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# Does innovation help to explain the effect of export on productivity ?
# Evidence from the French dairy industry

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**Abstract**

While there is strong evidence that becoming an exporter increases a firm's productivity, underlying mechanisms that explain such a relationship remain largely unexplored. This paper analyses the contribution of the complementarity between exporting and investment in technology as a potential driver of export-related productivity gains. We employ firm-level data on production and trade combined with information on *new products* in the French dairy industry to conduct a causal mediation analysis between exporting, innovation investment, innovation output and productivity. Our estimation result show that starting exports increase the productivity by 8 percentage points. Our mediation analysis reveals that innovation (investment and output) explains 31% of this productivity growth.

**Keywords:** gains from exports, international markets, productivity, innovation
**JEL classification:** F14 F61 L66

# 1 Introduction

Since the seminal work of Bernard, Jensen, and Lawrence (1995), numerous studies have demonstrated that exporting firms exhibit higher productivity compared to non-exporters. This is because exporters have higher productivity to start with, or because they become more productive after entering the export market. The former effect is related to the self-selection hypothesis (see for instance Melitz, 2003). On the other hand, the second hypothesis states that productivity increases after firms start operating in international markets. Despite the pervasiveness of the empirical work highlighting productivity gains from trade (Van Biesebroeck, 2005; De Loecker, 2007; Lileeva and Trefler, 2010; Park et al., 2010; Smeets and Warzynski, 2013; Atkin, Khandelwal, and Osman, 2017; Garcia-Marin and Voigtländer, 2019), there is still an ongoing debate as to whether exporting has a causal impact on firm productivity. Moreover, if entering in international markets helps firms to improve their productivity level, what are the mechanisms which explain such causal link? To fill this gap, this paper examines how innovation activities mediate the effect of exports on firm productivity.

We develop a mediation framework by considering the essential role of innovation activities, as intermediate variables, that lay in the causal pathway between exporting and productivity. This implies that export may impact productivity by altering the levels of innovation investments and/or innovation output, and consequently, productivity. More specifically, this paper aims to highlight two innovation-related mechanisms to explain export-productivity link. First, because of a larger market size, the ability to learn from knowledge spillovers in the foreign country, or because of competitive pressure from exporting firms based in other countries, exporting spurs the firm's incentive to invest in innovation activities, increases its probability of being an output innovator which in turn contributes to its productivity. We label this *innovation investment mechanism.* Second, because of contacts with customers and competitors in the foreign markets, exporting firm is more likely to be an output innovator, which in turn contributes to its productivity. We label this *innovation output mechanism.*

Furthermore, the *innovation investment mechanism* that we consider leads to three interconnected causal pathways: one from exports to investment in innovation, another from innovation investment to innovation output, and a third from innovation output to productivity, Whereas the *innovation output mechanism* leads to two interconnected causal pathways.

To test these causal pathways, our paper utilizes data covering *all* firms in the French dairy industry. A combination of several features makes the French dairy industry highly suitable for studying the mediation role of innovation on the productivity effect of exports. First, the French dairy products enjoy a good reputation on international markets. As a result, the industry is highly internationalized and many varieties are exported to several markets. Second, global demand for dairy products is growing worldwide, particularly in sub-Saharan Africa, South East Asia and the Middle East and North Africa. Third, dairy products, exhibits a lot of both vertical and horizontal differentiation. These attributes renders dairy products more prone to innovation and learning for firms operating in international markets. Fourth, thanks to the *Global New Product Database*, which provides detailed information on new product introductions, we are able to construct a relevant output innovation indicator that fits well with the specificity of the industry.

Our empirical approach builds on the workhorse framework of Crepon, Duguet, and Mairesse (1998) (henceforth CDM), which relies on linking firm-level data on innovation investment, innovation output and productivity. The CDM model incorporates three equations characterizing the stages of the innovation process: (*i*) R&D investment equation describing the determinants of research inputs, (*ii*) innovation function linking research inputs and innovation outputs, and (*iii*) (total factor) productivity equation linking innovations to productivity. Empirical studies built on this framework find that firm-level R&D investments increase innovation outputs, and these in turn, are positively correlated with firm-level productivity. Reviews of this literature are found in Hall, Mairesse, and Mohnen (2010), Hall (2011) and in Mohnen and Hall (2013). This paper contributes to this literature in three ways. First, we consider that export is endogenous to the innovation process and affects each stage of the process. We also add a fourth equation to the CDM model to take into account the endogeneity of the exports variable. Second, we use a panel data set of firms covering the period from 2010 to 2018; this allows us to control for unobserved firm heterogeneity, which may affect the estimation of the parameters of interest. Third, most papers in the CDM literature use the sequential instrumental variables approach as an estimation procedure. In this paper we have chosen to use a full information maximum likelihood approach (henceforth FIML). This is known to be more efficient than other approaches. More specifically, our empirical approach considers a four-nonlinear-simultaneous-equations model that includes individual effects and idiosyncratic errors correlated across equations. The joint distribution of this system does not have a closed form, and therefore cannot be derived analytically. We handle multiple integration due to the correlations of individual effects and idiosyncratic errors across equations using simulated maximum likelihood techniques.

Our results relate to a number of papers that span the trade and growth literature. Most directly, we contribute to a voluminous literature that seeks to identify the existence of the causal effect of exporting on firm's productivity. The evidence from these studies is mixed.[1] Two factors can explain this: First, researchers typically lack detailed information that is required to isolate changes that occur when firms start exporting. Empirical studies generally use revenue-based productivity measures, which reflect changes in productivity as well as changes in prices (De Loecker and Goldberg, 2014). This makes it impossible to identify the effect of exports on productivity, as the international trade literature has shown that the level of markups changes when firms start exporting (see for instance, De Loecker and Warzynski, 2012; Jafari et al., 2022). In addition, cost savings due to gains in productivity are passed on to buyers in the form of lower prices, leading to a downward bias in revenue-based productivity measures (Garcia-Marin and Voigtländer, 2019). While quantity-based productivity measures solve problems related to changing prices, standard datasets do not provide information such as output in physical unit to account for this changes. In this paper, we follow De Loecker et al. (2016) and use a control function approach to overcome the output prices' bias.

Second, detecting the causal effect of exports on productivity and other firm performance, such as innovation investment and innovation output, is not straightforward due to the endogeneity of the export variable. Indeed, firms with high productivity are likely to self-select into international markets, making it difficult to disentangle treatment effects of exporting from self-selection. The empirical literature suggests several approaches to deal with this problem. For instance, Atkin, Khandelwal, and Osman (2017) conducted a randomized controlled trial (RCT) applied to Egyptian rug manufacturers to examine how exporting affects profits and productivity. In their setup, the authors randomly assign handmade carpet producers an opportunity to export to high-income markets. In this way, the authors solve for the endogeneity problem at its source. The impact of exports can then be easily identified by comparing the means of treated and control producers. Another approach consist to exploit natural experiment, such as devaluation (Park et al., 2010) or trade liberalisation (Lileeva and Trefler, 2010; Bustos, 2011) to generates exogenous variation in export opportunity. Following Mayer, Melitz, and Ottaviano (2021), this paper constructs a firm-level export demand shock that responds to aggregate conditions in a firm's export destinations, but is exogenous to firm-level decisions, and uses it as an exclusion restriction in the equation describing export participation.

This paper is also in line with empirical studies that look at the potential role of investments in innovation as a potentially important component of the productivity-export link (e.g., Aw, Roberts, and Winston, 2007; Aw, Roberts, and Yi Xu, 2008; Aw, Roberts,

[1] Papers that have found no or only weak evidence include Clerides, Lach, and Tybout (1998), Bernard and Jensen (1999), Aw, Chung, and Roberts (2000), Delgado, Ruano, and Farinas (2002), Alvarez and López (2005) and Luong (2013). Papers that find positive effect of exporting on productivity include Van Biesebroeck (2005), De Loecker (2007), Lileeva and Trefler (2010), Park et al. (2010), Smeets and Warzynski (2013), Atkin, Khandelwal, and Osman (2017) and Garcia-Marin and Voigtländer (2019).

and Xu, 2011; Maican et al., 2022). These papers aim to provide empirical evidence on the innovation investment mechanism. Most of them, however, directly relate innovation investments to productivity and thus remain silent about the channels through which innovation investment affect productivity. Indeed, innovation investment must be seen as an input that creates new knowledge (or to assimilate new knowledge) that materialize in innovation output, which can be demand-creating or cost-reducing. Our results suggest that investment in innovation increase the firm's probability to be an output innovator, which in turn contributes to the productivity.

This paper contributes to the empirical literature that seeks to identify the impact of exporting on innovation measures. Many empirical studies have shown that exporting firms are more likely to invest in innovation, but the direction of causation is generally not clear. The questions we address in this paper are related to the small empirical literature that focuses on the causal impact of changes in export market conditions on the firm's investment in innovation and on innovation output. Most of these papers uses exogenous export market shocks, to identify a causal effect of exporting on firm innovation. For instance, Bustos (2011) documents a positive effect of a tariff reduction facing Argentine firms on their rates of product and process innovation. Lileeva and Trefler (2010) found that Canadian firms that expanded exporting in response to U.S tariff reductions, also engaged in more product innovation and had higher rates of technology adoption. Coelli, Moxnes, and Ulltveit-Moe (2022) use data from 65 countries and find a positive effect of the trade liberalization in the 1990s on firm patenting. This paper show that French dairy firm that expands its export markets in response to export demand shocks, increase its propensity to invest in innovation activities and its probability to be output innovator conditional to the former effect.

The remaining sections of the paper follow this organization: Section 2 briefly reviews the literature that addresses the impact of exporting on innovation and the influence of innovation on productivity. In Section 3, we discuss the selection of the dairy industry, examine data from French dairy firms, and introduce our new measure of innovation output, which is relevant to our study. Section 4 outlines the empirical framework and the estimation method, while Section 5 presents the results. Finally, Section 6 concludes.

# 2 Innovation and the export-productivity link: Theory and empirics

## 2.1 Literature review

*A. From exporting to innovation*

The idea that there are knowledge gains from export markets participation began with the case studies of Rhee, Pursell, and Ross-Larson (1984) and Westphal, Rhee, and Pursell (1984). These studies show that South Korean exporting firms benefit from their foreign buyers' technical and managerial expertise or from the expertise of other foreign contacts (e.g., competitors or suppliers). Early works, such as Nelson (1959) and Arrow (1962), consider that technological knowledge which is in the public domain is a public good. Like a smoke pollution, its effects are thought to be realised at no price by all firms located within the neighbourhood of the emission. Based on this logic, firms operating in international markets could therefore have access to technological knowledge directly available in their export markets. Furthermore, Grossman and Helpman (1991) explored the possibility that trade of goods act as a channel for information flows: intangible ideas spillover through the exchange of tangible commodities. For an exporting firm, trade opens up to the knowledge held by their trading partners and allows it to be incorporated into domestic production, enabling higher productivity. Along the same lines, Salomon (2006) pointed out that in the *learning by exporting* hypothesis, exporting firms are aware of technological discoveries in foreign markets and as such can acquire some technological knowledge and use it to improve their product or process innovation.

In addition to *learning by exporting*, the literature highlights at least two other explanations on the effect of exporting on firm productivity. According to the so called *competition effect*, strong competitive pressures in international markets may induce firms to take action in their productivity-enhancing strategies.[2] This mechanism is driven by strategic interactions between firms operating in the markets; indeed, strong competition in international market, may induce firms to have an incentive to move ahead of their competitors, by investing in innovation. This effect is similar to the escape-competition effect in Aghion et al. (2005) or the replacement effect in Arrow (1962).[3] Moreover, endogenous growth models predict that strong competition, e.g. in international markets, discourages innovation investment incentives by reducing post-entry rents (see for

[2] For an in-depth overview on the relationship between competition and innovation, see Cohen (2010).

[3] The escape-competition effect refers to the fact that stronger competition (e.g. in international markets) may increase the incremental profits from innovating, and thereby encourage innovation investments. The basic idea behind the replacement effect is that a monopolist has less incentive to innovate than a competitive firm, due to the monopolist's financial status quo. As Arrow puts it: "*The pre-invention monopoly power acts as a strong disincentive to further innovation*"

instance, Schumpeter, 1942; Aghion et al., 2020; Akcigit and Melitz, 2022). The competition effect, therefore, predicts an ambiguous impact of exporting on firms' investment in innovation. The third hypothesis that is related to the impact of export on firm productivity, is the *market-size effect*. It refers to the fact that firms, which operate in international markets, may face better demand opportunities to exploit their innovations, and hence have greater incentive to invest in costly innovation.

Although these three hypotheses predict that exporting affect the firm innovation activities there are distinct in several respect: First, all three hypotheses predict that having access to the export market encourages firms to invest in innovation activities, although the competition effect predicts a more nuanced impact. Second, learning by exporting predict that firm may also receives knowledge without necessarily investing in innovation-related activities; which is not the case for other hypotheses. The market-size effect by contrast would prompt a firm to intentionally invest in innovation in order to reap the benefits of access to an enlarged market; while the competition effect predict that firm may invest in innovation activities to escape competition. Third, while learning by exporting and market-size effects only impact the exporting firms, the competition effect impact both the exporting and the non-exporting firms. Indeed, standard trade models with heterogeneous firms (e.g., Melitz, 2003) emphasize that less productive firms (non-exporters) are not able to generate enough profits abroad to cover the fixed cost of entering foreign markets. Exporters are therefore only a subset of domestic firms. This subset of exporting firms varies with the characteristics of the foreign markets. Furthermore some works, such as Chaney (2008) and Chevassus-Lozza and Latouche (2012) show that the productivity of the least productive firm able to enter into a given foreign market, increases with competition in that market. Therefore, strong competition in foreign markets act as a barrier to entry for the less productive firms.

*B. From innovation to productivity*

Early work on the sources of productivity growth showed that growth in capital and labor explained less than half of this growth. Driven by the interest in the unexplained part of productivity growth, a large body of research on innovation and productivity in firms has accumulated. However, quantifying the importance of innovation for productivity is a challenging task. One reason for this is the difficulty of adequately measuring innovation. The empirical literature has long focused on input-oriented indicators of innovation. Following Griliches (1979), the majority of these studies used a production function approach as a theoretical backbone, including R&D-based measures as an additional input (see for instance, Schankerman, 1981; Griliches and Mairesse, 1984; Cuneo and Mairesse, 1984;

Jaffe, 1986; Griliches, 1987; Hall and Mairesse, 1995).[4] There are three main criticisms of Griliches (1979)'s model: first, only some of the firms are engaged in in innovation activities, and the sample of innovative firms is unlikely to be random. It is well-known that a restriction to the selected (innovative) sample may induce biased estimates (Heckman, 1979). Second, there is the major issue of the endogeneity of innovation, and more generally of the simultaneity in the model. Unobserved factors, e.g. dynamic firm managers, that drive innovation may also drive directly economic performance. Third, innovation investment doesn't affects productivity directly, but its outcomes does. Indeed, R&D or more general innovation expenditure translate into product as well as process innovations, both affecting productivity. However, the traditional approach of Griliches (1979) treats the innovation process as a *black box*.

