



HAL
open science

Market Power and Frictions in Supply Chains

Etienne Guigue

► **To cite this version:**

Etienne Guigue. Market Power and Frictions in Supply Chains. Economics and Finance. Institut Polytechnique de Paris, 2023. English. NNT : 2023IPPAG009 . tel-04159951

HAL Id: tel-04159951

<https://theses.hal.science/tel-04159951>

Submitted on 12 Jul 2023

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



INSTITUT
POLYTECHNIQUE
DE PARIS

NNT : 2023IPPAG009

Thèse de doctorat



Market Power and Frictions in Supply Chains

Thèse de doctorat de l'Institut Polytechnique de Paris
préparée à l'École nationale de la statistique et de l'administration économique

École doctorale n°626 de l'Institut Polytechnique de Paris (ED IP Paris)
Spécialité de doctorat : Sciences économiques

Thèse présentée et soutenue à Palaiseau, le 5 juillet 2023, par

Etienne Guigue

Composition du Jury :

Isabelle Méjean Professeure, Sciences Po (Département d'Economie)	Présidente
Pierre Dubois Professeur, Université Toulouse 1 Capitole (TSE)	Rapporteur
Mathieu Parenti Professeur Associé, Université Libre de Bruxelles (ECARES)	Rapporteur
Francis Kramarz Professeur, ENSAE (CREST)	Directeur de thèse

Remerciements – *Acknowledgments*

Le jour de gloire est arrivé, je termine ma thèse ! L'aventure fut longue, belle, bien que parfois chaotique, et l'issue est heureuse notamment grâce aux personnes qui ont contribué à l'aboutissement de ce projet, et que je souhaite remercier ici.

Je remercie tout d'abord Pierre Dubois et Mathieu Parenti d'avoir accepté les rôles engageant de rapporteurs pour ma thèse. Ce fût un honneur et un plaisir de pouvoir bénéficier de leur précieux retours, conseils et encouragements. J'espère avoir de multiples occasions de recroiser leur route à l'avenir.

Un grand merci ensuite bien sûr à mon directeur de thèse Francis Kramarz, qui a eu une grande confiance en moi dès mes débuts à ses côtés en tant qu'assistant de recherche, puis tout au long de ma thèse. Je suis heureux d'avoir l'opportunité de travailler avec lui sur un projet commun, et le remercie de m'avoir laissé une grande liberté de recherche par ailleurs. Son soutien dans de multiples dimensions, ses encouragements répétés, notamment à poursuivre des projets toujours ambitieux, et ses conseils m'ont porté tout au long de ce chemin en commun, jusqu'au *job market* et cette fin de thèse.

Je voudrais également remercier très chaleureusement Isabelle Méjean. Isabelle a toujours été disponible pour me donner des conseils aussi précis que précieux sur mes différents projets de recherche, qui en ont grandement bénéficié. Malgré son départ du CREST, même sans rôle officiel de directrice de thèse, et même sans intérêt particulier (tout du moins à l'origine ?) pour l'industrie laitière, elle m'a suivi et apporté un soutien très important tout au long de l'exigeant processus du *job market*, de la préparation jusqu'aux conseils dans la prise de décisions importantes concernant mon avenir. Je lui en suis extrêmement reconnaissant, et redevable.

I also would like to thank Samuel Kortum for his support throughout the job market. I am also particularly grateful to Sam, and Francis, for the opportunity I had to visit Yale University for a year under Sam's supervision. This year strongly influenced my personal and academic life. The work done with them during that year soundly shaped my perseverance and rigor in thinking through complex research questions, guiding me

in my research today. Sam, in particular, inspired me, for his ability to think about complex questions and make them more accessible to others, his dedication to soundly understanding economic mechanisms, and more importantly, for being such a humble and nice person.

Je souhaite également remercier tout particulièrement Philippe Choné, pour ses précieux conseils concernant mes travaux de recherche, mais aussi pour son soutien sans faille sur le *job market*. Je mesure la charge et l'engagement que cela représente et je lui en suis extrêmement reconnaissant. Merci également à Philippe, ainsi qu'à Thibaud Vergé, d'avoir constitué des TDs de Microéconomie riches et stimulants, qu'il fut un plaisir de dispenser à l'ENSAE.

Je souhaite remercier les doctorants du CREST que j'ai croisé et avec qui j'ai échangé. La liste est longue et j'en oublie sûrement : Reda Aboutajdine, Antoine Bertheau, Guillaume Bied, Léa Bou Sleiman, Arnault Chatelain, Pierre-Edouard Collignon, Léa Dubreuil, Marion Brouard, Héloïse Clolery, Maddalena Conte, Andréa Epivent, Antoine Ferey, Morgane Guignard, Germain Gauthier, Lucas Girard, Aymeric Guidoux, Anaïs Goburdhun, Mario Herrera, Myriam Kassoul, Margarita Kirneva, Raphaël Lafrogne-Joussier, Alice Lapeyre, Alexis Larousse, Clémence Lenoir, Claire Leroy, Pauline Lesterquy, Jérémy L'Hour, Denys Medee, Federica Meluzzi, Hugo Molina, Thomas Monnier, Clément Montes, Martin Mugnier, Riccardo Norbiato, Louis-Daniel Pape, Mitia Oberti, Ines Picard, Felix Pasquier, Anasuya Raj, Emilie Sartre, Yuanzhe Tang, Clémence Tricaud, Antoine Valtat, Théo Valentin, Pedro Vergara-Merino et Vincent Verger. Des mercis particuliers pour Morgane Cure, ce fût un plaisir d'être un de tes soldats sous ta férule de coordinatrice micro, ainsi qu'un de tes passagers des trajets matinaux vers le CREST. Merci Jérôme Trinh pour ta gentillesse et tes masterclasses au clavier notamment. Merci au royal Yuanzhe Tang pour ta bonne humeur quotidienne. Danke Felix Schleeff for always great feedbacks and sharing this great road trip in Gran Canaria. Merci à Pauline Carry et à mon frère d'arme Elio Nimier-David, pour leur gentillesse et leurs feedbacks toujours pertinents. Grazie mille to my former office mates Guidogiorgio Bodrato and Giulia Vattuone. Enfin, merci à Pauline Leveneur, également membre éminente de la team basket et Sud-Ouest du CREST, pour avoir rendu les journées de travail dans le bureau 4094 plus agréables.

L'aventure a été l'occasion de tisser ou de renforcer de solides amitiés avec celles et ceux qui ont fait partie de l'ensemble de l'aventure. Bérengère, qui a plus que participé à mon arrivée au CREST en tant qu'assistant de recherche, merci pour toutes ses discussions, bien au-delà de l'académique. Elia, avec qui j'ai également partagé le bureau 4094, merci pour ta bonne humeur au quotidien. Vient ensuite la team CRE(S)TINS.

Fabulous Fab, dont on ne compte plus les exploits aux échecs, en matière de tacles au-dessus du genou, ou bien encore de décimales de Pi. Gwen-Jiro, avec qui on peut toujours débattre de tout, malgré un goût prononcé pour la polémique autour des soi-disant mauvaises performances de l'OL. Jules, le poète, dont j'évoquerai simplement ici l'engagement prononcé dans des débats écornant un peu trop Neymar ou le PSG ; les murs du CREST en tremblent encore. Enfin merci à Yannick, souvent en chaussettes dans les couloirs du CREST ou en crampons dans les cages du ManCRESTER, parfois accroché au plafond, mais toujours fidèle au poste, de bon conseil, et de bonne humeur !

Je remercie évidemment mon ami et co-auteur Rémi Avignon avec qui j'ai partagé la majeure partie de l'aventure, comme décrit ci-après dans un paragraphe en co-écriture, un de plus, avec mes ajouts en italique. Les semaines standards, à nettoyer les données, lire des papiers, faire tourner les estimations. Les semaines où rien ne va, la tête dans les mains à ne plus rien comprendre. *Dans ces moments, les Magnans et retours RER, souvent accompagnés par les copains CRE(S)TINS, étaient encore plus précieux.* Et aussi, parce que ça arrive, les semaines où ça marche, où on comprend et on avance. *Je dois avouer que c'est pratique d'avoir un co-auteur qui a "le truc"!* Nous avons vécu pas mal de choses ensemble depuis notre rencontre en 2014 à l'ENS Cachan : en cours, en colocation à Gentilly, sur les terrains de basketball, de football, en vacances, et au quatrième étage du CREST donc. J'ai toujours pu compter sur lui dans les bons moments comme dans les plus compliqués, et je lui en suis très reconnaissant. *Je pense qu'on a encore un long chemin, académique mais pas seulement, à faire ensemble. Hâte de voir la suite.*

I also would like to thank my co-author Monica Morlacco. It is a pleasure to work and to share common research interests with you, despite the geographical distance and time difference.

Je souhaite aussi remercier les chercheurs du CREST que je n'ai pas encore remercié, pour leurs remarques et les discussions précieuses que j'ai pu avoir avec eux. Je suis en particulier reconnaissant envers Marie-Laure Allain, Geoffrey Barrows, Pierre Boyer, Claire Chambolle, Julien Combe (pour la préparation parfaite au job market, notamment), Gregory Corcos, Roxana Fernandez, Bertrand Garbinti, Xavier D'Haultfoeuille, Guillaume Hollard, Laurent Linnemer, Clément Malgouyres, Roland Rathelot, Alessandro Riboni, Pauline Rossi, Emmanuelle Taugourdeau, Arne Uhlendorff, Pablo Winant, et Yves le Yaouanq.

Je remercie également les membres de l'équipe administrative du CREST et de l'ENSAE, qui m'ont permis d'effectuer ma thèse dans de très bonnes conditions, notam-

ment Teddy Arif, Tristan Duchenne, Djamila Gherabi, Murielle Jules, Eliane Madelaine, Lyza Racon, Fanda Traore et Edith Verger.

Je tiens aussi à remercier le reste de la team roue libre de l'ENS Cachan, en plus de Rémi : Alexis (Gravelon), Benoit A. (Bengouss), Benoit N. (Tonton Bob), Karen (Le Champion de Padel), Léa (La Soum Toulousaine d'adoption), Mathilde (La Pince), Richard (Le Danseur-Maitre-Nageur-Sauveteur-Pompier-Médecin-Philosophe) et Théo (Le Génie Chanceux). Merci pour ces moments, dîners, verres, ou week-ends, qui sont autant de moments de décompression et de joie.

Merci à l'ensemble de l'équipe SG2 du Paris Basket 15. Les entraînements, matchs, et soirées m'ont toujours permis de décompresser dans un contexte éminemment sympathique.

Merci à Julien, un des rares amis cadurciens exilé à Paris, et à Marine, pour leur amitié et soutien.

Une dédicace toute particulière à Clément, un ami on ne peut plus précieux, ancien coloc *chez Lénine*, et compagnon de si nombreuses aventures depuis 12 ans déjà, et à Léa Dt, également ancienne colocataire du confinement et amie. Merci pour votre soutien à tous les deux. Dédicace également aux amis de prépa, en plus de Benoit et Clément, avec qui j'ai appris l'économie, partagé des kebabs et surtout de précieux moments : Antoine, Romain et Yohan. Merci au passage à Monsieur Vanhove, Monsieur Longatte, et Madame Rey, avec qui j'ai appris à penser de manière rigoureuse.

Je souhaite également remercier ma famille qui m'a toujours motivé et soutenu, depuis bientôt 30 ans donc, aouch. Lisa, Papa, Maman et François, j'ai de la chance de pouvoir compter sur vous comme source de courage et d'inspiration, et c'est grâce à vous que j'en suis là aujourd'hui.

Enfin, je remercie bien-sûr Lina, qui m'apporte tant et me rend heureux au quotidien. Merci de m'avoir supporté, dans tous les sens du terme, tout au long de ce processus long et souvent intense. C'est serein et le coeur léger que j'ai la chance de pouvoir partir avec toi vers de nouveaux horizons bruxellois puis bavarois.

A Papou et Manou.

Contents

General Introduction	5
1 Markups and Markdowns in the French Dairy Market	17
1. Introduction	18
2. Data and Key Facts on the French Dairy Market	22
2.1. Data	23
2.2. Industry Setting	23
2.3. Key Facts Suggesting the Existence of Buyer and Seller Power	25
3. A Theory of Margins, Markups and Markdowns	27
3.1. Production Function	27
3.2. Variable Profit Maximization	28
3.3. Markups, Markdowns, and Margins	30
3.4. Assumptions	32
3.5. Graphical Representation	32
4. Estimation	34
4.1. Recovering Margins through Marginal Costs Estimation	34
4.2. Disentangling Markups and Markdowns	37
5. Results	43
5.1. Average and Median Markdowns, Markups and Margins	44
5.2. Heterogeneity Dimensions	45
5.3. Pass-Through Analysis	49
6. Implications	58
6.1. Methodological Implications	58
6.2. Economic Implications	66
7. Conclusion	70
References	71
Appendix 1.A Recent Changes in the French Dairy Market	76
1.A1. Trends	76
1.A2. Regulatory and Structural Changes	77
Appendix 1.B Measurement	79

1.B1.	Labor and Capital	79
1.B2.	Output Prices and Quantities	80
1.B3.	Input Prices and Quantities	81
1.B4.	Firms and Groups	81
1.B5.	Cleaning	82
Appendix 1.C	Discussing Theoretical Assumptions	82
1.C1.	Variable Profit Maximization	82
1.C2.	Static and Dynamic Inputs	88
Appendix 1.D	Discussing Identification	88
1.D1.	Dairy Input/Output Matrix	88
1.D2.	Processing Function	89
1.D3.	Disentangling Markups and Markdowns	94
1.D4.	Competitive Labor	98
Appendix 1.E	Additional Results	100
1.E1.	Average Margin over Time	100
1.E2.	Average Markups - Bulk Products	101
1.E3.	Markup and Markdown Contributions by Product	102
1.E4.	Pass-Through Analysis - Graphical Representation	102
1.E5.	Additional Theoretical Pass-Through Derivations	103
1.E6.	Additional Reduced-Form Pass-Through Estimates - WMP Sellers	104
1.E7.	Illustrating the Role of a Price Floor	105
2	Quota Reforms and the Cream-Skimming of the French Milk Market	107
1.	Introduction	108
2.	Context, Data and Motivating facts	110
2.1.	The Quota Regulation	110
2.2.	Data	111
2.3.	Motivating Facts	112
3.	Theoretical Insights on Milk Production and the Role of Quotas	116
3.1.	A Simple Setting	116
4.	The Spatial Relocation Process	120
4.1.	Production	120
4.2.	Farms	124
5.	Across-Farm Misallocation and Reallocation	126
5.1.	The Restructuring Rhythm	126
5.2.	Restructuring Levels and Margins	127
5.3.	The Impact of Quotas on Between-Farm Inequality and Inefficiency	129
6.	Disentangling the Restructuring Effects of Farm Size and Spatial Constraint Loosening	131

6.1.	Discretizing the Inter- <i>Département</i> Divergence	131
6.2.	Spatial Heterogeneity in the Production Constraint Loosening	132
6.3.	<i>Département</i> -level Liberalization and Inter-Farm Reallocation	133
7.	Research Avenues	137
7.1.	Structural Model	137
7.2.	Causality and Difference-in-Difference Analyses	137
8.	Conclusion	140
	References	141
3	Market Power in Input Markets: Theory and Evidence	143
1.	Introduction	144
2.	A Framework for Estimating Input Market Power	148
2.1.	Theoretical Framework	148
2.2.	Estimating the Revenue Elasticities of Inputs	153
3.	Data	160
4.	Results	161
4.1.	Demand Shifters	161
4.2.	Revenue Elasticities	162
4.3.	Market Power in Input Markets	162
4.4.	Validation	163
5.	Buyer Power and the Aggregate Economy	166
5.1.	Environment	166
5.2.	Firm-Level Equilibrium	168
5.3.	Aggregation	169
5.4.	Calibration	171
5.5.	Results	171
5.6.	Discussion	173
6.	Conclusion	173
	References	175
	Appendix 3.A Additional Tables and Figures	180
	Appendix 3.B Theory Appendix	185
	3.B1. Proof of Lemma 1	185
	Appendix 3.C Price Bargaining in Buyer-Supplier Relationships	185
	Appendix 3.D Demand Estimation	188
	3.D1. Instrument Choice	188
	3.D2. Implementation	189
	3.D3. Identification Discussion	190
	3.D4. Specification	191
	Appendix 3.E Data Appendix	192

3.E1. Data Preparation	192
3.E2. Sample Selection	193
General Conclusion	195

General Introduction

A *supply (or value) chain* refers to the series of activities that are required to produce a product (or service). In such chains, different firms are involved to create value. Each firm in the chain adds value to the final product (or service), by transforming inputs into intermediate (or final) goods which are then used by the next firm in the chain (or consumed). The efficiency and competitiveness of a supply chain depend on the nature of the relationships between the different firms involved (respective bargaining power, coordination, trust...). Such relationships between heterogeneous firms can be affected by two particular inefficiency sources that are the object of this dissertation: (i) *market power* (henceforth MP) and (ii) (economic) *frictions*.

MP refers to the ability of a firm or group of firms to set prices. MP comes from a firm's ability to sell outputs at a high price (*i.e., imposing a markup*) as well as its ability to purchase inputs at a low price (*i.e., imposing a markdown*). MP can arise due to various factors, including the following ones which will be prevalent in the markets studied in this dissertation: (asymmetric) market concentration, product differentiation, economies of scale, or other factors, including regulation, that limit entry by potential competitors. The consequences of MP can be significant, as it may lead to higher prices for downstream consumers, lower prices for upstream producers, reduced welfare, and distorted value-added sharing in supply chains. Chapters 1 and 3 suggest two different empirical methodologies to measure a firm MP, and to disentangle buyer and seller power. Both methodologies can be suitable for application to different contexts. Chapter 1 complements the measurement exercise by evaluating how the existence of buyer and seller power affects the pass-through of shocks and policy interventions in value chains, while Chapter 3 explores the aggregated welfare consequences of buyer power.

Economic *frictions* refer to the barriers that impede the smooth functioning of markets and prevent them from achieving optimal outcomes. Common types of friction include switching, relocation, or transaction costs, but also regulation. Regulatory frictions are the legal and administrative requirements that firms and individuals must comply with when conducting economic activities. Chapter 2 studies the consequences of a particular regulation, milk production quotas, in the French dairy market. Chapter 2 shows how their introduction in 1984 and progressive removal (from 2008 to 2015) distorted the distribution of milk production across farms and space.

Overall, this dissertation aims to better understand the role of such inefficiencies in intertwined global and national value chains. To that end, this research leverages both empirical and theoretical tools, applied to value chains where such inefficiencies are found to be prevalent: the French dairy supply chain (Chapters 1 and 2) and global value chains where French manufacturing importers operate (Chapter 3). The rest of this general introduction presents each chapter in greater detail but mostly relegates academic contributions to the chapter-specific introductions.

Public authorities need to assess MP and its origins to design efficient policies. However, due to the difficulty of disentangling both sources of MP, the literature often only partially analyzes it, allowing firms to set prices on one side and assuming them to be price-takers on the other. This assumption may be misleading, understating MP or diverting attention from true inefficiency. Chapter 1 addresses these challenges by (i) suggesting a new methodology to separately identify buyer and seller power, and (ii) applying it to French dairy processors.

French dairy processors exert buyer power when purchasing raw milk, and seller power when marketing dairy products. This is due to the existence of (i) asymmetric concentration between atomistic farmers and concentrated processors, (ii) transportation costs creating segmented local markets, and (iii) increasing product differentiation along the supply chain. Most of these characteristics are also commonly found in other food value chains, in which buyer and seller power are often also a concern.

The analysis is based on plant-level data on dairy firms, with observations on prices and quantities of raw-milk input by origin and output by product from 2003 to 2018. Total margins are estimated relying on a production function approach, standard in the literature and more described in the Chapter. In order to separately identify markdowns and markups, we then suggest an approach hinging on firm arbitrage conditions and the existence of international commodity markets. In our application, we use the whole milk powder (henceforth WMP) market. WMP is (i) bought (resp. sold) by dairy firms without buyer (seller) power and (ii) substitutable with raw milk (with other dairy products sold). The price of WMP is set in global markets, so that the price-setting power of French dairy firms can be assumed away. Given substitutability, firms buying WMP optimally equalize the marginal costs of sourcing raw milk and WMP. Similarly, WMP sellers optimally trade off between producing an additional unit of a given dairy product or of WMP. In such multi-input and multi-product settings, the international price of a relevant commodity thus offers an empirical moment that helps separately identify markups and markdowns. Importantly, our estimating framework allows us to remain agnostic on the exact competition structures upstream and downstream, allowing a broad set of applications.

The results indicate that dairy firms generate an average margin rate of 56%. This

margin consists of a markdown rate of 19% and a markup rate of 41% implying that dairy firms on average purchase raw milk at a price 16% below its marginal contribution to their profits, while selling a dairy product at a price exceeding its marginal cost by 41%. These weighted averages however hide substantial heterogeneity across firms, products, and time. While the average total margin is relatively stable over time, the average contributions of markups and markdowns vary substantially over time.

We explore this time variation by analyzing how shocks (i) to the international WMP price and (ii) to French dairy farmer costs, spread differently through the supply chain. A reduced-form analysis reveals *incomplete pass-through* on raw milk and dairy products prices, that our model rationalizes by processor MP. Processors partly absorb such exogenous shocks affecting farmer revenues through adjustments in raw milk prices. Induced markdown variations reveal changes in the ability of processors to extract rent from farmers due to a *non-constant raw-milk supply elasticity*. Shocks then differently spread down the supply chain depending on the nature of competition in the output market, highlighting again the role of MP in shock transmission. On competitive intermediary products, processors cannot increase prices to transmit local farmer cost shocks. On final products, processors are able to transmit cost increases to retailers via markup increases. Overall, margin variations are mitigated through compensating markdown and markup adjustments.

These findings have important policy implications. First, through sole markdown adjustments, processors partially absorb shocks to commodity prices and to farm costs, smoothing variations in farmer profits but also impeding farmers from benefiting from positive downstream demand shocks. Second, also due to buyer power alone, 65% of the subsidies currently paid to farmers are diverted through raw milk price adjustments. Our results thus call for alternative policies aiming at promoting farmer countervailing seller power or for a price floor on raw milk, as such policies could be welfare-improving.

The second chapter aims to tackle the following question: How do input market fragmentation and liberalization affect production allocation? To answer this question, this chapter analyzes the impact of production quotas and their progressive removal in the French milk market. Milk production quotas were introduced in 1984 and removed in 2015, shaping the European dairy industry for more than thirty years. The objective of quotas was twofold: supporting farmer incomes and controlling produced quantities. Production quotas were first allocated to each European Union (EU) member state, imposing upper bounds on production at the national level. Each country could then internally allocate production quotas among milk producers.

In France, the implementation of quotas also aimed at reaching two additional goals: (i) refraining a growing production dispersion across farms, and (ii) attenuating territorial inequalities. French authorities thus opted for attributing quotas by *département*, thus

fixing their production level. Local authorities were then in charge of delivering quotas across farms, following a redistributive scheme favoring small farms to the detriment of larger farms. In 2003, a CAP reform aiming at reducing the distortive effects of regulation within European agricultural markets acted the progressive removal of quotas starting in 2008 and completed in 2015, after seven years of progressive quota increases.

The analysis is based on several datasets. The first one contains milk production and the number of farms at the *département*-year level for the 1995-2018 period. To complement these data, we also mobilize farm-year level quotas and production data, which we observe from 1995 to 2014 and from 2007 to 2018, respectively.

Leveraging these data, we show that production quotas generated two types of distortions. First, by mechanically fixing production shares across French *départements* at their pre-quota (1984) level, quotas stopped a natural spatial concentration for about 25 years, a process that restarted right after the start of the progressive quota removal in 2008. Second, the design of the quota system spurred the growth of small farms while constraining the expansion possibilities of larger farms. This redistributive scheme thus successfully refrained inequalities among farms growing until then, yet at the cost of distorting the competition-led cream-skimming of farms. Results finally show how the catching-up process in farm selection following the quota removal intervened more or less early across *départements*, depending on the stringency implied by quota constraints at the local level. These observations are rationalized with a simple model of perfect competition between heterogeneous farms. At the farm level, the effect of the liberalization ultimately depends on (i) the efficiency gains the farm can achieve with the liberalization and (ii) its location in a *département* sheltered from competition or constrained by quotas. This Chapter 2, for now somewhat descriptive, is a first step toward a more structural assessment of the *misallocation* created by the milk production quotas, in which we plan to leverage farm-to-firm network data.

The third chapter quantifies buyer power in input trade and evaluates its aggregate effects. MP is a particularly relevant issue in international trade, where high entry costs lead to concentrated import and export markets, and where “lock-in” effects in buyer-supplier relationships reduce market competitiveness. Despite the importance of input trade for a country’s economic performance, little is known about the incidence of buyer power in these settings, as the international trade literature typically assumes that importers act as price-takers. This chapter provides evidence of buyer power in input trade and quantifies its impact on the aggregate economy. Our approach combines a novel empirical methodology to estimate MP in input markets with a tractable equilibrium model to convert the buyer power estimates into welfare calculations. We apply our methodology using data from French manufacturing importers, which provides an ideal case study for our analysis, given France’s status as a large open economy and one of the world’s

largest importers.

Similarly to Chapter 1, we measure a firm's buyer power in a given input market as the wedge between the input's marginal cost and its price, i.e., the input price markdown. Also similarly to Chapter 1, we develop an empirical strategy for estimating importer-level markdowns in input trade that requires minimal assumptions about the structure of product and input markets and can be applied using standard trade and production data. The exact methodology then differs from the one used in Chapter 1. In Chapter 3, we demonstrate that the average importer's markdown across all input markets can be calculated as the ratio between the revenue elasticity of the imported inputs and the inputs' share in total firm revenues. The former is estimated while the latter is directly observed in the data.

Estimating such revenue elasticities and markdowns with the universe of trade and production data for the French manufacturing sector, we find evidence of substantial buyer power in input trade. The average firm-level markdown in input trade is 1.49 across all manufacturing industries, which is evidence of substantial price-setting power on the importers' side. While average (and median) markdowns significantly depart from competitive level (1) in every manufacturing industry, we document sizable heterogeneity in markdowns across industries and firms. Across firms, large and productive firms have relatively larger wedges than smaller, unproductive ones. Leveraging the granularity of import data, we also show how firm-level markdowns on imported inputs positively correlate with the average concentration faced by firms across their import markets.

In the last part of the chapter, we embed the model of firm behavior into a parsimonious macroeconomic framework to quantitatively evaluate the implications of the buyer power of importers for production and welfare in the economy. At the individual firm level, buyer power leads to inefficiently small firm size. At the aggregate level, micro-level input distortions lead to lower imports and overall lower output, as compared to a world where all firms behave as price takers in all input markets. The main theoretical insight from the macro model is that at the aggregate level, the buyer power of importers acts like a tariff on imports: it induces distortions on domestic production and the volume of trade, but it does so while improving the terms of trade. On the one hand, lower output and higher prices reduce consumer surplus. On the other hand, profits increase due to foreign rent shifting, and so does producer surplus. The overall effect of buyer power on domestic welfare depends on which of these two effects is larger, so it is ultimately an empirical question. The micro-level estimates from the first part of our paper are sufficient statistics to provide a quantitative assessment of these effects. In baseline calibrations, we find that (national) welfare is always higher in the distorted economy as compared to the efficient counterfactual benchmark. An important policy implication is that, because the buyer power of importers could increase national welfare, nationalistic governments may face weak incentives to restrain the MP of the largest firms.

Introduction Générale

Une *chaîne de valeur* (ou *d'approvisionnement*) désigne la série d'activités nécessaires à la production d'un produit (ou service), dans laquelle différentes entreprises sont impliquées pour créer de la valeur. Chaque entreprise de la chaîne ajoute de la valeur au produit final (ou service) en transformant les intrants en produits intermédiaires (ou finis), qui sont ensuite utilisés par l'entreprise suivante de la chaîne (ou consommés). L'efficacité et la compétitivité d'une chaîne de valeur dépendent des relations entre les entreprises impliquées (pouvoir de négociation, coordination, confiance...). Deux sources d'inefficacité peuvent en particulier affecter ces relations et font l'objet de cette thèse : (i) *le pouvoir de marché* (désigné par la suite par "PM") et (ii) les *frictions* (économiques).

Le PM désigne la capacité d'une entreprise ou d'un groupe d'entreprises à fixer les prix. Le PM provient de la capacité d'une entreprise à vendre des produits à un prix élevé (*c'est-à-dire à générer une markup*) et de sa capacité à acheter des intrants à un prix faible (*c'est-à-dire à imposer une markdown*) par rapport aux prix concurrentiels. Le PM peut être dû à plusieurs facteurs, dont certains prévalent dans les marchés étudiés dans cette thèse : la concentration (asymétrique) du marché, la différenciation des produits, les économies d'échelle, ou bien d'autres facteurs comme la réglementation, qui limitent l'entrée de potentiels concurrents. Les conséquences du PM peuvent être importantes, dans la mesure où il peut conduire à des prix plus élevés pour les acheteurs en aval, à des prix plus bas pour les producteurs en amont, à une réduction du bien-être, et à une distorsion de la répartition de la valeur ajoutée dans les chaînes d'approvisionnement. Les Chapitres 1 et 3 proposent deux méthodologies empiriques différentes visant à mesurer le PM global d'une entreprise et distinguer son PM à l'achat et à la vente. Les deux méthodologies peuvent être appliquées dans différents contextes. Le Chapitre 1 complète l'exercice de mesure en évaluant comment l'existence du pouvoir des acheteurs et des vendeurs affecte la transmission des chocs et des interventions de politique publique dans les chaînes de valeur, tandis que le Chapitre 3 explore les conséquences du PM à l'achat sur le bien-être.

Les *frictions* économiques désignent les barrières qui entravent la concurrence et le bon fonctionnement des marchés et les empêchent d'atteindre des résultats optimaux. Parmi les types de frictions classiques et présents dans les secteurs étudiés dans cette thèse figurent les coûts de transaction, de changement de fournisseur, de relocalisation, mais aussi de réglementation. Les frictions réglementaires touchent aux exigences légales et administratives que les entreprises (ou les particuliers) doivent respecter lorsqu'ils mènent des activités économiques. Le Chapitre 2 étudie les conséquences d'une réglementation particulière, les quotas de production laitière, mis en place sur le marché français en 1984. Plus spécifiquement, ce chapitre montre comment leur introduction puis leur élimination progressive (de 2008 à 2015) a affecté la distribution de la production laitière entre

exploitations et départements.

Dans l'ensemble, cette thèse vise à mieux comprendre le rôle de ces inefficacités dans des chaînes de valeur mondiales et nationales entrelacées. À cette fin, cette recherche mobilise des outils à la fois empiriques et théoriques, appliqués aux chaînes de valeur où de telles inefficacités sont présentes : la chaîne d'approvisionnement laitière française (Chapitres 1 et 2) et les chaînes de valeur mondiales dans lesquelles opèrent les importateurs français de produits manufacturés (Chapitre 3). Le reste de cette introduction générale présente plus en détail chaque chapitre de cette thèse, reléguant cependant les précisions sur les contributions académiques propres à chaque chapitre à leurs introductions respectives.

Les autorités publiques doivent évaluer le PM des entreprises et ses origines pour mettre en place une régulation efficace. Cependant, en raison de la difficulté liée à l'identification séparée des deux sources de PM, la littérature scientifique n'analyse souvent que partiellement le PM, via des modèles théoriques permettant aux entreprises de fixer les prix d'un côté mais supposant qu'elles sont "preneuses de prix" de l'autre côté. Cette hypothèse peut être trompeuse, en sous-estimant le PM ou détournant l'attention de la source d'inefficacité prédominante. Le Chapitre 1 répond à ces défis en (i) proposant une nouvelle méthodologie pour identifier séparément le PM à l'achat et à la vente, et (ii) en l'appliquant aux transformateurs laitiers français.

Les transformateurs laitiers français exercent du PM à l'achat lors de l'achat de lait cru et à la vente lors de la commercialisation de produits laitiers. Ceci est dû à l'existence (i) d'une concentration asymétrique entre des agriculteurs atomistiques et des transformateurs concentrés, (ii) des coûts de transport du lait cru qui créent des marchés locaux segmentés, et enfin (iii) une différenciation entre produits croissante le long de la chaîne d'approvisionnement. La plupart de ces caractéristiques sont présentes dans d'autres chaînes de valeur alimentaires, où le PM à l'achat et à la vente constitue souvent une préoccupation de politique publique.

L'analyse est basée sur des données au niveau des usines de transformation laitière, où sont observés les prix et les quantités de lait cru par origine côté intrant, et par produit côté production, de 2003 à 2018. Les marges totales sont estimées en utilisant une approche "fonction de production", standard dans la littérature et décrite plus en détails dans le chapitre. Afin d'identifier séparément les markdowns et markups, nous proposons une approche reposant sur les conditions d'arbitrage des entreprises et l'existence de marchés internationaux de produits de base. Dans notre application, nous utilisons le marché de la poudre de lait entier (ci-après WMP). La WMP est (i) achetée (respectivement vendue) par les transformateurs laitiers sans PM et (ii) substituable avec le lait cru (avec d'autres produits laitiers vendus). Le prix de la WMP est fixé sur les marchés mondiaux, de sorte que le PM des entreprises laitières françaises peut être supposé absent. Étant donné cette

substituabilité, les entreprises achetant de la WMP vont de manière optimale égaliser les coûts marginaux d'approvisionnement en lait cru et en WMP. De même, les vendeurs de WMP arbitrent de manière optimale entre la production d'une unité supplémentaire d'un produit laitier donné ou, alternativement, de WMP. Dans des contextes similaires, à intrants et produits multiples, le prix international d'un produit de base pertinent offre ainsi un moment empirique qui aide à identifier séparément les markdowns et markups. Il est également important de noter que notre méthode d'estimation nous permet de rester agnostique sur les structures de concurrence exactes en amont et en aval, permettant un large éventail d'applications potentielles.

Nos résultats indiquent que les entreprises laitières génèrent un taux de marge moyen de 56%. Cette marge se compose d'un taux de markdown de 19% et de markup de 41%, ce qui implique que les entreprises laitières achètent en moyenne le lait cru à un prix inférieur de 16% à sa contribution marginale à leurs profits, tout en vendant un produit laitier à un prix dépassant son coût marginal de 41%. Ces moyennes pondérées cachent cependant des hétérogénéités substantielles entre entreprises et produits, et au cours du temps. Alors que la marge totale moyenne est relativement stable dans le temps, les contributions moyennes des markups et markdowns varient considérablement.

Nous explorons cette variation temporelle en analysant comment les chocs (i) sur le prix international de la WMP et (ii) sur les coûts des producteurs laitiers français se propagent à travers la chaîne d'approvisionnement. L'analyse révèle une *transmission partielle* de ces chocs aux prix du lait cru et des produits laitiers, que notre modèle explique par la présence du PM des transformateurs. Les transformateurs absorbent partiellement ces chocs exogènes, qui affectent les revenus des producteurs, via des ajustements des prix du lait cru. Les variations induites révèlent des changements dans la capacité des transformateurs à extraire la rente des producteurs, du fait d'une *élasticité non constante de l'offre de lait cru*. Les chocs se propagent également différemment dans la chaîne en fonction de la nature de la concurrence sur le marché des différents produits laitiers, mettant encore une fois en évidence le rôle du PM dans la transmission des chocs. Sur les produits intermédiaires concurrentiels, les transformateurs ne sont pas capables d'augmenter leur prix et de transmettre les chocs locaux des coûts des producteurs. Au contraire, sur les produits finis, les transformateurs arrivent à transmettre ces augmentations de coûts, en négociant avec les distributeurs en aval. Dans l'ensemble, les variations de marges sont atténuées par des ajustements simultanés des markdowns et markups.

Ces résultats ont d'importantes implications en termes de politique publique. Tout d'abord, via leur PM à l'achat, les transformateurs absorbent partiellement les chocs de prix des produits de base et des coûts de production des fermiers, lissant les variations de profits des producteurs, mais empêchant également ces producteurs de bénéficier de chocs positifs de demande. Deuxièmement, également en raison du pouvoir de marché à l'achat des transformateurs, 65% des subventions actuellement versées aux agriculteurs

sont détournées via des ajustements des prix du lait cru. Nos résultats appellent donc à des formes de régulation alternatives visant à promouvoir le PM des producteurs laitiers ou à instaurer un prix plancher (mouvant) sur le lait cru.

Le Chapitre 2 répond à la question suivante : Comment la fragmentation et la libéralisation d'un marché d'intrants affectent-elles l'allocation de la production ? Pour y répondre, le Chapitre 2 analyse l'impact des quotas de production de lait et de leur suppression progressive sur le marché français du lait. Les quotas ont été introduits en 1984 puis supprimés en 2015, façonnant l'industrie laitière européenne pendant plus de trente ans. L'objectif de cette politique de quotas étaient double : soutenir les revenus des agriculteurs et limiter les quantités produites. Les quotas ont d'abord été attribués à chaque État membre de l'Union européenne (UE), bornant la production au niveau national. Chaque pays pouvait ensuite répartir de manière discrétionnaire les quotas entre les différents producteurs de lait.

En France, la mise en œuvre des quotas a également poursuivi deux objectifs supplémentaires : (i) freiner une dispersion croissante de la production entre exploitations laitières, et (ii) atténuer les inégalités territoriales dans la production de lait. Les autorités françaises ont donc opté pour l'attribution de quotas par département, fixant ainsi mécaniquement leur niveau de production. Les autorités locales étaient alors chargées de distribuer les quotas entre exploitations, selon un schéma redistributif favorable à la croissance des petites exploitations au détriment de celles des plus grandes. En 2003, une réforme de la PAC visant à réduire les effets distorsifs de la réglementation des marchés agricoles européens a été adoptée, conduisant à une suppression progressive des quotas débutée en 2008 et achevée en 2015, après sept ans d'augmentations progressives des quotas.

L'analyse empirique repose sur plusieurs bases de données. La première contient la production laitière et le nombre d'exploitations au niveau département-année pour la période 1995-2018. Pour compléter ces données, nous mobilisons également des données sur les quotas et la production au niveau exploitation-année, que nous observons respectivement de 1995 à 2014 et de 2007 à 2018.

Nous montrons en mobilisant ces données que les quotas ont généré deux types de distorsions. Premièrement, en fixant mécaniquement les parts de production à travers les départements français à leur niveau pré-quota (1984), les quotas ont interrompu une concentration spatiale naturelle pendant environ 25 ans, un processus qui a redémarré juste après le début de la suppression progressive des quotas en 2008. Deuxièmement, la conception du système de quotas a stimulé la croissance des petites exploitations tout en contraignant les possibilités d'expansion des plus grandes. Ce schéma redistributif a donc réussi à réfréner des inégalités entre exploitations jusqu'alors croissantes, mais au prix de distorsions dans la sélection naturelle des exploitations via des mécanismes concurrentiels.

Enfin, nos résultats montrent comment le processus de rattrapage dans la sélection des exploitations à la suite de la suppression des quotas est intervenu plus ou moins tôt selon la contrainte imposée par les quotas au niveau local.

Ces observations sont rationalisées via un modèle simple de concurrence parfaite entre exploitations agricoles hétérogènes. Le modèle théorique montre que l'effet de la libéralisation au niveau de l'exploitation dépend *in fine* (i) des gains d'efficacité que l'exploitation peut réaliser grâce à la libéralisation et (ii) de son emplacement dans un département protégé de la concurrence ou au contraire contraint par les quotas.

Ce deuxième chapitre, pour le moment quelque peu descriptif, est une première étape vers une évaluation plus structurelle de la *misallocation* créée par les quotas de production laitière, pour laquelle nous prévoyons de mobiliser des données sur le réseau producteurs-transformateurs.

Le Chapitre 3 quantifie le PM à l'achat des entreprises dans le commerce d'intrants et évalue ses effets au niveau agrégé. La concentration des marchés d'importation et d'exportation due aux coûts d'entrée élevés et les « effets de verrouillage » dans les relations acheteur-fournisseur entravent la concurrence sur les marchés internationaux, ce qui fait de l'étude du PM un sujet particulièrement important dans le commerce international. Malgré l'importance du commerce d'intrants dans la performance économique d'un pays, peu de choses sont connues de l'incidence du PM à l'achat, essentiellement car la littérature sur le commerce international suppose généralement que les importateurs sont "preneurs de prix". Le Chapitre 3 fournit des preuves concernant la présence de PM émanant des entreprises manufacturières françaises importatrices à l'achat d'intrants, et quantifie son impact sur l'économie agrégée. Notre approche combine une nouvelle méthodologie empirique pour estimer le PM à l'achat sur les marchés d'intrants avec un modèle d'équilibre tractable qui permet de convertir les estimations du PM à l'achat en calculs de bien-être. Nous mettons notre méthodologie en application en mobilisant des données sur les importateurs de produits manufacturés en France. Il s'agit d'une étude de cas idéale pour ce type d'analyse dans la mesure où la France est une grande économie ouverte et l'un des plus grands pays importateurs au monde.

De même que dans le Chapitre 1, nous mesurons le PM d'une entreprise à l'achat dans un marché d'intrants donné par la différence entre le coût marginal de l'intrant et son prix, c'est-à-dire la *markdown* sur le prix de l'intrant. De manière là-encore similaire au premier chapitre, cette méthodologie reste agnostique sur la structure exacte des marchés d'intrants et de produits, et peut être appliquée à d'autres contextes à l'aide de données à présent standard de commerce international et de production. La méthodologie exacte diffère cependant de celle utilisée dans le Chapitre 1. Dans le Chapitre 3, nous démontrons que la *markdown* moyenne de l'importateur sur l'ensemble de ces marchés d'intrants peut être calculée comme le ratio entre l'élasticité du revenu à la quantité d'intrants importés

et la part de ces intrants dans les revenus de la firme. Le premier objet est estimé tandis que le second est directement observé dans les données.

En utilisant les données de douanes et de production du secteur manufacturier français, nous estimons les élasticités du revenu aux intrants importés, et mettons en évidence l'existence de PM à l'achat d'intrants. La *markdown* moyenne sur toutes les industries manufacturières est de 1,49, démontrant une capacité importante de ces entreprises à fixer les prix d'achat. Alors que les *markdowns* moyennes (et médianes) s'éloignent significativement de leur niveau concurrentiel (1) dans chaque industrie manufacturière, nos résultats révèlent également une hétérogénéité considérable dans les *markdowns* estimées entre industries et entreprises. Les grandes entreprises, plus productives, sont capables d'extraire des marges plus importantes que les petites entreprises moins productives. En utilisant la granularité de nos données d'importation désagrégées, nous montrons également comment les *markdowns* sur les intrants importés estimées au niveau entreprise sont corrélées positivement avec la concentration moyenne à laquelle l'entreprise fait face sur son marché d'importation.

