Innovation Produit et Performance des Entreprises dans l'Industrie Laitière Française

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Résumé

Le processus de croissance des entreprises – en termes de productivité ou de performance à l'export – est une préoccupation majeure des décideurs politiques. Dans ce contexte, les innovations jouent un rôle crucial pour stimuler la performance des entreprises. Cette thèse étudie empiriquement l'impact de l'innovation « produit » (à distinguer de l'innovation « procédé ») sur la performance des entreprises. La revue de la littérature présentée dans le chapitre 1 décrit les mécanismes qui régissent la relation entre l'innovation et la productivité et la relation entre l'innovation et le comportement à l'export des entreprises. Le chapitre 2 présente une description de la notion d'innovation et de sa mesure dans la littérature économique. Nous présentons Global New Product Database (GNPD), la banque de données que nous utilisons pour construire une base de données innovation. Le chapitre 3 estime l'effet de l'innovation produit sur le comportement à l'export des entreprises laitières françaises. Nous montrons que l'introduction d'un nouveau produit influe positivement non seulement sur les prix proposés par l'entreprise mais aussi leur demande. Le chapitre 4 s'intéresse au rôle de l'innovation produit dans l'apprentissage acquis lors de l'exportation. Nous montrons que les exportations renforcent la capacité d'innovation des entreprises, qui à son tour augmente la productivité des entreprises. Le chapitre 5 traite de la persistance de l'innovation produit dans l'industrie laitière française. Nous montrons que les entreprises qui sont les plus susceptibles d'innover sont celles qui ont innové l'année précédente. Ainsi, cette thèse montre, grâce à une nouvelle mesure de l'innovation produit, que celle-ci permet aux entreprises d'exporter, d'augmenter leur productivité et de rester innovante.

Mots clés : Innovation produit ; Export ; Productivité ; Apprentissage par l'exportation ; Dynamique de l'innovation.

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Avant-propos

Les chapitres de cette thèse sont des articles qui sont en cours de préparation pour être soumis à des revues scientifiques à comité de lecture.

L'article du Chapitre 3 a été rédigé en collaboration avec mes directrices Sabine Duvaleix-Tréguer et Karine Latouche. Il sera soumis à une revue à comité de lecture dès qu'il aura fait l'objet d'une révision.

L'article du chapitre 4 a été co-écrit avec Mark Vancauteren professeur à l'université de Hasselt. Il sera soumis à une revue à comité de lecture dès lors qu'on intégrera la composante Pays-Bas dans notre analyse.

L'article du chapitre 5 sera soumis à une revue à comité de lecture dès qu'il aura fait l'objet d'une révision.

Acronyms

APE Activité Principale Exercée

CES Constant Elasticity of Substitution

CIS Community Innovation Survey

FARE Fichier Approché des Résultats d'Esane

GNPD Global New Products Database

ICT Information and Communication Technologies

INSEE Institut National de la Statistique et des Études Économiques

H2020 Horizon 2020

OCDE Organisation de Coopération et de Développement Économiques

PRODCOM PRODuction COMmunautaire

RD Recherche et Développement

SIREN Système d'Identification du Répertoire des ENtreprises

SIRET Système Informatique pour le Répertoire des Entreprises sur le Territoire

TFP Total Factor Productivity

UE Union Européenne

Introduction

Depuis les travaux pionniers de Schumpeter (1934), la littérature économique sur l'innovation, qu'elle soit théorique (Solow, 1956; Arrow, 1962; Uzawa, 1965; Romer, 1986; Lucas, 1988; Romer, 1990) ou empirique (Abramovitz, 1956; Geroski and Machin, 1992; Geroski and Toker, 1996; Yasuda, 2005) donne du crédit à l'existence d'une relation entre innovation et croissance économique. De ce fait, la promotion de l'innovation est au cœur des politiques publiques, et ce dans de nombreux pays. Les politiques mises en place par l'Union Européenne (UE) en sont un exemple. Pour surmonter les différences de croissance et de productivité entre l'UE et ses principaux concurrents mondiaux de l'époque – les États-Unis et le Japon –, le Conseil européen a défini en l'an 2000 une stratégie décennale visant à faire de l'UE " l'économie de la connaissance la plus compétitive et la plus dynamique du monde, capable d'une croissance économique durable, accompagnée d'une amélioration quantitative et qualitative de l'emploi et d'une cohésion sociale accrue ". [1] L'un des principaux objectifs de la stratégie de Lisbonne a été d'accélérer la transition vers une économie fondée sur la connaissance, dans laquelle l'éducation et la formation, la recherche et l'innovation contribuent efficacement à la croissance.

De manière plus générale, les Programmes-cadre pour la recherche et le développement technologique (en abrégé Programmes-cadre), sont des programmes de financement créés par l'Union européenne en vue de soutenir et d'encourager la recherche européenne à des fins de soutien à la compétitivité de l'industrie, conformément à l'Espace européen de la recherche. [2] Ces dispositifs permettent principalement de stimuler l'investissement en Recherche et Développement (R&D) au sein de l'UE. [3] Selon le rapport intermédiaire de la Commission nationale d'évaluation des politiques d'innovation [4], le budget Français consacré à l'intervention publique en faveur du huitième Programme-cadre (H2020), s'élève à 10 milliards d'euros en 2014. Ainsi, le budget consacré à innovation a plus que doublé en quinze ans de politiques d'innovation en France.

1. Rapport sur la Stratégie de Lisbonne, disponible ici.
2. L'Espace européen de la recherche est un concept créé par la Communauté européenne pour décrire sa politique en matière de recherche et d'innovation. Son but est de promouvoir une approche unifiée de la recherche de la part de la Communauté européenne élargie par rapport aux programmes strictement nationaux. Pour plus d'informations sur l'Espace européen de la recherche, lire Bellier (2008).
3. Selon un rapport Commission nationale d'évaluation des politiques d'innovation, les Programmes-cadre en France visent à corriger des faiblesses à caractère structurel. Le rapport est disponibleici
4. Téléchargeable ici

Cette place particulière accordée à l'innovation par les décideurs politiques soulève quelques questionnements. Comment intégrer le développement durable dans cette dynamique d'innovation ? Étant donné que les investissements en recherche et développement (R&D) atteignent des niveaux élevés dans tous les pays industrialisés, il est légitime de se demander si les entreprises françaises sont compétitives sur le plan international dans la transformation de leurs investissements de R&D en nouveaux produits et technologies de production ? Quelles sont les retombées économiques des activités d'innovation des entreprises ? L'innovation n'est pas une fin en soi, elle vise à améliorer la performance de l'entreprise. D'après Janz et al. (2003), les innovations doivent être évaluées sur la base de leur succès économique ou, plus généralement, sur la base de leur impact sur les mesures pertinentes de la performance des entreprises. Cette thèse vise principalement à répondre à la troisième question en examinant la relation entre l'innovation et la performance au niveau entreprise. Plus précisément, nous nous intéressons à la relation entre innovation, productivité et performance à l'export des entreprises.

Pour comprendre ce lien, il est important de commencer par analyser la relation entre productivité et exportation au niveau entreprise. Dans un travail fondateur, Bernard and Jensen (1995) montrent que les entreprises exportatrices ont en moyenne des performances économiques (productivité, salaire, ventes, chiffre d'affaire, capital, etc. . .) plus élevées que les entreprises non exportatrices. Dans la continuité de cet article, de nombreuses études empiriques ont examiné et mis en évidence le lien entre exportation et productivité des entreprises (Bernard and Jensen., 1997; Bernard and Jensen, 1999; Isgut, 2001; Bernard and Jensen, 2004; Van Biesebroeck, 2005; Bernard et al., 2007; De Loecker, 2007). Les raisons des écarts de productivité entre exportateurs et non-exportateurs sont largement traitées dans la littérature économique (voir, Wagner, 2007, pour une revue détaillée). Deux hypothèses permettent d'expliquer pourquoi les exportateurs ont une productivité plus élevée que les non-exportateurs. La première hypothèse stipule que ce sont les entreprises le plus productives qui participent automatiquement aux marchés d'exportation. La participation au marché international implique des coûts supplémentaires. Les coûts de transport, les coûts de distribution ou les coûts de production liés à l'adaptation des produits pour la consommation étrangère, constituent des obstacles à l'exportation pour les entreprises à faible productivité. Seules les entreprises les plus productives sont en mesure de couvrir ces coûts additionnels. Ainsi ce sont les entreprises les plus productives qui deviennent exportatrices (Clerides et al., 1998; Bernard and Jensen, 1999, 2004; Delgado et al., 2002). La seconde hypothèse porte sur le rôle de l'apprentissage par l'exportation. Les entreprises qui participent aux marchés internationaux sont exposées à une concurrence plus intense et doivent donc s'améliorer plus rapidement que les entreprises qui vendent leurs produits uniquement sur le marché domestique. Cette hypothèse stipule que les exportations rendent les entreprises plus productives (Blalock and Gertler, 2004; Van Biesebroeck, 2005; De Loecker, 2007; Atkin et al., 2017).

Dans cette thèse nous examinons le rôle des activités d'innovation dans ces deux hypothèses.

Plus précisément, Cette thèse étudie empiriquement et présente de nouveaux résultats sur les trois sujets clés suivants :

— Comment l'innovation affecte-t-elle l'auto-sélection des entreprises dans les marchés d'exportation ?

— Comment l'innovation affecte-t-elle l'apprentissage par l'exportation ?

— Les entreprises innovent-elles de manière persistante dans le temps ?

Les travaux empiriques proposés dans cette thèse sont basés sur des données d'un panel d'entreprises de l'industrie laitière française. L'avantage de se concentrer sur une industrie particulière dans un pays donné est que les effets intersectoriels ne viennent pas compliquer les liens de causalité. L'industrie laitière est un cas intéressant à étudier pour plusieurs raisons : premièrement, la demande globale en produits laitiers est croissante. D'après Chatellier (2016), l'industrie laitière bénéficie d'une augmentation soutenue de la demande globale, notamment dans les pays asiatiques où l'essor démographique se conjugue à une modification progressive des régimes alimentaires associée à une augmentation globale du pouvoir d'achat.[5] Deuxièmement, l'industrie laitière participe à améliorer la balance commerciale française, et dispose d'un large portefeuille de marchés à l'export. Troisièmement, elle fait partie des industries manufacturières les plus productives.[6],[7] Enfin, bien que ce soit l'une des industries les moins intensives en technologie, l'industrie laitière est l'une des plus innovantes, notamment en matière d'innovation produit.

La thèse est organisée en 5 chapitres.

Chapitre 1 Innovation et performance de l'entreprise : Une Revue de la Littérature. Le chapitre 1 passe en revue la littérature économique sur l'innovation et la performance de l'entreprise. Dans ce chapitre, je commence par m'intéresser à la relation entre les activités d'innovation et la productivité des entreprises. Les études empiriques ont traditionnellement utilisé une approche fondée sur la fonction de production comme cadre théorique, complétée par la R&D[8] comme intrant supplémentaire. Cette approche souffre d'au moins deux lacunes. Premièrement, le processus d'innovation, c'est-à-dire le lien entre les ressources consacrées à l'innovation et le résultat de l'innovation reste inconnu. Deuxièmement, seule une minorité d'entreprises est engagée dans la R&D ou dans des activités d'innovation en général. Ainsi restreindre l'échantillon aux entreprises innovantes uniquement peut induire des estimations biaisées. Pour pouvoir pallier à ces deux problèmes, une amélioration importante de cette modélisation a été faite par Crepon et al. (1998) (noté CDM dans la suite). Ces auteurs ont

5. Selon la FAO, la consommation mondiale de produits laitiers augmente de 2,5% par an. Pour plus de détails, voir le rapport semestrielle

6. Mesurée en terme de productivité du travail : valeur ajoutée par employé

7. Pour plus d'informations, lire le rapport final de la Commission européenne sur la position concurrentielle de l'industrie européenne de l'alimentation et des boissons, téléchargeable ici

8. La littérature économique considère généralement la R&D comme un stock de connaissance, d'où son appellation "*knowledge capital*" dans la littérature initiée par Griliches (1979)

développé un modèle empirique, permettant de faire le lien entre input de l'innovation, output de l'innovation et productivité. CDM ont estimé leur modèle pour les entreprises manufacturières françaises, et un nombre important d'études pour d'autres pays ont suivi. Cependant, le modèle CDM est essentiellement utilisé sur des données en coupe transversale. Puisque nous disposons aujourd'hui de plus en plus de données sur l'innovation, il serait intéressant de constituer des données de panel qui permettraient de corriger l'hétérogénéité non observée et d'examiner les aspects dynamiques de la relation.

Je m'intéresse ensuite à la relation entre innovation et exportations des entreprises. Les bases théoriques de cette littérature sont intrinsèquement liées à la relation entre la décision d'exporter des entreprises et leur productivité. Les travaux fondateurs de Bernard and Jensen (1999) et Melitz (2003) ont montré que seules les entreprises les plus productives choisissent d'exporter, car seules les entreprises dont le niveau d'efficacité dépasse un certain seuil sont en mesure de surmonter les coûts fixes liés à leur entrée sur le marché d'exportation. Cette littérature suppose généralement que la productivité des entreprises est exogène, et aléatoirement obtenue après leur entrée dans l'industrie. Bustos (2011) et Yeaple (2005) ont endogénéisé la productivité au niveau de l'entreprise, permettant ainsi aux entreprises d'influencer leur propre niveau d'efficience. Les activités d'innovation permettent à une entreprise d'accroître sa productivité. Dans le cadre théorique de Caldera (2010), les entreprises ont le choix entre deux technologies de production : soit elles innovent pour réduire leurs coûts marginaux de production et améliorer ainsi leur processus de production, soit elles restent telles quelles. Ainsi, dans ce cadre d'analyse, une partie de la productivité des entreprises innovantes est exogène. Grâce à ce modèle, Caldera (2010) fait deux prédictions. Premièrement, ce sont les entreprises les plus productives qui innovent. Ce résultat s'explique par le fait que le profit provenant de l'innovation est une fonction croissante de la productivité de l'entreprise. Deuxièmement, ce sont les entreprises innovantes qui sont les plus susceptibles d'exporter. Ce résultat s'explique par le fait que les entreprises innovantes trouvent les exportations plus rentable que les entreprises non-innovantes. En effet, comme les coûts marginaux de production des entreprises innovantes sont moins élevés, ils peuvent facturer un prix inférieur, ce qui fera augmenter les ventes totales plus que proportionnellement en raison d'une demande élastique. Une des principales limites du modèle de Caldera (2010) est qu'il considère l'innovation produit, comme une innovation qui réduit les coûts de production.

Chapitre 2 Données et mesure de l'innovation. Puisqu'il est question d'innovation, le chapitre 2 propose une description détaillée de l'innovation et comment elle est mesurée dans la littérature économique. La base de données concernant les nouveaux produits et que j'utilise dans mes travaux est ensuite présentée. En particulier, je présente plus en détail certaines informations sur les lancements de nouveaux produits sur le marché mondial. Je conclus ce chapitre en testant la pertinence de cette base de données en la comparant à celle utilisée dans la littérature.

Chapitre 3 Product Innovation and Export Strategy : An Application to French Dairy Firms. Le chapitre 3 examine l'effet de l'innovation produit sur la performance à l'export des entreprises. La principale question traitée dans ce chapitre est de mesurer comment une stratégie d'amélioration de la qualité par le biais de l'innovation produit influence la capacité des entreprises à exporter. Plus spécifiquement, nous examinons dans quelle mesure l'innovation produit influe sur les quantités vendues et les prix pratiqués sur les marchés étrangers. A cet effet, l'innovation produit est définie comme un processus menant au développement d'un nouveau produit dans lequel l'analyse et la compréhension des désirs, des besoins et des préférences des consommateurs jouent un rôle clé (Grunert et al., 2010). Un cadre empirique dans lequel l'innovation produit affecte à la fois la demande via la qualité (perçue par les consommateurs) et la production via le coût marginal est mobilisé. Du côté de la demande, la qualité perçue par les consommateurs est considérée comme une fonction de 3 composantes. La première composante est la qualité agrégée. Elle représente le consentement à payer des consommateurs. La deuxième composante est le goût des consommateurs et la dernière composante représente la capacité qu'a une entreprise exportatrice d'adapter ses variétés de produit aux préférences des consommateurs, qui est capturée ici par l'innovation produit. Du côté de la production, l'introduction d'un nouveau produit permet à une entreprise d'adapter ses produits à la demande spécifique du marché. L'effet de l'innovation produit sur le coût marginal de production est alors étroitement lié à cette demande. Par exemple, sur les marchés de destination où les possibilités de différenciation de la qualité sont importantes, les entreprises améliorent la qualité de leurs variétés de produits pour satisfaire les préférences des consommateurs. Le modèle proposé dans ce chapitre prédit un effet ambigu de l'innovation produit sur les quantités vendues. En effet, d'une part, l'innovation produit peut augmenter la demande via la qualité perçue, l'effet demande ; d'autre part, l'innovation produit implique des coûts marginaux et des prix plus élevés, ce qui entraîne une baisse de la demande pour les nouveaux produits, l'effet coût (ou prix). Les estimations empiriques montrent que l'introduction d'un nouveau produit induit une hausse des prix. Les résultats montrent également que l'effet demande est supérieur à l'effet coût.

Chapitre 4 The Role of Product Innovation on the Learning by Exporting : The Case of the French Dairy Industry. Le chapitre 4 examine le rôle de l'innovation produit dans le processus de l'apprentissage par l'exportation. Le processus d'apprentissage par l'exportation fait référence au mécanisme par lequel les entreprises améliorent leur productivité après leur entrée sur les marchés d'exportation (De Loecker, 2013). Les études empiriques qui ont cherché à tester l'effet d'apprentissage par l'exportation ont été réalisées principalement à l'aide de données indirectes, qui lient la productivité aux exportations. En effet, si l'exportation influe sur l'apprentissage et que l'apprentissage influe ensuite sur la productivité, il serait utile de le tester directement en utilisant des données sur l'exportation, l'apprentissage et la productivité (Crespi et al., 2008). D'après De Loecker (2013), les investissements en marketing, les relations avec des acheteurs étrangers, ou encore les investissements dans des activités d'innovation sont tous des mécanismes d'apprentissage. Dans ce chapitre, nous nous intéressons aux activités d'innovation comme mécanisme d'apprentissage. Cela revient donc à examiner deux relations. La première relation lie les exportations aux activités d'innovation (e.g. investissement en R&D). Les théories de la croissance endogène expliquent les effets des exportations sur les investissements en R&D (Romer, 1990; Grossman and Helpman, 1991). L'idée est qu'être exposé à une source plus riche de technologie sur les marchés d'exportation pourrait amener les entreprises à améliorer leur base de connaissances. Par conséquent, la propension à l'exportation d'une entreprise peut l'aider à accroître sa capacité en R&D. Plus précisément, Hobday (1995) élabore un modèle d'écart technologique pour illustrer comment les taux d'innovation sont augmentés par la demande des consommateurs étrangers. Le résultat du modèle est que l'exportation fait progresser la technologie de l'entreprise et, par conséquent, sa capacité à innover. La deuxième relation lie les investissements en R&D à la productivité des entreprises.[9] L'analyse empirique présentée pour prendre en compte toutes ces relations vise à étendre le modèle CDM de deux manières. Premièrement, les exportations sont endogènes au processus d'innovation. Deuxièmement, l'hétérogénéité non observée est corrigée en incluant des effets individuels dans notre modélisation.

Chapitre 5 Persistence of Product Innovation : An Empirical Investigation for French Dairy Firms. Le chapitre 5 s'intéresse aux facteurs déterminant des activités d'innovation des entreprises laitières françaises. Je m'intéresse particulièrement, à la dynamique de l'innovation . Plus précisément, je traite de la question suivante : est-ce que les entreprises innovent constamment au fil du temps ou est-ce qu'il y a des entrées et sorties régulières dans les activités d'innovation. La question de la persistance[10] de l'innovation est motivée par les preuves empiriques selon lesquelles les performances des entreprises en termes de productivité et d'exportation sont très asymétriques et que ces hétérogénéités persistent dans le temps.

Le dernier chapitre résume les principaux résultats de la thèse et en tire des conclusions.

9. Pour mémoire, les études théoriques et empiriques ayant traité de l'effet des investissements en R&D sur la productivité des entreprises sont abordées dans le chapitre 1.

10. Il y a persistance lorsqu'une entreprise qui a innové au cours d'une période innove à nouveau au cours de la période suivante.

Chapitre 1

Performances des entreprises et activités d'innovation : Une revue de la littérature

1.1 Introduction

Intuitivement, la notion d'innovation renvoie aux idées de nouveauté, de changement ou encore de progrès technologique. Cependant, l'innovation étant un phénomène complexe, diverses définitions de l'innovation sont apparues dans la littérature économique. Dans son ouvrage fondateur intitulé "*The Theory of Economic Development*", Schumpeter définit l'innovation comme "simplement le fait de faire de nouvelles choses ou de faire des choses qui sont déjà faites d'une nouvelle manière" (Schumpeter, 1934, p. 65). Schumpeter (1934) a précisé cette affirmation en identifiant une innovation comme l'un des cinq événements suivants : (i) l'introduction d'un nouveau bien - c'est-à-dire d'un bien que les consommateurs ne connaissent pas encore - ou d'une nouvelle qualité d'un bien, (ii) l'introduction d'une nouvelle méthode de production, (iii) l'ouverture d'un nouveau marché, (iv) la conquête d'une nouvelle source d'approvisionnement en matières premières ou en produits semi-finis, que cette source existe déjà ou qu'elle doive être créée au préalable, (v) création de nouvelles structures de marché dans une industrie. Ainsi, l'innovation consiste principalement à trouver de nouvelles et de meilleures façons de faire les choses et à introduire de nouvelles idées ou de nouveaux types de produits et services sur le marché. La définition de l'innovation peut varier d'une industrie à une autre. Bien que toutes les définitions de l'innovation englobent la mise en œuvre de nouveaux produits et processus, certains auteurs utilisent des concepts plus larges et incluent en outre, par exemple, l'amélioration des intrants matériels et intermédiaires, les changements dans les organisations commerciales, les changements dans les méthodes de commercialisation, ou même les changements sociaux, contractuels, juridiques ou de système (e.g., Stoneman, 2010). Ces définitions plus larges de l'innovation soulèvent la question de savoir si une innovation doit forcément être technologique. Dans sa version de 2005, le manuel d'Oslo rédigé par l'OCDE distingue deux formes d'innovation : les innovations technologiques et les innovations non technologiques. Les innovations technologiques couvrent les produits et procédés technologiquement nouveaux ainsi que les améliorations technologiques importantes de produits et de procédés qui ont été accomplies (OCDE, 1997, p. 130). Les innovations non technologiques couvrent l'innovation en matière de commercialisation et l'innovation organisationnelle.

Un autre aspect important abordé dans la littérature est de savoir pourquoi une entreprise innove. Une innovation peut être une source d'avantage commercial pour l'innovateur. Dans le cas des innovations de procédés visant à améliorer sa performance, l'entreprise obtient un avantage de coût par rapport à ses concurrents, ce qui lui permet d'obtenir une marge plus élevée au prix du marché en vigueur ou, selon l'élasticité de la demande, de combiner un prix inférieur et une marge plus élevée que ses concurrents pour accroître sa part de marché et ses bénéfices. Dans le cas de l'innovation de produits, l'entreprise peut obtenir un avantage concurrentiel en introduisant un nouveau produit, ce qui lui permet d'accroître sa demande. Ainsi, le but de ce chapitre est de présenter ce qu'il ressort de la littérature économique sur les effets des activités d'innovation des entreprises sur leur performance. Nous intéressons spécifiquement à la productivité et aux exportations comme mesure de la performance de l'entreprise.

1.2 Innovation et productivité des entreprises

L'investissement des entreprises dans l'innovation est un mécanisme clé qui permet d'améliorer leur performance au fil du temps. L'estimation de l'élasticité du retour sur investissement en R&D de l'entreprise a été l'un des principaux axes des études empiriques pendant des décennies. Une grande partie de la littérature empirique s'appuie sur la fonction de production de connaissances développée par Griliches (1979). Dans son étude fondatrice intitulée, "*Issues in Assessing the Contribution of Research and Development to Productivity Growth*", Zvi Griliches montre que l'investissement de l'entreprise dans la R&D crée un stock de connaissances qui entre dans la fonction de production de l'entreprise en tant qu'intrant additionnel. L'élasticité de cet intrant de la connaissance fournit une mesure du retour sur investissement en R&D de l'entreprise. Cette section s'attarde principalement sur deux points. Premièrement, nous présentons le modèle empirique de Hall (2011) construit autour de la fonction de production de connaissances développée par Griliches (1979) permettant ainsi de comprendre les mécanismes qui régissent la relation entre les activités innovantes des entreprises et leur productivité, et les différentes évolutions de cette méthodologie. Ensuite, nous analysons les recherches empiriques qui ont été menées sur la relation entre innovation et productivité des entreprises.

1.2.1 Modèle empirique entre l'innovation et la productivité des entreprises

Pour savoir de quelle manière les activités d'innovation des entreprises affectent leur productivité [1], il est important d'appréhender la notion de productivité. [2] Basé sur les travaux empiriques de Solow (1956), la notion de productivité est généralement définie par rapport à la façon dont elle est mesurée. Toutefois, Syverson (2011) définit la productivité comme l'efficacité dans la production : *"how much output is obtained from a given set of inputs"*; c'est-à-dire étant donnée un panier d'intrants, quel niveau de production une entreprise peut-elle atteindre ? Ainsi, pour des entreprises utilisant un même panier d'intrants, l'écart de production entre une entreprise par rapport à une référence (généralement l'entreprise la plus efficiente) est appelé productivité ou efficacité technique (Van Beveren, 2012). En se basant toujours sur la définition donnée par Syverson (2011), la productivité peut être vue comme un ratio output-input. La productivité du travail qui est définie comme le revenu par employé en est un exemple. De par sa simplicité, cette mesure de la productivité est énormément utilisée dans la littérature. Cependant, la quantité de travail n'étant pas le seul facteur de production, l'intensité d'utilisation des autres facteurs de production font de la productivité du travail une mesure biaisée. Ainsi, on retrouve aussi dans la littérature économique des mesures de la productivité qui sont invariables à l'intensité d'utilisation des facteurs de production observables ; ces mesures sont nommées productivité totale des facteurs (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Wooldridge, 2009).

Pour mesurer l'effet de l'innovation sur la productivité, supposons que le coût marginal de l'entreprise est donné par

$$m_{it} = \alpha_1 c_{it} + \alpha_2 l_{it} + \gamma k_{it}^S - \psi_{it} \tag{1.1}$$

Où m_{it} est le log du coût marginal, c_{it} est le log du capital, l_{it} est le log du nombre d'employés, et k_{it}^S est l'innovation de procédé. [3] Puisque l'innovation de procédé a pour but de réduire les coûts marginaux de l'entreprise, $\gamma < 0$. ψ_{it}, qui est l'efficacité de production de l'entreprise capture les différences en matière de technologie et est connue de l'entreprise, mais non observable par l'économiste. Puisque le coût marginal de l'entreprise n'est pas observé par l'économiste, le revenu est généralement utilisé pour les estimations. Pour cela, supposons que la demande de l'entreprise est donnée par

$$Q_{it} = Q_t \left(\frac{P_{it}}{P_t}\right)^{\eta} \exp(\varphi k_{it}^D + \varphi_{it}) \tag{1.2}$$

Où Q_t et P_t sont la demande agrégée et l'indice de prix de l'industrie et P_{it} est le prix. Puisque la majorité des innovations sont orientées vers de nouveaux produits et l'amélioration

1. Nous employons le terme productivité pour désigner le concept ; lorsqu'il s'agira de la mesure de la productivité, nous emploierons les termes *productivité totale des facteurs* (tfp) ou *productivité du travail*, selon la technique employée pour la mesure.

2. Lire Caves et al. (1982) pour une compréhension approfondie de la notion de productivité.

3. Dans leur modèle empirique, Hall (2011) propose d'ajouter une mesure des immobilisations incorporelles (telle que le stock des dépenses de R&D passées) comme input additionnel.

des produits, il est important d'inclure l'innovation produit comme variable influençant la demande. φ_{it} sont les facteurs inobservables (par l'économiste) qui influence la demande, tel que la qualité. L'élasticité de la demande η est négative et constante pour toutes les entreprises de l'industrie. En supposant que l'entreprise évolue dans un marché monopolistique concurrentiel, elle maximise son profit à court terme en fixant le prix de sa production à un niveau égal à une marge constante sur le coût marginal :

$$P_{it} = \left(\frac{\eta}{1+\eta}\right) \exp(m_{it}) \tag{1.3}$$

Étant donné ce prix optimal, le log du revenu de l'entreprise est

$$r_{it} = (1+\eta) \ln\left(\frac{\eta}{1+\eta}\right) + (1+\eta)(\alpha_1 s_{it} + \alpha_2 l_{it} - \omega_{it}) + (1+\eta)\gamma k_{it}^S + \varphi k_{it}^D + \ln \Phi_t \tag{1.4}$$

Où $\omega_{it} = \frac{1}{1+\eta}\varphi_{it} - \psi_{it}$, et $\ln \Phi_t = \ln Q_t - \eta \ln P_t$. Il ressort de l'équation 1.4 que le stock de connaissance, K, soit susceptible de contribuer à la productivité au travers de deux moyens. Premièrement, les investissements en innovation de procédé, k_{it}^S, affectent directement la productivité en améliorant l'efficience de production de l'entreprise ; et les investissements en innovation produit, k_{it}^S, affectent la productivité déplaçant la courbe de la demande pour les produits de l'entreprise. Puisque l'élasticité de la demande, η, est négative, l'effet de l'innovation de procédé sur la productivité basée sur le revenu est ambigu. Par exemple, l'innovation de procédé à un effet positif sur la productivité du travail (revenu par employé) si l'élasticité de la demande, $\eta < -1$. Contrairement à l'innovation de procédé, l'innovation produit à un effet non ambigu sur la productivité.

Le cadre empirique développée par Griliches (1979) peut être résumé par l'équation suivante,

$$y_{it} = \beta_0 + \beta_1 l_{it} + \beta_2 c_{it} + \beta_3 k_{it} + \beta_4 x_{it} + \varepsilon_{it} \tag{1.5}$$

Où y_{it} est le log. de la productivité du travail $(r_{it} - l_{it})$; dans la littérature empirique, le chiffre d'affaire ou la valeur ajoutée sont utilisés comme mesure de r_{it}. Le log. du nombre d'employés, l_{it}, est généralement inclus dans l'équation, ce qui permet de tester l'hypothèse de rendements d'échelle constants. c_{it} est le log. du capital physique. k_{it} représente le stock de connaissance ; Griliches (1979) et d'autres utilisent le log. de la R&D comme proxy de l'intrant de la connaissance. x_{it} est un vecteur représentant d'autres intrants additionnels. Lorsque la productivité du travail est mesurée par le chiffre d'affaire par employée, les intrants intermédiaires doivent être pris en compte. Le vecteur, x_{it} inclut aussi des variables dichotomiques pour prendre en compte les effets industriels. Cela permet de tenir compte des différences d'intégration verticale et le niveau global des connaissances technologiques de chacune des industries. Différentes versions du modèle de l'équation 1.5 ont été estimées par Griliches (1980), Griliches (1986), Griliches (1987), Schankerman (1981), Griliches and Mairesse (1984), Griliches and Mairesse (1991), Jaffe (1986), Cuneo and Mairesse (1984), Hall and Mairesse (1995) ou Bartelsman et al. (1996) à l'aide de donnée transversales ou de panel d'entreprises. L'élasticité estimée de la production par rapport à la R&D se situe entre 0,05 et 0,2. Dans la plupart de ces études, les élasticités estimées sont statistiquement non-significatives.

Au fil du temps, le cadre empirique proposé par Griliches (1979) a subi de nombreuses améliorations. Par exemple, le problème de double compte soulevé par Schankerman (1981) ou encore le problème l'exclusion des entreprises qui ne font pas de la R&D dans l'échantillon d'analyse (Mairesse and Cunéo, 1985). En effet, Schankerman (1981) fait valoir le fait que puisqu'une partie du capital humain et du capital physique proviennent de la R&D, inclure la R&D dans l'équation 1.5 pourrait biaiser les estimations. De même, Mairesse and Cunéo (1985) explique que la modélisation de Griliches (1979) ne s'applique pas sans ambiguïté aux entreprises qui ne font pas de la R&D, pour lesquelles le capital de recherche est en principe nul (et donc $k_{it} = -\infty$). Annuler l'élasticité du capital recherche pour les entreprises sans recherche revient à supposer implicitement que $k_{it} = 0$ (c'est à dire que le capital recherche vaut 1), ce que les auteurs jugent être assez arbitraire. L'étude de Pakes and Griliches (1984) est d'après nous la meilleure amélioration de la modélisation de Griliches (1979), car elle permet de prendre en compte les problèmes mis en évidence par Schankerman (1981) et Mairesse and Cunéo (1985). D'après ces auteurs, l'équation 1.5 qui met en relation la R&D et la productivité ne prend pas en compte ce qu'ils ont appelé la " fonction de production de connaissance " ; c'est-à-dire la production de connaissances à valeur commerciale ou le résultat de l'innovation comme le précise Lööf and Heshmati (2006). Pakes and Griliches (1984) suggèrent une fonction de production alternative, qui correspond au système à 3 équations suivant :

$$y_{it} = \alpha_n n_{it} + x_{3,it} b_3 + \varepsilon_{3,it} \tag{1.6}$$

$$n_{it} = \alpha_k k_{it} + x_{2,it} b_2 + \varepsilon_{2,it} \tag{1.7}$$

$$k_{it} = x_{1,it} b_1 + \varepsilon_{1,it} \tag{1.8}$$

Où l'équation 1.8 est l'équation de l'input de l'innovation représenté par le capital R&D. L'équation 1.7 est l'équation du résultat de l'innovation et n_i représente le log du nombre de brevets. L'équation 1.6 est celle de la productivité ; dans cette spécification, c'est le résultat de l'innovation, i.e. le nombre de brevet, qui affecte la productivité et non le capital R&D qui est considéré comme un intrant de l'innovation. Ainsi, l'élasticité estimée de la production par rapport au capital R&D s'écrit : $\beta_4 = \alpha_n \alpha_k$. $\varepsilon_{3,it}$, $\varepsilon_{2,it}$ et $\varepsilon_{1,it}$ sont les termes d'erreurs supposés non corrélés entre eux (Griliches, 1990). Toutefois, le cadre empirique développé par Pakes and Griliches (1984) ne considère pas le caractère endogène du résultat de l'innovation et du capital R&D. En effet, les entreprises décident d'investir dans l'innovation sur la base des rendements escomptés (Griliches, 1979; Jefferson et al., 2006; Aw et al., 2011). De plus, la modélisation de Pakes and Griliches (1984) exclut les entreprises qui n'investissent pas dans la R&D. Cependant, ces entreprises qui ne sont pas innovantes selon des critères formels peuvent en fait générer de nouvelles connaissances ou les acquérir sur le marché sous la forme de technologies, de droits, de licences. D'après Griffith et al. (2006), l'exclusion de ces entreprises au niveau de l'analyse empirique peut conduire à un biais de sélection significatif.

De nos jours, le modèle structurel de Crepon et al. (1998)–modèle CDM– est devenu le pilier dans l'analyse de la relation entre l'innovation et la productivité. [4] Le modèle CDM explique la productivité par le résultat des activités d'innovation et cette dernière par l'investissement dans la R&D, et suggère une méthode de correction de la sélectivité et de l'endogénéité inhérentes au modèle.

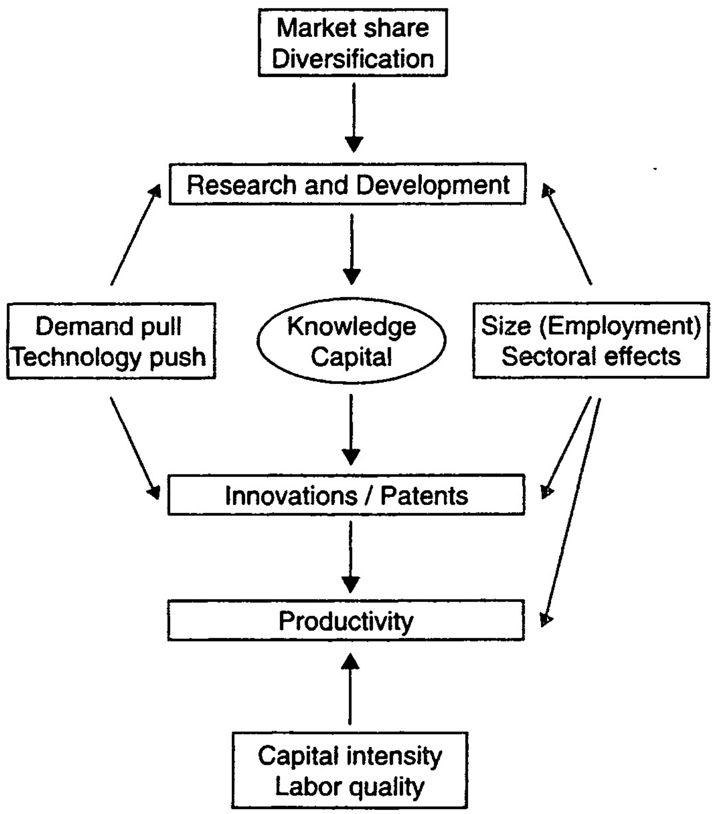

FIGURE 1.1 – Performance, innovation et R&D au niveau entreprise
Source: Tiré de Crepon et al. (1998, p. 118)

La figure (1.1) présente un diagramme schématique montrant la structure générale du modèle CDM. Le diagramme du modèle CDM est similaire à celui du modèle de Pakes and Griliches (1984), toutefois contrairement à ce dernier, il considère que la R&D et l'innovation sont endogènes. Ce modèle est généralement présenté comme un système récursif de trois blocs d'équations. Un premier bloc explique les déterminants de la probabilité d'investir dans la

4. D'après les études bibliométriques de Broström and Karlsson (2017) et Notten et al. (2017) portant sur la relation R&D, innovation et productivité. De plus, leur papier à été cité plus de 2300 fois selon google scholar.

R&D et l'intensité de la R&D :

$$d_{it} = \mathbb{1}\left[x_{0,it}b_0 + u_{0,it} > 0\right] \tag{1.9}$$

$$k_{it} = \begin{cases} x_{1,it}b_1 + u_{1,it} & \text{if} \quad d_{it} = 1, \\ 0 & \text{if} \quad d_{it} = 0, \end{cases} \tag{1.10}$$

Où d est une variable dichotomique indiquant si l'entreprise investit dans la R&D ou pas, k est l'intensité de la R&D, x_0 et x_1 sont des vecteurs de variables explicatives u_0 et u_1 sont les termes d'erreurs. L'équation 1.9 décrit la décision d'investir dans l'innovation ; et l'équation 1.10 détermine l'intensité d'investissement dans les activités innovantes. L'intensité d'investissement est mesurée dans Crepon et al. (1998) par le stock du capital en R&D par employé qui est calculé par la méthode de l'inventaire permanent. [5]

Le second bloc concerne les déterminants de la probabilité d'innover, d'une façon ou d'une autre, et l'intensité d'innovation, la R&D étant un de ces déterminants

$$i_{1,it} = \mathbb{1}\left[\alpha_k k_{it} + x_{2,it}b_2 + u_{2,it} > 0\right] \tag{1.11}$$

$$i_{2,it} = \begin{cases} \alpha_k k_{it} + x_{3,it}b_3 + u_{3,it} & \text{if} \quad i_{1,it} = 1, \\ 0 & \text{if} \quad i_{1,it} = 0, \end{cases} \tag{1.12}$$

où i_1 est une variable dichotomique indiquant si l'entreprise a développé une innovation ou non, et i_2 est l'intensité de l'extrant de l'innovation, x_2 et x_3 sont des vecteurs de variables explicatives, u_2 et u_3 sont les termes d'erreurs. Crepon et al. (1998) proposent les brevets et le pourcentage des ventes en produit innovant comme mesures de l'intensité de l'extrant de l'innovation. Comme susmentionné, ce bloc permet d'estimer la fonction de production de connaissances en fonction en fonction de la R&D et d'autres inputs du processus d'innovation.

Enfin, l'équation de la productivité qui consiste à expliquer la productivité du travail en fonction de l'extrant de l'innovation (i_1 ou i_2), et d'autres variables explicatives, x_4, telles que l'intensité du capital physique,

$$y_{it} = x_{4,it}b_4 + i_{it}\phi + u_{4,it} \tag{1.13}$$

où u_4 est le terme d'erreur. Cette équation est équivalente à l'équation 1.6 et est dérivée d'une fonction de production de type Cobb-Douglas dans laquelle les principaux inputs sont généralement le travail, le capital physique et la connaissance. Les systèmes formés par les équations 1.9, 1.10, 1.11 et 1.13 ou 1.9, 1.10, 1.12 et 1.13, sont schématiquement représenté par la figure (1.1). Le modèle CDM s'écrit donc comme un système récursif de quatre équations économétriques, dont trois sont généralement non-linéaires. La récursivité du système repose sur le fait que les 3 blocs du système sont clairement définis, chaque partie contribuant à déterminer la suivante. De plus, dans cette représentation, l'intensité de la R&D est potentiellement endogène dans la fonction de production de connaissance (équation 1.11 ou 1.12), et l'innovation est potentiellement endogène dans l'équation 1.13.

5. Voir Crepon et al. (1998), Antonelli and Colombelli (2011) pour plus de détails sur la méthode de calcul.

1.2.2 Procédure d'estimation

Le modèle CDM suppose une corrélation entre tous les termes d'erreurs du système. De plus, en estimant le système d'équations, il est important de tenir compte de la nature des données utilisées : les investissements en R&D sont tronqués ou censurés, les mesures de l'extrant de l'innovation sont des données dichotomiques, d'intervalle ou encore de comptage. Il faut également tenir compte du fait que le capital R&D est endogène dans les équations de l'innovation et que l'innovation est endogène dans l'équation de productivité. Cela plaide bien sûr en faveur de l'utilisation d'un estimateur du système d'équations simultanées. L'estimation simultanée du système permet de prendre en compte au maximum la corrélation des erreurs et fournit des estimateurs efficients. Toutefois, l'inconvénient de cette approche est que la distribution jointe des variables observables du système n'a pas de solution analytique, elle doit être évaluer numériquement. En pratique, le système est estimé par maximum de vraisemblance en information complète ; toutefois, à cause de sa lourdeur, en terme de temps de calcul pour la maximisation de la vraisemblance, peu d'étude on eut recours à cette procédure pour l'estimation d'un modèle CDM. A notre connaissance, uniquement les études de Mairesse and Robin (2011), Raymond et al. (2015) et Baum et al. (2016) ont utilisé cette procédure d'estimation.

La méthode des moindres carrés asymptotique est une procédure d'estimation plus souple que la méthode du maximum de vraisemblance en information complète. Cette procédure d'estimation peut être décrite en trois étapes : la première étape consiste à écrire les formes réduites de chacune des trois blocs d'équations du système ; ensuite estimer séparément chacune de ces formes réduites en prenant en compte la nature de la variable dépendante ; pour finir, utiliser ces paramètres auxiliaires estimés pour dériver les paramètres structurels du modèle en utilisant un estimateur des moindres carrés asymptotiques. Cette procédure d'estimation est particulièrement utile lorsqu'on ne souhaite pas spécifier complètement un modèle par une fonction de vraisemblance ou lorsque la maximisation de cette fonction est difficile. Cette méthode permet d'obtenir des estimateurs convergents et asymptotiquement normaux (voir Gourieroux et al. (1985), pour plus de détail sur la méthode des moindres carrés asymptotiques). A notre connaissance seules les études de Mairesse et al. (2005) et Benavente (2006) ont eu recours à cette méthode pour estimer un modèle de type CDM.

La procédure d'estimation la plus utilisée dans la littérature empirique est la méthode par variables instrumentales séquentielles. Dans cette procédure, chaque étape (exceptée la première) inclut dans les régresseurs la variable prédite de l'étape précédente (Mairesse and Robin, 2011). Par exemple, dans la première étape, un modèle Tobit généralisé est utilisé pour décrire à la fois la probabilité de conduire des activités de R&D et l'intensité des activités de R&D. Dans la deuxième étape, un modèle Probit ou un modèle de poisson est estimé pour décrire la fonction de production de connaissances (selon que la mesure de l'innovation soit dichotomique ou de comptage), en incluant dans les régresseurs la valeur prédite de l'intensité de la R&D (et non sa valeur observée). La troisième et dernière étape de la procédure consiste à estimer l'équation de productivité en incluant dans les régresseurs la valeur prédite de l'innovation. Dans cette procédure, le traitement des problèmes d'endogénéité mentionnés plus haut se fait en remplaçant (dans les deux dernières étapes) les variables explicatives potentiellement endogènes par leurs valeurs prédites obtenues dans l'étape précédente. Les biais consécutifs sur les erreurs standards suite à l'introduction de ces variables prédites sont généralement corrigés par bootstrap. Cette procédure nécessite l'utilisation d'instruments pour l'identification du système.