A huge step forward was taken by Crepon, Duguet, and Mairesse (1998) –hereafter CDM– who addressed these problems. The authors, look more thoroughly into the *black box* of the innovation process at firm-level. Not only the relationship between innovation input and productivity is analysed but also some light is shed on the process in between. They explicitly account for the fact that it is not innovation input but innovation output that increases productivity. Firms invest in innovation in order to develop process and product innovations, which in turn may contribute to their productivity. Their model is therefore a recursive system of equations where the innovation equation relating innovation input to innovation output measures, and the productivity equation relating innovation output to productivity. They also take care of the selection problem by adding one more equation in their system. This new equation describes the firms decision to invest in innovation. Finally, endogeneity problem is taking into account by the use of some kind of simultaneous equations system estimator such as the full information maximum likelihood, the generalized method of moments and the asymptotic least squares method. Nowadays, the CDM model is considered as the workhorse model to quantify the productivity effects of innovation activities.[5]

Finally, this literature review reveal two innovation mechanisms that explains the effect of exporting on productivity. In the first mechanism, starting to export induces firms to invest in innovation activities, which in turn contributes to the probability of being an output innovator; and being an output innovator increase the productivity level: we call this innovation investment mechanism. Furthermore, conditional on innovation investment, starting to export increases the firm probability of being an output innovator, which in turn contributes to the firm productivity level: we call this innovation output

[4] These studies estimate the output elasticity with respect to R&D between 0.05 and 0.20. However, most of these estimated elasticities are statistically insignificant.

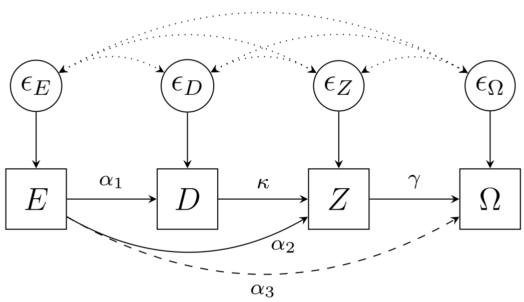
[5] See Hall (2011) and Mohnen and Hall (2013) for a review of empirical works on this topic.

mechanism.

## 2.2 Econometric issues: mediation analysis

Following the previous literature, table 1 shows the directed acyclic graph (DAG) on how innovation process affect the link between exporting and productivity. In this paper, we use the term causal mechanisms to represent the process through which exporting causally affects firm productivity. We study the identification of causal mechanisms, which is represented by the full arrows in the DAG of table 1. In this diagram, the causal effect of exporting ($E$) on productivity ($\Omega$) is transmitted through intermediate variables innovation input ($D$) and innovation output ($Z$). The pathways $\alpha_1$, $\kappa$ and $\gamma$ for innovation input and the pathways $\alpha_2$ and $\gamma$ for innovation output are used to affect the productivity. The dashed arrow, $\alpha_3$, represents all other possible causal mechanisms of exporting, such as buyer-seller relationships, product quality improvement, etc. Thus, the treatment effect of exporting is decomposed into the sum of the *indirect effect* (a particular mechanism through the mediators of interest, typically innovation process in our case) and the *direct effect* (which includes all other possible mechanisms).

Table 1: The mediating role of innovation in the relationship between exporting and productivity




**The causal Model**

$$
\begin{aligned}
E &= E(\epsilon_E) \\
D &= D(E,\epsilon_D) \\
Z &= Z(E,D,\epsilon_Z) \\
\Omega &= \Omega(E,Z,\epsilon_\Omega)
\end{aligned}
$$

*Notes:* The left panel gives the graphical representation of the mediating role of innovation on the relationship between exporting ($E$) and productivity ($\Omega$). The right panel presents the structural equations of the relationship. $D$ and $Z$ denote the input and output of the innovation, respectively.$\longrightarrow$, denote the causal mechanism of interest where the causal effect of exporting on productivity is transmitted through the intermediate variable. $\dashrightarrow$, all the other possible causal mechanisms. $\cdots$, reflect the possible correlation between unobserved confounders, $\epsilon_\Omega$, $\epsilon_Z$, $\epsilon_D$ and $\epsilon_E$.

To define the indirect effects formally within the potential outcomes framework, consider an experiment, where $n$ firms are assigned into the treatment group $E_i = 1$ (exporting) or the control group $E_i = 0$ (not exporting). Since the mediator, innovation input (resp. innovation output), can be affected by the treatment, there are two potential values, $D_i(1)$ (resp. $Z_i(1,D_i)$) and $D_i(0)$ (resp. $Z_i(0,D_i)$), of which only one will be observed, that is, $D_i = D_i(E_i)$ (resp. $Z_i = Z_i(E_i,D_i)$). Next, let $\Omega_i(e,z)$ the potential productivity level that would result if exporting and innovation output equal $e$ and $z$ respectively. Again, we observe only one of the potential productivity level, i.e. $\Omega_i = \Omega_i(E_i, Z_i(E_i, D_i(E_i)))$.

Now, we can define two indirect effects of exporting. The indirect effect using innovation input as mediator is,

$$\delta_{1,i} = \Omega_i(1, Z_i(1, D_i(1))) - \Omega_i(1, Z_i(1, D_i(0))) \tag{1}$$

and the indirect effect using innovation output as mediator is,

$$\delta_{2,i} = \Omega_i(1, Z_i(1, D_i(1))) - \Omega_i(1, Z_i(0, D_i(1))) \tag{2}$$

We also define the direct effect of exporting as,

$$\delta_{3,i} = \Omega_i(1, Z_i(1, D_i(1)))) - \Omega_i(0, Z_i(1, D_i(1))) \tag{3}$$

Then, the total effect of the exporting can be decomposed into the causal mediation and direct effects:

$$\delta_i = \Omega_i(1, Z_i(1, D_i(1))) - \Omega_i(0, Z_i(0, D_i(0))) = \delta_{1,i} + \delta_{2,i} + \delta_{3,i} \tag{4}$$

The key to understanding these equations is the following counterfactual question: what change would occur to the productivity if we change the innovation input (resp. innovation output) level from the value that would realize under the control condition, i.e. $D_i(0)$ (resp. $Z_i(0, D_i(1))$), to the value that would be observed under the treatment condition, i.e. $D_i(1)$ (resp. $Z_i(1, D_i(1))$) ? Because these two values of the mediator are those that would naturally occur as responses to changes in the treatment, the quantity of interests (defined in equations 4, 1, 2 and 3) formalizes the notion of a causal mechanism that the causal effect of the treatment is transmitted through changes in the mediator of interest. Under the potential outcomes framework, the fundamental problem of causal inference is that given any firm, we cannot observe the potential outcomes under the treatment and control conditions at the same time. Then, the key difficulty is to identify a counterfactual for the last term in the above equations.

A starting point for identifying the causal mechanisms of interests is the *sequential ignorability assumption* –SIA– of Imai, Keele, and Yamamoto (2010). Let $X_i$ be a vector of the observed pretreatment confounders for firm $i$. We'll come back later to the variables included in the vector $X_i$. Given these observed pretreatment confounders, SIA can be formally written as:

$$\{\epsilon_\Omega, \epsilon_Z, \epsilon_D\} \perp\!\!\!\perp \epsilon_E | X_i = x \tag{SI.1}$$

$$\epsilon_Z \perp\!\!\!\perp \epsilon_D | E_i = e, X_i = x \tag{SI.2}$$

$$\epsilon_\Omega \perp\!\!\!\perp \epsilon_Z | D_i = d, E_i = e, X_i = x \tag{SI.3}$$

where $0 < \Pr(E_i = e|X_i = x)$, $0 < \Pr(D_i(e) = d|E_i = e,X_i = x)$ and $0 < \Pr(Z_i(e,d) = z|D_i = d,E_i = e,X_i = x)$ for $e = 0,1$. Imai, Keele, and Yamamoto (2010) show that under SIA, the averages of the quantities of interest are identified. The main advantage of this assumption over other alternatives, (see for instance, Pearl, 2001; Robins, 2003; Petersen et al., 2006), is its ease of interpretation. SI.1 states that, given the observed confounders, the treatment assignment is independent of the potential outcome and the potential mediators. In our context, SI.1 ruled-out the possible existence of unmeasured confounders between exports and innovation and productivity. This seems to be unrealistic, since productive firms (self-selection hypothesis, see for instance Melitz, 2003) and/or innovative firms (conscious self-selection hypothesis, see for instance Yeaple, 2005) are more likely to start exporting. Therefore, a simultaneity bias emerges. Only a randomized experiment as in Atkin, Khandelwal, and Osman (2017), could guarantee that SI.1 hold.

SI.2 (resp. SI.3), state that once the observed confounders and observed exports status (resp. the observed confounders, observed exports status and the observed innovation investment status) are controlled for, the firm's decision to invest in innovation (resp. the innovation output) is ignorable. In other words, for instance, the ignorability of the innovation investment variable implies that among those firms who share the same exports status and the same characteristics, the innovation investment variable can be regarded as if it were randomized. However, we know that firms can anticipate the growth of their productivity and their innovative efforts are driven by this future prospect; therefore, innovation investment is endogenous to innovation output and innovation output is endogenous to productivity (Crepon, Duguet, and Mairesse, 1998). Hence, SI.2 and SI.3 hold if $X_i$ includes confounders that cause these endogeneity issues.

In this paper, we use a structural estimation approach that addresses all these endogeneity issues.

# 3 Data

## 3.1 Choice of industry

Our main data source is the French firm register, from which we retrieve information on production and trade in the dairy sector. We present these data in more detail in section 3.2. We also obtain information on product launched in French dairy sector from Global New Product Database.[6] In section 3.3, we describe how we use these data to construct a new measures of innovation output at the firm-level.

Apart from the availability of a innovation output measure that suited well with the specificity of the sector, the combination of several other features renders the dairy sector highly suitable for studying how innovation impact the causal relationship of exporting on firm productivity. First, dairy products, exhibits a lot of both vertical and horizontal differentiation. For cheese, for example, quality (as evaluated by experts) depends on the origin and processing of the milk, cheese production practices, the quality of other ingredient, etc. In addition, personal tastes also play an important role: consumers have different preferences regarding, e.g. the flavors (mild, milky, slightly acidic, tangy, salty, pungent, intense, etc...) and the texture (creamy, elastic, brittle, dry, grainy, thick, creamy, spreadable, etc...). These preferences are strongly influenced by customs, culture and national tastes and are therefore susceptible to vary across countries. The combination of both vertical and horizontal product attributes renders dairy products more prone to innovation and learning for firms operating in international markets; i.e., the taste of consumers in international markets may be a source of knowledge for exporting firms.

Second, as the third largest sectoral surplus in France, agrifood is one of the main strengths of French foreign trade. The sector alone accounted for 13% of total French exports in 2018 (€62 billion), enabling France to consolidate its position as the world's $6^{th}$ largest exporter of food products with a 5% market share. Regarding the French dairy industry, it enjoys a good reputation on international markets. As a result, the industry is highly internationalized and many varieties are exported to several markets. Hence, we are in a position to detect export markets entry, which is a key requirement for measuring the causal effect of exports.

Third, the global demand for dairy products is rising worldwide. For example, the largest percentage of total cheese consumption occurs in Europe and North America, where per capita consumption is expected to continue to increase. Consumption of cheese will also increase where it was not traditionally part of the national diet. In South East Asian

[6] See https://www.mintel.com/.

countries, urbanisation and income increases have resulted in more away-from-home eating, including fast food such as burgers and pizzas. While some regions are self-sufficient, e.g. India and Pakistan, total dairy consumption in Africa, South East Asian countries, and the Near East and North Africa is expected to grow faster than production, leading to an increase in dairy imports.

## 3.2 Data on production and trade

**Production data.** To estimate the firm productivity, we use firm-level balance-sheet from the `DGFiP-Insee`'s FARE database. The database combines administrative data (obtained from the annual profit declarations that firms make to the tax authorities, and from annual social data that provide information on employees) and data obtained from a sample of companies surveyed by a specific questionnaire to produce structural business statistics. We utilize data from the dairy products sector from 2010 to 2018. We retrieved the data on the value-added, capital stock, materials, labor, labor costs, investment and other. Due to the quality of the data, a fairly standard data cleaning procedure was implemented.[7] This resulted in an unbalanced dataset, which consisted of 5,289 observations spanning over 680 different firms from 2010 to 2018.[8] In Appendix A, we present the empirical strategy used to estimate the firm productivity.

Table 2 presents the evolution of the aggregate productivity between 2010 and 2018. We define the aggregate productivity in the industry as the weighted sum of firm productivity (Baily et al., 1992; Olley and Pakes, 1996).[9] We calculate this indicator using two productivity measures: The revenue-based total factor productivity, TFPR, and the quantity-based total factor productivity TFPQ.[10] Normalizing this index to 1 in 2010 allows us to compare the evolution of aggregate productivity for the different measures

[7] More formally, ($i$) we drop observations with missing value added, labor, capital stock, labor costs or materials; ($ii$) We drop firms with spell less than three years.

[8] Note that when implementing our econometric routine, the analytical sample is further reduced due to the initial period.

[9] We use the firm market-share as firm-specific weight.

[10] To understand the difference between these two measures of the firm productivity, assume that output is produced using a vector of inputs. Using a log-linear representation of the production function, with lowercase letters denoting the logarithms of the variables, and adopting the notation from De Loecker and Goldberg (2014): $q_{it} = x'_{it}\alpha + \omega_{it}$, where $\alpha$ is a vector of output elasticities and $\omega_{it}$ is the quantity-productivity, TFPQ. Generally, physical output is not available in the data, so that researchers rely on revenue. In this case, the production function is given by

$$r_{it} = x'_{it}\alpha + \underbrace{p_{it} + \omega_{it}}_{\pi_{it}}$$

where $\pi_{it}$ is the (log.) output price and $\pi_{it}$ is the revenue-productivity. When revenues are used as output variable, the residual term, $\pi_{it}$, reflects both output prices and quantity-productivity. Although we do not observe output in physical unit in our data, we estimate the TFPQ using a control function approach as in De Loecker et al. (2016) to control output and inputs prices variations. See Appendix A for more details.