Dans la dernière partie du Chapitre 3, nous intégrons cette modélisation microéconomique du comportement des entreprises dans un cadre macroéconomique parcimonieux pour évaluer quantitativement les conséquences de l'existence du PM de marché à l'achat sur la production et le bien-être dans l'économie. Au niveau entreprise, l'existence de PM à l'achat conduit à une taille d'entreprise inefficacement trop petite. Au niveau agrégé, les distorsions sur les marchés d'intrants au niveau microéconomique génèrent à une baisse des importations et une baisse globale de la production, par rapport à un scénario contrefactuel où toutes les entreprises sont "preneuses de prix" sur tous les marchés d'intrants. L'observation théorique principale du modèle macroéconomique réside dans le fait que le PM à l'achat des importateurs agit au niveau agrégé comme une taxe douanière sur les importations : il induit des distorsions sur la production domestique et le volume des échanges, tout en améliorant les termes de l'échange. D'une part, la baisse de la production et l'augmentation des prix réduisent le surplus des consommateurs. D'autre part, les profits augmentent dans l'économie nationale en raison de la baisse des prix à l'achat d'intrants importés, de même que le surplus du producteur. L'effet global du PM à l'achat sur le bien-être national dépend ainsi de la taille respective de ces deux effets, qui devient *in fine* une question empirique. Le modèle montre alors que nos estimations au niveau microéconomique constituent des statistiques suffisantes pour fournir une évaluation quantitative de ces effets. Dans les calibrations de base, nous constatons que le bien-être (national) est toujours plus élevé dans l'économie soumise aux distorsions par rapport à l'équilibre contrefactuel efficace. Une implication importante de politique publique réside alors dans le fait que les gouvernements nationaux peuvent avoir des incitations relativement faibles à limiter le PM des plus grandes entreprises, dans la mesure où le PM à l'achat de ces entreprises peut accroître le bien-être national.

Chapter 1

Markups and Markdowns in the French Dairy Market

Note: This chapter is co-authored with Rémi Avignon (INRAE-SMART).¹

Abstract

Separately measuring firm buyer and seller power is important for policy-making, but challenging. In this paper, we suggest a new methodology to do so and apply it to French dairy processors. These firms exert buyer power when purchasing raw milk, and seller power when marketing dairy products. The analysis is based on plant-level data on dairy firms, with observations on prices and quantities of raw-milk input by origin and output by product from 2003 to 2018. We rely on a production function approach to estimate total margins. The existence of a commodity, (i) substitutable as an input or as an output, and (ii) exchanged on global markets where firms are price-takers, allows us to separately estimate firm-origin markdowns and firm-product markups. We show this methodology can also be useful in other contexts, with more limited data. Markdown estimates imply that dairy firms on average purchase raw milk at a price 16% below its marginal contribution to their profits, while markup estimates indicate that firms sell dairy products at a price exceeding their marginal costs by 41%. Our results show substantial variations in buyer and seller power exploitation across firms, products, and time. We analyze how shocks to local farmer costs and international commodity prices pass through the supply chain. Processors partially absorb such shocks by adjusting markups and markdowns, thus smoothing variations in farmer revenues. It further implies that 65% of subsidies are currently diverted from farmers due to processor buyer power. A price floor on raw milk could be an alternative welfare-improving policy.

Keywords: Market Power, Value Chains, Markups, Markdowns, Pass-through.

¹We are grateful to Marie-Laure Allain, Claire Chambolle, and Francis Kramarz for their advice. We also thank Philippe Choné, Gregory Corcos, Basile Grassi, Samuel Kortum, Isabelle Méjean, Monica Morlacco, Michael Rubens, Frederic Warzynski, and Horng Wong. This chapter also benefited from feedback from participants at Aalto University, Bank of Italy, Católica Lisbon, CIRED, CREST, DICE, ESSEC, INRAE, LMU Munich, McGill University, Rennes Business School, Sciences Po, Stockholm School of Economics, University of Oslo, Toulouse School of Economics, Vrije Universiteit Amsterdam, and UC Davis ARE seminars, and at BECCLE, EARIE, EEA-ESEM, JEI, and RES 2022 conferences. This research benefited from financial support from the ANR “Investissements d’avenir” program under the ANR grant ANR-18-EURE-0005 (EUR DATA EFM).

1. Introduction

This paper addresses these challenges by (i) suggesting a new methodology to separately identify buyer and seller power, and (ii) applying it to French dairy processors. The suggested approach is especially relevant to study processor MP in food supply chains. In most such chains, processors are central: they purchase raw material from farmers and process it in final products sold to retailers or intermediate products sold to other processors. In such contexts, and as pointed out by [Sexton \(2013\)](#), processor buyer and seller power are a concern given supply chain structures favorable to their joint emergence. Indeed, most food industries feature at least one of the following characteristics: (i) asymmetric concentration between atomistic farmers and concentrated processors, (ii) transportation costs creating segmented local markets, and (iii) increasing product differentiation along the supply chain. In [Section 2.](#), we show the prevalence of all these features in the French dairy market.

Guided by these features, we build a structural model of multi-source and multi-product processors, exploiting buyer and seller power. The model is introduced in [Section 3.](#) It allows us to identify firm-origin-product level margins of French dairy processors, and to decompose them into firm-origin level markdowns and firm-product level markups. This decomposition relies on three definitions. The *margin* is the wedge between the price of a given product and its *accounting marginal cost* of production using milk from a given origin. This margin arises from overall MP. The *markdown* is the wedge between the net marginal revenue generated by the raw material (milk in our application) and the price paid by the firm. This markdown arises from buyer power. Finally, the *markup* is the wedge between the price of a product and its (economic) marginal cost. This markup arises from seller power. Due to buyer power, margins and markups differ. This difference stems from the fact that buyer power creates an *opportunity cost* of buying an additional unit of raw material (milk), appearing in the marginal cost but not in the accounting marginal cost.¹

In order to estimate the model, we exploit a *cost-side approach*, building on pioneering work by [Hall \(1988\)](#) and [De Loecker and Warzynski \(2012\)](#) who analyze markups assuming no markdowns. In line with recent papers by [Morlacco \(2019\)](#) and [Rubens \(2021\)](#), we incorporate in this framework the possibility of buyer power on input markets. Similarly to [Rubens \(2021\)](#), we assume perfect complementarity in the production process between the raw material and its processing, but depart from this framework by incorporating *multi-source* and *multi-product* firms.

The empirical analysis detailed in [Section 4.](#) relies on three main datasets: production, balance sheet, and technical data. Our production data provide prices and quantities at

¹The distinction is analogous to the one between price and marginal revenue in presence of seller power.

the firm-product level for output and at the firm-origin level for raw-milk input.² Balance sheet data contain labor and capital expenses of processors at the firm-level. In the technical data, we observe the dry matter content of milk intermediate consumption and processed output at the product-level.³ Importantly, this information reveals what quantity of milk input is needed to process a unit of each dairy product. This is a crucial point as allocating inputs observed at the firm-level is the main challenge to multi-product production function estimation.⁴ Our estimates are first based on the estimation of accounting marginal costs, which in our setting are the sum of (i) purchasing costs of raw milk and other pre-processed milk-inputs and of (ii) processing costs. Together production and technical data first allow us to estimate milk-input buying costs at the firm-origin-product level. We then use production and balance sheet data to estimate marginal processing costs at the firm level, following the literature estimating production functions.⁵ Having quantity and price data on both the input and output sides helps us overcome issues stressed by the literature, such as revenue data bias, input price bias, or price endogeneity due to MP upstream and downstream.⁶ Overall, we recover *margins and accounting marginal costs at the firm-origin-product level*, which is, to the best of our knowledge, new in this literature.⁷

In order to separately identify markdowns and markups, we suggest an approach hinging on firm arbitrage conditions and the existence of international commodity markets. In our application, we use the whole milk powder (henceforth WMP) market. WMP is (i) bought (resp. sold) by dairy firms without buyer (seller) power and (ii) substitutable with raw milk (with other dairy products sold). The price of WMP is set in global markets, so that the price-setting power of French dairy firms can be assumed away. Given substitutability, firms buying WMP optimally equalize the marginal costs of sourcing raw milk and WMP. Similarly, WMP sellers optimally trade off between producing an additional unit of a given dairy product or of WMP. In such multi-input and multi-product settings, the international price of a relevant commodity thus offers an empirical moment that helps separately identify markups and markdowns. The identifying assumption thus differs from [Rubens' \(2021\)](#) who relies on input supply estimation.⁸ Conversely, our es-

²A raw milk origin/market in the analysis will be one of the 85 French *départements* producing milk.

³Milk intermediate consumption encompasses raw milk from a specific origin, but also milk powder, bulk butter or bulk cream. Milk-processed products and their dry matter content are observed at the CN8 level.

⁴We view the use of such technical coefficients, which can be easily obtained, as an interesting tool for similar multi-product production function estimation in food processing.

⁵Seminal papers include [Olley and Pakes \(1996\)](#), [Levinsohn and Petrin \(2003\)](#), [De Loecker and Warzynski \(2012\)](#) and [Ackerberg et al. \(2015\)](#).

⁶Respectively stressed by [Bond et al. \(2020\)](#), [De Loecker et al. \(2016\)](#) and [Morlacco \(2019\)](#).

⁷Following various methodologies discussed in Section 1.D2., [De Loecker et al. \(2016\)](#), [Valmari \(2016\)](#) and [Dhyne et al. \(2017\)](#) estimate marginal costs at the firm-product level, but without heterogeneity by input.

⁸It also differentiates our approach from the *demand approach* ([Berry et al., 1995](#)) to estimate markups through the estimation of demand elasticities, which similarly requires stronger assumptions on compe-

timating framework allows us to remain agnostic on the exact competition structures upstream and downstream. This element of our analysis is crucial, as competition faced by dairy firms varies across markets and time.⁹ Such variation is also an interesting feature of a broad set of applications.

The results presented in Section 5. indicate that dairy firms generate an average margin rate of 56%.¹⁰ This margin consists of a markdown rate of 19% and a markup rate of 41% implying that dairy firms on average purchase raw milk at a price 16% below its marginal contribution to their profits, while selling a dairy product at a price exceeding its marginal cost by 41%. These weighted averages however hide substantial heterogeneity across firms, products, and time. The product variability is far from negligible, even when focusing on a specific sector as we do. The average markup rate is equal to 70% on final consumption goods, going above 100% for differentiated products such as yoghurts or cheeses, whereas the markup rate on homogeneous intermediary products is close to 0%. Most importantly, although the average total margin is relatively stable over time, the average contributions of markups and markdowns vary substantially over time. The average markdown rate fluctuates between 4% and 40% while the average markup rate lies between 27% and 61%.

We explore this time variation by analyzing how shocks (i) to the international WMP price and (ii) to French dairy farmer costs, spread differently through the supply chain. A reduced-form analysis reveals *incomplete pass-through* on raw milk and dairy products prices, that our model rationalizes by processor MP. Processors partly absorb such exogenous shocks affecting farmer revenues through adjustments in raw milk prices. Induced markdown variations reveal changes in the ability of processors to extract rent from farmers due to a *non-constant raw-milk supply elasticity*. Shocks then differently spread down the supply chain depending on the nature of competition in the output market, highlighting again the role of MP in shock transmission. On competitive intermediary products, processors cannot increase prices to transmit local farmer cost shocks. On final products, processors are able to transmit cost increases to retailers via markup increases. Overall, margin variations are mitigated through compensating markdown and markup adjustments.¹¹

tion.

⁹Regarding the evolution of competition in the French dairy market, we especially detail regulatory changes in Appendix 1.A2..

¹⁰Margin, markup, and markdown rates correspond to percentage deviations of each of these objects from 1, which would be their value prevailing in the absence of MP. The average rates presented here are weighted averages, based on dry matter content quantity weights.

¹¹We here contribute to the literature studying pass-throughs to assess seller power (Nakamura and Zerom, 2010; Weyl and Fabinger, 2013; Bergquist and Dinerstein, 2020) or buyer power (Zavala, 2020). An important implication of the joint exploitation of buyer and seller power is that complete pass-through to downstream prices occurs (i) under no or constant markups *and* markdowns, but also if (ii) markups and markdowns adjust in fully offsetting ways. Both points show the importance of disentangling buyer and seller power.

The paper's contributions are highlighted in Section 6.. Our first contribution is methodological and twofold. We first show the importance of taking into account processor buyer power. In particular, we would have overestimated markup rates by 37%, had we ignored buyer power and attributed the entire margin to seller power, as the production function approach traditionally does.¹² Our findings suggest that such estimated *markups* should be viewed as *margins*, coming from price-setting power *on both sides*, if there is reason to suspect buyer power in the sector of study. We demonstrate that distinguishing both is crucial (i) for understanding pass-throughs along supply chains, as markups and margins differently react to costs shocks, and (ii) because markdown adjustments alone make some support policies, e.g. farmer subsidizing, largely inoperative.

We also suggest *a new solution to disentangle buyer and seller power*, flexible enough to be applicable in other contexts. As mentioned, our approach relies on the existence of an input *or* output that (i) is substitutable with the input or output of interest, and (ii) on which firms do not have any price-setting power. As such, our methodology relates to papers relying on a *flexible input* (Dobbelaere and Mairesse, 2013; Wong, 2019; Yeh et al., 2022) where monopsony power is assumed away on a whole *type* of input (e.g materials) to recover its importance on another (e.g labor).¹³ The proposed approach follows a similar logic but at a more disaggregated level and *can be applied* to both input and output sides. It exploits the existence of commodity markets where price-setting power can be assumed absent in a less *ad hoc* way. As such, the methodology can be applied in many industries where similar commodity markets exist and in which processor buyer and/or seller power is a concern.¹⁴ Finally, our - to this extent - *sufficient-statistic* approach does not require estimating supply or demand, making it suitable for many industries in setting with varying competition.¹⁵

Our second contribution is to quantify both buyer and seller power of French dairy processors, which constitute a significant concern for regulating authorities but had never been estimated in a unified framework.¹⁶ Our results demonstrate that dairy firms exploit both buyer and seller power, and neither is negligible.¹⁷ It has important implications.

¹²This is notably the case of De Loecker and Warzynski (2012); De Loecker and Scott (2016); De Loecker et al. (2016); De Ridder et al. (2021), in contexts in which buyer power is less a prevalent concern (but could be present), to which we compare in Section 6.1..

¹³Morlacco (2019) applies similar arguments to domestically purchased materials in order to isolate buyer power on imported ones. M. Morlacco and E. Guigue are however currently working on a revision of Morlacco (2019), relying on a different estimation methodology.

¹⁴Such markets include other food commodities like wheat, corn, soybeans, livestock, coffee, tea, rice, sugar, or bananas, but also different products including metals, minerals, fertilizers, natural gas... This point and the applicability of the methodology to other sectors are further discussed in Section 6.1..

¹⁵These points are further discussed in Section 6.1..

¹⁶Related papers studying MP in dairy supply chains consider processor oligopsony power (Perekhozhuk et al., 2017; Grau and Hockmann, 2018) *or* oligopoly power (Cakir and Balagtas, 2012; Bonnet and Bouamra-Mechemache, 2016) in isolation, under varying assumptions on processors-retailers relationships.

¹⁷Buyer power was expected given the industry setting. Our results however also demonstrate pro-

First, through sole markdown adjustments, processors partially absorb shocks to commodity prices and to farm costs, smoothing variations in farmer profits but also impeding farmers from benefiting from positive downstream demand shocks. Second, also due to buyer power alone, 65% of the subsidies currently paid to farmers are diverted through raw milk price adjustments. Our results thus call for alternative policies aiming at promoting farmer countervailing seller power or for a price floor on raw milk, as such policies could be welfare-improving.¹⁸

Our work contributes to the literature analyzing MP in food supply chains, reviewed by Sheldon (2017). Importantly, he explains that, if this literature has long theoretically identified the importance of jointly studying buyer and seller power in such contexts (Sexton, 2000), it has however found "little empirical evidence for exertion of buyer power in either the United States or the EU".¹⁹ Our work also relates to the broader literature quantifying MP in various contexts. On the input side, a strand of the literature focuses on labor MP.²⁰ A recent development literature also studies MP issues, often relying on randomized or natural experiments for identification and focusing on one source of MP (buyer or seller power) in specific contexts.²¹ Our work can thus contribute to evaluating/understanding both MP forces exerted by intermediaries in global food value chain sourcing in developing countries.

2. Data and Key Facts on the French Dairy Market

We first introduce our data before detailing general facts on the French dairy market in order to provide the reader with some important background suggesting the existence of processor market power.²² Appendix 1.A complements this static picture with the recent evolution of the market motivating our approach, which is agnostic about the form of competition.

cessors' ability to generate high markups despite retailer countervailing buyer power.

¹⁸We thus complement Russo et al. (2011), theoretically showing the value of price floors in similar settings.

¹⁹He attributes this to technical reasons (methodology, lack of data) but also to "vertical coordination between downstream food processors and suppliers of raw agricultural commodities". See Sheldon (2017) for more detail. We believe the present paper tackles the mentioned challenges, as explained in Section 6.1..

²⁰Most relatedly, as Wong (2019) and Yeh et al. (2022), Tortarolo and Zarate (2018) explicitly authorize and quantify both markups and labor markdowns. They estimate total MP through a production function approach similar to ours but pin down labor markdowns with an estimation of labor supply elasticities.

²¹See Cajal-Grossi et al. (2019); Bergquist and Dinerstein (2020); Brooks et al. (2021); Bartkus et al. (2021); Leone et al. (2021) for instance. Zavala (2020) in particular relates to our work as he quantifies buyer power exerted by exporters on farmers in Ecuador, however ignoring exporter seller power.

²²Figures presented in this Section rely on our own computations and figures from the CNIEL website.

2.1. Data

Our analysis rests on several key datasets.

We first use data provided by the French Ministry of Agriculture²³: the *Enquête Annuelle Laitière* (EAL, 1995-2018), the *Enquête Mensuelle Laitière* (EML, 2013-2018), and the PRODCOM data for dairy products (2003-2018). They contain firm-level data regarding the production of dairy products and the collection of raw milk. All these data are available at a yearly frequency.

In the EAL, and regarding the output side, we observe for each dairy firm in France the quantity produced, for each dairy product (slightly more disaggregated than CN8). Thanks to our *PRODCOM* data, we are able to observe revenues and production at the firm-CN8-year level, for French dairy firms with more than 10 employees. This allows us to recover *unit values*, which we will use as a proxy for *factory-gate* prices in the analysis.²⁴ These price data are only available for the 2003-2018 period, which will thus be our period of analysis.

Regarding the input side, we also observe in the EAL the quantity of raw milk collected by each firm and in every French *département*. Thanks to the EML, we are able to observe firm-*département* prices paid for raw milk, for a subsample of firms and from 2013 to 2018. To complement these firm-level raw milk prices, we use data from a survey made by *FranceAgrimer*, which gives us average raw milk prices by French regions, covering the period 2000-2018.

We also use *dry matter content* (DMC) data jointly produced by the *Centre national interprofessionnel de l'économie laitière* (CNIEL), *FranceAgrimer* and the *Institut de l'élevage* (Idele), three institutes in charge of elaborating statistics on the French dairy market.²⁵ This information allows us to build an input-output matrix, by retrieving the quantity of milk needed to produce a dairy product, for each dairy input-product pair.

Finally, we complement this production and raw milk collection data with balance sheet data for French dairy firms, coming from FICUS and FARE databases of the French Institute of National Statistics (INSEE). These data contain the yearly firm-level expenses on labor and capital (among others) needed for the production function estimation.

2.2. Industry Setting

The dairy industry remains an important sector of the French economy, generating around 40 billion euros in 2018. France is the 2nd milk producer in Europe (after

²³We are thankful to Corinne Prost and FranceAgrimer for making this data available through the CASD.

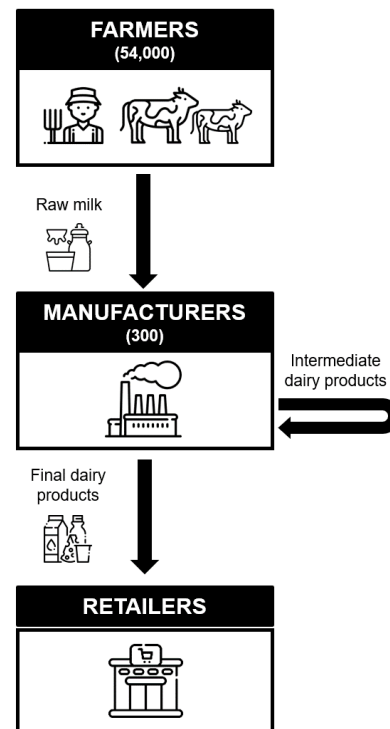
²⁴We discuss the validity of this proxy in Appendix 1.B2..

²⁵We are grateful to Jean-Noël Depeyrot for providing us this data.

Germany), and 8th in the world. Throughout the empirical analysis, we only consider cow milk, which represents 97% of the overall milk production. We also exclude Protected Designation of Origin (PDO) and organic milk, as our methodology relies on the assumption that milks from different origins are substitutable, which is not the case for these two labeled products.²⁶ The share of PDO milk (10%) is constant during the period whereas the organic milk share increased from 0.5% in 2000 to 3.5% in 2018.

The French dairy supply chain is typically organized along a vertical structure described in Figure 1. At the top of the chain, 54,000 farmers²⁷ produce raw milk. They sell milk to processors which process milk and other dairy intermediates (bulk products like cream, butter, skimmed, or whole milk powder) to produce dairy products. Although the industry counts 300 manufacturing groups, this stage of the chain is dominated by a handful of them, the top 5 alone representing 63% of purchases of raw milk. Processors then reach final consumers through wholesalers and retailers. Both processors and distributors are thus necessary intermediaries for most farmers to sell their production, as direct sales of dairy products by fully integrated structures are rare.

Figure 1.1: The Dairy Value Chain (2018)



The dairy supply chain has unique features which are important to have in mind when studying competition along the chain. Upstream, farmers generally milk cows twice a day and store raw milk in a cooling tank until it is collected by a single manufacturing plant which (in many instances) owns the tank. The processor is in charge of collection via a refrigerated truck every day or two, the same truck being used to collect raw milk from several farms. Due to conservation constraints of raw milk, this operation is costly, which explains why raw milk is always collected from farms close to the manufacturing plant (less than 60 kilometers on average).

More downstream, raw milk is processed by processors in order to produce either final

²⁶As explained in Section 4.2.

²⁷The average farm counts 66 cows in 2018.

goods (milk, cheese, butter, cream, yoghurts) sold to retailers (75% of processed milk) or intermediate products (milk powder, butter, cream) used in the dairy industry or in other food industries (25%). These intermediate products are directly exchanged between firms or traded through global commodity markets, where prices are determined by quotations. Over 99% of the milk processed in France was first produced within the country. In contrast, 40% of it ends up being exported as dairy products. Dairy processors are either private (45% of processed milk) or cooperative companies (55%). While most of the private firms are gathered into large business groups, some cooperatives have also become prominent actors in this industry.²⁸

2.3. Key Facts Suggesting the Existence of Buyer and Seller Power

We describe here various features of the French dairy industry that foster the existence of unbalanced bargaining relationships between raw milk producers and dairy firms.

Buyer Power: Asymmetric Concentration and Local Markets

As mentioned, milk production remains very dispersed in France (54,000 farms in 2018) while downstream manufacturing is concentrated (about 300 groups). Furthermore, the downstream stage is dominated by a handful of big groups, the top 3 representing 52% of the raw milk purchased in 2018, while the top 10 represents 75%. The French dairy value-added chain is thus characterized by extreme asymmetry; atomistic raw milk supplier face demand from very concentrated actors, favoring the emergence of buyer power.

Table 1.1: Competition on the raw milk Market (2018)

	Number of ...		Purchasing share (%) of the k largest buyers						
	Buyers	Farms	1	2	3	4	5	10	
<i>At the national level</i>	300	54,000	21	41	52	58	63	75	
<i>At the département level</i>									
Median	8	406	46	73	88	95	98	100	
Average ^a	13	1,588	43	67	81	89	93	98	

Départements representing less than 0.1% of the milk collection are dropped.

^a Quantity weighted average. A buyer is defined as a dairy manufacturing group.

Characteristics of the raw milk collection process imply that the French raw milk market should be considered as a collection of segmented local markets, where the potential for monopsony power is exacerbated. At the local level, the average farmer

²⁸The 2nd leading French group representing 20% of French milk collection is for instance a cooperative.

indeed faces a limited number of potential buyers (13) within a *département*. This (observed) *département*-level quantity-weighted average is an imperfect approximation of the relevant potential set of buyers for a given seller, which essentially depends on the distance to the plant of each of the surrounding buyers in the *département* and in the neighboring ones. It remains however instructive on the order of magnitude in competition between buyers at the local level. More strikingly, the local dairy markets are most of the time dominated by a handful of buyers. Table 1.1 above shows that the locally biggest group represents 46% of the median market, the top 2 constituting 73% of it, while the 4 biggest buyers typically represents 95% of the local raw milk collection. Consequently, the average *département* Herfindahl-Hirschman Index (HHI) is above 0.25.²⁹ Local milk markets can thus be considered as *highly concentrated*, according to US Antitrust Department's or European Commission's guidelines.

Seller Power

Table 1.2: Competition on the Dairy Products Market (2018)

	Number of ... Sellers	Market share (%) of the k largest sellers					
		1	2	3	4	5	10
<i>At the national level</i>	300	21	41	52	59	66	79
<i>At the product-level</i>							
Median	40	24	42	56	65	72	92
Average ^a	58	25	44	56	66	74	89

^a Revenue weighted average. A seller is defined as a dairy manufacturing group.

Unsurprisingly reflecting their importance on the raw milk market, dairy processors also represent highly concentrated *sellers*, the top 5 processors alone accounting for two third of the national market, and 72% of the median product market.³⁰)

French dairy firms may exploit market power when selling differentiated dairy products as they are very concentrated, with a few global players.³¹ This seller power can however be mitigated by the existence of countervailing buyer power emanating from downstream retailers, which are (i) highly concentrated in France and (ii) often grouped into purchasing alliances. Negotiations between these two types of actors can take various complex forms, which are beyond the scope of this paper.³²

²⁹See Figure 1.21 for evidence on recent concentration trends on the raw milk market.

³⁰The definition of a product market is here relatively loose, as we aggregate CN8 products into 7 categories: cheese, butter, cream, milk, milk powder, yoghurt.

³¹The biggest French group, Lactalis defines itself as the first world-leading dairy company.

³²We refer interested readers to Villas-Boas (2007); Allain et al. (2020) among many other papers. Our

3. A Theory of Margins, Markups and Markdowns

We develop a theory which relies, in its basic version, on two assumptions about processors: (i) they produce dairy products according to a Leontief production function and (ii) they maximize their variable profits by internalizing their effects on prices up- and downstream. This setup enables us to define markdowns, markups, and (total) margins.

3.1. Production Function

Technology Assumptions To produce y_{fj} kilograms of dairy product j , a dairy firm³³ f combines milk intermediate consumption m_{fij} - possibly coming from various markets i - with its processing technology. The production function is given by:

$$y_{fj} = \min \left\{ \underbrace{\sum_{i \in \mathcal{I}_f} \frac{m_{fij}}{e_{ij}}}_{\text{required milk inputs}}, \underbrace{F_j(L_f, K_f; \Omega_f)}_{\text{processing capacity}} \right\} \quad (1.1)$$

The production technology is a combination of two extremes. Through the *Leontief form*, we assume perfect complementarity between the required milk input quantity and the processing capacity. This reflects the fact that a given dairy product has to contain a minimal quantity of milk inputs. We define e_{ij} as the required quantity of milk input i to produce a unit of dairy product j . Through *linearity* in combining milk inputs from various markets i , we assume that they are perfect substitutes for producing product j , given technical coefficients e_{ij} . A processor thus only needs one type of milk input, but may use a variety of perfectly substitutable inputs.

The processing technology is common to all processors and is represented by the function $F_j(\cdot)$ which is assumed to be twice differentiable in each argument. For now, we assume a general product-specific processing function $F_j(\cdot)$, defined as a function of a firm's use of labor L_f and capital K_f . Finally, Ω_f characterizes the ability of firm f to process goods. More precisely, L_f and K_f can be defined as vectors of labor and capital quantities used for every product, while Ω_f can similarly be a vector of firm-product level efficiencies. Writing $F_j(\cdot)$ as a function of firm-level labor and capital quantities enables us to capture *economies of scope* when processing several goods.

Input Assumptions A dairy firm sources milk inputs from various markets i in its accessible set \mathcal{I}_f . It encompasses direct purchases of raw milk from farmers on local markets and/or intermediary dairy products from other processors. The latter are traded

theory acknowledges such complexity by remaining agnostic on the nature of the competition between firms, thus encompassing various types of negotiations.

³³Throughout the paper, a *dairy firm* or a *processor* indifferently refers to any firm processing milk inputs to produce dairy products.

through global and regulated markets, as we explain later. These pre-processed dairy products notably include milk powder (whole, half-skimmed, skimmed) and we discuss its substitutability with raw milk in greater detail in Section 4.2.. We assume milk inputs to be variable in the sense that sourcing and processing occur at the same period. This rules out the possibility for the processor to store milk inputs, which is a natural assumption for perishable raw milk, but a stronger one for intermediary dairy products such as milk powder. We also assume milk inputs to be static, in the sense that they only affect current profits, thus ruling out adjustment costs. We similarly assume labor to be variable, implying costless labor adjustment.³⁴

Finally, and standard in this literature, capital evolves from previous investments I_{ft-1} :

$$K_{ft} = (1 - \delta)K_{ft-1} + I_{ft-1},$$

δ is the depreciation rate.

Note that we ignore non-milk intermediary inputs (e.g energy, fruits for yoghurt...) which would enter the production function as perfect complements. We argue that they are small in comparison with milk inputs cost. Including them would not affect estimated processing coefficients but could marginally increase the estimation of marginal costs of production. We discuss this point in Appendix 1.C2..

3.2. Variable Profit Maximization

A processor f maximizes its current variable profit. Firm f can be multi-source and multi-product: milk inputs i are sourced from a market set \mathcal{I}_f and products sold j belong to \mathcal{J}_f . Both sets are defined one period ahead by firm f .³⁵

For each pair (i, j) , firm f optimally chooses the quantity m_{fij} of input i to dedicate to product j . Firm f also chooses the optimal quantity of labor L_f to hire at unit cost z_f to process these products.³⁶ This yields the following program:

³⁴This assumption is relatively strong. However, dairy processing mainly requires low-skilled work which reduces hiring and firing costs, and facilitates turnover.

³⁵See Appendix 1.C for a more detailed description of the underlying timing.

³⁶Capital is determined by past investments according to inter-temporal decisions which are separated from the program discussed here.

$$\begin{aligned}
& \max_{\{m_{fij}\}_{(i,j) \in \mathcal{I}_f \times \mathcal{J}_f}, \{l_{fj}\}_{j \in \mathcal{J}_f}} \sum_j p_{fj}(y_{fj})y_{fj} - \sum_i w_{fi}(m_{fi})m_{fi} - \sum_j z_f l_{fj} \\
& \text{s.t.} \quad y_{fj} = \min \left\{ \sum_i \frac{m_{fij}}{e_{ij}}, F_j(L_f, K_f; \Omega_f) \right\}, \forall j, \\
& \quad m_{fi} = \sum_j m_{fij}, \forall i
\end{aligned}$$

where L_f , K_f and Ω_f respectively are vectors of l_{fj} , k_{fj} and ω_{fj} , $\forall j \in \mathcal{J}_f$, other terms being simple scalars.

Firm f can exploit market power by internalizing its quantity effects on prices through the inverse demand it faces for product j , denoted $p_{fj}(y_{fj})$, and the inverse supply curve it faces on market i , denoted $w_{fi}(m_{fi})$.

Assuming concavity of the variable profit function, optimal purchases and production decisions are given by a first order condition with respect to m_{fij} for every (i, j) , which yields:

$$\underbrace{\left(1 + \varepsilon_{fj}^{D-1}\right) p_{fj}}_{\text{marginal revenue } MR_{fj}} = \underbrace{\left(1 + \varepsilon_{fi}^{S-1}\right) w_{fi} e_{ij} + \lambda_{fj}}_{\text{marginal cost } MC_{fij}}. \quad (1.2)$$

where the demand price-elasticity of j is

$$\varepsilon_{fj}^D \equiv \frac{\partial y_{fj}}{\partial p_{fj}} \frac{p_{fj}}{y_{fj}},$$

the supply price-elasticity is

$$\varepsilon_{fi}^S \equiv \frac{\partial m_{fi}}{\partial w_{fi}} \frac{w_{fi}}{m_{fi}}.$$

and λ_{fj} is the marginal processing cost (MPC) of product j . This MPC stems from variable processing cost minimization for a given production level.³⁷ We provide derivation detail in Appendix 1.C1..

Equation 1.2 states the equality between marginal revenue and marginal costs. Due to the existence of seller power, the marginal revenue differs from the downstream price, by a *wedge* equal to $1 + \varepsilon_{fj}^{D-1}$.

Due to the existence of buyer power on market i , the marginal cost MC_{fij} can be

³⁷It can also be defined as the Lagrangian multiplier, associated to the processing capacity constraint, of the reduced profit-maximization problem, in which milk capacity constraint is already satisfied.

written as:

$$MC_{fij} = \left(1 + \varepsilon_{fi}^{S-1}\right) w_{fi} e_{ij} + \lambda_{fj}. \quad (1.3)$$

and thus differs from what we hereafter refer to as the *accounting marginal cost*:

$$AMC_{fij} = w_{fi} e_{ij} + \lambda_{fj}. \quad (1.4)$$

The distinction between both objects appears due to the firm internalizing its effect on price when buying an additional unit of milk. As a consequence, the term $1 + \varepsilon_{fi}^{S-1}$ scales up the price of a unit of raw milk in the marginal cost expression. In contrast, the *accounting* marginal cost is computed taking the price as given. Both objects feature an additive structure due to the Leontief production function: any unit of milk input purchased needs to be processed, requiring an additional marginal processing cost λ_{fj} .

Note that first order conditions imply equality between the marginal revenue of producing an additional unit of product j (MR_j), and the marginal cost of sourcing and processing the required milk from market i MC_{fij} for every couple (i, j) . We thus have for every i firm f buys from:

$$MC_{fij} = MC_{fj}.$$

As extensively explained in Section 4., these arbitrage conditions, together with the existence of a commodity market where dairy firms do not have any price-setting power, will be the cornerstone of our identification strategy.

3.3. Markups, Markdowns, and Margins

In this section, and based on the first order conditions derived above, we define markups, markdowns, and total margins.

Markups

Definition 1. *The markup measures the ability of a firm to set a price above its marginal cost. The markup of firm f on product j is:*

$$\mu_{fj} \equiv \frac{P_{fj}}{\left(1 + \varepsilon_{fi}^{S-1}\right) w_{fi} e_{ij} + \lambda_{fj}} = \frac{1}{1 + \varepsilon_{fj}^{D-1}}.$$

This expression is derived from Equation (1.2). It links the ratio between price and the marginal cost of production with the demand elasticity: the less elastic is the demand (higher ε_{fj}^D) the higher is the markup. Under perfect competition on output j , the markup would be equal to one.

Markdowns

Definition 2. *The markdown measures the ability of a firm to purchase a milk input at a price below the input's marginal contribution to profit. The markdown of firm f on input i is:*

$$\nu_{fi} \equiv \frac{p_{fj} \left(1 + \varepsilon_{fj}^{D-1}\right) - \lambda_{fj}}{w_{fi}e_{ij}} = 1 + \varepsilon_{fi}^{S-1}.$$

This definition is derived from Equation (1.2), similarly to Definition 1. As expected, a firm's upstream market power depends on the supply elasticity: the less elastic is the supply, the higher is the markdown. Under perfect competition on input i , the markdown would be equal to one. Due to perfect complementarity between milk and other inputs, the production of an additional unit of output j requires an extra processing cost λ_{fj} . Hence, $p_{fj} \left(1 + \varepsilon_{fj}^{D-1}\right) - \lambda_{fj}$ is the marginal contribution to profit of an additional unit of output j . Adjusting by e_{ij} , we finally have, in the numerator, the marginal contribution to profit of an additional unit of input i to product j . Note that despite the multi-product setting, firm optimizing behavior requires markdowns on a given input market i to be product-invariant.

Margins

Definition 3. *The (total) margin measures the ability of a firm to set a price above its accounting marginal cost. We define the margin of firm f on product j sourcing milk from input market i as:*

$$M_{fij} \equiv \frac{p_{fj}}{w_{fi}e_{ij} + \lambda_{fj}}.$$

Using our definitions of markups and markdowns, the margin can be rewritten:

$$M_{fij} = (\theta_{fij}\nu_{fi} + (1 - \theta_{fij}))\mu_{fj} \quad (1.5)$$

where $\theta_{fij} \equiv \frac{w_{fi}e_{ij}}{w_{fi}e_{ij} + \lambda_{fj}}$ is the share of milk from i in the *accounting* marginal cost of producing j . The total margin on a unit of milk input i used in product j is thus a combination of the markdown on milk input i and the markup on product j , thus reflecting the overall market power of a firm. Under perfect competition on input i and output j , the margin would be equal to one. Deviations from perfect competition on either the input or the output market lead the margin to deviate from one. Due to the Leontief structure, the importance of the markdown on milk i is modulated by the importance of milk input i in the total marginal cost of processing product j , which translates into θ_{fij} . Finally, note that the term $(1 - \theta_{fij})$ enters without any

multiplicative term as we assumed no MP on labor, the only other variable input.³⁸

This definition encompasses special cases which have been studied in the literature. If $\theta_{fij} = 1$, we have $M_{fij} = \nu_{fi}\mu_{fj}$, implying that the margin is equal to the product of the markdown and the markup. This is the result of [Morlacco \(2019\)](#) who assumes substitutability between materials and labor and capital. As a consequence, the markdown proportionally scales up the total margin, similarly to the markup.

Ignoring buyer power ($\nu_{fi} = 1$), the margin reduces to $M_{fij} = \mu_{fj}$, *i.e* the total margin equalizes the markup. This is the classical result of various papers ([De Loecker and Warzynski \(2012\)](#); [De Loecker and Scott \(2016\)](#); [De Loecker et al. \(2016\)](#); [De Ridder et al. \(2021\)](#) among others) ignoring buyer power on intermediates/materials. By assumption, the existence of total margins is thus attributed to seller power only.

Finally, in the absence of seller power ($\mu_{fj}=1$), the margin is equal to $M_{fij} = \nu_{fi}\theta_{fij} + (1 - \theta_{fij})$, which tends towards ν_{fi} when θ_{fij} is close to unity. This, for example, relates to [Zavala \(2020\)](#), estimating markdowns of exporters when purchasing crops from Ecuadorian farmers, but taking (international) output prices as given.

3.4. Assumptions

For the sake of simplicity, the theoretical framework presented here is kept as simple as possible in order to derive markups, markdowns, and margins, in a consistent way. It relies on some assumptions that are relaxed in [Appendix 1.C](#) where we show how (i) we can rely on cost minimization only, (ii) we can incorporate intra-brand competition or (iii) horizontal collusion or vertical cooperation can be allowed.³⁹ Importantly, these extensions would not change our empirical results. The key intuition behind this robustness is that we do not rely on an estimation of the implied elasticities, so that underlying marginal revenue and marginal cost are free to encompass any economic cost of adjusting raw milk and dairy products prices perceived by the firm. Firm behaviors can thus take more complex forms than outlined here, as further explained in [Appendix 1.C1.](#)

3.5. Graphical Representation

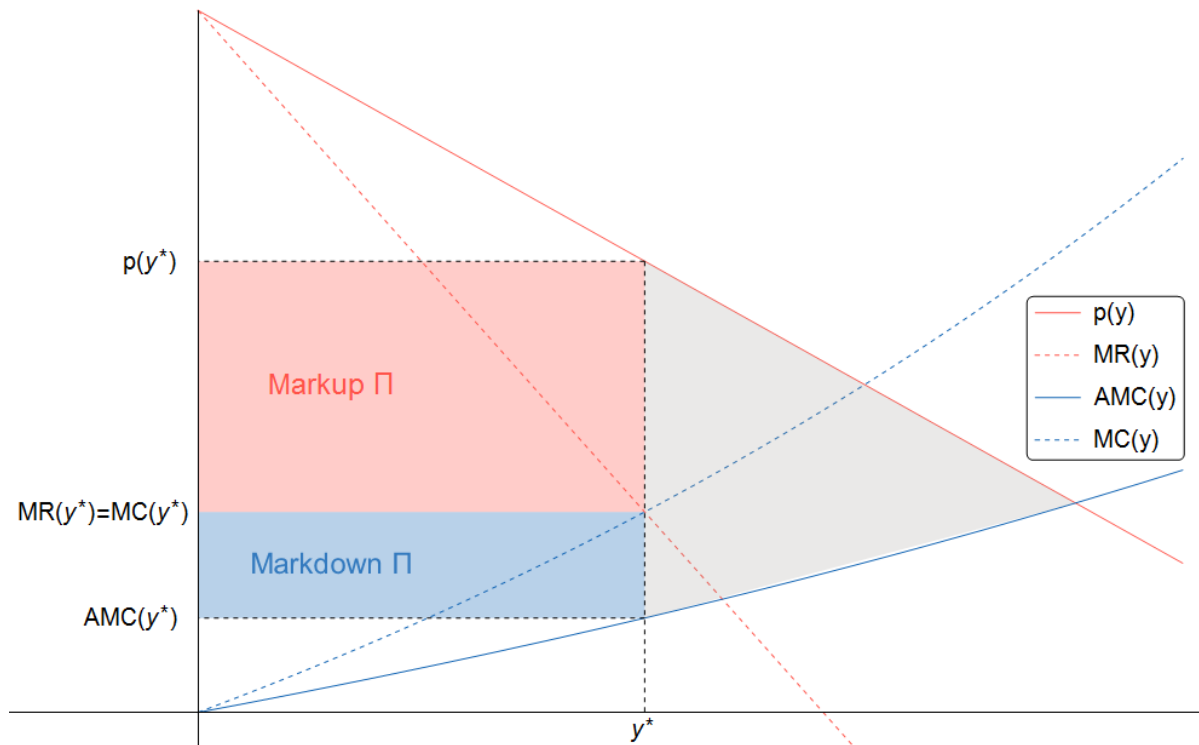
[Figure 1.2](#) represents the equilibrium of a single milk input and output firm, allowing us to drop subscripts. For the sake of representation, here we assume particular functional forms. Demand $p(\cdot)$ and marginal revenue curves $MR(\cdot)$ differ due to the existence of

³⁸We discuss this assumption, which can be relaxed in theory but is needed for estimation, in [Appendix 1.C](#).

³⁹This last aspect allows us to think about the behavior of vertically integrated cooperatives.

seller power. Accounting marginal costs $AMC(\cdot)$ and marginal cost $MC(\cdot)$ curves differ due to the existence of buyer power.

Figure 1.2: Equilibrium - Single Input/Output Firm



The equilibrium quantity (of input and output) is determined by the equality between marginal revenue and marginal costs. This simple representation stresses two important aspects: both buyer and seller power (i) reduce equilibrium input and output quantities, and (ii) pull-down input prices and inflate final prices. As such, they both decrease total welfare and redistribute from farmers and consumers to processors. The total rent captured by processors is thus the sum of markdown and markup rents, respectively represented by the blue and red rectangles.

