products).

The third source of information come from CUSTOMS dataset. This dataset provided detailed data on French exports flow for each French firm during the 2010-2017 period.

[10]The APE are issued in France by INSEE (Institut national de la statistique et des études économiques) to compagnies, micro-enterprises, and associations to classify the main activity strand. The code is assigned at the time of the structure's registration.

Table 1: Variables description and Descriptive statistics

			Standard Deviation		
Variable	Definition	Mean	Overall	Between	Within
Dependent variables					
Productivity	Value-added per employee, in log	4.171	0.626	0.589	0.308
Innovation output	1 if firm i has introduced at least one new products	0.206			
Innovation input	1 if firm i has invest in innovation activities	0.297			
Export status	1 if firm i has a positive trade flows	0.276			
Explanatory variables					
Capital	Tangible asset per employee, in log	5.024	1.078	1.091	0.313
Size	Number of employees, in log	2.373	1.711	1.738	0.238
Market share	Domestic market share, in log	-8.259	1.887	1.939	0.289
Age	Age of the firm	39.558	34.165	34.165	1.883
Wage	Cost of labor per employee, in log	3.781	0.440	0.368	0.275
Public	1 if firm i has received public funding for intangible invest.	0.359			
Foreign ownership	1 if firm i is a subsidiary of a foreign company	0.043			
Part of a group	1 if firm i belongs to a group	0.065			
R&D spillover	(innovating input firms)/(total firms) for firms in same sub-industry, excluding firm in question	0.253	0.033	0.029	0.019
Export spillover	(exporting firms)/(total firms) for firms in same Region, excluding firm in question	0.194	0.076	0.072	0.025

Source: data from FARE, GNPD and CUSTOMS datasets, authors' calculations.

Notes: The number of employees is in full-time equivalents.

3.1.3 Matching procedure

To identify a firm, all the databases of the French administration, including `CUSTOMS` and `FARE` datasets, use the same unique identifier, called `siren`. This simplifies the work when it comes to linking the different databases. However, for a given product, `GNPD` contains only the information that is observable on the packaging and the information on the collection site of the product. There is therefore no simple way to match a product with the firm that manufactured it. The matching procedure of `GNPD` with other databases is mainly based on the EC identification. The EC identification are the oval-shaped markings found on food products of animal origin in the European Community, required by European Union food safety regulations.[11] It identifies the processing plant that manufactured the product. The identification and health marks contains the following information: (*i*) the name of the country in which the product was processed, or more commonly its two-letter `ISO` country code; (*ii*) the national approval number of the facility where the food was processed, and (*iii*) the letters EC for European Community. We develop a matching algorithm to map new product launched with the corresponding French firms. The steps of the matching procedure are as follows:

- First, keep observations corresponding to dairy products (in variable `product category`) and new product (in variable `type of launch`).
- second, keep observations with an `ISO` country code corresponding to France, i.e. `FR`.
- third, concatenate the database with respect to the EC identification and year. This manipulation makes it possible to count the number of new products launched by EC identification in a given year.
- fourth, by using the file of approved milk and dairy products production establishments of the Ministry of Agriculture available here, we were able to associate the EC identification with the `siret` number of the manufacturing plant.[12]
- finally, aggregate observations from the 14-digits plant-level (`siret`) to the 9-digits firm-level (`siren`).

After this procedure, we obtain a firm-level innovation dataset which can be easily merged with other datasets. Table 1, summarize and define the selected variables from these datasets.Although our main firm-level administrative data source is comprehensive, with more than 7,800 observations spanning 1,467 different dairy firms from 2010 to 2017, we restrict our data sample for two reasons. First, we drop observations were values are missing for some variables (value-added, capital, number of employee, cost of labor and domestic turnover). Second, for a given firm we need at least three observations over

[11]See Regulation (EC) `No.853/2004` of the European parliament and of the council.

[12]The `siret` number (système d'identification du répertoire des établissements) identifies each firm's plants. It is composed of 14-digits: the 9-digits of the `siren` number + the 5-digits corresponding to a `nic` number (numéro interne de classement).

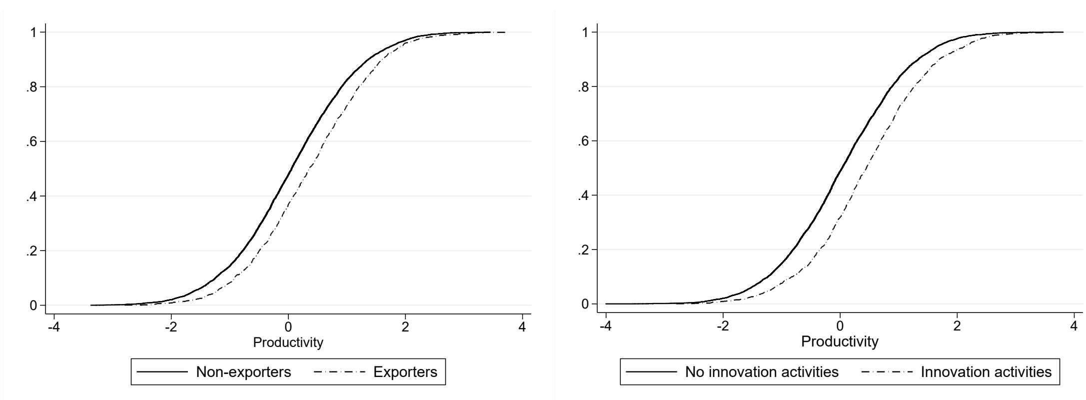
time, to be able to identify the parameters of the initial observations and the lagged dependent variables. Then, we drop firms with less than 3 observations. This reduces our working sample to 5,034 observations spanning 735 different dairy firms from 2010 to 2017.

Since, the (raw) data are an unbalanced panel, i.e. some firms enter and leave the sample during all periods, it is important to analyzes if the sample attrition is random or not before the cleaning procedure. Over the sample period, we find an annual average exit rate of 5%. To investigate the role of attrition, we construct a dummy variable, q_{it}, such that such that $q_{it} = 1$ when a firm leaves the sample at the period *t+1*, and $q_{it} = 0$ otherwise. using a Probit model, we estimate the probability for a given firm to leave the sample in period *t+1* conditional to their export participation, R&D investment, innovation output and labor productivity. We find no influence of either export participation, R&D investment or innovation output on the probability of leaving the sample. However, our estimates show that attrition becomes more likely as vessels become less productive. But, we believe this attrition has very little influence on our empirical analysis. Indeed, the pseudo-R^2 obtained with the Probit model is equal to 0.003. This very low figure may be interpreted as the proportion of attrition in the sample data.