1.2.3 Preuves empiriques

Le tableau 1.1 résume les études qui ont tenté d'estimer explicitement la relation entre la productivité et les mesures de l'innovation au niveau des entreprises en utilisant une modélisation de type CDM. Les estimations empiriques de la relation entre l'innovation et la productivité des entreprises par le modèle CDM, mettent en évidence une chaine de causalité : les investissements en R&D influent sur la création des connaissance (mesuré par les brevets, les nouveaux produits, etc...), qui à son tour influe sur la productivité des entreprises. La figure (1.1) décrit pas à pas la chaine de causalité et surtout, les facteurs explicatifs de chaque maillon de la chaine. Crepon et al. (1998) trouvent que l'incitation d'une entreprise à investir dans la R&D est déterminée par sa part du marché, sa capacité à diversifier ses activités, sa taille, l'évolution de sa demande et les opportunités technologiques auxquelles elle est soumise. De plus, l'intensité d'investissement dans la R&D est affectée par les même facteurs excepté la taille de l'entreprise. Pour l'innovation, les auteurs ont estimé deux versions de la fonction de production de connaissance (les brevets et le pourcentage des ventes en produits innovants). Toutefois, les deux versions de la fonction de production de connaissance mettent en évidence comme facteur déterminant l'intensité d'investissement en R&D, l'évolution de la demande et l'opportunité technologique. Pour finir, la productivité de l'entreprise, au-delà de l'innovation (brevet ou pourcentage des ventes), dépend également de la qualité de la main-d'œuvre, de l'intensité du capital et de la taille de l'entreprise.

Généralement, l'effort dans l'innovation est mesuré par les dépenses en R&D par employé, (Crepon et al., 1998; Janz et al., 2003; Benavente, 2006; Acosta et al., 2015; Siedschlag and Zhang, 2015; Baum et al., 2016; Peters et al., 2018), ou encore par les dépenses en activités innovantes (Masso and Vahter, 2008). Pour mesurer l'innovation, les auteurs utilisent des indicateurs tels que : le pourcentage de vente en produit innovant (Crepon et al., 1998; Mairesse et al., 2005; Benavente, 2006; Van Leeuwen and Klomp, 2006; Roper et al., 2008), le nombre de brevets (Crepon et al., 1998; Vancauteren et al., 2017), les ventes en produit innovant par employé (Criscuolo, 2009; Siedschlag et al., 2010; Mairesse et al., 2012) et des variables dichotomique indiquant si une entreprise a introduit une innovation ou non. Parmi les mesures dichotomiques, on peut distinguer celle qui mesure l'innovation technologique (Mairesse et al., 2012), l'innovation produit et l'innovation de procédé (Griffith et al., 2006; Mairesse et al., 2012; Acosta et al., 2015; Siedschlag and Zhang, 2015; Peters et al., 2018), l'innovation de marketing (Siedschlag and Zhang, 2015; Peters et al., 2018) et l'innovation organisationnelle (Acosta et al., 2015; Siedschlag and Zhang, 2015; Peters et al., 2018). Ces différentes mesures permettent de distinguer les processus responsables de la création de différents types de connaissances. La valeur ajoutée par employé (Crepon et al., 1998; Benavente, 2006), les ventes par employé (Janz et al., 2003; Siedschlag et al., 2010) ou encore le revenu par employé (Siedschlag and Zhang, 2015) sont les mesures couramment utilisées pour capter la productivité du travail.

Le tableau 1.1 résume un certain nombre d'études empiriques qui ont estimé l'élasticité de la productivité par rapport à l'extrant de l'innovation. A l'exception des travaux de Chudnovsky et al. (2006) sur des entreprises argentines et Mairesse et al. (2012) sur des entreprises chinoises, les études recensées s'intéressent aux entreprises des pays de l'OCDE. De plus, les études présentées utilisent le modèle CDM comme cadre empirique d'analyse. L'utilisation du modèle CDM implique que la majorité des estimations sont faites en coupe instantanée (les études de Parisi et al. (2006) Masso and Vahter (2008), Raymond et al. (2015), Baum et al. (2016), Teplykh (2018) sont des exceptions). Les élasticités estimées sont pour la plupart positives et significatives. L'amplitude de l'élasticité de la productivité par rapport à l'intensité de l'innovation produit varie énormément en fonction du secteur et du pays étudié. Les plus grandes élasticités enregistrées sont celles de l'étude de Mairesse et al. (2012) sur des entreprises manufacturières chinoises : variant entre 0,246 pour le secteur des équipements de transports et 1,119 pour le secteur des équipements électroniques. Les résultats montrent que l'amplitude est plus forte lorsque l'intensité de l'innovation produit est mesurée par les ventes de nouveaux produits par employé au lieu du pourcentage des ventes en produit innovant. D'après Mohnen and Hall (2013) les élasticités estimées tendent à être plus faibles lorsque le taux de croissance de la productivité est utilisé et lorsque la main-d'œuvre qualifiée ou le capital humain est pris en compte. La seule étude à avoir estimé une élasticité négative est celle de Roper et al. (2008) menée sur des entreprises irlandaises durant la période 1991-2002. Les auteurs expliquent cette élasticité négative par le cycle de vie d'un produit. En effet, les produits nouvellement introduits sont d'abord fabriqués de manière inefficace, ce qui a des conséquences négatives sur la productivité, avant de s'établir et d'être au centre des innovations de processus pour améliorer l'efficacité productive. Toutefois, Mohnen and Hall (2013) remarquent que l'étude de Roper et al. (2008) est la seule où l'utilisation du capital de connaissances sous forme de main-d'œuvre qualifiée a été intégrée comme variable de contrôle dans l'équation 1.13. Trois études se sont intéressés aux entreprises françaises. La première est celle menée par Crepon et al. (1998) sur un échantillon de plus de 4000 entreprises manufacturières françaises durant la période 1986-1990 ; l'élasticité estimée est de 0,07. Par la suite, Mairesse et al. (2005) estiment des élasticités de 0,23 et 0,05 dans les secteurs manufacturiers français de haute et de faible technologies durant la période 1998-2000, respectivement. Criscuolo (2009) trouvent une élasticité de 0,495 pour les entreprises du secteur manufacturier contre 0,443 pour les entreprises du secteur des services sur la période 2002-2004.

L'innovation est généralement étudiée dans le cadre d'une modélisation structurelle utilisant l'enquête communautaire sur l'innovation et d'autres enquêtes qui reposent sur une méthodologie comparable. Les enquêtes communautaires sur l'innovation portent sur les activités des entreprises en matière d'innovation. L'enquête vise à fournir des informations sur le caractère innovant des secteurs d'activités, les différents types d'innovation et les différents aspects du développement d'une innovation (objectifs, sources d'informations, financement public, dépenses en matière d'innovation, etc.) (OECD, 2005). La méthodologie unifiée de l'enquête communautaire sur l'innovation a permis d'effectuer des comparaisons entre pays (Mairesse and Mohnen, 2002; Lööf et al., 2003; Janz et al., 2003; Griffith et al., 2006). Les enquêtes communautaires sur l'innovation (CIS) sont conduites depuis 1992, pouvant aussi permettre une analyse de la relation entre l'innovation et la productivité dans le temps. Un problème dans l'étude de la relation innovation-productivité dans le long terme avec les données CIS est le fait que l'indicateur de l'innovation est lié à une période de référence de trois années consécutives. L'utilisation de cet indicateur pour les vagues annuelles induirait une forte dépendance artificielle entre l'innovation et la productivité due au chevauchement des périodes et au double comptage.[6] Ainsi, des études empiriques comme celles de Chudnovsky et al. (2006), Jefferson et al. (2006), Parisi et al. (2006), Masso and Vahter (2008), Raymond et al. (2015) ou encore Baum et al. (2016) souffrent de ce problème de chevauchement des périodes de temps.

6. Si l'on prend comme exemple l'enquête CIS 2010, une entreprise est définie comme innovatrice si elle a introduit une innovation au cours de la période 2010-2012 ; dans l'enquête CIS 2012, cet indicateur est lié à 2010-2012.

Table 1.1 – Etudes empiriques sur la relation entre l'innovation et la productivité des entreprises

Study	Country and period	Estimation procedure	Innovation	Productivity	Results
Crepon et al. (1998)	France 86-90	Asymptotic least squares	Innovative sales (%), patent count	Value added per employee	Productivity is positively correlated with innovation output, even when controlling for labor as well as for physical capital intensity.
Lööf et al. (2003)	Finland 94-96, Norway 95-97, Sweden 94-96	Sequential instrumental variables	Innovative sales per employee	Sales per employee	Innovation is an important factor contributing to economic growth for Norwegian and Swedish firms.
Janz et al. (2003)	Sweden Germany 98-00	Sequential instrumental variables	Innovative sales per employee and process dummy	Sales per employee	Elasticity of productivity wrt innovative sales is positive and significant in both countries. Process innovation appears to be negative in both countries, but only significant for German firms.
Mairesse et al. (2005)	France 98-00	Asymptotic least squares	Innovative sales (%)	Sales per employee	The need to instrument innovation and R&D reveals 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.

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Table 1.1 – *Continued from previous page*

Study	Country and period	Estimation procedure	Innovation	Productivity	Results
Benavente (2006)	Chile 95-98	Asymptotic least squares	Innovative sales per employee	Value added per employee	In the case of Chile, firms' productivity is not affected by innovative results, nor by research expenditures in the short run.
Duguet (2006)	France 1986-1990	Asymptotic least squares	Incremental and radical innovations	Total Factor Productivity	Radical innovations are the only significant contributors to TFP growth.
Lööf and Heshmati (2006)	Sweden 96-98	Sequential instrumental variables	Innovative sales per employee	Value added per employee	One conclusion regarding the use of different sources of data while using an identical model specification is that register data are preferable to survey data when both data sources are available.
Van Leeuwen and Klomp (2006)	Netherland 94-96	Sequential instrumental variables	Innovative sales per employee	Revenue per employee gr.	Authors show that the impact of innovation differs between measures of firm performance. They also show that the estimation of return on innovation investment benefits from the inclusion of more information on the technological environment of the firm.

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Table 1.1 – *Continued from previous page*

Study	Country and period	Estimation procedure	Innovation	Productivity	Results
Parisi et al. (2006)	Italia 1992-1997	Sequential instrumental variables	Product dummy Process dummy	Total factor Productivity	R&D can affect productivity growth by facilitating the absorption of new technologies.
Griffith et al. (2006)	Spain, UK, Fr., Germany 1998-2000	Sequential instrumental variables	Process dummy Product dummy	Sales per employee	The results suggest that the systems driving innovation and productivity are remarkably similar across these four country
Roper et al. (2008)	Irland North. Ireland 91-02	Sequential instrumental variables	Innovative sales (%) Product dummy Process dummy	Value added per employee, Sales growth	Innovation in both products and processes contribute positively to firm growth, with product innovation having a short-term “disruption” effect
Raffo et al. (2008)	France, Spain, Argentina, Brazil, Swiss	Sequential instrumental variables	Product dummy	Sales per employee	Firms tend to engage in innovation act. in order to achieve better economic perf. on a similar basis among countries.
Criscuolo (2009)	18 OECD countries 98-05	Sequential instrumental variables	Innovative sales per employee	Value added per employee	In Europe, the correlation between sales from product innovation and productivity is higher for larger firms, and for Brazil, Canada and New Zealand the correlation is higher among SMEs.

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Table 1.1 – *Continued from previous page*

Study	Country and period	Estimation procedure	Innovation	Productivity	Results
Mairesse et al. (2012)	China 05-06	Sequential instrumental variables	Innovative sales per employee	Sales per employee	The study sustains the national innovation strategy of improving research and development, especially at firm level. Innovation input is the key element for firm growth.
Masso and Vahter (2012)	Estonia 1998-2004	Sequential instrumental variables	Product dummy Process dummy	Value added per employee	The results indicate, surprisingly, that the association between technological innovation and productivity is stronger in the less knowledge- intensive service.
Raymond et al. (2015)	France Netherland 94-04	FIML	latent innovation propensity, innovation dummy	Sales per employee	The results provide evidence of robust uni-directional causality from innovation to productivity. Authors include individual effects
Acosta et al. (2015)	Spain 2003–2011	Sequential instrumental variables	Organisational, product and process dummies	Sales per employee	Study focuses on one industry. High correlation between innovation and productivity.
Siedschlag and Zhang (2015)	Irland 04-08	Sequential instrumental variables	Innovative sales per employee	Turnover per employee	Firms with international activities are more likely to invest in innovation, they are more likely to be successful in terms of innovation output, and they have a

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TABLE 1.1 – *Continued from previous page*

Study	Country and period	Estimation procedure	Innovation	Productivity	Results
					higher labour productivity.
Baum et al. (2016)	Irland 04-08	FIML	Innovative sales per employee	Value added per employee	These results cast doubt on earlier research which does not allow for sectoral heterogeneity .
Teplykh (2018)	France, U.K. Germany 04-12	GMM	Patent data	Sales per employee	Larger barriers for innovations, increased uncertainty and lower state dependence in research engagement, product creation and economic performance.
Peters et al. (2018)	Germany Irland, Uk 2006–2008	Sequential instrumental variables	Organisational, Market., product, process dummies	Sales per employee	Results indicate that innovation in service enterprises is linked to higher productivity. Among the innovation types considered, the largest productivity returns were found for marketing innovations.

1.3 Innovation et performance des entreprises sur le marché international

Si les travaux sur la relation entre la participation des entreprises aux marchés internationaux et leur productivité sont nombreux (Jovanovic, 1982; Hopenhayn, 1992; Melitz, 2003), la littérature a longtemps été silencieuse sur les sources des avantages de productivité associés à l'entrée des entreprises sur les marchés d'exportation. Basées sur les théories de la dynamique de l'industrie, les études dans le domaine ont longtemps continué à supposer que l'avantage de productivité qui a permis aux entreprises de commencer à exporter était exogène par nature. Dans cette section nous présentons les études qui se sont intéressées à l'"endogénéisation" de l'hétérogénéité des entreprises, leur permettant de s'engager dans des activités d'amélioration de la productivité (comme l'innovation) avant de s'engager sur les marchés internationaux.

1.3.1 La théorie sur la relation entre l'innovation et les exportations

Il existe plusieurs modèles dans la littérature économique qui expliquent le rôle de l'innovation dans le comportement à l'exportation (Wakelin, 1998; Lachenmaier and Wößmann, 2006).[7] La théorie du cycle de vie d'un produit de Vernon (1966) fut le premier modèle (macroéconomique) à expliquer la relation entre l'innovation et les exportations. Dans les descriptions conventionnelles de la théorie du cycle de vie du produit, le schéma suivant est généralement utilisé (Karlsson, 1988) :

1. Aux premiers stades d'un nouveau type de produit, lorsque plusieurs variantes peuvent entrer sur un marché donné, les investissements en R&D sont importants et largement canalisés vers le développement de produits. Au cours de cette phase scientifique ou créative, un haut niveau de compétences spécialisées est requis. Dans cette phase, les entreprises sont attirées par les agglomérations existantes, notamment en raison du besoin de main-d'œuvre qualifiée ;
2. Le développement de procédés au moyen de nouvelles machines (qui peuvent être exploitées par une main-d'œuvre moins qualifiée et possédant des compétences normalisées) a lieu au cours de la deuxième phase technologique ou d'application, lorsque le produit lui-même est mieux défini. Au fur et à mesure que le taux de changement de produit diminue, plus d'efforts sont investis dans le développement des procédés, ce qui permet d'affiner les techniques de production, d'automatiser les procédés et d'augmenter l'échelle de production. Même si l'intensité des compétences de la main-d'œuvre peut être réduite grâce à l'élaboration de procédés, l'élaboration de procédés nécessite encore des intrants de main-d'œuvre qualifiée. Dans cette phase d'expansion, l'emplacement le plus approprié est à proximité des grandes agglomérations : une main-d'œuvre qualifiée

7. Les effets du changement technologique ont aussi été étudiés dans les cadres d'analyses Ricardien et HOS par Dornbusch et al. (1977) et Jones (1970) respectivement.

est encore nécessaire, mais le besoin d'espace suffisant et d'accessibilité aux réseaux de transport de marchandises devient urgent ;

3. Enfin, dans la phase de maturité et de saturation du marché, le produit et le mode de production sont bien définis et l'accent est mis de plus en plus sur le développement des canaux de commercialisation et les efforts promotionnels. Au cours de cette phase, les produits peuvent être légèrement modifiés et donc différenciés aux yeux des clients. La différenciation est une forme mineure de développement de produits, puisqu'il s'agit de petites modifications qui comprennent le changement de marque, la publicité d'image et des changements mineurs dans les caractéristiques (physiques) des produits. Dans cette phase, le coefficient d'intrant de la main-d'œuvre qualifiée tend à être encore plus bas. Étant donné qu'il n'y a généralement pas de besoin important de main-d'œuvre qualifiée, l'emplacement le plus approprié se trouve généralement en périphérie. Les bas prix de la main-d'œuvre et des terres sont ici des considérations importantes.

Le cycle de vie d'un produit est généralement résumé par le figure (1.2). D'après la théorie du cycle de la vie d'un produit, le marché international est le prolongement du marché national, permettant ainsi de rentabiliser les dépenses initiales. En effet, les entreprises commencent par introduire le nouveau produit sur le marché domestique, après quoi elles commencent à expor-

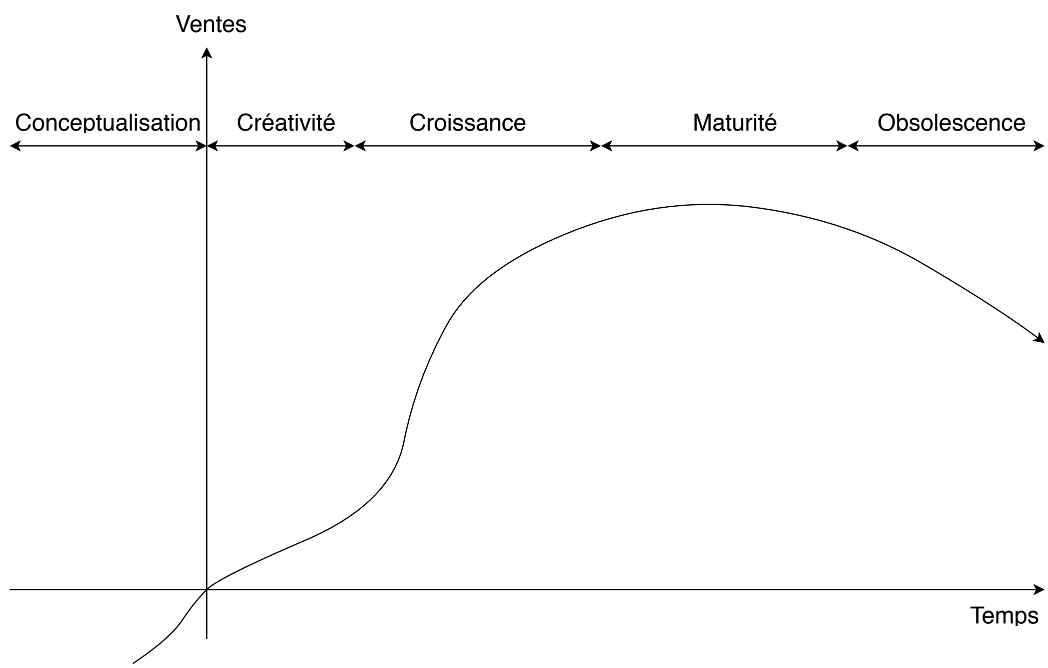

FIGURE 1.2 – Cycle de vie d'un Produit et ses différentes phases.
Source: Author

ter ledit produit. La rationalisation du processus de production, par exemple par des innovations visant à améliorer l'efficacité de la production, n'intervient qu'à un stade ultérieur.

Le principal argument de cette théorie est que les pays industrialisés sont capables d'être des pionniers dans l'innovation, ce qui conduit à l'exportation de leurs produits différenciés vers les pays moins développés (Posner, 1961; Vernon, 1966; Krugman, 1979). Ce qui, dans ce sens, est similaire aux modèles "*neo-endowment*" dans lesquels l'avantage concurrentiel des pays est fondé sur des dotations en facteurs, et de modèles "*technology-based*" dans lesquels l'avantage concurrentiel découle de la qualité de la main-d'œuvre. Les études basées sur les modèles de fonds de dotation soutiennent que les avantages fondés sur les facteurs peuvent être importants si l'entreprise détient le monopole naturel d'un facteur particulier. Les modèles de performance à l'exportation basés sur la technologie mettent principalement l'accent sur les investissements ou les réalisations des entreprises dans la mise en œuvre de nouvelles technologies ou dans le développement de nouveaux produits ou procédés. D'après Nelson (1993) et Metcalfe (1995), cette capacité dépendra des forces internes de l'entreprise, et du soutien disponible du système d'innovation régional ou national dans lequel l'entreprise opère. Dans ces différents modèles, le sens de la causalité va de l'innovation vers les exportations.

Par contre, les modèles des échanges basés sur les théories de la croissance endogène mettent en évidence la causalité inverse (Grossman and Helpman, 1993). Il existe trois raisons pour lesquelles les entreprises exportatrices sont les plus susceptibles d'innover. Premièrement, la concurrence sur les marchés étrangers oblige les entreprises à investir dans des activités d'innovation afin d'améliorer à la fois les produits et les procédés de production pour ainsi rester compétitives. Comme mentionné par Ganotakis and Love (2011), cela peut également inclure la nécessité pour une entreprise de faire des travaux de R&D afin de s'adapter à un ensemble différent d'exigences dans un pays étranger, telles que des normes techniques différentes. Deuxièmement, l'effet de l'apprentissage par l'exportation suggère que les entreprises exportatrices sont exposées à des connaissances provenant de clients étrangers, qui ne sont pas disponibles pour les entreprises exerçant uniquement sur le marché intérieur (Kobrin, 1991; Grossman and Helpman, 1991). Enfin, l'effet d'échelle, puisque les exportations élargissent le marché d'une entreprise, et comme les investissements en R&D sont en grande partie des coûts fixes, ces investissements peuvent être compensés par un volume de ventes plus important. Cela aide à améliorer la productivité et incite davantage à investir dans la R&D et dans d'autres activités d'innovation.

De récentes études basées sur les modèles théoriques (Jovanovic, 1982; Hopenhayn, 1992; Melitz, 2003) militent en faveur d'une relation positive entre l'innovation et le comportement à l'exportation des entreprises. Melitz (2003) construit un modèle basé sur la dynamique de l'industrie avec des entreprises hétérogènes opérant dans des industries en situation de concurrence monopolistique. C'est une extension du modèle de Krugman (1979) qui intègre une différence entre entreprise en terme de productivité. De plus, chaque entreprise tire sa productivité d'une distribution exogène qui permet de déterminer si elle produit ou pas, et une productivité seuil déterminée de manière endogène permet de savoir si elle exporte ou pas ; la figure (1.3) permet de décrire cette dynamique de l'industrie. Dans ce cadre d'analyse, les entreprises les plus pro-

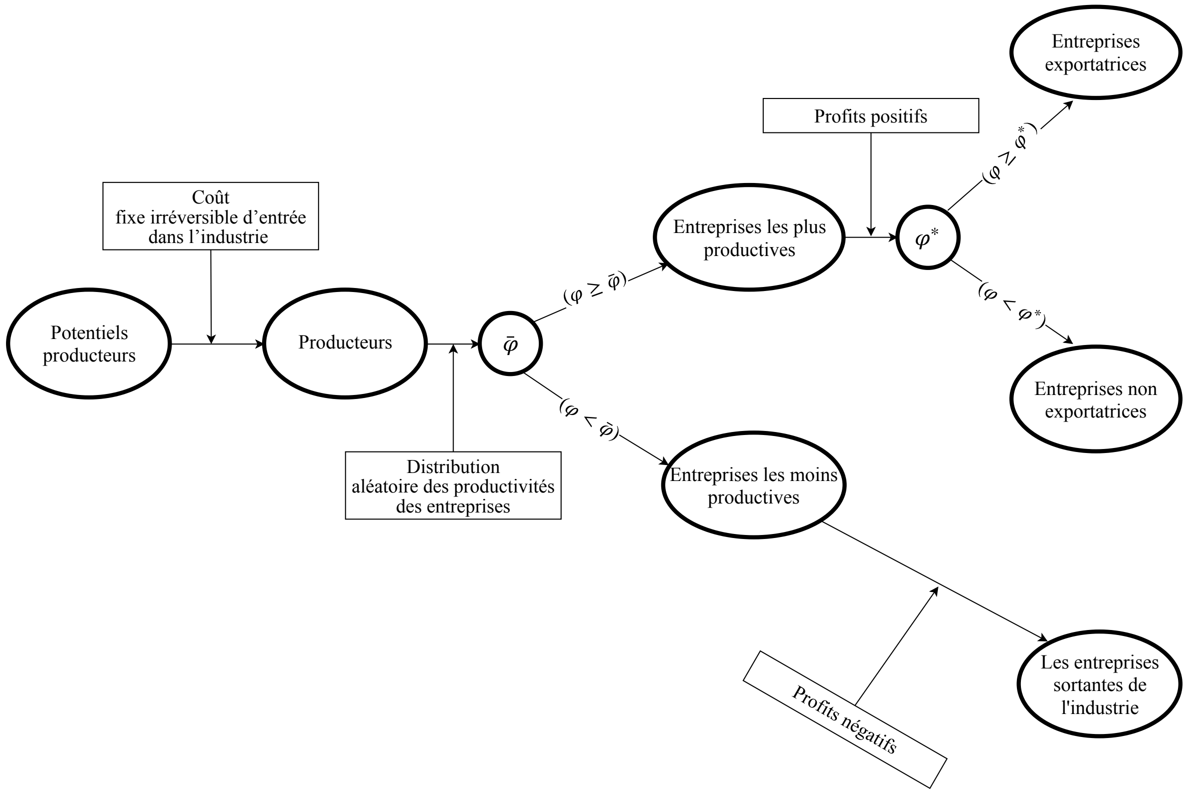

FIGURE 1.3 – Incertitude, productivité et entrées/sorties
Source: Tiré de Greenaway and Kneller (2007, p.137)

ductives (i.e. les entreprises avec un faible coût marginal) tirent des bénéfices plus élevés de la production, mais ce ne sont pas toutes les entreprises qui exportent. Seules celles dont les bénéfices sont suffisamment élevés pour couvrir les coûts irrécupérables le font. Ce résultat conduit à la conclusion que l'auto-sélection est fondamentale : les coûts irrécupérables et l'hétérogénéité des entreprises interagissent et les entreprises les plus productives s'auto-sélectionnent sur les marchés d'exportation. Il s'ensuit donc qu'il existe un lien direct entre la productivité et l'exportation. D'après Greenaway and Kneller (2007), un corollaire du modèle de Melitz (2003) est que les entreprises doivent augmenter leur productivité avant d'entrer sur le marché. D'autres contributions comme celles de Yeaple (2005) et Bustos (2011) ont cherché à endogénéiser la productivité au niveau de l'entreprise, permettant ainsi aux entreprises d'influencer leur propre niveau d'efficience, plutôt que de simplement l'observer à chaque période consécutive. Contrairement aux précédents modèles de la dynamique de l'industrie, les entreprises dans le modèle de Yeaple (2005) sont nées identiques. Après leur naissance, les entreprises ont la possibilité d'adopter une technologie de pointe, une technologie de production à faible coût unitaire ou une technologie à faible technologie à coût unitaire de production élevé. En présence de coûts fixes associés à l'adoption de technologie et à l'exportation, le modèle montre que seules les entreprises qui adoptent la technologie à faible coût unitaire sont en mesure de commencer à exporter. D'autres auteurs comme Costantini and Melitz (2007) analysent les décisions conjointes d'entrée, de sortie, d'exportation et d'innovation des entreprises en prévision de la libéralisation du commerce. Leurs conclusions soulignent l'importance de tenir compte du moment de la libéralisation du commerce dans l'analyse des décisions des entreprises en matière d'exportation et d'innovation. En particulier, ils montrent que l'anticipation d'une libéralisation du commerce peut motiver les entreprises à innover avant l'entrée sur les marchés d'exportation. La modélisation de Costantini and Melitz (2007) théorise une relation indirecte entre l'innovation et le comportement à l'export ; dans la mesure où les entreprises peuvent anticiper l'entrée sur le marché d'exportation et où leurs efforts d'innovation sont motivés par cette perspective d'avenir, une entreprise peut décider d'innover pour accroitre sa productivité et ainsi être plus susceptible d'exporter, selon l'hypothèse d'auto-sélection. Ainsi, l'effet causal va de l'innovation vers la productivité et de la productivité vers le comportement à l'exportation. Certaines études empiriques comme celle de Damijan et al. (2010), Van Beveren (2012) fournissent des preuves empiriques de l'hypothèse de Costantini and Melitz (2007). L'étude de Caldera (2010) est l'une des seules à avoir analysé directement la relation entre l'innovation et le comportement à l'exportation des entreprises. Le cadre d'analyse de Caldera (2010) suppose que la demande est modélisée selon le schéma standard utilisé dans la littérature récente sur le commerce (Melitz, 2003; Bernard et al., 2003). La demande est caractérisée par un consommateur représentatif avec des préférences CES sur un continuum de variétés i d'un bien q.

$$U = \left[\int_0^N q(i)di\right]^{1/\rho} \quad 0 < \rho < 1 \text{ et } i \in (0, N) \tag{1.14}$$

Le consommateur maximise son utilité sous la contrainte du budget : $\int_0^N p(i)q(i)di = E$, où E est la dépense agrégée. La fonction de demande s'écrit,

$$q(i) = \frac{E}{P}\left(\frac{p(i)}{P}\right)^{-\sigma} \tag{1.15}$$

Où $\sigma = 1/(1-\rho) > 1$ est l'élasticité de substitution entre les variétés de produit, qui est également égale à l'élasticité de la demande η lorsque le nombre de variétés N est grand (Bustos, 2011; Caldera, 2010), P est l'indice de prix qui d'après Bustos (2011) est égal a $\left[\int_0^N p(i)^{1-\sigma}di\right]^{\frac{1}{1-\sigma}}$.

L'offre est caractérisée par une industrie où les entreprises sont en concurrence monopolistique et où chaque entreprise produit une seule variété i de bien q ; l'entrée dans l'industrie est libre. Les entreprises dans l'industrie sont hétérogènes dans leur productivité en ce sens que les coûts marginaux varient d'une entreprise à l'autre. Cette composante intrinsèque de la productivité est indexée par φ_i. Pour entrer dans l'industrie, une entreprise paie des coûts fixes d'entrée et tire sa productivité d'une fonction de distribution cumulative de Pareto $G(\varphi) = 1 - \varphi^k$ avec $k > 1$. Après avoir observé leur productivité, les entreprises décident de quitter le marché ou de rester et de produire. Les entreprises survivantes ont le choix entre deux technologies de production : elles peuvent choisir d'innover pour diminuer les coûts marginaux de production et améliorer leur procédé de production, soit elles peuvent rester telles quelles. Les entreprises qui choisissent d'innover (*I=1*) doivent engager un coût fixe $f_{I=1}$, qui est plus élevé que le coût fixe des entreprises qui choisissent de ne pas innover (*I=0*) et doivent engager ($f_{I=1} > f_{I=0}$) pour maintenir le niveau actuel de la technologie ; toutefois, l'innovation entraîne une baisse des coûts marginaux de production $c_{I=1} < c_{I=0}$.

Les entreprises font un choix de prix et d'innovation qui maximise leurs profits. Dans le cas des préférences CES, le prix maximisant les profits (p^I) est une majoration constante par rapport au coût marginal (c_I), exprimée de façon plus formelle sous la forme suivante :

$$p^I(\varphi_i) = \frac{c_I}{\rho\varphi_i} \tag{1.16}$$

La quantité vendue (q^I), le revenu (r^I) et le profit (π^I) sont définis par les équations suivantes (Bustos, 2011; Caldera, 2010) :

$$q^I(\varphi_i) = EP^{\sigma-1}\left[\rho\frac{\varphi_i}{c_I}\right]^\sigma \tag{1.17}$$

$$r^I(\varphi_i) = p^I(\varphi_i)q^I(\varphi_i) = E\left[P\rho\frac{\varphi_i}{c_I}\right]^{\sigma-1} \tag{1.18}$$

$$\pi^I(\varphi_i) = \frac{1}{\sigma}r^I(\varphi_i) - f_I \tag{1.19}$$

Une entreprise choisira d'innover pourvu que le profit provenant de l'innovation ($\pi^{I=1}$) est supérieur au profit non innovant ($\pi^{I=0}$). Caldera (2010) suggère une auto-sélection des entreprises les plus productives dans la décision d'innover car les avantages de l'innovation sont une fonction croissante de la productivité des entreprises φ_i. Les entreprises les plus productives (plus grand φ_i) investiront dans l'innovation parce que l'augmentation des revenus provenant d'une réduction des coûts marginaux sera plus élevée, et ce d'autant plus que $\varphi_i$est élevée.

$$\pi^{I=1}(\varphi_i) > \pi^{I=0}(\varphi_i) \iff \frac{1}{\sigma}E(P\rho\varphi_i)^{\sigma-1}\left(c_{I=1}^{1+\sigma} - c_{I=0}^{1+\sigma}\right) > (f_{I=1} - f_{I=0}) \tag{1.20}$$

En tenant compte de l'analyse des fonctions bénéfices et coûts des entreprises, l'équation 1.20 montre que les entreprises innoveront lorsque les bénéfices liés aux innovations (côté gauche de l'équation) sont plus importants que les coûts de l'innovation (côté droit de l'équation).

En plus de servir le marché domestique, une entreprise a aussi le choix d'entrer sur le marché d'exportation. Le commerce international est onéreux et, pour exporter, les entreprises doivent supporter deux types de coûts commerciaux : un coût fixe à l'exportation f_x et les coûts variables (τ) qui dépendent de la quantité de produit échangée et sont inclus dans le modèle en tant que coûts de type iceberg. En supposant que les pays sont symétriques, le profit lié à l'export peut être exprimé comme :

$$\pi^{*I}(\varphi_i) = \tau^{1-\sigma} E(P\rho)^{\sigma-1} \frac{1}{\sigma} c_I^{1-\sigma} \varphi_i^{\sigma-1} - f_x \tag{1.21}$$

En comparant l'augmentation des bénéfices totaux provenant de l'exportation pour une entreprise innovante à l'augmentation des profits totaux provenant de l'exportation pour une entreprise non-innovante, Caldera (2010) met l'accent sur le fait que les entreprises innovantes seront plus susceptibles d'exporter que les entreprises non-innovantes. D'après cet auteur, une entreprise exportera si ses profits provenant des marchés domestique et international sont conjointement plus importants que les profits provenant du seul marché domestique. De ce fait, une entreprise innovante exporte si :

$$\left[\tau^{1-\sigma} E(P\rho)^{\sigma-1} \frac{1}{\sigma} \varphi_{I=1}^{\sigma-1}\right] c_{I=1}^{1-\sigma} > f_x \tag{1.22}$$

Alors qu'une entreprise non-innovante choisira d'exporter si :

$$\left[\tau^{1-\sigma} E(P\rho)^{\sigma-1} \frac{1}{\sigma} \varphi_{I=0}^{\sigma-1}\right] c_{I=0}^{1-\sigma} > f_x \tag{1.23}$$

Les expressions du côté gauche des équations 1.22 et 1.23 montre que le profit des entreprises innovantes est plus grand que celui des entreprises non-innovantes, alors que le coût fixe d'exportation (f_x) est le même pour les deux types d'entreprises. Cela est expliqué par le fait que la productivité des entreprises innovantes est plus grande que celle des entreprises entreprises non-innovantes ($\varphi_{I=1} > \varphi_{I=0}$) alors que leurs coûts marginaux de productions sont plus faibles ($c_{I=1} > c_{I=0}$).[8]

Il est important de noter que dans le modèle de Caldera (2010), l'effet causal va de la productivité vers l'innovation et de l'innovation vers les exportations. L'intuition derrière cette modélisation est la suivante. En investissant dans l'innovation, les innovateurs obtiennent un coût marginal de production inférieur à celui des non-innovateurs. Pour cette raison, les innovateurs peuvent proposer un prix inférieur à celui des non innovateurs, ce qui augmentera leurs ventes totales plus que proportionnellement parce que la demande est supposée être élastique. Ce résultat sera toujours valable puisque la productivité d'une entreprise qui choisit d'innover est strictement supérieure à celle d'une entreprise non innovante, car, par définition, l'entreprise innovante peut couvrir de manière rentable les coûts fixes d'innovation plus élevés tels que donnés par l'équation (1.20).

8. Confère équation 1.20

1.3.2 Preuves empiriques

Suivant le modèle théorique de Caldera (2010), une entreprise décidera d'exporter si son profit réalisé conjointement sur les marchés domestique et international dépasse le profit provenant uniquement du marché domestique (c'est-à-dire le profit provenant du marché international est strictement positif). Cette condition peut être formellement spécifiée comme un modèle à choix binaire de la participation au marché international, où le profit lié à l'export pour une entreprise donnée s'exprime comme une fonction de caractéristiques liées à l'entreprise et au marché :

$$y_i = 1 \text{ si } \pi_i^* = \beta I_i + \alpha TPF_i + \gamma Z_i + \eta_j + \omega_i \tag{1.24}$$

$$y_i = 0 \text{ sinon} \tag{1.25}$$

Où y_i désigne le statut de participation au marché international de l'entreprise i et vaut 1 si l'entreprise i exporte et vaut zéro sinon ; suivant l'équation 1.20 les déterminants principaux du statut d'exportation sont la productivité de l'entreprise (TPF_i) et leurs activités d'innovation (I_i). Le coefficient d'intérêt β mesure l'effet de l'innovation sur le statut d'exportation de l'entreprise. D'après l'intuition fournit par les modèles théoriques de Caldera (2010) et Bustos (2011), les entreprises innovantes sont censées produire à des coûts marginaux moindres et, par conséquent, réaliser des profits plus élevés. Cela se traduirait par un résultat positif et significatif du coefficient β indiquant que les entreprises innovatrices sont les plus susceptible d'exporter. Le vecteur Z_i désigne en outre d'autres caractéristiques de l'entreprise qui influencent les bénéfices à l'exportation et donc la décision de l'entreprise d'exporter, comme par exemple sa taille ou son âge. La variable η_j est une composante sectorielle qui mesure les différences entre les secteurs en termes de capacités technologiques ou de débouchés sur les marchés d'exportation (Caldera, 2010) ; ω_i est le terme d'erreur.

Comme décrit dans la section précédente, après qu'une entreprise ait fait le choix d'innover ou non, en plus de servir le marché domestique, les entreprises ont également le choix d'exporter ou non. Cependant, entrer dans le marché d'exportation est très couteux car les entreprises doivent supporter les coûts commerciaux constitués d'un coût unitaire variable qui prend la forme d'un coût de transport et un coût fixe constitué généralement du coût de la publicité des produits, de la recherche d'un partenaire commercial, de la mise en place des déclarations en douane, des procédures et les nouvelles méthodes comptables, etc. (Damijan et al., 2010; Chevassus-Lozza and Latouche, 2012; Cagé and Rouzet, 2015). Une entreprise va de ce fait s'engager à exporter si les ventes provenant du marché international sont supérieures aux coûts générés par les exportations ; en d'autres termes, le profit tiré des exportations doit être positif pour que l'entreprise s'engage à exporter. Ainsi, seules les entreprises ayant des coûts marginaux suffisamment faibles ont les profits assez grands pour couvrir ces coûts fixes d'entrée (Ganotakis and Love, 2011). Les entreprises exportatrices sont plus productives que les non-exportatrices pas seulement du fait des bénéfices découlant des exportations, mais parce qu'au départ, elles sont les entreprises les plus productives et peuvent donc surmonter les coûts fixes d'entrée sur les marchés étrangers. De ce fait, l'équation 1.26 est la plus généralement utilisée pour modéliser la décision d'exporter des entreprises (Bleaney and Wakelin, 2002; Cassiman and Martinez-Ros, 2007; Harris and Li, 2008; Caldera, 2010).

$$Pr(y_i = 1) = \Phi(\beta I_i + \alpha TPF_i + \gamma Z_i + \nu_i) \tag{1.26}$$

Où Y_{it} vaut 1 si l'entreprise i exporte et vaut zéro sinon ; les déterminants principaux du statut d'exportation sont la productivité de l'entreprise (TPF_i) et leurs activités d'innovation (I_i). Z_i un vecteur regroupant les autres caractéristiques de l'entreprise.

L'une des premières études à avoir utilisé un modèle similaire est celle de Wakelin (1998) ; l'auteur trouve un effet positif et significatif de l'innovation sur la probabilité d'exporter des entreprises en utilisant un échantillon de 320 entreprises manufacturières du Royaume-Uni. D'autre part, Roper and Love (2002) sur un échantillon de 1700 entreprises manufacturières du Royaume-Uni et 1300 en Allemagne, trouvent des résultats non-concluants sur la relation innovation-export. Ce résultat est conforté par l'étude de Bleaney and Wakelin (2002) portant sur un échantillon de 500 entreprises manufacturières au Royaume-Uni. Toutefois, n'intégrant pas la productivité des entreprises comme déterminant du statut d'exportation et ne contrôlant pas le biais possible d'endogénéité entre l'innovation et l'exportation, ces études ont été critiquées.

Pour faire face aux reproches faites aux études antérieures, Cassiman and Martinez-Ros (2007) utilisent un panel de 1600 entreprises manufacturières espagnoles en activité durant la période 1990-1999. Pour contrôler l'hétérogénéité inobservée des entreprises, ils ajoutent des effets aléatoires à la spécification de base. Outre un certain nombre de variables de contrôle, ils ajoutent le statut d'innovation retardé comme variable dépendante. Cela leur permet de contrôler l'endogénéité des décisions d'exportation et d'innovation. Plus précisément, si les entreprises ont une certaine connaissance de leurs perspectives sur le marché d'exportation, elles sont susceptibles de prendre leurs décisions en matière d'innovation avec cette perspective à l'esprit. En d'autres termes, dans la mesure où les entreprises peuvent anticiper leur entrée sur le marché d'exportation et si leurs efforts d'innovation sont entraînés par cette attente, l'innovation ne peut pas être considérée comme exogène à la décision d'exportation.

Pour prendre cet effet d'anticipation en compte, Cassiman and Martinez-Ros (2007) estiment tout d'abord l'équation 1.26 avec un simple probit et par la suite, ils estiment un autre modèle en instrumentant l'innovation par les dépenses en recherche et développement qui permettra de comparer les résultats. En termes de résultats, les auteurs ont constaté que l'introduction d'une innovation de produit conduit à une croissance de la probabilité d'exportation des entreprises. Quant à l'innovation de procédé, l'étude ne décèle aucun lien avec la propension des entreprises à exporter.

En utilisant les mêmes données et une méthodologie quasi semblable à celle de Cassiman and

Martinez-Ros (2007), Caldera (2010) trouve des effets significatifs de l'innovation de produit et de l'innovation de procédé sur la propension d'exportation des entreprises ; mais l'effet de l'innovation de procédé reste moins important que celle de l'innovation de produit.

Becker and Egger (2013) et Damijan et al. (2010) penchent pour une approche d'appariement par score de propension pour prendre en compte l'endogénéité potentielle entre la décision d'innovation et celle d'exportation des entreprises. Tandis que Becker and Egger (2013) mettent l'accent sur le lien de causalité allant de l'innovation à l'exportation, Damijan et al. (2010) examinent l'impact de causalité bidirectionnel. La particularité de l'étude de Becker and Egger (2013) est qu'elle prend explicitement en compte la corrélation pouvant exister entre l'innovation de produit et de procédé. Pour cela, ils distinguent quatre types d'entreprises : (i) les entreprises qui n'ont pas innover ; (ii) les entreprises qui ont effectué des innovations de produit, mais pas de procédé ; (iii) les entreprises qui ont effectué des innovations de procédé, mais pas de produit ; (iv) les entreprises qui ont effectué les innovations de produit et de procédé. Dans cette étude, les auteurs effectuent de nombreux appariements et montrent que l'effet causal de l'innovation de produit est supérieur à celui de l'innovation de procédé sur la décision d'exporter des entreprises ; toutefois, les entreprises qui effectuent l'innovation de produit et l'innovation de procédé ont une propension à exporter plus grande que celles qui n'effectuent qu'une seule activité d'innovation. Enfin, les entreprises qui effectuent l'innovation de produit ou de procédé ont une probabilité plus forte d'exporter que les entreprises qui n'innovent pas. Quant à Damijan et al. (2010), ils trouvent que l'innovation de produit et de procédé n'ont aucun effet sur la propension des entreprises à exporter en utilisant un échantillon de 437 entreprises manufacturières slovènes.