Table 2: Evolution of aggregate productivity from 2010 to 2018

| | | TFPR | | | TFPQ | | |
|---|---|---|---|---|---|---|---|
| Year | #firms | $\Pi_t$ | $\bar{\pi}_t$ | Cov. | $\Omega_t$ | $\bar{\omega}_t$ | Cov. |
| 2010 | 551 | 1.000 | 0.955 | 0.045 | 1.000 | 1.022 | -0.022 |
| 2011 | 584 | 1.007 | 0.930 | 0.077 | 0.998 | 1.008 | -0.010 |
| 2012 | 610 | 1.011 | 0.954 | 0.057 | 1.007 | 0.997 | 0.010 |
| 2013 | 618 | 1.044 | 0.972 | 0.072 | 1.010 | 1.018 | -0.008 |
| 2014 | 619 | 1.053 | 0.961 | 0.092 | 1.008 | 1.004 | 0.004 |
| 2015 | 622 | 1.098 | 0.991 | 0.107 | 1.011 | 0.996 | 0.015 |
| 2016 | 585 | 1.112 | 1.000 | 0.112 | 1.035 | 1.022 | 0.013 |
| 2017 | 562 | 1.109 | 0.999 | 0.110 | 1.038 | 1.048 | -0.010 |
| 2018 | 538 | 1.135 | 1.017 | 0.118 | 1.033 | 1.034 | -0.001 |

*Notes:* Both $\Pi_t$ and $\Omega_t$ are normalized to one in 2010. We follow the decomposition in Olley and Pakes (1996), whereby aggregate productivity $\Omega_t = \sum_i ms_{it}\omega_{it} = \bar{\omega}_t + \mathrm{cov}_t(ms_{it},\omega_{it})$, with $ms_{it}$ the market share. We apply the same decomposition to the profitability index $\Pi_t$. TFPR is the revenue-based total factor productivity; while TFPQ is the quantity-based total factor productivity. #firms is the number of firms present in the sample in a given year.

of productivity. The third column of the Table 2 show the aggregate productivity (based on TFPR) increase by 13% from 2010 to 2018. To explain this growth, follow Olley and Pakes (1996) and decompose (in the fourth and fifth columns, respectively) the aggregate productivity into a *within* component, $\bar{\pi}_t$, and a *covariance* term. The within component represent the unweighted mean productivity and accounts for the productivity growth generated within firms. The covariance term represent the sample covariance between the TFPR and the market-share. The larger this covariance, the higher the share of output that goes to more productive firms. Based on this decomposition, it seems that the productivity improvement shown in the third column reflects the reallocation from less revenue-productivity towards more revenue-productivity firms. However, this growth may simply reflect the positive correlation between firm market-share and price. To confirm this intuition, we carry out the same exercise using quantity-productivity to construct aggregate productivity. There are two interesting features. First, the aggregate productivity based on quantity-productivity (see the sixth column of Table 2) evolve more slowly compared to the change in aggregate revenue-productivity. Second, the covariance computed using quantity-productivity are substantially smaller—almost nonexistent.

There are at least two interesting results on this comparison exercise. First, there is substantial firm-level output price variation in our TFPR measure. Because we aim to identify export-related productivity gains, the use of TFPR as a proxy for the firm productivity yield a downward bias due to the output price variation (Garcia-Marin and Voigtländer, 2019). Second, the control function strategy developed in Appendix A so to estimate TFPQ, clearly rules out price variations.

**Export data.** To compute the export market expansion of the firm, we used the data on export from the French customs office (Direction Générale des Douanes et des Droits Indirects, DGDDI). This dataset gathers for each firm, all export flows, in value and quantity, by destination and by product category.[11] Indeed, all French firms must report their export sales according to the following criteria: Exports to each EU destination whenever within-EU exports exceeds 100,000 Euros; and exports to non-EU country whenever exports to that destination exceeds 1,000 Euros or a ton. Despite these limitations, the database is nearly comprehensive. Furthermore, we consider that a firm $i$ expand its export markets during the year $t$ if: $(a)$ exports of the firm $i$ must concern products produced by the firm, which limit the issue of carry-along-trade (see, Bernard et al., 2019), arising when firms export products that they do not produce themselves.[12] $(b)$ Firm $i$ must exports for the first time to country $j$ at year $t$ in our sample period, which avoids that dynamic gains from previous export experience that is destination-specific drive our results. Therefore, we define a firm-level export market expansion variable which takes the value of 1 if firm $i$ satisfy both conditions $(a)$ and $(b)$ at the year $t$ and 0 otherwise.

Table 3, provides some information on export expansion in two regions: inside Europe and outside Europe. The year 2010 is the beginning of our sample period, so export expansion can only be observed after this year. Table 3 show that the number of firms that expand their export markets in both regions continuously increase during the sample period. In addition, in the european market, a French dairy firm has exported to an average of one new destination; whereas the average number of new destinations is 2 when exporting outside europe.

## 3.3 Data on innovation

We want to test whether innovation output mediate the effect of export markets expansion on firm productivity. To this aims, we construct a novel measure of innovation output at the firm-level.

Mintel's Global New Product Database –here after GNPD– provide detailed information on dairy product launched in France. In addition to secondary information sources (such as Trade Shows, Press Releases, Media, Corporate Intelligence, etc...), Mintel mainly uses primary information sources to enrich GNPD. The primary source of information comes

[11] Product categories are recorded at the eight-digit level of the Combined Nomenclature, (`CN`).

[12] We ensure that the products exported by a firm are included in the industry to which it belongs. This is possible thanks to the correspondence tables provides by Eurostat. see RAMON - Reference And Management Of Nomenclatures

Table 3: Statistics on export expansion: inside and outside Europe

| | European countries | | | | Non european countries | | | |
|---|---|---|---|---|---|---|---|---|
| Year | #firms | Mean | S.E. | Max | #firms | Mean | S.E. | Max |
| 2011 | 114 | 1.67 | 1.01 | 5 | 71 | 1.82 | 1.37 | 7 |
| 2012 | 135 | 1.74 | 1.88 | 14 | 85 | 2.09 | 1.95 | 11 |
| 2013 | 144 | 2.03 | 2.35 | 19 | 100 | 2.27 | 3.66 | 23 |
| 2014 | 148 | 1.61 | 1.90 | 13 | 113 | 2.02 | 2.02 | 10 |
| 2015 | 155 | 1.84 | 1.51 | 8 | 123 | 2.28 | 2.02 | 9 |
| 2016 | 159 | 2.29 | 2.55 | 12 | 135 | 2.02 | 1.83 | 10 |
| 2017 | 162 | 1.66 | 1.55 | 9 | 134 | 1.85 | 1.51 | 7 |
| 2018 | 162 | 1.46 | 0.98 | 6 | 136 | 1.72 | 1.10 | 5 |

*Notes:* #firms is the number of firms that expands its exports markets in a given year.

from shoppers who receive a list of stores they visit weekly to monitor new products. The distribution channels that are monitored include supermarkets, the mass market, pharmacies, health food stores, mail order and Internet sales, and direct-to-consumer stores. When a newly product launched is identified, it is cross-referenced with the Mintel Shopper website so 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 the relevant information visible on the product packaging. The products are then sent to be photographed. Each product sheet is subject to a quality control by a team of editors before publication on the site. The products appear in GNPD within a delay of approximately one month after their launches or as close as possible to the launch.

Dairy products in GNPD are analyzed and categorized based on many factors including ingredients, packaging, marketing and innovation. There are five type of innovation registered in GNPD: (*i*) *Range extension*, it is used to document an extension to an existing range of products; e.g., new flavors of an existing products; (*ii*) *New packaging*, this type of innovation 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; (*iii*) *Reformulation*, this category is determined when the terms such as New Formula, Even Better, Tastier, Now Lower in Fat, or Great New Taste are indicated on the pack; (*iv*) *New product*, when the product is a new product introduction, including totally new brand. GNPD assigns a product to this category when the words "new product" can be seen directly on the packaging. Then this category represent products which is new for the firm and/or new for the market.

Although innovation is subdivided into four categories in GNPD, in this paper we consider goods belonging to the categories "new product", "new packaging" and "range extension" as innovation. We make this choice because only these categories suited-well to the definition of the innovation. Indeed, the latest version of the Oslo Manual (OECD, 2018) defines innovation as "a new or improved product or process (or combination thereof) that differs significantly from the firm's previous products or processes and that has been made available to potential users (product innovation) or brought into use by the unit (process innovation)." Product innovation encompass goods that have undergone significant improvements in functional characteristic such as quality (new product category) and convenience (new packaging category). Process innovations refer to improvements in the business functions such as marketing and sales (range extension category). Marketing innovation is now considered as part of process innovations in the latest version of the Oslo Manual (OECD, 2018).

*Linking innovation data with production and export data sources.* Linking French administrative data, i.e., production and export data-sets, is straightforward. The firm identifier (*siren* number) makes it possible to merge the two data-sets at firm-year level. Conversely, linking innovation data with the the two other data-sets is not straightforward. To link these data-sets, we needed to observe the innovation data at the same level of aggregation as the other, i.e., at firm-year level. To this end, we have developed an algorithm which, for each product launch recorded in GNPD, *(i)* identifies whether it was manufactured by a French firm; *(ii)* and if so, assigns the siren identifier of this firm to the launch. Appendix B provide more information on this algorithm.

After this procedure, we aggregate product launch data by siren identifier and year. Then, we define some innovation count variables. The first one is the number of new products introduced by a firm $i$ at the year $t$. An the second one, is the number of new packaging or range extension products introduced by a firm $i$ at the year $t$. Table 4 gives some statistics on these innovation counts variables. We can see that the number of firms that introduce new products increase from 96 to 177 during the sample period. The same pattern is observed for other type of launch. In addition, we can observed that on average a innovating firm have introduce at least 3 new products each year. Furthermore, the average number of new packaging or range extensions introduced each year by an innovative firm is 7. However, since these innovation count variables are likely to be subject to measurement errors, the innovation output variable we analyse in the empirical model takes the value of one if the firm introduced a new product, a new packaging product or range extension product and zero otherwise.

*Why not innovation survey ?* Most of empirical works use indicators from innovation

Table 4: Number of product launches

| | New products | | | | New packaging+ Range extension | | | |
|---|---|---|---|---|---|---|---|---|
| Year | #firms | Mean | S.E. | Max | #firms | Mean | S.E. | Max |
| 2010 | 96 | 3.34 | 3.89 | 16 | 54 | 6.24 | 8.49 | 36 |
| 2011 | 102 | 3.70 | 4.03 | 23 | 81 | 6.94 | 10.87 | 54 |
| 2012 | 120 | 3.29 | 3.75 | 17 | 101 | 7.64 | 12.87 | 70 |
| 2013 | 130 | 4.03 | 5.00 | 22 | 120 | 7.75 | 12.36 | 64 |
| 2014 | 142 | 3.45 | 4.45 | 25 | 135 | 7.87 | 11.78 | 71 |
| 2015 | 152 | 3.60 | 4.74 | 35 | 151 | 7.12 | 13.02 | 102 |
| 2016 | 163 | 3.31 | 3.96 | 23 | 154 | 7.64 | 11.62 | 64 |
| 2017 | 171 | 2.72 | 2.65 | 13 | 165 | 6.36 | 10.69 | 64 |
| 2018 | 177 | 2.97 | 3.92 | 29 | 165 | 6.15 | 9.99 | 79 |

*Notes:* #firms is the number of firms that launch products in a given year.

surveys, such as CIS survey, to measure innovation output at the firm-level.[13] The advantage of these indicators is that they follow the guidelines of the Oslo Manual. However, as pointed out by Mohnen (2019), the data from the innovation survey have certain characteristics that are important to keep in mind when using them in empirical research. If we want to build a longitudinal dataset using several waves of innovation surveys, we face at least three problems. First, it is difficult to conduct panel data analysis with the innovation survey data because of the stratified random sampling. Only large firms will be approached in every wave. Smaller firms might randomly not be included in every wave. This systematic inclusion of larger firms may create a selection bias in the results obtained. Secondly, longitudinal data sets are usually annual, whereas a wave of the innovation survey is conducted over a three-year period. This makes it difficult to match with other datasets. Third, there are also a problem of double counting due to overlapping time periods between two consecutive waves. As an example, The CIS 2016 collects information on firms innovation activities during the three years 2014 to 2016 inclusive; the 2018 survey collect the same information from 2016 to 2018.

[13]See Mohnen (2019) for an overview on the empirical measurement of innovation.

# 4 Empirical Model

Our aim is to analyse the effect of export market expansion on productivity and how innovation drive this relationship. For this purpose, this section presents a variant of the CDM model. We augment this model in two respect: first, we add the export market expansion as explanatory factor in each equation of the CDM model, suggesting that export market expansion affect each stage of the innovation process differently. Second, we take care of the endogeneity of export market expansion variable by adding an equation for this decision in the CDM model.

## 4.1 Extended CDM model

*A. Exports market expansion to new destinations*

Following the literature on international trade (see for instance, Roberts and Tybout, 1997; Bernard and Jensen, 2004; Das, Roberts, and Tybout, 2007), we assume that a firm decides to expands its export markets to new destinations by weighting the costs incurred against the expected benefit resulting from this decision. To model this decision, we use a a binary-choice approach of the form,

$$e_{it} = \begin{cases} 1, & \text{if } \mu_{1,t} + \beta_1' x_{it} + \epsilon_{1,it} \geq 0 \\ 0, & \text{otherwise,} \end{cases} \tag{5}$$

where $t = 1, \ldots, T_i$, $i = 1, \ldots, N$; where $e_{it}$ is an indicator variable that takes a value of 1 if a firm expands its export markets during the year $t$ and 0 otherwise. $\mu_{1,t}$ is a time effects reflecting variations in expansion profitability and costs that are common to all firms in a given year. These time effects may pick up the influence of trade-policy conditions, such as tariff reduction and public standard. In the vector $x_{it}$, we include firm's characteristics that affects both cost and benefit of exporting, such as past productivity (productivity observed at the initial period), size measured by the number of employees in $t-1$, capital measured by tangible fixed asset in $t-1$, and market-share measured as the turnover of the firm over the total turnover of the industry in $t-1$. We also include firm's characteristics that only affects cost of exporting, such as exporting share measured as total exports over firm turnover in $t-1$, the number of exporting countries during the period $t-1$ and the number of exporting countries since the initial period. All these variables represent the firm's experience in international markets and aims to capture fixed exporting costs. Using lagged values ensure that the observed confounders in the vector $x_{it}$ are observed prior the expansion decision. Finally, $\epsilon_{1,it}$ is an serially correlated unanticipated trade shock.