3.2 Preliminary analysis

In this section we perform a preliminary analysis to show whether the performing firms (export or R&D) have higher productivity compared to non-performing firms.

Figure 1: Cumulative distribution of productivity

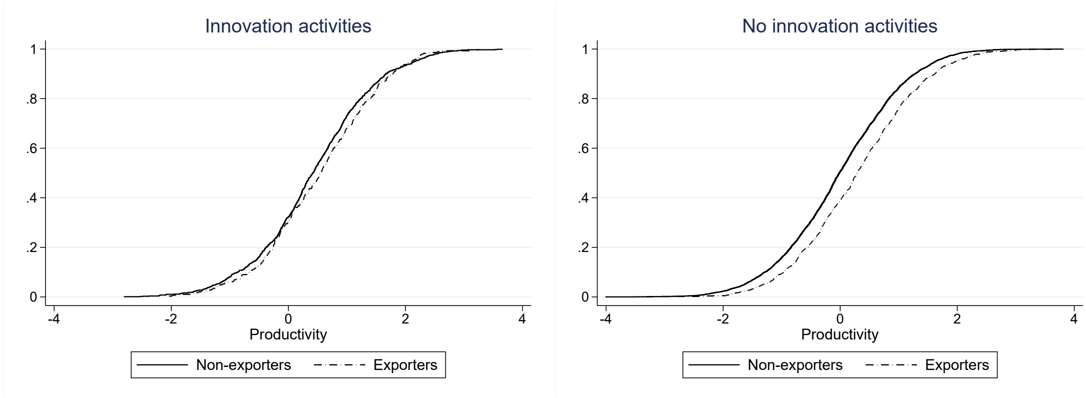


(a) Exporting or not (b) R&D or not

Note: Productivity distributions are drawn by regressing labor productivity on industry-year fixed effects and then plotting the residuals.

To do this preliminary analysis, we plot the distributions of productivity. In Fig. 1, we compare the productivity distributions of different samples of firms, e.g. exporters and non-exporters. The distribution of performers lies to the right of the distribution of non-performers, which suggests stochastic dominance. Hence, firms that invest in exports and/or R&D are more productive. This graphical analysis suggest the existence of two links: export-productivity and R&D-productivity.

Figure 2: Cumulative distribution of productivity



(a) Exporting or not (b) R&D or not

Note: Productivity distributions are drawn by regressing labor productivity on industry-year fixed effects and then plotting the residuals.

To test the relationship between exports, innovation and productivity, Fig.(2) compare the productivity distributions of exporters and non-exporters in the groups of R&D performers and non-R&D performers. For non-R&D performers, the productivity distribution of exporters is clearly to the right of that of non-exporters, which points towards stochastic dominance. In the group of R&D performers the productivity distributions seem to be closer to each other. This is suggestive of the fact that the relation between productivity and exports runs through R&D activities. However, this graphical inspection does not give us any information on the direction of the relationship between export, R&D and productivity. In this study, we suggest and test if the relationship is from exports to R&D, and from R&D to productivity.

4 Results

This section presents the main results of this study. Table 2 show the estimates of the model for exports, R&D, innovation and productivity in French dairy firms over the period 2010–2017, using `FIML` method describe in section 2.2.

4.1 Determinant of exports

The column (`I`) of the Table 2 reports estimates from our regression corresponding to the equation (2) of the model. The estimates reveal that firm propensity to export is positively associated with their size and export spillover from other firms. Indeed, we include in the estimation three dummy variables representing different categories, where the firms less or equal than three employees are the omitted base group.[13] The result show a monotonic relationship between firm propensity to export and their number of employees. However, only the export behavior of firms with more than 36 employees is significantly different from that of the reference group. In addition, we also find that propensity to export increase with the domestic market share. These findings indicates the importance of scale effects on exporting as suggested by the trade literature on scale-economy based exporting. Indeed, Larger firms can lower average production costs as output increases, and have lower average unit costs than smaller firms. Furthermore, as suggested by Bonaccorsi (1992), most firms will undertake growth within their domestic market first. However, at some point, the opportunities for domestic growth will become limited forcing firms to either stagnate or diversify their geographic market base. Using this logic, by the time firms begin exporting, they have already grown to larger firms status and capture a large market share within their domestic market.

In this study, export spillover is measure using exporters in the same regional location. Our result show that there are localized externalities positively associated with exporting. The propensity to export of a firm increase with the geographic concentration of export activity. This result can be explained by the fact that, the exchange of information between firms exporting to the same region reduces the individual fixed cost to export and increases the probability to export (see for instance, Aitken, Hanson, and Harrison 1997; Koenig, Mayneris, and Poncet 2010). We also include a set of regional dummies to control for other regional effects and externalities. All the regions are not equally endowed in transportation infrastructures. Indeed, to export easily, firms need, among others, airports, railroads or highways. The existence of a common border between the region and the destination country, increase the firm's propensity to exports. Conversely, none of the variables controlling for various aspects of ownership (Foreign ownership and part of a group) have a significant impact on the firms' likelihood to export. The results furthermore indicate that unobserved heterogeneity is a key factor for exporting. It still explains 68% of the unexplained variation in the export participation.

4.2 Determinant of R&D investments

Looking at the decision to engage in R&D (column (II) of the Table 2) shows that the probability of doing R&D increases significantly with the export participation, firm size, firm age and public support. The result show that, firms' incentives to undertake R&D investments increase with their activities in international markets. Hence, for exporting firms the net expected return on R&D investments can be larger than for non-exporting

[13]The different categories related to the number of employees are constructed on the basis of quartiles.

firms. There are at least two explanations for this result. First, firms that operate in international markets may have more exposure to new knowledge and face better demand opportunities to exploit their innovations, and hence have greater incentive to invest in costly innovation (e.g. Philippe Aghion et al. 2018; Lileeva and Trefler 2010; Peters et al. 2018). Another explanation would be that in order to compete in international markets exporters have to invest in new technology, which is often required to meet the needs of a more sophisticated demand (e.g. Philippe Aghion et al. 2018). We find that the firm's incentive to invest in R&D is 8.3% higher for exporting firms. Our results are consistent with previous empirical finding such as Peters et al. (2018) for German manufacturing firms or Bee Y. Aw, Roberts, and Xu (2011) for Taiwanese electronics firms.