Outre le statut d'exportation comme mesure de l'exportation, certaines études se sont intéressées à l'effet de l'innovation sur l'intensité d'exportation des entreprises. Wakelin (1998) utilise un modèle tronqué en zéro et trouve un effet non-significatif de l'innovation sur l'intensité d'exportation des entreprises. Gourlay and Seaton (2004) utilisent un panel de 1623 entreprises manufacturières du Royaume-Uni suivies durant la période 1988-2001 pour examiner l'effet de l'innovation sur l'intensité des exportations. Les auteurs adoptent une spécification Cragg (1971) et montrent que les dépenses en recherche et développement influencent positivement l'intensité des exportations. Contrairement aux études précédentes, Ganotakis and Love (2011) considèrent la possibilité des biais d'endogénéité et d'auto-sélection dans leur analyse. Ainsi, pour examiner la relation innovation-intensité d'exportation, ces auteurs utilisent un échantillon de 314 entreprises manufacturières britanniques provenant de l'Enquête NTBF (survey of UK new technology based firms). D'après ces auteurs, il existe deux problèmes économétriques qui apparaissent lorsqu'on étudie la relation innovation-export. Le premier, c'est le biais de simultanéité entre l'innovation et l'export et le deuxième problème est la possible auto-sélection parmi les exportateurs. Pour prendre en compte l'auto-sélection, les auteurs optent pour l'estimateur de Heckman (1979) pour décrire la relation innovation-export. Quant au biais de simultanéité, les auteurs incorporent l'approche par variable instrumentale (en instrumentant l'innovation par les dépenses en recherche et développement et par l'aide gouvernementale dans les activités d'innovation de l'entreprise) dans l'estimation du modèle de sélection. Leurs estimations valident la présence des biais susmentionnés et les auteurs ne trouvent aucun lien entre l'innovation et l'intensité des exportations.

1.4 Conclusion

Le présent chapitre a passé en revue une très vaste documentation concernant le lien entre innovation et performance des entreprises. Plus précisément, nous nous sommes intéressés aux études répondant à l'une des questions suivantes : (i) quel est l'effet de l'innovation (produit et procédé) sur la productivité des entreprises ? (ii) quel est l'effet de l'innovation sur la performance à l'export des entreprises ?

Pour la première question, nous avons revisité les études empiriques ayant utilisé le modèle CDM pour analyser la relation entre l'innovation et la productivité. Nous pouvons conclure de ce survol de la littérature empirique sur l'innovation et la productivité que l'innovation impacte positivement la productivité des entreprises, ou plus précisément impacte le revenu par employé. L'approche CDM occupe une place importante dans les études empiriques modernes sur l'innovation au niveau microéconomique. Pour progresser dans notre compréhension du lien entre l'innovation et la productivité, plusieurs pistes peuvent être proposées : premièrement, la construction de base de données longitudinale permettrait de corriger l'hétérogénéité non observée et d'examiner les aspects dynamiques de la relation. Deuxièmement, la disponibilité des données sur les prix permettrait d'enrichir le modèle en incluant l'effet indirect de l'innovation sur la productivité via les prix.

Quant au deuxième questionnement, les études empiriques penchent pour une corrélation positive entre l'innovation et la performance à l'export des entreprises. A notre connaissance, Caldera (2010) est la seule étude à avoir donner une explication théorique à cette relation au niveau entreprise. Le principal résultat de son modèle est que les entreprises qui innovent seront également plus susceptibles d'exporter. La raison en est que les innovateurs trouvent l'exportation plus rentable que les non-innovateurs, parce qu'ils ont des coûts marginaux de production moins élevés. Cependant, cette modélisation considère l'innovation comme un processus pour réduire les coûts de production. Toutefois, bien que la modélisation de Caldera (2010) participe à une meilleure compréhension de la relation entre l'innovation et la performance à l'export des entreprises, quelques pistes valent la peine d'être explorées. L'une des pistes les plus importantes est la prise en compte de l'innovation produit facteur d'amélioration de la qualité. Comme une grande partie de l'activité d'innovation est orientée vers de nouveaux produits et l'amélioration des produits, il est utile de réécrire l'équation de la demande pour permettre au stock de connaissances de modifier la courbe de la demande à laquelle l'entreprise est confrontée.

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Chapitre 2

Innovation : concept et mesures

Les analyses empiriques proposées dans cette thèse portent sur les effets des activités d'innovation sur la performance des entreprises (productivité et exportation) en utilisant des données de Global New Product Database (GNPD). Le principal but de ce chapitre est de présenter GNPD et de détailler les différentes étapes de la construction de la base de données innovation. Premièrement, ce chapitre fournit les définitions de base des indicateurs d'innovation tels que présentés dans le manuel d'Oslo et utilisés dans l'enquête communautaire sur l'innovation (Community Innovation Survey, CIS). Par la suite, il s'attarde sur les limites de l'utilisation de CIS lorsqu'on s'intéresse à certains secteurs particuliers comme l'industrie laitière. Pour finir, il présente GNPD et comment cette banque de donnée a été exploitée pour nos analyses.

2.1 Concept et définitions

Intuitivement, la notion d'innovation renvoie aux idées de nouveauté, de changement ou encore de progrès technologique. Cependant, l'innovation étant un phénomène complexe, diverses définitions de l'innovation sont apparues dans la littérature économique. Dans son ouvrage fondateur intitulé "*The Theory of Economic Development*", Schumpeter définit l'innovation comme "simplement le fait de faire de nouvelles choses ou de faire des choses qui sont déjà faites d'une nouvelle manière" (Schumpeter, 1934, p. 65). Schumpeter (1934) a précisé cette affirmation en identifiant une innovation comme l'un des cinq événements suivants : (*i*) l'introduction d'un nouveau bien - c'est-à-dire d'un bien que les consommateurs ne connaissent pas encore - ou d'une nouvelle qualité d'un bien, (*ii*) l'introduction d'une nouvelle méthode de production, (*iii*) l'ouverture d'un nouveau marché, (*iv*) la conquête d'une nouvelle source d'approvisionnement en matières premières ou en produits semi-finis, que cette source existe déjà ou qu'elle doive être créée au préalable, (*v*) création de nouvelles structures de marché dans une industrie. Ainsi, l'innovation consiste principalement à trouver de nouvelles et de meilleures façons de faire les choses et à introduire de nouvelles idées ou de nouveaux types de produits et services sur le marché. Généralement, les économistes utilisent le terme *innovation* pour désigner l'augmentation de la qualité et de la variété, ou la réduction du coût, des biens et des services fournis par le marché. La définition de l'innovation peut varier d'une industrie à une autre. Bien que toutes les définitions de l'innovation englobent la mise en œuvre de nouveaux produits et processus, certains auteurs utilisent des concepts plus larges et incluent en outre, par exemple, l'amélioration des intrants matériels et intermédiaires, les changements dans les organisations commerciales, les changements dans les méthodes de commercialisation, ou même les changements sociaux, contractuels, juridiques ou de système (e.g., Stoneman (2010)). Ces définitions plus larges de l'innovation soulèvent la question de savoir si une innovation doit forcément être technologique. Dans sa version de 2005, le manuel d'Oslo rédigé par l'OCDE distingue deux formes d'innovation : les innovations technologiques et non-technologiques. Les innovations technologiques couvrent les produits et procédés technologiquement nouveaux ainsi que les améliorations technologiques importantes de produits et de procédés qui ont été accomplies (OECD, 2005, p. 130). On distingue deux catégories d'innovation technologique :

L'**innovation produit** correspond à "*l'introduction d'un bien ou d'un service nouveau ou sensiblement amélioré sur le plan de ses caractéristiques ou de l'usage auquel il est destiné. Cette définition inclut les améliorations sensibles des spécifications techniques, des composants et des matières, du logiciel intégré, de la convivialité ou autres caractéristiques fonctionnelles*"(OECD, 2005). Les innovations de produit incluent l'introduction de nouveaux biens et services et les améliorations sensibles des caractéristiques fonctionnelles ou d'utilisation de biens et de services existants. Ce type d'innovation augmente les coûts fixes et variables des entreprises. Il est beaucoup plus orienté vers le marché et son objectif principal est de répondre aux besoins des clients.

L'**innovation de procédé** est la "*mise en œuvre d'une méthode de production ou de distribution nouvelle ou sensiblement améliorée. Cette notion implique des changements significatifs dans les techniques, le matériel et/ou le logiciel*"(OECD, 2005). Les innovations de procédé peuvent avoir pour but de diminuer les coûts marginaux de production. Toutefois, ce type d'innovation augmente les coût fixes de l'entreprise.

L'innovation non-technologique inclut deux catégories :

L'**innovation de commercialisation** est la "*mise en œuvre d'une nouvelle méthode de commercialisation impliquant des changements significatifs de la conception ou du conditionnement, du placement, de la promotion ou de la tarification d'un produit*"(OECD, 2005). Les innovations de commercialisation visent à mieux satisfaire les besoins des consommateurs, ouvrir de nouveaux marchés ou positionner d'une manière nouvelle un produit de la firme sur le marché afin d'augmenter les ventes. D'après Chen (2006), l'innovation de commercialisation réduit les coûts de transaction pour les consommateurs.

L'**innovation d'organisation** est la "*mise en œuvre d'une nouvelle méthode organisation-*

nelle dans les pratiques, l'organisation du lieu de travail ou les relations extérieures de l'entreprise"(OECD, 2005). L'innovation organisationnelle se réfère à l'introduction de pratiques commerciales nouvelles ou sensiblement modifiées, d'organisations sur le lieu de travail ou de changements dans les relations extérieures (Peters et al., 2018).

2.2 Mesures de l'innovation dans la littérature économique

L'analyse des articles inclus dans le premier chapitre montre que l'innovation est mesurée de diverses façons dans la littérature. L'innovation est une activité complexe et diversifiée comportant de nombreuses composantes en interaction, et les sources de données doivent en tenir compte (OCDE, 1997). Les dépenses en recherche et le développement (R&D) et les données sur les brevets ont largement été considérées dans la littérature comme des mesures de l'innovation. Toutefois, ces indicateurs présentent de nombreuses lacunes. La R&D représente un *intrant* au processus d'innovation qui ne débouche pas nécessairement sur des produits et/ou des procédés technologiquement nouveaux ou améliorés. Les analyses empiriques montrent que la R&D a tendance à surestimer l'innovation (Hall et al., 2010). Quant aux données sur les brevets, elles mesurent les inventions plutôt que les innovations (OCDE, 1997). Comme l'innovation est la traduction d'une invention en un produit ou procédé nouveau ou amélioré commercialisable, mesurer l'innovation en utilisant les données sur les brevets risque de surestimer l'*extrant* de l'innovation en incluant dans la mesure les inventions qui n'ont pas été transformées en produits ou procédés commercialisables (Becheikh et al., 2006).

Afin de remédier aux insuffisances de la mesure indirecte de l'innovation, de nouveaux indicateurs plus directs ont été élaborés. Les principaux indicateurs sont les suivants : (*i*) les mesures provenant des enquêtes sur l'innovation, et (*ii*) le nombre d'innovations (*comptage d'innovations*). La première mesure consiste en des enquêtes réalisées auprès des entreprises. Cette approche est qualifiée d'approche par *sujet* puisque l'information sur les innovations provient des entreprises par le biais de sondages. L'approche par enquête auprès des entreprises devient la méthode standard de collecte d'informations directes sur l'innovation (par exemple, l'Enquête Communautaire sur l'Innovation, CIS). Toutefois, les données des enquêtes sur l'innovation présentent certaines caractéristiques qu'il est important de prendre en compte lorsqu'on les utilise dans une recherche empirique (Mohnen, 2019). Premièrement, l'un des principaux inconvénients est que la signification et la représentativité des résultats dépendent largement des taux de réponse. Deuxièmement, les indicateurs de l'innovation obtenus sont dans une large mesure subjectifs. Troisièmement, il y a un problème de timing, en ce sens que l'innovation se rapporte à une période de trois ans alors que les quelques variables quantitatives ne se rapportent qu'à la dernière des trois années. Quatrièmement, il est difficile d'effectuer une analyse de données de panel avec les données de l'enquête sur l'innovation en raison de l'échantillonnage aléatoire stratifié. Seules les grandes entreprises seront approchées à chaque vague. Cette inclusion systématique des grandes entreprises peut créer un biais de sélection dans les résultats obtenus. Enfin, la méthode d'échantillonnage des enquêtes CIS est faite de telle sorte que l'échantillon des entreprises interviewées soit représentatif de l'industrie manufacturière dans son ensemble ; toutefois, lorsqu'on s'intéresse à une industrie spécifique (par exemple, industrie laitière) l'utilisation de CIS pourrait être problématique, en terme du nombre d'entreprises et de la représentativité de l'industrie. Le tableau 3.1 montre le nombre d'entreprises interviewées pour les enquêtes CIS (2004-2016) dans l'industrie laitière (Code APE[1] : 1051A, 1051B, 1051C, 1051D).

TABLE 2.1 – Nombre d'entreprises interviewées dans l'industrie laitière

CIS 2004	CIS 2006	CIS 2008	CIS 2010	CIS 2012	CIS 2014	CIS 2016
139	87	106	169	139	69	69

Source : Enquêtes communautaires sur l'innovation, 2002-2018

C'est pour ces raisons que nous n'utiliserons pas les données CIS pour nos travaux. Nos analyses sont menées grâce à une base de données innovation construite à partir Global New Product Database (*innovation count*) que nous jugeons être plus appropriée pour capter l'extrant de l'innovation dans des industries particulières comme l'industrie laitière.

2.3 Mintel Global New Product Database

Mintel Global New Product Database (dorenavant GNPD) est une banque de donnée construite par Mintel[2], qui offre une description détaillée des produits, et inclut des informations sur les ingrédients et les marques. Ainsi, cette base permet de mettre en évidence les tendances des nouveaux produits sur les marchés mondiaux, en particulier sur les biens de consommation en évolution rapide. A sa création en 1998, GNPD suivait les tendances de nouveaux produits lancés uniquement aux États-Unis ; depuis 2010, elle possède des renseignements sur des produits provenant de 62 pays, dont ceux de l'Europe (en particulier la France) et de l'Amérique du nord principalement et dans une moindre mesure les pays d'Afrique, d'Amérique du sud et d'Asie. Généralement, GNPD s'adresse aux fabricants, aux détaillants et aux fournisseurs qui participent à la commercialisation, à la vente, à la recherche ou à l'innovation de nouveaux produits et qui doivent identifier les nouvelles tendances, les concurrents, la marque et les ingrédients (Solis, 2016). Toutefois, GNPD est aussi utilisée comme source d'informations dans des études scientifiques : en alimentation et nutrition (Mitchell, 2008; Van Camp et al., 2010; Roodenburg et al., 2011; Gallagher, 2009; Van Camp et al., 2012; Menard et al., 2012; Slining et al., 2013; Martinez, 2013; Yangui et al., 2016; Souza-Monteiro and Hooker, 2017; Gilham et al., 2018; Dickie et al., 2018; Tennant and Bruyninckx, 2018), en environnement (Gouin et al., 2012; Zhang et al., 2015), en biotechnologie (Bouwmeester et al., 2009; Jankovic

1. Activité Principale Exercée
2. Mintel Group (crée en 1972) est une société d'études de marché privée basée à Londres. Leur spécialité est de suivre les tendances et les stratégies dans des secteurs particuliers comme l'industrie alimentaire.

et al., 2010; Lucas et al., 2015), en management (Anselmsson and Johansson, 2009; Chrysochou, 2010; de Barcellos et al., 2011; Krystallis and Chrysochou, 2011; Stanton et al., 2015; Rubera et al., 2016) et en économie (Pofahl and Richards, 2009; Li and Hooker, 2009; Allender and Richards, 2010). En économie, GNDP est généralement utilisé pour comprendre le comportement des consommateurs ; par exemple, Pofahl and Richards (2009) utilisent GNPD pour estimer les effets sur le bien-être des consommateurs américains (plus précisément Chicago) résultant de l'introduction de trois produits de jus en bouteille ; Allender and Richards (2010) utilisent GNPD pour estimer la variation potentielle du surplus des consommateurs californiens. A notre connaissance, aucune étude ne s'est intéressée à GNPD comme source d'information sur l'activité d'innovation dans les entreprises. Le but de cette section est de présenter de manière détaillée la construction d'une base de données innovation au niveau entreprise en utilisant GNPD.

2.3.1 Procédure de collecte des données de Mintel

Les *shoppers*– acheteurs– de Mintel sur le terrain identifient les nouveaux produits et documentent plusieurs caractéristiques du produit, y compris la société, la marque, les ingrédients, les informations nutritionnelles et les allégations [3]. Les *shoppers* sur le terrain reçoivent une liste des magasins qu'ils doivent visiter hebdomadairement pour cibler de nouveaux produits. Les canaux de distribution surveillés comprennent les supermarchés, le marché de masse, les pharmacies, les magasins d'aliments naturels, la vente par correspondance et Internet, et certains magasins de vente directe aux consommateurs. Les nouveaux produits sont expédiés aux bureaux de Mintel. Mintel surveille également d'autres sources d'information sur les nouveaux produits, notamment les publications commerciales, les salons professionnels, les sites Web des entreprises, les communiqués de presse et les bulletins d'information en ligne. Une équipe de couverture secondaire dresse une liste des lancements de nouveaux produits trouvés par d'autres sources et les envoie aux *shoppers* sur le terrain pour qu'ils identifient les produits hautement prioritaires.

Lorsqu'un nouveau produit est identifié, il fait l'objet d'une référence croisée avec le site Web Mintel Shopper afin de limiter la duplication des produits qui ont déjà été identifiés. Le produit est ensuite acheté et envoyé aux bureaux de Mintel. Les *shoppers* sur le terrain saisissent des données de base sur les produits sur le site Web Mintel Shopper, y compris la société, la marque, le produit, la description du produit, les ingrédients et les informations nutritionnelles. Ils traduisent également toutes les informations produit sur le recto, le verso et les côtés de l'emballage. Les produits sont ensuite expédiés au bureau de Mintel à Londres pour la saisie de données supplémentaires, la photographie des emballages et plusieurs niveaux de contrôle qualité. L'équipe de saisie des données Mintel enregistre les informations pertinentes de l'emballage, y compris les allégations du produit, les codes-barres, les ingrédients, les données

3. Ces informations proviennent du service de recherche économique Département de l'agriculture des États-Unis, https://www.ers.usda.gov/webdocs/publications/44672/18236_eib95.pdf?v=0

nutritionnelles et les informations sur les catégories de produit. Les *shoppers* sont contactés pour tout problème de qualité identifié à partir de l'entrée des données de base par le *shoppers*. L'équipe de saisie des données analyse ensuite toutes les informations contenues dans le progiciel et saisit les données. Les produits sont ensuite envoyés pour être photographiés. Chaque fiche produit fait l'objet d'un contrôle qualité par une équipe d'éditeurs avant publication sur le site. D'autres contrôles qualité sont effectués afin d'identifier les retouches nécessaires et le recyclage des *shoppers*. Les produits apparaissent dans la base de données dans un délai d'environ un mois après le lancement ou aussi proche que possible du lancement, y compris certains produits publiés avant leur date de lancement officiel. Les enregistrements de produit dans GNPD comprennent une date de publication (jour/mois/année), qui indique quand le produit a été ajouté.

Un rédacteur en chef examine les enregistrements à titre de contrôle de la qualité supplémentaire. D'autres problèmes de contrôle de la qualité soulevés par l'équipe de saisie des données, les équipes de consultants de GNPD et les commentaires des clients sont pris en compte en vue d'éventuels remaniements et recyclage si nécessaire.

2.3.2 Description de Global New Product Database

Pour cette thèse, nous nous sommes intéressé aux informations spécifique suivantes : le nom du produit, la description du produit, la date de relevé, le pays de relevé, la catégorie et la sous-catégorie de produit, la marque, le type de lancement, le code barre et le code de production (la figure 2.1 donne un aperçu de GNPD). Nous reviendrons plus tard sur la signification de ces informations. Les données dont nous disposons pour cette thèse s'étendent du 01/01/2010 au 31/12/2017, soit 8 ans.

Table 2.2 – Lancements de produits laitiers par zone géographique

	Zone géographique					
Année	Europe	Amérique du Nord	Moyen orient et Afrique	Amérique latine	Asie et Pacifique	Total
2010	6243	1479	518	1356	2616	12212
2011	6491	1571	596	1348	2875	12881
2012	7832	1611	686	1390	3033	14552
2013	8510	1862	683	1674	3114	15843
2014	9682	2236	844	2119	3725	18606
2015	10472	1807	1094	2481	4113	19967
2016	10314	2111	1047	2687	4352	20511
2017	10445	1993	1060	2534	4555	20587
Total	69989	14670	6528	15589	28383	135159

Source : Calculs de l'auteur à partir de Global New Product Database

RecordID	ProductDes~n	LaunchType	Category	SubCategory	DatePublis~d	Country	Company	BarCode	Production~e	AllImageLi~s	CountryofM~e	FormatType	PrimaryIma~k	Productsource
1920107	Parmig...	New Packaging	Dairy	Proces...	10/31/2012	Argentina		7798107181182		http:/...		Shredded	http:/...	Shopper
3415591	Soigno...	New Variety/Range Extension	Dairy	Fresh ...	9/4/2015	Germany		3523237506000	FR 86....	http:/...	France	Other	http:/...	Shopper
3158047	't Lee...	New Variety/Range Extension	Dairy	Fresh ...	5/14/2015	Belgium	't Lee...	5425016330029	BE HP1...	http:/...		Spread	http:/...	Shopper
3158025	't Lee...	New Variety/Range Extension	Dairy	Fresh ...	5/14/2015	Belgium	't Lee...	5425016330036	HP 110...	http:/...		Spread	http:/...	Shopper
2907035	't Lee...	New Product	Dairy	Fresh ...	1/14/2015	Belgium	't Lee...	5400112763506	BE HP1...	http:/...		Whole	http:/...	Shopper
3129007	Vrai L...	Relaunch	Dairy	Fresh ...	4/29/2015	France	1	3273220504055	FR 35 ...	http:/...	France	Spread	http:/...	Shopper
3140011	Vraí Y...	New Packaging	Dairy	Spoona...	5/12/2015	Spain	1	3273227440141	FR 48....	http:/...	France		http:/...	Shopper
1866240	Vrai Q...	New Variety/Range Extension	Dairy	Fresh ...	8/23/2012	Spain	1	3273227441407	FR 35-...	http:/...		Whole	http:/...	Shopper
2566755	Vrai Y...	New Packaging	Dairy	Spoona...	7/25/2014	France	1	3273220535608	FR 35 ...	http:/...	France		http:/...	Shopper
3586769	Vraí L...	New Variety/Range Extension	Dairy	Spoona...	11/26/2015	Spain	1	3273227033985	FR 35 ...	http:/...	France		http:/...	Shopper
3140007	Vraí Y...	New Packaging	Dairy	Spoona...	5/12/2015	Spain	1	3273227440011	FR 48....	http:/...	France		http:/...	Shopper
2525191	Vrai F...	New Packaging	Dairy	Soft C...	7/4/2014	France	1	3273220501887	FR 35 ...	http:/...			http:/...	Shopper
2567033	Vrai A...	New Packaging	Dairy	Spoona...	7/25/2014	France	1	3273220535363	FR 35 ...	http:/...	UK		http:/...	Shopper
3636839	Vrai F...	New Variety/Range Extension	Dairy	Soft C...	12/8/2015	France	1	3273220501986	FR 35 ...	http:/...	France		http:/...	Shopper
2485833	Vrai Y...	New Packaging	Dairy	Spoona...	6/11/2014	France	1	3273220539903	FR 48....	http:/...	France		http:/...	Shopper
3361793	Vrai Y...	Relaunch	Dairy	Spoona...	8/4/2015	France	1	3273220530375	FR 35 ...	http:/...	France		http:/...	Shopper
3361791	Vrai Y...	New Formulation	Dairy	Spoona...	8/4/2015	France	1	3273220530351	FR 35 ...	http:/...	France		http:/...	Shopper
1695110	Vrai O...	New Product	Dairy	Spoona...	12/29/2011	Russia	1		FR 35 ...	http:/...			http:/...	Shopper
3140009	Vraí E...	New Packaging	Dairy	Soy Yo...	5/12/2015	Spain	1	3273227484718		http:/...			http:/...	Shopper
3613663	Vrai F...	Relaunch	Dairy	Spoona...	12/7/2015	France	1	3273220530924	FR 35 ...	http:/...	France		http:/...	Shopper
2525157	Vrai F...	New Packaging	Dairy	Soft C...	7/4/2014	France	1	3273220501931	FR 35 ...	http:/...	France		http:/...	Shopper
2566601	Vrai A...	New Packaging	Dairy	Spoona...	7/25/2014	France	1	3273220535417		http:/...			http:/...	Shopper
3586773	Vraí L...	New Packaging	Dairy	Spoona...	11/26/2015	Spain	1	3273227035460	FR 35 ...	http:/...	France		http:/...	Shopper
3586771	Vraí L...	New Variety/Range Extension	Dairy	Spoona...	11/26/2015	Spain	1	3273227035415	FR 35 ...	http:/...	France		http:/...	Shopper
2522363	Vrai L...	New Packaging	Dairy	Fresh ...	7/2/2014	France	1	3273220504055	FR 35 ...	http:/...	France	Spread	http:/...	Shopper
3613661	Vrai F...	New Product	Dairy	Spoona...	12/7/2015	France	1	3273220530900	FR 35 ...	http:/...	France		http:/...	Shopper
2567425	Vrai Y...	New Packaging	Dairy	Spoona...	7/25/2014	France	1	3273220540787	FR 48 ...	http:/...	France		http:/...	Shopper
2485787	Vrai O...	New Packaging	Dairy	Spoona...	6/11/2014	France	1	3273220530375	FR 35 ...	http:/...	France		http:/...	Shopper
2485491	Vrai Y...	New Packaging	Dairy	Spoona...	6/11/2014	France	1	3273220540633	FR 48 ...	http:/...	France		http:/...	Shopper
2485795	Vrai L...	New Packaging	Dairy	Spoona...	6/11/2014	France	1	3273220535462	FR 35 ...	http:/...	France		http:/...	Shopper
2522169	Vrai L...	Relaunch	Dairy	Fresh ...	7/2/2014	France	1	3273220504093	FR 35....	http:/...	France	Spread	http:/...	Shopper
3586767	Vraí Y...	New Packaging	Dairy	Spoona...	11/26/2015	Spain	1	3273227030151	FR 35 ...	http:/...	France		http:/...	Shopper
2781051	Vrai Y...	New Packaging	Dairy	Spoona...	11/12/2014	France	1	3273220530153	FR 35 ...	http:/...	France		http:/...	Shopper
3140005	Vraí E...	New Packaging	Dairy	Soy Yo...	5/12/2015	Spain	1	3273227484794		http:/...			http:/...	Shopper
3312677	Vraí M...	New Packaging	Dairy	Butter	8/5/2015	Spain	1	3273227342216	FR 35 ...	http:/...			http:/...	Shopper
2485797	Vrai Y...	New Packaging	Dairy	Spoona...	6/11/2014	France	1	3273220540855	FR 35 ...	http:/...	France		http:/...	Shopper
1939351	Délice...	New Product	Dairy	Creamers	11/26/2012	Thailand	1 Imex	8858862900028		http:/...			http:/...	Shopper
3127393	1 De B...	New Product	Dairy	Soy Ba...	4/28/2015	Netherlands	1 de B...	8710871083188		http:/...		Liquid	http:/...	Shopper
2144520	100% S...	New Product	Dairy	Soy Ba...	8/15/2013	Mexico	100% Soya	7503007844606		http:/...	Mexico	Liquid	http:/...	Shopper
2656653	100% S...	New Packaging	Dairy	Soy Ba...	9/11/2014	Mexico	100% Soya	7503007844620		http:/...	Mexico	Liquid	http:/...	Shopper
2656635	100% S...	New Packaging	Dairy	Soy Ba...	9/11/2014	Mexico	100% Soya	7503007844743		http:/...	Mexico	Liquid	http:/...	Shopper
3419503	Batiso...	New Packaging	Dairy	Soy Ba...	9/23/2015	Mexico	100% Soya	7503007844651		http:/...	Mexico	Powder	http:/...	Shopper
3419501	Batiso...	New Packaging	Dairy	Soy Ba...	9/23/2015	Mexico	100% Soya	7503007844125		http:/...	Mexico	Powder	http:/...	Shopper
3419499	Batiso...	New Packaging	Dairy	Soy Ba...	9/23/2015	Mexico	100% Soya	7503007844583		http:/...	Mexico	Powder	http:/...	Shopper

FIGURE 2.1 – Snapshot Global New Product Database (GNPD)

Durant la période d'analyse, GNPD recense au total 135159 lancements de produits dans la catégorie "*produit laitier*"[4] ; soit en moyenne environ 1408 lancements de produits par mois durant la période d'observation. On peut aussi remarquer que quel que soit la zone géographique, le nombre de lancement de produit augmente avec les années (voir tableau 2.2 pour plus de détail). Toutefois, il est aisé de remarquer que les lancements de produit laitiers sont principalement observés en Europe, et dans une moindre mesure en Asie et en Amérique latine.

Les produits laitiers concernés par les nouveaux lancements sont principalement les fromages et dans une moindre mesure le beurre, les yaourts et lait à boire (voir tableau 2.3 pour plus de détails). La Variable qui nous intéresse principalement dans GNPD est `LaunchType` ; c'est une variable qui décrit le caractère innovant du produit. Les modalités de cette variable sont les suivantes :

— "Nouveau produit" : Ce type de lancement est attribué lorsqu'une nouvelle gamme, ligne ou famille de produits est rencontrée sur le marché ;

— "Nouvelle variété/extension de gamme" : Ce type de lancement dépend du champ Marque. Il sert à documenter une extension d'une gamme existante de produits dans GNPD ;

— "Nouvel emballage" : Ce type de lancement est déterminé en inspectant visuellement le produit pour voir s'il y a des changements, et aussi lorsque des termes tels que New Look, New Packaging, ou New Size sont écrits sur l'emballage ;

— "Nouvelle formule" : Ce type de lancement est déterminé lorsque des termes tels que Nouvelle formule, Encore mieux, Plus savoureux, Maintenant plus faible en gras, Nouveau et Amélioré ou Grand nouveau goût sont indiqués sur l'emballage ;

— "Relance" : Ce type de lancement est déterminé lorsqu'il est spécifié sur l'emballage, par le biais d'informations secondaires (salons professionnels, relations publiques, sites Web et presse) ou lorsqu'un produit a été à la fois reconditionné de manière significative et également reformulé. Si un produit est reformulé et reconditionné, ce type de lancement est sélectionné.

D'après les définitions sur les différents types d'innovation ci-dessus, la modalité "Nouveau produit" représente des innovations produit et dans une moindre mesure des innovations de commercialisation ; alors que les modalités "Nouvelle variété/extension de gamme", "Nouvelle emballage", "Reformulation" et "Relancement" sont des innovations de commercialisation. Il est important de noter que ses modalités sont mutuellement exclusives.

Le tableau 2.4 dénombre les lancements de produit laitiers par type de lancement et par sous catégories de produit. Il ressort que les types de lancement "Nouveau produit", "Nouvelle

4. GNPD contient un peu moins de 50 modalités de produits, allant des produits alimentaires et boissons (céréales petit-déjeuner, boisson alcoolisée, fruits et légumes, etc...) aux produits non alimentaires (lessive, produits capillaires, savon et produits de toilettes, etc.. . .). La catégorie "*produit laitier*" concerne les produits tels que : le beurre, la crème, yaourt à boire, lait évaporé, lait aromatisé, fromage frais, fromage à la crème, fromage à pâte dure et semi-durcie ou encore les fromages fondus.

Table 2.3 – Lancements de produits laitiers par zone géographique

	Zone géographique					
Sous-catégories	Europe	Amérique du Nord	Moyen orient et Afrique	Amérique latine	Asie et Pacifique	Total
Butter	2825	429	306	498	1111	5169
Cream	2734	425	319	543	390	4411
Creamers	330	599	91	164	479	1663
Curd & Quark	1867	264	84	231	403	2849
Drinking Yogurt & Liquid Cultured Milk	5452	795	546	2106	5017	13916
Evaporated Milk	114	54	86	102	71	427
Flavoured Milk	2197	370	602	948	4406	8523
Fresh Cheese & Cream Cheese	4038	551	414	666	292	5961
Hard Cheese & Semi-Hard Cheese	11438	2766	650	1664	1086	17604
Liquid Dairy Other	200	97	8	26	36	367
Margarine & Other Blends	1522	294	243	431	458	2948
Processed Cheese	3366	1031	581	1341	1686	8005
Shortening & Lard	131	32	11	39	39	252
Soft Cheese & Semi-Soft Cheese	9114	1569	620	1007	890	132
Soft Cheese Desserts	2408	81	28	162	139	2818
Spoonable Yogurt	14589	3627	892	2219	4542	25869
Condensed Milk	312	49	61	267	142	831
White Milk	3738	722	711	1956	3586	10713
Total	69989	1467	6528	15589	28383	135159

Source : Calculs de l'auteur à partir de Global New Product Database.

variété" et "Nouvel emballage" représentent un peu moins de 93% des occurrences présentes dans GNPD durant la période d'analyse. Avec GNPD, il est possible d'avoir différentes mesures de l'innovation et plusieurs niveaux d'analyse. Par exemple, il est possible de compter le nombre de nouveau produit lancé par une entreprise pour une année donnée ; il est aussi possible de compter le nombre de nouveaux produits lancés par une entreprise pour une sous-catégorie de produit donnée pour une année donnée ; nous pouvons encore aller plus loin en comptant le nombre de nouveaux produits lancés par une entreprise dans un pays donné pour une sous-catégorie de produit pour une année donnée. Le but des sections suivantes est de présenter les différentes étapes menées pour obtenir ces différentes mesures.

TABLE 2.4 – Lancements de produits laitiers par type de lancement

	Type de lancement					
Sous Catégories	Nouvelle Formulation	Nouvel Emballage	Nouveau Produit	Nouvelle Variété	Relance	Total
Butter	22	1653	2340	986	168	5169
Cream	68	1356	1654	1131	202	4411
Creamers	31	536	590	391	115	1663
Curd & Quark	30	672	1339	660	148	2849
Drinking Yogurt & Liquid Cultured Milk	295	3702	4676	4381	862	13916
Evaporated Milk	5	172	197	35	18	427
Flavoured Milk	201	2591	2810	2242	679	8523
Fresh Cheese & Cream Cheese	126	1263	2295	1931	346	5961
Hard Cheese & Semi-Hard Cheese	84	4306	6089	6473	652	17604
Liquid Dairy Other	9	66	182	92	18	367
Margarine & Other Blends	99	902	1065	649	233	2948
Processed Cheese	164	2103	2897	2366	475	8005
Shortening & Lard	4	55	156	24	13	252
Soft Cheese & Semi-Soft Cheese	135	2968	4923	4617	557	13200
Soft Cheese Desserts	74	436	1264	912	132	2818
Spoonable Yogurt	685	5440	8356	9949	1439	25869
Sweetened Condensed	8	349	362	84	28	831
White Milk	143	4494	3449	2004	623	10713
Total	2428	35270	48430	41705	7326	135159

Source : Calculs de l'auteur à partir de Global New Product Database

2.3.3 Construction de la base de données innovation

Le numéro `siren` est le numéro unique d'identification de chaque entreprise française. C'est ce numéro qui permet d'identifier chaque entreprise auprès des administrations. Le travail à effectuer ici est premièrement d'identifier les observations de GNPD pertinentes pour notre étude et ensuite trouver le numéro `siren` pour chaque observation pertinente. Les observations pertinentes font références aux produits fabriqués par les entreprises françaises. Dans les études utilisant les données de lancements de produit, le code barre est généralement utilisé pour identifier la provenance du produit (e.g. Rahkovsky et al. (2012)). Le code barre sur un produit peut permettre de connaitre le nom de la société à laquelle appartient le produit. Toutefois, lorsqu'on a affaire à de grandes entreprises, la société à laquelle fait référence le code barre est généralement différente de l'entreprise de fabrication du produit. Par exemple, certains codes-barres renvoient au GROUPE LACTALIS, qui est enregistré par l'administration française comme société de commerce de gros (activité principale exercée (APE), 4633Z), et non comme une entreprise manufacturière. Ce qui nous intéresse est de savoir si le produit a été fabriqué en France et si oui quel est le numéro `siren` de l'entreprise manufacturière qui a fabriqué le produit. Pour ce type de travail, l'estampille producteur (variable `ProductionCode`, figure 2.1) est plus adaptée que le code barre. L'estampille producteur est la marque d'identification et de salubrité. Pour les produits français, l'estampille producteur prend la forme suivante : `FR XX XXX XXX EC`. Ainsi, pour ne conserver que les produits laitiers français, nous ne conservons que les produits laitiers dont l'estampille producteur commence par `FR` (voir figure 2.4, pour un bref aperçu). On compte en tout 10979 produits laitiers ayant une estampille producteur française durant la période d'analyse, soit une peu plus de 8% des lancements de produit laitier recensés dans GNPD entre 2010 et 2017.

Table 2.5 – Lancements de produits laitiers français par zone géographique

	Zone géographique					
Année	Europe	Amérique du Nord	Moyen orient et Afrique	Amérique latine	Asie et Pacifique	Total
2010	781	23	18	23	29	874
2011	1040	20	21	20	69	1170
2012	1213	32	20	10	37	1312
2013	1356	26	30	16	43	1471
2014	1452	21	40	18	60	1591
2015	1438	13	74	21	101	1647
2016	1298	27	35	43	70	1473
2017	1283	10	48	30	70	1441
Total	9861	172	286	181	479	10979

Source : Calculs de l'auteur à partir de Global New Product Database

Le tableau 2.5 dénombre les occurrences de produit laitiers fabriqués par les entreprises françaises. Les lancements de produits laitiers français sont principalement observés en Europe (soit un peu moins de 90% des occurrences). Durant la période d'observation, le nombre de produit laitier français a augmenté en moyenne de 65% ; ce qui est similaire à l'évolution moyenne mondiale, soit 68%. Cependant, on peut observer un pic du nombre d'occurrences durant la période 2013-2015. Après avoir sélectionné uniquement les produits laitiers français, nous avons cherché pour chacun de ces produits le numéro `siren` de l'entreprise fabricante.

Pour effectuer cette recherche, nous avons aussi utilisé l'estampille producteur ; le but est de lier de manière directe ou indirecte l'estampille producteur avec un numéro `siren` du producteur en question. Pour cela, nous avons utilisé de nombreuses archives pour recouper les informations. Ces informations proviennent des fichiers publics du ministère de l'agriculture, du site internet du club tyrosémiophile de France [5] (pour les fromages), et du site internet société.com [6].

Comme mentionné plus haut, l'estampille producteur prend la forme suivante, `FR XX XXX XXX EC` dans lequel les deux premiers chiffres représentent le numéro du département de production, les trois suivant sont le code INSEE de la commune de production et trois derniers représentent le numéro de l'usine de production. Par exemple, la figure 2.2 présente l'image d'un Camembert lancé au Royaume-Uni en 2015. L'estampille producteur enregistré pour ce produit est `FR 14 162 001 EC` (voir panel 2.2b) ; grâce à la liste des établissements de production de lait et de produits laitiers agréés disponible en accès public sur le site internet du ministère de l'Agriculture, il est possible de relier cet estampille producteur avec le numéro système d'identification du répertoire des établissements (`siret`, voir figure 2.4). Le numéro SIRET est un identifiant numérique composé de 14 chiffres. Les 9 premiers chiffres est le numéro `siren` de l'entreprise à laquelle appartient l'unité `siret` et les 5 derniers chiffres représentent le numéro interne de classement (NIC). Il est constitué d'un numéro d'ordre séquentiel de quatre chiffres attribué à l'établissement et d'un chiffre de contrôle, qui permet de vérifier la validité de l'ensemble du numéro `siret`. Ansi, nous trouvons que l'estampille producteur `FR 14 162 001 EC` est associé à l'établissement dont le `siret` est `50199410700016`. En retenant uniquement les 9 premiers chiffres on obtient le `siren` suivant, `501994107`. Le Camembert de la figure 2.2 est donc fabriqué par la société Fromagère de Clecy.

Figure 2.2 – Nouveau Camembert
Source: GNPD

5. Consulté durant la première année de thèse et durant le stage de Master II : `http://www.club-tyrosemiophile.fr/collection.html`
6. `http://www.societe.com/`

RecordID	ProductDes~n	LaunchType	Category	SubCategory	DatePublis~d	Country	Company	BarCode	Production~e	AllImageLi~s	CountryofManufacture	FormatType	PrimaryIma~k	Productsource
1514171	Papill...	New Packaging	Dairy	Soft C...	3/24/2011	Austria	Fromag...	3177890001770	FR 12....	http:/...		Sliced	http:/...	Shopper
1691040	Papill...	New Product	Dairy	Soft C...	1/13/2012	Finland	Fromag...	3177890001107	FR 12....	http:/...		Wedge	http:/...	Shopper
1865446	M From...	New Product	Dairy	Soft C...	8/20/2012	UK	Morrisons	2323085702507	FR 12....	http:/...		Wedge	http:/...	Shopper
2906073	Papill...	New Packaging	Dairy	Soft C...	1/14/2015	France	Fromag...	3177890004016	FR 12....	http:/...		Wedge	http:/...	Shopper
1446431	Carref...	New Packaging	Dairy	Soft C...	11/25/2010	France	Carref...	3270190209904	FR 12....	http:/...		Block	http:/...	Shopper
2045438	Papill...	New Packaging	Dairy	Soft C...	4/15/2013	Austria	Fromag...	3177890001770	FR 12....	http:/...		Wedge	http:/...	Shopper
2328523	Papill...	New Packaging	Dairy	Soft C...	2/27/2014	France	Fromag...	3177890001671	FR 12....	http:/...		Wedge	http:/...	Shopper
1885491	Fromi ...	New Product	Dairy	Soft C...	9/11/2012	Ukraine	Fromi	3274012778968	FR 12....	http:/...		Wedge	http:/...	Shopper
1545301	Papill...	New Product	Dairy	Soft C...	5/11/2011	France	Fromag...	3177890001107	FR 12....	http:/...		Wedge	http:/...	Shopper
1837496	Papill...	New Variety/Range Extension	Dairy	Soft C...	7/17/2012	Ukraine	Fozzy ...	3177890001107	FR 12....	http:/...		Wedge	http:/...	Shopper
1674155	Papill...	New Packaging	Dairy	Soft C...	11/16/2011	France	Fromag...	3177890001107	FR 12....	http:/...		Wedge	http:/...	Shopper
1477673	Papill...	New Packaging	Dairy	Soft C...	1/25/2011	France	Fromag...	3177890004016	FR 12....	http:/...		Wedge	http:/...	Shopper
2274656	Papill...	New Packaging	Dairy	Soft C...	1/6/2014	Austria	Fromag...	3177890004016	FR 12....	http:/...		Wedge	http:/...	Shopper
3429325	Papill...	New Packaging	Dairy	Soft C...	9/7/2015	UK	Fromag...	3177890001008	FR 12....	http:/...		Other	http:/...	Shopper
1422408	Papill...	New Variety/Range Extension	Dairy	Soft C...	10/26/2010	Spain	Fromag...	3177890003354	FR 12....	http:/...		Block	http:/...	Shopper
1885491	Fromi ...	New Product	Dairy	Soft C...	9/11/2012	Ukraine	Fromi	3700443670651	FR 12....	http:/...		Wedge	http:/...	Shopper
3481963	Papill...	New Product	Dairy	Soft C...	10/12/2015	Norway	Fromag...	3177890001107	FR 12....	http:/...		Block	http:/...	Shopper
1968247	Papill...	New Packaging	Dairy	Soft C...	1/9/2013	France	Fromag...	3177890004016	FR 12....	http:/...		Wedge	http:/...	Shopper
1230122	Papill...	New Product	Dairy	Soft C...	2/9/2010	Switzerland	Fromag...	3177890001008	FR 12....	http:/...		Block	http:/...	Shopper
2272016	U Bio ...	New Variety/Range Extension	Dairy	Soft C...	12/23/2013	France	Système U	3256220508353	FR 12....	http:/...		Wedge	http:/...	Shopper
3631569	Ile de...	New Product	Dairy	Soft C...	12/1/2015	South Africa	Bongra...	0379827867210	FR 12....	http:/...	France	Wedge	http:/...	Shopper
2314893	Papill...	Relaunch	Dairy	Soft C...	2/13/2014	France	Fromag...	3177890001770	FR 12....	http:/...		Wedge	http:/...	Shopper
1236521	Repack...	New Packaging	Dairy	Soft C...	1/27/2010	Finland	Fromag...	3177890004016	FR 12....	http:/...		Wedge	http:/...	Shopper
3542567	Papill...	New Product	Dairy	Soft C...	11/11/2015	Greece	Fromag...	3177890001008	FR 12....	http:/...		Wedge	http:/...	Shopper
1653631	Roquef...	New Product	Dairy	Soft C...	10/18/2011	Austria	Fromi	3700443670651	FR 12....	http:/...		Wedge	http:/...	Shopper
1865446	M From...	New Product	Dairy	Soft C...	8/20/2012	UK	Morrisons	2323090702509	FR 12....	http:/...		Wedge	http:/...	Shopper
1472414	Papill...	New Packaging	Dairy	Soft C...	1/14/2011	Finland	Fromag...	3177890004016	FR 12....	http:/...		Wedge	http:/...	Shopper
2916667	Papill...	New Packaging	Dairy	Soft C...	1/17/2015	Austria	Fromag...	3177890001770	FR 12....	http:/...		Whole	http:/...	Shopper
2168638	Papill...	New Product	Dairy	Soft C...	9/17/2013	Portugal	Fromag...	3177890001008	FR 12....	http:/...		Wedge	http:/...	Shopper
3280725	Papill...	New Product	Dairy	Soft C...	7/7/2015	Mexico	Fromag...	3177890001008	FR 12....	http:/...	France	Block	http:/...	Shopper
2662019	Papill...	New Packaging	Dairy	Soft C...	9/17/2014	France	Fromag...	3177890001770	FR 12....	http:/...		Wedge	http:/...	Shopper
3117389	Agropu...	New Variety/Range Extension	Dairy	Soft C...	4/28/2015	Canada	Gabrie...	067400017786	FR 12....	http:/...	France	Wedge	http:/...	Shopper
2460183	Reflet...	New Variety/Range Extension	Dairy	Soft C...	6/3/2014	France	Carref...	3560070875436	FR 12....	http:/...		Wedge	http:/...	Shopper
3232829	Auchan...	Relaunch	Dairy	Soft C...	7/9/2015	Spain	Auchan	3596710333264	FR 12....	http:/...	France	Wedge	http:/...	Shopper
2857799	Auchan...	Relaunch	Dairy	Soft C...	12/17/2014	France	Auchan	3596710333264	FR 12....	http:/...	France	Wedge	http:/...	Shopper
3619695	Presid...	New Variety/Range Extension	Dairy	Soft C...	12/10/2015	Canada	Loblaws	060383155483	FR 12....	http:/...	France	Block	http:/...	Shopper
2798507	Lou Pé...	New Product	Dairy	Soft C...	11/18/2014	Spain	Sociét...	3149290003043	FR 12....	http:/...	France	Block	http:/...	Shopper
2822601	Deluxe...	New Variety/Range Extension	Dairy	Soft C...	11/28/2014	Netherlands	Lidl	20619732	FR 12....	http:/...	France	Whole	http:/...	Shopper
1566504	Lou Pe...	New Variety/Range Extension	Dairy	Soft C...	6/11/2011	France	Sociét...	3023260027218	FR 12....	http:/...		Whole	http:/...	Shopper
1630922	Casino...	New Variety/Range Extension	Dairy	Soft C...	9/29/2011	France	Casino	3222474630607	FR 12....	http:/...		Block	http:/...	Shopper
1627000	Pérail...	New Packaging	Dairy	Soft C...	9/12/2011	Austria	Sociét...	3149290003029	FR 12....	http:/...		Whole	http:/...	Shopper
3157987	Margal...	New Product	Dairy	Soft C...	5/16/2015	Belgium	Fromag...	3177890102095	FR 12....	http:/...	France	Whole	http:/...	Shopper
2804105	Pérail...	New Product	Dairy	Soft C...	11/21/2014	France	Fromag...	3177890100176	FR 12....	http:/...	France	Whole	http:/...	Shopper
1585809	Fromi ...	New Variety/Range Extension	Dairy	Soft C...	7/20/2011	Czech Republic	Fromi	3700443676523	FR 12....	http:/...		Whole	http:/...	Shopper

FIGURE 2.3 – Snapshot Global New Product Database (GNPD), uniquement les produits français.