In the empirical analysis that follows, we will be able to identify equilibrium objects $p(y^*)$, $MR(y^*) = MC(y^*)$, and $AMC(y^*)$, allowing us to quantify markups, markdowns, and margins, as well as associated rents. As our framework purposely remains agnostic on the exact competition contexts, and thus on the exact shapes of red and blue curves in Figure 1.2, we do not aim to compute the deadweight loss (in grey), nor to generate counterfactuals. However, variations of estimated equilibrium objects across time and markets will give a sense of the underlying shape of demand and supply curves, and imply important policy implications.

4. Estimation

We are ultimately interested in estimating margins, markups, and markdowns, provided that we directly observe prices p_{fj} and w_{fi} in the data. From definition 3, repeated below for convenience,

$$M_{fij} \equiv \frac{p_{fj}}{w_{fi}e_{ij} + \lambda_{fj}},$$

we see how we can recover total margins from the estimation of *accounting* marginal costs, which are the sum of the cost of buying at cost w_{fi} the quantity e_{ij} of milk input i present in a unit of output j , and marginal processing cost λ_{fj} . In Section 4.1., we argue that e_{ij} can be summarized using dry matter contents of milk input i and product j , which we observe in the data. We then show in Section 4.1. how we can estimate marginal processing costs, following a standard production function approach relying on our production data.

We then explain in Section 4.2. how we take advantage of the presence of dairy firms on multiple markets, including a commodity market where they do not have any price-setting power (be it as a buyer or as a seller), to disentangle both sources of MP and estimate firm-origin-level markdowns and firm-product-level markups.

4.1. Recovering Margins through Marginal Costs Estimation

Dry Matter Contents of Milk Inputs and Outputs

We explain here how we identify e_{ij} , the quantity of milk input i needed to produce a unit of output j . Together with our raw milk price data, this provides us marginal buying costs at the firm-origin-product level.

In practice, raw milk and dairy intermediates are bundles of multiple sub-inputs (water, fat, protein, lactose, minerals) which are also present in different proportions in various dairy outputs j . The two main sub-inputs are fat and proteins, which we sum to get *dry matter contents*. This methodology is commonly used by practitioners in the industry, which guarantees the quality and availability of the data. These measures give us e_j , the dry matter per unit of output j , observed at the CN8-level (and for some products slightly more disaggregated). These measures also give us e_i , the dry matter per unit of input i , observed at the *département*-year level for raw milk and at the CN8-level for dairy intermediates. Together, e_j and e_i allow us to construct $e_{ij} = \frac{e_j}{e_i}$, which represents the quantity of input i needed per unit of product j produced.

Table 1.3 shows concrete examples of e_i and e_j measurements. For example, 100 grams of butter contain 82 grams of fat and 0.75 grams of proteins so that $e_{butter} = 82.75$,

Table 1.3: Example of Dry Matter Contents in Dairy Inputs and Outputs

<i>DMC data</i>	Butter	Comté	Yoghurt	Raw milk ($i = Doubs, 2018$)
<i>Content (in g/100g)</i>				
Fat	82.00	31.20	2.69	3.95
Proteins	0.75	27.97	3.60	3.38
Dry Matter (e_j or e_i)	82.75	59.17	6.29	7.33
<i>Quantity of milk needed (in g/g)</i>				
e_{ij}	11.29	8.07	0.85	1

whereas 100 grams of yoghurt contain 2.69 grams of fat and 3.6 grams of proteins so that $e_{yoghurt} = 6.29$. Similarly, in the Doubs *département* in 2018, $e_{Doubs} = 7.33$. Using these characteristics, producing a kilogram of butter would require 11.29 kilograms (82.75/7.33) of milk from the Doubs *département*, while producing a kilogram of Comté cheese would require 8.07 kilograms (59.17/7.33) of such milk.

In our data, e_i are time-varying⁴⁰ while e_j are not. Table 1.3 illustrates the substantial heterogeneity in milk requirements e_j across dairy products⁴¹ and the importance of taking it into account. Dry matter contents e_i exhibit less variation across *départements* (and time), lying between 5.60 and 8.19 grams per 100 grams, for every French *département* during the 2003-2018 period.

Using these data, we assume that there is no waste of dry matter contents in the production process. This assumption appears credible and even necessary in our context as processors use fat or protein leftovers from the production of a given product in the production of other products. In doing so, they exploit complementarities in the production of several dairy products regarding the use of milk. Assuming optimal use thus seems reasonable, which the goodness of fit we find between the reconstituted demand for French raw milk and the actual raw milk collection confirms. We underestimate the demand for raw milk by 2 to 8% over the period, as shown in Appendix 1.D1.), a gap that can be explained by wastes in the production process that we do not allow.

Milk Marginal Processing Costs Estimation

We describe here our identification and estimation methodology for milk marginal processing costs. In the theoretical part of the paper, we allow processing costs to be firm-product-specific. In the empirical analysis which follows, we restrict them to be homogeneous within a firm across products, assuming that: $\forall j, \lambda_{fj} = \lambda_f$. This assumption

⁴⁰Time subscripts are dropped here to simplify notations.

⁴¹Interested readers can further explore this dimension in this public (and slightly more aggregated) version of the dry matter content data we use [here](#).

makes sense in our context, as explained in Appendix 1.D2..

Identification of Milk Marginal Processing Costs We assume that a firm f processes milk using variable labor l_f , and fixed capital k_f , in log terms. Firms differ in their ability to process milk ω_f . In our preferred specification, we assume the following Cobb-Douglas milk processing function:⁴²

$$\ln y_f = \ln F(.) = \beta_l l_f + \beta_k k_f + \omega_f, \quad (1.6)$$

where we drop time subscript again to simplify notation.

The firm-level quantity is obtained by summing quantities produced across products, where all quantities are expressed in the same unit (kilograms).⁴³ We thus have:

$$y_f = \sum_j y_{fj}.$$

The minimization of the variable cost function given the desired processing level of Y_f implies:

$$\begin{aligned} \min_{L_f} \quad & Z_f L_f \\ \text{s.t.} \quad & F(L_f, K_f, \Omega_f) - y_f^* \geq 0, \end{aligned}$$

At the optimum, we have:

$$\lambda_f = \frac{Z_f L_f^*}{\beta_l y_f^*}. \quad (1.7)$$

The marginal processing cost is thus equal to the expenditure on labor L_f divided by the labor elasticity of output β_l times the quantity of output produced. Identifying the firm-product-specific marginal costs thus requires estimating β_l .

Estimation Procedure In order to estimate the processing function, we follow the seminal literature, [Olley and Pakes \(1996\)](#), [Levinsohn and Petrin \(2003\)](#), and [Akerberg et al. \(2015\)](#), who deal with firm-specific efficiencies that are unobserved sources of endo-

⁴²In Appendix 1.D2., we compare the resulting estimated elasticities with the ones obtained with a Translog specification and to the empirical labor shares. We rely on the Cobb-Douglas functional form as a baseline as the coefficients estimated with a Translog exhibit very high (bootstrapped) standard errors. All empirical results however pertain using both specifications.

⁴³Note that this is equivalent to summing revenues across products and deflating by a price index that is the weighted average price. Indeed:

$$\frac{\sum_j p_{fj} y_{fj}}{\bar{p}_f} = \sum_j y_{fj} \iff \bar{p}_f = \sum_j p_{fj} \frac{y_{fj}}{\sum_j y_{fj}}.$$

geneity. We also incorporate methodologies of [De Loecker et al. \(2016\)](#) and [Rubens \(2021\)](#) to deal with unobserved exogenous input prices and quantities, and with (observed) endogenous prices upstream and downstream, *i.e.* firms exploiting MP on both sides of the market. We describe this approach in Appendix 1.D2..

Estimates We present in Table 1.11 in the Appendix our processing functions estimates for several specifications, including plain OLS and GMM, for our preferred Cobb-Douglas processing function specification.⁴⁴ All coefficients (i) are close to findings in the literature and (ii) confirm the importance of correcting for endogeneity.

The labor elasticity of output (0.739) is between the one found by [Rubens \(2021\)](#) (0.591) - who assumes a similar Leontief production function, though applied in a different context - and [De Loecker and Scott \(2016\)](#) (0.75), who have a Cobb-Douglas production function. Capital elasticities are less stable in the literature. Ours differs from [Rubens \(2021\)](#), who estimates 0.59 but is closer to [De Loecker and Scott \(2016\)](#), who estimate 0.30.⁴⁵ Using our estimates of β_l and equation (1.7), we can recover marginal costs at the firm-level.

In the rest of the empirical analysis, we thus write marginal costs (λ_f) at the firm level rather than at the theoretical firm-product level (λ_{fj}), consistently with our estimation procedure. Based on these estimates and definition 3, we have margin estimates:

$$M_{fij} = \frac{p_{fj}}{w_{fi}e_{ij} + \lambda_f}.$$

Having marginal processing cost and thus margins estimates in hands, we show here how we recover markups and markdowns of French dairy processors.

4.2. Disentangling Markups and Markdowns

In this section, we first highlight intuitions on how to separately recover a firm's markups and markdowns through its sales or purchases on a global commodity market. We then formally explain the identification, before detailing its empirical implementation using the whole milk powder (WMP) market. We conclude this section by discussing identification robustness.

⁴⁴Appendix 1.D2. also presents results for a Translog specification, conducted as a robustness check.

⁴⁵Our estimates of the capital elasticity may be downward biased due to measurement error, as suggested by [Collard-Wexler and De Loecker \(2016\)](#). Note that this capital elasticity does not directly affect subsequent results as estimating marginal processing costs only requires knowledge of the labor elasticity. In the translog production function, capital measurement, however, can contaminate our measured labor elasticity.

Intuition

The intuition for identification of markups and markdowns is based on Equation 1.5, repeated here for convenience:

$$M_{fij} = (1 + \theta_{fij} (\nu_{fi} - 1)) \mu_{fj} \quad (1.5')$$

where $\theta_{fij} \equiv \frac{w_{fi}e_{ij}}{w_{fi}e_{ij} + \lambda_{fj}}$ is the share of milk from i in the *accounting* marginal cost of producing j . As mentioned, once λ_{fj} is approximated by λ_f , we obtain estimates of M_{fij} and θ_{fij} . As Equation 1.5 holds for every source market i and product j in which firm f is present, we can exploit the underlying arbitrage conditions and the fact that firms trade inputs or outputs on markets where they do not have price-setting power.

Figure 1.3: Identification Intuition - Commodity Sellers

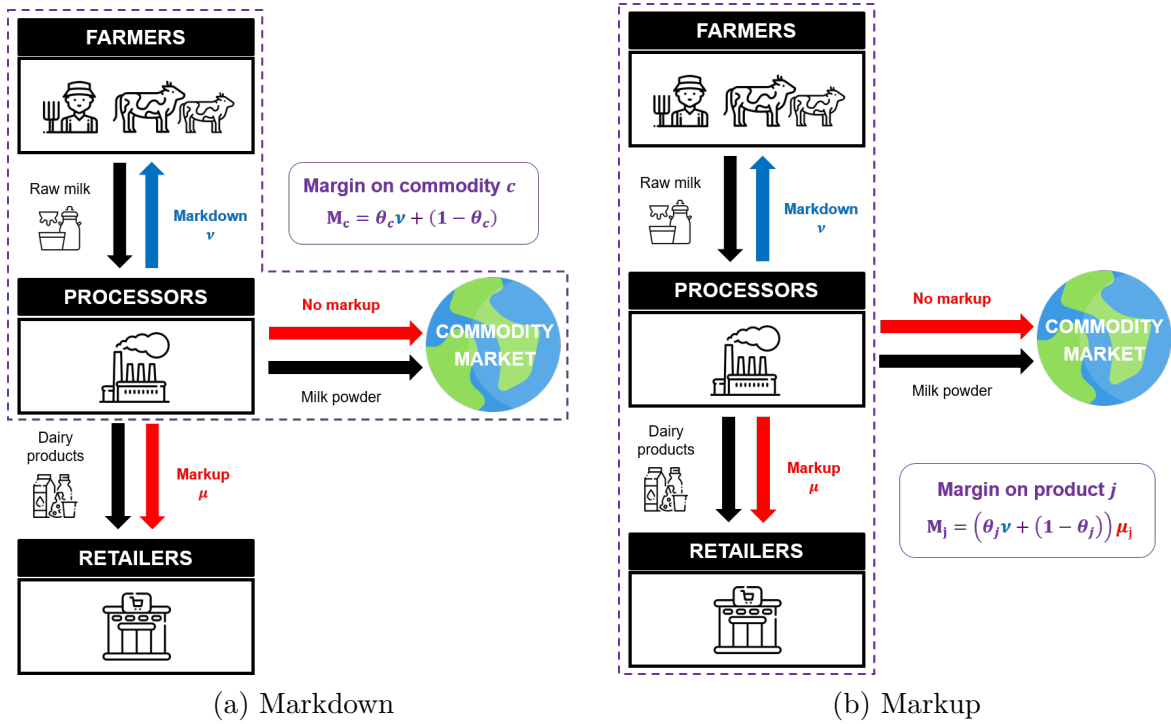


Figure 1.3 provides the intuition for identification in the case of processors selling on at least two markets, including one where they do not have seller power. For simplicity, we take a particular firm sourcing milk on a single market, allowing us to drop the corresponding subscripts. This firm has buyer power and a markdown ν on its milk market. In contrast, when such a firm sells on a market c , where it has no seller power ($\mu_c = 1$), its margin M_c is only determined by the markdown:

$$M_c = 1 + \theta_c (\nu - 1).$$

As M_c has previously been estimated, inverting the equation above allows the identi-

fication of the markdown v . Using Equation 1.5, we can then recover markups μ_j for all other products j sold by the firm, by inverting:

$$M_j = (\theta_j \nu + (1 - \theta_j)) \mu_j.$$

Figure 1.4: Identification Intuition - Commodity Buyers

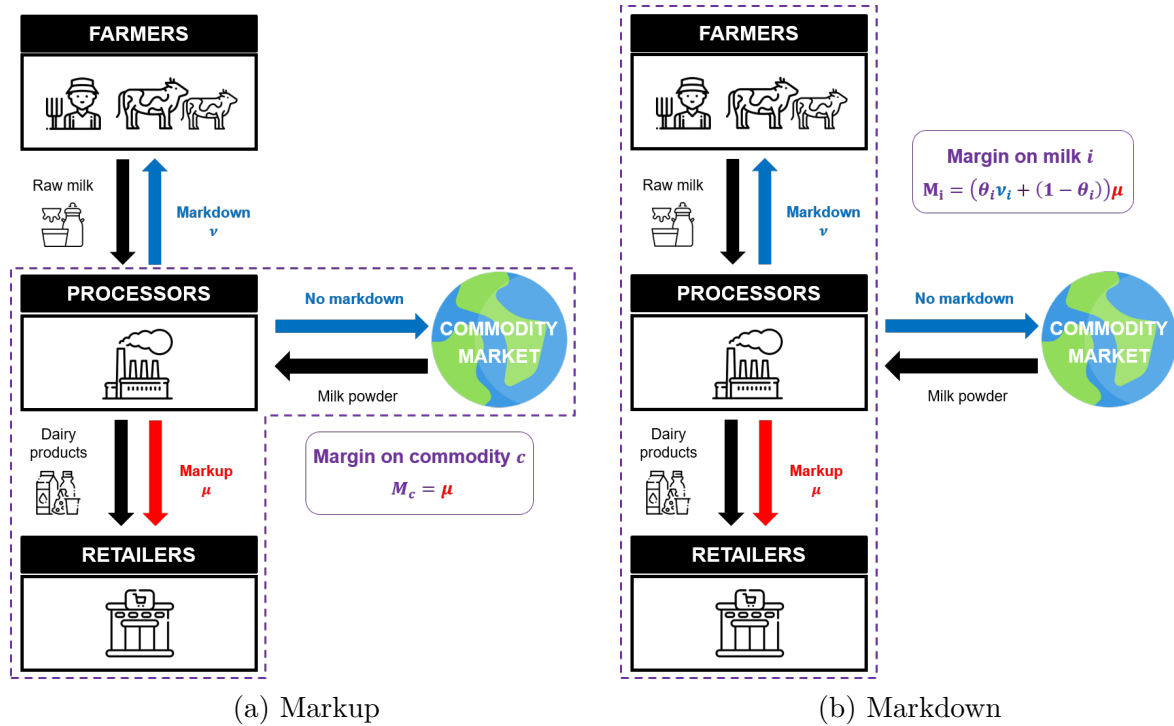


Figure 1.4 provides similar intuition for identification in the case of processors buying on at least two markets, including one where they do not have buyer power. For simplicity, we take a particular firm selling on a single market, allowing us to drop the corresponding subscripts. This firm has seller power and a markup μ on its output market. If such a firm purchases on a market c , where it has no buyer power ($\nu_c = 1$), its margin M_c is only determined by the markup:

$$M_c = \mu_c.$$

As M_c has been estimated, the equation above directly delivers the markup μ_c . Using again Equation 1.5, we can then recover markdowns ν_i for all other milk inputs i the firm purchases, by inverting:

$$M_i = (1 + \theta_i (\nu_i - 1)) \mu_c.$$

Identification

We here detail the exact identification of markups and markdowns for firms that either buy or sell a commodity, namely whole milk powder (WMP), on which they are price-

takers. Identification relies on processors trading off between using (resp. producing) WMP or using raw milk (producing another dairy product) on which they exert buyer (seller) power.⁴⁶

According to our theory, a firm can either be a seller or a buyer of WMP, or none of the two, but cannot *simultaneously* be both a seller and a buyer. The latter would imply losses on this trading activity, as the firm would buy and sell the same product, but would incur an additional marginal processing cost. Our theory rationalizes the fact that some firms sell WMP while some do not, as it reflects the ability of the former to process WMP at a marginal cost lower than the WMP price.

In what follows, the WMP price is denoted w_c . Similarly to what we do for technical coefficients e_{ij} , we also define $e_{ic} = \frac{e_c}{e_i}$ and $e_{cj} = \frac{e_j}{e_c}$, where e_c is the dry matter content of WMP, observed in the data.

Identification for WMP Sellers Here, identification stems from the fact that a firm is indifferent, for the marginal unit of milk purchased in a given market i , between using it to produce WMP, sold at exogenous price w_c , and using it to produce another product. Formally, identification relies on two first order conditions: with respect to the use of milk input i for producing and selling WMP,

$$\underbrace{w_c}_{\text{marginal revenue } MR_{fc}} = \underbrace{\nu_{fi} w_{fi} e_{ic} + \lambda_f}_{\text{marginal cost } MC_{fic}}, \quad (1.8)$$

and with respect to the use of the same milk input i for producing another product j ,

$$\underbrace{p_{fj} \mu_{fj}^{-1}}_{\text{marginal revenue } MR_{fj}} = \underbrace{\nu_{fi} w_{fi} e_{ij} + \lambda_f}_{\text{marginal cost } MC_{fij}}. \quad (1.9)$$

We directly get markdowns from (1.8), while (1.8) and (1.9) together identify markups:

$$\nu_{fi} = \frac{(w_c - \lambda_f)}{w_{fi} e_{ic}}, \quad \forall i \quad \text{and} \quad \mu_{fj} = \frac{p_{fj}}{(w_c - \lambda_f) \frac{e_{ij}}{e_{ic}} + \lambda_f}, \quad \forall j.$$

By definition, the markdown is the wedge between the marginal contribution to profit of milk and its price. As apparent in (1.8), a firm does not have seller power when selling WMP. The exogenous price of WMP (w_c), together with marginal processing cost (λ_f) and technical coefficients (e_{ic}), thus directly identifies the marginal contribution to profit of a unit of raw milk from i . The wedge between this marginal contribution to profit ($\frac{w_c - \lambda_f}{e_{ic}}$) and the observed price of raw milk (w_{fi}) is solely due to buyer power and identifies the

⁴⁶In Section 4.2., we explain to what extent we can extend the identification to firms that are inactive on the commodity market.

markdown.

By definition, the markup is the wedge between the price and the marginal cost of a product. As a firm has buyer power on the raw milk market i , an opportunity cost arises from allocating milk from i to produce product j rather than to produce WMP. This opportunity cost, determined by arbitrage conditions stemming from (1.8) and (1.9), is proportional to the marginal profit lost when renouncing to selling an additional unit of WMP ($w_c - \lambda_f$).⁴⁷ This opportunity cost also shifts depending on relative milk requirements, an additional unit of j requiring e_{ij} units of milk from i that could have been otherwise used to produce $\frac{e_{ij}}{e_{ic}}$ units of WMP. The wedge between the output price (p_{fj}) and the implied marginal cost, featuring this opportunity cost ($(w_c - \lambda_f) \frac{e_{ij}}{e_{ic}}$) and the marginal processing cost (λ_f), is solely due to seller power and identifies the markup.

Identification for WMP Buyers Here, identification stems from the fact that a firm is indifferent, for producing the marginal unit of a given product j , between using WMP, purchased at exogenous price w_c , and using raw milk. Formally, identification relies on two first order conditions: with respect to the use of WMP to produce a given product j ,

$$\underbrace{p_{fj} \mu_{fj}^{-1}}_{\text{marginal revenue } MR_{fj}} = \underbrace{w_c e_{cj} + \lambda_f}_{\text{marginal cost } MC_{fcj}}, \quad (1.10)$$

and with respect to the use of milk input i to produce the same product j ,

$$\underbrace{p_{fj} \mu_{fj}^{-1}}_{\text{marginal revenue } MR_{fj}} = \underbrace{\nu_{fi} w_{fi} e_{ij} + \lambda_f}_{\text{marginal cost } MC_{fij}}. \quad (1.11)$$

We identify markdowns from (1.10) and (1.11), while we directly get markups from (1.10):

$$\nu_{fi} = \frac{w_c e_{cj}}{w_{fi} e_{ij}}, \quad \forall i \quad \text{and} \quad \mu_{fj} = \frac{p_{fj}}{w_c e_{cj} + \lambda_f}, \quad \forall j.$$

By definition, the markdown is the wedge between the marginal contribution to profit of milk and its price. As a firm has buyer power when purchasing raw milk from i , an arbitrage arises between using milk from i or using WMP to produce product j , stemming from (1.10) and (1.11). A firm prefers to buy and use raw milk from market i - where it exerts buyer power - as long as the corresponding marginal cost is below the marginal cost of using WMP. At the optimum, a firm equalizes both marginal costs. It further implies a three-term equality between the marginal contribution to profit of a unit of j ($MR_{fj} - \lambda_f$), the marginal sourcing cost using raw milk ($\nu_{fi} w_{fi} e_{ij}$), and the marginal sourcing cost using WMP ($w_c e_{cj}$). Adjusting by technical coefficients e_{ij} eventually allows

⁴⁷For every unproduced and unsold unit of WMP, a firm loses w_c but saves marginal processing cost λ_f .

us to identify the marginal contribution to profit of a unit of milk from i . The wedge between this marginal contribution to profit ($\frac{w_c e_{cj}}{e_{ij}}$) and the observed price of raw milk (w_{fi}) is solely due to buyer power and identifies the markdown.

By definition, the markup is the wedge between the price and the marginal cost of a product. As apparent in (1.10), a firm does not have buyer power when purchasing WMP. The exogenous price of WMP (w_c), together with marginal processing cost (λ_f) and technical coefficients (e_{cj}), thus directly identifies the marginal cost of product j . The wedge between the output price (p_{fj}) and the implied marginal cost is solely due to seller power and identifies the markup.

Appendix 1.D3. provides additional graphical representations illustrating the main intuitions mentioned here.

Implementation

In our data, we observe and identify which firms sell bulk WMP, and at what price. We take the price on the commodity market as the market price for France, denoted w_c in the equations above, provided by the European Commission (EC) at the yearly level.⁴⁸ Contrary to sales, we do not observe firm-level purchases and prices of WMP, leading us to assume that firms which do not sell WMP are purchasers or, as discussed in Section 4.2., *potential* purchasers of WMP at the common market price w_c .

The Choice of Whole Milk Powder As other dairy commodities (butter, cream, or skimmed milk powder), WMP is sold on global markets at a price fixed by a quotation. WMP however features specificities that make it the most relevant commodity to back up our empirical analysis. First, WMP is one of the most internationally traded dairy commodities in the world. The European Union production and consumption shares are however relatively small, about 11 and 15% in 2018.⁴⁹ Around 70% of the global production comes from New Zealand, China, and Brazil, New Zealand alone representing 70% of total WMP exports. We can thus credibly assume that French processors have neither seller nor buyer power on this product, and consider its price as exogenous. Second, among all commodities used in the dairy industry, WMP is the most similar (in terms of fat and protein contents) to raw milk, given that it is essentially dry raw

⁴⁸These data can be found [here](#). Alternatively, we could have used the firm-level price at which these firms sell WMP. However, our data do not provide the buyer's identity nor the destination market. As a consequence, we do not know if these firms sell WMP (solely) through the commodity market c . In particular, such sales of bulk WMP potentially also encompass sales to other (French) firms in the food industry, that do not go through the commodity market. In order to avoid any identification issues, and maintain consistency with what we do for the identification of WMP buyers' markups and markdowns, we rely on EC market prices. Reassuringly, robustness checks based on the latter deliver similar results, as EC market prices and firm-level prices of WMP are on average very similar over time.

⁴⁹Source: <https://apps.fas.usda.gov/psdonline/circulars/dairy.pdf>.

milk. As a consequence, WMP is commonly used as a substitute for raw milk in the production process and enters the composition of many dairy products like yoghurts, milk, or (industrial) cheese.

Discussion

We view the identification for WMP sellers as quite natural. However, WMP is generally not produced by smaller processors, for which we instead rely on the identification based on the use or potential use of WMP as an input.

Such identification relies on WMP as a substitute for raw milk. In practice, WMP can almost always be replaced by raw milk, while using WMP in place of raw milk is not possible for every product (e.g. for raw milk cheese). However, the identification of markups and markdowns of a given firm remains valid as long as this firm relies on WMP as a substitute for raw milk for at least one product, which is a much less restrictive assumption. Processing yoghurts or industrial cheeses with such milk powder is for instance a common practice in the dairy industry. Moreover, substitution between raw milk and WMP only has to be possible on a positive part (and not on the entire part) of the milk input requirement. Finally, in order to avoid concerns about the substitutability between raw-milk inputs, we exclude labeled products (organic and Protected Designation of Origin) from our analysis.

Moreover, and importantly, markdown and markup expressions similar to the ones established for WMP buyers can be derived for firms that are *potential* WMP purchasers but are inactive on the WMP commodity market in equilibrium. The implied micro-foundation hinges on processors and farmers (Nash-)bargaining over the price of raw milk, where processors can rely on WMP to replace local raw milk in case of negotiation breakdown.⁵⁰

5. Results

In this section, we first show that dairy processors exploit both markups and markdowns, and that, *on average*, processor margins mostly come from markups. We then show that the relative contributions significantly vary across firms, products, and time. Finally, with a complementary pass-through analysis, we connect variations over time to changes in processor ability to exploit buyer and seller power in response to cyclical shocks.

⁵⁰See Appendix 1.D3. for further detail.

5.1. Average and Median Markdowns, Markups and Margins

Table 1.4 displays average and median markdowns, markups, and margins, over the whole period of analysis (2003-2018) and for different samples.⁵¹

The weighted average markdown is 1.19, meaning that dairy firms on average purchase raw milk at a price 16% ($1 - 1/1.19 \approx 0.16$) below its marginal contribution to their profits.⁵² While this figure appears relatively low, we document in subsequent analyses that it hides a substantial heterogeneity over time, which has important implications for farmer revenues, as well as for policy.

The weighted average markup equals 1.41, implying that, on average, the unit price of a dairy product sold by a French dairy firm exceeds the marginal cost by 41%. This weighted average markup inflates to 63% when we restrict to final consumption goods, which are relatively more differentiated. Both of these weighted averages are significantly higher than the corresponding median and simple averages, implying that bigger firms are able to impose higher markups, suffering relatively less than smaller sellers from the existence of countervailing buyer power emanating from concentrated retailers.

Table 1.4: Margins, Markdowns, and Markups - Estimates

Sample	Markdowns		Markups		Margins	
	All	All Prod.	Final goods	All Prod.	Final goods	
Average	1.18	1.21	1.50	1.44	1.82	
Weighted Average	1.19	1.41	1.63	1.56	1.81	
Median	1.16	1.06	1.41	1.35	1.83	
Observations	8,049	6,046	3,822	72,059	43,761	

Notes: Sample restricted to firms for which we manage to link raw milk collection and production. Markdowns computed based on raw milk prices at the regional level. Weighted averages based on quantity (dry matter content) shares upstream and downstream. Markdowns are observed at the group-*département*-time level, markups at the group-product-time level, and margins at the group-*département*-product-time level. Margins computed under an assumption of homogeneous milk sourcing across products for a given firm.

The industry's weighted average margin amounts to 1.56. It means that, on average, the unit price of a dairy product sold by a French dairy firm exceeds the accounting marginal cost by 56%. The difference with the weighted average markup shows the

⁵¹For all aggregated statistics in this section, we use raw milk prices at the regional level, which we have over the entire period. Using individual raw milk prices for the subsample of firms and years 2013-2018 delivers similar aggregated results for the corresponding period.

⁵²Over the rest of the analysis, the weighting scheme is based on dry matter contents of raw milk and of dairy products. Doing so, weighted average markdowns, markups, and margins reflect the weighted average market power imposed on a unit of dry matter content produced in France. Thus, they are to be interpreted as the MP consequences from the French dairy farmer's point of view.

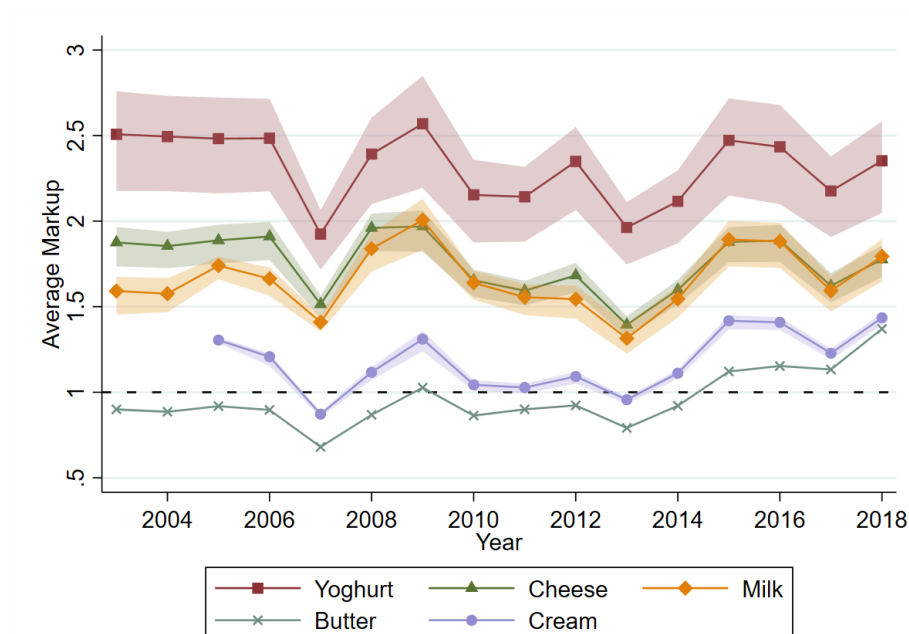
non-negligible contribution of buyer power. Moreover, this weighted average margin goes up to 81% when focusing on final consumption goods only, naturally reflecting the existence of higher markups on such products.

Overall, these results suggest that, *on average*, markdowns are relatively low compared to markups and that dairy firm margins mainly come from the exploitation of seller power, especially for larger firms. However, these averages hide a substantial amount of heterogeneity along several dimensions we discuss below.

5.2. Heterogeneity Dimensions

Heterogeneity Across Products

Figure 1.5: Markups on Final Consumption Goods - Product Category Averages



Notes: Weighted averages, using dry matter content quantity weights. Bootstrapped 95% confidence intervals (CI) displayed. CI emanate from errors in the estimation of the marginal processing cost and are thus proportional to its share in the total marginal cost of the considered product. Cream products average not displayed for 2003 and 2004 as products nomenclature does not allow to distinguish final from bulk cream before 2005.

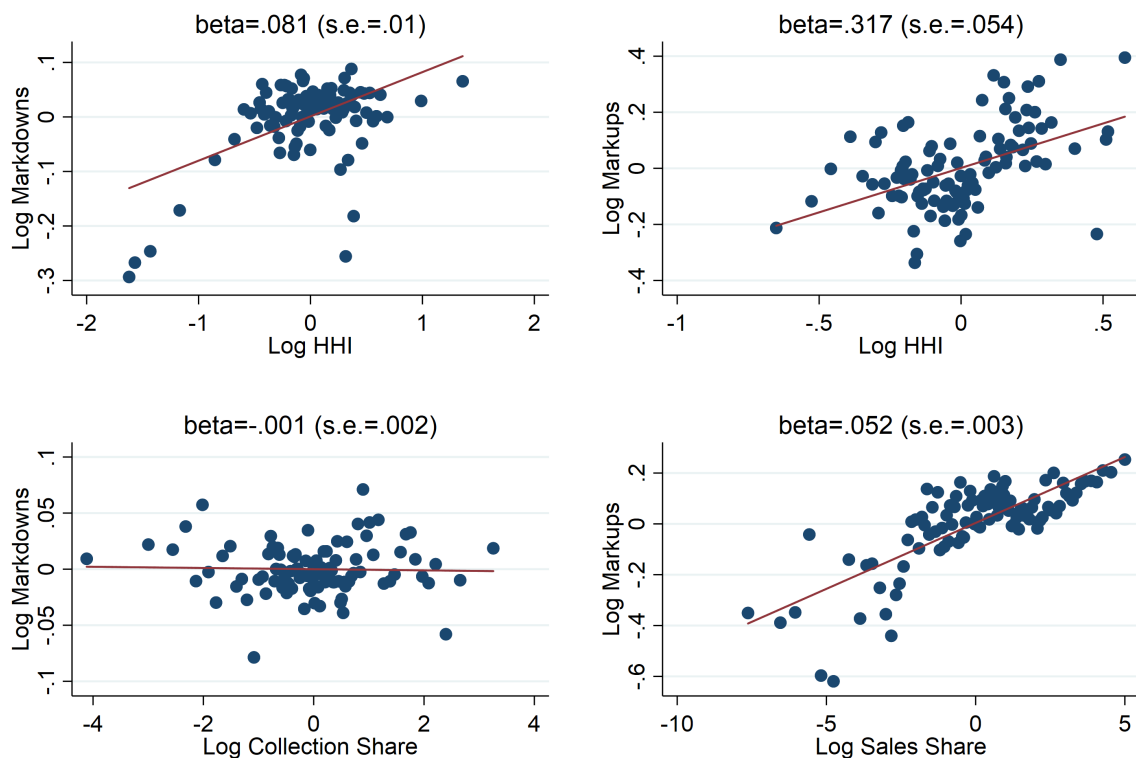
Computing weighted averages by product category shows how markups vary across final consumption goods and the importance of taking this dimension into account. Figure 1.5 shows that the average markup broadly lies between 1.5 and 2.5 for relatively differentiated products (yoghurt, cheese), whereas less differentiated products (cream, butter) have relatively low markups, close to unity.⁵³ As a result, the margin generated on low-

⁵³Figure 1.17 in the Appendix display average markups of bulk products.

markup products like cream merely comes from the markdown, showing the importance of taking both into account. These results show that product positioning can explain a large part of markup heterogeneity between firms, which is neglected when assuming a single-product production function.

Heterogeneity Across Firms and Markets

Figure 1.6: Market Power, Market Concentration and Market Shares



Notes: Observations at the market-time (up) and group-market-time (bottom) level, grouped into 100 equal-size bins in terms of the X-axis variable. All variables are demeaned by year on the up left-hand graph, by market and year on the up right-hand graph, and by market-year on the two bottom graphs.

Panel 1.6 plots our estimated measures of market power against usual variables, such as concentration measures (HHI) at the market level or market shares at the firm-market level. Both graphs at the top show how average markups and markdowns are higher in more concentrated markets, consistently with many theories such as Cournot or monopolistic competition. At the bottom right, we see that markups positively correlate with dairy firm sales shares within the market. These results are consistent with our interpretation that we do measure market power and not other frictions, as alternative explanations would not generate such patterns.

However, we do not find evidence of markdowns correlating with dairy firm milk collection shares. This result indicates that upstream prices are determined at the market level.

Heterogeneity in Market Power Exertion over Time

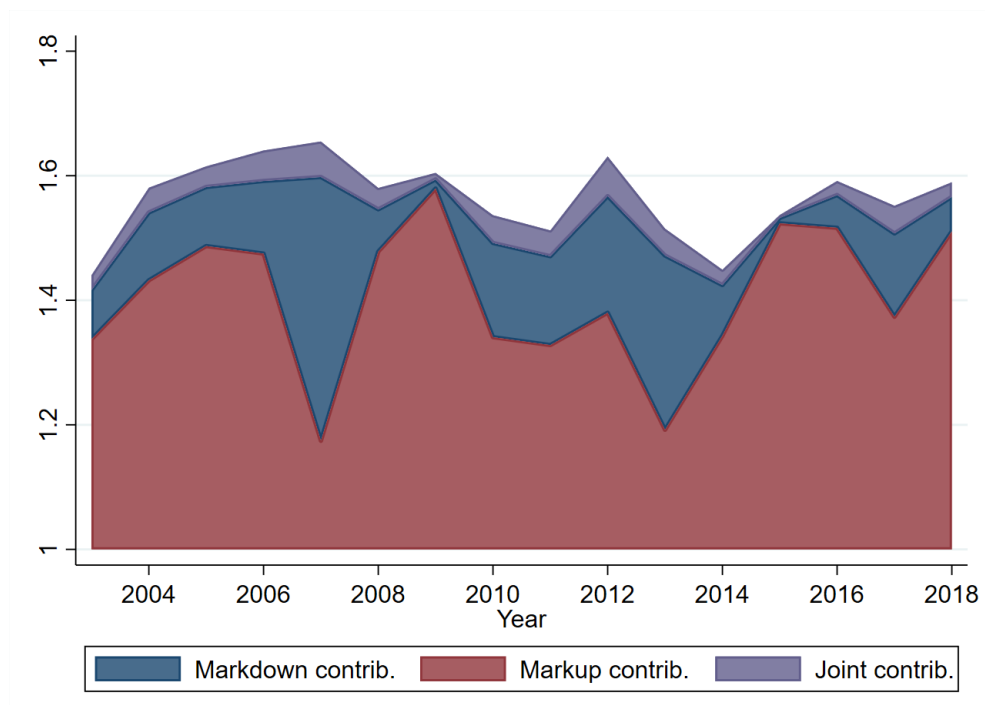
In this subsection, we first show that while dairy processor margins are relatively stable, markup and markdown contributions vary significantly over time.

Defining margin rates \tilde{M}_{fij} , markup rates $\tilde{\mu}_{fj}$ and markdown rates $\tilde{\nu}_{fj}$ with $\tilde{x} = x - 1$ for $x = \{\nu_{fi}, \mu_{fj}, M_{fij}\}$, we can rewrite Equation (1.5) and get:

$$\tilde{M}_{fij} = \underbrace{\theta_{fij}\tilde{\nu}_{fi}}_{\text{Markdown contrib.}} + \underbrace{\tilde{\mu}_{fj}}_{\text{Markup contrib.}} + \underbrace{\theta_{fij}\tilde{\nu}_{fi}\tilde{\mu}_{fj}}_{\text{Joint contrib.}} \quad (1.12)$$

This decomposition shows that the difference between margins and markups comes from two terms. First, the markdown rate contributes to the margin rate up to $\theta_{fij}\tilde{\nu}_{fi}$, *i.e.* proportionally to the milk share in marginal costs. Second, the markdown rate also contributes together with the markup rate, again proportionally to the milk share in marginal costs.

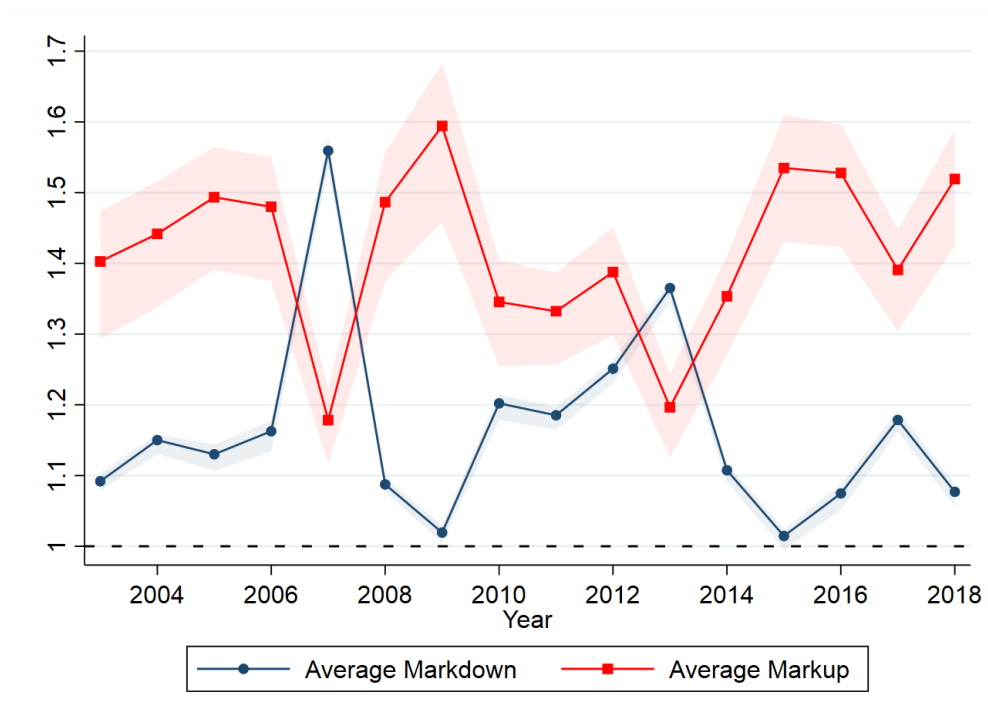
Figure 1.7: Margin Decomposition



Notes: Weighted averages, using dry matter content quantity weights. Weighted average margin computed under an assumption of homogeneous milk sourcing across products for a given firm. The confidence intervals associated with the different objects are not displayed here but can be found in Figures in 1.8 and 1.15.

Figure 1.7 plots the different terms of Equation 1.12 across time. While the average margin rate remains somewhat stable, around its 56% average over the period, the relative contribution of markups and markdowns vary during the period. This reflects the variation of markups and markdowns over time, as shown in Figure 1.8. Over the period, the average markdown rate fluctuates between 1% (2015) and 56% (2007), while the average markup rate lies between 18% (2007) and 59% (2009). Our estimates indicate that markdowns are higher than markups for two years of the period of analysis (2007 and 2013).

Figure 1.8: Markdowns and Markups



Notes: Weighted averages, using dry matter content quantity weights. Bootstrapped 95% confidence intervals (CI) displayed. CI emanate from errors in the estimation of the marginal processing cost (MPC), hence the narrower CI for the average markdown where MPC estimates only intervene for WMP sellers.