The results further provide evidence that the incentives to undertake R&D investments is a monotonic increasing function of the firm age. Firm age is measured using a set of four dummy variables distinguishing the age groups: ≤ 8 years, 9–20 years, 21–43 years, and ≥ 44 years. We include three dummy variables representing different age categories in the estimation, where firms between under eight years old are the omitted base group. The coefficients on the remaining three age groups are positive and statistically significant, indicating that older firms have higher incentive to invest in R&D than the base group. In addition, the magnitude of the coefficient is higher for the oldest firms, indicating higher incentive as the firm ages. The result also suggest that R&D incentive is a monotonic increasing function of firm size. This is consistent with the fact that the returns from R&D are higher where the innovator has a larger volume of sales over which to spread the fixed costs of innovation. In addition, Cohen (2010) argue that capital market imperfections confer an advantage on large firms in securing finance for risky R&D projects because size is correlated with the availability of internally generated funds. Moreover, firms which receive public funding exhibit a higher propensity to invest in R&D. This result is also consistent with the capital market imperfections hypothesis. The results furthermore indicate that unobserved heterogeneity is a key factor for R&D investment. It explains 38% of the unexplained variation in the R&D participation.

4.3 Determinant of innovation output

Considering next the innovation equation, Eq.(6), we find that firms' incentive to introduce new product increase with R&Dinvestment, market share, firm size and R&D spillover (see Column (`III`) of the Table 2). As expected, our result show that the effect of R&D investment on innovation output is statistically significant. This is consistent with the knowledge production function literature (R. E. Hall, Blanchard, and Hubbard 1986). However, its economic value seems to be not relevant. Indeed, we find that firm's propensity to introduce new product is 3% higher for R&D performers. This result show that R&D investment is important for innovation output; nevertheless, this investment is neither necessary nor sufficient to produce innovation. This is conistent with previous empirical findings in other EU food industry. For instance, the empirical study by Triguero and Córcoles (2013), focused on innovation in the Spanish food industry during the period 1997-2008, found that the firm's propensity to conducting product innovation 9% higher for R&D performers. Using sample of Italian food firms during the period 1995–2006, Maietta (2015) found that R&D investment increase by 2% the probability to conducting product innovation.

Furthermore, we find that propensity to introduce new product is positively associated with firm size and market share. This result is consistent with the fact that large firms have more internal finance and easier access to external finance. in addition, large firms are more likely to engage in risky projects and benefit from economies of scale. We also find that The R&D executed by other firm affect positively the propensity to introduce new product. However, this effect is not significant. This can be explained by the fact that knowledge in the dairy industry is mainly based on know-how; this kind of knowledge is less likely to be assimilated by other firms. In addition, some empirical studies on innovation show that many innovations in the food industry are produced by applying and transferring knowledge from other industries, such as pharmaceuticals industry (Galizzi and Venturini 1996), nanotechnology industry (Sastry et al. 2010) or biotechnology industry (Carew 2005). Collaboration with public research centers, technical centers, universities and schools is also an important source of technology transfer that is not taken into account. This could explain why unobserved heterogeneity is a key factor for innovation output. In fact unobserved heterogeneity explain more than 60% of unexplained variation in new product introduction.

4.4 Determinant of labor productivity

Finally, the estimates of the productivity equation show that labor productivity is function of innovation outptut, firm age, capital intensity and the number of employees. Column (IV) of the Table 2 presents the estimates, which are elasticities or semi-elasticities, since the dependent variable is the log of value-added per employee. We show that the coefficient of innovation output is positive and statistically significant. The productivity returns to innovation output is estimated to be 0.05. There is not much econometric research on the food industry with which to compare these results. However, this is in accordance with the findings report by B. H. Hall (2011), in French Low-tech manufacturing industries. This result constrast with those of Acosta, Coronado, and Romero (2015) who finds that the elasticity for the innovation output is 0.29 in Spanish food industry.

Other explanatory variables in the models presented in Table 2 (Column IV) are quite stable and statistically significant at the 1% level. We find that labor productivity is an monotonic decreasing function of the firm age. The estimated coefficients for firms in the 9-20 and 21-43 categories imply that they have less productivities than the base group, but the difference is not significant. The coefficients on the remaining age group are negative and statistically significant, indicating that older firms have lower productivities than the base group. This result may be due to the "inertia effects" leading firms to become inflexible and have difficulties in fitting the rapidly changing business environment in which they operate, as suggested by Barron, West, and Hannan (1994). Some firms tend to develop cultures that make their organizations inflexible, resistant to change, and inclined to stick to path-dependent traditions (A. Hall, Melin, and Nordqvist 2001). This is particularly true in dairy industry where the manufacturing techniques of dairy products are part of the French dairy culture. Finally, we find decreasing returns to scale and a physical capital elasticity of about 0.221.

4.5 Dynamics of export, R&D, innovation and productivity

In this subsection, we analyze the dynamics of export, R&D, innovation and productivity and the direction of causality between them. In order to assess true state dependence and take into account the endogeneity of lagged dependent variables, we use the solution propose by Wooldridge (2005).

Our result show persistence in export markets participation for French dairy firms. We find that last period's exporting status, $e_{i,t-1}$, has a strong positive effect on the probability of exporting this period. Then, past exporting experience helps firms survive in export markets. This result can be explain, by the fact that continuing exporting is less costly than re-entering in export markets, as suggested by our structural model.[14] In other word, there are substantial sunk costs involved in entering or exiting the export market (see for instance, Andrew B. Bernard and Jensen 2004; Das, Roberts, and Tybout 2007; Roberts and Tybout 1997). Indeed, sunk costs may prevent non-exporters from taking up such activities because, unlike established exporters, potential entrants have to take them into account in determining their prices. Conversely, they represent a barrier to exit for established exporters because they reduce costs of future exports activities and therefore make their pursuit more attractive. The state dependence of exporting is estimated to be 0.185. By way of comparison, Roberts and Tybout (1997) found evidence

[14]Eq.(1) implies that firms lose their investment in start-up costs if they are absent from the export markets for a single year. Thus all firms that did not export in period $t-1$ are treated the same in period t, regardless of their more distant history. Although Andrew B. Bernard and Jensen (2004) show that the sunk costs act like a slowly depreciating investment for U.S. manufacturing plants from 1984 to 1992.

of true export persistence in Colombian manufacturing plants. Using U.S. manufacturing plants, Andrew B. Bernard and Jensen (2004) show that exporting last year raises the probability of exporting today. The particularity of this study is that it shows sunk costs depreciating slowly over time, while Roberts and Tybout (1997) fails to find such evidence.