TABLE 2.6 – Nombre d'entreprises françaises ayant effectué au moins un lancement

Année	2010	2011	2012	2013	2014	2015	2016	2017
Nombre d'entreprise	155	184	176	192	212	222	207	225

Source : Calcul de l'auteur a partir de la base GNPD

Après avoir trouvé les numéros `siren` pour tous les lancements de produits laitiers français disponibles dans GNPD, nous pouvons connaitre les entreprises qui ont fait au moins un lancement durant la période d'analyse. Le tableau 2.6 montre qu'en moyenne 196 entreprises ont effectué au moins un lancement durant la période d'observation. De 2010 à 2017 le nombre d'entreprises a augmenté en moyenne d'environ 6,5% par an.

Afin d'évaluer la pertinence de notre base de données innovation, nous documentons la corrélation de la mesure de l'innovation obtenue avec les mesures existantes de l'innovation. Pour ce faire, nous avons utilisé l'enquête communautaire sur l'innovation. L'enquête CIS couvre les entreprises de plus de 10 salariés et la participation à l'enquête est volontaire. L'échantillon des entreprises interviewées est mis à jour tous les deux ans pour tenir compte des entreprises existantes, des entreprises nouvellement créées et des entreprises qui se sont développées pour satisfaire aux critères de sélection de l'échantillon. [7] Les informations contenues dans la base de données CIS sont basées sur les déclarations des entreprises. Les variables importantes comprennent les dépenses en innovation (dépenses internes de R&D, achat de R&D externe, dépenses d'acquisition de machines, d'équipements et de logiciels, acquisition d'autres connaissances externes) et les extrants de l'innovation (indicateurs pour l'innovation en matière de produits, procédé, organisation et marketing). Un innovateur en t est défini dans CIS comme une entreprise qui a déclaré avoir introduit des biens ou services nouveaux ou nettement améliorés à l'année t, *t-1* ou *t-2*. Pour tester la pertinence de notre mesure de l'innovation, nous utilisons trois vagues de l'enquête communautaire sur l'innovation : CIS2012, CIS2014 et CIS2016...

2.3.4 Sources d'informations additionnelles

Il est possible d'enrichir les connaissances sur ces entreprises en fusionnant la base obtenue avec d'autres sources de données. Les principales sources de données sont : les fichiers FARE, la base de donnée des Douanes et la base de donnée PRODCOM. Les fichiers FARE permettent d'avoir les informations sur les données comptables de l'entreprise (ventes, chiffre d'affaire, valeur ajouté, nombre d'employé, capital, salaire, etc..) ; ces informations sont mesurées au niveau entreprise et année. La base de donnée PRODCOM fournit les informations sur la production en valeur et en quantité ; ces informations sont ventilées par entreprise, par produit

7. pour plus d'informations, voir les recommandations méthodologiques de l'enquête communautaire sur l'innovation 2016, disponibles sur le site de l'UE

Table 2.7 – Corrélation avec les mesures de CIS

	Nouveaux produit			
	(1)	(2)	(3)	(4)
Innovation Produit	0.027**			
	(0.013)			
Innovation de commercialisation		0.031**		
		(0.013)		
Innovation Organisationelle			0.021*	
			(0.013)	
R&D				0.035**
				(0.014)

*$p<0.1$,**$p<0.05$, *** $p<0.01$.

et par année. Les informations des douanes portent sur les quantité et valeur exportés. Ces entreprises sont ventilées par entreprise, par produit, par pays de destination et par année. Ces bases de données sont décrite en détail dans les autres chapitres.

MINISTÈRE DE L'AGRICULTURE DE L'AGROALIMENTAIRE ET DE LA FORÊT

Liste des établissements de production de lait et de produits laitiers agréés CE / Raw milk and dairy products processing plant

12/10/2017

Numéro agrément /Approval number	SIRET/Local number	Raison SOCIALE - Enseigne commerciale /NAME	Adresse / Adress	Code postal/ Postal code	Commune/Town	Catégorie/Catégory	Activités associées/Associated activities
13.084.001	81161514500018	LA JACOURELLE	ROUTE DE SAINTE ANNE	13640	LA ROQUE-D'ANTHERON	PP	
13.085.001	39517587000017	EUROPAFROM	ZA PLAINE DU CAIRE	13830	ROQUEFORT-LA-BEDOULE	PP	0(CS)
13.088.001	47775376800019	GAEC GOUIRAN	17 RUE ADRIEN ISNARDON	13740	LE ROVE	PP	
13.089.860	31716980300010	GAEC RECONNU LA TAPY	MAS DE LA TAPY	13670	SAINT-ANDIOL	PP	
13.103.011	32954141100024	LYOFAL	ZA DE LA GANDONNE RUE DU REMOULAIRE	13300	SALON-DE-PROVENCE	PP	VIII( ), VI(PP), XIV(PP), X(PP)
13.105.001	30420232800023	FRIESLANDCAMPINA CHEESE FRANCE	ROUTE NATIONALE 7 EST 2820 RTE NATIONALE 7	13560	SENAS	PP	
13.215.105	53531687100016	LAITAJ	58 CHE DU VALLON DES PINS	13015	MARSEILLE 15E ARRONDISSEMENT	PP	
14.011.004	34379031700014	EARL DU BIEVILLE	LD BIEVILLE	14240	ANCTOVILLE	PP	
14.039.005	39239912700019	SCEA DES HAYES		14220	BARBERY	PP	
14.039.005	52341173400016	SCL DES HAYES	LA VIEILLE ABBAYE	14220	BARBERY	PP	
14.045.004	44911185500028	SKORUPA YOHAN	FERME DES GRANDS CHENES	14670	BASSENEVILLE	PP	
14.064.001	50199407300010	SOCIETE FROMAGERE DE JORT		14170	BERNIERES-D'AILLY	PP	
14.081.001	31223703500026	LES FROMAGERS DE TRADITION	LA HOUSSAYE	14170	SAINT-PIERRE-SUR-DIVES	PP	
14.091.004	38480304500010	SCEA DES BRUYERES	LD LE PETIT MALHEUR	14430	BOURGEAUVILLE	PP	
14.120.001	70920030700045	TRIBALLAT NOYAL	LE BOURG	14240	CAHAGNES	PP	
14.120.004	52033721300018	SCL DE BEAUMONT	DELLE DU CAIRON	14310	SEULLINE	PP	
14.126.014	53825533200016	LA TEURGOULE DE CAMBREMER	FERME DES MONDEAUX	14340	CAMBREMER	PP	
14.140.005	51232969900015	EARL DU LIEU FOIN	LD LE LIEU FOIN	14490	CASTILLON	PP	
14.149.001	43883513400026	ALAIN URBAN	BEAU ROGER RTE D AIRAN	14270	CESNY-AUX-VIGNES	PP	
14.162.001	50199410700016	SOCIETE FROMAGERE DE CLECY	23 RUE DU BERON	14570	CLECY	PP	
14.167.001	48937896800023	LC INODRY	ZONE NORMANDIAL 3 AV DU PAYS DE CAEN	14460	COLOMBELLES	PP	
14.200.308	31954394800115	NESTLE CLINICAL NUTRITION FRANCE	12 RUE MARECHAL MONTGOMERY	14480	CREULLY	PP	
14.227.004	32509984400012	EARL DE L ORAILLE		14430	DOUVILLE-EN-AUGE	PP	
14.243.007	34915430200013		FERME PORTES HELLINS	14600	EQUEMAUVILLE	PP	
14.258.024	42075661100018	SARL LA TABLE DE GUILLAUME	ZI SUD 10 CHE DE LA VALLEE	14700	FALAISE	PP	VI(PP), V(MP)
14.265.004	53197089500011	EARL FERME DE LA MOISSONNIERE	LA MOISSONNIERE	14140	LIVAROT-PAYS-D'AUGE	PP	

DGAL/SA/SDSSA/BETD

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FIGURE 2.4 – Snapshot Global New Product Database (GNPD), uniquement les produits français.

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Chapitre 3

Product innovation and export strategy : An application to French dairy firms [1]

3.1 Introduction

In modern economies, innovation is widely considered as the major driving force behind economic growth as well as industrial evolution. As a result, the promotion of innovation is increasingly at the core of public policies. European institutions repeatedly state that a sound innovation policy is the key to recovering EU competitiveness [2]. For example, to overcome the differences in growth and productivity between the EU and its leading global competitors of the time —the USA and Japan— the Lisbon Strategy in 2000 proposed the stimulation of innovation and knowledge through greater investment in R&D and Information and Communication Technologies (ICT) [3]. The promotion of innovation, which occupied an equally important place in The Lisbon Strategy, has grown in importance with the EU2020 Strategy. For instance, H2020, the largest Research and Innovation funding programme in Europe, encourages participation by business and small and medium-sized companies. It promotes industry and academia cooperation to ensure that the fruit of research is developed into new

1. This chapter, co-written with Sabine Duvaleix-Tréguer and Karine Latouche. This work is supported by a public grant overseen by the French National Research Agency (ANR) as part of the – "Investissements d'avenir" program (reference : ANR-10-EQPX-17 - Centre d'accès sécurisé aux données - CASD). This work is also supported by the project INNOV financed by the INRA metaprogramme DID IT (Diet impacts and determinants : Interactions and Transitions) for the access to the MINTEL-GNPD database.

2. Europe's deficit in terms of technological capacity and innovation became the symbol of the ground needing to be gained to assure EU competitiveness" (Final report of the Lisbon Strategy 2000-2010, p. 11). http://www.europarl.europa.eu/document/activities/cont/201107/20110718ATT24270/20110718ATT24270EN.pdf

3. The Lisbon Strategy states that 3% of the EU's GDP should be invested in R&D and that private investment in R&D should be promoted.

products [4]. In this paper, we are specifically interested in product innovation as a potential driving force for competitiveness that helps firms to attain quality differentiation on foreign markets. More precisely, we examine the relationship between product innovation and export behaviour in a theoretical model and test the predictions of this model with application to the French dairy industry. The main issue addressed is that of whether product innovation, i.e. quality-enhancing strategy, improves the export performance of firms. In particular, we examine the extent to which product innovation affects the quantity sold and the price charged on foreign markets.

Several theoretical explanations link product innovation and export behaviour in the literature. First, in the product life cycle models introduced by Vernon (1966) and extended by Klepper (1996), product innovation is an exogenous determinant of a country's exports. More recently, endogenous growth theory has explored the endogenous determination of technological change (innovation) as in Grossman and Helpman (1989), which suggests the possibility of a reverse causal direction running from export to innovation and capturing two different mechanisms. The first mechanism reflects the fact that when they operate on international markets firms must invest more heavily in innovation at product level to maintain or gain a competitive advantage. The second mechanism reflects the learning-by-exporting effect : exporting firms will be more likely to innovate if, for instance, there is learning-by-exporting. This means that exporters are more likely to introduce new products than domestic firms because they are exposed to knowledge not available to the firms serving the domestic market. A recent theoretical debate is linked to the role of the heterogeneity of firms (i.e. possessing different resource endowments), explaining the main patterns of internationalisation. In this literature, the underlying hypothesis is that exporting firms exhibit specific characteristics—higher productivity levels that enable them to bear the large costs required to compete in foreign markets (Melitz, 2003). However, models based on the heterogeneity of firms, e.g. Jovanovic (1982), Hopenhayn (1992), Melitz (2003), assume that the difference in productivity level is exogenous and thus fail to describe potential links between firm productivity, export decisions and innovation. Bustos (2011) extends this theoretical approach by allowing for the possibility that firms invest in innovation to both upgrade their technology and reduce the marginal cost of production. Innovative firms are therefore more likely to export as a result of both the expected benefits of product upgrading and the lower marginal costs, which allow firms to reduce selling prices. In Stoneman (2010), Bustos (2011) and Caldera (2010), product innovation is explicitly considered as product upgrading and is interpreted as a cost-reducing innovation that allows a firm to charge lower prices. The main finding of the Caldera (2010) model is that firms that innovate will also be more likely to export. The reason is that innovators find

4. See the Innovation Union Flagship Initiative. The European Commission is putting forward seven flagship initiatives to catalyse progress under each priority theme. For further information on the Innovation Union, see : https://ec.europa.eu/research/innovation-union/

exporting more profitable than non-innovators. As innovators have lower marginal production costs they can charge a lower price. This increases their total sales more than proportionally because demand is assumed to be elastic.

The quantification of the role of product innovation in export performance via quality improvement has been hindered by a lack of detailed data on innovation. In empirical literature, the variables used to quantify innovation are defined at firm level. An initial part of empirical literature uses a number of measurements of innovation process inputs such as expenditure on R&D in relation to total sales, the ratio of R&D employees to total staff and R&D dummy(Gruber et al., 1967; Wolter, 1967; Hirsch and Bijaoui, 1985; Schlegelmilch and Crook, 1988; Kumar and Siddharthan, 1994; Wakelin, 1998; Bleaney and Wakelin, 2002; Roper and Love, 2002; Gourlay and Seaton, 2004; Cassiman and Martinez-Ros, 2007; Girma et al., 2008; Harris and Li, 2008; Van Beveren and Vandenbussche, 2010; Caldera, 2010; Aw et al., 2011; Golovko and Valentini, 2011; Esteve-Pérez and Rodríguez, 2013). Studies using R&D to measure innovation give contradictory results. Using a regression of R&D expenditure in relation to total sales of firms in Spanish manufacturing industry, Caldera (2010) and Golovko and Valentini (2011) find a positive correlation between innovation and exports. Girma et al. (2008) and Esteve-Pérez and Rodríguez (2013) corroborate the previous studies by using an R&D dummy to measure innovation in Great Britain and for Spanish manufacturing industries respectively. Cassiman and Martinez-Ros (2007), Aw et al. (2007) and Girma et al. (2008) use an R&D dummy as innovation measure and fail to find a significant link between innovation and exporting, using firm-level data on manufacturing in Taiwan, Spain and Ireland respectively. This is in agreement with the results found by Van Beveren and Vandenbussche (2010) which show no correlation between (internal and external) R&D dummy and firm exports in the Belgian manufacturing industry. The second part of the literature focuses on a more direct product innovation measure, mainly based on the Community Innovation Survey (CIS) available at the European level and which collects information on the (product and process) innovations reported at firm level (Lachenmaier and Wößmann, 2006; Cassiman and Martinez-Ros, 2007; Love and Mansury, 2009; Damijan et al., 2010; Caldera, 2010; Van Beveren and Vandenbussche, 2010; Cassiman et al., 2010; Ganotakis and Love, 2011; Becker and Egger, 2013). When such measures are used, empirical studies show that the relationship between innovation and exports is more robust. The study by Cassiman and Martinez-Ros (2007) on Spanish manufacturing firms shows that product innovation is one of the main determinants of export probability. These results are corroborated by Caldera (2010) and Becker and Egger (2013) on Spanish and German manufacturing firms respectively. However, Damijan et al. (2010) and Van Beveren and Vandenbussche (2010)) find that product and process innovations are not correlated with exports in the Slovenian and Belgian manufacturing industries respectively.

The contribution by this article is threefold. First, we develop a trade model in which product innovation enters both supply and demand sides. Like Crozet et al. (2012), we argue that dairy industries conform reasonably well to the heterogeneous firm monopolistic competition assumption. We also argue that product innovation is user-oriented in food industries. Following Grunert et al. (2010), we define product innovation as a process leading to the development of a new product in which the integrated analysis and understanding of consumers' desires, needs and preferences play a key role. Hence, in our framework, product innovation is modelled as a utility shifter on the demand side. On the supply side, product innovation development generates additional production costs. Second, we use a new measure of product innovation. We use detailed information on "new" products from the Global New Product Database (GNPD) which provides all products launched around the world and explicitly referring to "new" attributes. Merged with the exports of dairy firms, we obtain a unique product-launch data set. Hence, we propose a new quantification of the role of product innovation on firm export performance in the empirical analysis. Third, this paper contributes to the increasing literature on the role of demand for differentiation in firm performance (Foster et al., 2008; De Loecker, 2011; Feenstra and Romalis, 2014; Hottman et al., 2016; Roberts et al., 2018). In a recent work, Aw et al. (2018) make an empirical distinction between consumers' taste (horizontal differentiation) product quality (vertical differentiation) using a control function approach. In their work, product quality and taste are identified by a firm-product and product-country specific components respectively. They find that taste is very important and accounts for about 50% of the variation in export revenue. In this article, we identify the effect of product upgrading (through product innovation) on demand by disentangling the innovation, quality and taste effects. In other words, we examine a breakdown of consumers' perception of quality into three components : product quality (vertical differentiation), (horizontal differentiation) and the potential of a variety to adapt to changing consumer preferences (product innovation in our case).

The article is set out as follows. The next section covers our theoretical framework and describes the equations to be examined in the empirical section. Section 3 describes the data used and the way in which these are combined. A preliminary analysis based on these data includes details of our empirical strategy. This strategy is focused in particular on the self-selection process highlighted in the preliminary analysis. The empirical results and the testing of the main predictions of the model are then described. A further sub-section deepens the results and goes further than our theoretical model before the conclusion.

3.2 Theoretical framework

Our model is driven by firm-based trade theory. We use a model in which product innovation operates as a utility shifter. Our intuition was that the introduction of an innovation enhances adaptation of a product to consumer preferences. Product innovation is therefore aimed at influencing consumer demand. A global economy consists of a collection of countries *j*. In each destination, the representative consumer allocates her/his revenue to the different varieties of each product *k*. We define variety, ω, as a unique combination of a producing firm *f*, product *k*, and country *j*. On the demand side, consumers in each country are assumed to have identical Cobb-Douglas preferences over differentiated products $U_j = \Pi_k U_{jk}^{\delta_{jk}}$ where U_{jk} is a strictly increasing and strictly concave upper-tier utility function that is twice continuously differentiable in all its arguments and δ_{jk} is the standard expenditure shares with $\sum_k \delta_{jk} = 1$.

The utility resulting from the consumption of each differentiated product k is given by :

$$U_{jk} = \left[\sum_i \int_{\omega \in \Omega_{ijk}} (\lambda_{ijk}(\omega) q_{ijk}(\omega))^{\frac{\sigma-1}{\sigma}} \, \mathrm{d}\omega \right]^{\frac{\sigma}{\sigma-1}} . \tag{3.1}$$

Where $q_{ijk}(\omega)$ is the quantity for variety ω of product k from country i that is consumed in country j and Ω_{ijk} denotes the endogenous set of these varieties. $\sigma > 1$ is the substitution elasticity between varieties. The term $\lambda_{ijk}(\omega)$ can be interpreted as the quality perceived by consumers in country j for variety ω of product k produced in country i. The term $\lambda_{ijk}(\omega)$ also captures the fact that consumers could value differently varieties of the same quality according to the fact that some varieties take into account the evolution of their preferences. Hereafter, we consider exporting firms on a given market i ; thus, for the sake of simplicity, we drop index i. We define product innovation as a process for developing a (new) product that will be sold on market *j*. This means that the innovation process includes integrated analysis and understanding of consumer's wants, needs and preference. We express $\lambda_{jk}(\omega)$ as

$$\lambda_{jk}(\omega) = \theta_{fk} \exp\left[-(\gamma_{jk} - \beta_{jk} \mathrm{Innov}_{jk}(\omega))\right] \tag{3.2}$$

The quality perceived , $\lambda_{jk}(\omega)$, is seen as a function of 3 components. The first component is the quality of product k produced by the firm *f*, θ_{fk} ; it reflects a firm-product-specific component that is common to destination markets. It can also be considered as the "vertical differentiation" component. The second component represents the taste of consumers in country j for product k imported from a given origin, γ_{jk}. It can also be considered as the "horizontal differentiation" component. The third component represents the ability of the exporting firm to adjust the variety of product k to consumer preferences . The latter component refers to product innovation, $\mathrm{Innov}_{jk}(\omega)$. In short, products are both horizontally and vertically differentiated in our model ; this is crucial for the identification of the effect of product innovation on export performance. Some standard calculations show that the equilibrium demand for variety ω of product k in countrty j is such that :

$$q_{jk}(\omega) = [\lambda_{jk}(\omega)]^{\sigma-1} E_{jk} P_{jk}^{\sigma-1} [p_{jk}(\omega)]^{-\sigma} \tag{3.3}$$

Where E_{jk} is the amount of income allocated to the differentiated product k in country j and P_{jk} is the price index in country j associated with product k. The price index is

$$P_{jk} = \left[\int_{\omega \in \Omega_{jk}} \left(\frac{p_{jk}(\omega)}{\lambda_{jk}(\omega)} \right)^{1-\sigma} \mathrm{d}\omega \right]^{\frac{1}{1-\sigma}} \tag{3.4}$$

On the production side, we assume that firms produce under monopolistic competition. Following Eckel and Neary (2010), Mayer et al. (2014), Duvaleix-Treguer et al. (2018) we assume that firms can produce any number of varieties but each additional variety entails a higher marginal cost. There is a fixed production cost F_{fk} for the firm for each product made (Bernard et al., 2011). We assume that each firm has *core competence*, corresponding to the product that forms its best sales. To rank products within firm, we use the Rank_{fk} notation representing variety rank. For the core product, $\text{Rank}_{fk} = 0$ and for peripheral products, $\text{Rank}_{fk} \geq 1$. Furthermore, the introduction of a new product allows a firm to match its products to specific market demand. The effect of product innovation on marginal cost of production is then closely related to this demand. For example, in destination markets where the scope for quality differentiation is large, firms upgrade the quality of their product varieties to satisfy consumer preferences in terms of high quality. Technology is such that the marginal cost of firm f associated with its variety of product k and exported to country j is given by

$$c_{fjk} = \tau_{jk} \frac{\exp(\beta_I \text{Innov}_{fjk}) \theta_{fk}^{\beta_\theta} W_f}{\varphi_{fk}} = \tau_{jk} \frac{\exp(\beta_I \text{Innov}_{fjk}) \theta_{fk}^{\beta_\theta} W_f}{\varphi_f \exp(-\beta_r \text{Rank}_{fk})} \tag{3.5}$$

Where $\beta_r > 0$. Note that, following (Eckel and Neary, 2010; Mayer et al., 2014; Duvaleix-Treguer et al., 2018), we assume that product-specific efficiency $\varphi_{fk} \equiv \exp(-\beta_r \text{Rank}_{fk}) \varphi_f$ is increasing in firm productivity, φ_f, and decreasing in product rank, Rank_{fk}. β_θ and β_I are the costs elasticities of quality θ_{fk} and innovation Innov_{fjk} respectively. W_f is a price index of inputs used by firm and τ_{jk} represents trade costs for product k shipped to country j. Marginal costs of producing good k for firm f adjusted for country j, c_{fjk}, are decreasing in firm productivity (efficiency in production) but increasing in product quality (firms pay extra costs to raise consumers' willingness-to-pay related to higher quality).

Demand for each variety of a product depends on the price of this variety, the price index for the product, the price indices for all other products and aggregate expenditure. If a firm is active in a market for the product, it supplies one of a continuum of varieties, and is hence unable to influence the price index for any product. The firm's profit maximization problem is therefore reduced to choosing the price of each product variety separately to maximize the profits derived from each one. This optimization problem yields the standard result that the equilibrium price of a product variety is a constant mark-up over marginal cost :

$$p_{fjk} \quad = \quad \frac{\sigma}{\sigma - 1} c_{fjk} = \frac{\sigma}{\sigma - 1} \frac{\tau_{jk} W_f \left[\exp(\beta_\theta \ln \theta_{fk} + \beta_I \text{Innov}_{fjk}) \right]}{\varphi_f \exp(-\beta_r \text{Rank}_{fk})}$$

Where β_θ and β_I are the costs elasticities of θ_{fk} and Innov_{fjk} respectively. τ_{jk} covers all exchange rate effects, tariffs and shipping costs between France and destination j for a given product k. Substituting equation(3.2) and equation (3.6) into equation (3.3), export quantity is given by :

$$q_{jk}(\omega) = E_{jk} P_{jk}^{\sigma-1} \left[\frac{\exp(\ln\theta_{fk} + \beta_{fk}\text{Innov}_{fjk} - \gamma_{jk})^{\sigma-1}}{\exp(\beta_\theta \ln\theta_{fk} + \beta_I \text{Innov}_{fjk} + \beta_r \text{Rank}_{fk})^\sigma} \right] \left[\frac{\sigma\tau_{jk} W_f}{\varphi_f(\sigma-1)} \right]^{-\sigma} \tag{3.6}$$

Estimating equations

Our first objective is to check whether the introduction of new product can affect the price charged by a firm in a specific market [5]. Because of the monopolistic competition and the CES assumptions, we can identify the cost elasticity of new product introduction by using equation (3.6). Taking the log of price in equation (3.6), we have the following equation for estimate :

$$\ln p_{fjk} = \textbf{cst} + \beta_I \text{Innov}_{fjk} + \beta_\theta \ln \boldsymbol{\theta}_{fk} + \beta_r \text{Rank}_{fk} + \textbf{FE}_f + \textbf{FE}_{jk} + \boldsymbol{\xi}_{fjk} \tag{3.7}$$

The term $\textbf{FE}_f$ is the firm individual effect controlling for firm heterogeneity (productivity φ_f, production factor prices W_f). The term $\textbf{FE}_{jk}$ is an individual destination-product individual effect covering heterogeneity in destination-product pair (trade costs τ_{jk}, markup, and foreign market structure). The variable Rank_{fk} is computed using all the products produced by the firm f. Our central variable is Innov_{fjk}, a dummy variable equal to 1 if the firm f has introduced a product innovation in country j for a given product k, and zero otherwise. A product innovation requires up-to-date understanding of consumer preferences and we thus assume that product innovation induces additional production costs. Our model allows us to distinguish the price (cost) elasticity of product innovation, β_I, from the price elasticity of the other quality component, β_θ. We expect that the price (cost) elasticity of product innovation will be positive.

With regard to quantity (in the case of exports), we take the log in equation (3.6) to specify that the quantity exported by a firm f in country j for a given product k is given by :

$$\ln q_{fjk} = \textbf{cst} + \alpha_I \text{Innov}_{fjk} + \alpha_\theta \ln \boldsymbol{\theta}_{fk} + \alpha_r \text{Rank}_{fk} + \textbf{FE}_f + \textbf{FE}_{jk} + \boldsymbol{\varepsilon}_{fjk} \tag{3.8}$$

With $\alpha_I = (\sigma-1)\beta_{fk} - \sigma\beta_I$, $\alpha_\theta = \sigma(1-\beta_\theta) - 1$ and $\alpha_r = -\sigma\beta_r$. The term $\textbf{FE}_f$ is the firm individual effect controlling for firm heterogeneity (productivity φ_f, production factor prices W_f). The term $\textbf{FE}_{jk}$ is a destination-product individual effect capturing heterogeneity in destination-product pair (trade costs τ_{jk}, P_{jk} and E_{jk}). Our coefficient of interest is α_I. There are two opposite effects, demand effect versus cost effect. First, the demand effect can be characterized as follows : the introduction of a product innovation can increase the quality of the product as perceived by consumers and, in turn, demand for the innovative variety. Second,

5. We define market as an combination of destination and product.

product innovation implies higher marginal costs and prices leading to smaller demand for an innovative variety (cost effect). We expect that product innovation has a positive effect on the quantity exported, i.e. the demand effect dominates the cost effect. We assume that product innovation raises prices but that it also raises consumer demand by a more than offsetting amount and the quantity of sales increases.

3.3 Data on the French dairy sector

We tested the theoretical predictions of the model on the French dairy industry with data for the years 2011 to 2017. Previous studies on innovation in the agrifood industries have identified some specific aspects. According to Grunert et al. (1997), Harmsen et al. (2000), Capitanio et al. (2009) or Acosta et al. (2015) the food industry is one of the most innovative industries in the manufacturing sector. For example, in the community innovation survey (CIS 2014), the agrifood industry is the second most innovative industry in France after the information and communication industry (table 3.1). However, it is also well known that the agrifood industry is one of the manufacturing industries with the smallest investment in R&D [6]. Although agrifood industries innovate more often than manufacturing industries as a whole (see table 3.1 for France), innovation-related spending is lower. For France, Daussin (2018) reports that 1.3% of the turnover of the agrifood industry was devoted to innovation in 2012-2014. During the same period, companies in manufacturing industries spent 3.4% of their turnover on innovation.

Table 3.1 – Percentage of innovative firms in French manufacturing industries

	Innovatives firms	Technological innovations		Non-technological innovation	
		Product	process	Organization	Marketing
Agri-foods industries	**69**	**31**	**33**	**39**	**37**
Dairies industry	66	22	29	39	43
Manufacturing industries	**60**	**31**	**32**	**35**	**24**

Source : French Community Innovation Survey (CIS 2014)

To explain this imbalance between low spending on R&D and high innovation production, Johnson and Evenson (1999), Wilkinson (1998), Levidow and Bijman (2002), Carew (2005), Sanguansri and Augustin (2006), Sastry et al. (2010) show that most inventions and innovations affecting food manufacturing efficiency come from outside the industry. Other authors prefer to emphasize the notions of consumer inertia and redundant technology to explain the

6. voir https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf

phenomenon. Indeed, authors such as Padberg and Westgren (1979), Galizzi and Venturini (1996) and Grunert et al. (1997) have shown that consumers of food industry products reveal a particular form of risk aversion in their choice of novelties. Consumers want new products, but these new products must be fairly similar to familiar products. Aware of this aversion, firms respond to this preference by introducing new products whose characteristics are generally only marginally different from those of existing ones. Galizzi and Venturini (1996) made the same observation, saying that the introduction of product innovations in the agrifood industry is not limited by the availability of technological opportunities but by the existence of specific conditions of demand. This opinion is consistent with the fact that agrifood industries are more focused on "marketing" innovations than other manufacturing industries ; in France, this observation is more marked in the dairy industry (Table 3.1).

Work was performed on several types of data to test the empirical predictions of the model for the French dairy sector : (i) the list of "new products" introduced on different markets and produced by French firms, (ii) information on the export behaviour of firms and (iii) information on all the products manufactured by companies. All this information is available for the French dairy sector. The empirical work is thus based on a single dataset linking three sources of information.

3.3.1 Global New Product Database

An exhaustive list of new product launches was used as information on product innovation at the firm-product-destination level. The product launch data come from the Global New Products Database (GNPD) compiled by Mintel [7]. We used data from 2011 that report all consumable products launched. This covers 62 of the world's major economies. The following information is available for each "new" product launched : country (country in which the launch was registered), product characteristics, the date of the launch in a specific country, launch type and production code. As its name indicates, GNPD can be considered as a global product launch database. All new product launches in a specific country are registered in the GNPD. More precisely, we use the category variable `LaunchType` available in the GNPD to measure product innovation output. This category variable has five modalities [8] :

— "new product" : This launch type is dependent on the Brand field. It is assigned when a new range, line, or family of products is encountered. This launch type is also used if a brand that already exists on GNPD, in one country, crosses over to a new sub-category ;

— "new variety/Range Extension" : This launch type is dependent on the Brand field. It is used to document an extension to an existing range of products on the GNPD ;

7. Mintel is a privately owned, London-based market research firm.

8. See GNPD glossary 2016, https://www.gnpd.com/gnpd/about/GNPD_Glossary_2016.1.pdf, for more details

— "new packaging" : This launch type is determined by visually inspecting the product for changes, and also when terms like New Look, New Packaging, or New Size are written on the pack ;
— "reformulation" : This launch type is determined when terms such as New Formula, Even Better, Tastier, Now Lower in Fat, New and Improved, or Great New Taste are indicated on the pack ;
— "relaunch" : This launch type is determined when specified on pack, via secondary source information (trade shows, PR, websites, and press) or when a product has been both significantly repackaged and also reformulated. If a product is reformulated and repackaged then this launch type is selected.

We use two variables for output measure of product innovation. We label the first variable *new product*, with the value 1 if firm f has introduced a new product for goods k in destination j. The variable *soft product innovation*, which take the value 1 if firm f has introduced a new packaging or an extension for goods k in destination j.

Three challenges were addressed with regard to GNPD information and to construct the dataset needed to test our theoretical mode empirically. Since our empirical work focused on French firms, the first challenge was to find items manufactured by French firms in the vast set of products listed in the GNPD.To do so, we use the production code variable available in GNPD. The production code refers to EC identification and health marks. In France, any establishment preparing, processing, handling or storing products of animal origin or food containing them and marketing such products to other establishments, including freezer vessels, factory vessels and vessels cooking crustaceans and molluscs, is subject to the health approval requirement. Products from an approved establishment shall bear an oval identification mark identifying that establishment. For French products, the EC identification takes the following form : `FR XX XXX XXX EC`. Considering that French firms are required to affix their approval number to their products [9] , we can consider that all French dairy products listed in GNPD have an approval number. So, to keep only French dairy products, we retain dairy products whose approval number begins by `FR`. The second challenge concerns the ID number (SIREN) of the firms that manufactured these products [10]. This ID number is crucial for our study because it is a key variable allowing the merging of our different databases. To find the ID number we use EC identification. In general, an approval number is assigned to a manufacturing plant ; in addition, we know that a firm is made up of one or more plants. Thus, with the approval number, it is possible to trace the manufacturing firm (and therefore to the firm's ID number). In practice, converting the plant approval number into the firm ID

9. See Regulation (EC) Nº 853/2004 of the European parliament and of the council.
10. In France, this firm ID number is called SIREN (Système d'Identification du Répertoire des ENtreprises) It's allocated by INSEE (Institut National de la Statistique et des Études Économiques) at the time of the firm's registration.

number is not straightforward as there is no link between the two identifiers. So, to achieve our goal we split the search for the firm ID number into two steps. First, with the plant approval number we found its SIRET identifier [11]. The SIRET (Syst‘eme d'identification du Répertoire des établissements) number is the plant identifier ; it consists of 14 digits, the first 8 of which are the identifier of the associated firm. In the second step, we keep the first 8 digits of this SIRET number of the plant to obtain the ID number (SIREN) of the associated firm. It is worth noting that we aim at identifying within-firm innovation strategies ; i.e. among all products manufactured by the firms, we seek to identify the products on which the firm has carried out innovative activities. This is the third and challenging (time-consuming) issue. This step will be detailed in the subsection on the PRODCOM dataset. An important issue is the validation of the content of the data set compared to existing data sets used to address innovation, such as the CIS data set often used in the empirical literature. Table 3.8 in Annex A shows the validation of this data set with the existing correlation between GNPD and CIS databases.

3.3.2 French customs dataset

This dataset provides a comprehensive record of the yearly values and quantities exported by French firms from 2011 to 2017 and collected by the French customs administration. The data include information on the final destination country of the product exported. The product is defined at the eight-digit level for each French exporting firm. For each firm-product-destination triplet, we use the unit value as a proxy for price ; the unit value is the ratio between the value and the quantity exported for a given firm-product-destination. As mentioned above, customs data use the eight-digit combined nomenclature product classification (hereafter cn8). The cn8 classification is based on the Harmonised Commodity Description and Coding System (HS) covering all the products that can be the object of international transactions and have a physical dimension. The first six digits are those of the Harmonized System (HS) and the last 2 digits correspond to HS subdivisions to meet EU tariff or statistical needs [12].

3.3.3 Production commercialized (PRODCOM) dataset

The PRODCOM dataset is the most comprehensive annual survey of firms with agrifood activities conducted by the French Ministry of Agriculture. It covers sales (in quantity and value) on the domestic and export markets of the products manufactured by the firm from 2011 to 2017. PRODCOM data are a comprehensive record of annual sales by eight-digit product level for each firm in the dairy industry. The firm's domestic sales (quantity and value) can then be calculated as follows :

$$q_{fik} = Q_{fk} - \sum_{j \neq i} q_{fjk} \tag{3.9}$$

11. It should be noted that the approval number (EC identification) is the plant identifier at European level ; at national level each plant is identified by another number upon registration (SIRET) ; and these two identifiers are distinct.

12. For a detailed description dairies product categories : http://www.conex.net/nc8/2017/en/04.html

where q_{fik} is the sales (quantity and value) of firm f for product k in France (i); Q_{fk} is the total sales (quantity and value) of firm f for product k from PRODCOM dataset; and q_{fjk} is the sales (quantity and value) of firm f for product k in destiantion j from custom dataset. Before implementing this calculation, is important to note that the eight-digit nomenclature from the PRODCOM dataset (call "'PRODCOM code"') is distinct to the eight-digit nomenclature from the customs dataset. While the PRODCOM code is based on 6-digit CPA [13] (Classification of Products by Activity), the cn8 is based on 6-digit HS [14] (Harmonized System). To merged these two datasets we convert the cn8 to PRODCOM code [15] (see Appendix B for a detailed description). Using the PRODCOM database, we measure the size of the firm as the total number of manufactured products. The size of the firm is usually measured as the number of employees. In our case, this choice implies losing a large number of observations. Using the total number of products manufactured by the firm avoids this drawback. It is worth noting that for the firms with both variables available the correlation rate between the number of employees and the number of products within firms is high (34.30%). Productivity is the total sales by the firms per product (total sales/total number of products).

3.3.4 Final dataset

Table 3.2 (and table 3.11 in Appendix D) describe the final dataset compiled for the empirical analysis. It is worth noting that one important variable in our model is product quality, θ_{fk}. We expect that the introduction of a "new" product (i.e. a product involving innovation) in a given market increases the demand for the product in this specific market. Thus checking for the other demand characteristics is crucial for the identification of the effect of product innovation. We do not observe product quality empirically; some empirical studies use input prices of imported material inputs as product quality proxy (Kugler and Verhoogen, 2009, 2012; Fan et al., 2015; Manova and Yu, 2017). This procedure consists of introducing equation (3.2) in equation (3.3) and estimating the log of this equation using the control function approach (see Aw et al. (2018) for details). Unfortunately, because of the lack of data on input prices, we use another approach to measure product quality. We follow Khandelwal et al. (2013) in defining "quality perceived" (quality as it enters consumer's utility, λ_{fjk}) as unobserved attributes that make consumers willing to purchase relatively large quantities of the variety despite the relatively high prices charged. The intuition behind Khandelwal's approach is price-conditioned, with a variety with a larger quantity being assigned higher perceived quality. We then define product quality, θ_{fk} as a firm-product specific component

13. The CPA is the classification of products (goods as well as services) at the level of the European Union (EU). Product classifications are designed to categorize products that have common characteristics. CPA product categories are related to activities as defined by the Statistical classification of economic activities in the European Community (NACE).

14. The Harmonized System is an international nomenclature for the classification of products. It allows participating countries to classify traded goods on a common basis for customs purposes.

15. For certain product categories, it's not possible to convert PRODCOM code to cn8; this is why we convert cn8 to PRODCOM code.

that is common across destination markets [16]. The relevance of this approach is based on the fact that we have all the information concerning firms' destination markets. With export data (from the French customs) we have information on all foreign markets where firms sell products. We use the production sold (PRODCOM) dataset to obtain information about the domestic market. Rank_{fk} is computed as in (Eckel and Neary, 2010) and Mayer et al. (2014). Whereas in these articles products are ranked in descending order of their total exported value at firm level, we propose to rank the products according to sales value at firm level for each product. In other words, we use the absolute rank of the product for the firm instead of the rank according to exports. We also cover the domestic market. For empirical analysis, Rank_{fk} is a dummy variable egal to zero if product k is the firm's core product and one otherwise.

Table 3.2 – Descriptive statistics

Variables	**Mean**	**Standard Deviation**	**Number of Observations**
Quantity	2.775	2.990	17,846
Price	1.208	0.942	17,846
Product quality	-0.078	0.525	1,952
Product rank	0.614	0.487	1,952
Productivity	16.217	1.251	831
Size	4.645	2.902	831

Notes : as shown in table 3.11,variables *Quantity* and *Prices* come from the French customs data and they are measured at the firm-product-country level (see section 3.2) ; *Productivity* and *Size* come from the PRODCOM antd they are measured at the firm level (see section 3.3) ; *Product quality* and *Product rank* have been computed using PRODCOM and they are measured at the firm-product level (see section 3.3)

3.4 Preliminary analysis and identification strategy

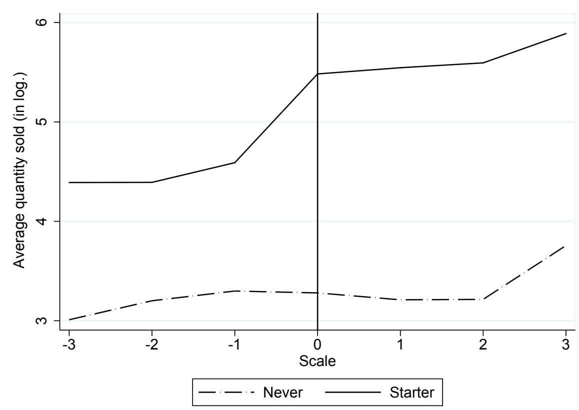
Here we focus on identifying the effect of product innovation on quantity and price. We start with a graphic framework to highlight important features that will drive our empirical strategy. Second, we show the econometric model that will be used to test the prediction of the theoretical model.