Overall, we do not find any particular trends in the evolution of total margins over the period of analysis, despite the concentration observed at the manufacturing level in the industry.⁵⁴ Multiple factors can explain this. Upstream, processors have incentives not to fully exploit their potentially increasing monopsony power in order to avoid too many exist of local suppliers. As shown by Mérel and Sexton (2017), concentration on local markets can - to that extent - even lead to better internalization of such effects by a relatively reduced number of relatively bigger firms. Downstream, the retailing stage of the value chain also is highly concentrated, letting room for countervailing retailer buyer

⁵⁴See Appendix 1.A1..

power.⁵⁵ Several purchasing alliances also have been created during the period of analysis, possibly reinforcing this countervailing buyer power, and explaining the absence of trends in the aggregate processor markup. Finally, processor concentration is endogenous and may arise in order to preserve margins.

Markups and markdowns appear to be strongly negatively correlated. In the subsequent pass-through analysis, we document the drivers of this relationship.

5.3. Pass-Through Analysis

In this subsection, we show with a pass-through analysis that variations in processor MP across time reflect endogenous adjustments following exogenous shocks to (i) WMP price and (ii) farmer costs. Upstream, in response, processors adjust raw milk prices and markdowns when facing raw milk supply curves characterized by non-constant elasticities. Downstream, the pass-through of upstream cost shocks is governed (i) by its incidence on the bargaining between processors and retailers regarding final goods and (ii) by standard perfect competition mechanisms for bulk products sold on commodity markets. To investigate these mechanisms, we proceed in three steps. Based on the model, we first examine the role of MP in shaping pass-throughs. We then leverage our identifying assumption to make pass-through predictions, before analyzing reduced-form results in light of these predictions.

Theoretical Pass-Through Predictions

First, we use the model to describe how shocks affect the chain and make predictions on pass-through that would have prevailed under perfect competition.

We start from the definition of the margin as the ratio of price and accounting marginal costs:

$$M_{fij}(x) = \frac{p_{fj}(x)}{w_{fi}(x)e_{ij} + \lambda_{fj}(x)}$$

All equilibrium objects are endogenous, which we make explicit here by writing them as functions of any variable x .

Passing the equation above to the log, taking the derivative with respect to x , and rearranging, our model predicts the following pass-through of the commodity price to the price of a given product j sold by firm f :

$$\varepsilon_x^{p_{fj}} = \varepsilon_x^{M_{fij}} + \theta_{fij} \varepsilon_x^{w_{fi}} + (1 - \theta_{fij}) \varepsilon_x^{\lambda_{fj}}, \quad (1.13)$$

where we, here and hereafter, note $\varepsilon_x^z \equiv \frac{\partial z}{\partial x} \frac{x}{z}$ for $z = \{M_{fij}, p_{fj}, \mu_{fj}, w_{fi}\}$, remembering

⁵⁵See Appendix 1.A2..

that $\theta_{fij} = \frac{w_{fi}e_{ij}}{w_{fi}e_{ij} + \lambda_{fj}}$ is the share of milk purchased in market i in the *accounting* marginal cost.⁵⁶ We thus see that a shock is passed through upstream and downstream prices but also possibly partly absorbed by margin adjustments.

We can further decompose underlying adjustments of the margin to see how markups and markdowns respectively adjust. To do so, we proceed in a similar way, starting from the definition of the markup (or equivalently from the first order condition of the variable profit maximization program), repeated here for convenience:

$$\mu_{fj}(x) = \frac{p_{fj}(x)}{\nu_{fi}(x)w_{fi}(x)e_{ij} + \lambda_{fj}}$$

This yields:

$$\varepsilon_x^{p_{fj}} = \varepsilon_x^{\mu_{fj}} + \tilde{\theta}_{fij} (\varepsilon_x^{\nu_{fi}} + \varepsilon_x^{w_{fi}}) + (1 - \tilde{\theta}_{fij}) \varepsilon_x^{\lambda_{fj}}, \quad (1.14)$$

where $\tilde{\theta}_{fij} = \frac{\nu_{fi}w_{fi}e_{ij}}{\nu_{fi}w_{fi}e_{ij} + \lambda_{fj}}$ is the share of milk purchases from i in the marginal cost of product j . As expected, the margin adjustment $\varepsilon_x^{M_{fij}}$ appearing in (1.13) decomposes into a proportional markup adjustment $\varepsilon_x^{\mu_{fj}}$ and an adjustment $\varepsilon_x^{\nu_{fi}}$ of the markdown on raw milk that affects the margin proportionally to the share $\tilde{\theta}_{fij}$ of milk purchases in marginal costs.

In the absence of upstream and downstream MP (*i.e* if $\nu_{fi} = \mu_{fj} = 1$ and $\varepsilon_x^{\mu_{fj}} = \varepsilon_x^{\nu_{fi}} = 0$), Equation (1.14) would collapse to:

$$\varepsilon_x^{p_{fj}} = \theta_{fij} \varepsilon_x^{w_{fi}} + (1 - \tilde{\theta}_{fij}) \varepsilon_x^{\lambda_{fj}}. \quad (1.15)$$

Comparing Equations (1.14) and (1.15) shows how the pass-throughs of economic shocks to upstream and downstream prices crucially depend on *adjustment* of processor markups and markdowns, *i.e* on the terms $\varepsilon_x^{\nu_{fi}}$ and $\varepsilon_x^{\mu_{fj}}$. It echoes a result shown by [Weyl and Fabinger \(2013\)](#): in the presence of seller power, pass-through rates crucially depend on the curvature of demand. Here, due to the presence of buyer power, pass-through rates also depend on the curvature of the supply curve. Note that through $\tilde{\theta}_{fij}$, pass-through also *directly* depends on the markdown *level*.

Pass-Through Identification

Pass-Throughs under the Identifying Assumption One can dig further into the theoretical pass-through predictions by relying on our identifying assumption that French

⁵⁶At this stage, variations in x can reflect any modification in market primitives (introduction or modification of a tax/subsidy, other firm-level or industry-wide cost shock, a firm entry, a merger...).

dairy processors do not have any price-setting power on the WMP commodity market, and can use WMP as an input or sell it as an output. Focusing on processors which do not sell WMP, thus assumed to be buyers, and starting from markup and markdown definitions for these firms we get:⁵⁷

$$\nu_{fi}(x) = \frac{w_c(x)}{w_{fi}(x)e_{ic}}, \forall i \quad \text{and} \quad \mu_{fj} = \frac{p_{fj}(x)}{w_c(x)e_{cj} + \lambda_f(x)}, \forall j,$$

Proceeding as above yields two expressions for the pass-throughs of shocks to the upstream raw milk price paid by firm f on market i :

$$\varepsilon_x^{w_{fi}} = \varepsilon_x^{w_c} - \varepsilon_x^{\nu_{fi}} \quad (1.16)$$

and to the downstream price of product j :

$$\varepsilon_x^{p_{fj}} = \varepsilon_x^{\mu_{fj}} + \theta_{fcj} \varepsilon_x^{w_c} + (1 - \theta_{fcj}) \varepsilon_x^{\lambda_{fj}} \quad (1.17)$$

where $\theta_{fcj} = \frac{w_c e_{cj}}{w_c e_{cj} + \lambda_{fj}}$ is the share of WMP purchases in the marginal cost of product j .

Pass-Through Predictions for the Reduced-Form Application We then focus on the theoretical impact of two particular types of shocks, that we will be able to identify in the data. First, our model naturally delivers insights on the pass-through of shocks in the price of WMP, observes in the data. Rewriting (1.16) and (1.17) with $x = w_c$, assuming for simplicity $\varepsilon_x^{\lambda_{fj}} = 0$ we get.⁵⁸

$$\varepsilon_{w_c}^{w_{fi}} = 1 - \varepsilon_{w_c}^{\nu_{fi}} \quad (1.18)$$

and

$$\varepsilon_{w_c}^{p_{fj}} = \varepsilon_{w_c}^{\mu_{fj}} + \theta_{fcj} \quad (1.19)$$

Equation (1.18) shows that markdown adjustments weaken or amplify the pass-through of WMP price shocks to the price of raw milk. In the absence of monopsony power ($\varepsilon_x^{\nu_{fi}} = 0, \forall x$), shocks to the commodity price would translate one for one to the price of raw milk ($\varepsilon_{w_c}^{w_{fi}} = 1$), purely reflecting the perfect substitutability between both inputs (dry matter contents).⁵⁹

Equation (1.19) similarly shows that markup reactions can attenuate or amplify the

⁵⁷We focus on firms assumed to be WMP buyers for the sake of simplicity. In Appendix 1.E5., we derive similar expressions for WMP sellers.

⁵⁸Robustness checks (to be added in the Appendix) confirms that $\varepsilon_x^{\lambda_{fj}} = 0$ empirically.

⁵⁹Under perfect competition with finitely elastic supply and demand, the literature has long shown that pass-through (of any shock to marginal cost) under perfect competition is incomplete and governed by the supply elasticity to demand elasticity ratio (see Jenkin (1872)). Here, given the perfect substitutability between raw milk and WMP (dry matter contents), the underlying processor demand is infinitely elastic. As a consequence, perfect competition pass-through equalizes the full pass-through (= 1), living no role for demand nor supply elasticity.

pass-through to downstream prices. In the absence of seller power ($\varepsilon_x^{\mu fj} = 0, \forall x$), the pass-through would be *complete*, to the extent that it would be proportional to the share of the commodity in the accounting marginal cost of product j ($\varepsilon_{w_c}^{p fj} = \theta_{fcj}$).⁶⁰

Second, we consider the pass-through of idiosyncratic shocks in the average French dairy farm costs, for which we will have a good measure, as further explained in the next subsection. Rewriting (1.16) and (1.17) with $x = I$, assuming that $\varepsilon_I^{w_c} = \varepsilon_I^{\lambda fj} = 0$, we get:

$$\varepsilon_I^{w_{fi}} = -\varepsilon_I^{\nu_{fi}} \quad (1.20)$$

and

$$\varepsilon_I^{p fj} = \varepsilon_I^{\mu fj} \quad (1.21)$$

(1.20) highlights a stark prediction from our model. Due to adjustments in buyer power exertion, the price of raw milk can respond to variations in farm costs. Without buyer power ($\varepsilon_I^{\nu_{fi}} = 0$), it would be fully determined by the international price of the substitutable WMP input, leaving no role for French dairy farmer costs ($\varepsilon_I^{w_{fi}} = 0$). We further discuss the implication of such a mechanism when going to the empirical results. (1.21) similarly shows that the pass-through of shocks to French dairy farm costs will be fully determined by markup responses. In contrast, they would not react under perfect competition.⁶¹

Reduced-Form Pass-Throughs

Methodology In order to assess the magnitude of the various adjustments, we estimate the elasticities ε_x^z for $z = \{M_{fij}, p_{fj}, \mu_{fj}, \lambda_{fj}, w_{fi}\}$ in a reduced-form way, for two types of equilibrium perturbations. We consider variations (i) in the WMP price and (ii) in French dairy farmer costs. To proxy for the latter, we use a French dairy farm cost index computed by the French Ministry of Agriculture since 2005.⁶² We consider both types of shocks as exogenous. French dairy farm costs for instance exogenously vary with the international prices of energy or of cow food (cereals, soy...).⁶³ We then regress the log of equilibrium objects (*i.e.* raw milk prices, markdowns, output prices, markups, and margins) on the log of these two variables. Note that regressions with raw milk and output prices as dependent variables are *purely* reduced-form in the sense that they do not rely on the model nor on estimates, whereas the other regressions involve estimated

⁶⁰Note that, by definition, $\nu_{fi} w_{fi} e_{ic} = w_c$ and thus $\tilde{\theta}_{fij} = \theta_{fcj}$, consistently linking (1.14), (1.16) and (1.17).

⁶¹We here impose for the sake of clarity that $\varepsilon_I^{\lambda fj} = 0$. It is however possible that marginal processing costs λ_{fj} co-move with French dairy farm costs, due to inflation for instance.

⁶²Consequently, the period of analysis for the pass-through results presented here spans from 2005 to 2018. The French dairy farm cost index is available online here: <https://idele.fr/ipampa>.

⁶³As the index incorporates measures of fixed and variable farm costs, we refer to farm costs, authorizing ourselves to confound average and marginal costs (for farmers only!).

objects. The regression results are reported in Table 1.5. Incorporating relevant interacted fixed-effects, we rely on variations over time in both the WMP price and in French dairy farmer costs to identify the corresponding *average* responses (elasticities) of equilibrium objects.

In what follows, we sequentially analyze results provided in Table 1.5, which focuses on processors buying WMP. We provide results for firms observed to be WMP sellers and for the entire sample in Tables 1.15 and 1.16 in the Appendix. All results pertain across the different samples. Intuitions remain similar in essence but differ in that they rely on input substitution patterns for WMP buyers, while relying on output substitution for WMP sellers. For the sake of clarity, we thus restrict attention to WMP buyers here.

In such context, the implied pass-through measures are to be understood as equilibrium co-movements between various equilibrium objects (prices and MP measures) and aggregate cost shifters.⁶⁴ We here simultaneously consider two cost shifters, which *correspond to two distinct types of shocks*. Indeed, in light of the model and the identification for WMP buyers, shocks to the WMP price have to be considered as shocks to processor *marginal costs* (henceforth, MC). This stems from the fact that at the optimum, our identification condition implies that WMP buyers adjust markdowns to equalize the marginal cost of producing a given product j using milk from i with the marginal cost of producing j using WMP from commodity market c :

$$MC_{fj} = \underbrace{w_c e_{cj} + \lambda_{fj}}_{\text{marginal cost } MC_{fcj}} = \underbrace{\left(1 + \varepsilon_{fi}^{S-1}\right) w_{fi} e_{ij} + \lambda_{fj}}_{\text{marginal cost } MC_{fij}}$$

In contrast, shocks to farmer costs negatively affect milk supply. These shocks pass through the supply chain via processors adjusting raw milk prices. They thus affect processor *accounting marginal costs* (henceforth, AMC), as defined by Equation (1.4), repeated here for convenience:

$$AMC_{fij} = w_{fi} e_{ij} + \lambda_{fj}$$

Figure 1.14 in the Appendix can further guide the interpretation of the results following below. By considering shocks on the WMP price, we consider shifts in processor equilibrium MC, represented by the horizontal green line. By considering shocks to farm costs, we consider shifts in milk supply curves and thus in processor AMC, represented by the increasing plain blue curve.⁶⁵ All other curves (demand, marginal revenue) are

⁶⁴This interpretation is similar to Amiti et al. (2014) who consider exchange-rate shocks, but "is different than the pass-through concept sometimes considered in the literature, which is the change in price for a single firm/product given an exogenous shock", as pointed out by Hong and Li (2017) (who study a similar industry-wide shock).

⁶⁵Through both the extensive (farm entry/exit) and intensive margins, shocks to farm costs can also

authorized to co-move in any way.

Table 1.5: Pass-Through: Reduced-Form Estimates - WMP Buyers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Milk Price	Markdown	Output Price	Markup	Margin	Output Price	Markup	Margin
	w_{fi}	ν_{fi}	p_{fj}	μ_{fj}	M_{fij}	p_{fj}	μ_{fj}	M_{fij}
WMP Price	0.231*** (0.015)	0.784*** (0.014)	-0.013 (0.023)	-0.638*** (0.036)	-0.073*** (0.009)	0.683*** (0.065)	0.047 (0.069)	0.582*** (0.022)
Farm Cost Index	0.661*** (0.014)	-0.697*** (0.015)	0.613*** (0.060)	0.378*** (0.094)	-0.203*** (0.030)	-0.088 (0.136)	-0.284* (0.167)	-1.070*** (0.051)
Obs	5,570	5,570	2,676	2,676	22,466	1,522	1,522	15,577
R2	0.695	0.789	0.972	0.846	0.847	0.927	0.797	0.806
Sample			Final goods	Final goods	Final goods	Bulk products	Bulk products	Bulk products
FE	fi	fi	fj	fj	fij	fj	fj	fij

Notes: Standard errors are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All variables are in log. Sample restricted to firms for which we manage to link raw milk collection and production, and WMP buyers only. The level of observation varies with the level at which the considered outcome is observed or estimated: (i) firm-*département*-year level for raw milk prices and markdowns (although prices used here are at the region-year level), (ii) firm-product-year level for output prices and markups, (iii) firm-*département*-product-year level for margins. Margins are computed under an assumption of homogeneous milk sourcing across products for a given firm.

Upstream Pass-through Estimated elasticities from columns (1) and (2) confirm the mechanisms previously outlined. In order to simply interpret the reduced-form results, we consider in the following discussion a 1% increase in the price of WMP and a 1% increase in the average French dairy farm cost respectively, holding the other constant. On the upstream side, a 1% increase in the WMP price leads processors relying on WMP as an input to adjust their sourcing mix. They substitute away from WMP in favor of raw milk. In doing so, they move up along the increasing raw milk supply curve, leading to increases in the price paid for raw milk, of 0.23% on average. This purely reduced-form result indicates an incomplete pass-through from the price of WMP to the price of raw milk ($\varepsilon_{w_c}^{w_{fi}} < 1$), in line with the existence of monopsony power and the theoretical results derived above. Equation (1.16) provides a rationale for this pattern: the pass-through incompleteness comes from the existence of buyer power and more precisely from endogenous markdown adjustments by processors, which increase their monopsony power exertion by 0.78% on average. The strongly positive and significant coefficient on markdowns confirms the intuition mentioned above: processors face supply curves featuring decreasing elasticities. They increase (resp. decrease) their markdowns when moving up (down) along the raw milk supply curve following a surge (decrease) in the price of the alternative WMP input. Overall, an increase in the price of the commodity thus *directly* increases processor MC, but its impact on processor AMC is smoothed by markdown adjustments on raw milk markets.

Compared to increases in the WMP price, increases in the average French dairy farm cost also lead processors to adjust raw milk prices and markdowns, but in a very different way. A 1% increase in the average French dairy farm cost results in a 0.66% alter the shape of milk supply and thus of processor AMC curves. It would be captured in our reduced-form estimates.

increase in the price processors (WMP buyers here) pay for raw milk. Again, after this shock, processors optimally adjust their sourcing strategy between purchasing raw milk and WMP. If processors had no buyer power, and as they trade off between raw milk and WMP, farmer cost shocks would not affect raw milk prices, which would be fully determined by the international WMP price. In contrast, due to buyer power, we observe a positive pass-through from French dairy farm costs to raw milk prices. The mechanism is the following. As farm costs increase, processors, which have incentives to preserve their local supply, consent to raw milk price increases. Processors however also adjust their sourcing mix here, this time substituting away from raw milk in favor of WMP (whose price is held constant here). While increases in farm costs primarily shift raw milk supply curves up, input substitution by processors also induces an endogenous decrease in raw milk demand, which graphically translates into a move (to the left) along the new supply curve. As a result, the markdown strongly decreases (-0.7%). Again, this is in line with decreasing elasticities along milk supply curves. A rationale is that, as raw milk demand decreases, French dairy farmers get closer to their cutoff exit level. At the local level, raw milk supply becomes very elastic through the extensive margin, leading processors - willing to preserve their local suppliers - to adjust buyer power exertion.

We now turn to shock pass-throughs on downstream markets.

Downstream Pass-through In order to investigate the pass-through of upstream cost shocks to downstream factory-gate prices, we separately consider two types of output markets. Columns (4), (5), and (6) focus on final consumption goods, essentially sold to retailers. As retailers are highly concentrated, factory-gate prices have to be considered as the result of a bargaining. Columns (4), (5), and (6) focus on intermediate goods, sold in bulk to other processors, merely through commodity markets. As we focus on firms not selling WMP here, such intermediate dairy products include butter, cream, and skimmed milk powder (SMP). As the WMP market, such markets are perfectly competitive. As a consequence, we expect very different pass-throughs of the considered cost shocks to output prices, depending on the competition in the considered market.

The first coefficient in Column (3) indicates that increases in the WMP price, and thus in processor MC, do not pass through final goods (factory-gate) prices. Again, this result is purely reduced-form, but the model helps interpretation. First, Equation (1.17) shows that we have a (totally) incomplete pass-through on final good prices, as $\varepsilon_{w_c}^{p_{fj}} < 0.75$, where 0.75 is the average value of the share $\tilde{\theta}_{fij}$ ($= \theta_{fcj}$) of raw milk purchases in MC. This confirms the existence of price-setting power on final goods. In contrast, the first coefficient in Column (6) indicates that increases in the WMP price, and thus in processor MC, almost fully pass through bulk product prices ($0.68 < 0.75$). This result aligns with

⁶⁵See Table 1.13 in the Appendix for more detail on the shares of milk purchases in MC.

the model predictions for perfectly competitive output markets.

The second coefficient in Column (3) indicates that increases in farm costs, leading to increases in raw milk prices and thus in processor AMC, strongly pass through final good prices. A 1% increase in farmer costs translates into a 0.61% increase in final good prices. This result supports the idea that final good prices are set through a bargaining between processors and retailers, as discussed below. The second coefficient in Column (6) nicely confirms a model prediction: variations in French dairy farm costs have no effect on the prices of products sold in competitive markets. This is the case of bulk products which are - as WMP, absent here - sold on *commodity* markets at exogenous prices.

Our model, together with the estimated markup adjustments from Columns (4), further rationalize purely reduced-form results from Columns (3). Pass-through of farmer and processor cost shocks to final good prices are governed by endogenous markup responses. A key insight here is that markup responses depend on the way the two types of cost shocks directly affect processors and thus the *bargaining between processors and retailers*. On one hand, shocks to processor MC through the lens of variations in the WMP price are largely mitigated by markdown increases. This leads strategic retailers to become more aggressive when negotiating with retailers on final good prices. As a result, processor markups severely decrease. A 1% increase in the WMP price results in final good markup decreases of -0.64%. On the other hand, shocks affecting farmer production costs are largely absorbed by processors, leading to an increase in their AMC. In turn, this surge in AMC is transmitted to retailers through increases in final product prices. On average, a 1% increase in farm costs results in final good markup increases of 0.38%.⁶⁶ This positive transmission of processor AMC (MC remaining constant) to final product prices reveals that retailers have (countervailing) buyer power. They thus internalize the variations in processor margins and their possible consequences in terms of their supplier exits.⁶⁷ In contrast, Column (7) shows that markups do not or barely respond to both types of shocks, showing the prevalence of perfect competition in commodity markets.⁶⁸

Given the various markdown and markup adjustments, the two types of shocks have a heterogeneous impact on processor margins. Markdown and final good markup adjustments operate in opposite directions in reaction to a 1% surge in the WMP price affecting processor MC. As both adjustments almost compensate each other,

⁶⁶This coefficient differs from the farm cost coefficient regressed output prices (0.61%), in contrast with Equation (1.21). It merely stems from the fact that, for clarity, we imposed $\varepsilon_I^{\lambda_{fj}} = 0$ in this equation. Here we have evidence that marginal processing costs λ_{fj} actually co-move with French dairy farm costs.

⁶⁷In any standard model of competition between sellers freely fixing prices, the optimal price would only on the contrary only depend on their MC.

⁶⁸The negative coefficient on farm costs significant at the 90% confidence level possibly results from marginal processing costs λ_{fj} co-moving with farm costs, e.g. due to inflation. This result does not pertain when considering WMP sellers or all types of processors, as shown in Tables 1.15 and 1.16 in the Appendix.

processor margins are only weakly affected (-0.07%). Markdown and final good markup adjustments also operate in opposite directions in reaction to a 1% surge in farm costs, which transmits to processor AMC due to buyer power. As retailers only partly absorb the shock, processor margins are somewhat strongly affected (-0.20%). Conversely, when considering commodity output markets, markdown adjustments following both types of shocks cannot be compensated by markup adjustments. As a consequence, total margins vary with markdowns. A 1% increase in the WMP price leads to increases in processor margins on (other) bulk products of 0.58%. It stems from the fact that other commodity prices co-move with the WMP price. In contrast, a 1% increase in the French dairy farm cost leads to an equivalent decrease in processor margins on bulk products (-1,07%). As processors cannot transmit increases in their AMC to commodity prices, their margins fully absorb the negative shock.

Overall, due to processor buyer power, shocks to farmer and to processor costs spread along the supply chain. Markdowns absorb international shocks to the WMP price, smoothing farmer revenues. Processors partly absorb French dairy farm cost shocks. The two types of shocks then differently affect the supply chain depending on endogenous markup adjustments. While international shocks to the WMP price are fully absorbed by farmers and processors, local farm cost shocks disseminate along the chain, and farmers, processors, and retailers are all - yet differently - impacted.

Pass-Through Implications The pass-through patterns identified here allow us to draw two types of implications. The first set of implications is methodological. Our results first show the importance of authorizing flexibility in pass-throughs when doing structural analysis, as they vary both across markets and depending on the type of shock. Second, the results presented here reaffirm the importance of taking buyer power into account in structural analysis, as well as in reduced-form studies of pass-throughs. Markups and margins, which would have been confounded had we ignored buyer power, react in very different ways - and sometimes in opposite directions - to different types of cost shocks. In contexts where buyer power is suspected, distinguishing margins and markups, or similarly MC and AMC, both in structural and in reduced-form pass-through analyses, thus appears crucial for a full understanding of adjustments to shocks within a supply chain.

Second, our pass-through estimates allow us to draw policy implications. In particular, markdown and markup adjustments to shocks in farm costs will also govern the way subsidies currently paid to dairy farmers are captured by downstream players. We tackle policy implications in further detail in Section 6.2..

6. Implications

6.1. Methodological Implications

In this subsection, we emphasize two methodological implications based on our results. First, we show the challenge of estimating MP when both buyer and seller power are present. In particular, we stress the importance of authorizing buyer power when quantifying seller power following a production function approach. Second, we show the difficulty of properly estimating MP relying on an estimation of the implied supply and demand elasticities when these objects of interest vary along the corresponding curves. In both cases, we compare our findings on markups and markdowns with the literature.

Buyer Power, Seller Power, and the Production Function Approach

In theory, any wedge between a firm's revenues and a firm's expenses on a given input can emanate from buyer power, seller power, or both. We show that erroneously assuming one of both sources of MP away when following a *production function approach* can lead to falsely attributing the entire wedge to the considered source.

To fix ideas, and in order to ease comparison with the production function approach literature, assume a profit-maximizing firm with technology $y = f(m)$, facing an inverse input supply $w(m)$ and an inverse output demand. The firm chooses m (or equivalently y) to maximize variable profit $p(y)y - w(m)m$. Rewriting the objective function in terms of output quantity y , and then deriving and rearranging the first order condition directly lets the total margin appear:

$$M \equiv \theta \frac{py}{wm} = \frac{1 + \varepsilon_S^{-1}}{1 + \varepsilon_D^{-1}} \quad (1.22)$$

where $\theta_m = \frac{\partial f(m)}{\partial m} \frac{m}{f(m)}$ is the output elasticity with respect to the input. (1.22) directly delivers the total *margin*. The margin can then be empirically recovered from the left-hand side thanks to an estimation of θ_m , conditional on observing revenues py and input expenses $w m$. This is the approach we followed throughout the paper.

If buyer power (on materials) is assumed away, the following first order condition and markup definition is derived instead:

$$\mu \equiv \theta \frac{py}{wm} = \frac{1}{1 + \varepsilon_D^{-1}} \quad (1.23)$$

The so-called *markup* is then similarly empirically recovered from the left-hand side. Equations (1.22) and (1.23) are the basis for the discussion below.

If buyer power is present, wedges estimated through a production

function approach emanate from both seller and buyer power, and shall be defined as (total) margins rather than markups. The expressions above aim at easing intuitive comparisons with the literature and differ in their shapes from our theoretical framework, mainly due to the Leontief production function that is assumed, creating an additive structure in the marginal costs.⁶⁹ However, in our context, assuming buyer power would have similarly led to assuming markups and margins to be equal. Following our wording, it would have implied confounding marginal costs and *accounting* marginal costs. Importantly, we would have similarly estimated marginal processing costs, which allows direct comparisons.

The *production function approach* literature typically assumes buyer power away, relying on equations similar to (1.23).⁷⁰ Reasons to do so include (i) data availability or simply (ii) a focus on seller power and estimating final consumption goods markups. As explained above, following such an approach, a total margin can be well estimated but is - *sometimes erroneously* - attributed to the sole seller power. Indeed, margins and markups are by assumption equalized. Had we done so, we would have assessed an average markup rate of 56% (instead of 41%), falsely equal to the margin rate. This amounts to an average markup rate overestimation of 37%. Moreover, in a context as ours where costs pass-through to prices upstream and downstream adjust over time, the bias varies accordingly. Hence, while we would have correctly estimated the annual markup rate in 2015, we would have overestimated it by 162% in 2013. Finally, our results (see Table 1.7) show that margins and markups sometimes vary in opposite directions, due to the presence of markdown adjustments, underlining the importance of authorizing market power on both sides.

Of course, the magnitude of the bias is highly context-specific, and its size is not surprising in the French milk market where the presence of buyer power was expected. It however indicates that, at least in sectors where buyer power is a possibility, *markups* estimated through such methodology may be more safely reinterpreted as *total margins*, emanating from seller power and buyer power.

Having this in mind, we compare our paper's estimates with markups estimated in the production function approach literature in Table 1.6. To the exception of [Tortarolo and Zarate \(2018\)](#) and [Rubens \(2021\)](#) (and us), all other papers here potentially confound markups and margins emanating from buyer power *on materials* and seller power, if both are present. [Tortarolo and Zarate \(2018\)](#) and [Rubens \(2021\)](#) rely on a production function approach to recover margins and an estimation of the supply elasticity of the input of interest, respectively labor and tobacco, to isolate markdowns from markups.⁷¹

⁶⁹As explained in Section 3. or in [De Loecker and Scott \(2016\)](#).

⁷⁰See for instance [De Loecker and Warzynski \(2012\)](#); [De Loecker and Scott \(2016\)](#); [De Loecker et al. \(2016\)](#); [De Ridder et al. \(2021\)](#).

⁷¹Doing so, [Rubens \(2021\)](#) estimates a very low markup for Chinese cigarette processors which he

Table 1.6: Margins and Markups in the Production Function Approach Literature

Paper	Margin	Markup	Industry
Tortarolo and Zarate (2018)	2.02 ^m	1.78 ^m	Manufacture
De Loecker et al. (2016)		1.78	Food & Beverages
De Loecker et al. (2020)		1.61	Manufacture, Retail & Wholesale
De Loecker and Scott (2016)		1.59	Beer
This paper	1.56	1.41	Dairy
Wong (2019)		1.38	Manufacture
De Ridder et al. (2021)		1.34	Manufacture
De Loecker and Warzynski (2012)		1.28	Manufacture
Yeh et al. (2022)		1.20	Various
Rubens (2021)	n.c	0.52	Cigarettes

Notes: Average margins are reported if a distinction with the markup is made (blank otherwise) and if communicated by the author(s) ("n.c." otherwise). Median margin and markdown - which is stressed by a "m" subscript - are reported when the average for at least one of both is not disclosed by the author(s). [Yeh et al. \(2022\)](#) and [Wong \(2019\)](#) distinguish the markup from the total margin on labor, but compute it as a margin that can also partly emanate from buyer power on materials.

We discuss in Section 6.1. such way of identifying markdowns. [Yeh et al. \(2022\)](#) and [Wong \(2019\)](#) allow for and measure a markdown on labor, but not on materials, similarly to most papers cited here. This assumption allows them to identify markups and labor markdowns - relying on (1.23) to pin down markups and dividing it by a labor version of (1.22) to get markdowns (on labor). Their estimates of markups *and* markdowns are thus subject to a similar bias if firms have buyer power on materials.

For comparison fairness' sake, the reader can note that we assumed away labor MP. We do so as we think the extent to which dairy firms can exploit labor MP is limited, for reasons further discussed in Appendix 1.D4.. Moreover, and as shown in the same Appendix, labor MP - if any - would affect our estimates to a limited extent. It would leave margin estimates unchanged. Margins would in such case be interpreted as resulting from the three implied MP forces. Interestingly, given the estimation framework relying on the price of WMP as an empirical moment, markdown estimates for WMP buyers would also be unaffected. The remaining markdown (of WMP sellers) and markup estimates would be only affected by labor MP through the induced bias in the estimation of marginal *processing* costs, which on average only represent (absent labor MP) 25% of total marginal costs. Overall, this point further stresses the difficulty of distinguishing different coexisting sources of MP. As shown in Section 6., we hereby contribute to the distinction between seller power and *buyer* power, leaving labor monopsony power out of the scope of this paper.

Regarding the rest of the papers cited here, the relevant comparison to be made thus is between our *margin* estimates and their *markup* estimates. Comparison exercises are explained by the presence of a monopsonistic buyer further downstream.

made difficult by differences in the context or in the period of study. Our margin estimates nevertheless align with markup estimates of De Loecker et al. (2016); De Loecker and Scott (2016); De Loecker et al. (2020), in contexts that are the closest to ours. Their estimates are however above our average markup estimate (1.41). Among other reasons, this can possibly be driven by the existence of some buyer power in the studied sectors. Although disregarded by the authors for practical concerns, processors in the "Food and Beverages" industries may in particular have some degree of buyer power for reasons similar to the ones outlined in our specific context.⁷² Our markup estimates align more with the literature's markups in the broader manufacturing sector (De Ridder et al., 2021; De Loecker and Warzynski, 2012), a possible interpretation being that these estimates may be less contaminated by buyer power, as it may be less of a concern in some manufacturing industries.

On a different note, notice that we included in Table 1.6 the weighted average levels of markups and margins on *all products* in the French dairy markets. This is typically the relevant point of comparison with other papers presented here, which most of the time do not distinguish between *final* and *intermediate* products. An exception is De Loecker and Scott (2016), who found - ignoring buyer power - an average markup of 1.59 on final beers.

Conversely, one can assume away markups and attribute the entire estimated margins to buyer power markdowns. In our context, this would have implied a 295% overestimation of markdown rates. Such an assumption would not have made sense in many contexts, but note that it could have been defended in our context, especially given the concentration levels observed at the retail level.

Overall, markups and markdowns have similar first order consequences on welfare. They lead to a reduction of quantities, an increase of prices faced by final consumers, and a decrease of the input price, so that total margins, that a *production function approach* allow to recover, appear as the appropriate measures of the overall distortion. Such an approach however can misname the origin of the inefficiency, if buyer (or seller) power is erroneously assumed away. In the pass-through analysis conducted in Section 5.3., we have shown that markups and margins, which would have been confounded had we ignored buyer power, react in very different ways - and sometimes in opposite directions - to different types of costs shocks. Confounding margins and markups can thus severely bias assessments and policy advice, which we view as an important concern.

⁷²De Loecker et al. (2020) study processors, but also retailers and wholesalers, which can also have buyer power, depending on the concentration at this stage of the chain.

Markdowns, Markups, and the Elasticity Approach

In this subsection, we highlight the challenges and caveats raised by any MP quantification relying on the estimation of demand or supply elasticities, and show their particular prevalence in the French dairy market context.

Although disregarded in the estimation, Definitions 1 and 2 also implied the following equations:

$$\mu_{fj} = \frac{1}{1 + \varepsilon_{fj}^D - 1} \quad \text{and} \quad \nu_{fi} = 1 + \varepsilon_{fi}^S - 1.$$

An alternative method to obtain markups and markdowns could thus have been to estimate demand and supply elasticities to recover markups and markdowns, following a so-called demand approach⁷³. In contrast, we decided (i) to exploit a production function approach to recover marginal costs and margins, and (ii) to leverage the existence of the commodity markets to disentangle markups and markdowns. Following such a methodology, we *reveal* the implied *equilibrium elasticities*, rather than *assuming* possible mechanisms at work by putting more theoretical structure on the model to be able to estimate the implied elasticities. This has several advantages, which we show below are particularly appealing in our context but also relevant in broader ones.

Our estimates of markups and markdowns are robust to numerous theoretical deviations regarding firm behavioral assumptions, which would not have been the case of an approach based on supply and demand elasticities estimation. In Appendix 1.C1., we show how we can accommodate a wide range of firm behaviors, such as (i) intra-brand competition internalization, (ii) collusion, (iii) vertical cooperation... Some dairy processors are likely deviating from the simple theory outlined in Section 3. in such ways. Nonetheless, since our estimating framework does not rely on estimating demand and supply elasticities, marginal revenue and marginal cost functions are free to take more complex forms than outlined in Section 3.. In particular, they can respectively encompass any economic cost of adjusting raw milk and dairy product prices perceived by the firm. Similarly, our estimation procedure allows for any type of bargaining between processors and retailers. This is due to the fact that we could fully rely on cost minimization only, as shown in Appendix 1.C1.. Given the importance of taking into account retailer strategic behavior highlighted by our pass-through analysis, we view this as a major advantage of the suggested methodology. Overall, markup and markdown estimates thus remain valid under a wide range of theoretical behaviors and competition models.

Related to this point and in the particular context of agricultural markets, Sexton (2013) points out the trade-off faced by processors between exploiting MP and preserv-

⁷³Following Berry et al. (1995), the literature has long applied the suggested methodology to estimate demand elasticities. However, a similar approach can be and has been used to estimate *supply* elasticities.

ing local supply.⁷⁴ This can alleviate MP and in particular generate a wedge between the true markdown and the one predicted by approaches relying on supply elasticities.⁷⁵ Considering the literature, we view such a mechanism as potentially partly explaining the strong magnitude of the markdown estimated by Rubens (2021) using a supply elasticity approach.⁷⁶ Finally, the hypothesis of supply-preserving considerations reducing the markdown is consistent with low markdowns estimates found by older literature which has tried to assess buyer power in various (U.S.) agricultural markets, exploiting other approaches, as summarized and explained in Crespi et al. (2012).⁷⁷

Table 1.7: Markdowns in the Literature

Paper	Markdown	Industry	Input
Rubens (2021)	4.37	Cigarettes	Tobacco leaf
Morlacco (2019)	2.11	Food & Beverages	Materials
Zavala (2020)	2.04	Agri-Food	Various crops
Wong (2019)	1.61	Manufacture	Labor
Yeh et al. (2022)	1.53	Various	Labor
Berger et al. (2022)	1.35	Various	Labor
This paper	1.19	Dairy	raw milk
Azar et al. (2019)	1.17	Various	Labor
Tortarolo and Zarate (2018) ⁷⁸	1.12	Manufacture	Labor
Crespi and Sexton (2005)	1.10	Agri-Food	Cattle. Potato & Rice
Various papers (90's-00's) ⁷⁹	1.00-1.03	Cattle ind.	Cattle

Moreover, *elasticity approaches typically rely on estimating reduced-form elasticities, which generally differ from structural elasticities.* This distinction, pointed out by Berger et al. (2022) who estimate markdowns on labor, is due to the fact that structural elasticities are a *partial equilibrium concept*, where a given firm takes its competitor behaviors as fixed. This is akin to our approach, relying on a Nash-equilibrium concept. On the contrary, any reduced-form elasticity estimates would encompass other firm adjustments and more general equilibrium effects.⁸⁰

Finally, even omitting the caveats mentioned above and willing to rely on (reduced-form) elasticities, *estimating demand and/or supply elasticities with the required level of flexibility raise practical challenges.* Upstream and downstream, our results outline an important heterogeneity in MP exertion across firms and markets, which the demand approach (as the production function approach) literature has come up with solutions

⁷⁴Which is crucial due to the existence of transportation and transaction costs.

⁷⁵See Appendix 1.C1. for a formal derivation.

⁷⁶The specific context also strongly supports the existence of strong buyer power. We refer the interested reader to Rubens's paper (2021) for more details.

⁷⁷These papers however assume constant MP exertion across time, and may have missed the type of underlying variations we document.

⁸⁰We refer the interested reader to section 2.1 of Berger et al. (2022) for further explanations.

to deal with.⁸¹ Our findings however also highlight the importance of variations in MP exertion across *time*. First, this heterogeneity dimension remains empirically difficult to tackle, as (i) data are not always available at a high-frequency level, and (ii) estimating methodologies often rely on the panel dimension. Moreover, the demand (and supply) approaches typically require variables to instrument endogenous prices, which are similarly not always available at a high-frequency level.⁸² Second, and more importantly, the variations in markups and markdowns from a year to the other we document respectively reflect (i) implied in changes processor-retailer bargaining and (ii) *non-constant elasticities along milk supply curves*.⁸³ Point (i) is the reason why demand estimation is generally performed when considering transactions between a firm and final consumers, assumed to be price-takers. From a theory viewpoint, point (ii) relates to the curvature of these raw milk *supply* functions here, *i.e.* to their second derivatives, and remains a not-yet answered challenge for the *demand* approach, which directly aims at identifying such functions.⁸⁴

We thus view our framework, which remains agnostic on exact supply and demand functions and rather (partly) reveals their shapes, as circumventing the mentioned challenges to buyer and seller power estimation. Applying this methodology to the French dairy market, we are able to disentangle markups and markdowns, and reveal their endogenous adjustments to demand and cost shocks, as well as the implied pass-throughs to upstream and downstream prices. Furthermore, we think such an approach to buyer and seller power estimation can be applied to other contexts, as discussed in what follows.

Applicability of the Estimating Framework to Other Settings

Overall, we suggest in this paper a new approach to disentangle buyer and seller power, easily applicable to the study of MP in other sectors, and especially suitable to quantify buyer and seller power in food supply chains.

First, we estimate the firm total margins with a production function approach. As mentioned, it requires increasingly available data and is fairly standard, and we refer the

⁸¹See [Berry and Haile \(2021\)](#) for a recent review.

⁸²An exception is [Döpfer et al. \(2021\)](#) who estimate processor markups across 100 products at the year-level following a demand approach and using high-frequency scanner data. Estimation and identification is based on [MacKay and Miller \(2022\)](#) relying on covariance restrictions on demand and supply shocks. However, in doing so, they crucially rely on a constant marginal costs assumption, ruling out the possibility of buyer power.

⁸³It can also reflect change in the competition context. We refer the interested reader to Appendix 1.A2. for more details on the first point.

⁸⁴As pointed out by [Berry and Haile \(2021\)](#), which we cite here: "For example, "pass-through" (e.g., of a tariff, tax, or technologically driven reduction in marginal cost) depends critically on second-derivatives of demand. It is not clear that a mixed-logit model is very flexible in this dimension. An alternative is nonparametric demand estimation, as in [Compiani \(2022\)](#), although many off-the-shelf nonparametric approaches lack the parsimony necessary to estimate demand systems with a large number of products or product characteristics." A similar challenge arises for estimating supply functions featuring non-constant elasticities.

reader to the corresponding literature for more details.⁸⁵ In doing so, we acknowledge the possibility of buyer power, participating, as seller power, to margins estimated this way.