The result show also a true state dependence in R&D investment in French dairy industry. Even after controlling for individual effects and initial R&D investment, last R&D investment status increase positively and significantly the incentive to undertake R&D in subsequent period. The key explanation for this result is the existence of sunk costs to undertake R&D project. Indeed, if a firm decides to undertake R&D, it has to incur start-up costs. Such R&D cost may include, establishing, equipping, and expanding R&D facilities, hiring and training specialized staff, and collecting information on novel market opportunities (Manez et al. 2009; Ganter and Hecker 2013). These fixed costs are generally not recoverable once realized, and can therefore be considered as sunk costs. As for exports, sunk costs represent a barrier to both entry into and exit from R&D activities. We find 17% increase in firms' incentive to undertake R&D, when they invest in R&D in previous period. This result is consistent with the findings of Castillejo et al. (2004) and Peters (2009) in Spanish manufacturing and German (manufacturing and service) firms, respectively.

Furthermore, our result reveal a true state dependence of new product introduction for French dairy firms. In other words, even after individual effects and the occurrence of new product introduction in the initial period are controlled for, achieving successful innovation output is time dependent in in French dairy industry. This result increase the credence for the "success breeds success" hypothesis. The notion behind this hypothesis is that a firm can gain some kind of locked-in advantage over other firms due to successful innovations (Peters 2009). Innovation success breeds innovation success by facilitating resource access. Since, innovation projects are characterised by high risks, and difficult for external financers to assess; then, revenu from previously successful innovations provide internal funding for further innovation. We estimate the true innovation persistence parameter to be 0.034 for French dairy firms. This result is consistent with the work of Duguet and Monjon (2004) who find true state dependence for innovation output in French low-tech industries. Same results are find by W. Raymond et al. (2010) and Ganter and Hecker (2013) in Dutch and German high-tech firms, respectively. However, our result contrast with those of W. Raymond et al. (2010) who fail to find true state dependence for Dutch low-tech firms. Finally, we find that the effect of past productivity on the current productivity level is significant. Hence, productivity is persistent over time. The lagged productivity term could reflect the influence of a slowly decreasing stock of knowledge (see for instance, Klette and Johansen 1998; Lokshin, Belderbos, and

Carree 2008). Lower values of the the state dependance parameter imply more rapid depreciation of the productivity and profit gains from an innovation.

We also interested to know what is the exact sequencing between export participation, R&D investment, innovation output and productivity. Then, we test the reverse causality running from productivity to innovation output, from innovation output to R&D investment and from R&D investment to export participation. To do so, we use the Granger non-causality test. For instance, Granger non-causality from productivity to innovation is the conditional independence of innovation from lagged productivity conditionally to lagged innovation.[15] Then testing Granger non-causality from productivity to innovation is equivalent to test the significance of lagged productivity on innovation output. Table 2 show result of Granger non-causality test. We find that the lagged feedback effect of productivity on innovation outptut is not economically nor statistically significant ($F(1;5{,}033) = 1.25; p - value = 0.318$). In addition, we also find that the lagged feedback effect of innovation output (resp. R&D investment) on R&D investment (resp. export participation) is not economically nor statistically significant. This finding suggest an unidirectional causality running from exporting to R&D investment, from R&D investment to innovation output and from innovation output to productivity.

[15] More clearly, Granger non-causality from ω_{it} to z_{it} is: $f(z_{it}|z_{i,t-1},x_{3,it},\omega_{i,t-1}) = f(z_{it}|z_{i,t-1},x_{3,it})$

Table 2: FIML estimate of the model.

Variable	Export participation Coef.[a]	S.E.	R&D investment Coef.	S.E.	Innovation output Coef.[a]	S.E.	Labor productivity Coef.	S.E.
Endogenous variables								
Parameters of interest (α_j)			0.370***	0.122	0.273**	0.110	0.052**	0.024
			[0.083]		**[0.026]**			
Lag. dep. var. (γ_j)	1.523***	0.148	0.694***	0.071	0.344***	0.116	0.330***	0.016
	[0.185]		**[0.166]**		**[0.034]**			
Exogenous variables								
Firm Age (reference group: $\leq$ 8 years)								
9-20 years	0.087	0.192	0.253**	0.114	0.084	0.191	-0.030	0.024
21-43 years	0.018	0.204	0.289**	0.117	0.176	0.205	-0.046	0.038
$\geq$ 44 years	-0.260	0.249	0.469***	0.126	-0.287	0.253	-0.091***	0.032
Market Share	0.287***	0.067			0.356***	0.069		
Foreign ownership	-0.246	0.325	0.285	0.225	0.284	0.276		
Part of a group	-0.366	0.323	-0.222	0.217	-0.036	0.281		
Wage	0.054	0.141	-0.086	0.074				
Firm size (reference group: $\leq$ 3 employees)								
3-8 employees	-0.307	0.187	0.058	0.092	-0.119	0.189		
8-36 employees	0.122	0.185	0.267***	0.101	0.213	0.184		
$\geq$36 employees	0.478**	0.218	0.546***	0.120	0.834***	0.208		
Export spillover	1.834**	0.884						
Public support			0.300***	0.079				
R&D spillover					0.876	0.757		
Capital intensity							0.221***	0.011
Number of employee							-0.074***	0.008
Causality test								
	$\boldsymbol{F_{stat} = 1.05}$		$\boldsymbol{F_{stat} = 2.03}$		$\boldsymbol{F_{stat} = 1.25}$			
	$\boldsymbol{P-value = 0.305}$		$\boldsymbol{P-value = 0.154}$		$\boldsymbol{P-value = 0.318}$			
Extra Parameters								
Initial observation	2.287***	0.324	0.687***	0.098	2.003***	0.253	0.222***	0.021
σ_{u_j}	1.445***	0.208	0.776***	0.077	1.285***	0.135	0.278***	0.123
Log likelihood					-4922.223			

Notes: The table reports the coefficients of covariates. Coefficients are normalized by a factor $1/\sqrt{\lambda_j^2+1}$ to recover the usual probit coefficients. Except Capital intensity and Number of employee, all variables considered as exogenous are lagged. ***, ** and * indicate significance on a 1%, 5% and 10% level, respectively. Each specification include industry-year dummies. Variables are defined in Table 1. j = 1,2,3,4. Values in bracket are the average partial effect.

4.6 Covariance matrix of residuals

Table 3 show the estimates of the correlations between individual effects and between error terms. The four equations are found to be correlated, mainly through the error terms. Indeed, there is no significant correlation between the individual effects in all equations. Instead, we observe a positive and statistically significant correlation, between the idiosyncratic error terms in all equations. Our estimation strategies, impose some structure on the idiosyncratic errors terms. Indeed, we assume that the correlation among equations come from a common unobserved factor, ξ_{it}. In our case, this factor may represent the unobserved foreign competition. In fact, during the observational period, *i.e.* 2010-2017, French import of dairy products increase, on average, by 2 percentage points per year.[16] Then, french dairy firms are facing growing foreign competition, which is not observed in our dataset.