3.4.1 Preliminary analysis

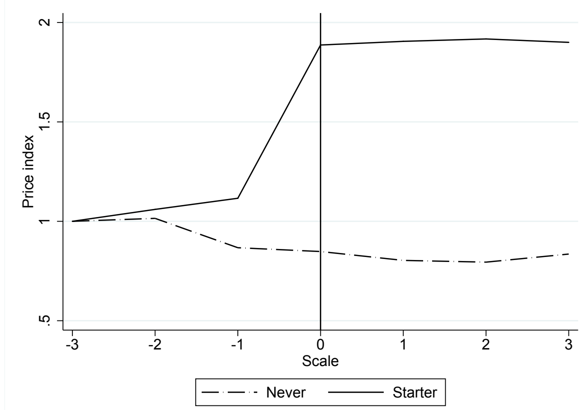
We are interested in whether the quantity sold and the price charged in a given market increase once the firm has introduced a product innovation in this particular market. We base the graphic analysis on a specific product market. We chose to work on the Belgian market for grated cheese. For comparative purposes, we had to limit this analysis to a given market and exports of grated cheese to Belgium call for a large number of observations. Figure 3.1 plots

16. See appendix C for more detail on this procedure

the trajectories of the average quantity of grated cheese sold and the average price charged by French firms in Belgium. The trajectories are observed three years before firms introduced product innovation for the first time on the Belgian grated cheese market during the period 2011-2017 and three years after this introduction. The horizontal axis is the time scale. Zero indicates the period when firms introduce product innovation for the first time. It is marked with a vertical line. For firms that never introduce product innovation throughout the sample period, zero is the median of this period. We divided our sample into three groups : the *Never* group consists of firms that never introduce product innovation on the Belgian grated cheese market, the *Starter* group consists of firms starting to introduce product innovation and the *Always* group is not represented in the figures but groups firms that always introduce product innovation during the sample period. Figure 3.1a shows the evolution of the quantity of grated cheese sold by French firms in Belgium before and after the introduction of a new product. This figure clearly shows a product innovation effect on the quantity sold. The average quantity sold by the firms in the *Starter* group increases drastically between the period -1 and 0 while this trend is not observed for firms in the *Never* group.



(a) Average quantity (in log)



(b) Average weighted-price

FIGURE 3.1 – Trajectories for quantity sold and price charged by french firms in the Belgium market of grated cheese
Source: Authors

To analyse the price evolution in the two groups, we compute an price index in two steps. First, for each product-country (kj) in each period s we calculate a weighted-average export price (P_{jks}), across all firms' log export unit values, $\ln(p^*_{fjks})$,

$$P_{jks} = \sum_f S_{fjks} \ln(p^*_{fjks}) \tag{3.10}$$

where S_{fjks} is a firm-specific weight, equal to $(q_{fjks}/\sum_f q_{fjks})$ and q represents the quantity sold. Then, normalizing this index to 1 in the period -3 (i.e, 3 year before the introduction of the new product) allows us to compare the evolution of price. Figure 3.1b present the price evolution for the two groups. The figure, clearly shows that prices exhibit a clear upward trend in the period following the introduction of a new product for the *Starter* group, although this upward trend is somewhat less pronounced (or inexistent) for firms in the *Never* group.

In Figures 3.1a and 3.1b, the product innovation effects involve the comparison of the right-hand side of the vertical line on the left. The left-hand side of the vertical line can also be used to show that, prior to the introduction of a new product, firms sold more or charged higher price than other firms (firms in the *Never* group). To deepen this graphic representation, table 3.3 shows the characteristics of the firms in the two groups (Starter and Never) that may explain the difference between them. It appears that product innovation is strongly correlated with the characteristics of firms. Firms in the *Starter* group are on average more productive and larger than firms in the *Never* group. Likewise, firms that perform product innovation sell products that are of higher quality on average. As in Caldera (2010), these results suggest that there might be self-selection in the decision to innovate. Only the more productive firms introduce new products. This issue must be tested and addressed in the econometric analysis.

Table 3.3 – Difference in firms' characteristics between *Starter* and *Never* groups before introduction of new product

	Means characteristics			
Variables	All	*Never*	*Starter*	Difference
Product quality	- 0.009	- 0.037	0.090	0.128***
Products' rank	0.306	0.311	0.280	0.032
Productivity	16.528	16.377	17.069	0.692***
Size	5.546	5.398	6.076	0.679***

Note : significance levels for the mean-comparison tests are 1% (***).

3.4.2 Addressing potential endogeneity concerns

In line with the empirical literature, we take into account different endogeneity issues that can arise when the link between innovation activities and export behaviour is analysed. First, Van Beveren and Vandenbussche (2010) identified different sources of endogeneity. The first source of endogeneity is that the selection by product innovation activities may be non-random and could bias our estimates of the product innovation effect. As shown in the preliminary analysis, empirical facts seem to support a self-selection process. Second, Costantini and Melitz (2007) stressed the importance of an anticipation effect in explaining the evolution of firm productivity. The authors analyse the joint entry, exit, export and innovation decisions of firms faced with trade liberalisation in a dynamic setting. They find that the anticipation of upcoming liberalisation can induce firms to innovate prior to their entry to the export market. Innovation decision is then endogenous to the export decision. This conscious self-selection (Alvarez and López, 2005; Van Beveren and Vandenbussche, 2010). Iacovone and Javorcik (2008) also seems to confirm firm quality upgrading (through product innovation) in anticipation of entering the export market. Third, exporting firms will be more likely to innovate if, for instance, there is learning by exporting. This implies that exporters are more likely to innovate than domestic firms because they are exposed to knowledge inputs not available to firms serving only their domestic market (Caldera, 2010). Therefore, the innovation decision is endogenous to the export decision. To account for the potential endogeneity between innovation and export decisions, Cassiman and Martinez-Ros (2007), Caldera (2010) and Van Beveren and Vandenbussche (2010) use an instrumental variables approach. As instruments, Caldera (2010) uses a variable measuring whether or not the firm is a recipient of public support for R&D. Cassiman and Martinez-Ros (2007) uses industry and time dummies together with the percentage of firms that made product innovation in the industry in a particular year. Van Beveren and Vandenbussche (2010), use firms' internal and external R&D decisions as instruments. Unfortunately, we do not have any R&D variables that could be an instrument for product innovation in our dataset. We propose a more direct approach to take this bias into account in our analysis. As in Damijan et al. (2010) and Becker and Egger (2013) we apply matching estimators.

The second source of endogeneity is the causality bias, also known as the persistence of exports decision (Aw et al., 2007). The causality bias arises when past exporting history is not properly surveyed. For this reason, Damijan et al. (2010) and Van Beveren and Vandenbussche (2010) focus only on first-time exporters when investigating the impact of firm-level innovation activities on the propensity to export of firms. The disadvantage of this approach is that not all the available information is used, and in particular information on firms that exported the previous year and that do not currently continue to export. Theoretical models suggest that hysteresis in exports may be due to the sunk costs incurred on entry to the export market (Krugman, 1999; Dixit, 1989a,b). Roberts and Tybout (1997) and Bernard and Jensen (2004) developed a dynamic discrete choice model of exporting behaviour that separates the roles of profit heterogeneity and sunk entry costs in explaining exporter status. Roberts and Tybout (1997) find that the likelihood of exporting in a given year, on condition of having exported in the previous year, hovers at around 90%. According to Campa (2004), this hysteresis effect decays exponentially. Including the export decision made in the previous year is therefore important for capturing the sunk cost effect while not attributing the export decision in following years to other motives, leading to biased coefficients (Cassiman and Martinez-Ros, 2007). Cassiman and Martinez-Ros (2007) and Caldera (2010) include one lag of the export status variable as an additional determinant when investigating the impact of firm-level innovation activities on the propensity of firms to export. In our sample, the transition probabilities for the different states of past to present export status reveal that more than 90% of the firms remain in the same state : exporters continue to export and non-exporters continue as non-exporters. About 6% of non-exporters become exporters. To deal with this potential bias, we consider export behaviour prior to product innovation as a confounding factor in our matching process.

3.4.3 Identification strategy

Our strategy aims at seeking the self-selection process (as suggested in section 4.1) while testing for the product innovation effects on export performance by creating control groups using reweighting based on average treatment models as suggested by Heckman et al. (1998). The objective is to evaluate the causal effect of the introduction of product innovation on exported quantity and price. The identifying assumption in estimating the treatment effect (introduction of product innovation) comes from the introduction of the state variables – see eqs (3.7) and (3.8) – in the reweighting procedure. The market is indexed by jk in equations (3.7) and (3.8). This notation includes the fact that firms can serve many markets (each with several products on several markets). Examining the self-selection process requires knowing when a firm introduces product innovation for the first time in a specific market during the sample period (2011-2017). Following De Loecker (2007), we start by rescaling the time periods in such a way that a firm introduces product innovation for the first time in a given market at time s_0. Let $Y_{fjk,s}$ be the outcome (exported quantity or price) at time s, $s = \{s_0, s_0 + 1, \cdots, S\}$; and D_{fjk} is awarded a value of 1 if firm f has introduced product innovation for product k in destination j for the first time during the period s_0. Under Stable Unit Treatment Value Assumption [17], for each triplet (f,j,k), the causal effect is defined as a comparison of $\mathbf{Y}(1)$ with $\mathbf{Y}(0)$, with only one of the two outcomes observed depending on the value taken by D_{fjk}. We define the average treatment effect of D_{fjk} on outcome (exported quantity and price) as

$$\tau^s = E\{\mathbf{Y}_s(1) - \mathbf{Y}_s(0)\} \tag{3.11}$$

Estimation of τ^s from observed data is identified by assuming the strongly ignorable assumptions (Rosenbaum and Rubin, 1983). The first assumption is the unconfoundedness hypothesis ; conditional on observed characteristics ($\mathbf{X}$), the systematic differences (on outcome) between firms that have introduce product innovation in a given market and firms that have not introduce product innovation in the same market must be attributable to introduction of product innovation in this specific market. Under unconfoundedness, τ^s equals to :

$$\tau^s = E\{\mathbf{Y}_s(1) - \mathbf{Y}_s(0)\} = E_{\mathbf{X}}\left[E(\mathbf{Y}_s|\mathbf{X}, \mathbf{D} = 1) - E(\mathbf{Y}_s|\mathbf{X}, \mathbf{D} = 0)\right] \tag{3.12}$$

17. The standard stable unit treatment value assumption states that the outcome of each firm is unaffected by the treatment assignments of other firms (whether within or across market). Under this assumption, each firm has two potential outcome $Y_{fjk}(D_{fjk})$ for $D_{fjk} = 0, 1$

The second assumption is the overlap hypothesis ; overlap implies that, for all possible values of the observed covariates, there is a positive probability of $D_{fjk} = 1$ or $D_{fjk} = 0$. According to Rosenbaum and Rubin (1983), under the previous assumptions, adjustment on the propensity score is sufficient to eliminate bias due to observed confounders ($\mathbf{X}$). The propensity score, e, is defined for each firm f in market jk as the probability that $D_{fjk} = 1$ given its observed covariates : $e(\mathbf{X}) = \Pr(\mathbf{D} = 1|\mathbf{X})$. The utility of the propensity score resides in the fact that

$$\tau^s = E\left[\frac{\mathbf{D}\mathbf{Y}_s}{e(\mathbf{X})} - \frac{(1-\mathbf{D})\mathbf{Y}_s}{1-e(\mathbf{X})}\right]. \tag{3.13}$$

Thus, τ^s can be estimated by comparing weighted averages of the observed outcomes using the inverse-probability weights $w_{fjk} = 1/e(\mathbf{X})$ for firms with $D_{fjk} = 1$ and $w_{fjk} = 1/1 - e(\mathbf{X})$ for firms with $D_{fjk} = 0$. The validity of this method depends, however, on the relevant specification of the propensity score (Li et al., 2013). τ^s can be estimated using the following strategy. First, the propensity score, $e(\mathbf{X})$, is estimated. Second, the estimated propensity scores are used to calculate the sample analogue of (3.13). Finally, the estimator of the asymptotic variance of τ^s is computed to account for the errors related to the propensity score estimated in the first step. If the propensity score is estimated by maximum likelihood, we can use the standard M-estimator to obtain the asymptotic variance (Wooldridge, 2007, 2010; Cerulli, 2014).

As mentioned above, the validity of eq (3.13) depends on the relevance of the propensity score estimation. Abadie (2005) suggests a non-parametric estimation of the propensity score using a power series of $e(\mathbf{X})$. However, we prefer the maximum likelihood estimation since the asymptotic variance of τ^s is more straightforward to obtain. The specification of the propensity score is based on equations (3.7) and (3.8) ; the firm f's decision to introduce product innovation in a specific market jk depends on product quality (θ_{fk}), product rank (Rank_{fk}), markets structure and firm individual effect. To account for the causality bias describe above, we include firm f's export status in market jk before the introduction of product innovation in this specific market, Z_{fjk}. Then we can express the propensity score, $e(\mathbf{X})$, as follows :

$$\hat{e}(\mathbf{X}) = \mathbf{\Lambda}(\alpha_1 Z_{fjk,s_0-1} + \alpha_2 \ln \theta_{fk,s_0-1} + \alpha_3 \text{Rank}_{fk,s_0-1} + \boldsymbol{\eta}_{jk} + \boldsymbol{\eta}_f) \tag{3.14}$$

Where $\mathbf{\Lambda}$ is the logistic cumulative distribution function. The re-scaling of the time periods implies that $\hat{e}(\mathbf{X})$ is obtained using variables prior to the period s_0, noted with the subscript $s_0 - 1$. This allows us to satisfy the exogenous condition between covariates and the decision to introduce product innovation in a given market. The choice of covariates to be included in the propensity score estimation must be guided by their simultaneous explanatory power on the decision to introduce product innovation and outcome (exported quantity or price) in a specific market (Caliendo and Kopeinig, 2008) ; this is why the specification of the propensity score (equation (3.14)) is based on covariates from equations (3.7) and (3.8). $\boldsymbol{\eta}_{jk}$ are market fixed-effects which capture the market-specific confounding factors. A full set of year dummies are also included to control for common aggregated demand and supply shocks. $\boldsymbol{\eta}_f$ are individual firm fixed-effects. To estimate equation (3.14), we consider an error-component approach and make distributional assumptions on the individual effects. We assume that the individual effects to be correlated with the observed covariates, $\mathbf{X}' = (Z, \ln\theta, \text{Rank})$,

$$\boldsymbol{\eta}_f = \gamma' \boldsymbol{X}_f + \alpha_4 \varphi_{f,s_0-1} + \alpha_5 \text{Size}_{f,s_0-1} + \boldsymbol{u}_f \tag{3.15}$$

Where $\boldsymbol{X'}_f = (\boldsymbol{X'}_{f1}, \ldots, \boldsymbol{X'}_{fh_f})$, $h \equiv jk$. φ_f is the productivity of the firm. $\boldsymbol{u}_f$ is an error term and is assumed to be independently and identically normally distributed with mean 0 and variance σ_u^2. This procedure allows us to take into account the firm's unobserved confounding factors that are common across markets. This weighting scheme is used to produce an estimator of τ_s and allows to account for imbalances in the distribution of the covariates ($\mathbf{X}$), market characteristics ($\boldsymbol{\eta}_{jk}$), observed and unobserved firm confounding factors $\boldsymbol{\eta}_f$ between the treated and untreated firms. In other words, weights eliminate a confounding component induced by the nonrandom assignment to the treatment.

We use the nonparametric estimator proposed by Li et al. (2013),

$$\hat{\tau}^s = \frac{\sum_{f \in jk} w_{jk} \hat{\tau}^s_{jk}}{\sum_{f \in jk} w_{jk}} \tag{3.16}$$

where $w_{jk} = \sum_{f \in jk} w_{fjk}$ and $\hat{\tau}^s_{jk}$ is the average treatment effect in market *jk* at the period *s*. It is expressed as follows :

$$\hat{\tau}^s_{jk} = \frac{\sum_{f \in jk}^{d_{fjk}=1} Y_{fjk,s} w_{fjk}}{w^1_{jk}} - \frac{\sum_{f \in jk}^{d_{fjk}=0} Y_{fjk,s} w_{fjk}}{w^0_{jk}}, \tag{3.17}$$

where $w^1_{jk} = \sum_{f \in jk}^{d_{fjk}=1} w_{fjk}$, $w^0_h = \sum_{f \in jk}^{d_{fjk}=0} w_{fjk}$ and $w_{fjk} = 1/\hat{e}(\mathbf{X})$. This nonparametric estimator is attractive because it includes some specificities related to each market. [18]

To summarize, our estimation strategy is describe as follows : first, we estimate the propensity score by substituting equation (3.15) into equation (3.14) and using a random-effect logit model (See the results of this estimation in Appendix D). Second, we use Minima and Maxima comparison proposed by Dehejia and Wahba (1999) to investigate the common support between *Starter* and *Never*. Finally, the estimated propensity score is used as weighting scheme to calculate the empirical evaluation of equation (3.13) given by the equation (3.16)

18. The common estimator of τ^s in its calculation :
$\hat{\tau}^s_0 = \sum_{D_{fjk}=1} \frac{Y_{fjk} w_{fjk}}{w^1} - \sum_{D_{fjk}=0} \frac{Y_{fjk} w_{fjk}}{w^0}$
is the weighted means of the two groups, treated firms and non-treated firms. It is the computation proposed with the Inverse Probalility Weighting -IPW- procedure with STATA for instance. Contrary to $\hat{\tau}^s$ (which was programmed by the authors and implemented with STATA for this study), $\hat{\tau}^s_0$ doesn't control for the market structure (i.e. the product-country specificities).

3.5 Empirical results : an application to the French dairy firms

This section describes our empirical findings on the effect of product innovation on export performance. Based on our identification strategy, we first test the predictions of our theoretical model and analyse how the introduction of a product innovation in a given market (product-country pair) impacts the quantity sold and the price charged by a firm in the given market. Second, we deepen the analysis by enlarging the market approach. We consider export behaviour either at the global level (without considering the country dimension) or accounting for country heterogeneity and focusing on certain particular zones.

3.5.1 Export strategy on a given market : the effect of product innovation

Table 3.4 shows the estimation of the introduction of product innovation in a given market on the quantity sold and price charged by a firm in this specific market. We distinguish between two types of product innovation : (1) introduction of a new product ; and (2) introduction of a soft product innovation [19]. Our findings show that the introduction of a new product has a positive and significant effect on the quantity sold. The average effect of the introduction of a new product on quantity is estimated to be 0.91 ; in other words, on average, the quantity sold by firms in the Starter group increase by 91% once they have introduced of new product. However, this effect declines over the years ; 3 years after the launching of a new product ($s_0 + 2$), the average treatment of the *Starter* is 0.65. The introduction of a new product also has a positive, significant effect on the price charged by the firms. On average, the prices charged by the firms in the *Starter* group increase by 7.40% once they have introduced of new product. In the way as quantity, the average treatment of the introduction of a new product on the price charged by firms decreases over time. Surprisingly, the average effect of the introduction of a soft innovation has a low positive and significant treatment effect on the quantity sold in the year the soft innovation is introduced and one year after introduction (towards ten per cent). On average, the quantity sold by firms in the Starter group increase by 1.08. This has no effect on prices.

Our results suggest that firms that introduce a new product sell a larger quantity of this product in a given market because the products match consumer preferences. These results are in line with the findings of Bernard and Jensen (2004) who show that in the case of the US product attributes affect foreign demand preferences. According to our empirical framework, product innovation has an ambiguous effect on quantity (if exported). On the one hand, the introduction of a new product can increase the product quality perceived by consumers and, in turn, demand for this new product (*demand effect*). On the other hand, product innovation implies higher marginal costs and prices leading to smaller demand for the new product (*cost effect*). The global positive effect highlighted in our results suggests that the demand effect

19. Note that soft innovation includes product innovation about new packaging or new variety

dominates the cost effect. Our study shows that the introduction of a new product raises the prices charged by firms. However, consumers are willing to buy this product as they perceive the new product as being of higher quality. This is in line with the findings of Baldwin and Harrigan (2011) who show that in the U.S. quality increases prices but demand increases by an amount more than offsetting this and higher quality firms sell more.

Our results also show a positive and significant effect of product innovation on price. This positive effect does not corroborate the results shown by Caldera (2010) who suggested that since innovators have lower marginal costs of production they can charge lower prices, which will increase total sales more than proportionally because demand is assumed to be elastic. We find that the cost elasticity of product innovation is positive and estimated to be 0.074 and decreases as time passes. This reduction can be interpreted as an experience-based cost saving (Buzzell and Wiersema, 1981a,b). One important result of this study is also the addressing of consumer evaluation of the introduction of new products. The average effect of product innovation on quantity reported in table 3.4 is an estimation of α_I from Equation **??**. We recall that $\alpha_I = (\sigma - 1)\beta_{fk} - \sigma\beta_I$, where β_{fk} is the consumers' valuation of a new product. By assuming that σ is 5.11 [20], consumers evaluation of a new product is estimated to be 0.313 in the year of its introduction. After one year, consumer evaluation of the new product is estimated to be 0.218 and 0.204 after two years. Consumers become used to buying the new product and their evaluation decreases as time passes.

3.5.2 global export's firm strategy : the effect of product innovation

We first described how the introduction of a new product affects the quantity sold and price charged by a firm in a given market. One another relevant analysis is to measure whether product innovation has an impact on a firm's decision to export. Product characteristics are now understood to be the cornerstones for firms to be able to sustain competition in domestic but even more so in global markets (Becker and Egger, 2013). Bernard and Jensen (2004) suggest that product upgrading may increase the probability of exporting if the product attributes determine the firm's decision to export. Iacovone and Javorcik (2008)) find that firms upgrade the quality of their products preceding an expansion into foreign markets.

20. the median elasticity of substitution across dairies products reported by Ossa (2015)

Table 3.4 – Estimates of product innovation on export behaviour in a specific foreign markets

Time	s_0				s_0+1				s_0+2			
	ATT	SE	Treated	Control	ATT	SE	Treated	Control	ATT	SE	Treated	Control
Quantity												
New product	0.910***	0.045	236	847	0.726***	0.054	188	588	0.649***	0.066	124	388
Soft innovation	1.081*	0.596	212	805	1.022*	0.549	176	578	0.869	0.732	126	384
Price												
New product	0.074***	0.009	236	847	0.033***	0.011	188	588	0.037***	0.014	124	388
Soft innovation	0.103	0.105	212	805	0.074	0.116	176	578	0.053	0.209	126	384

***, **, * Indicate significance at the 1, 5 and 10% level. Average treatment effect is compute using our identification strategy describe above. We recall that s_0 is the time period when firm introduce product innovation (new product or soft product innovation) in a given market. s_0+1 and s_0+2 denote 1 and 2 year after s_0, respectively. See table 3.10 (Panel A and B) in annex C for the estimation of the propensity score. S.E. is the Standard Errors

To test whether product innovation spurs the probability of exporting, we add extra information for the sub-samples of non-exporters and innovators. It is worth noting that we were not able to analyse the role of product innovation in the probability of exporting to a given market (product-country level). The reason is that for a given market all the firms providing innovation on this market are exporting. In other words, the innovation predicts perfectly the export decision. Our dependent variable, *exporter*, take the value one if firm f commercializes and exports product k and zero if firm f commercializes product k only in domestic market. For product innovation, we use two already-known dummy variables : *New product*, which takes values 1 when firm f introduce new product for good k (whatever the destination, including home country). *Soft product innovation*, which takes values 1 when firm f introduce soft product innovation for good k (whatever the destination, including home country). The causal effect of product innovation on propensity to export is identified using the procedure describe above.

The result in table 3.5 presents the causal impact of product innovation on exports' propensity. We find that introducing a new product has a positive and significant treatment effect on exports' propensity at least after a year ; the probability to export increases by 6.2% one year after the firm starts to innovate and the probability goes on increasing the years after. Two years after the introduction of the innovation ($s_0 + 2$), new product innovators increase their probability to export by 10.7%. This result is in line with the findings of Becker and Egger (2013) for Germany. The authors find that product innovation increases the probability to export by 8.8% and 8.5% after 1 and 2 years, respectively. The introduction of soft innovation has no impact on the probability to export at the global level.

We also test whether product innovation has an impact on the quantity exported and on the prices charged by the firms. To do so, we sum at the firm-product level the quantity exported and the price charged. Results are shown in 3.5. The introduction of a new product significantly impacts the quantity sold by the firms and the charged prices. These positive impacts start in the year of the innovation. This effect increases over time for the quantity sold ; the effects on prices increase one year after innovation and is maintained the year after. We have previously seen that soft innovation allows them to meet consumers' expectations in each market. It has no influence on global export performance contrary to new product introduction. The increasing role of the introduction of a new product over time at the global level (with regard to export probability, the quantity sold and the prices charged) is interesting. It shows that the dissemination of the firm's innovative product to several destinations is involved. This effect was not detected for a given market. It only appears when we account for the whole exporting strategy (i.e. accounting for all the destination markets for a given product of the firm).

TABLE 3.5 – Estimates of product innovation on export behaviour at the firm-product level in global foreign markets

Time	s_0				s_0+1				s_0+2			
	ATT	SE	Treated	Control	ATT	SE	Treated	Control	ATT	SE	Treated	Control
Probability to export												
New product	0.000	0.006	120	301	0.062***	0.011	103	267	0.107***	0.014	87	184
Soft innovation	-0.061	0.121	126	283	-0.133	0.121	108	246	-0.043	0.125	90	180
Quantity sold												
New product	0.323**	0.135	68	84	0.528***	0.120	62	78	1.049***	0.191	54	54
Soft innovation	-0.286	0.321	68	96	-0.469	0.684	59	89	-1.198	1.198	44	54
Price												
New product	0.067***	0.015	68	84	0.087***	0.014	62	78	0.083***	0.023	54	54
Soft innovation	0.127	0.210	68	96	0.051*	0.022	59	89	-0.134	0.209	44	54

***, **, * Indicate significance at the 1, 5 and 10% level. Average treatment effect is compute using our identification strategy describe above. We recall that s_0 is the time period when firm introduce product innovation (new product or soft product innovation) in a given market. s_0+1 and s_0+2 denote 1 and 2 year after s_0, respectively.

3.5.3 Firm export strategy according to geographical region : the effect of product innovation

One question remaining is that whether these gains vary according to the export destination. The destination pattern of exporters in our sample is shown in Table 3.6. We split our sample into 5 regions to reduce heterogeneity in consumer preferences : Africa, Asia, North America, South America and Europe. On average, 90% of the firms export to Europe (Western, Southern, Central and Eastern). Around a third of exporters sell their products in Asia and North America and only 20% of firms export to Africa and Latin America.

Table 3.6 – Market shares of exporters according to geographical regions, in percentage

Region	2011	2012	2013	2014	2015	2016	2017
Africa	22.881	22.689	19.835	23.009	21.552	18.852	21.311
Asia	33.051	34.746	39.831	38.136	44.068	42.373	47.458
Europe	88.983	89.831	94.068	84.746	88.136	93.220	91.525
North America	38.983	44.068	44.068	46.610	47.458	46.610	45.763
Latine America	16.102	17.797	19.492	17.797	16.949	21.186	18.644

Source : Customs dataset with authors calculation

This table clearly shows that a great majority of exporters ship their products to high-income countries (North America and Europe). It is worth noting that dairy markets are expanding worldwide with the trend varying according to market size and geographical area. FAO (2013) estimates that consumption per capita will increase between 2013 and 2023 in areas such as Asia and the Pacific (28.8%), Africa (23.9%) and to a lesser extent in Latin America and the Caribbean (12.1%) compared to Europe and North America (3.7% and 5.1% respectively). This predicted increase is due to both dynamic demography and the emergence of a middle-income class in Asia, Africa and Latin America. In this context, and because the consumption of dairy products in Europe is slowing, exports outside Europe are becoming an important issue for dairy firms. Understanding to what extent the introduction of product innovation improves company performance in a given zone is an important issue.

Table 3.7 shows the average effect of the introduction of a new product on quantity and price by region ; it appears that the average effect is positive in all cases but is heterogeneous from region to region. Comparing "Western Europe" and "Other European countries" to "North America" or "Asia" shows that the introduction of a new product has the highest impact on quantity for European countries. Conversely, the introduction of a new product has the highest impact on the price charged in Asia compared to the other areas.

TABLE 3.7 – Estimates of product innovation on export behaviour at the firm-product level according to the export region

	Western Europe	Others European Countries	North America	Asia
Price	0.016***	0.107***	0.113***	0.334***
	(0.003)	(0.008)	(0.042)	(0.050)
Quantity	1.030***	1.674***	0.707***	0.879***
	(0.057)	(0.052)	(0.074)	(0.298)

3.6 Conclusion

The objective of this article was to understand to what extend the introduction of innovation at the product level by a firm has a role on the export performances. First, we developed a theoretical model where product innovation entered as a utility shifter. The intuition behind this model was that the introduction of an innovation allows the product to be adapted to consumer preferences. This model highlighted the trade off between the increase in the marginal cost of production due to the introduction of innovation and the increase of consumer demand perceiving innovation as quality upgrading. The empirical test of the model predictions on the french dairy industry confirms that the quantity sold and the price charged on a given market (product-country pair) are significantly higher for "‘new"’ products. In other words, this empirical application confirms that the demand effect for product innovation is larger than the cost effect. Moreover, looking a the global export at the firm-product level, our results show that the introduction of a new product has a positive impact on the probability to export, the quantity sold and the charged prices one and two years after this introduction. And as expected, these results depend on the export area. The demand effect is higher in European area, whereas the charged prices are higher in Asia. Of course, all our estimates account for endogeneity issues. These results highlight one of the potential link between innovation and competitiveness at the firm-product level. In other words, the European policy in favor of innovation funding programmes and the willingness to involve small and medium-sized enterprises in that process sounds relevant. A further step would be to follow the enterprises involved in such innovation funding programmes to see whether these firms are those introducing "‘new products"’ some years afters.

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Appendix

Appendix A : Correlation between product innovation measures from GNPD and innovation measures from CIS

We used Global New Product Database for detailed information on firms' innovative activities. Then, in order to assess the relevance of our measure, we document its correlation with existing measures of innovation. For this purpose we used the Community Innovation Survey (CIS). The survey adheres to the Oslo Manual, which provides guidelines for the definition, classification, and measurement of innovation (OECD, 2005). The CIS data sets cover enterprises with more than 10 employees and participation in the survey is voluntary. The sample is updated every two years to account for exiting firms, newly founded firms, and firms that developed to satisfy the selection criteria of the sample [21]. Informations in CIS dataset is based on firms declarations. The core variables include innovation expenditures (in-house R&D expenditure, purchase of external R&D, spending on acquisition of machinery, equipment and software, acquisition of other external knowledge) and innovation outputs (indicators for product, process, organisational, marketing innovation) . A product innovation is defined in the questionnaire as follows : "New or significantly improved goods or services (Exclude the simple resale of new goods purchased from other enterprises and changes of a solely aesthetic nature)". Product innovator at year t is defined in CIS as a firm that reported that it had introduced new or significant improved good or services at year t, *t-1* or *t-2*. To test the relevance of our innovation measure, we use three waves of the Community Innovation Survey : CIS2012, CIS2014 and CIS2016.

21. For more informations read Community Innovation Survey 2016 Methodological recommendations, available on the E.U. website.

Table 3.8 – Correlation with innovation measure from CIS survey

	New product				soft innovation			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Product innovation	0.027**				0.062***			
	(0.013)				(0.016)			
Marketing innovation		0.031**				0.0.066***		
		(0.0.013)				(0.016)		
Organisational innovation			0.021*				0.000	
			(0.013)				(0.015)	
R&D dummy				0.035**				0.057***
				(0.014)				(0.017)

*$p< 0.1$,**$p <0.05$, *** $p <0.01$; regression (1) to (10) have a non-reported constant. Standard errors in parentheses are clustered at the firm-year level. Regression (1) to (8) include destinations-product-year fixed effects

Appendix B : Conversion nc8 to prodcom code

The Prodcom code is a nomenclature of "products" that the Member States of the European Community use to establish their production statistics. Each product is identified by an 8-digit PRODCOM commodity code. The first 4 digits of the code correspond to the classes of NACE 2.). The first 6 digits are the CPA code [22], while the last 2 digits show the classification of a heading within this CPA code.

prodcom list	Detailed description	cn8
10.51.11.33	Milk and cream of a fat content by weight of $\leq$ 1%, not concentrated nor containing added sugar or other sweetening matter, in immediate packings of a net content $\leq 2l$	04.01.10.10
10.51.11.37	Milk and cream of a fat content by weight of $\leq$ 1%, not concentrated nor containing added sugar or other sweetening matter, in immediate packings of a net content $> 2l$	04.01.10.90
10.51.11.42	Milk and cream of a fat content by weight of $>$ 1% but $\leq$ 6%, not concentrated nor containing added sugar or other sweetening matter, in immediate packings of a net content $\leq 2l$	0401[.20(.11 + .91)]
10.51.11.48	Milk and cream of a fat content by weight of $>$ 1% but $\leq$ 6%, not concentrated nor containing added sugar or other sweetening matter, in immediate packings of a net content $> 2l$	0401[.20(.19 + .99)]
10.51.12.10	Milk and cream of a fat content by weight of $>$ 6% but $\leq$ 21%, not concentrated nor containing added sugar or other sweetening matter, in immediate packings of $\leq 2l$	0401[.40(.10) + .50(.11)]
10.51.12.20	Milk and cream of a fat content by weight of $>$ 6% but $\leq$ 21%, not concentrated nor containing added sugar or other sweetening matter, in immediate packings of $> 2l$	0401[.40(.90) + .50(.19)]
10.51.12.30	Milk and cream of a fat content by weight of $>$ 21%, not concentrated nor containing added sugar or other sweetening matter, in immediate packings of $\leq 2l$	0401[.50(.31 + .91)]

22. At the 8-digit PRODCOM commodity code level based on 6-digit CPA (Classification of Products by Activity)

10.51.12.40	Milk and cream of a fat content by weight of $> 21\%$, not concentrated nor containing added sugar or other sweetening matter, in immediate packings of $> 2l$	0401[.50(.39 + .99)]
10.51.21.30	Skimmed milk powder (milk and cream in solid forms, of a fat content by weight of $\leq 1,5\%$), in immediate packings of $\leq 2,5kg$	0402[.10(.11 + .91)]
10.51.21.60	Skimmed milk powder (milk and cream in solid forms, of a fat content by weight of $\leq 1,5\%$), in immediate packings of $> 2,5kg$	0402[.10(.19 + .99)]
10.51.22.30	Whole milk powder or full cream powder (milk and cream in solid forms, of a fat content by weight of $> 1,5\%$), in immediate packings of $\leq 2,5kg$	0402[.21(.11 + .91) + .29(.11 + .15 + .91)]
10.51.22.60	Whole milk powder or full cream powder (milk and cream in solid forms, of a fat content by weight of $> 1,5\%$), in immediate packings of $> 2,5kg$	0402[.21(.18 + .99) + .29(.19 + .99)]
10.51.30.30	Butter of a fat content by weight $\leq 85\%$	0405[.10(.11 + .19 + .30 + .50)]
10.51.30.50	Butter of a fat content by weight $> 85\%$ and other fats and oils derived from milk (excluding dairy spreads of a fat content by weight $< 80\%$)	0405[.10(.90) + .90(.10 + .90)]
10.51.30.70	Dairy spreads of a fat content by weight $< 80\%$	0405[.20(.10 + .30 + .90)]
10.51.40.30	Unripened or uncured cheese (fresh cheese) (including whey cheese and curd)	0406[.10(.30 + .50 + .80)]

10.51.40.50	Grated, powdered, blue-veined and other non-processed cheese (excluding fresh cheese, whey cheese and curd)	0406[.20 + .40(.10 + .50 + .90) + .90(.01 + .13 + .15 + .17 + .18 + .21 + .23 + .25 + .29 + .32 + .35 + .37 + .39 + .50 + .61 + .63 + .69 + .73 + .74 + .75 + .76 + .78 + .79 + .81 + .82 + .84 + .85 + .86 + .89 + .92 + .93 + .99)]
10.51.40.70	Processed cheese (excluding grated or powdered)	0406[.30(.10 + .31 + .39 + .90)]
10.51.51.04	Condensed or evaporated milk, unsweetened	0402[.91(.10 + .30 + .51 + .59 + .91 + .99)]
10.51.51.08	Condensed or evaporated milk, sweetened	0402[.99(.10 + .31 + .39 + .91 + .99)]
10.51.52.41	Curdled milk, cream, yogurt and other fermented products	0403[.10(.11 + .13 + .19 + .31 + .33 + .39 + .51 + .53 + .59) + .90(.13 + .19 + .31 + .33 + .39 + .53 + .59 + .61 + .63 + .69 + .71 + .73 + .79)]
10.51.52.45	Flavoured liquid yoghurt or acidified milk (curdled milk ; cream ; yoghurt and other fermented products flavoured or containing added fruit ; nuts or cocoa)	0403[.10(.91 + .93 + .99) + .90(.91 + .93 + .99)]
10.51.52.63	Buttermilk powder	0403 90 11

10.51.52.65	Buttermilk	0403 90 51
10.51.53.00	Casein and caseinates	3501[.10(.10 + .50 + .90)]
10.51.54.00	Lactose and lactose syrup (including chemically pure lactose)	1702[.11 + .19]
10.51.55.30	Whey and modified whey in powder, granules or other solid forms, whether or not concentrated or containing added sweetening matter	0404[.10(.02 + .04 + .06 + .12 + .14 + .16 + .26 + .28 + .32 + .34 + .36 + .38)]
10.51.55.60	Whey and modified whey in liquid or paste forms ; whether or not concentrated or containing added sweetening matter	0404[.10(.48 + .52 + .54 + .56 + .58 + .62 + .72 + .74 + .76 + .78 + .82 + .84)]
10.51.56.00	Products consisting of natural milk constituents, n.e.c.	0404[.90(.21 + .23 + .29 + .81 + .83 + .89)]

Appendix C : Estimating product quality

The estimation of an index of quality at the firm-product level is challenging. With the production dataset at the firm-product level and the custom dataset at the firm-product-destination level, we estimate quality according to Khandelwal's definition (Khandelwal et al., 2013). We consider a global economy consisting of a collection of destination countries j. In each country, consumers allocate their revenue to the different varieties of each product k. Our definition of product categories follows the structure of European production data (PRODCOM dataset). A variety v is defined as a unique combination of a producing firm f and a product k and market m is defined as a unique combination of a destination country j and a product k. Consumers are assumed to have identical Cobb-Douglas preferences over differentiated products $U_j = \prod_k U_{jk}^{\delta_{jk}}$ where U_{jk} is a strictly increasing and strictly concave upper-tier utility function that is twice continuously differentiable in all its arguments and δ_{jk} is the standard expenditure shares with$\sum_k \delta_{jk} = 1$. The utility resulting from the consumption of each differentiated product is given by :

$$U_{jk} = \left[\sum_i \int_{\Omega_{ik}} (\lambda_{ijk}(v) q_{ijk}(v))^{\frac{\sigma-1}{\sigma}} \, \mathrm{d}v \right]^{\frac{\sigma}{\sigma-1}}. \tag{3.18}$$

Where $q_{ijk}(v)$ is the quantity purchased for each variety of product k, Ω_{ik} is the set of varieties of product k available in country j and produced in country i, σ is the substitution elasticity between varieties. The term $\lambda_{ijk}(v)$ can be interpreted as the quality perceived by consumers living in country j for products k and produce in country i. The term $\lambda_{ijk}(v)$ also captures the fact that consumer j could value differently varieties of the same quality according to consumer preferences. Therefore, products are both horizontally and vertically differentiated. More formally, we assume that :

$$\lambda_{ijk}(v) = \exp(\theta_{ik}(v) \varepsilon_{ijk}(v)) \tag{3.19}$$

Where $\theta_{ik}(v)$ reflects consumers' willingness-to-pay (or product quality) for each variety of product k ; and $\varepsilon_{ijk}(v)$ is an index of demand reflecting the taste of consumers in country j for each variety of product k. The equilibrium demand for variety v of product k in country j is such that :

$$q_{ijk}(v) = E_{jk}(P_{jk})^{\sigma-1}(\theta_{ik}(v)\varepsilon_{ijk}(v))^{\sigma-1}(p_{ijk}(v))^{-\sigma} \tag{3.20}$$

where E_{jk} is the amount of income allocated to the differentiated product k in country j and P_{jk} is the price index in country j associated with product k. To estimate the quality perceived by consumers living in country j for a variety v of a product k from France [23], λ_{fjk}, we use the methodology developed in Khandelwal et al. (2013). For a given price in a firm-destination-product triplet, a variety with a higher quantity is assigned higher quality. The quality for each firm-product-destination observation is estimated using the following equation,

$$\ln q_{fjk} = \sigma \ln p_{fjk} + \mathbf{FE}_{jk} + \eta_{fjk} \tag{3.21}$$

23. For a given product, variety v is supplied by a single firm.

with $\mathbf{FE}_{jk} = \ln\left[E_{jk}(P_{jk})^{\sigma-1}\right]$. We consider $\sigma = 5.11$ which corresponds to the median elasticity estimates associated with dairy product reported in Ossa (2015). Hence, estimated quality perceived by foreign consumers is $\ln\hat{\lambda}_{fjk} = \hat{\eta}_{fjk}/(\sigma-1)$. Then θ_{fk} is the firm-product-specific component of the quality perceived, that is common to all markets served (including foreign and domestic markets). We use two sources of data for estimation. The first source is firm-level trade data collected by French customs administration. These data provide a comprehensive record of the annual values and quantities exported by French firms from 2011 to 2017. Trade flows are disaggregated at the firm, country and eight-digit product category of the combined nomenclature (NC8). Information on the quantity sold on the domestic market was drawn from the PRODCOM dataset. The, latter is the most comprehensive annual business survey conducted by the French National Institute of Statistics and Economic Studies (INSEE) and covers product sales in the manufacturing industry. PRODCOM data are a comprehensive record of annual production sold by value and quantity by French firms from 2011 to 2017. Production is disaggregated at the firm and eight-digit product category. The quantity sold on the domestic market is then defined as the difference between the production sold and the quantities sold in all foreign countries [24].

Fixed effect estimation was used to obtain our product quality measurements, i.e. the quality perceived that is common to all markets served by a firm. Each firm-product combination (f, k) and c each product-country combination (k, j) is indexed by i. Product quality is then estimated using the following equation,

$$\ln\hat{\lambda}_{i,c} = \beta\text{Innov}_{i,c} + \alpha_i + \alpha_c + \varepsilon_{i,c} \tag{3.22}$$

and $\ln\hat{\theta}_{fk} = \hat{\alpha}_i = \overline{\ln\hat{\lambda}_i} - \hat{\beta}_{\text{FE}}\overline{\text{Innov}}_i$. For firm-product pair which is only observe in home country (i.e. non-exporters), product quality is non-identified $\ln\hat{\theta}_{fk} = \hat{\alpha}_i + \hat{\varepsilon}_{i,c}$. However, in this study, we are only interested in firms that have also supplied their products in the foreign market.

24. The eight-digit product category in prodcom and custom dataset is not defined in the same way. See appendix B for more informations.

Appendix D : Table

TABLE 3.10 – Propensity score estimation, RE logit

	Introduction of new product (Panel A)		**Introduction of soft innovation (Panel B)**	
Export status (Z_{fjk,s_0-1})	-0.272	(0.334)	-0.110	(0.369)
Quality ($\ln\theta_{fk,s_0-1}$)	0.916***	(0.356)	0.952***	(0.361)
Rank (Rank_{fk,s_0-1})	-1.686***	(0.358)	- 1.725***	(0.371)
Productivity (φ_{f,s_0-1})	0.770***	(0.161)	1.195***	(0.170)
Size (Size_{fjk,s_0-1})	- 0.038	(0.067)	- 0.010	(0.064)
product-country pair dummy	Yes		Yes	
Times dummy	Yes		Yes	
σ_u	1.177***	(0.217)	1.061***	(0.216
ρ	0.296***	(0.077)	0.255***	(0.077)
Log Likelihood	-432.549		-359.470	
Number of observation	1,081		1,015	

Notes : ***,** and * indicate significance on a 1%, 5% and 10% level, respectively. Estimations are based on Gauss–Hermite quadrature approximations using 12 quadrature points. Estimations also includes average of covariates and a constant term.

Table 3.11 – Variable description

Variables	Detailed description	Dataset
Quantity	Quantity sold by the firm f for product k in country j at the date t (in log.)	Custom
Price	Unit value of product k for firm f in country j at the date t (in log.)	Custom
Product quality	Quality of product k produced by firm f at the date t	Custom PRODCOM
Product rank	Rank of product k in firm f. Rank takes the value 0 if the product k is the firm core-product and 1 otherwise	PRODCOM
Size	The number of product commercialized by firm f	PRODCOM
Productivity	Total sales of firm f divided by the size at the date t (in log.)	PRODCOM
New product	Take the value one if firm f has introduced new product for good k in country j at the date t and 0 otherwise	GNPD
Soft innovation	Take the value one if firm f has introduced soft product innovation for good k in country j at the date t and 0 otherwise	GNPD

Chapitre 4

The role of product innovation on the learning by exporting proccess : An empirical investigation for French dairy firms [1]

4.1 Introduction

The relationship between firm's performance and exports has been largely explored in the literature. Since the seminal work of Bernard and Jensen (1995), many studies have shown the higher performance characteristics (e.g. higher wage, higher productivity, greater capital intensity, more workers, etc...) of exporting firms relative to non-exporters. According to these studies, two mechanisms can explain the strong positive correlation between firms' exports status and their performance. The first is related to self-selection ; this mechanism is closely related to the hypothesis of sunk cost in entering in the export market (Dixit, 1989; Krugman, 1989; Baldwin, 1990; Roberts and Tybout, 1997). In accordance with these findings, Melitz (2003) provides a theoretical framework for modeling firms' export decisions, in which heterogeneous firms face sunk costs of entry and uncertainty concerning their productivity. The model shows that only the most productive firms enter the export market. The self-selection hypothesis induces that the causality link is tied to the productivity to exporting. [2]

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

The second mechanism is learning by exporting (hereafter, LBE).[3] According to De Loecker (2013), LBE simply refers to the mechanism whereby firms improve their productivity after entering export markets. In a similar way, Castellani (2002) refers to LBE as a change in the stochastic process governing firms' productivity that is induced by export behaviour. However, not all exporting effects on productivity refer to LBE mechanism. For example, the exploitation of economies of scale from the largest markets may induces static efficiency gains (Castellani, 2002; Silva et al., 2012). Hence, LBE is not simply the outcome of the presence in the export market. Some authors, such as Serti and Tomasi (2008), Andersson and Lööf (2009) and De Loecker (2013), mention that experience and commitment of exporters or buyer-seller relationships are key drivers of LBE mechanism. Silva et al. (2012) suggest that, LBE process is based on fierce competition, contacts with foreigner buyers, and new problems that challenge technological development and can produce dynamic efficiency gains. The detection of LBE effects is important for the design of economic policy. Indeed, if LBE really exists, then governmental support to encourage firms to export is justified as an attempt to internalize positive externalities (Silva et al., 2012).