Second, we suggest a new way of disentangling markups and markdowns, relying on the existence of at least one *competitive product* that is *substitutable* with the input (resp. output) on which there is monopsony (monopoly) power. In using an input where firms do not exert monopsony power, we follow the recent production function approach literature relying on the existence of so-called *flexible inputs*.⁸⁶ However, in doing so, such papers rely on somewhat *ad hoc* assumptions that monopsony power is absent on one aggregate type of variable inputs, typically assuming away buyer power on overall materials, an assumption that is likely violated for at least some inputs. Our methodology has a similar spirit, but (i) goes one step further in disaggregation and (ii) applies the same logic to output markets. Doing so, one can rely on the existence of products on which buyer or seller power can be *safely* assumed away. In our application to the French dairy market, we use the existence of the WMP commodity market. Such commodity markets, as listed by the World Bank, are also present in many other industries: energy (coal, oil, gas), beverages (cocoa, coffee, tea), oils and meals (coconut/soybean/palm/sunflower oil...), grains (maize, rice, wheat...), food (bananas, beef/chicken/sheep meat, oranges, shrimps, sugar...), raw materials (cotton, rubber, tobacco...), metals and minerals (aluminum, steel, nickel...)...⁸⁷ In many of these industries, notably food and beverages industries, buyer and seller power are a concern, for reasons akin to those outlined in the analysis of the French raw milk market. This concern is particularly important in emerging economies, where local or international intermediary price-setting power, can largely harm development (Sexton et al., 2007). In such contexts, our approach provides a useful tool to disentangle monopsony and monopoly power.

Moreover, the suggested tool is especially practical to quantify buyer power in a context of limited data. Based on firm arbitrage conditions, our theoretical model indeed microfound a markdown imposed by processors that, for most of them, simply is the ratio of the substitutable commodity (here WMP) price and of the price of the raw material (here milk), adjusted for their elasticity of substitution (here the respective dry matter contents). This implies that one can gauge buyer power in broader applications, with-

⁸⁵See Olley and Pakes (1996), Levinsohn and Petrin (2003), De Loecker and Warzynski (2012) and Akerberg et al. (2015), among others. Putting aside the critique by Bond et al. (2020), the minimal data requirement for estimating total margins through a production function approach is to observe firm-level revenues and expenses on a variable input, available in many datasets.

⁸⁶A flexible input is defined as a freely-adjustable input on which firms do not exert monopsony power. See Dobbelaere and Mairesse (2013), Morlacco (2019), Wong (2019) and Yeh et al. (2022) for different applications. M. Morlacco and E. Guigue are however currently working on a revision of Morlacco (2019), relying on a different estimation methodology.

⁸⁷More generally, Rauch (1999) provide a systematic classification of internationally traded products in *commodities* (referred to as products trade obeying an *organized exchange*), *reference priced* products (whose prices could similarly be exploited), and *differentiated* products, which could be helpful for broader applications of our methodology.

out prior marginal processing cost estimation, only relying on the corresponding price data. Commodity prices data are directly available online, while unit prices of the input considered can be found at a level of disaggregation which depends on the data availability. To the least, one can rely on average prices of the raw material, scrutinized and made available by local authorities or international institutions. The elasticity of substitution between the commodity and the raw material can be assumed equal to one when a fairly homogeneous product is considered, as in most food industries mentioned above. For others, an adjustment similar to what we do with dry matter contents data can be implemented.

6.2. Economic Implications

In this subsection, we highlight the consequences of processor MP on farmer revenues and public policy efficiency.

Processor Market Power, Farmer Subsidies, and Farmer Revenues

We find what one could consider as "low" markdown levels, 19% on average. However, farmer profits ultimately depend on the prices set by processors for raw milk, and thus not only on the markdown level, but on both buyer and seller market power. Their joint exploitation by processors indeed generates a distortive wedge between the prices of processed products and the price of raw milk. This wedge, which translates into what we defined as the total margin, is remarkably important - 56% on average - and stable over time. Both sources of market power thus largely contribute to (i) diminishing the value added created in the dairy market and (ii), distorting its allocation in favor of processors to the detriment of farmers.

Second, fluctuations in the degree of buyer power exerted by processors have important consequences on farmer revenues. Overall, markdown adjustments by processors smooth raw milk prices. On one hand, during dairy market downturn phases (2009, 2015), dairy firms compress their markdowns, and the weighted average markdown is *almost* pushed down to the competitive level (1). It however remains above it. On the other hand, processors conversely increase markdowns to remarkably high levels (1.4 on average) when facing positive demand shocks (2007, 2013). Our pass-through results indicate that processors also largely absorb farm cost shocks. The presence of buyer power thus partly insures farmers against conjunctural shocks, smoothing their revenues. However, it constantly implies a price below its competitive value over time.

Overall, absent buyer power, farmers would thus (i) earn a bigger share of the value added generated in the supply chain and (ii) be able to benefit from good conjecture times to reconstitute financial buffers undermined during downturns. This is an important concern as French dairy farmers are notoriously suffering from weak revenues. According

to the French Livestock Institute, in 2021, 42% of dairy farms are in a critical financial situation, *i.e.* indebted in the medium and long run and without cash flow. To cope with these structural imbalances, the Common Agricultural Policy (CAP) massively subsidizes dairy farmers. As a consequence, CAP subsidies to farmers represent around 80% of their revenues.

Our model provides a rationale through which processors eventually divert these subsidies through their buyer power. Indeed, any exogenous revenue supplement granted to farmers shifts downward raw milk supply curves. In turn, processors internalize that their supplier profitability increases, implying decreases in raw milk supply elasticities, and increase their markdowns in response. Such reasoning aligns with the results from our pass-through analysis. In Table 1.17, reduced-form estimates show how a 1% increase in French dairy farm costs on average results in a 0.65% increase in the price of raw milk.⁸⁸ This average equilibrium pass-through is informative about the ability of processors to capture subsidies paid to farmers. It implies that, for the marginal euro of subsidy given to farmers between 2005 and 2018, 65% of it is on average diverted from farmers due to processor buyer power. This statement comes from an interpretation of a marginal increase in farmer subsidy as a marginal decrease in their average or marginal costs.⁸⁹

However, as processors interact with highly concentrated retailers for some of their dairy product sales, a part of the subsidy diverted from farmers is captured by retailers. We here (still) consider an increase of 1% in the average subsidy. While it allows processors to increase markdowns by 0.61% on average, it also conducts to adjustments on some of their output markets. Indeed, on one side, final product prices decrease by 0.65%, and markups decrease by 0.40% on average. It results from downstream strategic retailers internalizing increases in farmer subsidies and endogenous increases in their supplier markdowns. Overall, total margins on final products only increase by 0.12%. A large part of farmer subsidies is thus transmitted even more down the chain.⁹⁰ On the other side, processors sell bulk products in competitive commodity markets. On such markets, products are sold at exogenous international prices and processors are able to keep the diverted subsidy amount. Indeed, as prices do not react, margins on such activity increase by 0.87% on average. Overall, the sharing of the part of the subsidy originally diverted due to processor buyer power depends on the structure of the processor output markets. Averaging on all products sold, the results reported in Table 1.17 in the Appendix indicate

⁸⁸Here and hereafter, we use reduced-form pass-through estimates conducted on the entire sample of French dairy processors, rather than pass-through estimates for WMP buyers presented in Table 1.5.

⁸⁹A few remarks are worth mentioning here. First, as we find strong evidence of non-constant raw milk supply elasticities, it is important to emphasize that this subsidy incidence is to be interpreted as *marginal*. Second, as (i) our farm cost index measures average costs, and (ii) as French dairy farmer subsidies are for some part coupled with production and for some other part coupled with land, we do not take a stand on whether the subsidy considered here is a unit or lump-sum subsidy. In theory, both can affect raw milk supply elasticity through the extensive (farm entry/exit) and intensive margins, and thus markdowns.

⁹⁰An open question is to know if part of it ends up being transmitted to final consumers.

that a 1% increase in the average subsidy inflate processor margins by 0.40%.⁹¹

While part of the subsidy diverted from farmers to processors may be ultimately passed to retailers, our analysis shows *the source of the inefficiency undoubtedly is processor buyer power*. We thus view the processor buyer power documented here as a major policy concern and suggest more adequate remedies below.

Policy Recommendations

Our findings call for setting up a price floor on raw milk as a possible alternative policy to replace inefficient subsidies to farmers. In the context described above, a price floor would correct the value-added distortion, redistributing revenues from processors to farmers. It could at least partly replace direct subsidies to farmers which are in practice inefficient, as revealed by our simple model and estimates.

Importantly, and maybe explaining why such a policy has never been implemented in France, such a price floor on an input price would be in opposition to the conventional wisdom of regulating authorities. Indeed, such an idea is typically perceived as likely to harm consumer welfare through increased final prices and an additional deadweight loss. As already evoked in the theoretical work of Russo et al. (2011), who suggest similar policy remedies for agricultural markets based on a simple model, this prior merely results from the predominance of theoretical work relying on constant processor marginal costs.⁹² This assumption is equivalent to assuming infinite elasticity of the raw milk supply, prohibiting the existence of markdown and the possibility to have a raw milk price set below its optimal level.

Such reasoning for instance motivated the removal of the price recommendation for standardized raw milk in France in 2008. Until then, the CNIEL (National Interprofessional Center for the Dairy Economy) was regularly updating this *recommended price*, resulting from negotiations between farmer and processor representatives, a recommendation in practice closely followed by processors. This functioning was then abandoned following a decision of the French regulation authority, which declared the practice as anti-competitive. Our results, which do not indicate a stark increase in markdowns after 2008 suggest that processor buyer power has not been much affected by this decision.

Up to 2003 (before the period of analysis) the European dairy industry was further supported through *intervention prices* on the various commodities (milk powder, butter, cream), aiming at maintaining a decent price for raw milk further upstream. When the commodity price fell below a certain threshold level (the *intervention price*), the European Union purchased the necessary quantity to restore the price level. Purchased quantities

⁹¹We plan to investigate more underlying heterogeneity here.

⁹²We view our work, empirically showing the existence of the type of distortions assumed in the theoretical work of Russo et al. (2011), as usefully complementing their work in this aspect.

were then stored and later resold and/or exported at a loss.⁹³ Our model shows this policy was ineffective in raising farmer revenues since partly captured by processors through markdown increases. Additionally, our results suggest it distorted raw milk allocation between products toward more production of commodities and fewer final products.

In contrast to the type of work that motivated the removal of the *recommended price*, our model and estimates show that a price floor on raw milk would correct value-added sharing and increase farmer profits without necessarily harming consumer welfare. A price floor would first mechanically increase raw milk prices and decrease processor markdowns. This would have first order effects on value-added sharing, rebalancing it in favor of farmers. By largely neutralizing processor buyer power, it would lead to increases in raw milk quantity produced in equilibrium, thus having first order effects on welfare through increases in farmer profits.⁹⁴

Overall, the total effects on consumer welfare depend on downstream adjustments. In reaction to a price-floor introduction, internalizing processor markdown decreases, and retailers could consent to (undergo) higher markups, as suggested by our pass-through analysis. As a consequence, and depending on retailer reactions, the effect on final prices is unclear, and depends on margin absorption by processors and retailers. Our pass-through results on the effect of farm cost increases suggest the overall effect on processor margins would be negative, in contrast with margin-inflating subsidies. To the least, and given the potential welfare-improving effects, such a policy shall be seriously considered, as a potential substitute to largely inefficient and distortive subsidies. In practice, such a price floor would have to be regularly adjusted, following farm cost indexes - already computed by institutes scrutinizing the industry - and commodity price fluctuations, in line with our model.

Another alternative policy remedy could be to promote farmer countervailing seller power, for instance by authorizing farmers to regroup into producer organizations to bargain with processors. After having long been forbidden, since perceived as anti-competitive, such organizations have been authorized by French regulating authorities (2012), but the take-up, for institutional reasons beyond the scope of the paper, so far remains modest.⁹⁵

Downstream, our results question the efficiency of policies regulating processor-retailer negotiations. Despite the authorization of several retailer mergers and purchasing alliances during the period of analysis, supposedly improving retailer countervailing buyer power and consumer welfare, our results show some large processors are able to charge important markups. Having in mind that an additional margin can actually be imposed on final

⁹³See Appendix 1.A2. for further detail.

⁹⁴Intuitions for such first-order effects regarding a price floor introduction are gathered in Figures 1.20 and 1.21 of Appendix 1.E7., showing its effects for firms that initially buy and sell WMP respectively.

⁹⁵We refer the interested (French-reading) reader to the Ministry of Agriculture's report on the "[Mise en œuvre de la contractualisation dans la filière laitière française](#)", available online.

prices by retailers, effects on consumer welfare are likely to be significant. To the least, mergers between large dairy processors shall thus be (more) carefully scrutinized.

7. Conclusion

In this paper, we suggest a new methodology to separately identify buyer and seller market power, and apply it to French dairy processors. We rely on a production function approach to estimate total margins. The existence of a commodity, (i) substitutable as an input or as an output, and (ii) exchanged on global markets where firms are price-takers, allows us to separately estimate firm-origin markdowns and firm-product markups. This approach could be applied to other contexts, such as global food supply chain sourcing in developing countries, in which both buyer and seller power exerted by trade intermediaries are an important issue.

The joint exertion of buyer and seller power by firms, as we show is the case for French dairy processors, has several broad implications. First, we show they have to be simultaneously considered. Our results indicate that we would have largely misidentified the inefficiency origin, had we ignored buyer power and attributed the entire margin to seller power, as the production function approach traditionally does. We show such *markups* estimated following such an approach should be viewed as *margins*, coming from price-setting power *on both sides*, if there is reason to suspect buyer power in the sector of study. As markups and margins differently react to costs shocks, distinguishing both is crucial to understand how shocks pass through supply chains.

Finally, buyer power can have important policy implications. In our context, through sole markdown adjustments, processors partially absorb shocks to commodity prices and to farm costs, smoothing variations in farmer profits but also impeding farmers from benefiting from positive demand shocks. Second, also due to buyer power alone, 65% of the subsidies currently paid to farmers are diverted. Our results thus call for alternative welfare-improving policies, aiming at promoting farmer countervailing seller power or for a price floor on raw milk.

References

- Akerberg, D. A., K. Caves, and G. Frazer (2015). Identification Properties of Recent Production Function Estimators. *Econometrica* 83(6), 2411–2451. _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.3982/ECTA13408>.
- Allain, M.-L., R. Avignon, and C. Chambolle (2020). Purchasing alliances and product variety. *International Journal of Industrial Organization* 73, 102641.
- Amiti, M., O. Itskhoki, and J. Konings (2014). Importers, exporters, and exchange rate disconnect. *American Economic Review* 104(7), 1942–78.
- Azar, J., S. Berry, and I. E. Marinescu (2019). Estimating labor market power. *Available at SSRN 3456277*.
- Azzam, A. and T. Park (1993). Testing for switching market conduct. *Applied Economics* 25(6), 795–800.
- Bartkus, V. O., W. Brooks, J. P. Kaboski, and C. E. Pelnik (2021, September). Big Fish in Thin Markets: Competing with the Middlemen to Increase Market Access in the Amazon. NBER Working Papers 29221, National Bureau of Economic Research, Inc.
- Berger, D., K. Herkenhoff, and S. Mongey (2022). Labor market power. *American Economic Review* 112(4), 1147–93.
- Bergquist, L. F. and M. Dinerstein (2020). Competition and entry in agricultural markets: Experimental evidence from kenya. *American Economic Review* 110(12), 3705–47.
- Berry, S., J. Levinsohn, and A. Pakes (1995). Automobile prices in market equilibrium. *Econometrica* 63(4), 841–890.
- Berry, S. T. and P. A. Haile (2021). Foundations of demand estimation. In *Handbook of Industrial Organization*, Volume 4, pp. 1–62. Elsevier.
- Biscourp, P., X. Boutin, and T. Vergé (2013). The effects of retail regulations on prices: Evidence from the loi galland. *The Economic Journal* 123(573), 1279–1312.
- Bond, S., A. Hashemi, G. Kaplan, and P. Zoch (2020, April). Some Unpleasant Markup Arithmetic: Production Function Elasticities and their Estimation from Production Data. Technical Report w27002, National Bureau of Economic Research, Cambridge, MA.
- Bonnet, C. and Z. Bouamra-Mechemache (2016). Organic label, bargaining power, and profit-sharing in the french fluid milk market. *American Journal of Agricultural Economics* 98(1), 113–133.

- Bouamra-Mechemache, Z., R. Jogeneel, and V. Réquillart (2008). Removing eu milk quotas, soft landing versus hard landing. Technical report.
- Brooks, W. J., J. P. Kaboski, I. O. Kondo, Y. A. Li, and W. Qian (2021, September). Infrastructure Investment and Labor Monopsony Power. *IMF Economic Review* 69(3), 470–504.
- Cajal-Grossi, J., R. Macchiavello, and G. Noguera (2019, January). International Buyers' Sourcing and Suppliers' Markups in Bangladeshi Garments. CEPR Discussion Papers 13482, C.E.P.R. Discussion Papers.
- Cakir, M. and J. V. Balagtas (2012). Estimating market power of us dairy cooperatives in the fluid milk market. *American Journal of Agricultural Economics* 94(3), 647–658.
- Caprice, S. and P. Rey (2015). Buyer power from joint listing decision. *The Economic Journal* 125(589), 1677–1704.
- Collard-Wexler, A. and J. De Loecker (2016, July). Production function estimation and capital measurement error. Working Paper 22437, National Bureau of Economic Research.
- Compiani, G. (2022). Market counterfactuals and the specification of multiproduct demand: A nonparametric approach. *Quantitative Economics* 13(2), 545–591.
- Crespi, J. M., Z. Gao, and H. H. Peterson (2005). A simple test of oligopsony behavior with an application to rice milling. *Journal of Agricultural & Food Industrial Organization* 3(2).
- Crespi, J. M., T. L. Saitone, and R. J. Sexton (2012). Competition in us farm product markets: Do long-run incentives trump short-run market power? *Applied Economic Perspectives and Policy* 34(4), 669–695.
- Crespi, J. M. and R. J. Sexton (2005). A multinomial logit framework to estimate bid shading in procurement auctions: Application to cattle sales in the texas panhandle. *Review of industrial organization* 27(3), 253–278.
- De Loecker, J., J. Eeckhout, and G. Unger (2020). The rise of market power and the macroeconomic implications. *The Quarterly Journal of Economics* 135(2), 561–644.
- De Loecker, J., P. K. Goldberg, A. K. Khandelwal, and N. Pavcnik (2016). Prices, markups, and trade reform. *Econometrica* 84(2), 445–510.
- De Loecker, J. and P. T. Scott (2016, December). Estimating market power Evidence from the US Brewing Industry. Working Paper 22957, National Bureau of Economic Research. Series: Working Paper Series.

- De Loecker, J. and F. Warzynski (2012, October). Markups and Firm-Level Export Status. *American Economic Review* 102(6), 2437–2471.
- De Ridder, M., B. Grassi, G. Morzenti, et al. (2021). The hitchhiker’s guide to markup estimation. Technical report.
- Dhyne, E., A. Petrin, V. Smeets, and F. Warzynski (2017, July). Multi Product Firms, Import Competition, and the Evolution of Firm-product Technical Efficiencies. Technical Report w23637, National Bureau of Economic Research, Cambridge, MA.
- Dhyne, E., A. Petrin, V. Smeets, and F. Warzynski (2021). Theory for Extending Single-Product Production Function Estimation to Multi-Product Settings. pp. 31.
- Dobbelaere, S. and J. Mairesse (2013). Panel data estimates of the production function and product and labor market imperfections. *Journal of Applied Econometrics* 28(1), 1–46.
- Döpfer, H., A. MacKay, N. Miller, and J. Stiebale (2021). Rising markups and the role of consumer preferences. *Available at SSRN 3939126*.
- Grau, A. and H. Hockmann (2018). Market power in the german dairy value chain. *Agribusiness* 34(1), 93–111.
- Hall, R. E. (1988). The relation between price and marginal cost in US industry. *Journal of political Economy* 96(5), 921–947. Publisher: The University of Chicago Press.
- Hong, G. H. and N. Li (2017). Market structure and cost pass-through in retail. *Review of Economics and Statistics* 99(1), 151–166.
- Horn, H. and A. Wolinsky (1988). Bilateral monopolies and incentives for merger. *The RAND Journal of Economics*, 408–419.
- Jenkin, F. (1872). 3. on the principles which regulate the incidence of taxes. *Proceedings of the Royal Society of Edinburgh* 7, 618–631.
- Koontz, S. R., P. Garcia, and M. A. Hudson (1993). Meatpacker conduct in fed cattle pricing: An investigation of oligopsony power. *American Journal of Agricultural Economics* 75(3), 537–548.
- Leone, F., R. Macchiavello, and T. Reed (2021). The falling price of cement in africa.
- Levinsohn, J. and A. Petrin (2003). Estimating production functions using inputs to control for unobservables. *The review of economic studies* 70(2), 317–341. Publisher: Wiley-Blackwell.

- MacKay, A. and N. Miller (2022). Estimating models of supply and demand: Instruments and covariance restrictions. *Available at SSRN 3025845*.
- Mérel, P. and R. J. Sexton (2017). Buyer power with atomistic upstream entry: Can downstream consolidation increase production and welfare? *International Journal of Industrial Organization* 50, 259–293.
- Morlacco, M. (2019). Market power in input markets: Theory and evidence from french manufacturing. *From Micro to Macro: Market Power, Firms' Heterogeneity and Investment, Luxembourg. EIB*.
- Muth, M. K. and M. K. Wohlgenant (1999). Measuring the degree of oligopsony power in the beef packing industry in the absence of marketing input quantity data. *Journal of Agricultural and Resource Economics*, 299–312.
- Nakamura, E. and D. Zerom (2010). Accounting for incomplete pass-through. *The review of economic studies* 77(3), 1192–1230.
- Olley, G. S. and A. Pakes (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica* 64(6), 1263–1297.
- Perekhozhuk, O., T. Glauben, M. Grings, and R. Teuber (2017). Approaches and methods for the econometric analysis of market power: A survey and empirical comparison. *Journal of Economic Surveys* 31(1), 303–325.
- Rauch, J. E. (1999). Networks versus markets in international trade. *Journal of international Economics* 48(1), 7–35.
- Rubens, M. (2021). Market Structure, Oligopsony Power, and Productivity. pp. 72.
- Russo, C., R. E. Goodhue, and R. J. Sexton (2011). Agricultural support policies in imperfectly competitive markets: Why market power matters in policy design. *American Journal of Agricultural Economics* 93(5), 1328–1340.
- Schroeter, J. and A. Azzam (1991). Marketing margins, market power, and price uncertainty. *American Journal of Agricultural Economics* 73(4), 990–999.
- Sexton, R. J. (2000). Industrialization and consolidation in the us food sector: Implications for competition and welfare. *American Journal of Agricultural Economics* 82(5), 1087–1104.
- Sexton, R. J. (2013). Market power, misconceptions, and modern agricultural markets. *American journal of agricultural economics* 95(2), 209–219.

- Sexton, R. J., I. Sheldon, S. McCorriston, and H. Wang (2007). Agricultural trade liberalization and economic development: the role of downstream market power. *Agricultural Economics* 36(2), 253–270.
- Sheldon, I. M. (2017). The competitiveness of agricultural product and input markets: A review and synthesis of recent research. *Journal of agricultural and applied economics* 49(1), 1–44.
- Tortarolo, D. and R. D. Zarate (2018). Measuring imperfect competition in product and labor markets. an empirical analysis using firm-level production data.
- Valmari, N. (2016, March). Estimating Production Functions of Multiproduct Firms. ETLA Working Papers 37, The Research Institute of the Finnish Economy.
- Villas-Boas, S. B. (2007). Vertical relationships between manufacturers and retailers: Inference with limited data. *The Review of Economic Studies* 74(2), 625–652.
- Weyl, E. G. and M. Fabinger (2013). Pass-through as an economic tool: Principles of incidence under imperfect competition. *Journal of Political Economy* 121(3), 528–583.
- Wong, H. C. (2019). Understanding high-wage and low-wage firms. *Available at SSRN 3446088*.
- Wooldridge, J. M. (2009). On estimating firm-level production functions using proxy variables to control for unobservables. *Economics letters* 104(3), 112–114.
- Yeh, C., C. Macaluso, and B. Hershbein (2022, July). Monopsony in the us labor market. *American Economic Review* 112(7), 2099–2138.
- Zavala, L. (2020). Unfair trade? market power in agricultural value chains. Technical report, Mimeo. Yale University. url: <https://www.lzavala.com/about>.

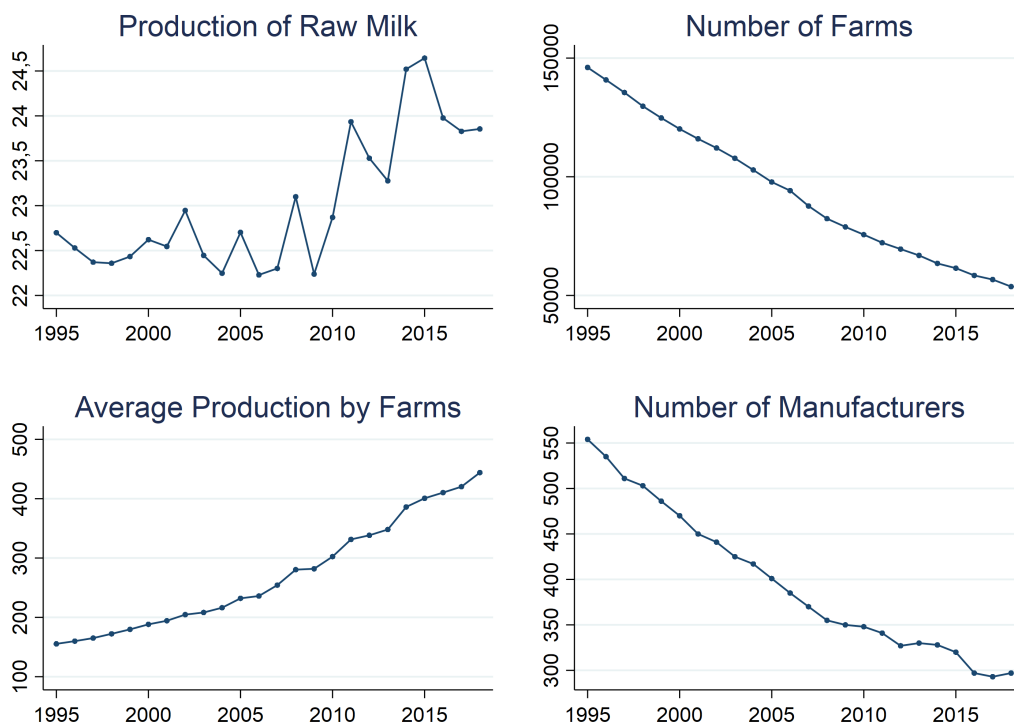
Appendix - Chapter 1

Appendix 1.A Recent Changes in the French Dairy Market

In this Section, we detail structural and regulatory changes the French dairy market experienced over the last 20 years. They motivate our (quasi-)competition-agnostic approach.

1.A1. Trends

Figure 1.9: Dairy Industry Trends

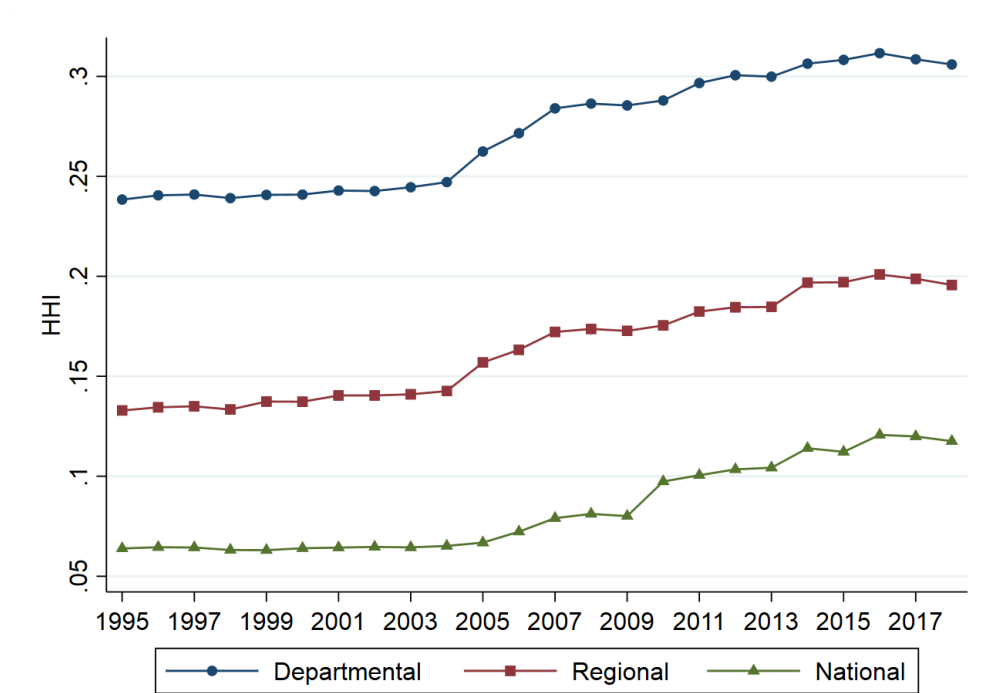


The number of farms producing raw milk has steadily decreased since 1995, from around 150,000 to 54,000. Concomitantly, and naturally reflecting the increase in national production, the yearly milk production of the average farm tripled to reach 450,000 liters. The average farm nevertheless remains relatively small (66 cows) and mostly organized around a familial nucleus, the controversial *farm of a thousand cows* remaining a short-lived exception (2014-2020).

One stage downstream, the processing of raw milk into dairy products is made by increasingly concentrated manufacturing groups (300 in 2018 against 550 in 1995). 4 of

them are among the top 15 groups at the world level, including the world-leading dairy group. Figure 1.21 shows the consequences of this ongoing concentration of raw milk market over the 20 last years, a phenomenon that has accelerated over the last years. The concentration results from a structural trend but also from various events, such as mergers of big dairy firms or the relocation of the milk activity following the quota removal. The declining number of manufacturing groups is reflected in the Herfindahl-Hirschman Index (HHI), growing at national but also at regional scales since 2006, to attain substantially high levels, especially at the local (*département*) level.

Figure 1.10: Raw Milk Collection HHI



Notes: HHI based on group-level market shares. Dry matter content quantity weighted averages for regional and national HHI.

1.A2. Regulatory and Structural Changes

Regulatory Changes

During the 2003-2018 period, the French dairy industry's regulatory context regularly changed. Upstream, the market has long been highly regulated before being liberalized. Downstream, the commercial negotiations between processors and concentrating have also undergone notable changes.

From 1984 to 2015, the European Union (EU) raw milk market was regulated by production quotas. Each member state was endowed with a maximum amount of production decided at the EU level, which it could freely allocate among its national farmers. In 2003,

the Common Agricultural Policy officially engaged towards a progressive liberalization of the dairy industry, following a so-called *soft landing* (Bouamra-Mechemache et al., 2008) strategy in order to leave the quotas regime and foster greater competition. Quotas were increased by 2% (2008) and 1% (2009-2015) every year before being definitively removed in 2015. Consequently, as regards France, the production of raw milk by farms is since then not administratively determined anymore but is the result of bilateral contracts linking processors and farmers. Moreover, raw milk prices have also been liberalized. Up to the spring 2008, the CNIEL (National Interprofessional Center for the Dairy Economy) was regularly publishing a recommended price resulting from negotiations between farmers and processor representatives, a recommendation in practice closely followed by processors. This functioning was abandoned after the French regulation authority declared the practice as anti-competitive. There are concerns that these institutional changes may have been to the detriment of farmers, rarely organized and less used to bargain than manufacturing groups.⁹⁶

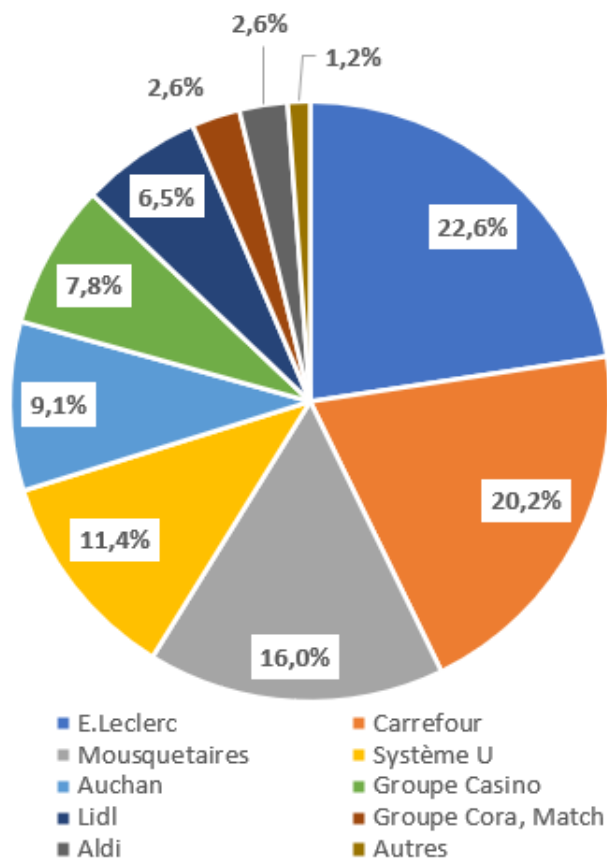
The European dairy industry was further supported through *intervention prices* on bulk products (milk powder, butter). When a commodity price dropped below a certain threshold level (the *intervention price*), the European Union purchased the necessary quantity to maintain a decent price. Purchased quantities were then stored and later resold and/or exported at a loss. Following the Common Agricultural Policy (CAP) reforms of 1999 and 2003, these intervention levels were progressively reduced, until becoming in practice ineffective. More generally, after the 2003 CAP reform, price support policies - because pushing to more production - were progressively replaced by less-distortive direct subventions to farmers.

⁹⁶See for instance this study summary: [Study of Measures against Market Imbalance: What Perspectives after Milk Quotas in the European Dairy Sector?](#).

Commercial Relations between Processors and Retailers

In France, the 2000s were marked by debates about the regulation of the retail sector. In 2008, the Economic Modernization Act (*Loi de Modernisation de l'Economie*, in French) removed the non-discriminatory price obligation imposed on processors since the *Galland Act* (1996). The Galland Act was constraining processors to sell a given product to different retailers at a similar price, which in practice had effects akin to price floors (Biscourp et al., 2013). More recently, two waves of purchasing alliance formations (2014, 2018) have been scrutinized by competition authorities and economists for their possible anti-competitive effects (Caprice and Rey, 2015; Allain et al., 2020). As striking in Figure 1.11, retailers are highly concentrated in France, with the 7 dominating players representing 94% of the food market. Purchasing alliances may thus have reinforced their countervailing buyer power.

Figure 1.11: Food Retail Shares (2018)



Source: www.kantarworldpanel.com

Overall, these changes soundly modified commercial relations and bargaining power along the entire dairy supply chain, *i.e* between farmers and processors on the upstream side, and between processors and retailers further downstream. We acknowledge and take into account these important policy changes in our analysis by remaining agnostic on competition structures both up- and downstream.

Appendix 1.B Measurement

1.B1. Labor and Capital

This section describes how we build our measures of labor and capital quantities, using FICUS, FARE and OECD STAN data.

Wage Bill We measure the wage bill as the sum of wages and social security payments, under variables names *saltrai* and *charsoc* in FICUS, and *redi_r216* and *redi_r217* in FARE. In doing so, we follow [De Ridder et al. \(2021\)](#).

Capital We measure capital as the tangible fixed assets, under variable names *immocor* in FICUS, and *immo_corp* in FARE. We here follow [De Ridder et al. \(2021\)](#) and [Wong \(2019\)](#) among others using similar data. [De Ridder et al. \(2021\)](#) in particular explains why this approach is better than the *perpetual inventory* method in this data context while delivering similar capital measures.

Deflators In order to estimate the production function, we need to recover labor and capital *quantities*. To do so, we deflate wage bills and capital variables with industry-level deflators from the OECD STAN database. The industry is here defined as the "Foods products, beverages and tobacco" industry, which is the finest level for which we have data for the entire period of analysis. Both labor and capital are deflated using the industry-level Gross Output deflator. As highlighted by [De Ridder et al. \(2021\)](#), this is consistent with the assumption that dairy firms operate on competitive labor and capital markets with equal prices.

1.B2. Output Prices and Quantities

Data used here come from the *Enquête Annuelle Laitière* (EAL, 1995-2018), the *Enquête Mensuelle Laitière* (EML, 2013-2018) and the PRODCOM database for dairy products (2003-2018). They contain firm-level data regarding the production of dairy products and the collection of raw milk. In the EAL, and regarding the output side, we observe for each dairy firm in France the quantities of dairy products produced, by product (slightly more disaggregated than CN8). Thanks to our *PRODCOM* data, we are able to observe revenues and production at the firm-CN8-year level, for French dairy firms with more than 10 employees. This allows us to recover *unit values*, which we use as proxy for *factory-gate* prices in the analysis. These price data are only available for the 2003-2018 period, which will as a consequence be our period of analysis.

The unit values observed are thus firm-product-level weighted averages of more disaggregated unit values. On one hand, a product is defined at the CN8 level, which is typically the most disaggregated level observed in such data but may have some heterogeneity at a more disaggregated level. Our estimates can thus be subject to composition effects if such heterogeneity is present. However, we do not find particular structural changes in markups estimated which could be driven by such composition effects. Moreover, our classification allows us to distinguish bulk products sold as intermediates from final consumption goods. On the other hand, we do not observe heterogeneity in prices

charged by a given processor for a given product for different buyers.

In the estimation, we only use quantities and unit values from the PRODCOM database. We solely use the EAL data and their more disaggregated products classification to identify (and drop) PDO and organic products, which we disregard for now, as they do not align with our assumption of substitutability of milk inputs of different origins.

To avoid inconsistencies, we harmonize units of counts in our quantity data, which are eventually all expressed in kilograms. In the original dataset, quantities are either expressed in kilograms of fat, or in kilograms of dry equivalent, which we convert into kilograms using our dry matter content data. When expressing output at the firm level to perform the production function estimation, we sum the quantities, expressed in kilograms, of the different processed products.

1.B3. Input Prices and Quantities

Raw Milk

In the EAL, we observe the quantity of raw milk collected by each firm and in every *département*. Thanks to the EML, we are able to observe firm-*département* prices paid for raw milk, for a subsample of firms, and only for the 2013-2018 period. Importantly, these data are price data and not *unit values*. To complement this firm-level raw milk prices, we use data from a survey made by *FranceAgrimer*, which gives us average raw milk prices by French regions, covering the period 2000-2018.

Whole Milk Powder Prices

We use Whole Milk Powder market prices for France provided online by the European Commission (<https://agridata.ec.europa.eu/extensions/DashboardPrice/DashboardMarketPrices.html>).

1.B4. Firms and Groups

Firms The production function estimation is done at the firm level, where a firm is a SIREN. We match PRODCOM with FICUS and FARE data thanks to this unique firm identifier.

Groups Some results are then presented at the business group level. We recover these groups using the *Liaisons Financières entre Sociétés* (LIFI) data which allows us to observe financial relationships between French firms, including dairy firms. In order to more accurately describe the French dairy market reality, we complemented these financial links with a substantial amount of research online to find out additional business relationships

in the market. In doing so, we marginally adjusted groups as defined by LIFI, including business relationships that are not necessarily translated into ownership relationships.

1.B5. Cleaning

In the spirit of cleanings described in [Dhyne et al. \(2017\)](#), we compute the median ratios of capital over wage bill, milk usage respectively over capital and over labor, and wage bill over labor (average wage), then excluding observations more than five times the interquartile range below or above the median. This leads us to drop 649 observations (firm-year couples), leaving us with 7,996 observations for the estimation (see [Table 1.11](#)).

Appendix 1.C Discussing Theoretical Assumptions

1.C1. Variable Profit Maximization

Timing

In this Section, we consider a timing that microfounds the variable profit maximization on which our model relies. In the first stage, dairy firms take long-term decisions which determine the competitive environment for their purchases of each input i and for the sales of each output j . On the downstream side, these decisions encompass, for example, the choice of dairy products produced by the firm \mathcal{J}_f , the corresponding quality levels, and distribution networks. On the upstream side, among other choices, firms decide the set of markets in which they source their milk-input \mathcal{I}_f . In the second stage, dairy firms maximize their current variable profit, competing upstream and downstream. On both sides, competition can take any usual form (Cournot, Bertrand, Monopolistic competition, etc). A Nash equilibrium of these two-stage game defines all the relevant information that affects firm individual supply and demand curves (quantities, prices, varieties, etc...), respectively denoted by A_{fj} and A_{fi} . Then, in equilibrium, each firm maximizes its variable profit knowing which individual demand and supply curves it faces, anticipating that all other firms play Nash equilibrium. This two-stage game yields first order conditions linking firm marginal costs, markups, and markdowns.

In doing so, the product-specific demand faced by firm f on product j would rewrite $p_{fj}(y_{fj}, A_{fj})$ and its market-specific supply would rewrite $w_{fi}(m_{fi}, A_{fi})$. In [Section 3.](#), we simply respectively summarize them by $p_{fj}(\cdot)$ and $w_{fi}(\cdot)$, where indices fj and fi encompass competitive environments.

First Order Conditions

Processor f maximizes its current variable profit by choosing for each pair (i, j) , which quantity m_{fij} of input i to dedicate to product j and also the optimal quantity of labor

L_f to hire at unit cost z_f to process these products. This yields the following program:

$$\begin{aligned} & \max_{\{m_{fij}\}_{(i,j) \in \mathcal{I}_f \times \mathcal{J}_f}, \{l_{fj}\}_{j \in \mathcal{J}_f}} \sum_j p_{fj}(y_{fj})y_{fj} - \sum_i w_{fi}(m_{fi})m_{fi} - \sum_j z_f l_{fj} \\ & \text{s.t.} \quad y_{fj} = \min \left\{ \sum_i \frac{m_{fij}}{e_{ij}}, F_j(L_f, K_f; \Omega_f) \right\}, \forall j, \\ & \quad m_{fi} = \sum_j m_{fij}, \forall i \end{aligned}$$

where L_f , K_f and Ω_f respectively are vectors of l_{fj} , k_{fj} and ω_{fj} , $\forall j \in \mathcal{J}_f$, other terms being simple scalars.

At the optimum, both terms of the Leontief production function are equal such that:

$$y_{fj} = \sum_i \frac{m_{fij}}{e_{ij}} = F_j(L_f, K_f, \Omega_f)$$

Variable Processing Cost Minimization The variable profit maximization implies that the variable processing cost is minimized, which results from the following program:

$$\begin{aligned} & \min_{\{l_{fj}\}_{j \in \mathcal{J}_f}} \sum_j z_f l_{fj} \\ & \text{s.t.} \quad y_{fj} = F_j(L_f, K_f, \Omega_f), \forall j \end{aligned}$$

The associated Lagrangian for each product j is:

$$\mathcal{L} = \sum_j z_f l_{fj} + \sum_j \lambda_{fj}(y_{fj} - F_j(L_f, K_f, \Omega_f))$$

First order conditions give:

$$\lambda_{fj} = \frac{z_{fj}}{\frac{\partial F_j(L_f, K_f, \Omega_f)}{\partial l_{fj}}}, \forall j \quad (1.24)$$

By definition, the Lagrange multiplier λ_{fj} is equal to the marginal processing cost of producing an additional unit of y_{fj} . The solution of this problem gives the minimum processing cost $C_f(M_f)$ using the milk input vector $M_f = (m_{f11}, \dots, m_{fij}, \dots, m_{fIJ})$ to produce the output vector $Y_f = (y_{f1}, \dots, y_{fj}, \dots, y_{fJ})$.