Table 3: Correlation estimates

	Coefficient	Standard Errors
Correlation between idiosyncratic errors terms		
τ_{12}	0.271***	0.081
τ_{13}	0.135***	0.053
τ_{14}	0.178***	0.078
τ_{23}	0.357***	0.112
τ_{24}	0.115***	0.044
τ_{34}	0.146***	0.038
Correlation between individual effects		
ρ_{12}	0.139	0.111
ρ_{13}	0.024	0.093
ρ_{14}	0.062	0.089
ρ_{23}	0.035	0.096
ρ_{24}	0.021	0.068
ρ_{34}	0.130	0.083

Notes: ***, indicate significance at the 1% level. Correlation between errors terms are recovered as follows $\tau_{ij} = \lambda_i \lambda_j / \sqrt{(\lambda_i^2 + 1)(\lambda_j^2 + 1)}$

[16] Imports play a significant but highly variable role in French domestic consumption of dairy products, depending on the market. Direct household purchases account for half of national consumption of dairy products; 9% of these purchases are made up of imported dairy products. Imported products purchased by households are mainly branded products (e.g. Italian cheeses) or competing products in the lower price segments (e.g. packaged milk, grated cheese). The agri-food industries use 39% of the national consumption. The latter are distinguished by a more intense recourse to imports (55% of dairy products purchased come from imports). This market concerns mainly ingredients derived from milk, such as butter, milk powder, whey powder, etc.. They are used in a wide variety of forms in the cookie industry, chocolate, ice cream production, pastry, animal feed, baby food, etc.(see Chatellier et al. 2020 for more detailed information.)

Firms that face increased foreign competition are the most likely to participate in the export market. The increase in foreign competition forces domestic firms to relinquish a portion of their share of their domestic market. Exporting firms will more than make up for the loss of their domestic sales with sales in the new export markets and increase their combined revenues (Bustos 2011; Melitz 2003). In addition, the incentive to innovate increase with foreign competition due to *"escape-competition effect"*. Indeed, some theoretical models (e.g. P. Aghion et al. 2005; P. Aghion, Harris, and Vickers 1997), have pointed out that competition may spur innovation, because it may increase the incremental profits that firms obtain by investing in innovation. Finally, pressure from foreign competition spurs firms' productivity. A popular mechanism is that intensified competition will reduce X-inefficiencies at the firm level (See for instance De Loecker et al. 2016; De Loecker 2011).

5 Conclusion

This paper investigates the role of product innovation on learning by exporting process. Much of empirical studies who attempt to test learning by exporting mostly used indirect data, which linked productivity to export. Learning by exporting should be measured using information on specific learning channels through which firms get knowledge in order to become more productive. In this study, we consider innovation activities as one of these learning channels. In order to test it, we propose a methodology based on the well-established structural CDM model. Based on prior works in international economics, we assume that export participation as an endogenous component of the innovation process. We estimate three relationships (exports-to-innovation inputs, innovation inputs-to-innovation output and innovation output-to-productivity) in a four nonlinear dynamic simultaneous equation model including individual effects and idiosyncratic errors correlated across equations. The model is estimated by full information maximum likelihood (*FIML*). We use data on the French dairy industry for the period 2010-2016 to test whether (i) exporters have higher returns to investment in innovation; (ii) investment in innovation raises innovation output and (iii) innovation output increases firm productivity.

The econometric analysis indicates that endogeneity biases seem to be important and have to be accounted for. The results show that exporting firms invest more in innovation activities than non-exporting firms. We also find that firms with higher innovation investment are able to increase their number of new products. The analysis highlights that, with respect to internal and external knowledge, different factors seem to be crucial for success with the introduction of new products. In line with other studies, the results confirm that product innovation has a positive impact on productivity. The estimated output elasticity of knowledge capital, proxy by the number of new products, of about 0.04. At the end, we find that, the indirect productivity elasticity of export participation is estimated to be 0.71%.

6 Appendix A: Numerical evaluation of the likelihood of the model

6.1 Using Cholesky decomposition

After obtained joint density, the next step consists in deriving the the likelihood, which are obtained by integrating out individual effects with respect to their normal distribution. Formally, we have

$$L_i = \int_{\mathrm{IR}^4} \prod_{0_i+1}^{T_i} \ell^*(\omega_{it}, z_{it}, d_{it}, e_{it}|u_1, u_2, u_3, u_4)\phi_4(u_1, u_2, u_3, u_4)\,\mathrm{d}u_1\mathrm{d}u_2\mathrm{d}u_3\mathrm{d}u_4$$

Evidently, L_i cannot be derived analytically. Let $\mathbf{L}$ be the Cholesky decomposition of $\boldsymbol{\Sigma}_{\boldsymbol{u}}$; that is $\boldsymbol{\Sigma}_{\boldsymbol{u}} = \mathbf{LL'}$. It follow that $(u_1,u_2,u_3,u_4)' = \mathbf{L}\boldsymbol{\psi_i}$, where $\boldsymbol{\psi_i}$ is a vector of independent standard normal random variables. Then, we can write the L_i as

$$L_i = \int_{\mathrm{IR}^4} \left\{ \prod_{0_i+1}^{T_i} \ell^* \left(\cdots \mid (u_1,u_2,u_3,u_4)' = \mathbf{L}\psi_i \right) \right\} \phi\left(\psi_1\right) \phi\left(\psi_2\right) \phi\left(\psi_3\right) \phi\left(\psi_4\right) d\psi_1 d\psi_2 d\psi_3 d\psi_4$$

Now the univariate integral can be approximated using Gauss–Hermite quadrature. The Gauss–Hermite quadrature states that

$$\int_{\mathrm{IR}} e^{-z^2} f(z)\mathrm{d}z \approx \sum_{m=1}^{M} w_m f(a_m)$$

where w_m and a_m are, respectively, the weights and abscissas of the Gauss-Hermite quadrature with M being the total number of integration points. The accuracy of the approximation increases with the number of integration points, M. The weights and abscissae can be found in mathematical textbooks. Now, consider a 4-dimensional quadrature grid containing M quadrature points in all dimensions. Let the vector of abscissas $\mathbf{a}_k = (a_{m_1}, a_{m_2}, a_{m_3}, a_{m_4})'$ be a point in this grid, and let $\mathbf{w}_k = (w_{m_1}, w_{m_2}, w_{m_3}, w_{m_4})'$ be the vector of corresponding weights. Then, the Gauss–Hermite quadrature approximation to the likelihood L_i is

$$L_i = \sum_{m_1=1}^{M} \sum_{m_2=1}^{M} \sum_{m_3=1}^{M} \sum_{m_4=1}^{M} \left[\left\{ \prod_{0_i+1}^{T_i} \ell^* \left(\cdots \mid (u_1,u_2,u_3,u_4)' = \mathbf{L}\mathbf{a}_k \right) \right\} \left\{ \prod_{s=1}^{4} w_{m_s} \right\} \right]$$

This full information maximum likelihood was implemented in `STATA` using `gsem` or `ml` modules.