Empirical studies about LBE mechanism provided mixed results. While some studies tend to show evidence of LBE effect (Biesebroeck, 2005; De Loecker, 2007; Crespi et al., 2008; Lileeva and Trefler, 2010; De Loecker, 2013), other studies fail to find evidence of such a mechanism (Clerides et al., 1998; Bernard and Jensen, 1999; Aw et al., 2000; Delgado et al., 2002; Castellani, 2002; Wagner, 2002). To identify the learning mechanism, the literature has developed many empirical approaches.[4] However, a common feature of these approaches is that they analyze the causal effect of exports on productivity. A drawback with these approaches is that they analyze LBE in a reduced way. As suggested by Silva et al. (2012), LBE should be measured using information on the specific mechanisms through which firms acquire knowledge in order to become more productive. Indeed, if exporting does affect learning, and learning then affects productivity, it would be valuable to test this relationship directly using data on exports, learning, and productivity (Crespi et al., 2008).[5] According to De Loecker (2013), investment in marketing, upgrading in product quality, innovation activities, or dealing with foreign buyers can be channels through which LBE mechanism operates. This paper focuses on firms' innovation activities as a learning-by-exporting mecanism's channel.

For this purpose, we assess two relationships. The first relationship goes from exports to innovation activities (e.g. R&D investment). The relationship between export and R&D investment

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

4. Table 4.9 in Appendix B summarizes these approaches.

5. The difficulty in accessing learning data hinders that procedure. In our knowledge, only Crespi et al. (2008) use a direct measure of learning (from Community Innovation Survey data) to analyze LBE mechanism.

can be explained by endogenous growth theories. Grossman and Helpman (1991) show that trade reveals information to exporters and give them access to the knowledge stocks of their trading partners. Exporters are more likely to invest in R&D than domestic firms because they are exposed to knowledge inputs not available to incumbent firms serving the domestic market. According to Salomon and Shaver (2005), export provides at least two types of knowledge : markets and technological knowledge. First, consumer preferences in international markets (market knowledge) may differ from those of their domestic counterparts. Thus, exposure to foreign markets can provide additional information to exporters not available in domestic market. In addition, Clerides et al. (1998) argue that, exposure to export markets forces firms to alter and customize their product range to the needs of different international markets. More investments are needed to understand and assimilate these additional informations. Second, for the technological knowledge, the idea is that being exposed to a richer source of technology on export markets could lead firms to improve their knowledge base. Empirical studies show positive effect of firm's export decisions on R&D investment. For instance, Aw et al. (2007) use Taiwanese data to analyze a firm's decisions to export and invest in R&D. They find that exporters need to produce effective R&D in order to generate efficiency gains. Additionally, Girma et al. (2008) find that previous export experience enhances the innovative capability of Irish firms. Such results are also found in Blind and Jungmittag (2004), Salomon and Shaver (2005), Salomon and Jin (2008), Salomon and Jin (2010).

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

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

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

4.2 Literature review

This section summarises the important empirical findings concerning the determinants of exports, investment in R&D, innovation output and productivity.

4.2.1 Exports participation

The new trade theories highlight the presence of firm heterogeneity as explanations of participation in export markets, based on the established link between productivity and the fixed costs of entering export markets. This leads to an expectation of a positive link between productivity and export. For instance, following theoretical models of entry and exit, Melitz

(2003) shows that only the most productive firms self-select into exporting, since only firms with an efficiency level above a certain threshold are able to overcome the fixed costs associated with entry into the export market. Several empirical studies find a strong correlation between firms' propensity to exports and their productivity. Wagner (2007) and Greenaway and Kneller (2007) provide a review on this extensive literature.

The relationship between size and firms' decision to export remains one of the most analyzed relationships in economic and business literature (Wakelin, 1998; Bernard and Wagner, 2001). The assumption that firm size is positively associated with probability to export is often taken for granted and its acceptance has led public sector officials to focus on finding ways to improve the export activities of small firms. There are some theoretical reasons for this. First, there is an abundant theoretical literature that internationalization requires appropriate resources. Small firms have a resource disadvantage compared to large firms and may therefore not be able to cover fixed export costs. Another explanation lies with the firms' growth life cycle. According Bonaccorsi (1992), most firms will undertake growth within their domestic market first. However, at some point, the opportunities for domestic growth will become limited forcing firms to either stagnate or diversify their geographic market base. In addition, risk perception may explain the positive link between firm export behaviour and size. Decision-makers in small firms should a priori perceive higher risk in international activities, due to the lack of appropriate information. Finally, size can be view as a proxy for several effects. Because of scale economies, larger firms may have lower marginal costs, which would increase the probability of exporting. The largest firms have more resources for incurring entry costs into foreign markets.

Others factors, such as technological capabilities (Bernard and Jensen, 2004; Verhoogen, 2008; Brambilla et al., 2012), market structure (Das, 1982; Zhao and Zou, 2002; Clougherty and Zhang, 2009), ownership structure (Brainard, 1997; Bernard and Jensen, 2004), import status, capital intensity (Bernard and Jensen., 1997; Bernard and Jensen, 2004; Van Biesebroeck, 2005; De Loecker, 2007; Ma et al., 2014) and spillover (Aitken et al., 1997; Clerides et al., 1998; Bernard and Jensen, 2004) can also affect export markets participation.

4.2.2 Innovation input

Besides the export status, an important determinant explaining innovation activities is found in Schumpeter (1942), who states that large firms in concentrated markets have an advantage in innovation. Thus, firm size is generally considered as an important determinants of innovation activities. There are several explanations as to why large firms are more likely to invest in innovation activities than small firms. First, innovation activities involve large fixed costs, and these can only be covered by large firms. Second, there may be economies of scale and scope in the innovation production function. Third, large diversified firms are in a better position to exploit unforeseen innovations. Fourth, large firms can undertake many activities at any time and hence spread the risks of innovation. Fifth, large firms have better access to external finance. Many empirical studies test and find a significant effect of firms' size on innovation expenditures activities (Worley, 1961; Hamberg, 1964; Scherer, 1965; Bound et al., 1984; Cohen et al., 1987).[6] Furthermore, Cohen and Klepper (1996) suggest that within an industry and among R&D performers, R&D rises monotonically with firm size. More recently, empirical studies suggest a U-shaped relationship (Bound et al., 1984; Felder et al., 1996).

Another important determinant of innovation investments is market structure. According to Schumpeter (1942), ex ante product market power stimulates innovation activities because it increases monopoly rents from innovation and reduces the uncertainty associated with excessive rivalry which tends to reduce the incentive to innovate. Furthermore, market power increases firms' profits and provides firms with internal funds necessary to innovate. This Schumpeterian hypothesis is generally formulated as follow : monopoly rents boost firms' efforts to innovate. Studies such as Horowitz (1962), Mansfield (1963), Kraft (1989), Crepon et al. (1998), Czarnitzki et al. (2014) or even Hashmi and Van Biesebroeck (2016) provides empirical evidence supporting this hypothesis. In endogenous growth models, Romer (1990), Aghion and Howitt (1992) and Grossman and Helpman (1991), also suggested a negative relationship between competition pressure and innovation activities. On the other hand, Arrow (1962) argues that a monopolist's incentive to innovate is less important for competitive firm, due to the monopolist's financial interest in the status quo. Arrow states that the preinvention monopoly power acts as a strong disincentive to further innovation. Hence, product market competition spurs innovation. Empirical studies such as Porter (1990), Geroski (1990), Baily and Gersbach (1995), Nickell (1996), Blundell et al. (1999), Symeonidis (2002), and Beneito et al. (2015) support this point of view. Futhermore, Aghion et al. (2005) argued in favour of and find evidence of an inverted-U relationship between competitive pressure and innovation. They develop a model where competition may increase the incremental profit from innovating ("escape-competition effect"), but competition may also reduce innovation incentives for laggards firms ("Schumpeterian effect"). The balance between these two effects changes between low and high levels of competition, generating an inverted-U relationship. Tingvall and Poldahl (2006), Tingvall and Karpaty (2011), Polder and Veldhuizen (2012), Askenazy et al. (2013), Bos et al. (2013) and Hashmi (2013) provide empirical evidence of this inverted-U relationship between competitive pressure and innovation.

Some others characteristics can affect investment in innovation. Cohen (2010) summarizes informations about firm and industry characteristics. Firm characteristics which have been

6. See Cohen and Levin (1989), Cohen and Klepper (1996), Ahn (2002), Klette and Kortum (2004) and Cohen (2010) for survey of empirical studies testing the Schumpeter hypotheses.

found to explain innovation activities are : cash flow (Caves et al., 1980; Antonelli, 1989; Hao et al., 1993; Himmelberg and Petersen, 1994; Hall, 2002), degree of diversification (Scherer, 1965; Grabowski, 1968; Mceachern and Romeo, 1978; Scott and Pascoe, 1987; Henderson and Cockburn, 1996; Crepon et al., 1998), ownership structure (Harris, 1991; Love et al., 1996; Bishop and Wiseman, 1999; Love and Roper, 2001), firm's age (Balasubramanian and Lee, 2008; Cucculelli, 2017) and technological opportunity (Scherer, 1965, 1982; Pakes and Griliches, 1984; Scott, 1984; Jaffe, 1988; Geroski, 1990; Jaffe et al., 1993; Klevorick et al., 1995; Adams et al., 2003; Leiponen and Drejer, 2007). Industry characteristics may also be important for innovation activities. Industry characteristics include demand (Schmookler, 1962, 1966; Stoneman, 1979; Kleinknecht and Verspagen, 1990; Geroski and Walters, 1995; Acemoglu and Linn, 2004; Cerda, 2007), and appropriability (Taylor and Silberston, 1973; Mansfield, 1981; Cohen and Walsh, 2000).

4.2.3 Innovation output

Since the measures of innovation inputs have long been considered as measures of innovation output, few studies have distinguished innovation input from innovation output, implying that the factors determining innovation input are also valid for the innovation output. However, innovation efforts are presented as the most traditional determinants of firms' innovative capacity. Innovation effort is related to the innovation output by the knowledge production function (Pakes and Griliches, 1984), where R&D is considered as an input. Indeed, investment in innovation is the main mechanism for developing technological skills and new products (see Crepon et al. (1998); Mairesse et al. (2005); Griffith et al. (2006); Baum et al. (2016); Peters et al. (2018) and others). [7] External and internal knowledge can also be considered as determining factors of innovation success. According to Cohen and Levinthal (1989), firms' absorptive capacities denote the firms' ability to identify, assimilate and exploit knowledge from their environment. Some empirical findings show evidence of the relationship between internal knowledge and innovation. For instance, Love and Roper (2001) and Klomp et al. (2001) shows positive impact of internal knowledge on innovation output, for German and Dutch firms respectively. Prior findings show that the uncertainty and complexity of innovation processes have increased, the costs for the development of new products and processes have risen, and product life cycles have shortened (Peters, 2008). These evolutions have intensified the need for external knowledge. Since only a small share of firms are engaged in R&D, the transmission of technology becomes a crucial element in firm's development. External knowledge can be split up into formal cooperation (Klomp et al., 2001; Siedschlag and Zhang, 2015) and industrial sources (Crepon et al., 1998; Peters, 2008; Baum et al., 2016).

7. For a detailed review on this links, see Hall (2011), Mohnen and Hall (2013) .

4.2.4 Productivity

There is an abundant literature on the factors that explain why some firms are more productive than others (see Bartelsman et al. (1998) for a detailed review of the determinants of productivity). Theoretical models of human capital and growth are built around the hypothesis that the knowledge and skills embodied in humans directly raise productivity and increase the ability to develop and to adopt new technologies. In order to explore its implications and open the way for its empirical testing, this basic hypothesis can be formalized in different ways. The simplest one involves introducing the stock of human capital as an additional input in the production function. The second possibility is to include the stock of human capital in the model as a determinant of the rate of technological progress. Several studies provide empirical evidence for correlation between technological capabilities and productivity at the firm-level (Nelson et al., 1981; Barron et al., 1987; Bishop, 1994; Hall and Mairesse, 1995; Black and Lynch, 1996; Crepon et al., 1998; Bartelsman et al., 1998; Benavente, 2006; Baum et al., 2016). Others factors relate to managerial abilities and management practices (Lichtenberg and Siegel, 1990; Baily et al., 1990; Bloom et al., 2012), regulation (Olley and Pakes, 1996), and international exposure (Doms and Jensen, 1998; De Loecker, 2007, 2013; Siedschlag and Zhang, 2015; Peters et al., 2018)

4.3 Econometric methodology and empirical implementation

This section presents an econometric model to show how firm's export decision affect productivity level through innovation activities. More specifically, the mechanism we model is that the firm's decision to export spurs the firm's investment in innovation, which in turn contributes to their innovation output. Ultimately, high innovation output (intensity) shifts the distribution of the productivity. The firm chooses to participate in export markets if the expected payoff resulting from this exports-productivity process is positive. This expected payoff will vary across firms with differences in their characteristics, such as their past productivity and size.

Firms export in order to increase their investment in innovation, which in turn may affect developement of new product, and therefore rise their productivity. Our model therefore includes four components, the first three components are those of the CDM model. The research relation linking innovation investment to exports, the innovation equation relating innovation investment to innovation output measures, and the productivity equation relating innovation output to productivity. The last component link export markets participation to its determinants. This last component takes into account that export activity is not exogenous to the innovation process. The next subsections discuss each of these components in more details.

4.3.1 Exports participation equation

To identify and quantify factors that increase the probability to export, we estimate a reduced linear version of the export participation choice described by equations (4.1) and (4.2) following a similar approach to Roberts and Tybout (1997) and Bernard and Jensen (2004). [8] Following these authors, a firm will decide to export if the expected revenue from export is greater than the cost it faces. This condition can be specified formally as the following binary choice model of exports participation, where the export profits of firm i at time t are expressed as a reduced function of the firm's and market characteristics :

$$d_{it} = \mathbb{1}[d^*_{it} \geq 0] \quad (4.1)$$

$$d^*_{it} = \beta'_1 x_{1,it} + \eta_{1,i} + \varepsilon_{1,it} \quad (4.2)$$

where $t = 1, \ldots T_i$, $i = 1, \ldots N$ and $\mathbf{1[\ldots]}$ is an indicator function that takes on the value 1 if the expression between square brackets is true and 0 otherwise. Thus, d_{it} denotes the export status of firm i at time t, taking the value 1 when the firm exports and 0 otherwise. $\eta_{1,i}$ is an individual effect which captures time-invariant unobserved firm heterogeneity (such as managerial ability) that may affect the export decision ; $\varepsilon_{1,it}$ is the error term capturing unobserved factors. The vector x_1 further denotes other firm exogeneous characteristics influencing export profits and thus the firm decision to export. The vector β'_1 captures the effects of firms characteristics on exports participation.

In accordance with the litterature review, we include firm characteristics such as firm size and importation as explanatory variables. Firm size is measured by the number of employees (*SIZE*) and market share (*MSHARE*) ; and importation is measured by the firms' import status (*IMPORT*). We expect a positive effect of *SIZE* and *IMPORT* on the probability to export. As mentioned in the previous section, the literature on export participation emphasises that certain characteristics, like ownership or export externalities are of crucial importance to explain export decision. The firm's ownership structure is captured by two dummies variables : *GROUP* which takes the value 1 if on wehhter the firm is part of a French group and 0 otherwise ; *FOREIGN* which takes the value 1 if on whether the group's headquarter is located abroad and 0 otherwise. We expect the dummies variables *FOREIGN* and *GROUP* to have a positive impact on the probability to export. We also include in our specification the capital intensity measured by the tangible asset per employee (*CAPINT*) ; the market structure measured by the Herfindahl-Hirschman index (*HERFIN*) and export's externaties (*REGEXT*) ; and firm age (*AGE*) measures firm's experience in terms of the number of years since the creation of the firm.

8. More precisely, Roberts and Tybout (1997) develop a dynamic discrete choice model of export behavior that separates the roles of profit heterogeneity and sunk entry costs in explaining firms' export status.

4.3.2 The innovation input equation

In CDM model, the first equation explains firms' investments in innovation activities. the literature identifies R&D as the most relevant input in the innovation process. Therefore, the first equation of the CDM model is known as the research equation. Several studies have shown the strong relationship between investments in R&D and innovation output in manufacturing industries. [9] Let us assume that a latent variable for fims investment in innovation activities k_{it}^*, depends on firm export statuts, d_{it}, some exogeneous observable characteristics, x_2, an unobserved time-constant effect $\eta_{2,i}$, and an error term $\varepsilon_{2,it}$, that is

$$k_{it} = k_{it}\mathbb{1}[k_{it}^* \geq c] \quad (4.3)$$

$$k_{it}^* = \alpha_2 d_{it} + \beta_2' x_{2,it} + \eta_{2,i} + \varepsilon_{2,it} \quad (4.4)$$

where $t = 1, \ldots T_i$, $i = 1, \ldots N$ and $\mathbf{1[\ldots]}$ is an indicator function that takes on the value k_{it} if the expression between square brackets is true and 0 otherwise ; β_2' is the vector of the coefficients of interest, and α_2 is the semi-elasticity of investment in innovation relative to export status. We assume that k_{it}^* is observed if k_{it}^* is above a given threshold c. We can normalize the threshold to zero since x_2 contains an intercept term.

In accordance with the Schumpeterian tradition, we include firm size (*SIZE* and MSHARE) and market structure (*HERFIN*) as explanatory variables. We also include some firm characteristics, such as cashflow, R&D spillover and firm lifecycles. The cashflow are proxied by the capital intensity (*CAPINT*) and the profit margin which is measured by the ratio between value-added and turnover (*PMARGIN*). The claim that cashflow affects investment in capital knowledge constitutes one of Schumpeter's arguments for an advantage of large firm (Cohen, 2010). R&D spillover is measured by the percentage of R&D performers in a specific region (*RDSPILL*) and firm lifecycles is captured by firm age (*AGE*). In addition, firm-specific variables reflecting whether the firm received public funding (*PUBLIC*), whether the firm is part of a group (*GROUP*) and whether the group's headquarter is located abroad (*FOREIGN*) are included. As mentionned in Peters (2008), firms which are part of a group may have easier access to external capital in a world of capital market imperfections. However, we expect a negative link between foreign-owned and innovation investment. Howells (1984) argue that innovation activities usually take place at or in close proximity to the firms' headquarters. As mentioned above, market or industry characteristics like demand, technological opportunities and effective appropriability conditions may be important for innovation activities. These concepts are very complex and cannot be readily observed since managers can hardly be surveyed to give reasonable direct estimates of them. Hence, to capture these effect we include a sector-specific components.

9. For reviews on this extensive literature, we refer to Hall (2011) and Mohnen and Hall (2013).

4.3.3 The innovation output equation

The third equation explains the innovation output measured by the number of new products launched, n_{it}. We assume that the count, n_{it}, is generated according to the following conditional cumulative distribution function,

$$\mathbb{P}(n_{it}|\eta_{3,i}) = \frac{\mu_{it}^{n_{it}} \exp(-\mu_{it})}{n_{it}!} \tag{4.5}$$

where $\mathbb{P}(\cdot)$ denotes the 'probability of,' $\eta_{3,i}$ is a random variable representing unobserved individual effect, and $\mu_{it} \equiv E(n_{it}|k_{it}, x_{3,it}, \eta_{3,i})$. We use a log-linear model for specifying the conditional mean of n_{it} given $k_{it}, x_{3,it}, \eta_{3,i}$:

$$\ln(\mu_{it}) = \alpha_3 k_{it} + \beta_3' x_{3,it} + \eta_{3,i} \tag{4.6}$$

To explain the innovation output, x_3 contains all variables included in the vectors x_2, except R&D spill-over (*RDSPILL*) and public support *(SUPPORT)*. We assume that R&D spill-over and public support do not enter directly in the innovation equation, but only indirectly through innovation investment. This imposes some *a priori* structure on the model, which seems reasonable enough, and which helps identification by allowing us to consider the R&D spill-over and public support as instruments.

An important feature of our new product data is that it includes a large number of zeroes ; 75% of our sample.[10] There are many reasons why some firms do not launch any new products. There may be reasons for not starting innovation activities at all, or factors that slow innovation activity or have a negative effect on expected results. These include cost factors (risks, higher cost, financial constraints), knowledge factors (technological capabilities, lack of information on technology or lack of information on markets), market factors (uncertain demand for innovative goods), and legal factors (regulations or tax rules). In our specification, we have included value added and profit margin as a proxy for cash flow to take into account the effects of financing constraints. However, these two variables are not sufficient to account for the importance of the factors limiting innovative activities of companies ; and this may be a potential source of endogeneity in our model. Assuming that all factors that hinder firms' innovation activities are summarized in a single heterogeneous term, $\varepsilon_{3,it}$; then the expression (4.6) can be rewritten as follow :

$$\ln(\mu_{it}) = \alpha_3 k_{it} + \beta_3' x_{3,it} + \eta_{3,i} + \varepsilon_{3,it} \tag{4.7}$$

10. This nonnegligeable number of zeroes, is also observed by others authors on patent data. For instance, Bound et al. (1984) they represent about 60% of their sample using U.S.A data. Crepon and Duguet (1997) observe that 73% their sample includes panel-year firms with zero patent applications using French data ; similarly, Vancauteren et al. (2017), observe for the Netherland that zero patent firms represent 79% of their sample.

where ε_3 is assumed to have a normal distribution with zero mean and variance $\sigma^2_{\varepsilon_3}$.[11] Winkelmann (2008) points out a statistical reason for the normality assumption. If an error captures the effect of omitted regressors, we can establish normality by the central limit theorem.

4.3.4 The Productivity equation

The last stage in the CDM framework, is the productivity equation. This equation explains the output production as a function of production inputs. An augmented Cobb-Douglas is generally used as production function. Equation (4.6) is the log-transformed production function and describes the link between productivity, y_{it}, and knowledge capital proxied by the product innovation output, as well as some other exogeneous explanatory variables includes in the vectors, $x_{4,it}$:

$$y_{it} \quad = \quad \alpha_4 \ln(n_{it}) + \beta_4' x_{4,it} + \eta_{4,i} + \varepsilon_{4,it} \tag{4.8}$$

The parameters of interest are α_4 and β_4' ; they can be interpreted as output elasticities of the corresponding input factors. $\eta_{4,i}$ is the time-invariant unobserved individual effects and $\varepsilon_{4,it}$ is the error term. The vector of explanatory variables, $x_{4,it}$, include ownership structure (*GROUP* and *FOREIGN*) and international exposure (*IMPORT*). To control for regulation effect, we include a sector-specific component.

4.3.5 Estimation strategy

Taken together, the export market participation, innovation investment, innovation output and productivity equations form a non recursive system :

$$\begin{cases} d_{it} & = \mathbb{1}[\beta_1' x_{1,it} + \eta_{1,i} + \varepsilon_{1,it} \geq 0] \\ k_{it} & = k_{it}\mathbb{1}[\alpha_2 d_{it} + \beta_2' x_{2,it} + \eta_{2,i} + \varepsilon_{2,it} \geq c] \\ \mu_{it} & = \exp\left(\alpha_3 k_{it} + \beta_3' x_{3,it} + \eta_{3,i} + \varepsilon_{3,it}\right) \\ y_{it} & = \alpha_4 \ln(n_{it}) + \beta_4' x_{4,it} + \eta_{4,i} + \varepsilon_{4,it} \end{cases} \tag{4.9}$$

However, the specificity of this model is the specific nature of each variable of interest : export decision, d_{it}, is a dummy, investments in innovation,k_{it}, are censored data and new products,

11. Another reason to include an heterogeneous term is that we use product launch data (GNPD) to have informations on new products. GNPD only contains informations on product characteristics. There is no firm's identification number that would allow us to properly merge this dataset with other datasets. We tried to find firm's identification numbers, but it proved impossible to find out all the firms' identification numbers. In fact 95% of new product introduced were traced to France. Therefore, there are two kinds of zeroes : first, when a firm has launched a new product, but this has not been registered, or has been incorrectly registered in GNPD, and second, when firm has not introduced any new products. As in Hausman et al. (1984) and Crepon and Duguet (1997), we have only a proportion, p_{it}, of firms' new products ; then if the observed number of new products, n_{it}, given the real number of new product, n^*_{it}, is distributed as a binomial variate with probability, p_{it}, and the real number of new products is Poisson distributed with parameter $\exp(\alpha_3 \exp(k_{it} + \beta_3' x_{3,it} + \eta_{3,i})$, then the observed number of new products is Poisson distributed with parameter $\alpha_3 \exp(k_{it} + \beta_3' x_{3,it} + \eta_{3,i} + \ln(p_{it}))$. Since $\ln(p_{it})$ is unknown, it constitutes a source of heterogeneity.

n_{it}, are count data. In addition, one possible drawback with this system is that explanatory variables are often determined jointly with the dependent variable, i.e. they are not exogenously given. [12] Indeed, the export status is endogeneous in the innovation input equation, investment in innovation is endogenous in innovation output equation, and new product is endogeneous in the productivity equation. Thus, for each of the equations taken separately, we cannot assume that the explanatory variables and their respective disturbance are uncorrelated. To overcome the endogeneity problem, the system of 4 equations are jointly estimated, allowing for a correlation between all these four processes. The variance-covariance matrices for the error terms, $\boldsymbol{\Sigma}_{\boldsymbol{\varepsilon}}$, and individual effects, $\boldsymbol{\Sigma}_{\boldsymbol{\eta}}$, takes the following forms :

$$\boldsymbol{\Sigma}_{\boldsymbol{\varepsilon}} = (\sigma_{\varepsilon_k \varepsilon_j})_{4\times 4},\ \sigma_{\varepsilon_k \varepsilon_j} = \begin{cases} \sigma^2_{\varepsilon_k}, & \text{if} \quad k = j \\ \tau_{kj}\sigma_{\varepsilon_k}\sigma_{\varepsilon_j}, & \text{if} \quad k \neq j \end{cases} \tag{4.10}$$

$$\boldsymbol{\Sigma}_{\boldsymbol{\eta}} = (\sigma_{\eta_k \eta_j})_{4\times 4},\ \sigma_{\eta_k \eta_j} = \begin{cases} \sigma^2_{\eta_k}, & \text{if} \quad k = j \\ \rho_{kj}\sigma_{\eta_k}\sigma_{\eta_j}, & \text{if} \quad k \neq j \end{cases} \tag{4.11}$$

where $k = \{1, 2, 3, 4\}$ and $j = \{1, 2, 3, 4\}$. By writting the expression (4.11), we have implicitly assumed a random effect for the unobserved individual effects. The fixed effect (FE) models are generally preferred in practice because it has less limitation on the assumption of the distribution of $\eta_{k,i}$. Because there is no general solution in the literature regarding how to estimate a FE non linear panel data model, this study therefore applies the random effect model. In the random effects model, the individual-specific effect is a random variable that is uncorrelated with the explanatory variables. Chamberlain (1984) observes that if $\eta_{k,i}$ is correlated with explanatory variables in period t then it will also be correlated with explanatory variables in period s, where $t \neq s$. Thus, lags and leads of explanatory variables should be included in the regression to avoids this potential correlation. Following Mundlak (1978) we futher assume that the individual heterogeneity depends on the strict exogenous variables in the following way :

$$\eta_{k,i} = b_{0,k} + \bar{x}_{k,i} b_{1,k} + a_{k,i} \tag{4.12}$$

where $k = \{1, 2, 3, 4\}$, the term $\bar{x}_{k,i} = T_i^{-1} \sum_{t=1}^{T_i} x_{k,it}$ denotes the time averages of $x_{k,it}$; $a_{k,i}$ are the "true" random effect and $a_{k,i} \perp x_{k,it} | \bar{x}_{k,i}$; $b_{1,k}$ and $b_{0,k}$ are to be estimated. The matrix of the true random effect, $\boldsymbol{\Sigma}_{\boldsymbol{a}}$, takes the following form :

$$\boldsymbol{\Sigma}_{\boldsymbol{a}} = (\sigma_{a_k a_j})_{4\times 4},\ \sigma_{a_k a_j} = \begin{cases} \sigma^2_{a_k}, & \text{if} \quad k = j \\ \rho_{kj}\sigma_{a_k}\sigma_{a_j}, & \text{if} \quad k \neq j \end{cases} \tag{4.13}$$

The conditional likelihood function of one individual, denoted by $l_{i|a_i}$ is written as :

$$\ell_{i|a_i} = \prod_{t=1}^{T_i} f(y_{it}, n_{it}, k_{it}, d_{it} | \boldsymbol{x}, \boldsymbol{a}_i, \bar{\boldsymbol{x}}, \boldsymbol{\varepsilon}_{it}) \tag{4.14}$$

12. To limit the potential endogeneity problem, all time-varying explanatory variables include in $x_{1,it}, x_{2,it}, x_{3,it}$, and $x_{4,it}$ are lagged

where $\boldsymbol{x} = (x_{1,it}, x_{2,it}, x_{3,it}, x_{4,it})$, $\bar{\boldsymbol{x}} = (\bar{x}_{1,i}, \bar{x}_{2,i}, \bar{x}_{3,i}, \bar{x}_{4,i})$, $\boldsymbol{a}_i = (a_{1,i}, a_{2,i}, a_{3,i}, a_{4,i})$ and $f(\cdot)$ denote the joint cumulative distribution function for an observation. The unconditional (to the individual random effects) joint density for the i^{th} individual is obtained by integrating out $\boldsymbol{a}_i$ with respect to the quadrivariate normal distribution. Formally,

$$\ell_i(y_{it}, n_{it}, k_{it}, d_{it}|\boldsymbol{x}, \boldsymbol{a}_i, \bar{\boldsymbol{x}}, \boldsymbol{\varepsilon}_{it}) = \int_{\boldsymbol{a}_i} \prod_{t=1}^{T_i} f(y_{it}, n_{it}, k_{it}, d_{it}|\boldsymbol{x}, \boldsymbol{a}_i, \bar{\boldsymbol{x}}, \boldsymbol{\varepsilon}_{it}) g(\boldsymbol{a_{1,i}}) \mathrm{d}\boldsymbol{a_i}$$

where $g(\boldsymbol{a_{1,i}})$ denotes the density function of the quadrivariate normal distribution. The evaluation of this individual likelihood function requires the computation of a quadruple integral. Evidently this integral cannot be derived analytically. Following Raymond et al. (2015), we can use a sequential Gauss-Hermite quadrature to evaluate ℓ_i. The individual joint density unconditional to the individual effects can be approximated by :

$$\ell_i \approx \Gamma \sum_m^M \sum_p^P \sum_q^Q \sum_r^R \omega_m \omega_p \omega_q \omega_r \exp(c_m c_p^* c_q^* c_r^*) \left(\prod_{t=1}^{T_i} f(y_{it}, n_{it}, k_{it}, d_{it}|\boldsymbol{x}, \boldsymbol{a}_i, \bar{\boldsymbol{x}}, \boldsymbol{\varepsilon}_{it}, c_m, c_p, c_q, c_r) \right) \tag{4.15}$$

where

$$\Gamma = |\boldsymbol{\Sigma_a}| \, \pi^{-2} \left(\sigma_{a_1}\sigma_{a_2}\sigma_{a_3}\sigma_{a_4}\right)^{-2} \Big[(1-\rho_{12}^2)(1-\rho_{13}^2)(1-\rho_{14}^2)(1-\rho_{14}^2)(1-\rho_{23}^2)(1-\rho_{24}^2)(1-\rho_{34}^2)\Big]^{1/2}$$

$$c_p^* = c_p^*(c_m, c_p, \boldsymbol{\rho}), \;\; c_q^* = c_q^*(c_m, c_p, c_q, \boldsymbol{\rho}), \;\text{ and } c_r^* = c_r^*(c_m, c_p, c_q, c_r, \boldsymbol{\rho})$$

c_m, c_p, c_q, c_r are the abscissae and $\omega_m, \omega_p, \omega_q, \omega_r$ are the weights of the quadrature ; and M, P, Q, R are the total numbers of integration. Numerical tables with values of c_m, c_p, c_q, c_r and $\omega_m, \omega_p, \omega_q, \omega_r$ formulated in mathematical text books ; and $|\boldsymbol{\Sigma_a}|$ is the determinant of $\boldsymbol{\Sigma_a}$.

At each evaluation of the likelihood function, it is necessary to compute $N \times M \times P \times Q \times R$ joint cumulative distribution functions, $f(\cdot)$; where N is the total number of firms. However because of the complexity of the joint distribution, $f(\cdot)$, the implementation of this technique is computationally cumbersome and extremely time-consuming, eventually rendering this solution infeasible. To overcome this issue, we make some assumptions on idiosyncratic errors.

The full correlation of the idiosyncratic errors in CDM model implies that the forces which have an impact on the estimated probability of being engaged in R&D also influence the estimated elasticity of productivity and vice versa (Lööf and Heshmati, 2006). This study aims to show that participation in export enter endogeneously in the structural CDM system. Then, we extend the full correlation assumption. The forces that have an impact on the estimated probability of being engaged in export also influence the estimated elasticity of productivity and vice verca. These assumptions of bi-directional causal relationships are supported by studies on export and productivity carried out in the past few decades. [13] Hence, we assume that correlations among export decision, innovation investment, innovation output and productivity equations is due to unobserved factors which enter in all equations. This specific form of endogeneity can be avoided by imposing some structural constraints on the residuals,

$$\varepsilon_{1,it} = \lambda_1 \boldsymbol{\xi}_{it} + \epsilon_{1,it} \tag{4.16}$$

$$\varepsilon_{2,it} = \lambda_2 \boldsymbol{\xi}_{it} + \epsilon_{2,it} \tag{4.17}$$

$$\varepsilon_{3,it} = \lambda_3 \boldsymbol{\xi}_{it} + \epsilon_{3,it} \tag{4.18}$$

$$\varepsilon_{4,it} = \lambda_4 \boldsymbol{\xi}_{it} + \epsilon_{4,it} \tag{4.19}$$

where $\boldsymbol{\xi}_{it}$ is the heterogeneity term which is common to all equations, ϵ_1, ϵ_2, ϵ_3 and ϵ_4 are the new "idiosyncratic" errors, $\lambda' = (\lambda_1, \lambda_2, \lambda_3, \lambda_4) \in \mathbb{R}^4$ are free factor loadings to be estimated along the other parameters. To close the model, we require the covariates to be all exogenous ; to this end we use lagged covariates in x_1, x_2, x_3 and x_4. In addition we assume some distributional conditions

$$D(\boldsymbol{\xi}|\epsilon_1, \epsilon_2, \epsilon_3, \epsilon_4) = D(\boldsymbol{\xi}) \tag{4.20}$$

$$\epsilon_k \perp \epsilon_j | \boldsymbol{\xi} \tag{4.21}$$

where $k \neq j$, $k, j = \{1, 2, 3, 4\}$, $D(\cdot)$ denote the "distribution of". Condition (4.20) is the usual random effects assumption, which requires the unobserved individual heterogeneity term, $\boldsymbol{\xi}$, to be independent of all explanatory variables in the system as well as independent of errors ϵ_1, ϵ_2, ϵ_3 and ϵ_4. The condition (4.21) states that, conditional on $\boldsymbol{\xi}$, the new "idiosyncratic" errors are independent to each others. However, this does not rule out some dependences between ϵ_1, ϵ_2, ϵ_3 and ϵ_4. With conditions 4.16-4.21, the quadrivariate normal distribution for ε_1, ε_2, ε_3 and ε_4, i.e. $f(\cdot)$, is simply rewritten as the product of four distributions functions,

$$\begin{aligned} f_{it} &= h_{it}(y_{it}, n_{it}, k_{it}, d_{it} | \boldsymbol{x}, \boldsymbol{a}_i, \bar{\boldsymbol{x}}, \boldsymbol{\xi}_{it}) \\ &= \boldsymbol{h}_4(A_{it} + \lambda_4 \boldsymbol{\xi}_{it}) \times \boldsymbol{h}_3(B_{it} + \lambda_3 \boldsymbol{\xi}_{it}) \times \boldsymbol{h}_2(C_{it} + \lambda_2 \boldsymbol{\xi}_{it}) \times \boldsymbol{h}_1(D_{it} + \lambda_1 \boldsymbol{\xi}_{it}) \end{aligned} \tag{4.22}$$

13. See Wagner (2007) for a discussion on the causal relationship, in both directions, between exports and productivity. Capturing this dynamic relationship, which goes in both directions, between export and productivity, need the time aspect to be taken into account. As noted by Lööf and Heshmati (2006), ideally with long time series, one would study how export in year $t - \tau$ influences productivity in year t and how productivity in year t influences the exporting in year $t + \tau$. However, since our panel is rather short, we analyse a recursive equation system with current productivity depending on curent export and with curent export depending on past productivity rather than the current one.

where $\boldsymbol{h}_4$, $\boldsymbol{h}_3$, $\boldsymbol{h}_2$ and $\boldsymbol{h}_1$ is the appropriate distribution functions, and

$$
\begin{aligned}
A_{it} &= \alpha_4 \ln(n_{it}) + \beta_4' x_{4,it} + b_{0,4} + \bar{x}_{4,i} b_{1,4} + a_{4,i} \\
B_{it} &= \alpha_3 k_{it} + \beta_3' x_{3,it} + b_{0,3} + \bar{x}_{3,i} b_{1,3} + a_{3,i} \\
C_{it} &= \alpha_2 d_{it} + \beta_2' x_{2,it} + b_{0,2} + \bar{x}_{2,i} b_{1,2} + a_{2,i} \\
D_{it} &= \beta_1' x_{1,it} + b_{0,1} + \bar{x}_{1,i} b_{1,1} + a_{1,i}
\end{aligned}
$$

Bratti and Miranda (2011) enumerate at least three advantages of using a common latent factor structure : (1) flexibility to combine appropriately chosen conditional and marginal distributions that generate the joint distribution that the researcher wants to use ; (2) natural interpretation of the factors loadings, since latent factor enter into the equations as observed covariates ; (3) parsimonious representation of error correlations in models with a large number of equations. However, it implies some variance–covariance restrictions. In our case, the variance–covariance matrix, $\boldsymbol{\Sigma}_{\boldsymbol{\varepsilon}}$, must be retrieved from only $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ and $\sigma_{\boldsymbol{\xi}}$. Carneiro et al. (2003) note that these restrictions may have arbitrary content and conclude that it is important to use economic theory to justify any specific identification scheme. In our case, the unobserved factor, $\boldsymbol{\xi}_{it}$, can be for example the technological capability residual. Dosi (1988) defines technological capability as different degrees of technological accumulation and different efficiencies in the innovative search process. Hence, technological capability contributes to the achievement of higher levels of economic performance for firms, since it allows incremental improvements due to the use of new technologies. Superior technological capabilities can provide firms the potential to be engaged in international markets (Bernard and Wagner, 2001; Bernard and Jensen, 2004; De Loecker, 2007), and can help firm to be more innovative (Nelson and Winter, 1982; Cohen and Levinthal, 1990; Malerba and Orsenigo, 1993), and to have higher productivity (Abowd et al., 1999; Fox and Smeets, 2011; Bartelsman et al., 2014; Lebedinski and Vandenberghe, 2014). To put it simply, the omission of unobservable factors which enter in all four equations is likely to generate correlation between all three error terms.[14]

4.4 Data and descriptive statistics

The underlying data set comes from three sources : *FARE* (Fichier approché des résultats d'Esane), French customs and Mintel Global New Products database (GNPD). The data we use cover the period 2010-2016.

4.4.1 Data

The *FARE* files makes it possible to produce structural business statistics, i.e. an annual snapshot of the population of firms belonging to the productive system and their main characteristics. The FARE files collect statistical data, compiled by INSEE (Institut national de

14. In practice, it is impossible to identify separately, λ_3, $\sigma_{\boldsymbol{\xi}}$ and σ_{ϵ_3}. Hence, in eqs (4.16), (4.17) and (4.19), ε_1, ε_2 and ε_4 are expressed in function of ε_3.

la statistique et des études économiques) for its statistical purposes (national accounts data, annual statistics on business results and performance, studies). They are based on data from several sources : tax data, social data and statistical survey data. FARE provides balance-sheet data at firm level (sales, turnover, value-added, employment, capital, wages, intangible assets, etc.) and information about the firm's location, industry classification, etc... We only consider firms within dairy industry (Nace rev 2 : 1051). [15] The data includes on average 1,252 firms with a total number of 5,753 observations over the period 2010-2016. Before implementing the merging of FARE with other data sources, we perform a series of operations to clean data. We drop observations with missing values in some variables, such as : turnover, number of employees, tangible and intangible assets, sales or value-added. After the cleaning process, the unbalanced panel of firms used in this study includes on average 592 firms with a total number of 3,049 observations over the period 2010-2016.

To have informations on new product, we use an exhaustive list of new product launches. The product launch data come from the Global New Products Database (GNPD) constructed by Mintel. [16] This database reports observations since 2010 and reports all consumables product launched. It covers 62 of the world's major countries. For each consumable product launched, the following information is available : registered country (country in which the launch was registered), product characteristics, the date of the launch in a specific country, product launch type and production code. To construct our innovation dataset, we face two challenges. Since our work focuses on French firms, the first challenge is to find in this vast set of products, those manufactured by French firms. To do so, we use the production code variable avalaible in GNPD. The production code refers to EC identification and health marks. In France, any establishment preparing, processing, handling or storing products of animal origin or food containing them and marketing such products to other establishments, including freezer vessels, factory vessels and vessels cooking crustaceans and molluscs, is subject to the requirement of health approval. Products from an approved establishment shall bear an oval identification mark identifying that establishment. For French products, the EC identification takes the following form : `FR XX XXX XXX EC`. Considering that French firms are required to affix their approval number to their products [17], we can consider that all French dairy products present in GNPD have an approval number. In order to keep only French dairy product, we only retain dairy products whose approval number begins by `FR`.

After having found the french product launches, the second challenge concerns the ID number

15. The NACE rev 2 code represents the European classification for the economic activities of firms. In france, dairy industry is divided into four sectors according to the firm's main activity : 1051A for manufacture of liquid milk and fresh products, 1051B for butter production, 1051C for cheese production and 1051D for other dairy product manufacturing

16. Mintel is a privately owned, London-based market research firm.

17. See Regulation (EC) N^{o} 853/2004 of the European parliament and of the council

(SIREN)[18] of the firms that manufactured these products. This ID number is crucial for our study because it is a key variable allowing the merger between our different databases. To find the ID number we use EC identification. An approval number is usually assigned to a plant ; in addition, we know that a firm gets one or more plants. So theoretically, with the approval number, it is possible to trace back to the manufacturing firm (and therefore the firm's ID number). In practice, changing from the plant approval number to the associate to firm ID number is not straightfoward, as there is no link between these two identifiers. To achieve our goal we split the search for the firm ID number into two steps. First, with the plant approval number we found the SIRET identifier of this plant.[19] The *SIRET* (Système d'identification du Répertoire des établissements) number is the plant identifier ; it contains14 digits, the first 8 are the identifier of the associated firm. In the second step, after having found the SIRET number of the plant, we only had to keep the first 8 digits of this SIRET number to have the ID number (SIREN) of the associated firm.

To measure new product, we use categorical variable `LaunchType` avalaible in GNPD. This categorical variable has 5 modalities :[20]

— "*new product*" : This launch type is assigned when a new range, line, or family of products is signaled. This launch type is also used if a brand that already exists on GNPD, in one country, crosses over to a new sub-category ;

— "*new variety/range extension*" : This launch type is dependent on the Brand field. It is used to document an extension to an existing range of products on the GNPD ;

— "*new packaging*" : This launch type is determined by visually inspecting the product for changes, and also when terms like New Look, New Packaging, or New Size are written on the pack ;

— "*reformulation*" : This launch type is determined when terms such as New Formula, Even Better, Tastier, Now Lower in Fat, New and Improved, or Great New Taste are indicated on the pack ;

— "*relaunch*" : This launch type is determined when specified the on pack, via secondary source information (trade shows, PR, websites, and press) or when a product has been both significantly repackaged and also reformulated. If aproduct is reformulated and repackaged then this launch type is selected.