*B. Firm decision to invest in innovation*

To model the firm's decision to invest in innovation (e.g. R&D, worker training and/or technology upgrading), we follow Manez et al. (2009) and use a binary-choice approach of the form

$$d_{it} = \begin{cases} 1, & \text{if } \mu_{2,t} + \alpha_2 e_{it} + \beta_2' x_{it} + \epsilon_{2,it} > 0 \\ 0, & \text{otherwise.} \end{cases} \tag{6}$$

where $t = 1, \ldots, T_i$, $i = 1, \ldots, N$; where $d_{it}$ takes the value of 1 if the firm $i$ invests in innovation in period $t$, and 0 otherwise. The term $\mu_{2,t}$ is the year effects reflecting temporal variations in investment profitability and costs that are common to all firms within a year. These time effects pick up the influence of macro conditions, such as appropriability and technology opportunity. The vector $x_{it}$ is the same vector of firm's characteristics as in equation 5. These variables are expected to influence firm-level innovation investment profits and/or costs. We also consider that export markets expansion to new destinations, $e_{it}$, is likely to induce firm to decide to invest in innovation (see among others, Aw, Roberts, and Winston, 2007; Bustos, 2011; Aw, Roberts, and Xu, 2011; Peters, Roberts, and Vuong, 2022; Maican et al., 2022). Indeed, for firm that expands their export markets, the expected return on innovation investments can be larger than for other firms. This is because of a larger market-size, the ability to learn from knowledge spillovers in the foreign country, or because of competitive pressure from exporting firms based in other countries. Therefore, we expected that $\alpha_2$ is positive. Finally, $\epsilon_{2,it}$ is an serially correlated unanticipated shock.

The identification of $\alpha_2$ is important for the mediating effect of innovation investment. The assumption SI.1 state that given the observed confounders, $x_{it}$, the firm's decision to expands its export markets is independent to its investment decision. This assumption makes it possible to identify the parameter $\alpha_2$. However, this is an strong assumption. Indeed, we know that, innovative firms are more likely to start exporting: This is the conscious self-selection (see for instance, Yeaple, 2005).[14] Therefore, a simultaneity bias emerges. Hence, the assumption SI.1 hold if the vector $x_{it}$ includes all confounders that simultaneously affect innovation investment and export expansion. If not, we cannot consider $\epsilon_{1,it}$ to be independent of $\epsilon_{2,it}$.

*C. Innovation output equation*

The concept of a knowledge production function has been introduced by Griliches (1979) to measure the contribution of innovation inputs and knowledge spillovers to productivity growth. The basic assumption is that the output of the innovation process is an outcome

[14]In the Yeaple (2005)'s framework, firms have the possibility to adopt either a high-technology, low unit cost or low-technology, high unit cost production process. The low unit cost technology entails a higher fixed cost of technology adoption. In the presence of fixed costs to enter the export market, only those firms that adopt the low unit cost technology will be able to start exporting.

from innovation investment, that is,

$$z_{it} = \begin{cases} 1, & \text{if } \mu_{3,t} + \alpha_3 e_{it} + \kappa d_{it} + \beta_3' x_{it} + \epsilon_{3,it} > 0 \\ 0, & \text{otherwise.} \end{cases} \tag{7}$$

where $z_{it}$ is a dummy variable that takes the value of 1 if a firm $i$ is an output innovator, and 0 otherwise. Equation 7 models the firm's probability to be an output innovator as a latent function of its characteristics and market conditions; where $\mu_{3,t}$ is a year effects to control for macroeconomic condition, such as appropriability and technological opportunity. $x_{it}$ is the same vector of firm's characteristics as in equation 5. These variables are expected to influence the propensity of a firm to be an output innovator. In addition, we also consider that among those firms who share the same investment status and the same characteristics, firms that expands its export markets to new destinations is likely to be an output innovator. This is what we call learning by exporting. Entering new markets allows firms to acquire new knowledge without having to invest in innovating. Therefore, we expected that $\alpha_3$ is positive. Finally, $\epsilon_{3,it}$ is a serially correlated error term.

The identification of $\kappa$ is important for the mediating effect of innovation investment. The assumption SI.2 state that given the observed confounders, $x_{it}$, and the observed export status, the firm's decision to invest in innovation is independent to its propensity to introduce innovation output. This assumption makes it possible to identify the parameter $\kappa$. However, this assumption is also rather strong. In fact, we know that firms can anticipate their new products introduction or their new process development by investing in innovation activities. Therefore, the innovation investment decision is endogenous to the introduction of innovation output. The assumption SI.2 hold if the vector $x_{it}$ includes all confounders that simultaneously affect both innovation investment and innovation output. If not, we cannot regard $\epsilon_{2,it}$ as orthogonal to $\epsilon_{3,it}$. Furthermore, the identification of $\alpha_3$ is important for the mediating effect of innovation output. However, this parameter would be biased due to conscious self-selection if there are unmeasured confounders that affect both export expansion and innovation output: in such a case, $\epsilon_{3,it}$ will be correlated with $\epsilon_{1,it}$; *i.e.*, the assumption SI.1 does not hold.

*D. Productivity equation*

To estimate the effects of export market expansion and innovation output on firm productivity, we use the following equation,

$$\omega_{it} = \mu_{4,t} + \alpha_4 e_{it} + \gamma z_{it} + \beta_4' x_{it} + \epsilon_{4,it} \tag{8}$$

where $\omega_{it}$ is the (log) firm productivity; where $\mu_{4,t}$ is the year effects reflecting temporal variations in productivity that are common to all firms in a given year; $x_{it}$ is the same vector of firm's characteristics as in equation 5. These variables are expected to affect the productivity of the firm. In addition, we also consider that among those firms who share the same innovation output status and the same characteristics, firms that expands its export markets to new destinations become more productive. Therefore, we expected that $\alpha_4$ is positive. This effect is consistent with other causal mechanisms explaining the export/productivity relationship. Finally, $\epsilon_{4,it}$ is a serially correlated error term.

The identification of $\gamma$ is important for both, the mediating effects of innovation investment and innovation output. The assumption SI.3 state that given the observed confounders, $x_{it}$, and the observed export status, the firm innovation output is independent to its productivity level. This assumption makes it possible to identify the parameter $\gamma$, but it rather strong, since the relationship between innovation output and productivity has a simultaneity problem: self-selection into innovation activities (see for instance Caldera, 2010). This makes innovation output endogenous in the productivity equation. Assumption SI.3 holds if there are no unmeasured confounding factors between the innovation output and productivity equations: *i.e.*, $\epsilon_{3,it}$ is orthogonal to $\epsilon_{4,it}$.

*Measuring quantity-based productivity.* The measurement of firm-level productivity is an important issue in the identification of the impact of exports. The literature typically uses revenue-based measures of total factor productivity (TFPR), which also reflect changes in market performance such as: mark-ups, product mix and product quality (De Loecker and Goldberg, 2014). This may be problematic for identification purposes, as the international trade literature suggests that measures of market performance are likely to be affected by exports (Verhoogen, 2008; Mayer, Melitz, and Ottaviano, 2014; Mayer, Melitz, and Ottaviano, 2021; Jafari et al., 2022). In order to overcome this problem, quantity-based measures of total factor productivity (TFPQ) are used (see for instance, Smeets and Warzynski, 2013; Atkin, Khandelwal, and Osman, 2017; Garcia-Marin and Voigtländer, 2019). In Appendix A, we present our approach for the TFPQ estimation in more detail.

Our approach relies on a Cobb-Douglas production function using value added as output and capital and labor as inputs. Then, TFP is measured as a residual of this production function. We distinguish between a persistent productivity term $\omega_{it}$ and an idiosyncratic term that captures transitory productivity shocks and measurement error. As firms condition input decisions on its productivity, consistent estimation of the production function faces an endogeneity problem. As in Ackerberg, Caves, and Frazer (2015), we implement the 2-stages GMM procedure that implicitly inverts the material input demand to obtain a proxy for unobserved productivity in the first stage. In the second stage, the procedure rely on the law of motion for productivity estimation. Importantly, as argued by De Loecker (2013), we explicitly introduce the policy variables of interest in the equation governing the evolution of firm-level productivity, which makes the innovation output and export expansion also appear in the control function.

Moreover, since output and inputs are observed in nominal terms, we deal with *output price* (Klette and Griliches, 1996) and *input prices* (De Loecker et al., 2016) biases. In fact, using nominal variables introduces firm-specific price deviations in the error term of the production function, which leads to a endogeneity problem. Several factors are likely to limit the severity of these problems. First, we use a price deflator that captures price evolution common to all firms in a narrowly defined diary industry. [15] Second, differences between firm-specific deviations from output and input prices indices appear with opposite signs. To the extent that firms paying higher input prices also charge higher output prices, therefore the two terms may cancel each other out (De Loecker and Goldberg, 2014). In addition, we use a control function for the remaining prices differences. We assume that differences in input and output prices are driven by the differences in average wage per hour of labor, the firm-level export output price, the firm-level import input prices and the segment-year dummies.[16] After controlling for these price differences, we expect the estimated productivity to be a measure of the TFPQ.

## 4.2 Estimation and identification strategies

For the estimation purposes, we consider an error-components approach, such as $\epsilon_{j,it} = \varepsilon_{j,it} + u_{j,i}$; where $j$ = 1,2,3,4, where $u_{j,i}$ are the time-invariant unobserved confounders and $\varepsilon_{j,it}$ denotes the idiosyncratic errors encompassing other time-varying unobserved confounders. More formally, we assume that the vectors $u = (u_{1,i}, u_{2,i}, u_{3,i}, u_{4,i})'$ and $\varepsilon = (\varepsilon_{1,it}, \varepsilon_{2,it}, \varepsilon_{3,it}, \varepsilon_{4,it})'$ are independently and identically (over time and across individuals) normally distributed with means 0 and covariance matrices $\mathbf{\Sigma}_{\boldsymbol{\varepsilon}}$ and $\mathbf{\Sigma}_{\boldsymbol{u}}$ respectively, and independent of each other.

$$\mathbf{\Sigma}_{\boldsymbol{\varepsilon}} = \begin{pmatrix} 1 & & & \\ \tau_{12} & 1 & & \\ \tau_{13} & \tau_{23} & 1 & \\ \tau_{14}\sigma_4 & \tau_{24}\sigma_4 & \tau_{34}\sigma_4 & \sigma_4^2 \end{pmatrix} \text{ and } \mathbf{\Sigma}_{\boldsymbol{u}} = \begin{pmatrix} \sigma_{u_1}^2 & & & \\ \rho_{12}\sigma_{u_1}\sigma_{u_2} & \sigma_{u_2}^2 & & \\ \rho_{13}\sigma_{u_1}\sigma_{u_3} & \rho_{23}\sigma_{u_2}\sigma_{u_3} & \sigma_{u_3}^2 & \\ \rho_{14}\sigma_{u_1}\sigma_{u_4} & \rho_{24}\sigma_{u_2}\sigma_{u_4} & \rho_{34}\sigma_{u_3}\sigma_{u_4} & \sigma_{u_4}^2 \end{pmatrix}.$$

[15] The value added were deflated using valued added deflators from the OECD STAN. For capital, we use the the gross fixed capital formation deflator from EUROSTAT.

[16] Segment is defined at the five-digit level, using the NACE Rev.2 classification: Manufacture of fresh milk products (1051A), Manufacture of butter (1051B), Cheese Manufacturing (1051C) and Manufacture of dry dairy products (1051D).

The scalars $\{\rho_{jk}\}_{j\neq k}$ and $\{\tau_{jk}\}_{j\neq k}$ with $k$,$j$ = 1,2,3,4, governs the correlation between the unobserved firm heterogeneity, $u_j$ and $u_k$, and the correlation between idiosyncratic errors, $\varepsilon_{j,it}$ and $\varepsilon_{k,it}$, respectively. These correlation parameters tells us whether the sequential ignorability assumption holds or not.

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

$$L_i = \int_{\Re^4} \prod_{0_i+1}^{T_i} \ell_{it|u}(\omega_{it},z_{it},d_{it},e_{it}) \times \phi(u_{1,i}, u_{2,i}, u_{3,i}, u_{4,i})\, \mathrm{d}u_{1,i}\mathrm{d}u_{2,i}\mathrm{d}u_{3,i}\mathrm{d}u_{4,i} \qquad (9)$$

where $\ell_{it|u}(\omega_{it},z_{it},d_{it},e_{it})$ is the the joint density function of the model, $\phi(\cdot)$ is the quadrivariate normal density function of $(u_{1,i}, u_{2,i}, u_{3,i}, u_{4,i})'$.[17] The 4-dimensional integral of normal densities renders standard Maximum likelihood infeasible. We use simulated maximum likelihood techniques (SML) to solve the computational problem of evaluating 4-dimensional integrals (See for instance, Train, 2003). More precisely, four uncorrelated Halton sequences of dimension $R$ are first obtained. Then, random draws from density $\phi(\cdot)$ are simulated using the Halton sequences, a Cholesky decomposition, and the inverse cumulative normal distribution. Next, for each draw (which is a four-dimension vector), the conditional likelihood of the $i$-th firm is evaluated. Finally, an average of the $R$ simulated conditional likelihoods is taken. This average is the contribution of the $i$-th firm to the overall simulated likelihood – an approximation of the quadruple integral in Eq.9. Halton sequences have been shown to achieve high precision with fewer draws than uniform pseudo-random sequences because they have a better coverage of the [0,1] interval (for more on this topic see Train, 2003). Furthermore, Maximum simulated likelihood is asymptotically equivalent to maximum likelihood as long as $R$ grows faster than $\sqrt{N}$ (Gourieroux and Monfort, 1993). More details on this procedure are give in appendix (C).

Technically the model is identified through functional form (see Heckman, 1978). However, in spite of this formal identification even in the absence of exclusion restrictions, our estimation procedure, like others, may suffer from "tenuous identification" and including equation-specific covariates may be important to ensure the empirical identification of the parameters of interest when real data are used (Bratti and Miranda, 2011; Miranda, 2011). Hence, specifying exclusion restrictions to help identification is a good practice. Therefore, we need at least three exclusion variables; each for innovation output, innovation investment and export expansion equations.