6.2 Using multiple-step Gauss Hermite quadrature

where $\prod_{0_i+1}^{T_i} \ell_{it|\boldsymbol{u}}$ is the likelihood function of firm i, conditional on the individual effects; $\phi_4(\boldsymbol{u})$ is the quadrivariate normal density function of $(u_{1,i},u_{2,i},u_{3,i},u_{4,i})'$. Define

$$A_{it} = \mu_{1,t} + \gamma_1 e_{i,t-1} + \beta_1' x_{1,it} + b_{0,1} + b_1'\bar{x}_{1,i} + a_1 e_{i,0} \tag{18}$$

$$B_{it} = \alpha_2 e_{it} + \mu_{2,t} + \gamma_2 d_{i,t-1} + \beta_2' x_{2,it} + b_{0,2} + b_2'\bar{x}_{2,i} + a_2 d_{i,0} \tag{19}$$

$$C_{it} = \alpha_3 d_{it} + \mu_{3,t} + \gamma_3 z_{i,t-1} + \beta_3' x_{3,it} + b_{0,3} + b_3'\bar{x}_{3,i} + a_3 z_{i,0} \tag{20}$$

$$D_{it} = \alpha_4 z_{it} + \mu_{4,t} + \gamma_4 \omega_{i,t-1} + \beta_4' x_{4,it} + b_{0,4} + b_4'\bar{x}_{4,i} + a_4 \omega_{i,0} \tag{21}$$

the likelihood function of firm i at the period t, conditional on the individual effects is written as

$$\begin{aligned}\ell_{it|\boldsymbol{u}} = \; & \tfrac{1}{\sigma_{\varepsilon_4}}\phi\left(\tfrac{\omega_{it}-D_{it}-u_{4,i}}{\sigma_{\varepsilon_4}}\right)\Phi\left[Z_{it}^o\left(\frac{C_{it}+u_{3,i}+\frac{\tau_{34}}{\sigma_{\varepsilon_4}}(\omega_{it}-D_{it}-u_{4,i})}{\sqrt{1-\tau_{34}^2}}\right)\right]\\ & \Phi\left[D_{it}^o\left(\frac{B_{it}+u_{2,i}+\frac{\tau_{24.3}}{\sigma_{\varepsilon_4}}(\omega_{it}-D_{it}-u_{4,i})-\tau_{23.4}q_{3,it}(C_{it}+u_{3,i})}{\sqrt{1-R_{2.43}^2}}\right)\right]\\ & \Phi\left[E_{it}^o\left(\frac{A_{it}+u_{1,i}+\frac{\tau_{14.32}}{\sigma_{\varepsilon_4}}(\omega_{it}-D_{it}-u_{4,i})-\tau_{13.42}Q_{3,it}-\tau_{12.43}Q_{2,it}}{\sqrt{1-R_{1.432}^2}}\right)\right]\end{aligned} \tag{22}$$

where $q_{3,it} = 2z_{it} - 1$, $q_{2,it} = 2d_{it} - 1$; $Z_{it}^o = 1$ if firm innovate and $Z_{it}^o = -1$ otherwise; $D_{it}^o = 1$ if firm invest in R&D and $D_{it}^o = -1$ otherwise; $E_{it}^o = 1$ if firm export and $E_{it}^o = -1$ otherwise; $Q_{2,it} = q_{2,it}(B_{it} + u_{2,i})$ and $Q_{3,it} = q_{3,it}(C_{it} + u_{3,i})$,

$$\tau_{24.3} = \frac{\tau_{24} - \tau_{34}\tau_{23}}{1-\tau_{34}^2}, \tau_{23.4} = \frac{\tau_{23} - \tau_{34}\tau_{24}}{1-\tau_{34}^2}, R_{2.43}^2 = \frac{\tau_{24}^2 + \tau_{23}^2 - 2\tau_{34}\tau_{24}\tau_{23}}{1-\tau_{34}^2}$$

$$\begin{aligned}\tau_{12.43} &= \frac{\tau_{12} + \tau_{14}\tau_{23}\tau_{34} + \tau_{13}\tau_{24}\tau_{34} - \tau_{14}\tau_{24} - \tau_{12}\tau_{34}^2 - \tau_{13}\tau_{23}}{1 + 2\tau_{34}\tau_{24}\tau_{23} - \tau_{34}^2 - \tau_{24}^2 - \tau_{23}^2}\\ \tau_{13.42} &= \frac{\tau_{13} + \tau_{12}\tau_{24}\tau_{34} + \tau_{14}\tau_{24}\tau_{23} - \tau_{12}\tau_{23} - \tau_{13}\tau_{24}^2 - \tau_{14}\tau_{34}}{1 + 2\tau_{34}\tau_{24}\tau_{23} - \tau_{34}^2 - \tau_{24}^2 - \tau_{23}^2}\\ \tau_{14.32} &= \frac{\tau_{14} + \tau_{12}\tau_{23}\tau_{34} + \tau_{13}\tau_{23}\tau_{24} - \tau_{13}\tau_{34} - \tau_{14}\tau_{23}^2 - \tau_{12}\tau_{24}}{1 + 2\tau_{34}\tau_{24}\tau_{23} - \tau_{34}^2 - \tau_{24}^2 - \tau_{23}^2}\\ R_{1.432}^2 &= \frac{\tau_{12}^2 + \tau_{13}^2 + \tau_{14}^2 + 2\tau_{12}\tau_{14}\tau_{23}\tau_{24} + 2\tau_{13}\tau_{12}\tau_{24}\tau_{34} + 2\tau_{14}\tau_{12}\tau_{23}\tau_{34}}{1 + 2\tau_{34}\tau_{24}\tau_{23} - \tau_{34}^2 - \tau_{24}^2 - \tau_{23}^2}\\ &-\frac{2\tau_{14}\tau_{13}\tau_{34} + 2\tau_{14}\tau_{12}\tau_{24} + 2\tau_{13}\tau_{12}\tau_{23} + \tau_{12}^2\tau_{34}^2 + \tau_{13}^2\tau_{24}^2 + \tau_{14}^2\tau_{23}^2}{1 + 2\tau_{34}\tau_{24}\tau_{23} - \tau_{34}^2 - \tau_{24}^2 - \tau_{23}^2}\end{aligned}$$