18. In France, this firm ID number is called SIREN (Système d'Identification du Répertoire des ENtreprises). It's allocated by INSEE (Institut National de la Statistique et des Études Économiques) at the time of the firm's registration

19. It should be noted that the approval number (EC identification) is the plant identifier at European level ; at national level each plant is identified by another number upon registration (SIRET) ; and these two identifiers are distinct.

20. See GNPD glossary 2016, `https://www.gnpd.com/gnpd/about/GNPD_Glossary_2016.1.pdf`, for more details.

We are only interested on the modality *new product* to compute our innovation measure. We define *product innovation output* as the number of new products introduced by a firm i at the year t.

Our third dataset is the firm-level trade data collected by French customs administration. These data provide a comprehensive record of the yearly exported and imported quantities by French firms from 2010 to 2016. The customs data are an comprehensive record of annual shipments by destination country at the eight-digit product level for each French exporting firm. In this study, exporter is a firm that reports positive export sales whatever the product category and the destination country.

The detailed definitions of the variables used in this study are presented in Table 4.8 in appendix A. For the empirical analysis, we focus on French dairy industry (see Table 5.1). The French dairy industry consists of four sectors : the manufacturing of liquid milk and fresh product (code nace : 1051A), butter production (code nace : 1051B), cheese production (code nace : 1051C) and other dairy product manufacturing (code nace : 1051D). Based on OECD data, these sectors all have R&D-sales ratios below 0.025 ; this makes the French dairy industry, a low-tech industry. Our final sample consists of observations between 2010-2016 on all firms in Frecnh dairy industry with at least two consecutive observations and nonmissing information on the needed variables. There are a total of 3049 observations and an average of 592 firms ; i.e. an average of 5.15 observations for each firm. Since our data are an unbalanced

TABLE 4.1 – Industry characteristics by sector, overall sample

	Manufacture of liquid milk and fresh products	Butter production	Cheese production	Other dairy product manufacturing	Total
TFP[a]	2.725	2.719	2.676	2.789	–
Number of new product[a]	1.501	1.677	0.415	0.363	– –
Share of innovation investment[a,b]	0.557	0.376	0.555	0.405	– –
Exporters[a]	0.393	0.548	0.247	0.404	–
Number of employee	150	173	49	129	–
Number of firms	75	7	476	34	592
Observations	341	31	2531	146	3049
Exit rate[b]	6.906	7.826	3.864	5.904	5.173

[a] Value of the average firm in overall sample. [b]Values are in percentage

panel, i.e. some firms enter and leave the sample during all periods, it's important to study the sample attrition. Over the sample period, we find an annual average exit rate of 5%. This rate is higher in the butter manufacturing sector than in the cheese manufacturing sector. It should be noted that attrition may occur because of nonreporting or firm death. To investigate the role of attrition in our data, we construct a dummy variable, q_{it}, such that such that $q_{it} = 1$ when a firm leaves the sample at the year *t+1*, and $q_{it} = 0$ otherwise. We estimate the probability $\Pr(q_{it} = 1)$ using random logit models and present the estimates in Table 4.5 in appendix A. We find that the probability of leaving the sample is not explain by the firms' characterics. In others words, there is no significant difference in firm characteristics (i.e. productivity, innovation activities and exports), in their last year of observation when comparing the firms that stay in the sample and those that exit the sample. Then, the sample attrition in our sample can be considered as random.

4.4.2 Preliminary analysis

Tables 4.2 (and tables 4.6 and 4.7 in Appendix C) shows some simple descriptive statistics, means and standard deviation, to present the main characteristics of our sample. Table 4.2 gives the means and standard deviations (overall, between and within) of the dependent and explanatory variables used in our sample. The main information given in this table is the different variances of the variables. The importance of this information lies in the estimation procedure ; i.e. error components model. We are particularly interested in the within variations of the different explanatory variables. Whatever the variable, it appears that the observed dispersion is mainly due to variations between firms. In addition, within variations appear to be small. [21] For instance, the between standard deviation of *SIZE* is estimated to be 1.630, while the within standard deviation is only 0.200. Futhermore, it appear that 27% of firms in the sample have participate in exports market at least once during the period 2010-2016. In addition, firms invest on average 0.543% of their total sales in innovation activites. [22]

One important point in this study is to show that exporters are more likely to enter into the innovation process. In this sub-section we perform a preliminary analysis to test it. Following Bernard and Jensen (1999), we run the following OLS regression

$$x_{it} = \alpha + \beta EXPORT_{it} + \gamma SIZE_{it} + \text{Year}_t + \text{Ind}_j + \xi_{it} \tag{4.23}$$

where x_{it} refers to the characteristics of firm i at period t, including the firm's measures for innovation process, i.e. productivity, innovation output and innovation investment. *EXPORT* is an export dummy equals to one when the firm is an exporter and zero otherwise, *SIZE* is the log of the number of employees working in firm i at year t, and Year_t and Ind_j denote year

21. this observation implies that integration of means of explanatory variables in our model could could cause a collinearity problem with explanatory variables.

22. Average share of innovation investment is $\exp(-5.215)$

TABLE 4.2 – Means and standard deviations dependent and explanatory variables, 2010-2016

			Standard Deviations		
Variables	**Definition**	**Mean**	**Overall**	**Between**	**Within**
Dependent variables					
TFP	Total factor productivity	2.687	0.311	0.282	0.182
INNOV	Number of new product introduced	0.547	1.998	1.833	0.976
RDSPEND	Intensity of innovation investment (in log)	-5.215	1.523	1.564	0.366
EXPORT	Export performer (0/1)	0.274			
Explanatory variables					
CAPINT	Capital intensity (in log)	4.943	0.953	1.031	0.268
HERFIN	HHI (in log)	0.013	0.053	0.053	0.036
GROUP	firm belongs to a group	0.134			
FOREIGN	firm is a subsidiary of a foreign company (0/1)	0.031			
IMPORT	Import performer (0/1)	0.136			
REGEXT	Export externaties	0.281	0.136	0.131	0.040
RDSPILL	R&D spillover	0.304	0.096	0.083	0.051
PMARGIN	Profit margin (in log)	2.912	0.578	0.646	0.195
MSHARE	Market share (in log)	- 3.071	2.030	2.244	0.512
SUPPORT	Public support (0/1)	0.375			
AGE	Age (in log)	3.453	0.930	0.999	0.115
SIZE	Size (in log)	2.648	1.601	1.630	0.200

and sectors fixed effects. The exporter premium is captured by coefficient β ; it reveals the percentage differential between exporters and non exporters. Table 4.3 presents the estimation results from equation (4.23). Exporters appear to be significantly different from non-exporters. Exporters sell more (26.3%), operate on a larger scale, invest more in innovation (58.90%), and are more productive (11.5%). These results are in line with the findings of Bernard and Jensen (1995) for USA, Bernard and Jensen. (1997) for Germany, **?** for Columbia and De Loecker (2007) for Slovenia.

4.5 Results

Table 4.4 show the estimates of our model of the augmented CDM model for export, innovation and productivity in the French dairy industry over the period 2010-2016.

TABLE 4.3 – Firm characteristics differentials between exporters and non exporters

Firm charactreristic	β	R^2
Variables for innovation process		
RDSPEND	0.589	0.024
INNOV	0.166	0.258
TFP	0.115	0.067
Other firm characteristic		
MSHARE	0.263	0.737
VALUE-ADDED	0.095	0.929
SIZE	2.190	0.378

Note : All coefficients are significant at the 1%. All regressions include a size effect except for the employment regression.

4.5.1 Determinants of export participation

Part A of the Table 4.4 presents the estimates of the probability to participate into export. The propensity to export is estimated by a random probit model as a function of firm size, import status, ownership structure, capital intensity, market structure, export externality, firm age and lagged productivity. We also include sector specific effects and time fixed effects. With regard to the firm-level determinants of export, the results are consistent with those found in the previous literature. We find that firm size (measured as the number of employees and market shares) increases the probability to export. For the number of employees, we include in the estimation three dummy variables representing different categories, where the firms between 1 and 9 employees are the omitted base group. The estimated coefficients for firms in the 10–20 category implies that they have a higher probability to export than the base group, but the difference is not significant. The coefficients on the remaining groups are positive and statistically significant, indicating that firms with higher number of employees are more likely to export than the base group. The results indicate the importance of scale effects on exporting as suggested by the trade literature on scale-economy based exporting. We also find that firms' market share is positively correlated with their probability to export. Ownership structure is proxy by two dummies : *GROUP* and *FOREIGN*. Our estimation shows that firms belonging to a group are more likely to export than other firms ; however the difference is statistically insignificant. We also find a positive and significant effect of the foreign-ownership dummy on the probability to export. This result suggests that foreign-owned firms are more likely to export than domestic owned one. This result is in line with the literature on multinational firms suggesting that subsidiaries of foreign firms find it easier to export because they take advantage of the intra-industry distribution channels and contacts (Brainard, 1997; Bernard and Jensen, 2004).

Furthermore, we find a positive effect of age on the probability to export. This suggests that the probability to export increases with firm age. In industrial economy, firm age are positively related with firm efficiency (Peters et al., 2017). Efficient producers are more likely to survive and grow, so age may pick-up the efficiency differences across producers. The relationship between import and export status is positive and significant. This result suggests that importers are more likely to penetrate the foreign market than non-importers. The lower price or/and the higher quality of the imported inputs may affect the firm export scope (Bas and Strauss-Kahn, 2014). Another explanation of this link is that : by importing, firm can establish relationships with companies abroad that may subsequently become customers or distribution channels in foreign markets. Our results also show that the firm decision to export is positively linked to the presence of other exporters in the same region and industry. Aitken et al. (1997) argue that externalities of this form reduce the cost of access to foreign markets.

Finally, we find a positive and significant effect of the lagged TFP on exporting. The positive coefficient of the lagged TFP suggests that firms that are more productive are more likely to export. This result suggests that the most productive firms self-select into foreign markets, which is in line with the theoretical predictions of the Melitz (2003)'s model and the empirical findings of Bernard and Jensen (1999) and Bernard and Jensen (2004). We also find negative and significant effect of capital intensity (capital-labor ratio) on export probability. This result differs from the findings of Bernard and Jensen (1999) and Bernard and Jensen (2004) on U.S. manufacturing firms. However, using transaction-level data for the 2000–2006 period, Ma et al. (2014) show that Chinese new exporters add products that are less capital-intensive than their existing products and drop those that are more capital-intensive in subsequent years.

4.5.2 Determinants of innovation investment

Part B of Table 4.4 presents the estimates of the innovation investment. The innovation input intensity is estimated using a random Tobit model. As determinants, we include firm characteristics such as, international exposure, firm size, firm age, public support, ownership structure, market structure, profitability and spillover. We also include sector specific and year fixed effects. The values reported in part B of Table 4.4 represents the estimates of the (semi-) elasticities. Our estimation shows that the semi-elasticity of export status are positive and significant. This results is consistent with the fact that the largest export market provide the highest returns to investment in innovation as modeled by Lileeva and Trefler (2010) and Costantini and Melitz (2007) and Aw et al. (2008). Exporters are more likely to invest in innovation by 2.2%.

With regard to the other firm-level determinants of investment in innovation, the results are consistent with those found in the previous literature. The first result is that size, as measured by the number of employees and by the market shares, has a positive and significant effect on

Table 4.4 – Full Information Maximum Likelihood estimates of the model

Variables	Coefficient	Standard Errors
PART A. *Export participation*		
TFP (lag)	0.447***	0.101
CAPINT	- 0.252***	0.048
HERFIN	- 1.509***	0.560
GROUP	0.104	0.111
FOREIGN	0.394**	0.200
IMPORT	0.238**	0.098
MSHARE	0.226***	0.035
SUPPORT	0.368***	0.072
AGE	0.110**	0.049
EXPEXT	1.903***	0.255
SIZE CLASS		
$D_{10\leq \text{Size}\leq 20}$	0.161	0.175
$D_{20<\text{Size}\leq 50}$	1.210***	0.168
$D_{\text{Size}>50}$	1.558***	0.201
INTERCEPT	- 1.271***	0.537
PART B. *Investment in innovation activities*		
EXPORT	0.022**	0.012
CAPINT	- 0.002	0.010
HERFIN	0.033	0.071
GROUP	0.132***	0.050
FOREIGN	0.183*	0.099
IMPORT	0.002	0.014
PMARGIN	0.066***	0.013
RDSPILL	0.108**	0.044
MSHARE	0.015***	0.005
SUPPORT	0.082***	0.010
AGE	- 0.062***	0.014
SIZE		
$D_{10\leq \text{Size}\leq 20}$	0.053***	0.019
$D_{20<\text{Size}\leq 50}$	0.119***	0.024
$D_{\text{Size}>50}$	0.206***	0.032
INTERCEPT	- 0.652***	0.129
PART C. *Innovation output : Number of new products introduced*		
RDSPEND	8.082***	0.459
CAPINT	- 0.317***	0.102
HERFIN	- 0.860	0.734
GROUP	0.297***	0.057
FOREIGN	- 1.230	0.832
IMPORT	0.361***	0.102
PMARGIN	- 0.048	0.122
MSHARE	0.313***	0.053
AGE	- 0.098***	0.033

Table 4.4 : Full Information Maximum Likelihood estimates of the model (suite)

Variables	Coefficient	Standard Errors
SIZE		
$D_{10\leq \text{Size}\leq 20}$	1.491**	0.680
$D_{20<\text{Size}\leq 50}$	3.006***	0.661
$D_{\text{Size}>50}$	3.332***	0.680
INTERCEPT	0.355	0.113
PART D. *Total Tactor Productivity*		
INNOV	0.041**	0.017
IMPORT	0.103***	0.018
GROUP	- 0.009	0.017
FOREIGN	0.065**	0.032
SIZE	- 0.025***	0.002
INTERCEPT	2.610***	0.041
Idiosyncratic errors		
σ_{ε_2}	0.056***	0.013
σ_{ε_3}	0.137***	0.040
σ_{ε_4}	0.348***	0.053
τ_{12}	0.023**	0.010
τ_{13}	- 0.056***	0.013
τ_{14}	0.011**	0.005
τ_{23}	- 0.411***	0.092
τ_{24}	0.078**	0.035
τ_{34}	- 0.189***	0.043
Individual effects		
σ_{a_1}	0.505***	0.190
σ_{a_2}	0.384***	0.144
σ_{a_3}	3.208***	1.098
σ_{a_4}	0.024***	0.009
ρ_{12}	0.188**	0. 018
ρ_{13}	0.157***	0.022
ρ_{14}	0.119**	0.056
ρ_{23}	0.120***	0.006
ρ_{24}	0.091*	0.051
ρ_{34}	0.076***	0.023
Log-likelihood	-3325.876	
Observations	3,049	

Three dummies of category of sector and a time dummy are included in each equation. ***, **and * indicate significance on a 1%, 5% and 10% level, respectively. Estimations are based on Gauss–Hermite quadrature approximation using eleven quadrature points. We also include individual time-average of covariates in each equation.

innovation input intensity. For the number of employees, the semi-elasticity for firms in the 10–20, 20-50 and >50 employees categories are estimated to be 5.3%, 11.9% and 20.6% higher than the base group, respectively. In addition, all these semi-elasticities are statistically significant. These results are in line with the Schumpeterian literature. In addition, a 1% increase in the market shares raises the investment in innovation by 0.015%. The firm ex-ante market power spurs the investment in innovation. Moreover, firms which receive public funding in the previous period, exhibit higher innovation input than firms without previous financial support. Our estimation shows that firms with public support are more likely to invest in innovation by 8.2%.

Furthermore, our results show a negative and significant effect of age on innovation investment. This means that younger firms invest more in innovation activities. Studies in industrial evolution, such as Huergo and Jaumandreu (2004a), Huergo and Jaumandreu (2004b) or Cucculelli (2017) suggest that the likelihood of innovation activities changes along firm life. In Huergo and Jaumandreu (2004b), a downward sloping line connects the probability of innovation to the firm age. To measure firm profitability (cash flow), we use the value added-turnover ratio (profit margin). We find a positive and significant relationship between profitability and investment in innovation. Firms with higher profit margin invest more in innovation. 1% increase in value added-turnover ratio increases the investment in innovation by 0.07%. The Schumpeterian literature already stressed the importance of internal funds to finance innovation projects. Ownership structure is also positively correlated with innovation investment. Our estimation shows that firms belonging to a group are more likely to invest in innovation than other firms. We also find that foreign-owned firms are more likely to invest in innovation than domestic incumbents. One explanation is that firms which are part of a conglomerate may have easier access to external capital in a world of capital market imperfections.

4.5.3 Determinants of innovation output

Part C of Table 4.4 presents the estimates of the innovation output. The intensity of innovation output is measured by the number of new products. Because of the nature of our data, we estimate a random Poisson model. The explanatory variables include investment in innovation, capital intensity, market structure, market share, size, import, age and ownership structure. As shown in part C of Table 4.4, innovation output increases with investment in innovation, firm size, market share and imports ; while it decreases with capital intensity and age. An increase in the innovation expenditure intensity by 1% is associated with an increase in innovation output by 8.08%. This result is in line with other empirical findings. The estimated elasticity of product innovation output with respect to innovation input is somewhat higher compared to those reported in the literature. For example, using patent count data, Crepon et al. (1998) estimated an elasticity of 1.08 in French manufacturing industry. Mairesse et al. (2005) estimated an elasticity of 3.60 in low-tech French industry, using the shares of innovative sales as measure of innovation output. One explanation of this difference is that we use investment in innovation rather than R&D investment. In addition to the expenditures for R&D, we cover expenditures for the acquisition of machinery, external knowledge, training, product preparation and marketing related to innovation activities. This is important since in food industry, most of firms innovate without investing in formal R&D activities.

With regard to the other firm-level determinants of innovation output, the results show that firm size is correlated with innovation output. We find that the innovation output increases with the number of employees and with the market shares. More precisely, 1% increase in market share is associated with 0.31% increase in innovation output. The result further provides evidence that firm age is negatively link with innovation. Hence, young firms introduce more new products than older firms.

4.5.4 Determinants of productivity

Part D of table 4.4 presents the estimates of the productivity. The firm productivity is measured by the Total Factor Productivity. The figures shown in the table are marginal effects. Part D of Table 4.4 displays the results related to the impact of innovation output on TFP. As predicted by the international trade and investment literature, we find that foreign-owned firms have a higher productivity than domestic firms. For instance, on average, the productivity of foreign-owned firms are 6.5% higher than for domestic firms. In addition, we find that importing inputs would increase firm's productivity by 10.3%. One potential explanation for this result is that imports affect firm productivity through expanding varieties as well as improved input quality (Halpern et al., 2015).

In line with several other empirical studies, the results confirm significant productivity effects of product innovations for French dairy firms. We find that, 1% increase in innovation output raises firm productivity on average by 0.04%. These are within the range reported by Hall et al. (2010) in their review of the literature. We also corroborate the findings by Mairesse et al. (2005), the innovation output has an positive impact on firm productivity only when the endogeneity of innovation is properly taken into account. In fact, when innovation is treated as exogenous, the elasticity of TFP with respect to innovation output drops from 0.04% to 0.02% and becomes statistically insignificant.[23] In our analysis, endogeneity of innovation activities (input and output) and export operates through the covariance matrices of the individual effects and the idiosyncratic errors. The correlation between innovation output and productivity, τ_{43} and ρ_{43} usually being statistically significant.

23. Results not tabulated but available upon request

The short-run return to export participation : innovation activities as learning process. One point of this study is to test the learning by exporting which occurs through innovation activities (*LBE-I*). Our framework allows us to measure the short-run benefits of exporting. The short-run gain captures changes in total factor productivity in the subsequent period. In this study, *LBE-I* refers to the indirect productivity elasticity of exports, which can be simply defined as the product of the productivity elasticity of innovation, α_4, by the innovation elasticity of R&D, α_3, and by the R&D elasticity of exports, α_3. Using the results reported in Table 4.4, the indirect productivity elastisticity of export market participation is estimated to be 0.71%.

Covariance matrix of idiosyncratic errors and individual effects. In order to capture correlation among the four equations, we account for individual effects in each equation of the model. The significance of the standard error for individual effects rejects the absence of unobserved individual effects. The correlations between the unobserved individual effects are all positive. This result suggests a positive long-run return to exporting. Instead, we observe a negative and statistically significant correlation, between the idiosyncratic error terms in the innovation output equation and all other equations. For instance, the unobservable factors that increase the number of new product introduced are negatively correlated with the unobservable factors that increase total factor productivity. Raymond et al. (2015) explain this phenomenon by a missing adjustment cost term. In order to increase the number of new products, firms may need to increase their number of employees, which in the short run may lead to a decrease in total factor productivity because of adjustment costs and time to learn.

4.6 Conclusion

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

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

Appendix A : Market share and diversification index

The market share and diversification index are computed following Crepon et al. (1998)'s methodology. We use detailed informations provided by the Fare dataset. We considered the decomposition of sales for two segments : manufacturing and service activities. Let $S_{it,k}$ be the sales of firm i at the year t for its activity k, $S_{it} = \sum_k S_{it,k}$ and $S_{t,k} = \sum_k S_{it,k}$ are respectively the overall sales of firm i in year t (over all its activities) and the overall sales on activity k at the year t (over all firms). The market share $s_{it,k}$ of firm i at the year t on activity k and the share of activity k at the year t in firm i total sales are thus equal to :

$$s_{it,k} = S_{it,k}/S_{t,k} \text{ and } b_{it,k} = S_{it,k}/S_{it} \tag{4.24}$$

Then for each diversified firm i at the year t we defined the weighted average market share s^w_{it} and the diversification index d_{it} as :

$$s^w_{it} = \sum_k b_{it,k} \times s_{it,k} \text{ and } \frac{1}{d_{it}} = h_{it} = \sum_k b^2_{it,k} \tag{4.25}$$

with d_{it} being the inverse of the Herfindahl concentration index h_{it} of the firm sales. For a non diversified firm (i.e. firm with no service activity), we have $s^w_{it} = s_{it}$ and $d_{it} = h_{it} = 1$

Appendix B : Random logit Estimates of Attrition

Table 4.5 – Random logit Estimates of Attrition

Variables	(1) RE logit		(2) RE logit		(3) RE logit		(4) RE logit	
	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.
TFP	- 0.851	0.823	- 0.911	0.831	- 1.043	0.849	- 1.029	0.848
INNOV			- 0.984	0.691	- 0.989	1.358	- 1.004	1.360
RDSPEND					- 1.906	3.720	- 1.647	3.814
EXPORT							- 0.400	0.979
SIZE	- 0.455	0.676	- 0.537	0.691	- 0.607	0.709	- 0.584	0.709
Observations	2,639		2,639		2,639		2,639	
Log likelihood	-82.770		-82.184		-81.601		-81.517	

s.e. mean standard error. Time and sectoral fixed effects are included in each equation. We also include individual time-average of the corresponding variable

Appendix C : Means and standard deviations for dependent and explanatory variables

Table 4.6 – Means and standard deviations for dependent and explanatory variables, by year

	2010		**2012**		**2014**		**2016**	
Variables	Mean	S. D.	Mean	S. D.	Mean	S. D.	Mean	S. D.
TFP	2.640	0.305	2.622	0.319	2.693	0.297	2.805	0.314
INNOV	0.400	1.604	0.500	1.804	0.579	2.066	0.605	2.055
RDSPEND	- 5.139	1.572	- 5.162	1.491	- 5.239	1.479	- 5.285	1.576
EXPORT	0.279		0.261		0.255		0.288	
CAPINT	4.868	0.968	4.936	1.008	4.885	0.974	5.129	0.931
HERFIN	0.010	0.053	0.020	0.061	0.008	0.043	0.009	0.044
GROUP	0.127		0.136		0.128		0.138	
FOREIGN	0.031		0.023		0.034		0.032	
IMPORT	0.143		0.125		0.139		0.139	
EXPEXT	0.293	0.126	0.269	0.120	0.265	0.130	0.301	0.165
RDSPILL	0.294	0.081	0.298	0.098	0.294	0.092	0.337	0.065
PMARGIN	2.895	0.625	2.911	0.596	2.932	0.557	2.928	0.578
MSHARE	- 3.002	2.126	- 3.129	1.945	- 3.249	2.145	- 2.935	1.934
SUPPORT	0.376		0.364		0.351		0.415	
AGE	3.408	0.955	3.424	0.953	3.425	0.943	3.536	0.900
SIZE	2.577	1.628	2.551	1.581	2.671	1.570	2.708	1.657

Table 4.7 – Means and standard deviations for dependent and explanatory variables, by type of firms

	Overall sample		**Exporter**		**R&D performer**		**Product innovators**	
Variables	Mean	S. D.	Mean	S. D.	Mean	S. D.	Mean	S. D.
TFP	2.687	0.311	2.782	0.292	2.699	0.300	2.774	0.292
INNOV	0.547	1.998	1.636	3.405	0.579	2.365	–	
RDSPEND	- 5.215	1.523	- 4.926	1.345	–		- 4.800	1.638
EXPORT	0.274		–		0.385		0.703	
CAPINT	4.943	0.953	4.877	0.754	4.878	0.866	4.980	0.670
HERFIN	0.013	0.053	0.015	0.052	0.014	0.053	0.019	0.062
GROUP	0.134		0.267		0.179		0.303	
FOREIGN	0.031		0.075		0.045		0.086	
IMPORT	0.136		0.374		0.188		0.413	
EXPEXT	0.281	0.136	0.353	0.151	0.307	0.139	0.370	0.156
RDSPILL	0.304	0.096	0.333	0.092	0.322	0.099	0.343	0.093
PMARGIN	2.912	0.578	2.741	0.582	2.943	0.554	2.823	0.537
MSHARE	- 3.071	2.030	- 1.231	1.862	- 2.638	2.095	- 0.859	1.877
SUPPORT	0.375		0.663		0.498		0.692	
AGE	3.453	0.930	3.393	0.758	3.321	0.865	3.325	0.804
SIZE	2.648	1.601	4.246	0.134	3.142	1.597	4.734	1.354

Appendix D : Description of variables

TABLE 4.8 – Description of variables

Variable	Definition
TFP	The Total Factors Productivity of firm i in year t
INNOV	The number of new products launched by a firm i in year t
RDSPEND	Investment of firm i in intangible assets in year t
EXPORT	1 if a firm i exports in year t and 0 otherwise.
SIZE	Total number of employees for firm i at the year t (in log)
GROUP	1 if the firm i belongs to a group in year t ; and 0 otherwise
FOREIGN	1 if the firm i is a subsidiary of a foreign firm in year t ; and 0 otherwise
AGE	Age of firm i in year t (in log)
CAPINT	Investment of firm i in tangible assets in year t (in log)
IMPORT	1 if a firm i imports in year t and 0 otherwise.
HERFIN	Equivalent number of activites of firm i in year t
MSHARE	Average market share of firm i in year t
EXPEXT	The number of exporting firms divided by the number of firms belonging to the same region and industry
SUPPORT	1 if the firm i received public funding for intangible investments in year t ; and 0 otherwise.
PMARGIN	Ratio between value-added and turnover for firm i in year t (in log)

TABLE 4.9 – Empirical studies on the learning by exporting

Study	Country and time period	Measure of efficiency	Methodology	Result
Clerides et al. (1998)	Columbia, 1983-91 ; Morocco, 1984-1990	Average variable cost, labor productivity	Generalized Method Moments	Weak evidence of LBE effects. Only Moroccan apparel and leather producers
Aw et al. (2000)	Taiwan, 1981, 1986, 1991 Korea, 1983, 1988, 1993	Total Factor Productivity	Ordinary Least Square	No evidence for LBE effects
Delgado et al. (2002)	Spain, 1991-96	Total Factor Productivity	Non-parametric approach	No evidence for LBE effects
Wagner (2002)	Germany, 1978–1989	Labor productivity	Matching technique	No evidence for LBE effects
Girma et al. (2004)	UK, 1988–99	Labor productivity growth, TFP growth	Diff-in-diff and matching	Weak evidence for LBE effects. Learning occur one year after firm entering in export markets
Biesebroeck (2005)	Nine african countries, 1992–96	Output	Random effect	Evidence of LBE effects for LBE effects
De Loecker (2007)	Slovenia, 1994–2000	Total Factor Productivity	Diff-in-diff and matching	Strong evidence of LBE effects. The Learning effect raise with experience in export markets
Crespi et al. (2008)	UK, 1991–93 1994–96, 1998–2000,	Labor productivity growth	Ordinary Least Square	Evidence of LBE effects. Authors use direct measure of learning
De Loecker (2013)	Slovenia, 1994–2000	Total Factor Productivity	Non-parametric Estimation	Evidence of LBE effects

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Chapitre 5

Persistence of innovation in French dairy industry [1]

5.1 Introduction

An important issue in the innovation economic is whether, and to what extent, firms that innovate once have a higher probability to innovate again in subsequent periods. This phenomenon is known in the literature as "*innovation persistence*" or "*state dependence*". From a theoretical point of view, innovation persistence (at firm level) is deeply rooted in the Schumpeterian view of industry dynamics (Crespi and Scellato, 2015). In Schumpeterian literature, there are two main patterns of innovation activities. The first one is a *creative destruction* pattern (*Mark I*) where technological change follows a process in which innovation creates just temporary monopoly power, with new and innovative firms replacing exiting firms. The second one is a *creative accumulation* pattern (*Mark II*) where technological change is the outcome of a gradual process of technological accumulation. Thus, the assessment of innovation persistence has important implications for our understanding of knowledge production processes and long-run industry dynamics.

Understanding the dynamic of innovation activities is also important from a policy standpoint. Policymakers have long been convinced that innovation promotion is beneficial to economic growth. For example, to overcome the differences in growth and productivity between the EU and its leading global competitors of the time —the USA and Japan— the Lisbon Strategy in 2000 proposed the stimulation of innovation and knowledge through greater investment in

1. This work is supported by a public grant overseen by the French National Research Agency (ANR) as part of the – "Investissements d'avenir" program (reference : ANR-10-EQPX-17 - Centre d'accès sécurisé aux données - CASD). This work is also supported by the project INNOV financed by the INRA metaprogramme DID IT (Diet impacts and determinants : Interactions and Transitions) for the access to the MINTEL-GNPD database.

R&D and Information and Communication Technologies (ICT). [2] The promotion of innovation, which occupied an equally important place in The Lisbon Strategy, has grown in importance with the EU2020 Strategy. For instance, H2020, the largest Research and Innovation funding programme in Europe, encourages participation by business and small and medium-sized companies. It promotes industry and academia cooperation to ensure that the fruit of research is developed into new products. [3] The identification of the *true state dependence* [4] suggests that public policies can produce long lasting effects on firms' innovation performances if they are able to induce firms to shifting towards more innovative patterns. In this context, a cumulative process of learning of both benefiting firms and public authorities can lead to virtuous processes able to increase the overall effectiveness of policy interventions.

The literature presents at least three theoretical arguments in favor of the persistence of innovation at firm level. The first argument is the "success-breeds-success" hypothesis. It was introduced by Mansfield (1968). This hypothesis states that a firm's innovation success broadens its technological scope, which increases the probability of success of subsequent innovations. Actual innovative success positively affects further innovations in subsequent years. Moreover in the line of the "success-breeds-success" hypothesis, Phillips (1971) points out that successful innovations have a positive impact on the conditions for further innovation through high market power. An alternative explanation of "success-breeds-success" originated from the existence of financial constraints on innovation investment. Innovation activities are usually characterized by long-term commitments, significant financial investments and high risks. Due to the imperfection of capital market, the flow of internal financing is the main determinant of innovation spending (Arrow, 1962; Himmelberg and Petersen, 1994).

The second argument is the sunk costs hypothesis. The production of new knowledge deriving from R&D efforts is affected by substantial sunk costs. R&D related assets are typically unrecovered, their economic returns are defined in the long term and they require smooth investment plans (Crespi and Scellato, 2015). Such characteristics contribute to generate barriers and make technological innovation a systematic component of the firm strategy, once the

2. The Lisbon Strategy states that 3% of the EU's GDP should be invested in R&D and that private investment in R&D should be promoted.

3. See the Innovation Union Flagship Initiative. The European Commission is putting forward seven flagship initiatives to catalyse progress under each priority theme. For further information on the Innovation Union, see : https://ec.europa.eu/research/innovation-union/

4. According to Heckman (1981) there are two potential sources for persistent behavior. First, it might be caused by *true* state dependence. This means that a structural dependence exists in the sense that the innovation activities in one period itself enhances the innovation activities in the subsequent period. Second, firms may possess certain characteristics, which make them particularly innovative. If these characteristics themselves show persistence over time, they induce persistence in innovation behavior. If such attributes are unobserved (e.g. risk attitudes) but correlated over time and not appropriately controlled for in estimation, past innovation may appear to affect current innovation merely because it picks up the effect of the persistent unobservable characteristics (Peters, 2009). This is the spurious state dependence.

firm has incurred the non-recoverable R&D start-up costs (Sutton, 1991). Sunk costs represent a barrier to both entry into and exit from R&D activities.

The third argument is the knowledge accumulation hypothesis. This hypothesis stipulates that experience in innovation is associated with dynamic increasing returns in the form of learning-by-doing and learning-to-learn effects, which enhance knowledge stocks and the probability of future innovations (Le Bas et al., 2011). According to the evolutionary theory (See Nelson and Winter, 1977; Pavitt, 2003, for more details), technological capabilities are a decisive factor in explaining innovation. Technological capability does not depreciate rapidly over time, and therefore knowledge that has been used to produce past innovations can be applied to develop subsequent innovations (Huang and Yang, 2010). These three arguments provide complementary and self-reinforcing rather than competing hypotheses about the source of persistency. The concept of sunk costs is correlated to the generation of internal competencies through the investment in learning (Crespi and Scellato, 2015). The knowledge accumulation and the "success breeds success" hypothesis interplay, giving rise to a virtuous circle in which profits fund R&D and other technology activities and, a time period later, they enable the learning process to continue (Le Bas and Poussing, 2014).

This paper reports on an investigation of the innovation persistence based on a firm-level panel data set for the dairy industry in France. This is an interesting case because innovation output is high in dairy indusry. According to Grunert et al. (1997), Harmsen et al. (2000), Capitanio et al. (2009) or Acosta et al. (2015), the dairy industry is one of the most innovative industries in the manufacturing sector. For example, the community innovation survey 2014 (CIS 2014) shows that the agrifood sector drives by the dairy industry is the second most innovative industry in France after the information and communication industry. Moreover, by focusing on a particular industry in a given country, we can avoid the potential for cross-industry effects to complicate persistence in innovation.
This paper contributes to the empirical literature on innovation in a number of ways. First, it analyzes persistence using innovation output indicators from *innovation count* other than patents or innovation surveys indicators. Second, this is the first time that innovation count (follow the *object* approach) is translated into the *subject* approach to study innovation persistence.[5] Third, we estimate a dynamic two-part model, using an unbalanced panel of firm data accounting for unobserved heterogeneity through individual effects. The incidence and the intensity of innovation are estimated jointly, allowing a correlation between the processes governing the introduction of new products, and the generation of the number of new products. Both equations of the model follow a dynamic specification. We use an estimation

5. The *subject* approach collect information about a particular firm, while in the *object* approach, the basic statistical unit is an innovation.

technique suggested by Wooldridge (2005b) to handle the initial conditions problem in count data model and we generalized this for two-part model. Fourth, none of the previous empirical papers investigating the innovation persistence has dealt, to our knowledge, with one specific manufacturing industry.

The rest of this paper is organized as follows. Section 2 summarizes the findings of the empirical studies on the persistence of innovation. In Section 3, we present *Global New Product Database* (innovation count) and give more detailed on the panel data construction. Section 4 presents the econometric model, estimation techniques, and the empirical specification. Section 5 contains the estimating results for the persistence of innovation. The final section concludes.

5.2 Previous empirical studies

Empirical studies on the persistence of innovation is quite limited. Three types of studies are identified according to the innovation indicators. They are patent- and innovation survey-based.

Using the European Patent Office (OTAF-SPRU database) for five European countries (Germany, France, UK, Italy and Sweden) for the period 1969-1986, Malerba et al. (1997) focused on the question whether persistence exists, irrespective of its origin. Their results show that the persistence of the innovative activity plays an important role in explaining the concentration of technological activity. Only small fractions of firms were able to persist in patent activities. Geroski et al. (1997) estimate a proportional hazard model to capture the drivers of the duration of innovation spells, using patent records for UK during the period 1969–1988. The results suggest that just a minority of firms is persistently innovative. The result that patent activities exhibit only a little degree of persistence, was confirmed by Cefis and Orsenigo (2001) and Cefis (2003) using a transition probability matrix approach. The tendency to patent varies between industries (Archibugi and Pianta, 1996). For diverse reasons [6] some firms would prefer to protect their innovations by other appropriability methods (Archibugi and Pianta, 1996; Mansfield, 1985). Innovations are not necessarily patented, patent data is thus a distorted measurement of innovation (Becheikh et al., 2006). In addition, according to Duguet and Monjon (2004) patents measure the persistence of innovative leadership rather than of innovation behavior.

The innovation survey data allows differentiating the analysis of persistence as captured by different input and output indicators of innovation activities. Only a few studies use R&D indicators as a variable for studying innovation persistence. Using a panel of Spanish firms

6. high costs, cumbersome patenting procedures, etc...

for the period 1990-2000, Castillejo et al. (2004) show that past R&D experience had affected the current decision to engage in R&D. However, R&D represents an input to the innovation process that does not necessarily lead to innovation. Thus, R&D data would seem to be an over-estimated measure of innovation since it includes aborted R&D efforts. Raymond et al. (2010) is one of the first (with Duguet and Monjon, 2004) to use innovation survey to analyze innovation persistence. They study the persistence of innovation in Dutch manufacturing firms using three waves of Community Innovation Surveys (CIS), for the period 1994–2002. They found that firms in the high-tech sector innovated persistently, while this was not the case for low-tech firms. Clausen et al. (2012) analyze the persistence of product innovation for manufacturing in Norway during the period 1997-2006. They use a panel database created by merging four waves of Community Innovation Survey. They find that compared to process innovation, product innovation is highly persistent over the time. Le Bas and Poussing (2014) use two waves of the Community Innovation Survey conducted in Luxembourg for manufacturing firms, during the period 2002-2008. They show that technological innovators are more inclined to remain in the same state. Haned et al. (2014) analyze the impact of organizational innovation on the patterns of technological innovation persistence, using three waves of French Community Innovation Surveys. Their findings indicate a positive effect of organizational innovation on the dynamics of technological innovation. Most studies that use innovation survey find strong innovation persistence. At least two reasons [7] may explain this high persistence of innovation activities. 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 large firms may create a selection bias in favor of these firms (i.e. most innovative firms). Second, there is overlapping problem. Innovation generally refers to a three-year period. Using this indicator for yearly waves would induce an artificial high persistence due to overlapping time periods and double counting (Peters, 2009).

This review makes clear that : first, Persistence was furthermore found to differ across industries, but inter-sectoral differences were consistent across countries suggesting that persistence is technology-specific (Peters, 2009). That is why this study focuses on a specific industry. Second, previous studies focused on patent, R&D and innovation survey to investigate the persistence of innovation at firm level. Our study attempts to give new insight into the innovation persistence at firm level using innovation count.

5.3 Data

To have informations on new product, we use an exhaustive list of new product launches. The product launch data come from the Global New Products Database (GNPD) construc-

7. Other than the true state dependence.

ted by Mintel.[8] This database reports observations since 2010 and reports all consumables product launched. It covers 62 of the world's major countries. For each consumable product launched, the following information is available : registered country (country in which the launch was registered), product characteristics, the date of the launch in a specific country, product launch type and production code. To construct our innovation dataset, we face two challenges. Since our work focuses on French firms, the first challenge is to find in this vast set of products, those manufactured by French firms. To do so, we use the production code variable avalaible in GNPD. The production code refers to EC identification and health marks. In France, any establishment preparing, processing, handling or storing products of animal origin or food containing them and marketing such products to other establishments, including freezer vessels, factory vessels and vessels cooking crustaceans and molluscs, is subject to the requirement of health approval. Products from an approved establishment shall bear an oval identification mark identifying that establishment. For French products, the EC identification takes the following form : `FR XX XXX XXX EC`. Considering that French firms are required to affix their approval number to their products[9], we can consider that all French dairy products present in GNPD have an approval number. In order to keep only French dairy product, we only retain dairy products whose approval number begins by `FR`.

After having found the french product launches, the second challenge concerns the ID number (SIREN)[10] of the firms that manufactured these products. This ID number is crucial for our study because it is a key variable allowing the merger between our different databases. To find the ID number we use EC identification. An approval number is usually assigned to a plant ; in addition, we know that a firm gets one or more plants. So theoretically, with the approval number, it is possible to trace back to the manufacturing firm (and therefore the firm's ID number). In practice, changing from the plant approval number to the associate to firm ID number is not straightfoward, as there is no link between these two identifiers. To achieve our goal we split the search for the firm ID number into two steps. First, with the plant approval number we found the SIRET identifier of this plant.[11] The *SIRET* (Système d'identification du Répertoire des établissements) number is the plant identifier ; it contains14 digits, the first 8 are the identifier of the associated firm. In the second step, after having found the SIRET number of the plant, we only had to keep the first 8 digits of this SIRET number to have the ID number (SIREN) of the associated firm.

8. Mintel is a privately owned, London-based market research firm.
9. See Regulation (EC) Nº 853/2004 of the European parliament and of the council
10. In France, this firm ID number is called SIREN (Système d'Identification du Répertoire des ENtreprises). It's allocated by INSEE (Institut National de la Statistique et des Études Économiques) at the time of the firm's registration
11. It should be noted that the approval number (EC identification) is the plant identifier at European level ; at national level each plant is identified by another number upon registration (SIRET) ; and these two identifiers are distinct.

To measure new product, we use categorical variable `LaunchType` avalaible in GNPD. This categorical variable has 5 modalities :[12]

— "*new product*" : This launch type is assigned when a new range, line, or family of products is signaled. This launch type is also used if a brand that already exists on GNPD, in one country, crosses over to a new sub-category ;

— "*new variety/range extension*" : This launch type is dependent on the Brand field. It is used to document an extension to an existing range of products on the GNPD ;

— "*new packaging*" : This launch type is determined by visually inspecting the product for changes, and also when terms like New Look, New Packaging, or New Size are written on the pack ;

— "*reformulation*" : This launch type is determined when terms such as New Formula, Even Better, Tastier, Now Lower in Fat, New and Improved, or Great New Taste are indicated on the pack ;

— "*relaunch*" : This launch type is determined when specified the on pack, via secondary source information (trade shows, PR, websites, and press) or when a product has been both significantly repackaged and also reformulated. If aproduct is reformulated and repackaged then this launch type is selected.

We are only interested on the modality *new product* to compute our innovation measure. We define, product innovation as the number of new product introduced by a firm i at the year t. However, this innovation dataset is truncated, in that it contains only innovators ; i.e. firms that have introduced at least one new product. In order to complete this dataset with other firms in French dairy industry, we use Fare (Fichier Approché des Résultats Esane) dataset. FARE collect statistical data, compiled by INSEE (Institut national de la statistique et des études économiques) for its statistical purposes (construction of national accounts data, annual statistics on business results and performance, studies). They are based on data from several sources : tax data, social data and statistical survey data. FARE provide at firm-level balance-sheet data (sales, turnover, value-added, employment, capital, wages, intangible assets, etc...). The final dataset cover the period 2010-2017 and the resulting panel is about 3343 observations.

The French dairy industry consists of four sectors : the manufacturing of liquid milk and fresh product (code nace : 1051A), butter production (code nace : 1051B), cheese production (code nace : 1051C) and other dairy product manufacturing (code nace : 1051D). Our final sample consists of observations between 2010-2017 on all firms in Frecnh dairy industry with at least three observations over time, two of which need to be consecutive, to be able to identify the parameters of the lagged dependent variables. There are a total of 3343 observations and an average of 592 firms ; i.e. an average of 5.65 observations for each firm.

12. See GNPD glossary 2016, https://www.gnpd.com/gnpd/about/GNPD_Glossary_2016.1.pdf, for more details.

Table 5.1 – Industry characteristics by sector, overall sample

	Manufacture of liquid milk and fresh products	Butter production	Cheese production	Other dairy product manufacturing	Total
Number of new product[a]	1.501	1.677	0.415	0.363	–
Number of employee	150	173	49	129	–
Number of firms	75	7	476	34	592
Observations	360	37	2806	140	3343

[a] Mean of the overall sample.