Simplified Variable Profit Maximization The profit maximization problem of the processor is then simplified as follows:

$$\max_{\{m_{fij}\}_{(i,j) \in \mathcal{I}_f \times \mathcal{J}_f}} \sum_j p_{fj} \left(\sum_i \frac{m_{fij}}{e_{ij}} \right) \sum_i \frac{m_{fij}}{e_{ij}} - \sum_i w_{fi}(m_{fi})m_{fi} - C_f(M_f)$$

The first order condition for every m_{fij} yields Equation (1.2):

$$\begin{aligned} \left(\frac{\partial p_{fj}(\cdot) y_{fj}}{\partial y_{fj}} \frac{y_{fj}}{p_{fj}} + 1 \right) p_{fj} &= \left(\frac{\partial w_{fi}(\cdot) m_{fi}}{\partial m_{fi}} \frac{m_{fi}}{w_{fi}} + 1 \right) w_{fi} e_{ij} + \lambda_{fj} \\ \iff (1 + \varepsilon_{fj}^D)^{-1} p_{fj} &= (1 + \varepsilon_{fi}^S)^{-1} w_{fi} e_{ij} + \lambda_{fj}. \end{aligned}$$

Generalization

We here show how the simple setting of Section 3. can be generalized in multiple (and compatible) ways, without having any impact on the empirical analysis.

Vertical Cooperation A lot of French dairy processors are cooperatives. They represent about half of the milk collection in France. The term "cooperatives" however hides a variety of functioning, which makes their proper modelization difficult. Some of them (mostly small ones) are fully vertically integrated, and the value-added sharing within them can take various forms. Some cooperatives are not fully integrated but rather regroup distinct manufacturing firms and long-serving suppliers. As such, some have evolved towards a more private structure. The biggest cooperative, which represents 20% of the French milk collection is for instance owned for half of it by private actors. Its functioning is based on an additional premium paid to its milk suppliers for every ton of milk furnished.⁹⁷

We propose here a simple of modelization of this wide range of possible (vertically) cooperative behaviors. Denoting α_f the parameter characterizing firm f interest in its supplier revenues, firm f objective function writes:

$$O_f = \sum_j p_{fj}(y_{fj})y_{fj} - (1 - \alpha_f) \sum_i w_{fi}(m_{fi})m_{fi} - z_f L_f$$

$0 \leq \alpha_f \leq 1$, and the bigger the α , the more important the cooperation, $\alpha_f = 0$ bringing us back to the non-cooperative behavior. The corresponding first order condition yields:

$$\underbrace{\left(1 + \varepsilon_{fj}^D\right)^{-1} p_{fj}}_{\text{marginal revenue } MR_{fj}} = \underbrace{\left(1 + \varepsilon_{fi}^S\right)^{-1} w_{fi} e_{ij} + \lambda_{fj}}_{\text{marginal cost } MC_{fj}}. \quad (1.25)$$

⁹⁷Which is included in the price we observe in the data.

Importantly, authorizing such cooperative behaviors does not alleviate the markdown definition (nor the markup and the margin definitions):

$$\nu_{fi} \equiv \frac{\left(p_{fj} \left(1 + \varepsilon_{fj}^{D-1} \right) - \lambda_{fj} \right)}{w_{fi} e_{ij}} \quad (1.26)$$

However, at the equilibrium we now have the equality between the markdown and a product of the supply elasticity and the cooperative distortion term:

$$\nu_{fi} = (1 - \alpha_f) \left(1 + \varepsilon_{fi}^{S-1} \right).$$

Given that our empirical analysis hinges on (1.27) rather than on the equality between the markdown and the supply elasticity, our results are robust to any cooperative behaviors taking such forms. In particular, it can include supply-preserving behaviors by dairy firms, be they private or cooperative actors. Such behaviors even provide a rationale for markdowns below one (high values of α_f).

Collusion In a similar manner to the one used for modeling vertical cooperation, one can extend the model to allow for possible collusive behaviors. We present here a version allowing downstream collusion, but we could similarly allow for upstream collusion. Being able to allow for collusion downstream is particularly important as cartels have actually been deterred during the period of analysis. Between 2006 and 2012, 11 firms belonging to the so-called "yoghurt cartel" have for instance colluded in determining prices when selling yoghurts to retailers.

We propose here a simple modelization of such collusive behaviors wide range of possible (vertically) cooperative behaviors. Denoting γ_f the parameter characterizing firm's f interest in some of its competitor profits (for instance belonging to a cartel C), the firm's f objective function writes:

$$O_f = \sum_j p_{fj} (y_{fj}) y_{fj} + \gamma_f \sum_{f' \in C} \sum_{j'} p_{f'j'} (y_{fj}) y_{f'j'} - \sum_i w_{fi} (m_{fi}) m_{fi} - z_f L_f$$

$0 \leq \gamma_f \leq 1$, and the bigger the γ , the more important the collusion, $\gamma_f = 0$ bringing us back to the non-collusive behavior. The corresponding first order condition yields:

$$\underbrace{\left(1 + \varepsilon_{fj}^{D-1} \right) p_{fj} + \gamma_f \sum_{f' \in C} \sum_{j'} \varepsilon_{f'j'j}^{D-1} p_{f'j'} \frac{y_{f'j'}}{y_{fj}}}_{\text{marginal revenue } MR_{fj}} = \underbrace{\left(1 + \varepsilon_{fi}^{S-1} \right) w_{fi} e_{ij} + \lambda_{fj}}_{\text{marginal cost } MC_{fj}}. \quad (1.27)$$

Importantly, authorizing such collusive behaviors does not alleviate the markup definition

(nor the markdown and the margin definitions):

$$\mu_{fj} \equiv \frac{p_{fj}}{\left(1 + \varepsilon_{fi}^{S-1}\right) w_{fi} e_{ij} + \lambda_{fj}}. \quad (1.28)$$

However, at the equilibrium we now have the equality between the markup and a Lerner index authorizing collusion:

$$\mu_{fj} = \frac{1}{\left(1 + \varepsilon_{fj}^{D-1}\right) + \gamma_f \sum_{f' \in C} \sum_{j'} \varepsilon_{f'j'j}^D \frac{-1 p_{f'j'} y_{f'j'}}{p_{fj} y_{fj}}}.$$

Given that our empirical analysis hinges on (1.27) rather than on the equality between the markup and the demand elasticity, our results are robust to any colluding behaviors taking such forms.

Intra-Brand Competition Internalization Generalizing the variable profit maximization introduced in Section 3. to allow for intra-brand competition is straightforward.

We first rewrite firm's f objective function to incorporate its vector Y_{f-j} of quantities of products other than j produced, in order to make explicit the internalization of intra-brand competition:

$$\Pi_f = \sum_j p_{fj}(y_{fj}, Y_{f-j}) y_{fj} - \sum_i w_{fi}(m_{fi}) m_{fi} - z_f L_f$$

The corresponding maximization program yields a first order condition very similar to (1.2):

$$\underbrace{\left(1 + \varepsilon_{fjj}^{D-1}\right) p_{fj} + \sum_{j' \neq j} \varepsilon_{fj'j}^D \frac{p_{fj'} y_{fj'}}{y_{fj}}}_{\text{marginal revenue } MR_{fj}} = \underbrace{\left(1 + \varepsilon_{fi}^{S-1}\right) w_{fi} e_{ij} + \lambda_{fj}}_{\text{marginal cost } MC_{fj}}.$$

We accordingly define the marginal processing cost (MPC) of product j as

$$\lambda_{fj} \equiv \sum_{j'} \frac{\partial c_{fj'}(\cdot)}{\partial y_{fj}},$$

where $c_{fj}(y_{fj}, Y_{f-j})$ is firm f 's processing cost for product j , which is obtained by the minimization of the total processing cost.

We also define the own (cross) demand price-elasticity of j for $j = j'$ (for $j \neq j'$) as

$$\varepsilon_{fj'j}^D \equiv \frac{\partial y_{fj} p_{fj'}}{\partial p_{fj'} y_{fj}},$$

and we still have the supply price-elasticity as

$$\varepsilon_{fi}^S \equiv \frac{\partial y_{fi}}{\partial w_{fi}} \frac{w_{fi}}{m_{fi}}.$$

The implied markup is:

$$\mu_{fj} \equiv \frac{p_{fj}}{MC_{fj}} = \frac{1}{1 + \sum_{j'} \varepsilon_{fj'j}^D \frac{-1 p_{fj'} y_{fj'}}{p_{fj} y_{fj}}}.$$

This expression is quite similar to the classical single product markup expression. Again, the more inelastic the demand (higher ε_{fjj}^D) the higher the markup. However, the markup here also takes into account intra-brand competition (through $\varepsilon_{fjj'}^D$ for $j \neq j'$) which affects the marginal revenue of selling an extra unit of product j . Whenever product j and j' are substitutes (resp. complements), a reduction of p_{fj} to sell an extra unit of j decreases.

Again, it stresses out the flexibility of our estimates based on cost rather than elasticities estimation.

Cost Minimization We show here that we can relax the profit maximization assumption and only rely on variable cost minimization to similarly define our three objects of interest: markdown, markup, and total margin. This has the advantage of not having to define any demand function that processors face when selling to retailers. Thus, negotiations between both types of actors are free to take any form.

Each dairy firm solves the following variables costs minimization program:

$$\begin{aligned} \min_{m_{fij}} \quad & \sum_i w_{fi}(m_{fi})m_{fi} + c_{fj}(y_{fj}) \\ \text{s.t.} \quad & y_{fj} = \min \left\{ \sum_i \frac{m_{fij}}{e_{ij}}, F_j(L_f, K_f; \Omega_f) \right\}, \forall j \end{aligned}$$

where we *only* assume an increasing firm-dept specific supply curve $w_{fi}(\cdot)$.

Denoting λ_{fj}^y the associated Lagrange multiplier, the first order condition yields:

$$MC_{fj} \equiv \lambda_{fj}^y = \left(1 + \varepsilon_{fi}^{S-1}\right) w_{fi} e_{ij} + \lambda_{fj}$$

By definition, the Lagrange multiplier associated with the cost minimization program is equal to marginal costs.

We thus similarly recover markdown, markup, and margin definitions: $\mu_{fj} \equiv \frac{p_{fj}}{MC_{fj}}$, $\nu_{fi} \equiv \frac{MC_{fj} - \lambda_{fj}^y}{w_{fi} e_{ij}}$ and $M_{fij} \equiv \frac{p_{fj}}{AMC_{fij}}$.

As logical since totally abstracting from the demand side, we do not have anymore

equality between marginal revenue and marginal costs. As a consequence, (i) the markup does not explicitly relate to the demand elasticity, and (ii) the markdown has to be interpreted as the wedge between the *shadow cost* of a unit of milk (rather than its marginal contribution to profit) and its price.

1.C2. Static and Dynamic Inputs

Correlations shown in Table 1.8 are reassuring evidence that labor, milk, and materials are all variable and statically chosen, while capital is more dynamic.

Table 1.8: Correlations between Yearly Growth Rates

	Labor (wage bill)	Capital	Milk Inputs
Output $\% \Delta_t$	0.20	0.09	0.68
Output $\% \Delta_{t+1}$	0.08	0.10	0.06

Ignoring Materials other than Milk Inputs

We exclude non-milk intermediary inputs from marginal cost estimation. We argue that this restriction is unlikely to have a significant impact on our marginal cost estimates. We compute the ratio between the raw milk expenses declared in the production data (*i.e.* EAL) over total intermediary expenses recorded in balance sheet data (*i.e.* FICUS-FARE). The remaining gap between this ratio and 1 is at least partly explained by intermediary dairy inputs purchases (such as WMP and other commodities), which we do not observe but which are however taken into account in our theory. Any residual gap would result from non-milk intermediary inputs purchases, which seem to be insignificant. The sample used for this ratio is restricted to firms and years for which we observe prices at the firm-*département*-year level.

Table 1.9: Milk to Materials Expenses Ratio

Average	Median	P25	P75	Obs.
0.78	0.88	0.65	0.95	980

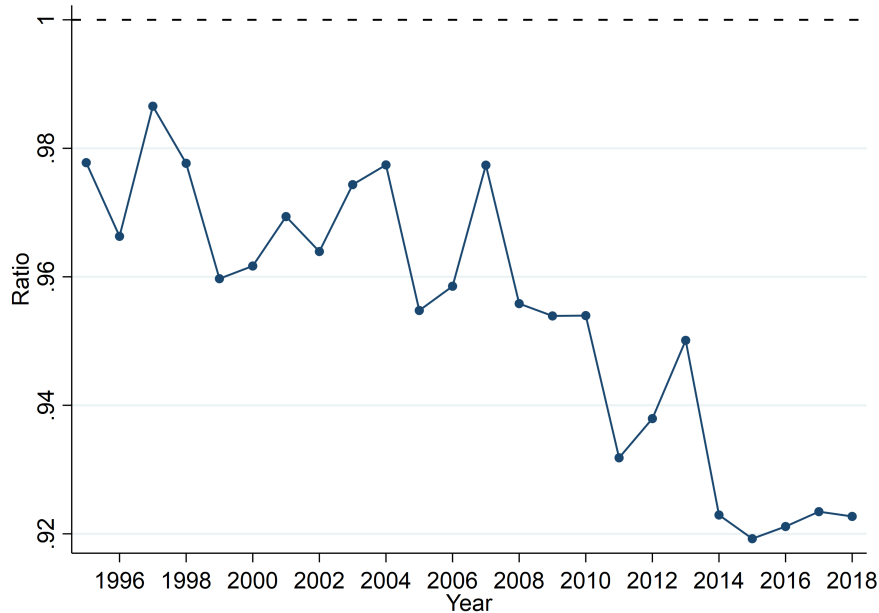
Appendix 1.D Discussing Identification

1.D1. Dairy Input/Output Matrix

We plot here the ratio between the simulated processor needs, in raw milk, generated from production data using our dry matter content data, and the actual raw milk production. Over the period, the underestimation of the demand is contained between 2 and

8 percent which can be explained by waste in the processing process which is assumed to be zero when dry matter content data are constructed.

Figure 1.12: Estimated DMC needs vs. Real demand (Collection + Imports)



Notes: Ratio between the estimated needs in dry matter contents (DMC) and the actual demand. The estimated needs in DMC is recovered from the production data and technical coefficients of DMC of milk and of dairy products. The actual milk demand is the sum of raw milk collection from our industry data and imports of WMP found in the BACI database from CEPII.

1.D2. Processing Function

Specification

Estimating marginal processing costs at the product level is challenging and requires strong assumptions. There are few papers dealing with multi-product production function estimation.⁹⁸ The main issue is that inputs are generally reported at the firm level. As a consequence, papers coping with multi-product production function estimation rely on 2 sets of important assumptions. On the one hand, some impose an allocation rule of inputs observed at the firm level to each product (see [De Loecker et al. \(2016\)](#) and [Valmari \(2016\)](#)). Despite their methodological differences, these papers ultimately consider a multi-product production function as a sum of mono-product production functions, once having allocated inputs to the different products. This amounts to assuming no complementarity in producing various products, an assumption that does not seem well-suited for our analysis. As we mentioned before, milk inputs are a bundle of sub-inputs split during the processing of different products. Moreover, we cannot implement [De Loecker](#)

⁹⁸In this paragraph, we follow the literature's vocable about *production* function, but the reader shall keep in mind that we here want to estimate what we refer to as the *processing* function.

et al.’s (2016) methodology as it relies on mono-product firms, which are very rare in the French dairy industry context, even at a relatively aggregated product level (see Table 1.10 in Appendix 1.D2.). On the other hand, Dhyne et al. (2017, 2021) develop a general multi-product production function which presents the advantage of not having to allocate inputs to be estimated. The drawback of this specification is that it requires at least as many variable inputs as products to identify marginal costs at the product level, something we do not have. Overall, it appears reasonable to assume a firm-level processing function in our case. Our scope of analysis is limited to the industry of ”Operation of Dairies and Cheese Making” (NC4-level), which is the level at which De Loecker et al. (2016) estimate production functions. Within this industry, firms seem to have a fairly similar mix in labor and capital regardless of their product specialization, as we show in Table 1.10 in Appendix 1.D2.). Labor cost shares in firm total processing costs (defined as labor and capital costs) indeed turn out to be very close to 0.8 for each product-group we consider. Finally, in our estimates, processing costs (estimated at the firm-level) on average only represent 25% of firm accounting marginal costs, milk input purchases at the firm-origin-*product*-level constituting the remaining 75%.

Empirically, the labor shares displayed in Table 1.10 are supportive of firm-level production technology, as labor share distribution of specialized firms is remarkably constant across product categories. Moreover, the small number of mono-product firms in the dairy industry reflected by the number of observations in Table 1.10 also motivates our choice of not implementing a production function estimation relying on them *à la* De Loecker et al. (2016).

Table 1.10: Labor Shares by Product Category, Monoproduct Firms

	Butter	Cream	Cheese	Milk	Powder	Yoghurt
Average	0.79	0.77	0.80	0.83	0.78	0.84
Median	0.79	0.73	0.78	0.77	0.83	0.81
P5	0.62	0.65	0.57	0.57	0.60	0.64
P25	0.74	0.70	0.71	0.71	0.75	0.74
P75	0.86	0.81	0.88	0.84	0.93	0.89
P95	0.94	1.00	0.97	1.00	1.00	0.96
Obs.	91	54	1,878	188	110	383

Notes: Specialized firms here defined as firms for which at least 80% of milk purchased is transformed into that product. Labor shares computed assuming a constant depreciation rate of capital over 10 years.

Estimation

Adding time t and dropping firm f subscripts to Equation (1.6), the estimating equations are:

$$y_t = \beta_l l_t + \beta_k k_t + \beta_{ll} l_t^2 + \beta_{kk} k_t^2 + \beta_{kl} k_t \cdot l_t + \epsilon_t,$$

where the technical efficiency term ϵ_t is assumed to split into two parts: $\epsilon_t = \omega_t + \eta_t$.

η_t is an i.i.d. error that the firm does not influence (e.g., measurement/specification errors). ω_t reflects firm-specific technical efficiency, observed by the firm but not by the econometrician. We now describe how we deal with three issues typically encountered in such contexts.

(i) Unobserved Firm-Specific Efficiencies

ω_t is assumed to be first-order Markov and is the source of the well-known simultaneity problem as firms observe it before choosing labor l_t . By assumption, k_t responds to ω_t with a lag as investments made in period $t - 1$ take effects in period t . Thus, k_t is possibly correlated with the expected value of ω_t given ω_{t-1} ($E[\omega_t|\omega_{t-1}]$) - but this assumption guarantees that the innovation in the productivity shock, $\xi_t = \omega_t - E[\omega_t|\omega_{t-1}]$ is unknown at time $t - 1$ the investment was made and therefore uncorrelated with current k_t .

Following [Olley and Pakes \(1996\)](#) and [Levinsohn and Petrin \(2003\)](#), we use the existence of a proxy variable h_t for the technical efficiency shock, which is assumed to be a function of unobserved productivity ω_t , capital k_t , and other variables z_t , which we denote $h_t(k_t, \omega_t, z_t)$. Assuming this function is a bijection in ω_t - conditional on k_t and other variables z_t - we can then invert the proxy variables to get $\omega_t = g(k_t, h_t, z_t)$. We thus include a function of k_t , h_t , and z_t in the estimation to control for ω_t . We define z_t later as it will also address problems (ii) and (iii), among others. Following [Wooldridge \(2009\)](#), and as commonly done in the literature, we use a single index restriction so that:

$$\omega_t = g(k_t, h_t, z_t) = c(k_t, h_t, z_t)' \gamma, \quad (1.29)$$

where we choose $c(\cdot)$. In practice, we use multivariate 2^{nd} order polynomials. We can now rewrite $E[\omega_t|\omega_{t-1}] = f(c(k_t, h_t, z_t)' \gamma)$, where we impose a similar single index restriction on $f(\cdot)$. Using our assumptions to re-express (1.29) yields:

$$y_t = \beta_l l_t + \beta_k k_t + \beta_{ll} l_t^2 + \beta_{kk} k_t^2 + \beta_{kl} k_t \cdot l_t + E[\omega_t|\omega_{t-1}] + \xi_t + \eta_t,$$

where remember that $\xi_t = \omega_t - E[\omega_t|\omega_{t-1}]$. For a given set of parameters $\beta =$

$(\beta_l, \beta_k, \beta_{ll}, \beta_{kk}, \beta_{kl})$ to be estimated, the error is:

$$[\xi_t + \epsilon_t](\beta) = y_t - \beta_l l_t + -\beta_k k_t - \beta_{ll} l_t^2 - \beta_{kk} k_t^2 - \beta_{kl} k_t \cdot l_t - f(c(k_t, h_t, z_t))' \gamma$$

Denoting $\tilde{\beta}$ the true parameters values, the conditional moment restriction $[\xi_t + \epsilon_t](\tilde{\beta}) = 0$ identifies β .

(ii) Unobserved Exogenous Input Prices and Quantities

Following [De Loecker et al. \(2016\)](#), we acknowledge the existence of a potential input price bias, as we use labor⁹⁹ and capital in monetary terms. To reduce this bias, we use industry-level labor and capital deflators. We further include average wage per worker (a proxy for labor quality) and downstream market shares in the control function $g(\cdot)$. The latter are good proxies for output quality, as they positively correlate with input quality in a large class of theoretical models. We refer to [De Loecker et al. \(2016\)](#) for a more formal explanation.¹⁰⁰

(iii) Endogenous Prices Upstream and Downstream

We choose the firm's milk demand as our proxy for ω_t , as both shall be positively correlated. With endogenous prices downstream and upstream, high milk input demand can also result from low markups and/or low markdowns rather than high productivity. As highlighted by [De Loecker et al. \(2016\)](#) and [Rubens \(2021\)](#), a large class of competition models can deliver markdowns and markups as functions of markets shares on the corresponding market, upstream and downstream, respectively.¹⁰¹ We thus incorporate these variables in the control function z_{ft} for ω_t and define:¹⁰²

$$z_{ft} = (s_{ft}^m, s_{ft}^y)$$

where s_{ft}^m and s_{ft}^y are firm's f average market shares in milk input and output markets.

⁹⁹We also have total employment in our data, which less accurately reflects the number of hours worked.

¹⁰⁰Contrary to [De Loecker and Warzynski \(2012\)](#), we do not include downstream prices (observed from 2003) here, as it would reduce the estimating sample and time window, which spans from 1995 to 2018.

¹⁰¹In such models, markdowns and markups also depend on prices, plus an additional elasticity parameter. We do not include prices, as they would drastically reduce the estimating sample. Given that we use quantities of products and milk in the estimation, we think this is not a major concern.

¹⁰²Using again a 2^{nd} order polynomial for flexibility concerns.

Estimates

Table 1.11: Processing Function Estimates - firm-level

	OLS	GMM - CD	GMM - TL
β_l	0.534*** (0.035)	0.739*** (0.035)	0.585*** (0.145)
β_k	0.252*** (0.027)	0.138*** (0.021)	0.121 (0.083)
β_{ll}			0.098*** (0.029)
β_{kk}			0.066*** (0.018)
β_{kl}			-0.149*** (0.044)
Obs.	7,996	7,996	7,996
R2	0.974		
Labor Quality Control	No	Yes	Yes
Market Power Controls	No	Yes	Yes
Firm and Year F.E.	Yes	Yes	Yes

Notes: OLS sample restricted to be the same as GMM samples, further reduced due to the presence of lagged variables. Labor quality is corrected for by introducing firm-level average wage control. Market power is controlled by introducing upstream and downstream market share controls. Standard errors are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ $p < 0.1$

We present in Table 1.11 our processing functions estimates for several specifications. Assuming a translog production function, the average estimate of the output elasticity of labor is 0.79, and the average output elasticity of capital is 0.14. These estimates are close to the Cobb-Douglas estimates (0.74 for labor and 0.14 for capital). Moreover, all quantiles of the distribution of elasticities resulting align well with their counterparts in the empirical distributions of labor, and capital shares in total processing costs (labor and capital costs), as shown in Table 1.12. Correcting for endogeneity seems to be important as GMM Cobb-Douglas elasticities differ significantly from those obtained by plain OLS regressions with firm and year fixed effects.

Robustness

Table 1.12 shows how all quantiles of the distribution of elasticities resulting from the translog specification relatively well align with their counterparts in the empirical distribution of respectively labor and capital shares in total processing costs (labor and capital costs).

Table 1.12: Translog Elasticities and Input Shares

	Average	Median	P5	P25	P75	P95	Obs.
Labor Elasticity	0.79	0.79	0.65	0.73	0.86	0.95	2,736
Capital Elasticity	0.14	0.14	0.01	0.09	0.19	0.24	2,736
Labor Share in Processing Costs	0.73	0.73	0.57	0.66	0.80	0.90	2,736
Capital Share in Processing Costs	0.27	0.27	0.10	0.20	0.34	0.43	2,736

Notes: Distributions winsorized at 1% and 99%. Labor shares computed assuming a constant depreciation rate of capital over 10 years.

As a robustness check, we conducted the estimation exercise using an alternative measure for the elasticity of output to labor required to retrieve marginal costs, using the firm-level elasticities implied by our Translog estimates. All results presented in the paper are robust to this alternative specification.

Table 1.13: Share of Milk Purchases in Marginal Costs

	Ignoring buyer power	With buyer power
	θ_{fij}	$\tilde{\theta}_{fij}$
Average	0.68	0.70
Weighted Average	0.76	0.78
Median	0.72	0.74
Observations	72,059	72,059

Notes: Sample restricted to firms for which we manage to link raw milk collection and production.

Table 1.13 shows the average and median shares θ_{fij} of raw milk purchases in marginal costs. These shares appear in several structural equations throughout the theoretical and pass-through analysis.

1.D3. Disentangling Markups and Markdowns

Identification Intuition - Toy Examples

WMP Sellers A firm that is observed selling WMP trades off between producing dairy products and WMP. Figure 1.13 conveys the main general intuitions, representing the equilibrium for a stylized firm sourcing milk on a given market i , and selling a given dairy product j and commodity c . Without loss of generality and for simplicity, we also assume here that $e_{ij} = e_{cj} = 1$, *i.e.* that milk and the commodity transform one for one into product j and commodity c , so that $y_i = y_j + y_c$.

In such a simple example, combining both underlying firm's first order conditions amounts to equalizing the marginal revenues of each output with the marginal costs of milk input i , implying that:

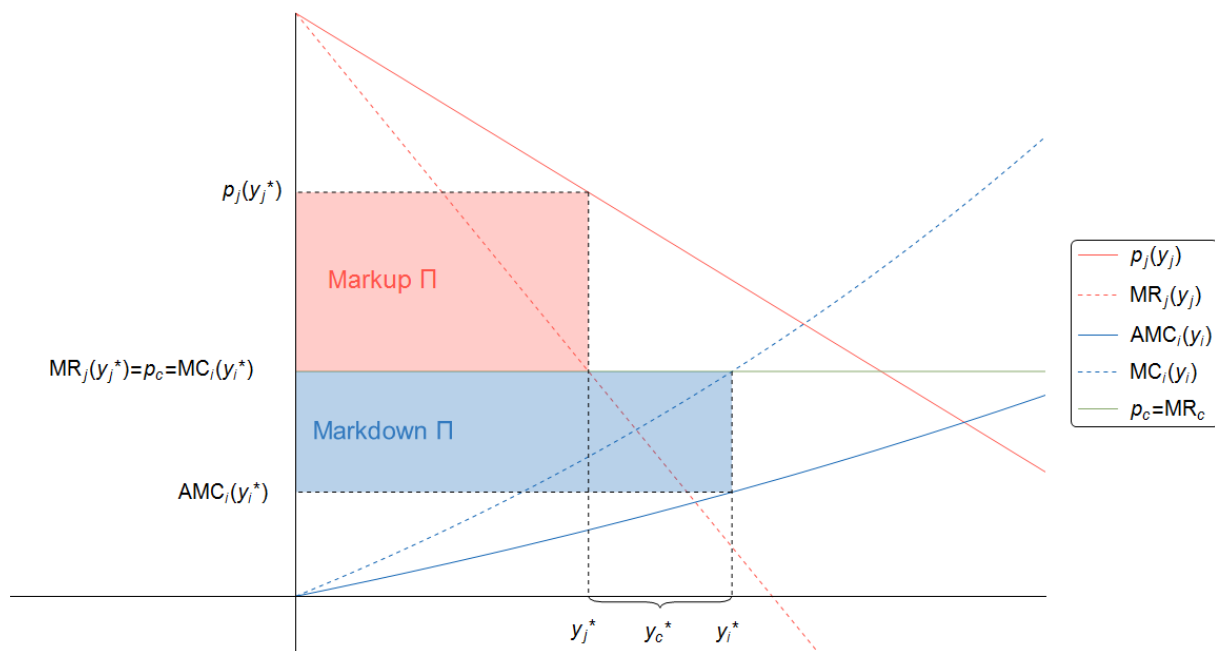
$$p_c = MR_j(y_j^*) = MC_i(y_i^*)$$

Arbitrage conditions and the commodity price thus allow identifying marginal revenue of product j and marginal costs of input i .

The firm produces and sells output j rather than commodity c as long as the marginal revenue MR_j of product j is above the commodity price p_c . For the optimal quantity of output j , MR_j and p_c are equalized, and the ratio between the price of product j and p_c delivers the markup.¹⁰³

The firm produces and sells commodity c as long as the commodity price p_c is above the marginal costs MC_i of processing milk i into the commodity. For the optimal quantity of milk input i (and thus for optimal quantities of both outputs j and c), p_c and MC_i are equalized, allowing us to identify the markdown. This stresses that firms selling commodities must be efficient enough (λ_f low enough) to do so. Our data confirm this intuition, as we observe a small number of larger firms selling WMP.

Figure 1.13: Equilibrium for Commodity Sellers



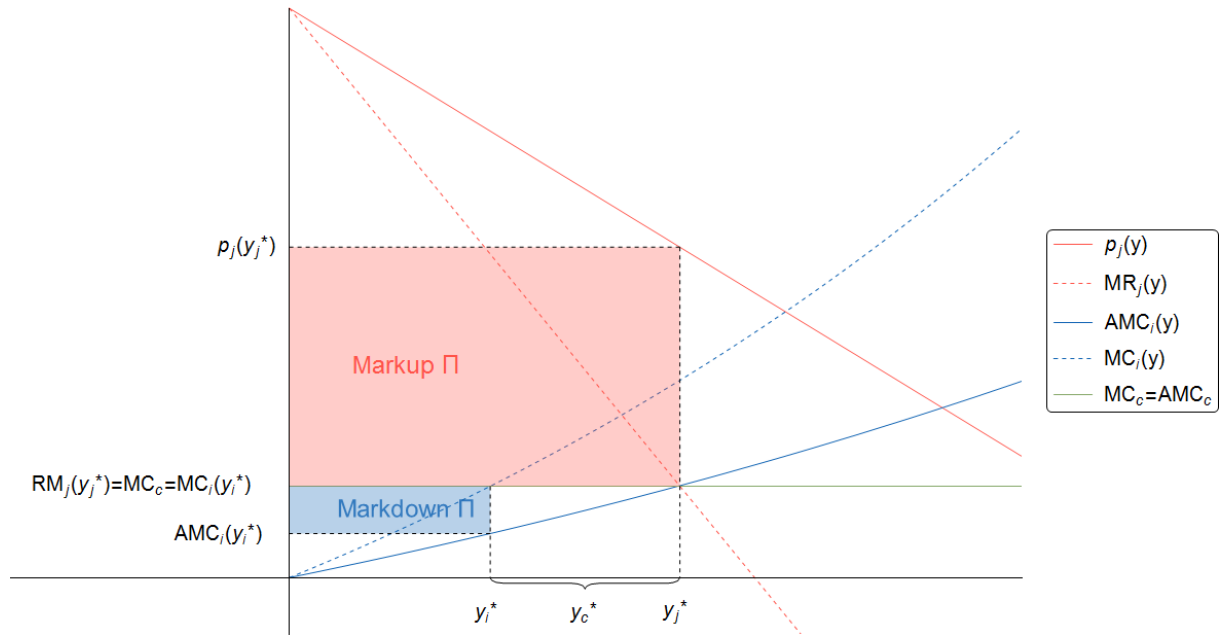
WMP Buyers Figure 1.14 displays general intuitions for a firm assumed to produce and sell one product j , processing milk i and commodity c . It thus illustrates intuitions

¹⁰³Noticing that the markup estimates for a commodity seller collapse to $\mu_{fj} = \frac{p_{fj}}{w_c}$ when $e_{cj} = 1$.

for identification of markups and markdowns of WMP buyers, evoked in subsection 4.2.. Underlying firm's first order conditions, *i.e.* equalizing marginal revenue of output j with the marginal cost of each input i and c , implies that:

$$MR_j(y_j^*) = AMC_c(y_c^*) = MC_i(y_i^*)$$

Figure 1.14: Equilibrium for Commodity Buyers



Firms Inactive on the WMP Market

In the main text, we assume that processors are active on the WMP market, either as buyers or sellers. In practice, we observe in the data whether or not a processor sells WMP, and assume non-sellers to be buyers. Our estimates of markdowns for non-buyers are possibly biased. We propose here a credible game in which the markdown empirical counterpart of a processor inactive on the WMP market is the same as for a buyer, *i.e.*

$$\nu_{fi} = \frac{w_c}{w_{fi}e_{ic}}.$$

We assume the following game:

Stage 1: Processors sign a contract with their clients defining prices and quantities exchanged. Processors choose the network of farms constituting their supply for each *département* i .

Stage 2: In each *département*, processors and farmers engage in a Nash-in-Nash bargaining (Horn and Wolinsky, 1988).¹⁰⁴

¹⁰⁴In this type of negotiation, firms engage in secret negotiations, they form passive beliefs and are

Stage 3: Each farmer decides which quantity to offer at the negotiated price. Processors can complete their milk input sourcing with commodity purchases.

Resolution: In Stage 3, farmers in each *département* decide which quantity of raw milk to supply observing w_{fi} . The aggregation of individual supplies yields the processor-*département* inverse supply $w_{fi}(m_{fi})$. In Stage 2, each processor f enters in bargaining with farmers within its supply network in *département* i . The farmer bargaining weight is denoted α . The farmer contracting profit is $w_{fi} \times m_{fi}(w_{fi})$, and their status-quo profit is 0 as the processor sourcing network is fixed in Stage 1. The processor gain from trade negotiating with farmers of *département* i is the cost difference from sourcing its needs in milk inputs from *département* i rather than sourcing it on the commodity market.

$$\max_{\{w_{fi}\}} \alpha \ln [w_{fi} \times m_{fi}(w_{fi})] + (1 - \alpha) \ln \left[m_{fi}(w_{fi}) \times \left(\frac{w_c}{e_{ic}} - w_{fi} \right) \right]$$

The first order condition of this problem gives:

$$\frac{w_c}{w_{fi}e_{ic}} = \frac{1 + \varepsilon_i^{S-1}}{1 + \frac{\alpha}{\varepsilon_i^{S-1}}}$$

This last expression shows that the markdown expression for a firm inactive on the WMP market is the same as for a WMP buyer. In the particular case where $\alpha = 0$, the processor has all the bargaining power and we find $\frac{w_c}{w_{fi}e_{ic}} = 1 + \varepsilon_i^{S-1}$.

Estimates - WMP Buyers vs. WMP Sellers

Table 1.14: Markdowns and Markups - WMP Buyers vs. WMP Sellers

Sample	Markdowns		Markups	
	WMP Buyers	WMP Sellers	WMP Buyers	WMP Sellers
Average	1,20	1,09	1,18	1,34
Weighted Average	1,22	1,11	1,46	1,36
Median	1,17	1,06	1,02	1,18
Observations	6,610	1,439	4,989	1,057

Notes: Sample restricted to firms for which we manage to link raw milk collection and production. Markdowns computed based on raw milk prices at the regional level. Weighted averages based on quantity (dry matter content) shares upstream and downstream. Markdowns at the group-*département*-time level, markups at the group-product-time level, margins at the group-*département*-product-time level.

”schizophrenic” (negotiation breakdown in a *département* does not affect negotiations in others).

Table 1.14 shows summary statistics for markup and markdown estimates of WMP buyers and WMP sellers respectively. Median and simple average markdowns (resp. markups) estimated for WMP buyers are slightly above (below) markdowns (markups) estimated for WMP sellers. Given the identification methodology, this comes from the fact that:

$$w_c - \lambda_f < w_c$$

This corresponds to the idea that the opportunity cost of renouncing to sell WMP for WMP sellers is below the price of WMP on the commodity market. This result can partly come from a limitation of our methodology. Throughout the empirical analysis, we assumed a firm-level processing cost. A marginal processing cost of commodities that would be lower than the marginal processing cost of final goods - within the same firm - could for instance drive the pattern observed.

1.D4. Competitive Labor

Discussion

Throughout the analysis, we assume away labor market power because we think it is likely limited in this industry, for three main reasons. First, dairy firms are (i) relatively smaller on the labor market(s) than they are on milk markets, which implies both that they are likely to have a limited labor MP, and if any, it would be of a second-order magnitude compared to buyer power on raw milk. Second French processors are confronted with regulation, especially when hiring low-skilled workers. An important part of such workers is hired at the minimum wage, a level at which the labor supply is inelastic, implying no room for wage-setting power. Finally, dairy firms may not necessarily operate in a monopsony environment when recruiting high-skilled workers. For such workers, given the rural places where dairy firms essentially operate, high-skilled workers may be a relatively rare resource, balancing the relationship in their favor.

Theoretical Impact of Labor Market Power

That being said, we examine in the following what would be the impact of the existence of labor MP on our theoretical results, before turning to its impact on empirical estimates.

Adding an additional source of MP would affect the first order condition of the variable profit maximization, and consequently some definitions of our objects of interest. The first order conditions would rewrite:

$$\underbrace{\left(1 + \varepsilon_{fj}^{D-1}\right) p_{fj}}_{\text{marginal revenue } MR_{fj}} = \underbrace{\left(1 + \varepsilon_{fi}^{S-1}\right) w_{fi} e_{ij} + \left(1 + \varepsilon_L^{S-1}\right) \lambda_{fj}}_{\text{marginal cost } MC_{fj}}. \quad (1.30)$$

Due to the existence of monopsony power on the labor market, the marginal cost MC_{fj} would additionally feature the supply elasticity of labor ε_L^S . This would imply redefining markups and markdowns in Definitions 1 and 2, replacing λ_{fj} by $(1 + \varepsilon_L^{S-1})\lambda_{fj}$. Doing so would be necessary to acknowledge the contribution to the total margin of a markdown on the labor market, which, starting from (1.30), would be defined in the following way:

$$\nu_L \equiv \frac{(1 + \varepsilon_{fj}^{D-1})p_{fj} - (1 + \varepsilon_{fi}^{S-1})w_{fi}e_{ij}}{\lambda_{fj}} \quad (1.31)$$

The markdown on the labor market would have an interpretation akin to the markdown on raw milk markets, as being the wedge between the marginal contribution of labor to profit, and its shadow cost.

While the theoretical definitions of markups and markdowns would be affected by the presence of labor MP, the margin definition would be left unchanged, as the *accounting marginal cost* remains identical.

Impact of Labor Market Power on the Estimation

If firm f had wage-setting power, its variable cost minimization program would be:

$$\begin{aligned} \min_{L_f} \quad & Z_f(L_f)L_f \\ \text{s.t.} \quad & F(L_f, K_f, \Omega_f) - y_f^* \geq 0, \end{aligned}$$

Given labor monopsony power, the implied marginal processing cost (MPC) would be:

$$\tilde{\lambda}_f = (1 + \varepsilon_L^{S-1}) \frac{Z_f L_f^*}{\varepsilon_f^{Y,L} y_f^*}.$$

It would differ from our original definition of $\lambda_f = \frac{Z_f L_f^*}{\varepsilon_f^{Y,L} y_f^*}$, which in such context would have to be interpreted as the *accounting* MPC. If there was labor monopsony power, then $1 + \varepsilon_L^{S-1} > 1$, implying $\tilde{\lambda}_f > \lambda_f$.

As mentioned above, *the presence of such labor MP would not affect the margin estimates*. It would however impact our markup and markdown estimates in different ways, depending on the firm's status. If firm f is a WMP buyer, its markups and markdowns have been estimated as:

$$\nu_{fi} = \frac{w_c}{w_{fi}e_{ic}}, \quad \forall i \quad \text{and} \quad \mu_{fj} = \frac{p_{fj}}{w_c e_{cj} + \lambda_f}, \quad \forall j.$$

From these definitions and the discussion above, it is straightforward to see that *the presence of labor MP would leave unchanged our markdown estimates for WMP buyers*.

It would however lead to an overestimation of their markups, which should have featured $\tilde{\lambda}_f$ instead of λ_f . In such a case, a part of the margin that is due to the existence of markdown on wages would have been falsely attributed to monopoly power.

If firm f is a WMP seller, its markups and markdowns have been estimated as:

$$\nu_{fi} = \frac{(w_c - \lambda_f)}{w_{fi}e_{ic}}, \forall i \quad \text{and} \quad \mu_{fj} = \frac{p_{fj}}{(w_c - \lambda_f)e_{cj} + \lambda_f}, \forall j.$$

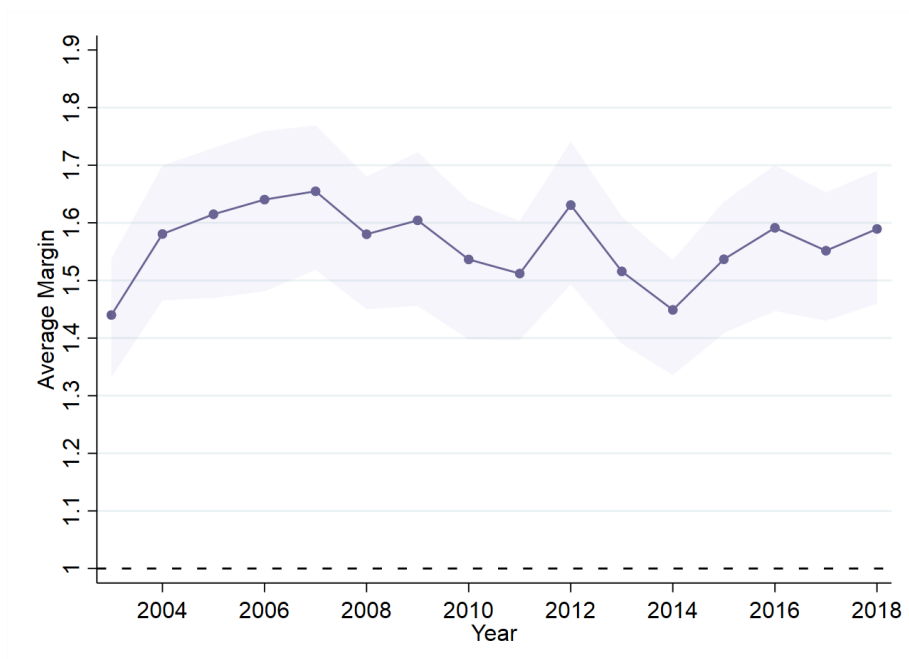
For reasons similar to the ones mentioned above, the markdown would be overestimated. The bias in the estimated markup on product j depends on its dry matter content and the WMP one (the commodity c). The markup would be overestimated (resp. underestimated) if $e_j < e_c$ (if $e_j > e_c$), *i.e* if product j is less (more) dry matter intensive than WMP.