We begin by the innovation output and innovation investment variables. For these endogenous variables, we use lagged values as instruments. Lagged explanatory variables

[17]More detail on the joint density function are given in Appendix (C).

are a common strategy used in economics in response to endogeneity concerns in observational data.[18] However, as Bellemare, Masaki, and Pepinsky (2017) have shown, when using the lagged variable as an instrument, the identification strategy depends on the endogeneity problem faced by the researcher. In the context of unobserved confounding variables problem, lagged value of the endogenous explanatory variable should be a valid instrument, if there are no dynamics among unobservables variables. The authors concludes that *"... this assumption of no dynamics among unobservables could in principle be defensible. But ... without careful arguments on substantive grounds, lagged explanatory variables should not be used for identification purposes."* While the assumption of no dynamics among unobservables is strong in the context of unobserved confounding variables, it becomes more reasonable when we consider an endogeneity problem due to measurement errors. Indeed, there is no reason to expect measurement errors to be serially correlated. Therefore in the context of measurement errors, lagged explanatory variables should be used for identification purposes. Finally, in this paper, we consider that the endogeneity of innovation output and innovation investment are solely due to measurement errors in variables. We have made this choice because, according to empirical literature, measurement errors explain the endogeneity problem in the CDM framework. As stated by Mairesse, Mohnen, and Kremp (2005), *"We interpret the need to instrument innovation and R&D as revealing important measurement errors in the innovation intensity variables, and to a lesser extent in the innovation binary indicators and in the R&D intensity variable and binary indicator."* Furthermore, Mairesse and Robin (2017) conduct a formal assessment on the importance of measurement errors in the CDM research–innovation–productivity relationships. To do so, the authors compare different panel estimators and find significant attenuation biases in innovation output and productivity equations.

Furthermore, since we are using $d_{i,t-1}$ and $z_{i,t-1}$ as instruments for $d_{it}$ and $z_{it}$ respectively, this could create an initial condition problem; *i.e.,* $d_{i,t-1}$ and $z_{i,t-1}$ could be correlated with $\epsilon_{2,it}$ and $\epsilon_{3,it}$ through $u_{2,i}$ and $u_{3,i}$, respectively. To solve the initial conditions problem here the strategy suggested by Wooldridge (2005) is used. This approach consists of using the first observation that is available in the sample, $d_{0_i}$ and $z_{0_i}$, as additional covariates in the equations 6 and 7, respectively. This approach is a guarantee of the exogeneity of the variables $d_{i,t-1}$ and $z_{i,t-1}$.

Although the endogeneity problem of the innovation variables can be explained by the measurement error problem, this is not the case for the export market expansion vari-

[18] In 2014 alone, Bellemare, Masaki, and Pepinsky (2017) count a total of 11 published articles in prominent economics journals that either involved endogeneity as a justification for lagging an explanatory variable.

able. Unobservable confounding variables or simultaneity problem due to self-selection into international market (see Melitz, 2003) are more likely to explain the endogeneity of export expansion variable. Using a sample of Chinese firms during the Asian financial crisis (1995-2000), Park et al. (2010) use the 1995–1998 change in log exports as the instrument for the 1995–2000 change in log exports, and show that this IV strategy yield results very similar to OLS; while IV strategy based on exchange rate variation between China and other countries, reveal that their OLS estimates are downward biased. Therefore we do not use lagged export expansion variable as instrument. Instead, we construct a variable that captures the demand shocks on the international market faced by French dairy firms.

This variable is composed of two elements, a trade shocks and a firm-level measure of shock exposure. We first describe the trade shock component. Following Mayer, Melitz, and Ottaviano (2021) and Aghion et al. (2022), we construct a aggregate export demand and used it as trade shocks. Let $M_{s,c,t}$ denote the aggregate import flow in product $s$ into country $c$ from all countries except France at year $t$.[19] $M_{s,c,t}$ reflects the size of the ($s$,$c$) export market during the year $t$. The larger is $M_{s,c,t}$, the larger is a French firm's potential demand foreign market ($s$,$c$). The underlying idea is that subsequent changes in destination $c$'s imports for product $s$ from the world (excluding France) will be a good proxy for the change in export demand faced by this firm (Mayer, Melitz, and Ottaviano, 2021; Aghion et al., 2022). Whether a french firm takes advantage of this foreign demand shocks, depends on its fixed and marginal costs of exporting. We assume that the probability a firm exports to country $c$ depends on its marginal costs, past history of exporting in the area to which country $c$ belongs and the distance between France and country $c$; the last two are used as proxy for fixed costs.[20] In the first year we observe the firm (year $t_0$) we regress an exporter to country $c$ dummy on these three variables. This generates a prediction that the firm $i$ exports to country $c$ in year $t_0$. We use this prediction as the firm exposure to the trade shock. More formally, The trade shock for firm $i$ between $t$ and $t-1$ is constructed as:

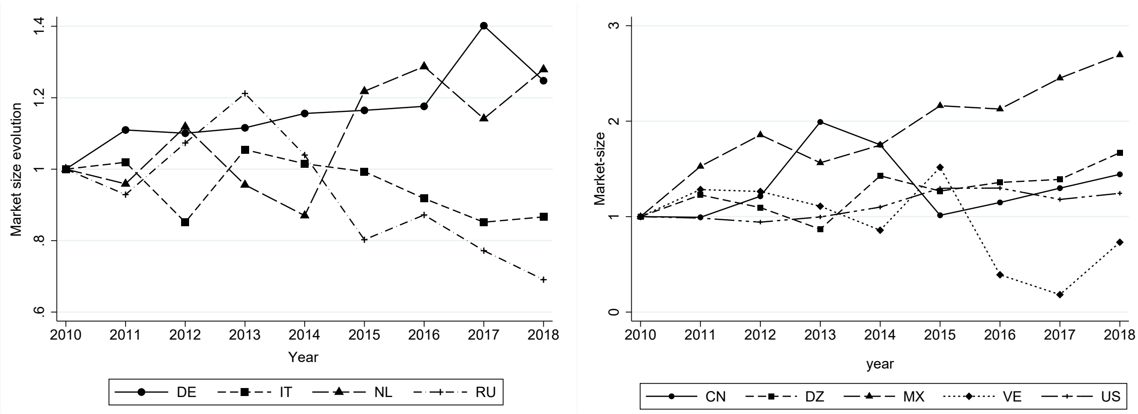
$$\mathrm{TS}_{it} = \sum_{c,s} w_{i,c,t_{0_i}} \left( \frac{M_{c,t} - M_{c,t-1}}{0.5\left(M_{c,t} + M_{c,t-1}\right)} \right), \tag{10}$$

so that firm $i$ has never exported to country $c$; where $M_{c,t} = \sum_s M_{s,c,t}$. The intu-

[19]To measure $M_{s,c,t}$, we use data from the CEPII's BACI database. This data is based on the UN database COMTRADE, provides bilateral trade flows in value and quantity for each pair of countries from 2010 to 2018 at the HS6 product-level.

[20]We use the average variable cost as proxy for marginal costs. We obtain total variable costs from the firm accounting data as the sum of the total material cost and the total wage bill. Production is proxy by the revenues.

Figure 1: Dairy products market-size evolution




(a) Top four importers (Europe) (b) Top four importers (outside Europe)

*Note:* Market-size are calculated as the total import of dairy products in country $c$ at the year $t$. 2010 market-size s are normalized to one.

ition behind the use of this variable is that: We expect that the change in market size is sufficiently large enough to induce firms to enter in that specific market, since the export profit increase with market-size while the costs are fixed. Figures 1 provide information on the 2010-2018 evolution of market size for the top 4 (inside and outside Europe) importers of dairy products over the period. These figures show large and non-monotonic movements in market-size: this is likely to affect the firm propensity to start exporting to these specific countries. In addition, the variable Trade shock$_{it}$ is reasonably uncorrelated with outcomes of interest (productivity and innovation measures) except via the channel of interest (exportation). Therefore this variable enter the export market expansion equation but are excluded from the other equations.[21]

[21] Furthermore, this variable is based on arguably exogenous changes in the market-size of all trading partners and on each firm's exposure to those changes given their pre-shock export exposure. In other words, while the preshock, $w_{i,c,t_{0_i}}$, are a choice variable of the firm, once they are predetermined, the differential change in exports propensity due to the variation of the market-size is reasonably exogenous.

# 5 Empirical Evidence

This section show the results of our estimation. We present only the results under the relaxation of the sequential ignorability assumption.[22] The model is estimated by maximum simulated likelihood where 200 Halton draws were used. Adding more Halton draws did not significantly change the log-likelihood, standard errors or coefficients.

## 5.1 Main results

Table 5 presents the results obtained by relaxing the sequential ignorability assumption. We present four different panels in this Table. The first table, panel $(A)$, shows the estimates of the following parameters: $\alpha_2$, $\alpha_3$, $\alpha_4$, $\kappa$, and $\gamma$. The second results, panel $(B)$, present the estimates of the exclusion variables with a statistic to describe their strength as instrument. The third results, panel $(C)$, present the estimates of the average causal mechanisms: $\bar{\hat{\delta}}$, $\bar{\hat{\delta}}_1$, $\bar{\hat{\delta}}_2$, and $\bar{\hat{\delta}}_3$. The last results, panel $(D)$, show the LR test of the model.

To assess the relevance of our model, we carried out a LR test. This test consists of comparing two models: a first restricted model in which the correlation coefficients are assumed to be all zero; and a second model in which no constraints are imposed. This test can be summarised by the following null hypothesis, $H_0$: $\tau_{12} = \cdots = \tau_{34} = \rho_{12} = \cdots = \rho_{34} = 0$. The rejection of this null hypothesis implies that the sequential ignorability hypothesis is not relevant in our case. Panel $(D)$ show the result of the test. With a LR statistic (equal to 35.68) higher than the $\chi^2_{0.01}(12) = 26.22$, we can conclude that the hypothesis $H_0$ is rejected, at the 1% significance level. Therefore, our multivariate model is substantive and adds over and above the evidence from four separate univariate models. These results therefore support a rejection of the sequential ignorability assumption. Moreover, the AIC and BIC yield the same result.[23]

To improve identification, we use trade shocks, $TS_{it}$, and lagged value of innovations variables, $d_{i,t-1}$ and $z_{i,t-1}$, as instrument for export expansion, innovation investment and innovation output equations, respectively. Panel $(B)$, present the effect and the significance of these variables in their respective equation. First of all, we find a positive and highly significant effect of the demand shock on the expansion of the export market. This result is consistent with the expectation that a positive demand shock would be an incentive for firms to start exporting. This finding is similar to previous empirical works that use aggregate trade shocks, e.g., exchange rate or tariff reductions, for instrumenting

[22]The results obtained under the sequential ignorability assumption are presented in the appendix D.

[23]To carry out these tests, we estimated both, the restricted and the unrestricted models using maximum simulated likelihood with 200 Halton. The results for the IC and BIC are not reported, but are available upon request.

Table 5: The mediating role of innovation variables on the impact of export market expansion on firm productivity

| | Export expansion | Innovation investment[a] | Innovation output[a] | Productivity |
|---|---|---|---|---|
| Variables | (1) | (2) | (3) | (4) |
| *Panel A. Parameters of interest* | | | | |
| $z_{it}$ | | | | $0.084^{***}$(0.022) |
| $e_{it}$ | | $0.239^{***}$(0.083) | $0.198^{***}$(0.068) | $0.055^{**}$ (0.026) |
| $d_{it}$ | | | $0.395^{***}$(0.085) | |
| *Panel B. Exclusion variables* | | | | |
| $TS_{it}$ | $0.167^{***}$(0.012) [193.7] | | | |
| $d_{i,t-1}$ | | $0.103^{***}$(0.007) [216.5] | | |
| $z_{i,t-1}$ | | | $0.156^{***}$(0.039) [16.0] | |
| *Panel C. Causal mechanisms of export expansion* | | | | |
| | $\bar{\hat{\delta}}$ | $\bar{\hat{\delta}}_1$ | $\bar{\hat{\delta}}_2$ | $\bar{\hat{\delta}}_3$ |
| | (1′) | (2′) | (3′) | (4′) |
| | $0.080^{***}$(0.027) | $0.008^{***}$(0.003) | $0.017^{***}$(0.005) | $0.055^{**}$ (0.026) |
| *Panel D. Wald test for correlation parameters* | | | | |
| $H_0 : \rho_{12} = \rho_{13} = \rho_{14} = \rho_{23} = \rho_{24} = \rho_{34} = \tau_{12} = \tau_{13} = \tau_{14} = \tau_{23} = \tau_{24} = \tau_{34} = 0$ | | | | |
| LRT= 35.68 | | | | |
| p-value = 0.0004 | | | | |

*Notes:* To save space we report only the parameters of interest. Specification is estimate using Simulated Maximum Likelihood based on 200 Halton draws. The results stay virtually unchanged when we use 250 or 300 Halton draws. [a]We report the average partial effect rather than the estimated coefficients. Appendix C gives more detail on our FIML estimation procedure. All equations includes year dummies and an intercept. Standard Error are in parenthesis. $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$. Values in bracket are F-statistic.

export participation (see for instance, Park et al., 2010; Lileeva and Trefler, 2010; Bustos, 2011; Brambilla, Lederman, and Porto, 2012).

Regarding the role of the lagged value of innovation output, $z_{i,t-1}$, on current innovation output, $z_{it}$, our estimation shows a positive and highly significant (p-value less than 0.01) effect (column 3 of the Panel $(B)$). Since our estimation accounts for individual effects and handling properly the initial conditions, we can infer the existence of a true state dependence of innovation output. The true state dependence state that past innovation achievement impact the probability of current innovation. The causal relationship between past and current innovation output can be explain by the cumulative nature of knowledge (for theoretical consideration, see Nelson and Winter, 1982; Cohen and Levinthal, 1990; Romer, 1991). A wide range of empirical works, such as Geroski, Van Reenen, and Walters (1997), Raymond et al. (2010), Raymond et al. (2015) or Chemo Dzukou (2021), support this finding. Furthermore, we also find true state dependence of innovation investment (column 2 of the Panel $(B)$). Indeed, past innovation investment has a positive and highly significant effect on the probability of investing in innovation in the subsequent period. A common hypothesis put forward in the literature to explain the causal effect of past innovation investment on current innovation investment is that of *sunk cost*. There are start-up costs for setting up an R&D department or hiring R&D staff when a firm decides to engage in innovation activities. These fixed costs, once incurred, are generally non-recoverable and can therefore be considered as sunk costs (Sutton, 1991; Peters, 2009). These sunk costs constitute an exit barrier for firms that have invested in innovation, as they are not recovered if the firm stops innovating. Innovation investment also act as a barrier to entry, since potential entrants have to take them into account when setting their prices. This finding is consistent with the works of Peters (2009) and Manez et al. (2009).