5.4 Econometric model

We aim to investigate the persistence of innovation output in French dairy industry using the number of new products as an indicator of innovation output. Our innovation measure is then a discrete count variable. Using the Poisson or Negative-Binomial models can be helpful to modeling it. Figure 5.1 below gives a histogram for this variable. In our dataset, we observed a non-negligible number of zero. The conspicuous spike at zero in this variable can be due to a process other than the event count process. The preponderance of zeros can be explained because French dairy industry consists of "non-innovating" firms that have not introduced any new product in year t (86.66%) and "innovating" firms that have introduced at least one new product in year t (13.34%). The latent class interpretation of this variable suggests a two level decision process, the regime and the event count (Greene, 2009). To model the innovation persistence, we use a sample selection model for count event as proposed in Terza (1998), Greene (2001), Greene (2006), Greene (2007) and Greene (2009). Then our econometric model consists of an equation for "participation" and a model for the event count that is conditioned on the outcome of the first decision. The third part of the specification is the observation mechanism that links the two processes : the participation equation and the count outcome model. To model the dynamic process of a firm's innovation behavior, the dynamic unobserved effects model is employed here. The model explains the probability to introduce a new product by a firm and the extent of these innovations in terms of the number of new products introduced. First, we assume that firm i introduced a new product in period t $(d_{it} = 1)$ if the current expected profits of the new product, d^*_{it}, is positive. We then specify the dynamic of the firm's decision to introduce a new product d^*_{it} that depends on the previous decision, $d_{i,t-1}$, on observable explanatory variables, w_{it}, and on unobserved firm-specific attributes, $\eta_{1,i}$, that are assumed to vary between firms and constant over time. The structural model is specified as follows :

$$d^*_{it} = \alpha_1 d_{i,t-1} + \beta'_1 w_{it} + \eta_{1,i} + \varepsilon_{1,it} \tag{5.1}$$

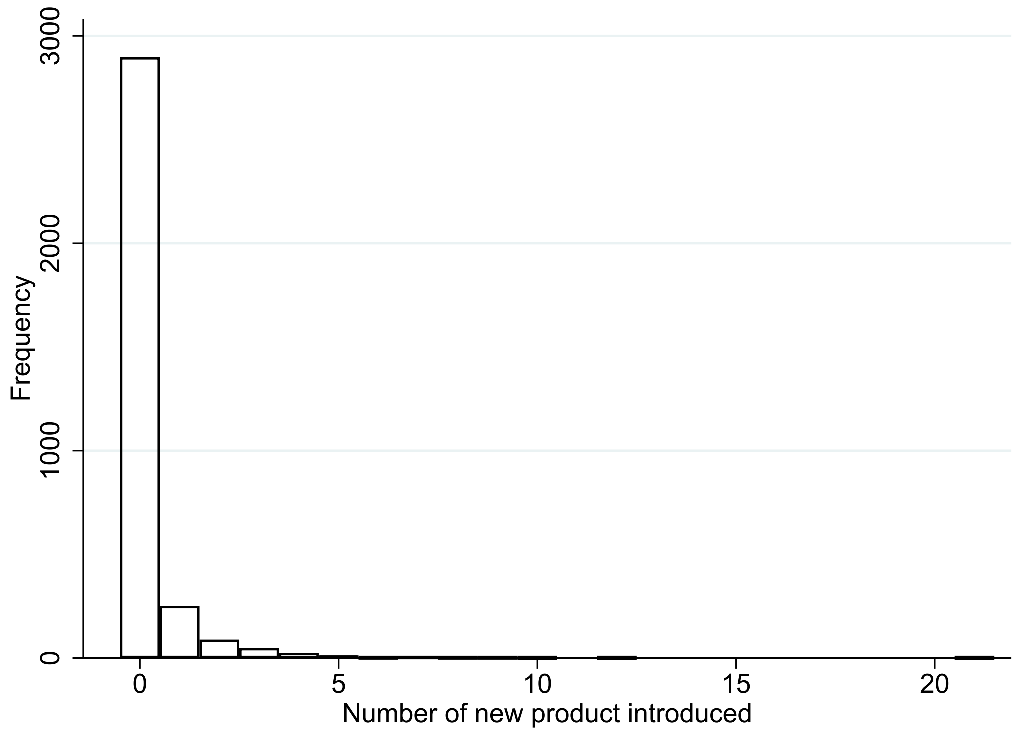

FIGURE 5.1 – Frequency
Source: GNPD 2010-2017, Author

where $i = 1, \ldots, N$, $t = 1, \ldots, T_i$; $\varepsilon_{1,it}$ is the error term, capturing the effect of other time-varying influences. It assume that $\varepsilon_{1,it} | d_{i0}, \ldots, d_{i,t-1}, w_{it}$ is independently and identically distributed as $\mathcal{N}(0,1)$ and that $\varepsilon_{1,it} \perp (d_{i0}, w_i, \eta_{1,i})$ where $w_i = (w_{i1}, \ldots, w_{iT})$. If d^*_{it} is positive, we can observe that a firm introduce a new product, where $\mathbb{1}$ denotes the indicator function.

$$d_{it} = \mathbb{1}\left[d^*_{it} > 0\right] \tag{5.2}$$

Second, we assume that the number of new products, y_{it}, introduced by in the period t by a firm i is generated according to the following conditional cumulative distribution function,

$$\mathbb{P}(y|\varepsilon_2, \eta_2) \quad = \quad \begin{cases} \text{not defined} & \text{if} \quad d_{it} = 0 \\ \mu^y \exp(-\mu)/y! & \text{if} \quad d_{it} = 1 \end{cases} \tag{5.3}$$

with

$$y \quad = \quad \begin{cases} 0 & \text{if} \quad d_{it} = 0 \\ 1, 2, 3, \ldots & \text{if} \quad d_{it} = 1 \end{cases} \tag{5.4}$$

where $\mathbb{P}$ denotes "probability of," η_2 is the unobserved firm-specific attributes that are assumed to vary between firms and constant over time, and $\mu_{it} \equiv E(y_{it} | y_{i,t-1}, x_{it}, \varepsilon_{2,it}, \eta_{2,i})$. Term ε_2 is the idiosyncratic error following a normal distribution. A statistical reason for the normality assumption is pointed out by Winkelmann (2008) : if an error captures the effect of omitted regressors, we can establish normality by the central limit theorem. In our dataset, we have no informations on factors hampering innovation activities.[13] Then, $\varepsilon_{2,it}$ capture the effects of these factors. For firm that introduced new product in year t, we use a log-linear model for specifying the conditional mean of y_{it} given $y_{i,t-1}, x_{it}, \varepsilon_{2,it}, \eta_{2,i}$. The overall model is written as

$$d_{it} = \mathbb{1}\left[\alpha_1 d_{i,t-1} + \beta_1' w_{it} + \eta_{1,i} + \varepsilon_{1,it} > 0\right] \tag{5.5}$$

$$\ln(\mu_{it}) = \begin{cases} \alpha_2 y_{i,t-1} + \beta_2' x_{it} + \eta_{2,i} + \varepsilon_{2,it} & \text{if} \quad d_{it} = 1 \\ 0 & \text{if} \quad d_{it} = 0 \end{cases} \tag{5.6}$$

Equations (5.5) and (5.6) are jointly estimated, allowing for a correlation between the introduction of a new products and the generation of the number of new products. There are at least two econometric issues that should be dealt with in the above model : the unobserved individual effect, η_i, and the initial condition for the dynamic model. To deal with the first problem of unobservable individual effect in a panel data model, both random effect and fixed effect models that treat for the individual effect as a random variable and fixed parameter respectively, are standard estimation methods. The fixed effect model has less limitation about the assumption of the distribution of the unobserved individual effect, making it preferable in practice. Wooldridge (1995), Kyriazidou (1997), Rochina-Barrachina (1999) or Dustmann and Rochina-Barrachina (2007) have used panel fixed effect estimators for sample selection models, where both the selection equation and the linear equation of interest contain individual effects which are correlated with the explanatory variables. Because there is no general solution in the literature regarding how to estimate a dynamic non linear model with fixed effect, this study therefore applies the random effect model.

As far as the problem of the initial condition for the dynamic model is concerned, Wooldridge (2005b) suggests a simple solution. He assumes that the individual heterogeneity depends on the initial condition and the strict exogenous variables in the following way :

$$\eta_{1,i} = b_{0,1} + b_1' \bar{w}_i + a_1 d_{i,0} + u_{1,i} \tag{5.7}$$

$$\eta_{2,i} = b_{0,2} + b_1' \bar{x}_i + a_2 y_{i,0} + u_{2,i} \tag{5.8}$$

where $\bar{w}_i$ and $\bar{x}_i$ denotes the time-average of w_{it} and x_{it} respectively. These vectors are included to allow for correlation between individual effects and the explanatory variables, w_{it} and x_{it} in all time periods ; a_1 and a_2 capture the dependence of the individual effects on the initial conditions. The Wooldridge's approach to handling the initial condition problem consists to

13. A numerous of studies have show that innovation activity may be hampered by a number of factors. There may be reasons for not starting innovation activities at all, or factors that slow innovation activity or have a negative effect on expected results.

model the distribution of the unobserved effect conditional on the initial value and explanatory variables. The vectors $u = (u_1, u_2)$ and $\varepsilon = (\varepsilon_1, \varepsilon_2)$ are assumed to be *i.i.d* and follow a normal distribution with mean 0 and a variance-covariance matrices

$$\Omega_\varepsilon = \begin{pmatrix} 1 & \tau\sigma_{\varepsilon_2} \\ \tau\sigma_{\varepsilon_2} & \sigma^2_{\varepsilon_2} \end{pmatrix} \quad \text{and} \quad \Omega_u = \begin{pmatrix} \sigma^2_{u_1} & \rho\sigma_{u_1}\sigma_{u_2} \\ \rho\sigma_{u_1}\sigma_{u_2} & \sigma^2_{u_2} \end{pmatrix} \tag{5.9}$$

By assuming the independance of observations over time, the conditional joint density for the T_i observations of the i^{th} individual is :

$$f_i(y_i, d_i|x_i, w_i, \beta, \eta_i, \tau) = \prod_{t=1}^{T_i} f_{it}(y_{it}, d_{it}|x_{it}, w_{it}, \beta, \eta_i, \tau) \tag{5.10}$$

where $f_{it}(y_{it}, d_{it}|x_{it}, w_{it}, \beta, \eta_i, \tau)$ is the density for an observation and it takes the following form :

$$\begin{aligned} f_{it}(y_{it}, d_{it}|x_{it}, w_{it}, \beta, u_i, \tau) = & \left[(1 - d_{it}) + d_{it} \times \left(\frac{\exp\{-\exp(A_{2,it} + u_{2,i})\}}{y_{it}!} \times \exp\{y_{it}(A_{2,it} + u_{2,i})\}\right)\right] \\ & \times\Phi\left((2d_{it} - 1) \times \frac{A_{1,it} + u_{1,i} + \frac{\tau}{\sigma_{\varepsilon_2}}\varepsilon_{2,it}}{\sqrt{1-\tau}}\right) \end{aligned} \tag{5.11}$$

where

$$A_{1,it} = \alpha_1 d_{i,t-1} + \beta_1' w_{it} + b_{0,1} + b_1'\bar{w}_i + a_1 d_{i,0} \tag{5.12}$$

$$A_{2,it} = \alpha_2 y_{i,t-1} + \beta_2' x_{it} + b_{0,2} + b_1'\bar{x}_i + a_2 y_{i,0} + \varepsilon_{2,it} \tag{5.13}$$

The joint density for an individual, conditional to the vector of the individual random $u = (u_1, u_2)$ is then

$$\begin{aligned} f_i(y_i, d_i|x_i, w_i, \beta, u_i, \tau) = \prod_{t=1}^{T_i} & \left[(1 - d_{it}) + d_{it} \times \left(\frac{\exp\{-\exp(A_{2,it} + u_{2,i})\}}{y_{it}!} \times \exp\{y_{it}(A_{2,it} + u_{2,i})\}\right)\right] \\ & \times\Phi\left((2d_{it} - 1) \times \frac{A_{1,it} + u_{1,i} + \frac{\tau}{\sigma_{\varepsilon_2}}\varepsilon_{2,it}}{\sqrt{1-\tau}}\right) \end{aligned} \tag{5.14}$$

After obtaining the conditional joint density shown in equation (5.14), the next step consists in deriving the unconditional counterparts to $f_i(y_i, d_i|x_i, w_i, \beta, u_i, \tau)$ which are obtained by integrating out u_i with respect to their normal distribution :

$$\ell_i = \ell_i(y_i, d_i|x_i, w_i, \beta, \sigma_{u_1}, \sigma_{u_2}, \tau, \rho)$$

$$\begin{aligned}
\ell_i &= \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} f_i(y_i, d_i|x_i, w_i, \beta, u_i, \tau) \times g(u_i|, \rho, \sigma_{u_1}, \sigma_{u_2})\, \mathrm{d}u_{1,i}\mathrm{d}u_{2,i} \\
&= \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} \frac{1}{2\pi}\frac{f_i(y_i, d_i|x_i, w_i, \beta, u_i, \tau)}{\sqrt{\sigma_{u_1}^2\sigma_{u_2}^2(1-\rho^2)}} \times \\
&\quad \exp\left[\frac{-1}{2(1-\rho^2)}\left\{\left(\frac{u_{1,i}}{\sigma_{u_1}}\right)^2 - 2\rho\left(\frac{u_{1,i}}{\sigma_{u_1}}\right)\left(\frac{u_{2,i}}{\sigma_{u_2}}\right) + \left(\frac{u_{2,i}}{\sigma_{u_2}}\right)^2\right\}\right] \mathrm{d}u_{1,i}\mathrm{d}u_{2,i} \qquad (5.15)
\end{aligned}$$

This double integral can be approximated by two-step Gauss-Hermite quadrature.This technique was originally proposed by Raymond et al. (2010) in the case of type 2 tobit model on panel data. Two step Gauss Hermite quadrature technique relies on a decomposition of the two-dimensional normal distribution for the individual effects into a one-dimensional marginal distribution and a one-dimensional conditional distribution(Mulkay, 2017).

The unconditional joint density for the i^{th} individual is rewritten as :

$$\ell_i(y_i, d_i|x_i, w_i, \beta, \sigma_{u_1}, \sigma_{u_2}, \rho) = \int_{-\infty}^{+\infty} H_i(u_{2,i}) \times \exp\left[-\frac{1}{2}\frac{(u_{2,i}/\sigma_{u_2})^2}{1-\rho^2}\right] \mathrm{d}u_2 \qquad (5.16)$$

with

$$\begin{aligned}
H_i(u_{2,i}) = \frac{1}{2\pi}\frac{1}{\sqrt{\sigma_{u_1}^2\sigma_{u_2}^2(1-\rho^2)}} \int_{-\infty}^{+\infty} f_i(y_i, d_i|x_i, w_i, \beta, u_i, \tau) \times \\
\exp\left[-\frac{1}{2(1-\rho^2)}\left\{\left(\frac{u_{1,i}}{\sigma_{u_1}}\right)^2 - 2\rho\left(\frac{u_{1,i}}{\sigma_{u_1}}\right)\left(\frac{u_{2,i}}{\sigma_{u_2}}\right)\right\}\right] \mathrm{d}u_1 \qquad (5.17)
\end{aligned}$$

The Gauss–Hermite quadrature states that

$$\int_{-\infty}^{-\infty} f(z)\exp(-z^2) \simeq \sum_{m=1}^{M} \omega_m f(a_m) \qquad (5.18)$$

where ω_m and a_m are respectively the weights and abscissae of the quadrature with M being the total number of integration points. By doing a change in variable such that $(u_1/\sigma_{u_1}) = z_1\sqrt{2(1-\rho^2)}$ and using expression (5.18), the expression (5.17) can be approximated by :

$$\begin{aligned}
H(u_2) \simeq \frac{1}{\pi\sqrt{2\sigma_{u_2}^2}} \sum_{m=1}^{M} \omega_m f_i\left(y_i, d_i|x_i, w_i, \beta, u_2, \tau, a_m\sigma_{u_1}\sqrt{2(1-\rho^2)}\right) \times \\
\exp\left(\frac{\rho\sqrt{2}}{\sqrt{1-\rho^2}}\left(\frac{u_2}{\sigma_{u_2}}\right) a_m\right) \qquad (5.19)
\end{aligned}$$

By introducing this new expression into equation (5.16) and making a second change in variable, $(u_2/\sigma_{u_2}) = z_2\sqrt{2(1-\rho^2)}$, we have

$$\ell_i(y_i, d_i|x_i, w_i, \beta, \sigma_{u_1}, \sigma_{u_2}, \rho, \tau) = \frac{\sqrt{1-\rho^2}}{\pi} \int_{-\infty}^{-\infty} \sum_{m=1}^{M} \omega_m \ell_i \Bigg(y_i, d_i|x_i, w_i, \beta, a_m\sigma_{u_1}\sqrt{2(1-\rho^2)}, \\ z_2\sigma_{u_2}\sqrt{2(1-\rho^2)}, \rho \Bigg) \times \exp\left[2\rho a_m z_2\right] \times \exp\left[-z_2^2\right] \, \mathrm{d}z_2 \quad (5.20)$$

A second Gauss-Hermite quadrature can be used to compute this integral. Then the final expression of the individual joint density unconditional to the individual effects can be approximated by

$$\ell_i(y_i, d_i|x_i, w_i, \beta, \sigma_{u_1}, \sigma_{u_2}, \rho, \tau) = \frac{\sqrt{1-\rho^2}}{\pi} \sum_{p=1}^{P} \sum_{m=1}^{M} \omega_p \omega_m \exp\left[2\rho a_m a_p\right] f_i \Bigg(y_i, d_i|x_i, w_i, \beta, \tau, \\ a_m\sigma_{u_1}\sqrt{2(1-\rho^2)}, a_p\sigma_{u_2}\sqrt{2(1-\rho^2)} \Bigg) \quad (5.21)$$

where ω_m, ω_p, a_m and a_p are, respectively, the weights and abscissas of the first and second stage Gauss-Hermite integration, with M and P being the first and second stage total number of integration points. Equations (5.5) and (5.6) are correlated through the individual effects ($\rho \neq 0$) and the idiosyncratic errors ($\tau \neq 0$). The model is identified through the functional form. Hence, vectors x_{it} and w_{it} may contain the same elements.

5.5 Empirical specification

As for the explanatory variables, theoretical and empirical studies have identified numbers of determinants. Innovation investment is considered as a main determinant of persistence. This determinant is closely related to the sunk cost hypothesis and knowledge accumulation ; firms that have strong R&D investment are more prone to innovating persistently. To capture this effect, we use R&D variables as explanatory variables. We define a R&D performer as a firm which invests in intangible assets in year t.

Firm size is an important determinant for innovation activities. Here we measured firm size by the number of employees and market shares. Schumpeter (1942), stated that large firms in concentrated markets have an advantage in innovation. Hence, firm size and market structure are generally considered as determinants of innovation. There are several explanations as to why large firms are more likely to invest more in innovation activities than small firms. First, innovation activities involve large fixed costs, and these fixed costs can only be covered by large firms. Second, there may be economies of scale and scope in the innovation production function. Third, large diversified firms are in a better position to exploit unforeseen innovations. Fourth, large firms can undertake many activities at any one time and hence spread the risks of innovation. Fifth, large firms have better access to external finance. Many empirical studies test and found significant effect of firms' size on innovation expenditures activities (Worley, 1961; Hamberg, 1964; Scherer, 1965; Bound et al., 1984; Cohen et al., 1987).[14] However, Cohen and Klepper (1996) show that, among innovation performers, innovation rises monotonically with firm size, within an industry.

Another important determinant of innovation investments is market structure. We use the Herfindahl-Hirschmann index to proxy market structure. According to Schumpeter (1942), ex ante product market power stimulates innovation activities because it increases monopoly rents from innovation and reduces the uncertainty associated with excessive rivalry that tends to reduce the incentive to innovate. Furthermore, the possession of market power increases firms' profits, which provide firms with internal funds necessary to innovate. This Schumpeterian hypothesis is generally formulated as follow : monopoly rents boost firms' efforts to innovate. Studies such as Horowitz (1962), Mansfield (1963), Kraft (1989), Crepon et al. (1998), Czarnitzki et al. (2014) or even Hashmi and Van Biesebroeck (2016) provided empirical evidences of this hypothesis. Endogenous growth models, Romer (1990), Aghion and Howitt (1992) and Grossman and Helpman (1991), also theorized negative relationship between competition pressure and innovation activities. In other hand, Arrow (1962) argued that a monopolist's incentive to innovate is less than that of a competitive firm, due to the monopolist's financial interest in the status quo. Arrow states that, the pre-invention monopoly power acts as a strong disincentive to further innovation. Hence, product market competition spurs innovation. Some empirical studies such as Porter (1990), Geroski (1990), Baily and Gersbach (1995), Nickell (1996), Blundell et al. (1999), Symeonidis (2002), and Beneito et al. (2015) also supported this point of views.

Some others characteristics impact innovation. Cohen (2010) summarized informations into firm and industry characteristics. Firm characteristics which have been found to explain innovation activities are : profitability (Caves et al., 1980; Antonelli, 1989; Hao et al., 1993; Himmelberg and Petersen, 1994; Hall, 2002), wage(Love and Roper, 2001; Klomp et al., 2001), ownership structure (Howells, 1984; Harris, 1991; Bishop and Wiseman, 1999; Love and Roper, 2001), exports (Alvarez and Robertson, 2004; Salomon and Shaver, 2005; Girma et al., 2008; Filipescu et al., 2013) and firm age (Balasubramanian and Lee, 2008; Cucculelli, 2017).

Industry characteristics may be important for innovation activities. Industry characteristics include demand (Schmookler, 1962, 1966; Stoneman, 1979; Kleinknecht and Verspagen, 1990; Geroski and Walters, 1995; Acemoglu and Linn, 2004; Cerda, 2007), technological opportunity

14. See Cohen and Levin (1989), Cohen and Klepper (1996), Ahn (2002), Klette and Kortum (2004) and Cohen (2010) for survey of empirical studies testing the Schumpeter hypotheses.

(Pakes and Griliches, 1984; Scherer, 1965; Scott, 1984; Jaffe, 1988; Jaffe et al., 1993; Geroski, 1990; Klevorick et al., 1995; Adams et al., 2003; Leiponen and Drejer, 2007) and appropriability (Taylor and Silberston, 1973; Mansfield, 1981; Cohen and Walsh, 2000). Thus we include dummies for sectors (5-digit NACE level). In order to avoids the potential problem of endogeneity between explanatory variables and new product introduction, all explanatory variables are lagged. Detailed definition of variables used and statistics descriptive are presented in table 5.3.

5.6 Result

5.6.1 Evidence from transition probabilities

Our analysis aims to identify the state dependence property that characterizes the product innovation process. Following an established literature, we rely on transition probabilities that have been frequently used to test the hypothesis that prior innovation matters in innovation processes (see for instance, Cefis and Orsenigo, 2001; Peters, 2009; Raymond et al., 2010; Antonelli et al., 2013). Table 5.2 provides the results for transition probabilities obtained on the full sample of firms observed in the entire period. Our calculations show the presence of innovation persistence at the firm level. Nearly 57% of the innovators in one year persisted in innovation in the subsequent year while 43% becomes non-innovators. Similarly, 94% of the non-innovators maintained this status in the following period while 7% commenced innovation activities. The state dependence is defined as the difference between the probability to remain

TABLE 5.2 – Transition probabilities, 2010-2017

	Innovation status in $t+1$	
	Non-innovator	innovator
Innovation status in t		
Non-innovator	93,15	6,85
Innovator	43,74	56,26

Note : We define the innovator as the observations which exhibit positive number of new products. We also define the non-innovator as the observations which don't exhibit positive number of new products.

in the status of innovators and the probability to become innovators. Hence, we find that on average, prior innovation activities increase the probability of the current ones by 49%. However, Figure 5.2 demonstrates the state dependence by years. For each point of time, we compute the state dependence of innovation between the current and the prior year. The result suggests that the state dependence seems to decreases over the years. However, the minimum value is 43%, observed during the period 2016-2017. [15]

15. Which is slightly high.

Table 5.3 – Variables description and Descriptive statistics

			Standard Deviation		
Variable	Definition	Mean	Overall	Between	Within
New product	Number of new products introduced in the market by a firm i in year t	0.278	1.047	0.699	0.740
Explanatory variables					
Profitability	Value added per employee in year t (in log.)	5.812	0.894	0.900	0.256
Wage	Cost of labor per employee in year t (in log.)	3.639	0.356	0.305	0.207
Market shares	The share of turnover for firm i in sector j in year t (in log.)	-3.001	2.137	2.130	0.558
Foreign firm	1 if firm i is a subsidiary of a foreign firm in year t and zero otherwise.	0.032			
R&D performer	1 if firm i have invest in intangible assets in year t and zero otherwise.	0.654			
Size	The number of employee in year t	2.772	1.600	1.610	0.170
Part of a group	1 if firm i belongs to a group in year t and zero otherwise	0.147			
Exporter	1 if firm i export in year t and zero otherwise	0.308			
Firm age	Firm age at the beginning of year t (in log.)	3.447	0.860	0.907	0.079
HHI	Hirschman–Herfindahl Index in year t	0.013	0.054	0.040	0.038

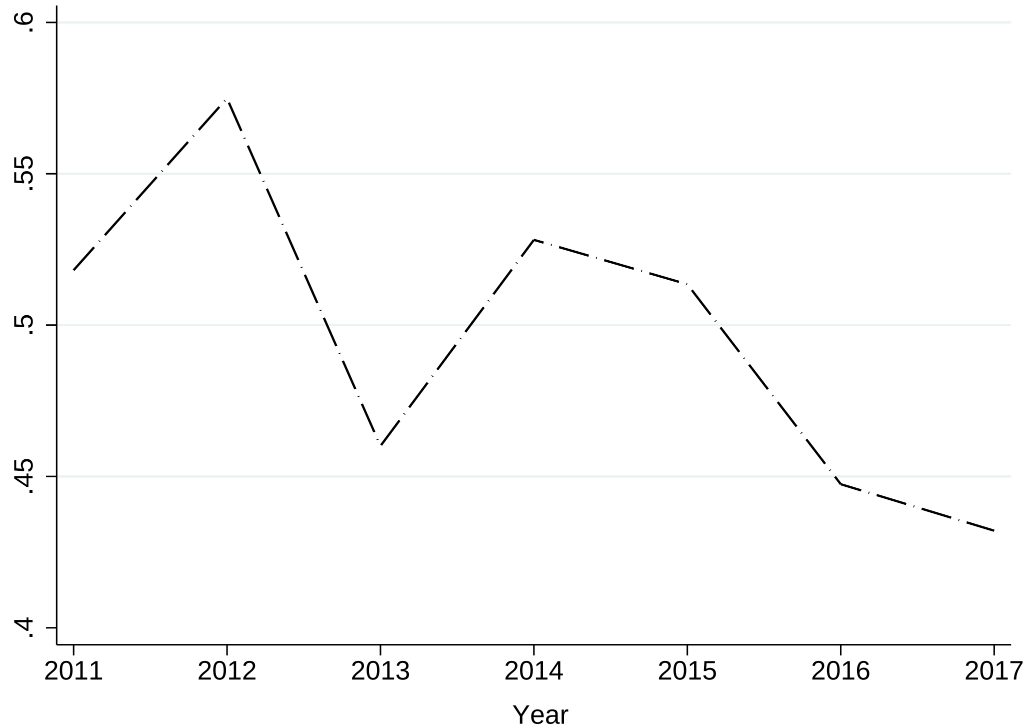

FIGURE 5.2 – State dependance by year
Source: Author calculation

The data seem to provide initial evidence of significant persistence in innovation. However,we argue that it is important to emphasize how the above results, while suggesting the presence of some form of inter-temporal stability in innovation, do not yet provide a sound answer to two key questions : how much of the observed persistence can be labelled as true persistence driven only by previous innovation ? Moreover, which factors explain this persitence ?

5.6.2 Results from dynamic panel data analyses

In Table 5.4, we report our results for different specifications of the Two Part model. In order to show the importance of considering individual effects and dealing with the problem of initial conditions, we follow Raymond et al. (2010) and present the results of the estimates for three variants of the dynamic two-part model. More precisely, we present the estimation results of the specification without taking into account the individual effects (Spec. A) in the first column and those of the same specification taking into account the individual effects but the initial conditions assumed to be exogenous (Spec. B) in the second column. These results should be compared to the estimates in the third column resulting from the estimation of the model, the individual effects being correlated with the initial conditions (Spec. C). One limitation of the estimator is that strict exogeneity of the explanatory variables is assumed (see for instance, Wooldridge, 2005b,a, p.483). This implies that feedback effects from innovation on future values of the explanatory variables are ruled out, which seems to be contestable for some of the variables usually explaining innovation, e.g. firm size (Peters, 2009). To deal with this issue, all explanatory variables include in the model are lagged.

TABLE 5.4 – Dynamic two part model estimates.

			Individual Effects			
Variable	No Individual Effects Spec. *A*		Exogenous Initial Condition Spec. *B*		Endogenous Initial Condition Spec. *C*	
Current innovation status						
Past innovation status	1.061*** [0.218]	(0.079)	0.550*** [0.079]	(0.113)	0.414*** [0.056]	(0.111)
Market shares	0.053 [0.008]	(0.040)	0.085 [0.019]	(0.056)	0.062 [0.014]	(0.021)
Profitability	0.212 *** [0.008]	(0.075)	0.312*** [0.006]	(0.103)	0.329*** [0.004]	(0.106)
Exports	0.207*** [0.030]	(0.074)	0.251** [0.032]	(0.101)	0.221** [0.027]	(0.103)
Firm age	-0.076* [-0.012]	(0.039)	-0.098* [-0.021]	(0.060)	-0.089 [-0.021]	(0.061)
R&D performer	0.034 [0.005]	(0.072)	0.063 [0.008]	(0.088)	0.074 [0.009]	(0.089)
Wage	-0.129 [-0.021]	(0.142)	-0.144 [-0.032]	(0.181)	-0.117 [-0.027]	(0.183)
Foreign owner	-0.150* [-0.021]	(0.090)	-0.291* [-0.036]	(0.145)	-0.214 [-0.025]	(0.152)
Part of a group	0.406*** [0.058]	(0.100)	0.669*** [0.084]	(0.165)	0.595*** [0.071]	(0.167)
HHI	-0.031** [-0.005]	(0.015)	-0.045** [-0.010]	(0.021)	-0.042** [-0.010]	(0.021)
Size (reference group : Very small size)						
Small	0.509** [0.078]	(0.232)	0.547* [0.075]	(0.289)	0.576** [0.075]	(0.291)

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Table 5.4 – *Continued from previous page*

Variable	No Individual Effects Spec. A		Individual Effects: Exogenous Initial Condition Spec. B		Individual Effects: Endogenous Initial Condition Spec. C	
Medium	0.891*** [0.134]	(0.231)	1.101*** [0.145]	(0.295)	1.069*** [0.136]	(0.297)
Large	1.419*** [0.278]	(0.255)	1.721*** [0.285]	(0.333)	1.603*** [0.255]	(0.335)
Intercept	-1.461*	(0.747)	-1.527	(0.978)	-1.813*	(0.996)
Current number of new product introduced						
Past number of new product introduced	0.069***	(0.016)	0.040**	(0.019)	0.032*	(0.018)
Market shares	0.018	(0.039)	0.020	(0.043)	-0.009	(0.040)
Profitability	0.156*	(0.082)	0.177*	(0.093)	0.135*	(0.086)
Exports	0.017	(0.093)	0.009	(0.096)	-0.012	(0.094)
Firm age	0.067	(0.053)	0.044	(0.056)	0.044	(0.054)
R&D performer	0.017	(0.081)	0.005	(0.081)	-0.039	(0.081)
Wage	-0.018	(0.184)	-0.056	(0.186)	0.022	(0.186)
Foreign owned	-0.047	(0.102)	-0.091	(0.109)	-0.047	(0.106)
Part of a group	-0.012	(0.123)	0.056	(0.140)	0.031	(0.132)
HHI	-0.035	(0.023)	-0.039*	(0.024)	-0.030	(0.023)
Intercept	1.077	(0.800)	1.231	(0.806)	0.739	(0.819)
Extra Parameters						
Init. innov. statut	–		–		0.813*** [0.123]	(0.163)
Init. number of new prod. introduced	–		–		0.107***	(0.036)
σ_{ε_2}	0.417***	(0.048)	0.384***	(0.063)	0.384***	(0.062)
τ	-0.454**	(0.187)	-0.719***	(0.252)	-0.774***	(0.218)
σ_{u_1}	–		0.997**	(0.406)	1.116**	(0.502)

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Table 5.4 – *Continued from previous page*

Variable	No Individual Effects Spec. A	Individual Effects: Exogenous Initial Condition Spec. B		Individual Effects: Endogenous Initial Condition Spec. C	
σ_{u_2}	–	0.170**	(0.079)	0.122*	(0.068)
ρ	–	0.999***	0.000	0.999***	(0.010)
Observations		3343			
Log likelihood	-1612.404	-1588.715		-1569.494	

Notes : ***, ** and * indicate significance on a 1%, 5% and 10% level, respectively. Average Partial Effects in brackets. Time dummies and sector dummies are included in all equations. All explanatory variables are lagged.

As mentioned earlier, the persistence of innovation may be spurious. The existence of true persistence in innovation may be ascertained by verifying that, after accounting for individual effects and properly handling the initial conditions problem, the effect of the lagged dependent variable is, economically and statistically, relevant (Raymond et al., 2010). However, both the model that assumes the absence of individual effects and the model that accounts for individual effects are rejected using a likelihood ratio test. Hence, the full model is the preferred one where equations (5.5) and (5.6) account for individual effects and assumes endogenous initial conditions.

For the participation equation, all three variants specifications show that the persistence parameter is positive and highly significant. The specification without individual effect shows that the coefficient of the lagged innovation status is very large and positive, revealing that having innovations during the previous year has a positive effect on the probability of undertaking innovations in the current year. The magnitude (average partial effect) of the persistence in innovation is 0.218. Conducting innovation in the previous year increases the probability of undertaking innovations by more than 20%. In line with the results for transition probability, the result of the state dependence is higher and quite similar (0.218 versus 0.49). [16] The estimate of the state dependance obtained with model A is similar to that obtained by Duguet and Monjon (2004) in French manufacturing insdutry. However, these results are spirious since they do not allow for unobserved effects. When properly handling the unobserved heterogeneity (through individual effect) and the initial conditions problem, the effect of lagged innovation status on the current innovation status is positive and highly significant but the magnitude of this effect is small (see spec. C). Indeed, conducting product innovation in the previous year increases the probability of undertaking product innovations by only 5.60%. The results further show

16. The state dependance obtained using spec. (A) without explanatory variables is 0.495.

that the initial condition is also highly significant. This implies a correlation between firms' initial innovation status and the unobserved heterogeneity. Futhermore, the results indicate that unobserved heterogeneity is important for innovation persistence. unobserved effect accounts for about 52.74% the unexplained variance.

The remaining variables in the participation equation,i.e. firm size, market concentration, exports, profitability and ownership structure, also have significant effects. Firm size which is measured by the number of employees is positively correlated with the probability to introduced new products. The number of employee is measured using a set of four dummy variables distinguishing the size groups : 1-4 employees, 4-9 employees, 10-29 employees, and $\geq$30 employees. Then, we include three dummy variables representing different firm size categories in the estimation, where firms between one and four employees are the omitted base group. The coefficients on the three groups are positive and statistically significant, indicating that large firms are more likely to introduce new products than the base group. The magnitude of the estimates is higher for the largest firms, indicating higher probability to introduce new products for large firms. We find that the firms in ex-ante higher concentrated markets decrease significantly the probability to introduce new products. One explanation might be that firms in less competitive markets are less aware of consumer preferences which leads to a lower acceptance rate of new products and, hence, to a lower innovation success. Exporting rises firm's probability to introduce new products by 3%. Moreover, firms that are part of a group exhibit a higher propensity to innovate.

For the event count model, equation (5.6), the estimates of the parameters in the specification A and in the specification B are similar. The persistence parameter is positive and highly significant. Furthermore, profitability affects positively the number of new products. After accounting for individual effects that are correlated with the initial conditions (Spec. C), the persistence parameter remains significant at the 10% level, but small in magnitude compared to other specifications. This means that the number of new products introduced in previous year affects the number of new products introduced in current year. In addition, equations (5.5) and (5.6) are found to be correlated. Indeed, we find a negative correlation between the two idiosyncratic errors. The negative sign on this correlation indicates that the unobservable factors that increase the probability to introduce new products are negatively correlated with the unobservable factors that increase the number of new products introduced. We also find high and positive correlation between individual effects.

5.7 Conclusion

This study investigates the persistence of innovation and the dynamics of innovation output in the French dairy industry based on a panel data during the period 2010-2017. Thanks to the *Global New Product Database*, we construct a new firm-level panel data, which gives us a new insight into the analysis of the persistence of innovation. In estimating the dependence of past innovation performance, we introduce lagged dependent variables as explanatory terms and use a Two Part model accounting for individual effects and handling the initial conditions problem. The econometric analysis reveals that innovation experience is an important driver for innovation behaviour.

Our results show that innovation output are highly persistent at the firm level. True state dependence occurs when a firm that has introduced a new product in the current year introduce a new product in the next period. Past experience, either in innovation, is an incentive to remain an innovator. Furthermore, the number of new products introduced in previous year affects, albeit to a small extent, the number of new products introduced in the current year. Our result gives credence that there is persistence in innovation output when innovation is measured by the appearance of new products and the intensity of innovation output. Our results contrast with those of Peters (2009) and Triguero and Córcoles (2013) who find a high magnitude for state dependence for German (manufacturing and services) firms and Spanish manufacturing firms, respectively. The results further highlight the role of firm's characteristics on the dynamics in firms' innovation behaviour. In addition to past innovation experience, firm size, firm age, profitability, exports and ownership structure have been found to be important in generating innovations over time. The individual effects and their correlation with the initial conditions are important to account for when estimating the "participation" equation and the model for the event count. Both processes are shown to be positively and significantly correlated through the individual effects, and negatively and significantly correlated through the idiosyncratic errors.

Our results confirm the characteristics inherent in the innovation process identified by economic theory. First, the innovation process is dynamic and our result increases the credence for the "success breeds success" hypothesis. Second unobserved heterogeneity play an important role in accounting for differences in innovation behavior and must be modeled. Finally, as in Raymond et al. (2010) qualitative and quantitative measures of innovation must be modeled jointly as they are closely related to one another. Since innovation behaviour is characterised by true state dependence, innovation-stimulating policy programs open up potential additional long-lasting effects.

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Conclusion

Cette thèse a étudié empiriquement l'impact de l'innovation produit sur la performance des entreprises en se penchant sur trois sujets différents.

1. Comment l'innovation affecte-t-elle l'auto-sélection des entreprises dans les marchés d'exportation ?
2. comment l'innovation affecte-t-elle l'apprentissage par l'exportation ?
3. les entreprises innovent-elles de manière persistante dans le temps ?

Ces trois sujets ont largement été traités dans la littérature. Cependant, cette thèse apporte de nombreuses originalités qui permettent d'améliorer la compréhension du mécanisme de l'innovation produit et de ses effets sur la performance des entreprises. Pour l'ensemble des sujets traités, mes investigations portent sur une unique industrie évitant ainsi les effets intersectoriels pouvant affecter nos estimations. Grace à la base de données *Global New product Database*, nous disposons d'une nouvelle mesure de l'innovation qui est l'innovation observée par les consommateurs sur leur lieu d'achat.

Dans le chapitre 3, il était question d'analyser l'effet de l'innovation produit sur la performance à l'export des entreprises. Ce chapitre contribue à la littérature en proposant une modélisation théorique dans laquelle l'innovation produit est considérée comme une composante essentielle de la demande. Partant de l'hypothèse qu'un nouveau produit introduit sur un marché donné intègre les préférences des consommateurs du dit marché. Nos prédictions montrent que l'innovation produit affecte la performance à l'export de deux façons distinctes et opposées. Premièrement, l'introduction d'un nouveau produit affecte positivement la demande d'une variété du fait de l'augmentation de la qualité de cette variété (l'effet demande). Deuxièmement, l'introduction d'un nouveau produit influence positivement le prix de la variété proposée (l'effet coût). Ainsi, l'introduction d'un nouveau produit améliore la performance à l'export seulement si l'effet demande est supérieur à l'effet coût. Ces prédictions théoriques sont testées et confirmées pour les entreprises de l'industrie laitière française.

Le chapitre 4 s'intéressait au rôle de l'innovation produit dans l'apprentissage par l'exportation. Ce chapitre contribue à la littérature de manière méthodologique. Nous proposons en effet une modélisation empirique, basée sur le modèle structurel de Crepon et al. (1998). Nous étendons le modèle CDM de différentes manières. Premièrement, nous intégrons la décision d'exporter comme une composante endogène au processus d'innovation. Deuxièmement, nous prenons en compte l'hétérogénéité inobservée en intégrant des effets individuels dans chaque équation du modèle. Troisièmement, nous considérons que les équations du modèle sont corrélées deux à deux à travers leurs termes d'erreurs et leurs effets individuels. Nous proposons une procédure d'estimation, similaire à celle de Raymond et al. (2015), basée sur l'estimateur du maximum de vraisemblance à information complète. Les résultats montrent que : *i*) les exportations influencent positivement les investissements en recherche et développement des entreprises ; *ii*) les investissements d'une entreprise en recherche et développement augmentent leur nombre de nouveaux produits ; *iii*) le nombre de nouveaux produits introduit par une entreprise à un effet positif sur sa productivité et *iv*) l'innovation produit est l'un des canaux par lequel le processus d'apprentissage l'exportation est observé.

Le chapitre 5 apporte de nouvelles preuves sur la question de la persistance de l'innovation grâce à la nouvelle base utilisée. A partir des matrices de transition, il ressort que le comportement des entreprises en matière d'innovation produit est persistant dans le temps. Ce résultat est confirmé par les estimations économétriques. Ce qui veut dire qu'innover au cours d'une période augmente significativement la probabilité d'innover pendant les périodes suivantes. Le fait que l'innovation persiste dans le temps implique que les programmes politiques de stimulation de l'innovation ouvrent la voie à des effets potentiellement durables car ils n'affectent pas seulement les activités d'innovation en cours mais sont susceptibles d'induire un changement permanent en faveur de l'innovation. En outre, la persistance de l'innovation pourrait être l'une des causes des asymétries observées dans les distributions de la productivité et de la performance à l'export.

UNIVERSITE BRETAGNE LOIRE ECONOMIE ET GESTION

UNIVERSITÉ DE NANTES

Titre : Innovation Produit et Performance des Entreprises dans l'Industrie Laitière Française

Mots clés : Innovation produit ; Export ; Productivité ; Apprentissage par l'exportation ; Dynamique

Résumé : Le processus de croissance des entreprises -- en termes de productivité ou de performance à l'export -- est une préoccupation majeure des décideurs politiques. Dans ce contexte, les innovations jouent un rôle crucial pour stimuler la performance des entreprises. Cette thèse étudie empiriquement l'impact de l'innovation « produit » (à distinguer de l'innovation « procédé ») sur la performance des entreprises. La revue de la littérature présentée dans le chapitre 2 décrit les mécanismes qui régissent la relation entre l'innovation et la productivité et la relation entre l'innovation et le comportement à l'export des entreprises. Le chapitre 3 présente une description de la notion d'innovation et de sa mesure dans la littérature économique. Nous présentons *Global New Product Database* (GNPD), la banque de données que nous utilisons pour construire une base de données innovation. Le chapitre 4 estime l'effet de l'innovation produit sur le comportement à l'export des entreprises laitières françaises. Nous montrons que l'introduction d'un nouveau produit influe positivement non seulement sur les prix proposés par l'entreprise mais aussi leur demande. Le chapitre 5 s'intéresse au rôle de l'innovation produit dans l'apprentissage acquis lors de l'exportation. Nous montrons que les exportations renforcent la capacité d'innovation des entreprises, qui à son tour augmente la productivité des entreprises. Le chapitre 6 traite de la persistance de l'innovation produit dans l'industrie laitière française. Nous montrons que les entreprises qui sont les plus susceptibles d'innover sont celles qui ont innové l'année précédente. Ainsi, cette thèse montre, grâce à une nouvelle mesure de l'innovation produit, que celle-ci permet aux entreprises d'exporter, d'augmenter leur productivité et de rester innovante

Title : Product Innovation and Firm Performance in French Dairy Industry

Keywords: Product innovation; Exports; Productivity; Learning by exporting; State dependence.

Abstract : The process of firm growth – in terms of productivity or export performance – is a major concern for policy makers. In this context, innovations play a crucial role in stimulating firm performance. This thesis empirically studies the impact of "product" innovation (as distinct from "process" innovation) on the performance of firms. The literature review presented in Chapter 2 describes the mechanisms that govern the relationship between innovation and productivity and the relationship between innovation and firms' export behaviour. Chapter 3 presents a description of the notion of innovation and its measurement in the economic literature. We present Global New Product Database (GNPD), the database we use to construct an innovation database. Chapter 4 estimates the effect of the innovation produced on the export behaviour of French dairy firms. We show that the introduction of a new product has a positive impact not only on the prices offered by the company but also on their demand. Chapter 5 examines the role of product innovation in the learning by exporting process. We show that exports strengthen the innovative capacity of firm, which in turn increases the productivity of firms. Chapter 6 deals with the persistence of product innovation in the French dairy industry. We show that the firms that are most likely to innovate are those that innovated the previous year. Thus, this thesis show, thanks to a new measure of product innovation, that it allows companies to export, increase their productivity and remain innovative.