Quantitatively, such biases would however remain limited, as the estimated MPC λ_f (to be inflated by the potential wage markdown) only represents around 25% of the total marginal costs, the remaining part being constituted by raw milk or WMP purchases.

Appendix 1.E Additional Results

1.E1. Average Margin over Time

Figure 1.15: Average Margin Over Time

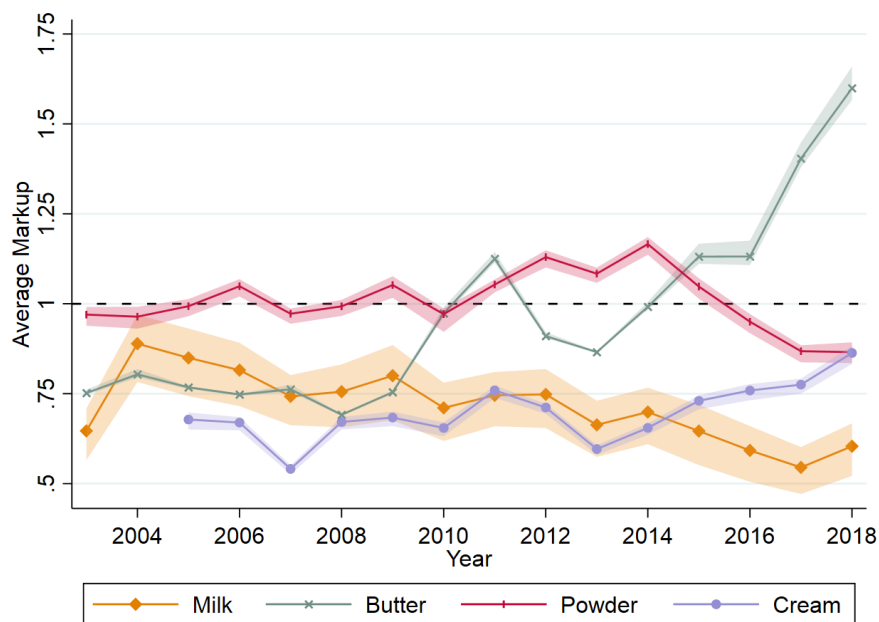


Notes: Weighted average, using dry matter content quantity weights. Bootstrapped 95% confidence interval displayed.

1.E2. Average Markups - Bulk Products

Among bulk products, and as shown in Figure 1.17, milk powder features an average markup of around one. The milk powder category encompasses WMP - on which our methodology imposes a markup equal to one for a subsample of firms - but also skimmed milk powder. Markup estimates on bulk products markets are noisier than on final consumption goods, as only a few French processors sell on such markets. Interestingly, markups are close to or below one on such products, either directly sold to other processors or sold on global commodity markets, on which our estimating procedure does not impose a constraint. We view this feature as supporting the idea that French manufacturing firms are price takers when selling bulk dairy products.

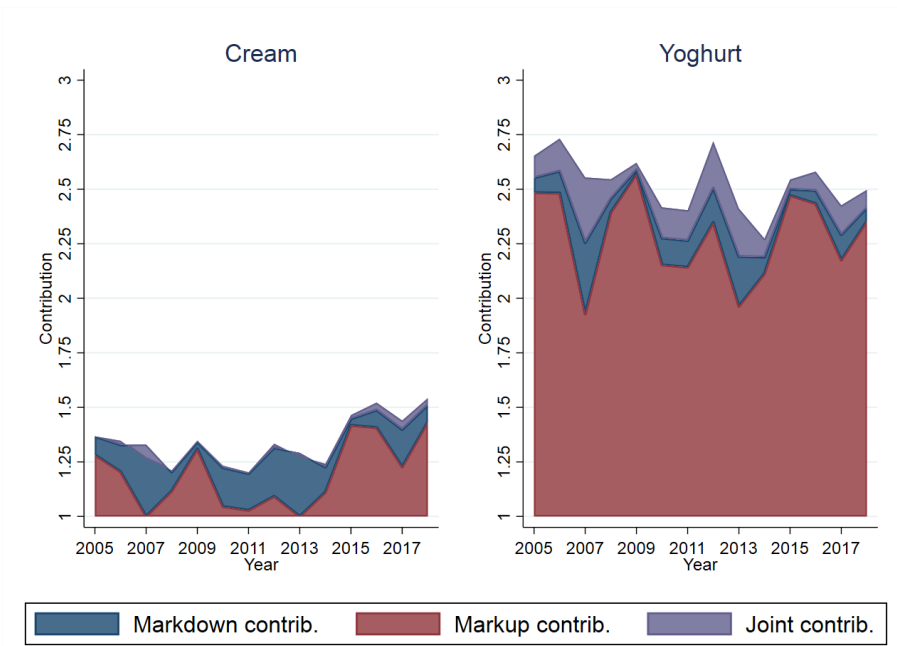
Figure 1.16: Markups on Bulk Products - Product Category Averages



Notes: Weighted averages, using dry matter content quantity weights. Bootstrapped 95% confidence intervals (CI) displayed. CI emanate from errors in the estimation of the marginal processing cost and are thus proportional to its share in the total marginal cost of the considered product. Cream product average not displayed for 2003 and 2004 as products nomenclature does not allow to distinguish final from bulk cream before 2005.

1.E3. Markup and Markdown Contributions by Product

Figure 1.17: Markup and Markdown Contributions - Product Category Averages



Notes: Weighted averages, using dry matter content quantity weights.

1.E4. Pass-Through Analysis - Graphical Representation

Figure 1.18: Impact of an Increase of the Commodity Price for Commodity Buyers

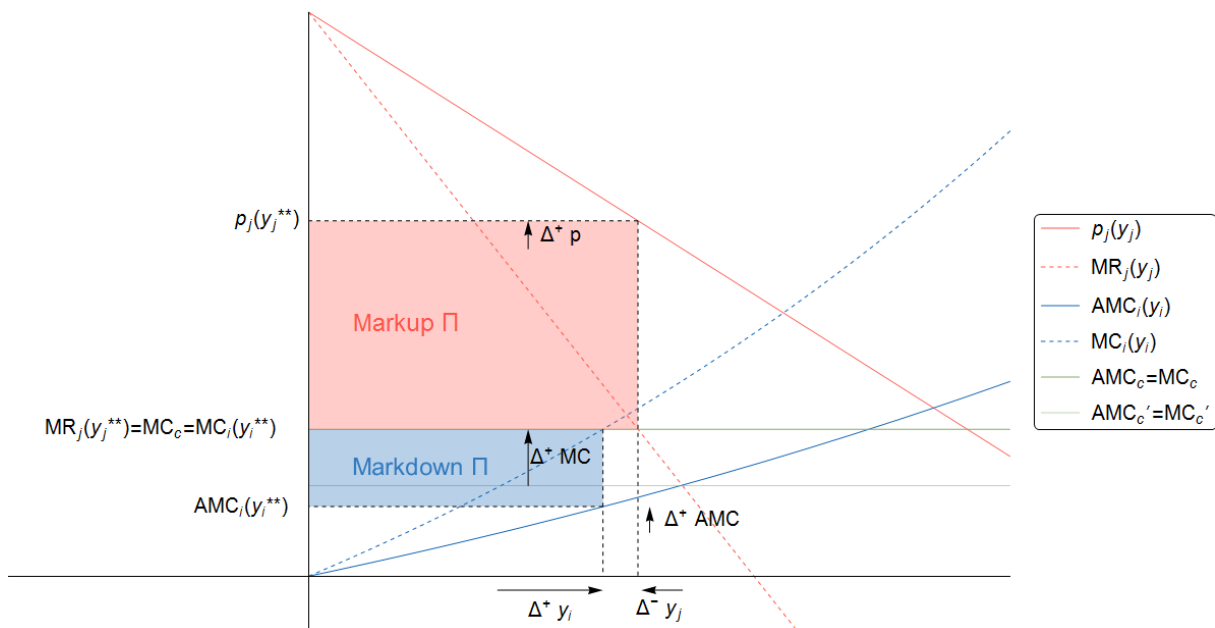
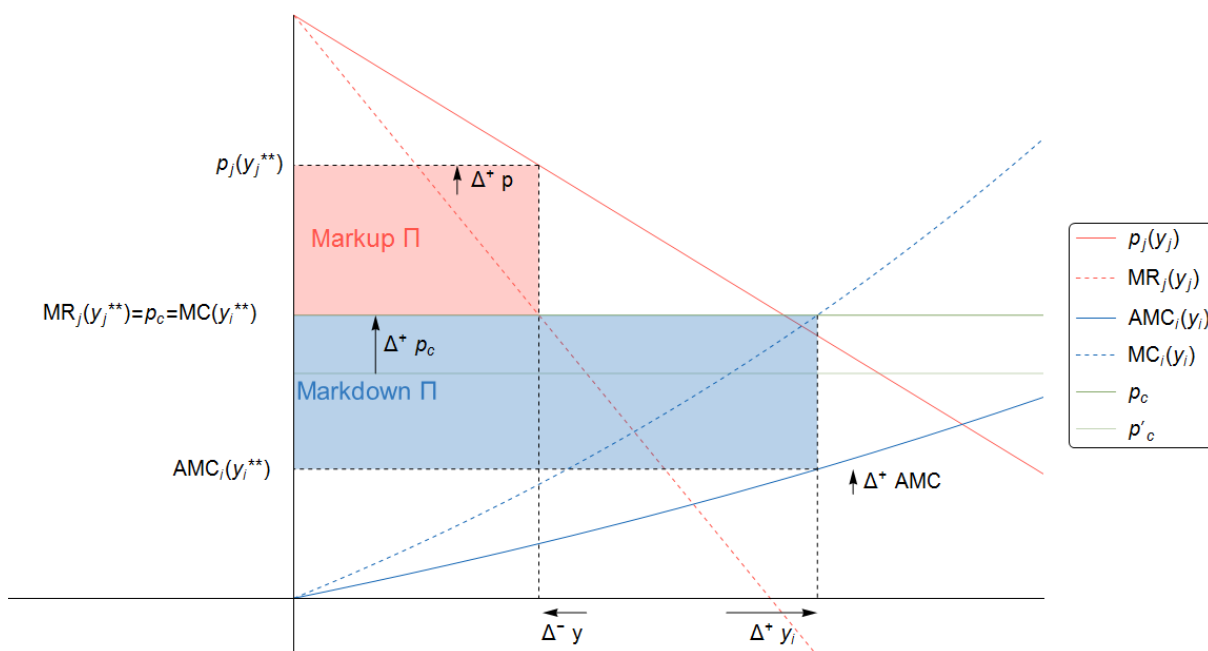


Figure 1.19: Impact of an Increase of the Commodity Price for Commodity Sellers



1.E5. Additional Theoretical Pass-Through Derivations

Pass-Through for WMP Sellers

Under the identifying assumption that WMP sellers do not have seller power in the WMP market, their markdowns and markups are defined as follows:

$$\nu_{fi} \frac{(w_c - \lambda_f)}{w_{fi} e_{ic}}, \forall i \quad \text{and} \quad \mu_{fj} = \frac{p_{fj}}{(w_c - \lambda_f) e_{cj} + \lambda_f}, \forall j.$$

We consider here variations in the price w_c at which they are able to sell WMP. Proceeding as in Section 5.3., both definitions yield the following pass-throughs on upstream prices:

$$\varepsilon_{w_c}^{w_{fi}} = \tilde{\theta}_{fic}^{-1} - \varepsilon_{w_c}^{\nu_{fi}}, \quad (1.32)$$

and downstream prices

$$\varepsilon_{w_c}^{p_{fj}} = \varepsilon_{w_c}^{\mu_{fj}} + e_{cj} \frac{w_c}{p_{fj}} \mu_{fj}. \quad (1.33)$$

Pass-Through with Endogenous Marginal Processing Cost

We proceed in a similar way as in Section 5.3. but authorizing λ_{fj} to adjust, *i.e.* considering it as an endogenous object $\lambda_{fj}(w_c)$.

Starting from the margin definition, (1.13) rewrites:

$$\varepsilon_{w_c}^{p_{fj}} = \varepsilon_{w_c}^{M_{fij}} + \theta_{fij} \varepsilon_{w_c}^{w_{fi}} + (1 - \theta_{fij}) \varepsilon_{w_c}^{\lambda_{fj}}, \quad (1.34)$$

Starting from the markup definition, (1.14) rewrites:

$$\varepsilon_{w_c}^{p_{fj}} = \varepsilon_{w_c}^{\mu_{fj}} + \tilde{\theta}_{fij} (\varepsilon_{w_c}^{\nu_{fi}} + \varepsilon_{w_c}^{w_{fi}}) + (1 - \tilde{\theta}_{fij}) \varepsilon_{w_c}^{\lambda_{fj}},$$

or, in the absence of MP (rewriting (1.15)):

$$\varepsilon_{w_c}^{p_{fj}} = \theta_{fij} \varepsilon_{w_c}^{w_{fi}} + (1 - \theta_{fij}) \varepsilon_{w_c}^{\lambda_{fj}}.$$

Finally, (1.16) is unchanged:

$$\varepsilon_{w_c}^{w_{fi}} = 1 - \varepsilon_{w_c}^{\nu_{fi}}$$

while (1.17) rewrites:

$$\varepsilon_{w_c}^{p_{fj}} = \varepsilon_{w_c}^{\mu_{fj}} + \theta_{fcj} + (1 - \theta_{fcj}) \varepsilon_{w_c}^{\lambda_{fj}}$$

1.E6. Additional Reduced-Form Pass-Through Estimates - WMP Sellers

Table 1.15: Pass-Through: Reduced-Form Estimates - WMP Sellers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Milk Price	Markdown	Output Price	Markup	Margin	Output Price	Markup	Margin
	w_{fi}	ν_{fi}	p_{fj}	μ_{fj}	M_{fij}	p_{fj}	μ_{fj}	M_{fij}
WMP Price	0.239*** (0.018)	0.824*** (0.044)	0.067 (0.050)	-0.667*** (0.062)	-0.089*** (0.009)	0.748*** (0.128)	-0.101 (0.138)	0.791*** (0.034)
Farm Cost Index	0.595*** (0.041)	-0.262** (0.077)	0.796*** (0.183)	0.555** (0.255)	0.015 (0.034)	0.181 (0.298)	0.281 (0.362)	-0.465*** (0.069)
Obs	1,259	1,259	489	489	15,337	408	408	9,620
R2	0.649	0.762	0.972	0.775	0.761	0.916	0.596	0.568
Sample			Final goods	Final goods	Final goods	Bulk products	Bulk products	Bulk products
FE	fi	fi	fj	fj	fij	fj	fj	fij

Notes: Standard errors are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All variables are in log. Sample restricted to firms for which we manage to link raw milk collection and production, and WMP sellers only. The level of observation vary with the level at which the considered outcome is observed or estimated: (i) firm-*département*-year level for raw milk prices and markdowns (although prices used here are at the region-year level), (ii) firm-product-year level for output prices and markups, (iii) firm-*département*-product-year level for margins. Margins computed under an assumption of homogeneous milk sourcing across products for a given firm.

Table 1.16: Pass-Through: Reduced-Form Estimates - All Firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Milk Price	Markdown	Output Price	Markup	Margin	Output Price	Markup	Margin
	w_{fi}	ν_{fi}	p_{fj}	μ_{fj}	M_{fij}	p_{fj}	μ_{fj}	M_{fij}
WMP Price	0.229*** (0.011)	0.779*** (0.017)	-0.007 (0.020)	-0.646*** (0.032)	-0.108*** (0.007)	0.697*** (0.057)	0.012 (0.061)	0.653*** (0.017)
Farm Cost Index	0.647*** (0.010)	-0.609*** (0.070)	0.638*** (0.057)	0.404*** (0.088)	-0.126*** (0.022)	-0.032 (0.124)	-0.158 (0.152)	-0.871*** (0.043)
Obs	6,840	6,840	3,172	3,172	38,038	1,936	1,936	25,263
R2	0.683	0.776	0.972	0.839	0.809	0.929	0.795	0.754
Sample			Final goods	Final goods	Final goods	Bulk products	Bulk products	Bulk products
FE	fi	fi	fj	fj	fij	fj	fj	fij

Notes: Standard errors are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All variables are in log. Sample restricted to firms for which we manage to link raw milk collection and production. The level of observation varies with the level at which the considered outcome is observed or estimated: (i) firm-*département*-year level for raw milk prices and markdowns (although prices used here are at the region-year level), (ii) firm-product-year level for output prices and markups, (iii) firm-*département*-product-year level for margins. Margins computed under an assumption of homogeneous milk sourcing across products for a given firm.

Table 1.17: Pass-Through: Reduced-Form Estimates - All Firms

	(1)	(2)	(3)	(4)	(5)
	Milk Price	Markdown	Output Price	Markup	Margin
	w_{fi}	ν_{fi}	p_{fj}	μ_{fj}	M_{fij}
WMP Price	0.229*** (0.011)	0.779*** (0.017)	0.265*** (0.031)	-0.392*** (0.035)	0.210*** (0.010)
Farm Cost Index	0.647*** (0.010)	-0.609*** (0.070)	0.386*** (0.061)	0.195** (0.080)	-0.409*** (0.022)
Obs	6,840	6,840	5,119	5,119	63,557
R2	0.683	0.776	0.964	0.878	0.856
FE	fi	fi	fj	fj	fij

Notes: Standard errors are in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All variables are in log. Sample restricted to firms for which we manage to link raw milk collection and production. The level of observation varies with the level at which the considered outcome is observed or estimated: (i) firm-*département*-year level for raw milk prices and markdowns (although prices used here are at the region-year level), (ii) firm-product-year level for output prices and markups, (iii) firm-*département*-product-year level for margins. Margins computed under an assumption of homogeneous milk sourcing across products for a given firm.

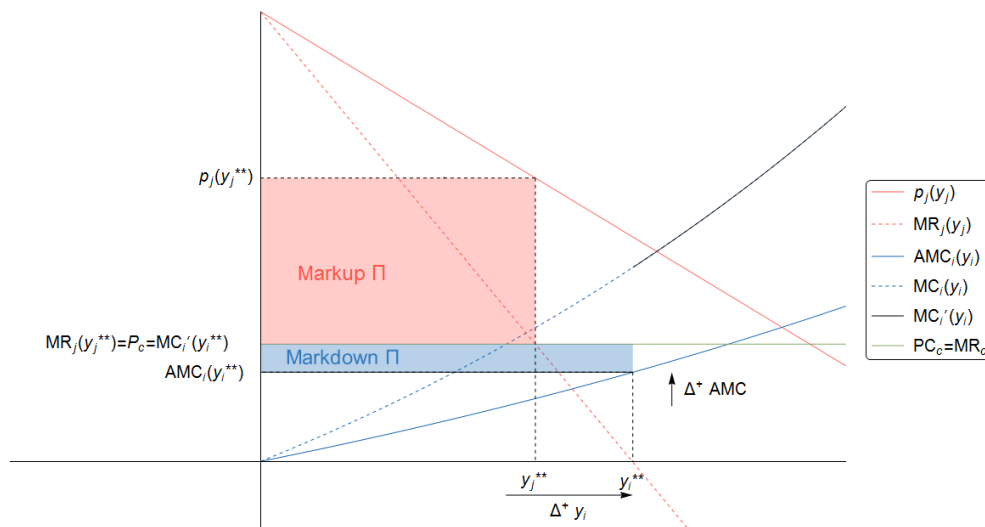
1.E7. Illustrating the Role of a Price Floor

The main intuitions regarding the impact of a price floor are gathered in Figures 1.20 and 1.21 of Appendix 1.E7., showing its effects for firms that initially buy and sell WMP respectively.

As mentioned, *absent strategic downstream retailers*, the price floor would in our theory have no impact on downstream dairy product markets, because firms sell the same quantity in both equilibria with and without a price floor.

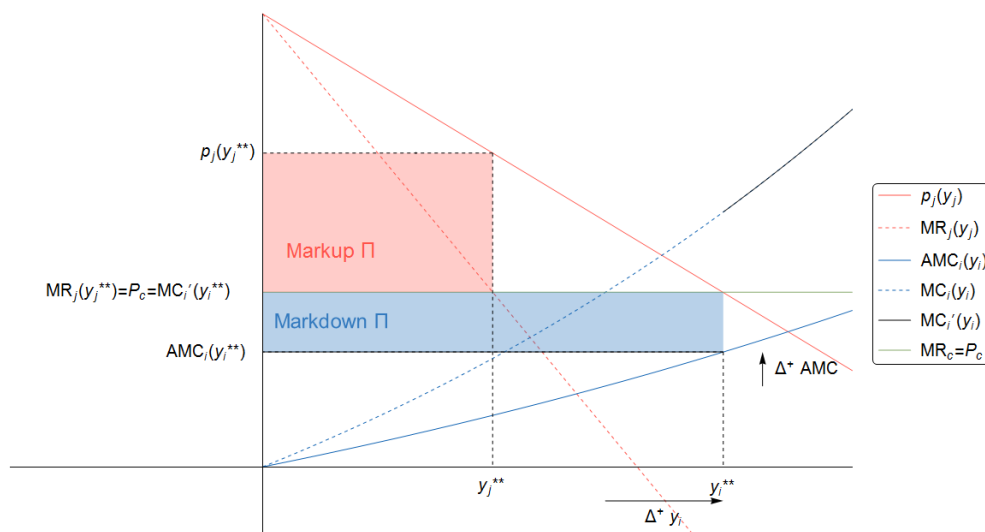
Upstream, the price floor induces similar effects for both types of firms: increasing prices and quantities on raw milk markets. Setting a price floor – at an efficient level – mechanically modifies the milk supply curve faced by processors. At the price floor level, milk supply becomes flat, and so does the marginal cost of processors. This implies that processors' buyer power is diminished: they become price takers on the first units of raw milk purchased, at a price equal to the price floor. At some point, raw milk supply intersects with the price floor level, and the marginal cost curve jumps and becomes increasing again. This intersection determines the new and larger quantity of milk purchased by processors.

Figure 1.20: Price Floor - WMP Buyers



The surplus of milk purchased is - in this simple world - sold on commodity markets. This implies that firms that were initially purchasing WMP have substituted it with raw milk, and are now WMP sellers.

Figure 1.21: Price Floor - WMP Sellers



Chapter 2

Production Quota Reforms and the Cream-Skimming of the French Milk Market

Note: This chapter is co-authored with Rémi Avignon (INRAE-SMART).¹

Abstract

How do input market fragmentation and liberalization affect production allocation? This paper analyzes the impact of production quotas and their progressive removal on the French milk market. We show that production quotas generated two types of distortions. First, by mechanically fixing production shares across French *départements* at their pre-quota (1984) level, quotas stopped a natural spatial concentration for about 25 years, a process that restarted right after the beginning of the quota removal process in 2008. Second, the design of the quota system spurred the growth of small farms while constraining the expansion possibilities of larger farms. This redistributive scheme thus successfully refrained inequalities among farms growing until then, yet at the cost of distorting the competition-led *cream-skimming* of farms. We finally document how the catching-up process in farm selection following the quota removal intervened more or less early across *départements*, depending on the stringency implied by quota constraints at the local level. We rationalize these observations with a simple model of perfect competition between heterogeneous farms. At the farm level, the effect of the liberalization ultimately depends on (i) the efficiency gains the farm can achieve with the liberalization and (ii) its location in a *département* sheltered from competition or constrained by quotas. In subsequent analysis, we plan to build a structural model to assess better the (re)allocative effects of such input market liberalization.

Keywords: Market Fragmentation, Market Liberalization, Misallocation, Production Quotas.

¹We are grateful to Marie-Laure Allain, Claire Chambolle, and Francis Kramarz for their advice. We also thank Isabelle Méjean. This research benefited from financial support from the ANR “Investissements d’avenir” program under the ANR grant ANR-18-EURE-0005 (EUR DATA EFM).

1. Introduction

How do input market fragmentation and liberalization affect production allocation? This paper analyzes how French dairy farms have been affected by the introduction of milk production quotas in 1984 and their removal in 2015. This quota regime has shaped the European dairy industry for more than thirty years. Its implementation originally replaced a European price support policy which previously led to a huge overproduction in the early 1980s. Therefore, the objective of the quota introduction was twofold: supporting farmer incomes and controlling produced quantities.

Production quotas were first allocated to each European Union (EU) member state, imposing upper bounds on production at the national level. Each country could then internally allocate production quotas among milk producers. In France, the implementation of quotas also aimed at reaching two additional goals: (i) refraining a growing production dispersion across farms, and (ii) attenuating territorial inequalities. French authorities thus opted for an attribution of quotas by *département*, thus fixing their production level. Local authorities were then in charge of delivering quotas across farms, following a redistributive scheme favoring small farms to the detriment of larger farms. In 2003, a CAP reform aiming at reducing the distortive effects of regulation within European agricultural markets acted the progressive removal of quotas starting in 2008 and completed in 2015, after seven years of progressive quota increases.¹

Backed by a simple model, we distinguish the effects quotas had due to the constraints imposed on farm sizes from those due to the implied constraints on the spatial allocation. This model allows us to make easily testable predictions on the market evolution following the quota removal.

In order to test these predictions, we exploit several datasets. The first one contains milk production and the farm number at the *département*-year level for the 1995-2018 period. To complement these data, we also mobilize farm-year level quotas and production data, which we observe from 1995 to 2014 and from 2007 to 2018, respectively.

Using these data, we make observations that confirm the theoretical predictions. Through the fixed allocation at the *département* level, quotas have completely stopped a growing spatial concentration, freezing the distribution of milk production across space for 25 years. The concentration process restarted with the gradual quota removal, resulting in an ongoing polarization of *département* market shares, as production grows in initially important *départements* and declines in initially smaller ones. Moreover, we show that exit rates of farms in inefficient *départements* largely anticipated the quota removal, farmers probably taking into account expected profits in the long run.

Due to the redistributive scheme French policymakers opted for, the growing inequali-

¹We carefully describe the specificities of the French allocation scheme and the details of the quota removal in Section 2.1..

ties in farm production and revenues were successfully restrained during the quota period. On the contrary, the quota removal eventually authorized large farms to grow relatively faster than small, a phenomenon which was completely inverted by the quota redistributive scheme. The containment of inequalities between farms and *départements* thus overall appears to have come at the cost of generating distortions which altered the natural *cream-skimming* of the French milk market, slowing down the selection process of the most efficient farms by protecting the least efficient ones.

We also document the reallocation dynamics that progressively led the French milk market to its current (2018) structure. On the one hand, we show that the spatial relocation process started in 2008, following the first quota increases, and quickly strengthened over the subsequent years. On the other hand, we exhibit evidence that the inter-farm reallocation processes initiated at various dates across territories, depending on the stringency of quota constraints at the *département* level. We show that consistently with our theoretical setting, individual farm evolutions under the quota regime and the progressive liberalization ultimately depend on their geographical localization and position in the farm size distribution.

The present work is part of a literature studying the impact of the quota liberalization on the dairy market. Its expected impact on international dairy trade was largely studied *ex ante* (Bouamra-Mechemache et al., 2002b,a; Lips and Rieder, 2005; Witzke and Tonini, 2009). Bouamra-Mechemache et al. (2008) in particular compare the respective expected effects of a *soft landing* strategy, *i.e* the gradual increase of quotas before their complete removal, as ultimately adopted, and a *hard landing* one. The literature evaluating quota effects and removal *ex post* is scarcer. Huettel and Jongeneel (2011); Zimmermann and Heckelei (2012); Samson et al. (2016) study the effects of quotas and their removal on dairy farms structures and growths in Europe, but none of them addressed the questions raised by quotas redistributive schemes such as the one implanted in France. In Section 7.1., we evoke several strands of more general literature we aim at building on in the future, in order to have a more structural assessment of the quota (introduction and liberalization) allocative effects, and of its different margins.

The rest of the paper is structured as follows. Section 2 precisely details the quota regulation, our data, and facts motivating the theoretical elements introduced in Section 3. These facts also guide subsequent empirical analyses of the spatial distribution of milk production presented in Section 4 and the description of the distortions generated across farms, shown in Section 5. Section 6 presents the dynamics of the liberalization across farms and space. Finally, Section 7 discusses possible further theoretical and empirical developments - and Section 8 concludes.

2. Context, Data and Motivating facts

2.1. The Quota Regulation

Historical Context

The milk quota regulation was implemented in 1984² in the European Union (EU)³, as a part of the Common Agricultural Policy (CAP). The CAP has been created in 1962 with the primary goal of enhancing modernization and production of agriculture in Europe, and restrictions induced by the introduction of production rights thus mark an important shift. Before 1984, milk production was encouraged by numerous policies, such as guaranteed prices, public storage, protectionism, and export subsidies. As a consequence, the quantity of milk produced was growing fast, about +2.5% each year on average in the EU over the 1970-1983 period.⁴ These production-supporting policies led to an important overproduction at the beginning of the 1980s. In 1983, the EU milk production exceeded its consumption needs by 20%, among which 13% were stored (the famous "mountains of butter") and 7% exported - at a loss - outside the EU. During the same year, the EU support price was 12% above the world average price of milk. The costs of production-supporting policies were evaluated to lie between 15% and 20% of the total production value. In such a context, regulating authorities opted for the creation of production quotas to protect farmer revenues and reduce the costs of the milk market regulation. Quotas were progressively introduced, at a level 3% below the 1984 European production, before being gradually decreased by 7% over the years until 1992, when they were eventually stabilized.

Milk Quota Implementation

The production of each member state was decided at the European level. Then, each state could decide how to allocate production rights among its farmers. In France, quotas were initially allocated at the *département* level, based on the 1983 production levels. In turn, production rights were allocated across farmers within *départements* depending on the land owned by farmers. This implied that a farmer had to buy more land in order to acquire more production rights.

The modernization process of milk production over the years before the quota implementation was very heterogeneous across farms and territories. The French quota allocation scheme was thus designed according to a redistributive perspective of countering the rising concentration of milk production and revenues between territories (*départements*) and farmers. Further production divergences between *départements* were therefore me-

²See [Council Regulation \(European Economic Community\) - No 856/84 of 31 March 1984](#) (in French).

³We here indifferently speak of the European Union and the European Economic Community.

⁴All the figures mentioned in this paragraph comes from the [Rapport de la Commission d'Enquête du Sénat No 341 \(1991-1992\)](#) (in French).

chanically impeded by the quota system, as quotas were initially split by *départements* depending on their initial production shares. Importantly, no transfer of production rights between *départements* was authorized until 2012.⁵

In order to limit growing inequalities across farms in terms of production and revenue, a system of quota taxes was also implemented. When the land was transferred between two existing farms, quotas associated with the land were taxed in order to feed a *département* reserve, with a levy rate increasing with the buyer size. Quotas available in the *département* reserve were then attributed to farmers by a *département* committee, along a similarly redistributive scheme. Quotas were in priority allocated to relatively smaller farms and new young farmers, in order to facilitate their installation before the potential leftovers were split between relatively increasingly bigger demanding farms. This overall generated distortions, encouraging the growth of relatively smaller farms and discouraging the growth of relatively bigger ones.

The Quota Removal: A *Soft Landing*

The 2003 CAP reform aimed to reduce the distortive effects of regulations in European agricultural markets. In the dairy market, this policy will, associated with the growing world demand for dairy products, led the European authorities to plan the suppression of milk quotas. A *soft landing* strategy - meaning that quotas would be progressively increased between 2008 and 2015 - was decided. EU quotas were increased by 2% in 2008-2009 and by 1% each year until 2014-2015, before their total removal from 2015-2016 onward.

2.2. Data

Our analysis rests on the exploitation of several datasets, provided by the French Ministry of Agriculture⁶: the *Enquête Annuelle Laitière* (EAL, 1995-2018), the *Base Quotas* (Quotas Database, 1995-2014), and the *Enquête Livraisons* (EL, 2015-2018). From the EAL, we use the milk production and the farm number at the *département*-year level.⁷ To complement this data, we mobilize the Quota Database and the EL, which contains farm-level location, quotas, and production data. More precisely, the former gives us the quantity of quotas delivered to each farm for each year of the 1995-2014 period. For the years 2007 to 2014, the database also contains the actual milk production/sales of each

⁵From 2012 to the complete removal of quotas in 2015, the repartition of quotas was delegated to "bassins laitiers" (instead of *départements*), which are agglomerations of several neighboring *départements*, thus authorizing such transfers to happen, but only within these narrowly defined regions.

⁶We are particularly thankful to Corinne Prost and FranceAgrimer for making this data available to us through the CASD.

⁷The EAL actually provides these measures at the buyer-*département*-year level, but we do not use the buyer dimension for now. We plan to extensively use this dimension in subsequent analyses, see 8..

farm, similar to the EL for the years 2015 to 2018.⁸

Importantly, in what follows, we use quantity data when available. For the study of farm-level behaviors before 2007, we have to use quotas data. Throughout the analysis of intensive growth rates by size of farms conducted in Sections 5. and 6., we interpret these quotas data *as if* they were production data. In reality, the growth rates obtained may be lower bounds to the actual production growth rates. A check of respective trends for the overlapping years 2007 to 2014 for which we have individual quotas and produced quantities however confirms that quotas are a good proxy for quantities when considering farms' relative sizes and relative growth rates.

2.3. Motivating Facts

In this section, we present some aggregate trends which motivate the theoretical setup presented in Section 3. and highlight some questions raised by the progressive quota removal, treated in the rest of the paper.

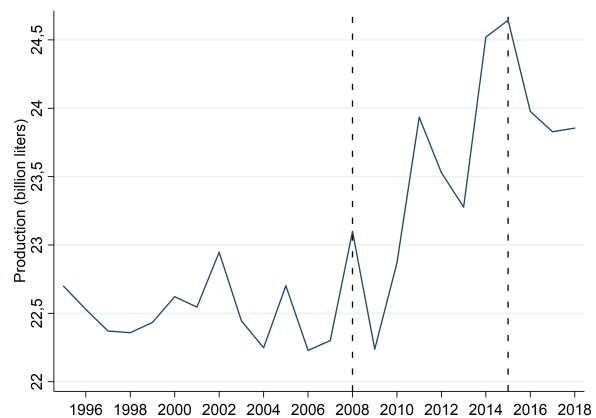
Milk Production and its Spatial Distribution

First, national milk production started to significantly rise in 2008, after having been basically stable since 1995. The progressive quotas increase was thus accompanied by a surge in raw milk production, and production quotas thus arguably seem to have impeded the growth of milk production at the national level, unsurprisingly reaching their primary goal to limit overproduction. Finally, the drop of production in 2016 (before its stabilization) may be seen as the joint

consequence of (i) the increased competition at the European level following the complete quota removal, and (ii) the introduction of incentives to farms to reduce quantities produced after a new overproduction crisis in 2015-2016.

Through their practical implementation by *départements* in France (described in Section 2.1.) quotas also froze the spatial repartition of milk production. Indeed, as shown by Figure 2.2, quotas mechanically stabilized production shares across *départements* between 1996 and 2007, thus stopping a trend of spatial concentration of the milk production at

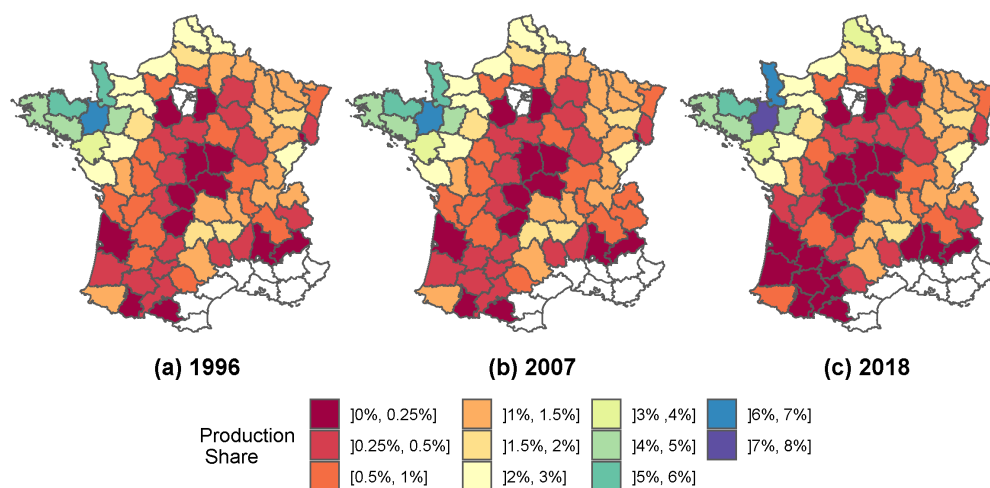
Figure 2.1: Milk Production in France



⁸Again, this dataset actually contains this information at the buyer-farm-year level but we here also abstract from the buyer dimension for now.

its 1996 level.⁹ In 2018, at the end of the period of analysis and after the gradual quota removal initiated in 2007, milk is more produced in initially large producing *départements*, and much less in initially small producing *départements*, from the South West of France for instance.

Figure 2.2: *Département* Production Shares

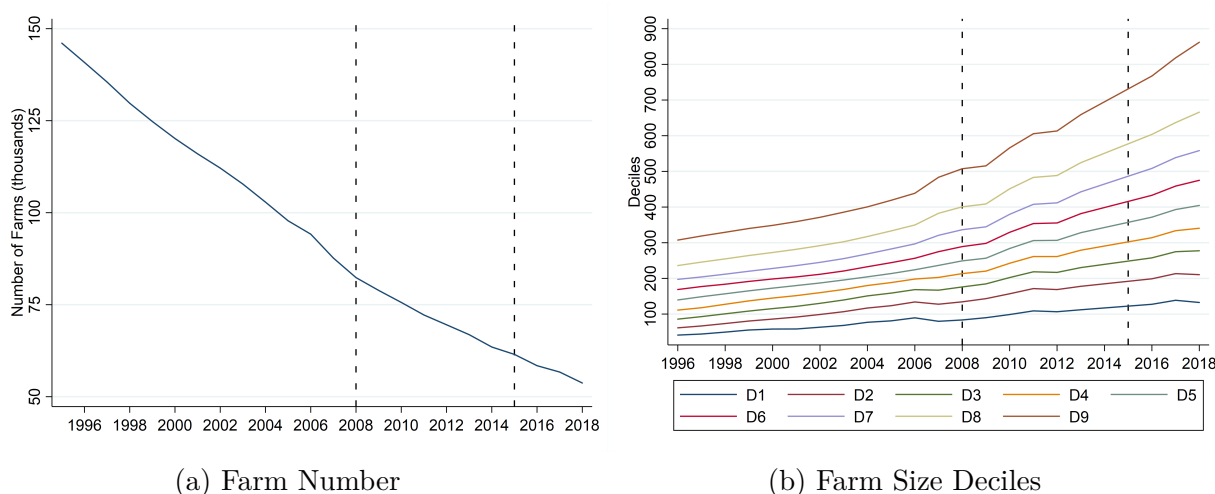


Notes: *Départements* in white have a null or negligible milk production.

In the first part of our analysis (Section 4.), we try to assess how much and how quotas impeded the local growth or decline of milk production in the different territories, and thus slowed down its spatial concentration in France.

Farm Structure

Figure 2.3: Farm Number and Distribution



Notes: (a) Number of raw-milk producers in France. (b) Farm raw-milk production deciles, thousand liters.

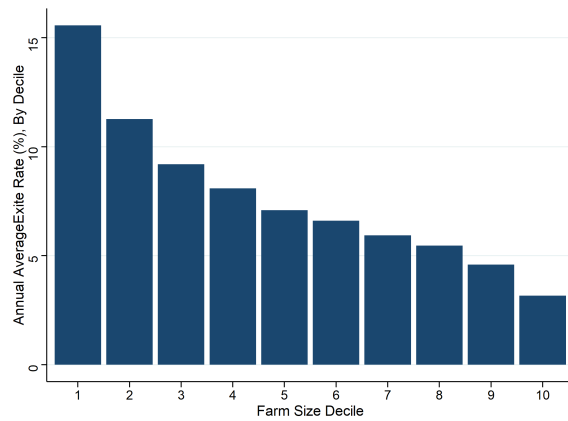
⁹Itself similar to its pre-quota 1983 level.

Figure 2.3 (a) constitutes primary evidence that the introduction of quotas did not stop the long-run trend towards greater concentration of milk production across a smaller farm number. Indeed, the farm number steadily decreased from 150,000 to around 55,000 between 1996 and 2018. As the production significantly increased after 2008, the yearly milk production of the average farm drastically increased, from 150,000 to 450,000 liters. This trend is common to many agricultural markets in developed countries and is essentially the result of technical progress and increasing (or even increasingly increasing) returns to scale. While the quotas did not stop this *cream-skimming* process, it may however have altered it, due to the way they were implemented, aiming at favoring relatively smaller farms. Figure 2.3 (b) corroborates this intuition by showing how all deciles of the distribution of farm productions increased and widened from 1996 to 2018, but seemingly faster once the quotas started to rise.

Moreover, Figure 2.4 presents average exit rates of farms by size deciles over the whole period of analysis. Exit rates are markedly decreasing with the size of the farm.¹⁰ We view this pattern as suggesting that more productive farms are generally larger and use it as a basis for the theoretical setting developed in Section 3..

In the second part of our analysis (Section 5.), we document how quotas constrained the distribution of milk production *across farms*, both *within* and *across départements*.

Figure 2.4: Exit Rates by Farm Size Deciles

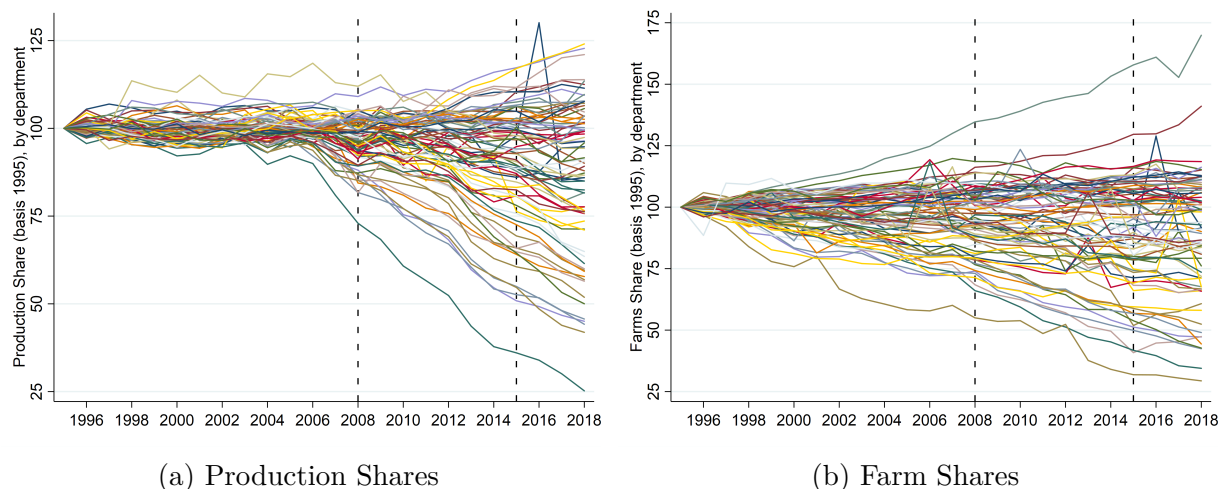


Notes: Average annual exit rates by decile, 1996-2018.