The relative strength of these different sets of instruments is measured by the F-statistics reported at the end of the panel $(D)$. The F-stat of 193.7, 216.5 and 16.0 for demand shocks, lagged innovation investment and lagged innovation output, respectively, are above the thresholds of the value of 10 whhich is the treshold for detecting weak instruments.

Panel $(A)$ show the estimation result of the interested parameters in the model. Column 2 of the Table 5 confirm the existence of a strong positive relationship between an increase in export market expansion and changes in the propensity to invest in innovation, an effect that is statistically significant at the 1% level. Moving to column 3 of the Table 5, the estimated effects of export market expansion and innovation investment on the probability to be an output innovator is positive and significant at the 1% level. Finally, column 4 of the Table 5, shows positive and significant effects, at the 1% level, of export market expansion and innovation output on firm productivity. These results are consistent with the recent empirical evidence discussed in the Literature Review section. Overall, all structural parameters, $\alpha_2$, $\alpha_3$, $\alpha_4$, $\kappa$, and $\gamma$ are statistically different from zero at 5% level of significance; suggesting that export expansion impacts firm-level productivity through at least oine of the three mechanisms discussed in previous sections. Now, a crucial question is which mechanisms are the most important in terms of magnitude.

The total effect of export market expansion on firm productivity is estimated to be 0.08 (column $1'$ of the panel $C$). Suggesting that when a firm enters a new export market, its productivity is, on average, 8% higher than it would have been if it had not expanded its export market. In addition, with a p-value less than 0.01, the total effect of export market expansion on firm productivity is statistically significant. The decomposition of this total effect into direct and indirect effects is of primary interest. The estimate of the direct effect is equal to 0.055 (column $4'$ of the panel $C$); and therefore contributes to 68.75% of the total effect. This result suggests that mechanisms other than innovation are at play when we look at the relationship between exports and productivity at the firm level.

Regarding indirect effects, the causal effect of export expansion on firm productivity that operates through innovation investment, *innovation investment mechanism*, depends on how export market expansion affects innovation investment, how innovation investment affect innovation output, and how innovation output affect productivity. Using the expression 1, we can derive the first average causal mediation effect, ACME, as follows,

$$\bar{\hat{\delta}}_1 = (NT)^{-1} \sum_{i,t} \hat{\delta}_{1,it} \tag{11}$$

where

$$\begin{aligned} \hat{\delta}_{1,it} = & \left[g\left(\omega_{it}|z_{it}=1, e_{it}=1, x_{it}\right) - g\left(\omega_{it}|z_{it}=0, e_{it}=1, x_{it}\right)\right] \times \\ & \left[\Pr\left(z_{it}|d_{it}=1, e_{it}=1, z_{i,t-1}, x_{it}\right) - \Pr\left(z_{it}|d_{it}=0, e_{it}=1, z_{i,t-1}, x_{it}\right)\right] \times \\ & \left[\Pr\left(d_{it}|e_{it}=1, d_{i,t-1}, x_{it}\right) - \Pr\left(d_{it}|e_{it}=0, z_{i,t-1}, x_{it}\right)\right] \end{aligned}$$

The result of this calculation is reported in column $2'$ of the panel $C$. The causal effect of export expansion on firm productivity through innovation investment is estimated to be 0.008; which represents 10% of the total effect of export expansion on productivity. Next, the causal effect of export expansion on productivity that operates through innovation output, *innovation output mechanism*, depends how export market expansion affect innovation output, and how innovation output affect productivity. Using the expression 2, we can derive this second ACME as follows,

$$\bar{\hat{\delta}}_2 = (NT)^{-1} \sum_{i,t} \hat{\delta}_{2,it} \tag{12}$$

where

$$\begin{aligned} \hat{\delta}_{2,it} = & \left[g\left(\omega_{it}|z_{it}=1, e_{it}=1, x_{it}\right) - g\left(\omega_{it}|z_{it}=0, e_{it}=1, x_{it}\right)\right] \times \\ & \left[\Pr\left(z_{it}|e_{it}=1, z_{i,t-1}, x_{it}\right) - \Pr\left(z_{it}|e_{it}=0, z_{i,t-1}, x_{it}\right)\right] \end{aligned}$$

The result of this calculation is reported in column $3'$ of the panel $C$. Conditional on the *innovation investment mechanism*, we find that, the causal effect of export expansion on firm productivity through innovation output is estimated to be 0.017; which represents 21.25% of the total effect. Overall, the *innovation mechanisms* explain for around a third of the causal effect of exporting on productivity.

## 5.2 Robustness Check

*A. Robustness I – Statistical*

We conduct several exercises to show the statistical robustness of our results. In the previous section, we have shown that the instruments used to explain the endogenous variables do not suffer from the weak instrument problem. In this section, we check if the *exogeneity* and *exclusion restriction* assumptions hold.

Exogeneity of variables $d_{i,t-1}$ and $z_{i,t-1}$ in equations 6 and 7 respectively is discussed in the previous sections. Their exogeneity is guaranteed thanks to the Wooldridge (2005) approach that we applied. Therefore we focus our attention on the exogeneity of $TS_{it}$ in equations (6), (7) and (8). This instrument is based on arguably exogenous changes in the market size and on each firm's exposure to those changes given their preshock. While the preshock is a choice variable of the firm, once they are predetermined, the differential change in decision to start exporting to a given destination due to the market-size is reasonably exogenous. However, since the random-effects estimator exploits both the *within* (due to the market-size) and the *between* (due to the preshock) variations, to identify the effect of $TS_{it}$ on $e_{it}$, the question is, how important is the market-size variation in this effect? To show that specific variation in market-size induces firms to export to that destination, we use placebo tests. First, we regress lagged values of $e_{it}$ on $TS_{it}$. The colunms 1-3 of the Table 6 show results. The estimated effects is positive and statistically significant; however, in terms of magnitude, these effects are close to 0 and are much more weaker than the effect of $TS_{it}$ on $e_{it}$ (see column 1 of the Table 5); suggesting that change in market-size increases substantially the probability to start exporting to that destination. The second test involves the construction of placebo demand shocks for each firm and then showing that export market expansion does not respond to this placebo shock. To this end, we randomly permute market-size across destinations and years to construct placebo demand shock as in equation 10. Column 4 of the Table 5 shows the result of the effect of the placebo demand shock on export market expansion. The estimated effect is found to be positive but statistically insignificant. These results highlight that export expansion responses to $TS_{it}$ cannot be simply explained by the preshock.

One strategy for determining whether the instruments satisfy the exclusion restriction is to use a placebo population test that reproduces the reduced form analysis in a population in which the instrument could not affect the endogenous variable. For example, the exclusion restriction assumption states that the firm-level trade shock, $TS_{it}$, affects the mediators (innovation variables) and the ultimate outcome (productivity), only through export expansion. Therefore, if we run the reduced-form regressions (e.g, the firm-level trade shock on productivity) on a sub-sample of firms that never exported during the

Table 6: Robustness. Importance of market-size variation in the effect of $TS_{it}$ on Export Market Expansion.

| | Dep. Variable: Export Market Expansion | | | |
|---|---|---|---|---|
| Variable | 1 Year Lag (1) | 2 Year Lag (2) | 3 Year Lag (3) | (4) |
| $TS_{it}$ | $0.015^{***}$(0.005) | $0.019^{***}$(0.005) | $0.013^{***}$(0.005) | 0.047 (0.132) |

*Notes:* The Table reports the average partial effects of the coefficient of $TS_{it}$ from equation 5. Instead of $e_{it}$, we use 1 year, 2 year and 3 year lagged of $e_{it}$ variable to obtain results in columns 1, 2 and 3, respectively. Result in column 4 is obtain by replacing $TS_{it}$ in equation 5 by the placebo shock. We use random-effects probit model for all estimations. $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

sample period, we should find no effect. The results of these reduced-form regressions are shown in columns 1–3 of the Table 7: the coefficients of interest is around 0 and statistically non-significant, suggesting that the exclusion restriction assumption is more trustworthy for the variable $TS_{it}$. We apply the same strategy to test the exclusion restriction assumption for the variables $d_{i,t-1}$. However, we cannot restrict the reduced-form regression on the sub-sample of firms that never invested in innovation activities during the sample period, since $d_{i,t-1}$ would be always 0. In contrast, we focus on two consecutive years, $t$ and $t+1$, and remove from the sample firms that invest in innovation activities in $t+1$, whatever their status in $t$. Therefore, the sub-sample contains two types of firm: $(i)$ firms that invested in innovation activities in $t$, but not in $t+1$ and $(ii)$ firms that did not invested in innovation activities in $t$ and $t+1$. We then regress $d_{i,t-1}$ on innovation output, $z_{it}$. The columns 4 and 5 of the Table 7 gives the results of such regression for the consecutive years 2010-2011 and 2017-2018. We find that the effect of $d_{i,t-1}$ on innovation output is not significantly different from zero. By applying the same approach, we also test the exclusion restriction assumption for the variable $z_{i,t-1}$ (see columns 6 and 7 of the Table 7).

Table 7: Robustness. Placebo test for exclusion restriction.

| | | | | $z_{it}$ | | $\omega_{it}$ | |
|---|---|---|---|---|---|---|---|
| | $d_{it}$ (1) | $z_{it}$ (2) | $\omega_{it}$ (3) | 2011–2012 (4) | 2017–2018 (5) | 2011–2012 (6) | 2017–2018 (7) |
| $TS_{it}$ | 0.004 | 0.004 | 0.015 | | | | |
| | (0.012) | (0.004) | (0.064) | | | | |
| $d_{i,t-1}$ | | | | -0.024 | -0.001 | | |
| | | | | (0.124) | (0.328) | | |
| $z_{i,t-1}$ | | | | | | -0.009 | -0.009 |
| | | | | | | (0.059) | (0.061) |

*Notes:* $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

*B. Robustness II – More Discussion*

*B.1. Markups adjustment and quality improvement*

Although our measure for productivity controls for variations in markups and quality; a natural concern is whether our results on the mediating role of innovation variables reflect heterogeneous responses across firms in adjusting their markups and/or improving their output quality which can be correlated with innovation activities. We address this issue by using the (log.) markups and a measure of quality as ultimate outcomes.

In order to estimate the markups at the firm level, we follow the set-up developed by De Loecker and Warzynski (2012). Their approach relies on the assumption of standard cost minimization for variable inputs free of adjustment costs and relate the output elasticity of an input to the share of that input's expenditure in total sales (Curzi, Garrone, and Olper, 2021). More details on the estimation of firm-level markups can be found in the Appendix A. If the mediating role of innovation on the effect of exporting on productivity reflects markups adjustment (due to the investments), we expect that the innovation output variable affects positively and significantly the markups of the firm. To test this, we re-estimate our equations system using the FIML estimation; however, we have replaced the firm productivity variable in equation 8 by the firm markups variable. Panel ($G$) of the Table 8 shows the result of such estimation. As might have been expected, the effects of export expansion on innovation investment and on innovation output, and the effect of innovation investment on innovation output have not changed. For the last causal chain, we find that innovation output increase the markups of the firm; however with a p-value higher than 0.1, this effect is statistically not significant. This suggests that innovation does not explain the relationship between exporting and markups. Thus, the innovation mechanisms highlighted above do not reflect changes in markups.

Moreover, the innovation mechanisms highlighted above that may explain the relationship between exporting and productivity may also reflect quality upgrading? Unfortunately, we don't have a direct measure of output quality in our data. However, to test this mechanism we use a measure that increases monotonically with output quality, namely marginal cost.[24] Following Amiti, Itskhoki, and Konings (2019), we use the average variable cost as a proxy for marginal costs.[25] We compute average variable costs as the sum of the total material cost and the total wage bill over the total firm revenue. Using this measure as an ultimate outcome, we find that innovation output has a negative and

[24]To illustrate the relationship between marginal cost and product quality, we assume generic functional form $MC(W_{it},\Omega_{it})$; where $W_{it}$ is an input prices index and $\Omega_{it}$ is the TFPQ. Since, $MC(\cdot)$ is increasing in $W_{it}$ and decreasing in $\Omega_{it}$, we can write the log. of marginal cost as $mc(w_{it},\omega_{it}) = w_{it} - \omega_{it}$; where the lower case variables denote the log. of the upper case variables. Assuming that dairy firms do not have monopsony power, an increase in input prices, $w_{it}$, may imply that firms purchase higher quality inputs and therefore produce higher quality output.

[25]We refer to Amiti, Itskhoki, and Konings (2019) for theoretical concerns.

Table 8: Robustness check: alternative explanation

*Panel G. The mediating role of innovation variables on the impact of export market expansion on firm markups*

| | Export expansion | Innovation investment | Innovation output | Markups | |
|---|---|---|---|---|---|
| Variables | (1) | (2) | (3) | (4) | |
| $z_{it}$ | | | | 0.027 | (0.032) |
| $e_{it}$ | | 0.240***(0.083) | 0.201***(0.068) | 0.116 | (0.103) |
| $d_{it}$ | | | 0.391***(0.085) | | |

*Panel H. The mediating role of innovation variables on the impact of export market expansion on marginal cost*

| | Export expansion | Innovation investment | Innovation output | Marginal cost | |
|---|---|---|---|---|---|
| Variables | (5) | (6) | (7) | (8) | |
| $z_{it}$ | | | | -0.061*** | (0.010) |
| $e_{it}$ | | 0.236***(0.079) | 0.182***(0.061) | -0.011** | (0.007) |
| $d_{it}$ | | | 0.347***(0.078) | | |

*Panel I. The mediating role of innovation variables on the impact of export market expansion on marginal cost. We include productivity as additional control variable in marginal cost equation.*

| | Export expansion | Innovation investment | Innovation output | Marginal cost | |
|---|---|---|---|---|---|
| Variables | (9) | (10) | (11) | (12) | |
| $z_{it}$ | | | | 0.013** | (0.006) |
| $e_{it}$ | | 0.236***(0.079) | 0.182***(0.061) | 0.005 | (0.003) |
| $d_{it}$ | | | 0.347***(0.078) | | |

*Notes:* To save space we report only the parameters of interest. Specification is estimate using Simulated Maximum Likelihood based on 200 Halton draws. Appendix C gives more detail on our FIML estimation procedure. All equations includes year dummies and an intercept. Standard Error are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

statistically significant impact on marginal cost (Panel $(H)$ of the Table 8). Since the marginal cost is negatively correlated to productivity, we interpret this negative effect of innovation on marginal cost as an increase in firm productivity. It should be noted, however, that this result does not suggest that innovation output has a negative effect on quality, but rather that the effect of innovation output on productivity dominates the effect of innovation on output quality (input prices index). To highlight this point, we control for productivity variation in the marginal cost equation by including our measure of firm productivity as an additional control variable. Panel $(I)$ of the Table 8, shows the result of this procedure. Conditional on productivity, the effect of innovation output on marginal cost becomes positive and is statistically significant at 5% level. This result suggests that our main result may also reflect quality improvement. However, as the results of these tests (Panels ($H$) and ($I$)) show, productivity growth and quality improvement are not mutually exclusive.