The integral in Eq.(15) can be approximated by Gauss-Hermite quadrature, as suggested by W. Raymond et al. (2007).[17] This method consists of a four successive Gauss-

[17] The authors proposes a method to implement maximum likelihood estimation of the dynamic panel

Hermite quadrature approximations. It relies on a decomposition of the two dimensional normal distribution for the individual effects into a one-dimensional marginal distribution and a one-dimensional conditional distribution, successively. More specifically, Gauss-Hermite quadrature, states that

$$\int_{\mathbb{R}} e^{-z^2} f(z)\mathrm{d}z \approx \sum_{m=1}^{M} w_m f(a_m) \tag{23}$$

where w_m and a_m are, respectively, the weights and abscissas of the Gauss-Hermite quadrature with M being the total number of integration points. The accuracy of the approximation increases with the number of integration points, M. The weights and abscissae can be found in mathematical textbooks. Using sequentially the expression (23), the individual likelihood can be written as,

$$\begin{aligned}
\ell_i \quad \approx \quad & \frac{\Delta \times \Xi}{\pi^2} \sum_{m_4=1}^{M_4} w_{m_4} \prod_{t=0_i+1}^{T_i} \frac{1}{\sigma_{\varepsilon_4}} \phi\Big(\frac{\omega_{it} - D_{it} - a_{m_4}[\cdots]}{\sigma_{\varepsilon_4}}\Big) \\
& \sum_{m_3=1}^{M_3} w'_{m_3} \prod_{t=0_i+1}^{T_i} \Phi\left[Z^o_{it}\left(\frac{C_{it} + a_{m_3}[\cdots] + \frac{\tau_{34}}{\sigma_{\varepsilon_4}}(\omega_{it} - D_{it} - a_{m_4}[\cdots])}{\sqrt{1-\tau^2_{34}}}\right)\right] \\
& \sum_{m_2=1}^{M_2} w'_{m_2} \prod_{t=0_i+1}^{T_i} \Phi\left[D^o_{it}\left(\frac{B_{it} + a_{m_2}[\cdots] + \frac{\tau_{24.3}}{\sigma_{\varepsilon_4}}(\cdots - a_{m_4}[\cdots]) - \tau_{23.4}Q'_{3,it}}{\sqrt{1-R^2_{2.43}}}\right)\right] \\
& \sum_{m_1=1}^{M_1} w'_{m_1} \prod_{t=0_i+1}^{T_i} \Phi\left[E^o_{it}\left(\frac{A_{it} + a_{m_1}[\cdots] + \frac{\tau_{14.32}}{\sigma_{\varepsilon_4}}(\cdots - a_{m_4}[\cdots]) - \tau_{13.42}Q'_{3,it} - \tau_{12.43}Q'_{2,it}}{\sqrt{1-R^2_{1.432}}}\right)\right]
\end{aligned}$$

where

data type 2 and 3 tobit models. There is also a paper by Wladimir Raymond et al. (2015) which use the sequential Gauss-Hermite quadrature approach for nonlinear dynamic simultaneous equations models.

$$
\begin{aligned}
w'_{m_3} &= w_{m_3} e^{-2\Lambda_{34} a_{m_3} a_{m_4}/\sqrt{\Lambda_{33}\Lambda_{44}}} \\
w'_{m_2} &= w_{m_2} e^{-2a_{m_2}/\sqrt{\Lambda_{22}}\left((a_{m_3}\Lambda_{23}/\sqrt{\Lambda_{33}})+(a_{m_4}\Lambda_{24}/\sqrt{\Lambda_{44}})\right)} \\
w'_{m_1} &= w_{m_1} e^{-2a_{m_1}/\sqrt{\Lambda_{11}}\left((a_{m_2}\Lambda_{12}/\sqrt{\Lambda_{22}})+(a_{m_3}\Lambda_{13}/\sqrt{\Lambda_{33}})+(a_{m_4}\Lambda_{14}/\sqrt{\Lambda_{44}})\right)} \\
\Delta &= 1-\rho_{12}^2-\rho_{13}^2-\rho_{14}^2-\rho_{23}^2-\rho_{24}^2-\rho_{34}^2+\rho_{13}^2\rho_{24}^2+\rho_{12}^2\rho_{34}^2+2\rho_{23}\rho_{24}\rho_{34} \\
&\quad +2\rho_{13}\rho_{14}\rho_{34}+2\rho_{12}\rho_{14}\rho_{24}+2\rho_{12}\rho_{13}\rho_{23}-2\rho_{13}\rho_{14}\rho_{23}\rho_{24} \\
&\quad -2\rho_{12}\rho_{14}\rho_{23}\rho_{34}-2\rho_{12}\rho_{13}\rho_{24}\rho_{34} \\
\Xi &= (1-\rho_{12}^2)(1-\rho_{13}^2)(1-\rho_{14}^2)(1-\rho_{23}^2)(1-\rho_{24}^2)(1-\rho_{34}^2) \\
\Lambda_{11} &= \frac{1+2\rho_{23}\rho_{24}\rho_{34}-\rho_{23}^2\rho_{24}^2\rho_{34}^2}{\Delta} \\
\Lambda_{22} &= \frac{1+2\rho_{13}\rho_{14}\rho_{34}-\rho_{13}^2\rho_{14}^2\rho_{34}^2}{\Delta} \\
\Lambda_{33} &= \frac{1+2\rho_{12}\rho_{24}\rho_{14}-\rho_{12}^2\rho_{24}^2\rho_{14}^2}{\Delta} \\
\Lambda_{44} &= \frac{1+2\rho_{23}\rho_{12}\rho_{13}-\rho_{23}^2\rho_{12}^2\rho_{13}^2}{\Delta} \\
\Lambda_{12} &= \frac{\rho_{12}-\rho_{12}\rho_{34}^2-\rho_{14}\rho_{24}-\rho_{13}\rho_{23}+\rho_{13}\rho_{34}\rho_{24}+\rho_{14}\rho_{34}\rho_{23}}{\Delta} \\
\Lambda_{13} &= \frac{\rho_{13}-\rho_{13}\rho_{24}^2-\rho_{14}\rho_{34}-\rho_{12}\rho_{23}+\rho_{12}\rho_{24}\rho_{34}+\rho_{14}\rho_{24}\rho_{23}}{\Delta} \\
\Lambda_{14} &= \frac{\rho_{14}-\rho_{14}\rho_{23}^2-\rho_{12}\rho_{24}-\rho_{13}\rho_{34}+\rho_{13}\rho_{23}\rho_{24}+\rho_{12}\rho_{23}\rho_{34}}{\Delta} \\
\Lambda_{23} &= \frac{\rho_{23}-\rho_{23}\rho_{14}^2-\rho_{14}\rho_{34}-\rho_{12}\rho_{13}+\rho_{12}\rho_{14}\rho_{34}+\rho_{24}\rho_{14}\rho_{13}}{\Delta} \\
\Lambda_{24} &= \frac{\rho_{24}-\rho_{24}\rho_{13}^2-\rho_{12}\rho_{14}-\rho_{23}\rho_{34}+\rho_{23}\rho_{13}\rho_{14}+\rho_{12}\rho_{13}\rho_{34}}{\Delta} \\
\Lambda_{34} &= \frac{\rho_{34}-\rho_{34}\rho_{12}^2-\rho_{23}\rho_{24}-\rho_{13}\rho_{14}+\rho_{13}\rho_{12}\rho_{24}+\rho_{23}\rho_{12}\rho_{14}}{\Delta}
\end{aligned}
$$