*B.2. Heterogeneity in initial productivity level*

To shed further light on the heterogeneous impact of export expansion on firm productivity, we study the effects across the initial productivity. We estimate our equations system for two separate samples: firms falling above and below the median value of the initial productivity sample distribution. The results are presented in Table 9. Interestingly, the effects of export expansion on innovation investment, on innovation output and on productivity are more pronounced for firms with initial productivity below the median. This result is in line with a complementary channel in which exporting and investment in innovation go hand in hand. And, initially less productive firms will make this joint decision only if the productivity gains are substantial (Lileeva and Trefler, 2010). Indeed, productive firms are already close to the technology frontier required to compete in international markets, while unproductive firms need to see major productivity increases to render exporting profitable.

Table 9: Robustness check: heterogeneity

| *Panel J. Initial productivity above the median* | | | | |
|---|---|---|---|---|
| | Export expansion | Innovation investment | Innovation output | Productivity |
| Variables | (1) | (2) | (3) | (4) |
| $z_{it}$ | | | | $0.053^{**}$ (0.026) |
| $e_{it}$ | | $0.163^{***}$(0.055) | $0.137^{**}$ (0.070) | 0.023 (0.024) |
| $d_{it}$ | | | $0.418^{***}$(0.102) | |
| *Panel K. Initial productivity below the median* | | | | |
| | Export expansion | Innovation investment | Innovation output | Productivity |
| Variables | (5) | (6) | (7) | (8) |
| $z_{it}$ | | | | $0.114^{***}$(0.031) |
| $e_{it}$ | | $0.321^{***}$(0.115) | $0.267^{***}$(0.042) | $0.091^{***}$(0.037) |
| $d_{it}$ | | | $0.366^{***}$(0.081) | |

*Notes:* To save space we report only the parameters of interest. Specifications are estimated using Simulated Maximum Likelihood based on 200 Halton draws. Appendix C gives more detail on our FIML estimation procedure. Standard Error are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

## 6 Conclusion

According to the international trade literature, trade, *e.g.* exports, leads to productivity gains. This argument has been supported by ample empirical evidence, but nothing has been said about the mechanisms through which export participation may affect the productivity of the firm. The theoretical literature on growth and trade has emphasized that the superior performance of international firms may reflect the endogenous decisions of these firms to invest in innovation, which in turn may generate innovations output and productivity improvements. Firms engaging in international markets may have better opportunities to realize profits that become available as a result of their endogenous innovative activities and this, in turn, creates greater incentives for them to invest in innovation. In addition to this mechanism, the productivity gains from trade can also be explained by the fact that, for an exporting firm, trade opens up to the knowledge that is held by their trading partners that can be incorporated into their production process so to increase productivity. These two mechanisms place innovation as a potential component of the productivity-export link.

In this paper, we provide empirical evidence on the role of innovation activities as an important component of the productivity-export link. In order to highlight the two innovation mechanisms that explain the causal effect of export on productivity, we develop a mediation analysis framework that is based on two causal chains. In the first causal chain, firms that start exporting increase their propensity to invest innovation activities, which in turn affects the probability to be an output innovators, which in turn contributes to their productivity; we call this *innovation investment mechanism*. In the second mechanism, conditional on innovation investment, firms that start exporting increase their probability to be an output innovators, which in turn rises their productivity; we call this *innovation output mechanism*. We then present an empirical model based on the Crepon, Duguet, and Mairesse (1998)'s model. This empirical model allows us to describe the two innovation mechanisms empirically, taking into account numerous endogeneity problems. This empirical model is implemented on a panel of French dairy firms, observed over the period 2010-2018.

Our results show that the total effect of starting to export to a new destinations on firm productivity is estimated to be 0.08. Suggesting that when a firm enters a new export market destinations, its productivity is, on average, 8% higher than it would have been if it had not expanded its export market. Now, the question we are answering here is how much innovation contributes to this productivity growth? Beginning by the innovation investment mechanisms, we find that by entering a new export market destinations induce firms to invest in innovation activities. Indeed, the expected return on innovation investments can be larger for exporting firms because of a larger market size or because of strong competition from other firms (from other countries) operating in foreign country. In addition, we find that firms that invest in innovation activities are more likely to be output innovators. We also find that output innovators have, on average, higher productivity than non-innovators. In term of magnitude, the innovation investment mechanism is evaluated to be 0.008. This corresponds to 10% of the total effect of starting to export to a new destinations on firm productivity. Regarding the innovation output mechanism, our estimation reveals that conditional on innovation investment, entering a new export market destination increases the probability of the firm to be an output innovator. This result is consistent with the learning by exporting hypothesis, where firms gain new knowledge through their participation in the international market. In term of magnitude, the innovation output mechanism are evaluated to be 0.017. This corresponds to 21% of the total effect of starting to export to a new destinations on firm productivity. Finally, we also find that 69% of the productivity growth is not explained by the innovation mechanisms, which leaves scope for the study to other mechanisms.

As our results hold for one particular industry, we are cautious in generalizing our findings. However, we believe that two mechanisms, highlighted by this study, contribute to existing literature trade and productivity. Finally it would be interesting to test the mechanisms presented in this paper based on data from other industries; specially for high-tech industry.

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# A Production function

## A.1 Estimation

Let us consider the following physical production function:[26]

$$q_{it} = f(k_{it}, l_{it}; \beta) + \omega_{it} + \epsilon_{it} \tag{13}$$

Where $q_{it}$, $l_{it}$, and $k_{it}$ are respectively the logs. of output, labor and capital; all expressed in physical units. $\beta$ contains all the relevant coefficients. We distinguish between a persistent productivity term $\omega_{it}$, which is known by the firm and thus affects the firm's input choices, and an idiosyncratic term $\epsilon_{it}$ that captures the unknown elements that affect the output, transitory productivity shocks and measurement error. As it is standard in the production function estimation literature, we consider flexible approximations to $f(\cdot)$. The advantage of using this class of production functions is that one can rely on proxy methods to obtain consistent estimates of $\beta$ (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg, Caves, and Frazer, 2015). To ease exposition, in what we will explicitly write equation (13) in its Cobb-Douglas form.

However, output in physical units is not available in our data; therefore, we follow the empirical literature and use the following *value-added* production function,

$$va_{it} = \beta_k k_{it} + \beta_l l_{it} + p^Q_{it} + \omega_{it} + \epsilon_{it} \tag{14}$$

where $va_{it}$ is the deflated value-added and where $p^Q_{it}$ is the deflated output price. Since, $p^Q_{it}$ is unobserved, it generates an *output price bias* whenever it differ from zero in a way that is correlated with input choice (Klette and Griliches, 1996). For instance, firm who charge high markups sell less, and thus buy less inputs.

In addition, capital is in monetary values $\tilde{k}_{it}$, rather than in physical units $k_{it}$, so any variation in capital prices due to differences in technological sophistication is latent. As for output price, if this latent differences quality and utilization of capital are correlated with output quality, this may induces an *input price bias* as discussed by De Loecker et al. (2016). For example, the PDO (Protected Designation of Origin) labeling of cheese has been established by the European Union (EU) as a quality policy that assures the authenticity of a cheese produced in a specific region by applying traditional production

[26] More formally, we assume that firms used fixed proportion of raw milk to produce a certain quantity of output. For example, on average, 11 and 8 kilograms of milk are used to produce 1 kilogram of butter and cheese, respectively. Since milk cannot be substituted with either labor or capital, we can use a production function is Leontief in raw milk, that is, $Q_{it} = \min\{\beta_d D_{it}, \Omega_{it} F(L_{it}, K_{it}; \beta)\}$ where $D_{it}$ is the quantity of dry matter of raw milk.

methods. It guarantees that every step of the preparation (milk production, transformation and maturation) is carried out in a set geographic area corresponding to the product's region of origin, and using recognised techniques and particular specifications inspected by public authorities and independent third-party bodies.[27] As a results, PDO cheeses are capital intensive products compared to other cheeses. This is also the case for the labor variable since we use the total wage bill $\tilde{l}_{it}$, rather than the number of employee in full time equivalent, $l_{it}$. We make this choice because the biases causes by both capital and labor prices can be partly offset by the output-price bias De Loecker and Goldberg (2014); De Loecker and Eeckhout (2018). We can thus rewrite equation (14) as:

$$va_{it} = \beta_k \tilde{k}_{it} + \beta_l \tilde{l}_{it} + \underbrace{p^Q_{it} - \beta_k p^K_{it} - \beta_l p^L_{it}}_{B(\cdot)} + \omega_{it} + \epsilon_{it} \tag{15}$$

where $p^K_{it}$ and $p^L_{it}$ are the deflated prices of capital and labor, respectively. Since the hypotheses that allow us to consider that inputs prices and output price biases cancel each other out are rather strong (see, De Loecker and Goldberg, 2014), we use a control function, $B(\cdot)$, to capture the remaining differences (De Loecker et al., 2016). As argument of $B(\cdot)$, we use the average wage per hour of labor $p^L_{it}$, the firm-level export output price $p^X_{it}$, the firm-level import input price $p^I_{it}$ and segment-year dummies, $\chi_{it}$. This last variable is particularly important because there is considerable price heterogeneity across dairy products segment. For example, butter and cheese are considered to be high value-added products, which is not the case for other dairy products.

As firms condition input decisions on $\omega_{it}$, consistent estimation of equation (15) faces an endogeneity problem. In order to address this problem, we follow Ackerberg, Caves, and Frazer (2015) and assume that demand in intermediates inputs is strictly monotonic in productivity conditional on the included variables, which means that it can be inverted to write

$$\omega_{it} = h_t \left( \tilde{m}_{it}, \tilde{k}_{it}, \tilde{l}_{it}, p^L_{it}, p^X_{it}, p^I_{it}, \chi_{it} \right) \tag{16}$$

where $\tilde{m}_{it}$ is the log of deflated intermediates inputs expenditures. We put all the pieces together and write the estimating equation as

$$va_{it} = \beta_k \tilde{k}_{it} + \beta_l \tilde{l}_{it} + B\left(p^L_{it}, p^X_{it}, p^I_{it}, \chi_{it}\right) + h_t \left( \tilde{m}_{it}, \tilde{k}_{it}, \tilde{l}_{it}, p^L_{it}, p^X_{it}, p^I_{it}, \chi_{it} \right) + \epsilon_{it} \tag{17}$$

To consistently estimates equation(17), we closely follow the two-step procedure developed in Ackerberg, Caves, and Frazer (2015). In the first step, we obtain the estimates

[27]see https://www.produits-laitiers-aop.fr/en/what-is-a-pdo/

of $\hat{\phi}_{it}$ and $\hat{\epsilon}_{it}$ by running the following OLS regression:

$$va_{it} = \phi_t \left( \tilde{m}_{it}, \tilde{k}_{it}, \tilde{l}_{it}, p^L_{it}, p^X_{it}, p^I_{it}, \chi_{it} \right) + \epsilon_{it} \tag{18}$$

where $\phi(\cdot)$ is a third-order polynomial function. In the second step, the elasticities of production parameters are estimated through GMM, using the inputs orthogonal to the unexpected productivity shock as instruments. After the first stage, we can employ the estimated value $\hat{\phi}_{it}$ to compute the estimate for productivity, as following:

$$\omega_{it} = \hat{\phi}_{it} - \beta_k \tilde{k}_{it} - \beta_l \tilde{l}_{it} - B \left( p^L_{it}, p^X_{it}, p^I_{it}, \chi_{it} \right) \tag{19}$$

This second stage relies on the law of motion for productivity. We allow the law of motion of productivity to depend on export market expansion ($e_{it}$), innovation output ($z_{it}$) as described by the following $g(\cdot)$ function:

$$\omega_{it} = g(\omega_{i,t-1}, e_{it}, z_{it}) + \xi_{it} \tag{20}$$

where $\xi_{it}$ is the TFP innovation. Therefore we can substitute equation (19) into equation (20) to derive an expression for the TFP innovation $\xi_{it}(\beta)$ as a function of only observables and unknown parameters $\beta$.

Given $\xi_{it}(\beta)$, we can write the moments identifying conditions as:

$$E \left[ \xi_{it}(\beta) \begin{pmatrix} \tilde{k}_{it} \\ \tilde{l}_{it} \\ p^L_{it} \\ p^X_{i,t-1} \\ p^I_{i,t-1} \\ \chi_{it} \\ e_{i,t-1} \\ z_{i,t-1} \end{pmatrix} \right] = 0 \tag{21}$$

The identifying restrictions are that the TFP innovations are not correlated with currentlabor and capital,which are thus assumed to be dynamic inputs in production. These moment conditions are fully standard in the production function estimation literature (Ackerberg, Caves, and Frazer, 2015).

Once the output elasticities have been estimated, computing markups becomes a simple task. We follow Rubens (2023) and define as,

$$\theta_{it} = \left(\frac{s_{it}^L}{\beta_l} + s_{it}^M\right)^{-1}, \text{ with } s_{it}^M = \frac{\exp(m_{it})}{\exp(r_{it} - \hat{\epsilon}_{it})} \text{ and } s_{it}^L = \frac{\exp(l_{it} + w_{it})}{\exp(r_{it} - \hat{\epsilon}_{it})}.$$

where $r_{it}$ is the deflated turnover; where $\hat{\epsilon}_{it}$ is the residual from the first stage of the production function estimation. This correction purges revenue shares from variation unrelated to technology or market power.

# B Merging GNPD with other datasets

To identify a firm, all the databases of the French administration, including export data and production data, use the same unique identifier, called siren. This simplifies the work when it comes to linking the different databases. The main challenge is to merge either of these two datasets with GNPD. The merging procedure of GNPD with other datasets is 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.[28] It identifies the processing plant that manufactured the product. The EC identification 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 firm. The steps of the matching procedure are as follows:

- Preliminary works
  - We keep all observations (each observation refers to a product launch) belonging to dairy products category, since our work focuses specifically on this industry;
  - We drop all observations where the EC identification number is missing.
  - We keep only product launches in France; the reason for this is that, the introduction of a new product takes place first on the domestic market; hence, a French product considered as new in a foreign market (e.g. Belgium) has a strong chance to have been launched beforehand on the French market.
  - We keep observations with an `ISO` country code corresponding to France, i.e. `FR`;
- Retrieving `siren` identifier for each product launched
  - We use the list dairy products processing plant publicly available on the Ministry of Agriculture website;[29] this list makes the correspondence between the EC identification and the `siret` number. The `siret` number (système d'identification du répertoire des établissements) is a number used by the French administration to identify the plants of a firm. 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).

[28] See Regulation (EC) No.853/2004 of the European parliament and of the council.
[29] This official list is available here

# C Likelihood function and numerical integration

Let us define,

$$
\begin{aligned}
A_{it} =& \mu_{1,t} + \beta_1' x_{it} \\
B_{it} =& \mu_{2,t} + \beta_2' x_{it} + \alpha_2 e_{it} \\
C_{it} =& \mu_{3,t} + \beta_3' x_{it} + \alpha_3 e_{it} + \kappa_3 d_{it} \\
D_{it} =& \mu_{4,t} + \beta_4' x_{it} + \alpha_4 e_{it} + \kappa_4 z_{it}
\end{aligned}
$$

we can write 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 as

$$
\begin{aligned}
\frac{1}{\sigma_4}\phi\Big(\frac{\omega_{it} - D_{it} - u_{4,i}}{\sigma_4}\Big)\Phi_3\Bigg(&\frac{q_{1,it}\left(A_{it} + u_{1,i} + \frac{\tau_{14}}{\sigma_4}\varepsilon_{4,it}\right)}{\sqrt{1-\tau_{14}^2}}, \frac{q_{2,it}\left(B_{it} + u_{2,i} + \frac{\tau_{24}}{\sigma_4}\varepsilon_{4,it}\right)}{\sqrt{1-\tau_{24}^2}}, \\
&\frac{q_{3,it}\left(C_{it} + u_{3,i} + \frac{\tau_{34}}{\sigma_4}\varepsilon_{4,it}\right)}{\sqrt{1-\tau_{34}^2}}; q_{1,it}q_{2,it}\tau_{12}', q_{1,it}q_{3,it}\tau_{13}', q_{2,it}q_{3,it}\tau_{23}'\Bigg) \qquad (22)
\end{aligned}
$$

where $\varepsilon_{4,it} = \omega_{it} - D_{it} - u_{4,i}$, $q_{1,it} = 2e_{it} - 1$, $q_{2,it} = 2d_{it} - 1$ and $q_{3,it} = 2z_{it} - 1$; where $\Phi_3(\cdot)$ is the trivariate standard normal distribution function and,

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

After obtaining the conditional likelihood function shown in Eq.(22) the next step consists in deriving the unconditional counterparts to $\ell_{it|u}(\omega_{it}, z_{it}, d_{it}, e_{it})$, which are obtained by integrating out the individual effects with respect to their distribution. Formally, the likelihood function of one firm, starting from $t = 1$ is written as

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

Evidently, $L_i$ cannot be derived analytically since the multivariate integral is generally not tractable. We can use a change-of-variables technique to transform it into a set of nested univariate integrals. Let $\mathbf{A}$ be the Cholesky decomposition of $\mathbf{\Sigma_u}$; that is, $\mathbf{\Sigma_u} = \mathbf{AA}'$. It follows that $(u_{1,i}, u_{2,i}, u_{3,i}, u_{4,i})' = \mathbf{A}\boldsymbol{v_i}$, where $\boldsymbol{v_i}$ is a vector of independent standard normal random variables. More formally, the individual likelihood can be rewrite as

$$
\begin{aligned}
L_i \;=\; & \int_{v_{0,i}} \int_{v_{1,i}} \int_{v_{2,i}} \int_{v_{3,i}} \prod_{0_i+1}^{T_i} \frac{1}{\sigma_3} \times \phi\Big(\frac{\omega_{it} - D_{it} - a_{4,1}v_{0,i} - a_{4,2}v_{1,i} - a_{4,3}v_{2,i} - a_{4,4}v_{3,i}}{\sigma_3}\Big) \times \\
& \Phi_3\Bigg(\frac{q_{1,it}\left(A_{it} + a_{1,1}v_{0,i} + \frac{\tau_{03}}{\sigma_3}\varepsilon_{3,it}\right)}{\sqrt{1-\tau_{03}^2}}, \frac{q_{2,it}\left(B_{it} + a_{2,1}v_{0,i} + a_{2,2}v_{1,i} + \frac{\tau_{13}}{\sigma_3}\varepsilon_{3,it}\right)}{\sqrt{1-\tau_{13}^2}}, \\
& \frac{q_{3,it}\left(C_{it} + a_{3,1}v_{0,i} + a_{3,2}v_{1,i} + a_{3,3}v_{2,i} + \frac{\tau_{23}}{\sigma_3}\varepsilon_{3,it}\right)}{\sqrt{1-\tau_{23}^2}}; q_{1,it}q_{2,it}\tau_1^{'}, q_{1,it}q_{3,it}\tau_2^{'}, q_{2,it}q_{3,it}\tau_3^{'}\Bigg) \\
& \times\phi(v_{0,i})\phi(v_{1,i})\phi(v_{2,i})\phi(v_{3,i})\, \mathrm{d}v_{0,i}\mathrm{d}v_{1,i}\mathrm{d}v_{2,i}\mathrm{d}v_{3,i}
\end{aligned}
$$

where $u_{0,i} = a_{1,1}v_{0,i}$, $u_{1,i} = a_{2,1}v_{0,i} + a_{2,2}v_{1,i}$, $u_{2,i} = a_{3,1}v_{0,i} + a_{3,2}v_{1,i} + a_{3,3}v_{2,i}$ and $u_{3,i} = a_{4,1}v_{0,i} + a_{4,2}v_{1,i} + a_{4,3}v_{2,i} + a_{4,4}v_{3,i}$; and where $a_{l,k}$ are the components of $\mathbf{A}$ and takes the following form: $a_{1,1} = \sigma_{u_0}$, $a_{2,1} = \rho_{01}\sigma_{u_1}$, $a_{3,1} = \rho_{02}\sigma_{u_2}$, $a_{4,1} = \rho_{03}\sigma_{u_3}$, $a_{2,2} = \sigma_{u_1}\sqrt{1-\rho_{01}^2}$, $a_{3,2} = \sigma_{u_2}(\rho_{12} - \rho_{01}\rho_{02})/\sqrt{1-\rho_{01}^2}$, $a_{4,2} = \sigma_{u_3}(\rho_{13} - \rho_{01}\rho_{03})/\sqrt{1-\rho_{01}^2}$, $a_{3,3} = \sigma_{u_2}\sqrt{1-\rho_{01}^2-\rho_{02}^2-\rho_{12}^2+2\rho_{01}\rho_{02}\rho_{12}}/\sqrt{1-\rho_{01}^2}$, $a_{4,3} = \sigma_{u_3}(\rho_{23} - \rho_{02}\rho_{03} - \rho_{12}\rho_{13} - \rho_{01}^2\rho_{23} + \rho_{01}\rho_{03}\rho_{12} + \rho_{01}\rho_{02}\rho_{13})/\sqrt{(1-\rho_{01}^2)(1-\rho_{01}^2-\rho_{02}^2-\rho_{12}^2+2\rho_{01}\rho_{02}\rho_{12})}$ and $a_{4,4} = (\sigma_{u_3}^2 - a_{4,1}^2 - a_{4,2}^2 - a_{4,3}^2)^{1/2}$. Now this multiple univariate integral can be approximated using simulation technique. We use the simulated maximum likelihood method (for a detailed discussion on SML, see, Train, 2003). More specifically, we evaluate the integral as follow:

1. Generate four independent uniform [0,1] random variables, $k_0^r$, $k_1^r$, $k_2^r$ and $k_3^r$

2. calculate $\tilde{v}_0^r = \Phi^{-1}(k_0^r)$, $\tilde{v}_1^r = \Phi^{-1}(k_1^r)$, $\tilde{v}_2^r = \Phi^{-1}(k_2^r)$ and $\tilde{v}_3^r = \Phi^{-1}(k_3^r)$

3. calculate $v_0^r = a_{1,1}\tilde{v}_0^r$, $v_1^r = a_{2,1}\tilde{v}_0^r + a_{2,2}\tilde{v}_1^r$, $v_2^r = a_{3,1}\tilde{v}_0^r + a_{3,2}\tilde{v}_1^r + a_{3,3}\tilde{v}_2^r$ and $v_3^r = a_{4,1}\tilde{v}_0^r + a_{4,2}\tilde{v}_1^r + a_{4,3}\tilde{v}_2^r + a_{4,4}\tilde{v}_3^r$

4. The simulated likelihood for an individual firm for this $r$th draw of $v_0$, $v_1$, $v_2$ and $v_3$ is calculated as

$$
\begin{aligned}
\tilde{L}_i^r = \Bigg[ & \prod_{0_i+1}^{T_i} \frac{1}{\sigma_3} \times \phi\Big(\frac{\omega_{it} - D_{it} - a_{4,1}v_{0,i}^{(r)} - a_{4,2}v_{1,i}^{(r)} - a_{4,3}v_{2,i}^{(r)} - a_{4,4}v_{3,i}^{(r)}}{\sigma_3}\Big) \times \\
& \Phi_3\Bigg(\frac{q_{1,it}\left(A_{it} + a_{1,1}v_{0,i}^{(r)} + \frac{\tau_{03}}{\sigma_3}\varepsilon_{3,it}\right)}{\sqrt{1-\tau_{03}^2}}, \frac{q_{2,it}\left(B_{it} + a_{2,1}v_{0,i}^{(r)} + a_{2,2}v_{1,i}^{(r)} + \frac{\tau_{13}}{\sigma_3}\varepsilon_{3,it}\right)}{\sqrt{1-\tau_{13}^2}}, \\
& \frac{q_{3,it}\left(C_{it} + a_{3,1}v_{0,i}^{(r)} + a_{3,2}v_{1,i}^{(r)} + a_{3,3}v_{2,i}^{(r)} + \frac{\tau_{23}}{\sigma_3}\varepsilon_{3,it}\right)}{\sqrt{1-\tau_{23}^2}}; q_{1,it}q_{2,it}\tau_1^{'}, q_{1,it}q_{3,it}\tau_2^{'}, q_{2,it}q_{3,it}\tau_3^{'}\Bigg)\Bigg]
\end{aligned}
$$

5. Repeat steps 1-4 many times, for $r = 1, \ldots, R$

6. The simulated likelihood for an individual firm is

$$\tilde{L}_i = \frac{1}{R} \sum_{r=1}^{R} \tilde{L}_i^r$$

The generation of the four independent uniform [0,1] random variables is done by Halton sequences instead of uniform pseudo-random sequences. Halton draws have been shown to achieve high precision with fewer draws than uniform pseudorandom sequences because they have a better coverage of the unit square interval (Train, 1999; Bhat, 2001). This characteristic of the Halton sequence ensures a better coverage of the multidimensional area of integration and reduces the computation time of the `SML`. The estimation routine leads to consistent results if the total number of draws, $R$ tends to infinity as the number of observations tends to infinity. in particular, $R$ should increase at a rate greater than the square root of the sample size.

# D Additional results

## D.1 Results under sequential ignorability assumption

The sequential ignorability assumption rules out the existence of unmeasured confounders. Therefore, we can estimate the system equation by equation in order to obtain the parameters of interest. The results of the estimation are presented in the Table 10. To save space, only the parameters of interest are shown in the Table. Panel ($A$) reports the magnitude of the effect of the parameters of interest; and the panel ($B$) reports on the different causal mechanisms of the effects of export market expansion.

Table 10: The mediating role of innovation variables on the impact of export market expansion on firm productivity: Sequential Ignorability Assumption

| Variables | (1) | | Innovation investment[a] (2) | | Innovation output[a] (3) | | Productivity (4) | |
|---|---|---|---|---|---|---|---|---|
| *Panel A. Main parameters of the model* | | | | | | | | |
| $z_{it}$ | | | | | | | 0.025* | (0.015) |
| $e_{it}$ | | | 0.112 | (0.097) | 0.151** | (0.076) | 0.027 | (0.021) |
| $d_{it}$ | | | | | 0.139** | (0.070) | | |
| *Panel B. Causal mechanisms of export expansion* | | | | | | | | |
| | $\bar{\hat{\delta}}$ (1′) | | $\bar{\hat{\delta}}_1$ (2′) | | $\bar{\hat{\delta}}_2$ (3′) | | $\bar{\hat{\delta}}_3$ (4′) | |
| | 0.031 | (0.021) | 0.000 | (0.000) | 0.004* | (0.002) | 0.027 | (0.021) |

*Notes:* To obtain results in columns (2) and (3), we regress equations 6, 7 using a random-effects probit model. Column (4) is obtained by regressing equation 8 using random-effects linear model. All the estimated equations include variables in the vector $x_{it}$ as observed confounders. We also include variables used as excluded instruments in their respective equation. [a]The values reported in table are the average partial effects and values in parentheses are the standard error obtained using delta method. $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.1$.

Panel ($A$) shows the estimation of equations 6 and 7 using a random-effects probit model (columns (2) and (3)) and the estimation of equation 8 using a random-effects linear model (column (4)). We shows that firms that expand their export markets to new destinations also increase both their propensity to invest in innovation and their probability of being an output innovator; and also increase their productivity. The estimated effect of $e_{it}$ in the innovation investment and productivity equations, column (2) and column (4) respectively, is positive but not statistically significant (p-value higher than 0.10 for both). In contrast, the estimated effect of $e_{it}$ in the innovation output equation, column (3), is positive and statistically significant (p-value greater than 0.05). In terms of magnitude, the average partial effect is estimated to be 0.151. This result suggests that the probability of being an innovator increases by 15% for firms that enter new export destinations. In addition, we find that the effect of innovation investment, $d_{it}$, on innovation output is positive and statistically significant (p-value less than 0.05).This effect is estimated to be 0.139; which suggests that investment in innovation activities has a 14% increase in the firm's propensity to be an output innovator. Finally, the effect of innovation output, $z_{it}$, on productivity is positive and marginally statistically significant (p-value greater than 0.05); which suggests that, on average, innovation output contributes 3% to productivity growth.

In term of magnitude, the effects of export expansion are much more larger when unobserved confounders are controlled for. This suggest an negative selection between export markets expansion and firm performance measures (innovation investment, innovation output and productivity). For example, in order to expands their export markets firms have to increase the capacity of their production lines, and so take on new workers; which in the short run may lead to a decrease in productivity and in enhancing-productivity activities because of adjustment costs and time to learn.