where w_{m_k}, w_{m_k} and M_k (k = 1,2,3,4) are respectively the weights, abscissae and total number of points of the quadrature in each stage; $Q'_{2,it} = q_{2,it}(B_{it} + a_{m_2}[\cdots])$, $Q'_{3,it} = q_{3,it}(B_{it} + a_{m_3}[\cdots])$ and $a_{m_k}[\cdots] = a_{m_k}\sigma_{u_k}\sqrt{2}/\sqrt{\Lambda_{kk}}$. This individual likelihood can be evaluated in `Stata Software` using the `ml` module.

However because of the complexity of the joint distribution, $\ell_{it|u}$, the implementation of this technique is computationally cumbersome and extremely time-consuming, eventually rendering this solution virtually unfeasible.[18] To increase the computational feasibility, we use the latent variable approach that allows us to transform a problem in which calculation of the likelihood involves evaluating a four dimensional integral into a problem where only a one dimensional integral needs to be evaluated. More formally, we assume that the inherent endogeneity of the system of equations can be summarized in a single

[18] In addition, to avoid convergence problems in the iterative search for a maximum likelihood, we are forced to fix some parameters of the variance-covariance matrix $\boldsymbol{\Sigma_\epsilon}$, arbitrarily.

term, ξ_{it}, such that

$$\begin{aligned}
\varepsilon_{1,it} &= \lambda_1\xi_{it} + \epsilon_{1,it} \\
\varepsilon_{2,it} &= \lambda_2\xi_{it} + \epsilon_{2,it} \\
\varepsilon_{3,it} &= \lambda_3\xi_{it} + \epsilon_{3,it} \\
\varepsilon_{4,it} &= \lambda_4\xi_{it} + \epsilon_{4,it}
\end{aligned}$$

where $\epsilon_{1,it}$, $\epsilon_{2,it}$, $\epsilon_{3,it}$ and $\epsilon_{4,it}$ are the idiosyncratic error terms, which are independent of each other; and λ_1, λ_2, λ_3 and λ_4 are free factor loadings to be estimated along the other parameters. The term ξ_{it} is an unobserved heterogeneity factor common to all equations. If there are many unobserved factors, then the sum of them may converge to a normal distribution by virtue of a central limit theorem. Hence, we assume that ξ_{it} follows the standard normal distribution. We will return later to the economic significance of ξ_{it}. However, the cost of using this approach is that it implies some variance–covariance restrictions. Explicitly, we have,

$$\Sigma_\epsilon = \begin{pmatrix} \lambda_1^2+1 & & & \\ \lambda_1\lambda_2 & \lambda_2^2+1 & & \\ \lambda_1\lambda_3 & \lambda_2\lambda_3 & \lambda_3^2+1 & \\ \lambda_1\lambda_4 & \lambda_2\lambda_4 & \lambda_3\lambda_4 & \lambda_4^2+\sigma_{\epsilon_4}^2 \end{pmatrix} \tag{24}$$

and there are implicit variance–covariance restrictions as the seven unknown elements of the variance–covariance matrix, Eq.(13), must be retrieved from only four parameters (λ_2,λ_3,λ_4,$\sigma_{\epsilon_4}^2$).[19] This reparametrization reduces the dimension of integration in Eq.(22) from 4 to 1. Indeed, we have,

$$\begin{aligned}
\ell_{it|\boldsymbol{u}} &= \int_{-\infty}^{+\infty} \frac{1}{\sqrt{\lambda_4^2+\sigma_{\epsilon_4}^2}}\phi\left(\frac{\omega_{it}-D_{it}-\lambda_4\xi_{it}-u_{4,i}}{\sqrt{\lambda_4^2+\sigma_{\epsilon_4}^2}}\right)\times\Phi\left[Z_{it}^o\left(\frac{C_{it}+u_{3,i}+\lambda_3\xi_{it}}{\sqrt{\lambda_3^2+1}}\right)\right] \\
&\quad\times\Phi\left[D_{it}^o\left(\frac{B_{it}+u_{2,i}+\lambda_2\xi_{it}}{\sqrt{\lambda_2^2+1}}\right)\right]\times\Phi\left[E_{it}^o\left(\frac{A_{it}+u_{1,i}+\lambda_1\xi_{it}}{\sqrt{\lambda_1^2+1}}\right)\right]\phi(\xi_{it})\,\mathrm{d}\xi_{it}
\end{aligned}$$

Using this new expression of the conditional likelihood, the unconditional likelihood, ℓ_i, can be maximized by integrate out individual effects using sequential Gauss-Hermite quadrature as before. The identification of our model is based on functional form and restrictions on the variance-covariance matrix, $\boldsymbol{\Sigma_\varepsilon}$. However, we also use exclusion restrictions to ensure the empirical identification of the parameters of interest. Finally, some variables that we consider exogenous may be endogenous. For example, sense of

[19] we fixed $\lambda_1 = 1$ for identification of other factors loading,λ_2,λ_3,λ_4. More specifically, the coefficients that our model estimate are $\lambda_2' = \frac{\lambda_2}{\lambda_1}$,$\lambda_3' = \frac{\lambda_3}{\lambda_1}$,$\lambda_4' = \frac{\lambda_4}{\lambda_1}$.

the causality between export spillover and export behavior is not clearly determined. Indeed, as suggested by Koenig, Mayneris, and Poncet (2010), if firm i's export behavior depends on the neighboring firms' behavior, the latter is itself impacted by firm i's export performance; which induces a reverse causality problem. In addition, simultaneity may be an issue, since unobserved supply-side or demand-side shocks could affect both the export performance of firm i and the performance of its neighbors. To address this potential endogeneity problem, we lag right-hand side variables, x_k $k = 1,2,3,4$, one year.

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