¹⁰This pattern is constant over the period as later shown in Figure 2.14 (b).

The Relocation Process

Figure 2.5: Relocation



Notes: (a) Average production share by *département*, basis 100 in 1995. (b) Average farm number share by *département*, basis 100 in 1995.

Figures 2.5 (a) and (b) show the contrast between respective timings of the spatial relocation of production on one hand and of farms on the other hand. Whereas the spatial relocation of production essentially took place after the beginning of the quota removal process (2008), the *département* farm shares kept diverging during the entire period. Efficiency gains associated with farm size increases may thus have occurred at various times, depending on the territory. In the last section of our analysis (Section 6.), we try to identify these dynamic efficiency gains, as well as their timing and determinants.

3. Theoretical Insights on Milk Production and the Role of Quotas

This section describes simple theoretical elements which guide us throughout our empirical analysis.

3.1. A Simple Setting

We view raw milk production as requiring an important fixed cost (land, material) associated with an increasing marginal cost such that each farm has an efficient size minimizing its average cost (denoted y^{eff}). We think about a more *productive* farm as a farm having lower production costs and a higher efficient size. This assumption is consistent with the decreasing relationship between exit probabilities and farm sizes observed in Figure 2.4.

We consider that a farm's productivity depends on:

- (1) Its intrinsic quality, randomly drawn in a given distribution which shifts according to a *département*-specific parameter¹¹,
- (2) Technical progress, increasing over the years.

(1) helps catch two empirical regularities: (i) high heterogeneity in farm sizes, as suggested by Figure 2.3 (b), and (ii) heterogeneity in production shares across *départements*, as shown on Figure 2.2. (2) is an empirically established fact in many developed agricultural markets, including the French milk market, and is consistent with the steady decrease in the farm number observed in Figure 2.3 (a).

Farms are price-taking, and their profit maximization consists in choosing whether or not to be active in the market (extensive margin) and how much to produce (intensive margin). These decisions depend on their productivity and the market environment (milk equilibrium price, quotas). For simplicity, we assume that demand is perfectly inelastic and constant over time so that price variations are fully determined by the supply.

In France, the quota implementation has generated constraints on production at two different levels: at the farm level and at the *département* level. We hereafter analyze the theoretical effects of these two types of constraints, separately taken.

Farm Size Constraints

As mentioned, the implementation of quotas in France aimed to reduce farm size dispersion by making the marginal cost of acquiring production rights increasingly expensive

¹¹We do not specify a particular law here, but any Normal or Fréchet laws with a *département*-specific position parameter, for instance, would suit the analysis.

above some determined thresholds. For simplicity, we here assume that individual quotas consist of a fixed quantity threshold that producers cannot exceed. This simplification is thus a particular case in which the marginal cost of growing above the quota threshold is infinite. In what follows, we compare farm production decisions in the absence and in the presence of an individual quota threshold.

Farm Production Without Size Constraints

Under a quota-free equilibrium, each farm chooses the quantity produced so as to equalize its marginal cost and the market price of raw milk. The least productive farm active on the market thus makes a null profit, producing the quantity y^{eff} which minimizes its average cost. All other active farms make a positive profit and produce a quantity higher than y^{eff} , and the more productive the farm is, the bigger its production and profit are. In this context, the price of milk determines the total supply through two margins: (1) the number of active farms (*extensive margin*) and (2) individual quantities produced by such farms (*intensive margin*).

Farm Production with Moving Size Constraints

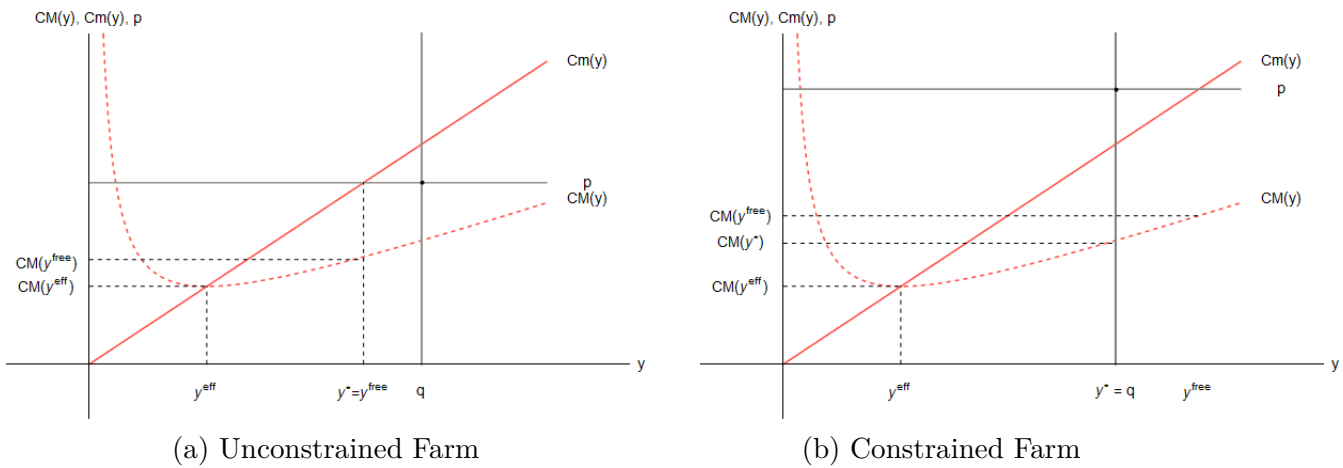
Under a quota regime, the quantity produced by a given farm may be constrained or not, depending on the market price, the quota threshold, and its individual productivity. Figure 2.6 and 2.7 distinguish two cases: when the quota threshold is above the farm efficient quantity y^{eff} and when it is below¹². In Figure 2.6 (a) and (b), the quota q is above y^{eff} and the price p is above $CM(y^{eff})$. In both cases, the considered farm decides to produce a quantity $y^* > y^{eff}$ and makes a positive profit.

In Figure 2.6 (a), the quota is also greater than the farm's optimal quantity, *i.e.* $q > y^{free}$, and the farm is unconstrained. In practice, we view this case as representing small farms, which are also relatively less productive according to our theoretical setting. These farms would thus not benefit from a quota increase as their production already is unconstrained. Actually, as the quota increase is associated with a market price decrease (due to more productive competitors' supply growth), such farms reduce the quantities produced and make less profit. These farms can exit the market if the price goes below the minimum of their average cost.

In Figure 2.6 (b), the quota is lower than the farm optimal quantity, *i.e.* $q < y^{free}$, and such a constrained farm thus produces $y^* = q$. This can describe farms of intermediate sizes, with similarly intermediate productivities. The effect of a quota increase on this type of farm is thus theoretically ambiguous. On the one hand, the quota increase allows

¹²The reader can read these scale-free graphs in two ways. First, and as we do here, one can consider p and q levels as fixed across the figures, and consider that marginal and average costs shift from one graph to the other. Alternatively, one can consider fixed marginal and average costs and shifts in p and q .

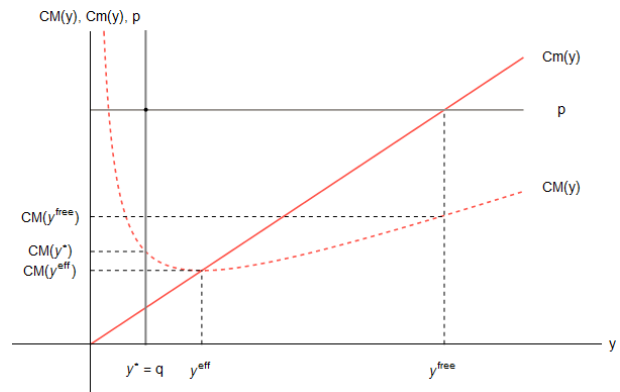
Figure 2.6: Farm Equilibrium with a Quota Above the Efficient Quantity



them to produce more and converge to the optimal quantity y^{free} . On the other hand, their supply is locally increasing with price. As a consequence, if the price drop induced by increases in quantities produced by incumbents is sufficiently important, these farms reduce their quantities and make lower profits.

In Figure 2.7, the quota is lower than the efficient quantity y^{eff} , and the farm equilibrium quantity is thus $y^* = q$. In this case, the farm cannot reach its efficient quantity, due to the quota. We thus view this case as describing relatively big and highly productive farms. A quota increase may thus allow such farms to converge to their efficient size y^{eff} . As a consequence, these farms always increase their quantity after a rise in their individual quota level, even if the market price drops.

Figure 2.7: Farm Equilibrium with a Quota Below the Efficient Quantity



Overall, under the quota regime, supply is constrained. Our theory thus predicts an equilibrium involving too many active farms and a sub-optimal allocation of production between them. Indeed, the more productive is a farm, the more downward distorted will be its quantity. As a consequence, the constraints on individual supplies of relatively more productive farms help relatively less productive farms to enter (or stay on) the market and to produce more. This supply distortion drives the milk market price upper than the one which would have prevailed without quotas. The following proposition summarizes the effects of loosening farm size constraints (only), predicted by our theory.

Theoretical Prediction 1. *All else being equal, the loosening of constraints on farm sizes within a market leads:*

- (i) *a sufficiently small (resp. large) farm to decrease (increase) its quantity produced,*
- (ii) *active farms below a certain size threshold to exit the market.*

Spatial Distribution Constraints

A second constraint imposed by the quota implementation scheme is that the share of each *département* in national production is fixed.

Production Allocation Without Spatial Constraints

In a quota-free market, each farm's individual quantity is determined by the market price and its productivity. National competition across farms defines an equilibrium price for which the least productive farm active on the market produces its efficient quantity y^{eff} at its minimal average cost. As a result, production is efficiently split between *départements*. Differences in *département* market shares reveal heterogeneity in the natural *département*-specific part of farms' productivities, the *département* with the highest market share being the one with a farms' productivity distribution the most concentrated to the right. With technical progress over the years, farm costs go down and the optimal quantity for a given price p goes up. As the demand is inelastic, the total quantity sold on the market is fixed, and the price thus goes down, the supply adjusting until turning back to the initial quantity. This adjustment implies that less efficient farms exit the market. Due to the heterogeneity in productivity distributions across *départements*, exits are concentrated in *départements* with the lowest market shares.

Production Allocation With Moving Spatial Constraints

Assume that spatial distribution of milk production was *ex ante* optimal, before the implementation of quotas. Once quotas are introduced, production is fixed across *départements*, which become separated markets. This generates market-specific prices and the productivity cut-off levels of the least efficient active farm in each location are also *département*-specific. As a consequence, spatial production allocation becomes more and more inefficient, as long as technical progress increases. Indeed, the farm number decreases at the same rhythm in each *département*, whereas the heterogeneous distributions of productivities across them would have generated divergences in a free market with a unique price and cut-off level. When quotas are removed, convergence in prices implies that exit increases and (surviving) farm production decreases in small *départements*, whereas opposite changes occur in large *départements*.

Theoretical Prediction 2. *All else being equal, the loosening of *département* production constraints:*

- (i) leads a sufficiently small (resp. large) *département* to a decrease (increase) in its overall production,
- (ii) generates similar sign variations of optimal productions for all active farms within a *département*.

Bringing the Model to the Data

This section presents a stylized theoretical framework that aims to extract the main mechanisms at stake under the quota regime and during the liberalization process, delivering testable predictions. This model relies on two observables: the adjustment of market prices and equilibrium quantity changes. In the empirical part of this paper, we only focus on quantities that are sufficient to test theoretical predictions and reveal price changes. Quantities have two main advantages compared to prices: (i) they allow to document the heterogeneous impact of the policy changes not only across markets but also across farms within a market, and (ii) nominal prices would not be informative. In fact, we would ideally use *real* prices of milk, which would require for our purpose deflating raw prices by time-varying production costs that are also highly dependent on production systems differing across territories. Moreover, it would also raise the question of the evolution of opportunity costs, notably the evolution of the cost of land due to the evolution of its economic yield.

Finally, our theoretical predictions separately consider the effects of the removal of constraints induced by quotas on farm and *département* sizes respectively. In practice, both types of constraints are gradually removed, and the observed resulting dynamics reflect joint effects. However, as shown in Section 6., divergences in production dynamics across *départements* along the entire period of analysis implied different effective liberalization timings, allowing us to partly disentangle both types of effects.

4. The Spatial Relocation Process

In this section, we show the dynamics of the relocation process across *départements*, and its interaction with both the quota regime and its removal. We first focus on the relocation of production, before considering one of the extensive margins through which it took place: the repartition of farms across the French territory.

4.1. Production

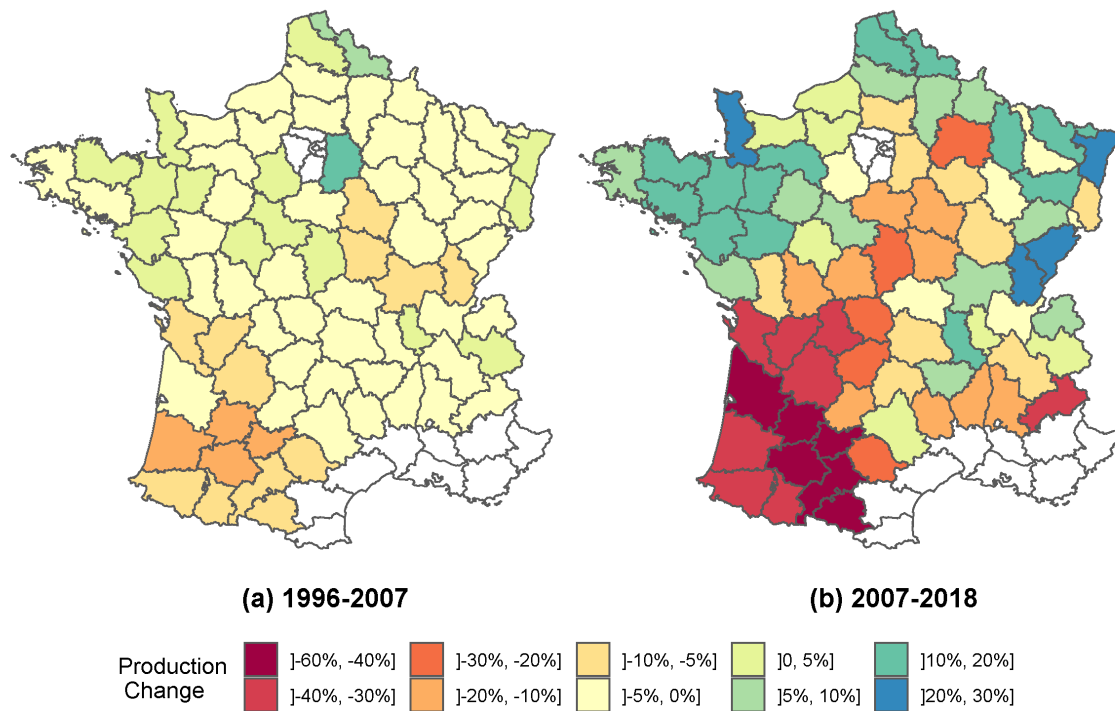
Heterogeneous Territorial Dynamics

Figures 2.8 (a) and (b) display production variations by *département*, between 1996 and 2007 on the left-hand side, and between 2007 and 2018 on the right-hand side. We

can thus compare the respective evolutions of production (a) over 11 years of stable quota regime and (b) during the 11 subsequent years marked by the *soft landing* phase and the quota removal.

Under the stable quota regime, the production in each *département* is generally very stable, the variations of production in absolute values over the period being generally lower than 5%. The South-West region of France appears as an exception with a reduction of production greater than 10% in several *départements*. During the liberalization period, production changes are much starker. South-West *départements* bear the greatest production losses, with production decreases generally higher than 30%. Central *départements* also experiment declines in milk production. Conversely, milk production markedly increases in the North, North-West, and, North-East *départements*. Such divergences can essentially be explained by the restart in 2008 of a concentration process stopped by the introduction of quotas in 1984, which were held stable until 2007, as a comparison between Figures 2.2 and 2.8 suggests. We come to this in greater detail in the following subsection.

Figure 2.8: Production



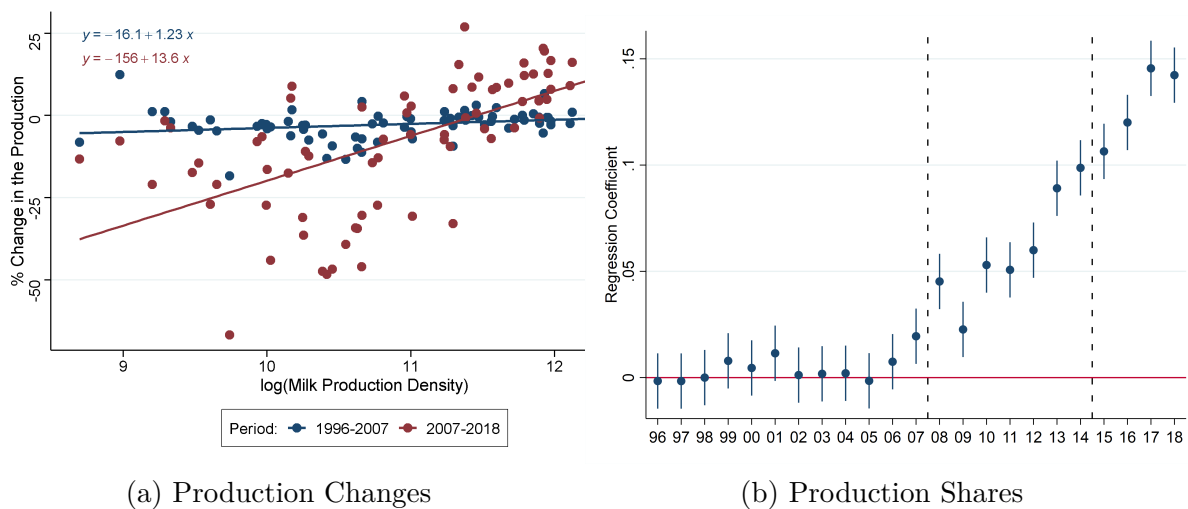
Notes: *Département*-level production % change between two years: (a) 2007 vs. 1996, (b) 2018 vs. 2007.

The Restart of an Aborted Concentration Process

Figures 2.9 (a) and (b) show more evidence of how the concentration process restarted in 2008, thanks to the production liberalization.

Figure 2.9 (a) plots production variations introduced in Figure 2.8 against *département*

production densities at the beginning of the period of analysis (1996). Under the stable quota period, in blue, production levels are relatively stable for all *départements*, with a small positive correlation between production change and *département* density (regression coefficient of 1.23, significant at 5%, and $R^2 = 0.07$). Conversely, production variations are important between the beginning of the liberalization phase in 2008, and 2018. Interestingly, these changes are significantly much more strongly positively correlated with the initial *département* milk production densities (regression coefficient of 13.5, significant at 1%, and $R^2 = 0.40$).

Figure 2.9: Concentration across *Départements*

Notes: (a) *Département*-level production % change between two years (2007 vs. 1996 and 2018 vs. 2007) against the log of the initial *département* milk density. Initial density is defined as the milk production by km^2 of agricultural land in 1996. (b) Regression coefficient, details in the text.

These results are in line with Theoretical Prediction 2, the quota removal having released high growth potentials which were so far limited in the initially more productive *départements*. This increase in competition on the contrary led relatively less productive *départements* to incur milk production declines.

Figure 2.9 (b) delivers a similar assessment, with a greater focus on the timing of the liberalization. It displays the estimated coefficient $\hat{\beta}_1^t$ from the following regression:

$$s_{it} = \beta_0 + \sum_{t \geq 1996} \beta_1^t s_{i1995} \times D_t + \beta_2 \times s_{i1995} + \gamma_t + \gamma_i + \epsilon_{it} \quad (2.1)$$

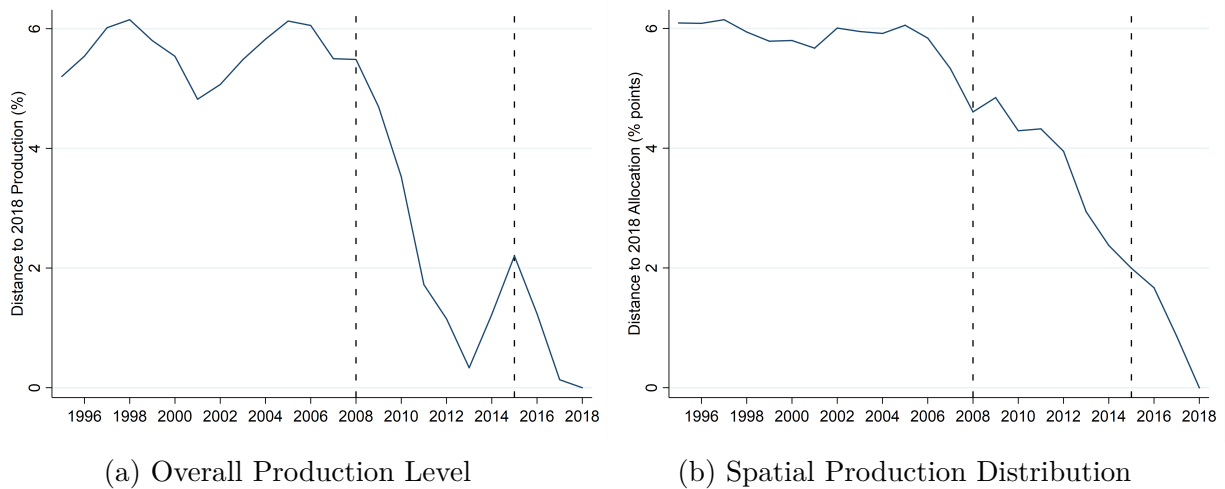
where $s_{it} = m_{it}/m_t$ is the production share of *département* i at time t ¹³, $s_{i1995} = m_{i1995}/m_{1995}$ is the initial production share of *département* i , D_t is a dummy for year t , and ϵ_{it} is the error term. Finally, we include time and *département* fixed effects, denoted by γ_t and γ_i , to control for time trends common to all *départements* and *département*-specific

¹³ m denoting milk quantities.

(and time-invariant) characteristics respectively. As we here consider production shares, Figure 2.9 (b) thus confirms how the quota regime impeded the spatial concentration of milk production in France, and how its gradual removal authorized this process to restart. Furthermore, it indicates how this specialization process immediately kicks in following the first wave of quota increases in 2008 and keeps strengthening over time until the end of the period of analysis, suggesting an unachieved convergence towards a new steady state.

The Evolution of Spatial Production Distortions

Figure 2.10: Production Distortions



Notes: (a) % deviation of the production level in a given year compared to its 2018 level. (b) Distance between the production repartition across *départements* in a given year and its 2018 repartition. More details below.

The production increase and divergences in the evolution of production levels and shares across *départements* observed after the liberalization was mechanically impossible under the quota regime. Thus, quotas seem to have stemmed natural market forces both towards more production and more concentration. Based on the production and its repartition in 2018 (our last observed year), we can thus have an idea of the distortions quotas created with respect to these dimensions. Of course, one obvious limitation of such reasoning is that the liberalization process is still going on, and the milk market did not yet reach its new natural *steady state*, as aforementioned. However, our measure still remains instructive for considering the timing of the convergence and reallocation processes.

Figure (a) plots the distance between the production of the considered year and the production in 2018, in percentage. This graph essentially shows how the production converged towards its natural level relatively fast, between the first quotas increases of

2008 and 2015, before diverging again due to the introduction of the new production-decrease-prone policies.

Perhaps more interestingly, Figure (b) plots a measure of spatial distortions, which we define as follows:

$$L_t = \frac{1}{2} \sum_i |s_{it} - s_{i2018}|$$

where remember $s_{it} = m_{it}/m_t$ is the production share of *département* i at time t . We thus compute the distance between the distribution of milk production across space over each year with its distribution in 2018. To conserve the zero-sum game nature of production relocation, we take half of the cumulative distance for each year, which prevents double-counting milk reallocation movements. Again, there is a convergence towards the 2018 equilibrium starting as soon as quotas started to increase, in 2008. Our measure thus grossly implies that 6% of the milk production was misallocated relatively to 2018, due to the presence of quotas. Such a conclusion may appear a bit premature, given other changes which occurred over the period. None of them however seem to have the potential to drive the heterogeneous dynamics observed across *départements* since 2008. Moreover, as the relocation process across space appears to be not finished yet, this measure can be interpreted as a lower bound compared to the true allocative distortions induced by quotas.

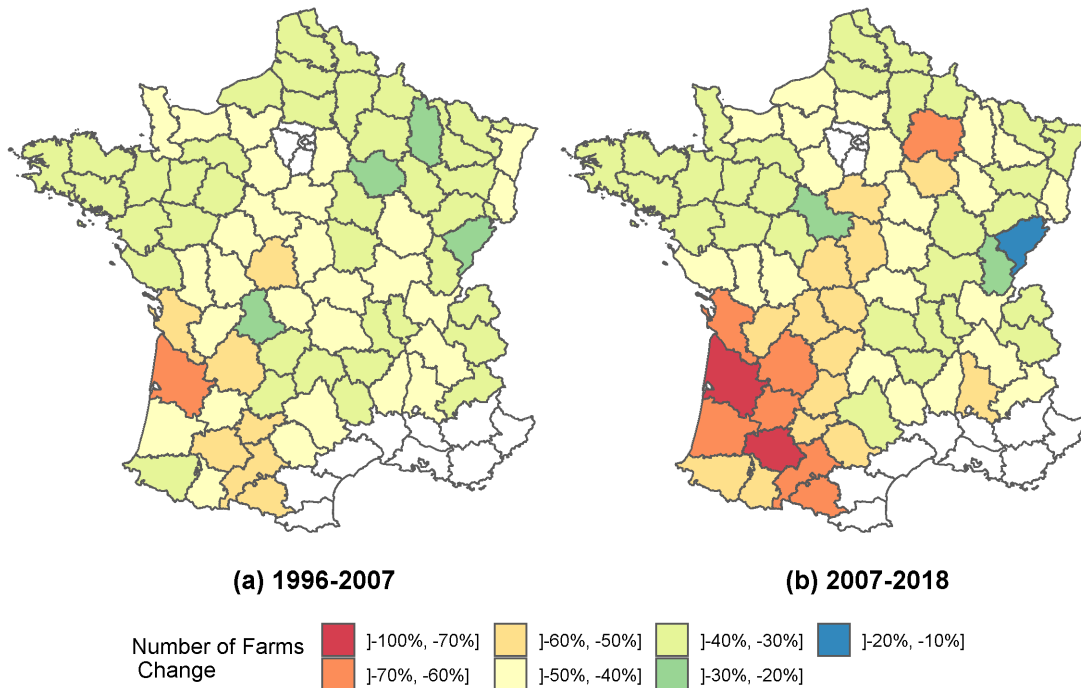
4.2. Farms

We have shown how quotas aborted the production relocation before its gradual removal allowed it to restart. We now more specifically turn to one particular margin of adjustment, the evolution of the repartition of the farm number across the territory.

Heterogeneous Territorial Dynamics

Contrary to what we see for production, but in line with the steady decrease observed at the national level, the dynamics in terms of the repartition of farms appear to have been less clearly altered by the existence of quotas. Figure 2.11 thus contrasts with Figure 2.8, in that farms destruction rates seem to have remained relatively constant across time for most *départements*. An exception to this seems again to be some *départements* from the South West of France, where farm destruction rates drastically increased during the quota removal process. More generally, the farm number seems to decrease faster in relatively less specialized *départements*, consistently with the observed milk relocation, which results presented in the following subsection confirm.

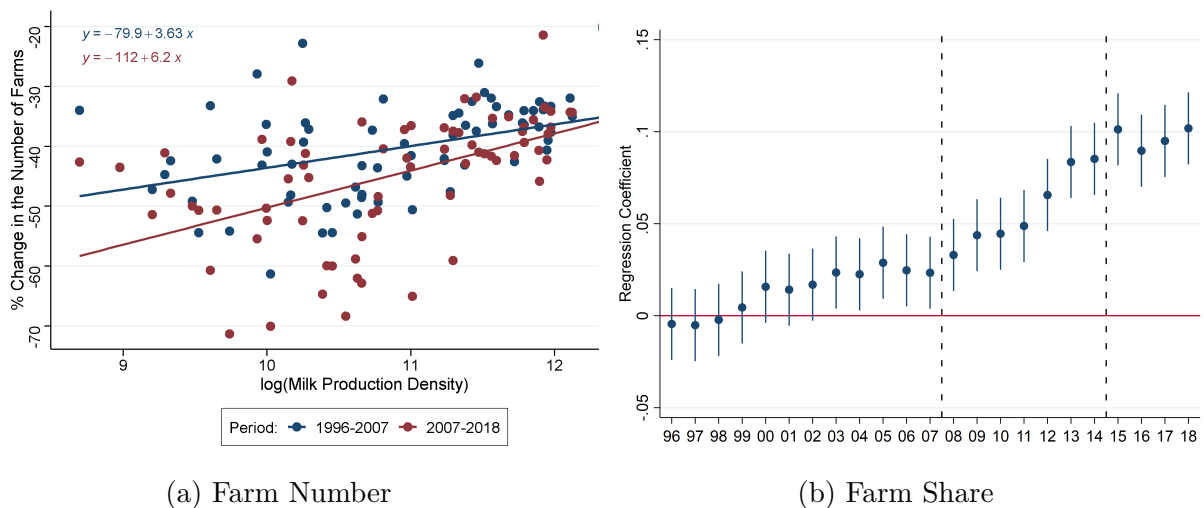
Figure 2.11: Farm Number



Notes: *Département*-level farm share % change between two years: (a) 2007 vs. 1996, (b) 2018 vs. 2007.

The Fostering of a Specialization Process

Figure 2.12: Specialization



Notes: (a) *Département*-level % changes in the farm number between two years (2007 vs. 1996 and 2018 vs. 2007) against the log of the initial *département* milk density. Initial density is defined as the milk production by km² of agricultural land in 1996. (b) Regression coefficient, details in the text.

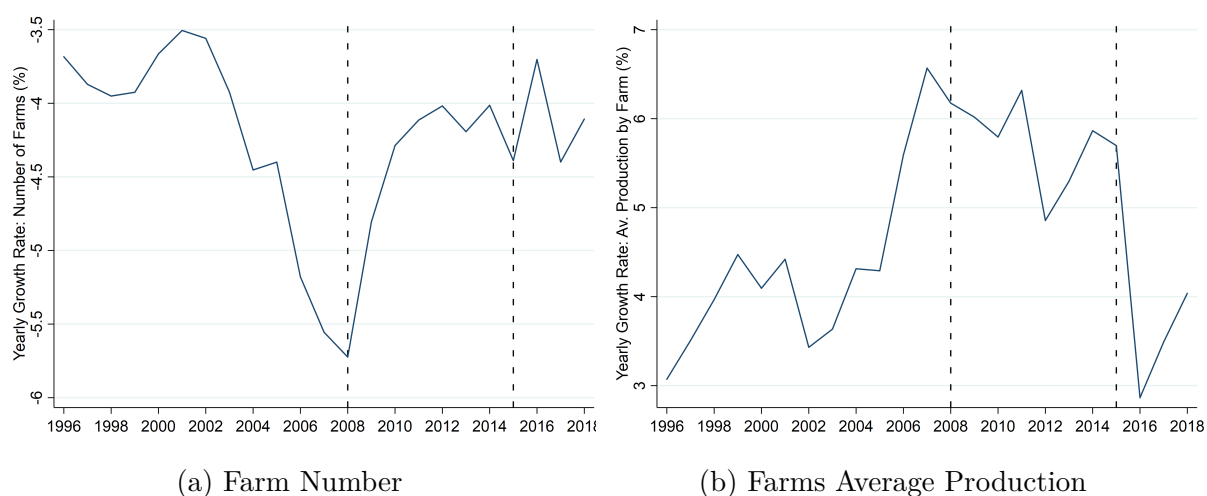
Applying a methodology similar to the one described in Section 4.1. to the evolution of the farm number across *départements* and time¹⁴ delivers a much more nuanced conclusion regarding the role of quotas in the dynamics of the farm number by *département*. The farm number decreases faster in small territories even before the end of quotas (regression coefficient of 3.63, significant at 1%, and $R^2 = 0.20$), but the difference in decrease rates is accelerated after 2007 (regression coefficient of 6.20 significant at 1%, and $R^2 = 0.30$). Our theory delivers a plausible argument to explain differences in farms' destruction rates before the production liberalization. First, in less productive *départements*, the share of farmers unconstrained by quotas is relatively more important than in more productive *départements*. As a result, technical change allows more productivity gains in inefficient *départements* than in efficient *départements*, leading to a faster decrease in the farm number. This argument is in line with the Theoretical Prediction 1 (ii).¹⁵ Overall, distortions induced by quotas on farm number and repartition across the territory seem to be relatively more limited than the ones caused on production and its location.

5. Across-Farm Misallocation and Reallocation

In this section, we document how quotas and their gradual removal have affected the farms selection process and the distribution of milk production *across farms*.

5.1. The Restructuring Rhythm

Figure 2.13: Growth Rates



¹⁴We run a regression similar to (2.1) for constructing (b), where the only difference regards the outcome variable, which now is the *département farm share* on a given year.

¹⁵We show later in the paper (Section 6.) that the constraints implied by production quotas were actually loosening even before 2008 in the least efficient *départements*.

Figure 2.13 (a) shows the evolution of the yearly growth rate of the farm number over the period of analysis. As the farm number steadily decreases from 1996 to 2018, the growth rate is constantly negative.¹⁶ From 1996 to 2002, this destruction rate is relatively stable, around 3.75%, before significantly increasing between 2003 and 2010, peaking at 5.6% in 2008. Interestingly, this peak follows the announcement in 2003 of the gradual quota removal starting in 2008. The acceleration of the decline in the farm number between 2003 and 2008 can thus be seen as an anticipation by the least efficient farmers that the liberalized market equilibrium will be less favorable to them. This results from the fact that dairy production requires significant long-term investments, and farms, therefore, take into account future expected profits, anticipating long-term equilibria in their investment decisions. After this acceleration, the farm destruction rate stabilizes again at a level of around 4%, slightly higher than the one prevailing under the quota regime before the announcement of its end.

Figure 2.13 (b) shows how the growth rate of the average farm size changes over the entire period. The growth rate increases during the pre-liberalization period (1996-2008), going from 3% to about 6%, then stabilizes at relatively high levels (around 6% per year) during the transition phase (2007-2014) before dropping to 3-4% after total liberalization (2015-2018). The increase in farm growth rate during the pre-liberalization period is directly linked to the acceleration of the rate of decline in the farm number. Exit has two positive mechanical effects on farm size: first, the exiting firms are generally small (see Figure 2.14 (b)), which pulls up the average size, and second, as production is constrained by quotas, maintaining the production level implies an increase in the size of each firm. During the transition phase, maintaining this high growth rate is made possible by the production increase. At the very end of the period, total production decreases and the growth rate seems to tend towards its initial level, which may essentially result from the quantity-reducing effects of the introduction of incentives to reduce production in 2015.

These aggregate trends overall hide disparities of exits and growth rates of farms over time, which we now turn to.

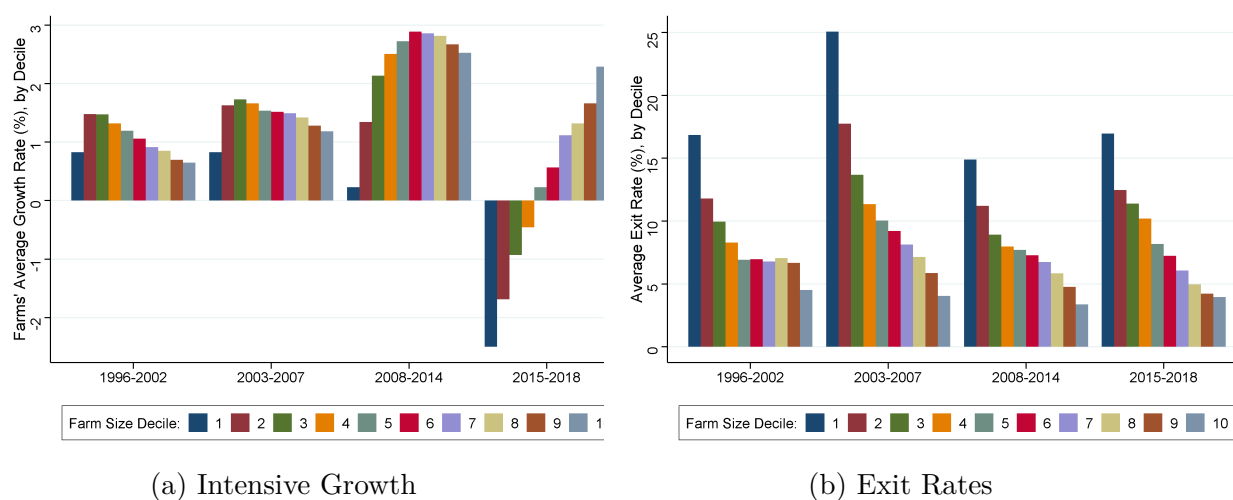
5.2. Restructuring Levels and Margins

Figure 2.14 (a) displays the average yearly intensive growth rate of farms, across deciles of the size distribution, averaged over each period. The *intensive growth* here refers to the growth of farms from a given size decile, *conditional on surviving*. In order to avoid issues linked to incomplete years of production, we drop farms that are in their first or last years of activity. Under the stable quota regime (1995-2007), the constraints implied by quotas are binding, and the intensive growth rates of farms in the lowest deciles of the distribution are driven up by the redistributive properties of the quotas repartition

¹⁶For this reason, we refer to it as a destruction rate and describe it in absolute terms in what follows.

scheme, whereas the growth of large farms is largely discouraged (as described in section 2.1). As a consequence, if we disregard the very first decile, intensive growth rates under the quota regime are decreasing with farm ranks in the size distribution. During the transition period (2008-2014) the picture starts to be different as quotas gradually increase, being less and less constraining. This results from the fact that the increase in milk supply is pulling prices down. Firms producing more than their efficient quantity reduce their supply while the most efficient firms can reduce their marginal costs through increased production, consistently with theoretical prediction 1.

Figure 2.14: Margins



Notes: By size deciles, averaged over the given period: (a) Annual intensive growth rates, conditional on surviving, dropping entrants and exiters, based on individual quotas (1996-2006) and quantities (2007-2018); (b) Farms annual exit rates.

Finally, once the quotas are completely removed (2005-2018), smaller farms are no longer protected by the redistributive scheme, and mechanisms at stake in the transition period are amplified. As a consequence, the smaller farms experience important decreases in their production, while bigger and more efficient farms grow faster, consistently with our theory.

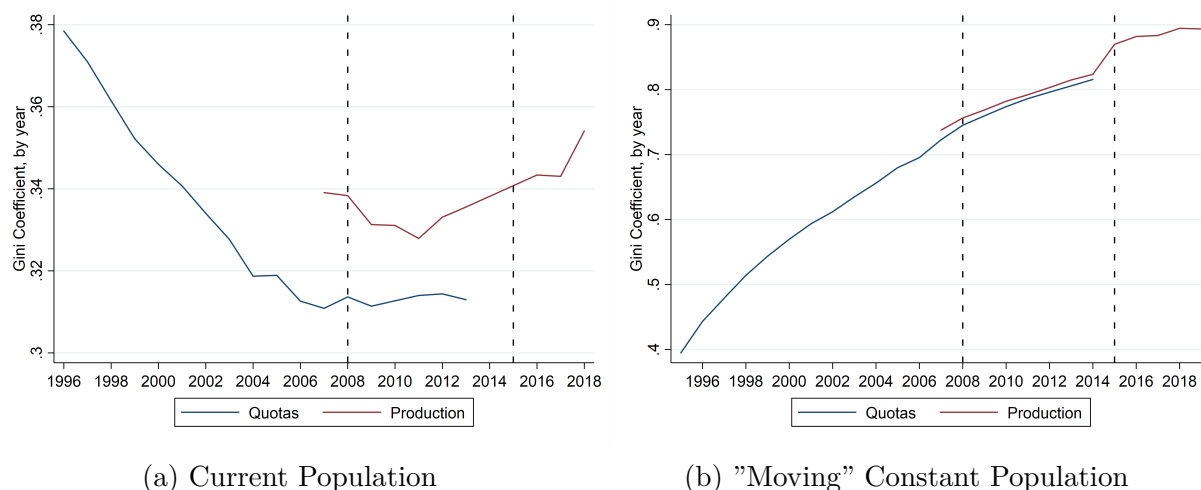
Figure 2.14 (b), displays exit rates of farms, across deciles of the size distribution, averaged over each period. The clear takeaway of this graph is that the exit probability is decreasing with the relative size of a farm over the entire period. The downward size distortion weighing on bigger farms under the quota regime does not seem to increase their probabilities of exiting, consistently with our departure assumption that larger farms are the most efficient. In line with trends already mentioned on the total farm number, exit rates increase during the years preceding the quota removal, especially for smaller farms, which tends to confirm they anticipated the negative effects of the quota removal, right from its announcement in 2003.

Milk production quotas thus seem to have largely distorted the intensive growth margins in favor of smaller farms, and to a lesser extent also affected the extensive margin, at least in terms of exit rates. Overall, by favoring relatively smaller farms, the quota regime thus seems to have slowed down the natural concentration dynamics of milk production in France.

5.3. The Impact of Quotas on Between-Farm Inequality and Inefficiency

Between-Farm Inequality

Figure 2.15: Gini Coefficients



Notes: Gini coefficients of the distribution of quotas and production levels across farms, based on individual quotas (1996-2014) and quantities (2007-2018). Samples: (a) Current population; (b) "Moving" Constant Population. More details below.

The management of milk production quotas in France aimed at two goals: containing inequalities between (i) farm revenues and (ii) between territories. In this Section, we focus on the first objective by considering dispersion in quantities produced.¹⁷ Figure 2.15 displays the evolution of the Gini coefficient of farms' production levels. Figures (a) and (b) plot this measure across time for each year, with a current population (the standard measure) and a "moving" constant population of farms respectively. To build the second one, we affect a value infinitesimally close to zero¹⁸ to exiting farms for all the subsequent years of analysis. In doing so, we take into account the importance of exits in evaluating inequality. The "moving" term refers to the fact that new entrants are integrated into the sample across years. Finally, the Gini coefficients are computed based

¹⁷We do not observe farm revenues, but quantity is arguably a good proxy for revenue when studying dispersion, given the relatively homogeneous milk pricing setting.

¹⁸Instead of zeros which are not supported by Gini coefficient computations.

on individual farm quotas and quantities depending on their availability across time, and both measures reassuringly exhibit similar broad patterns during the overlapping years.

Both measures show how quotas limited inequality between farms, especially when considering the current population panel, where quantities dispersion steadily decreased from 1996 to 2007, before stabilizing during the transition phase and eventually rising after the complete quota removal. Figure 2.15 (b) naturally shows steadily growing inequalities across time under the quota regime, due to the aforementioned importance of farm exits across all years of analysis. However, this complementary dispersion measure starkly rises once the quotas are completely removed, as a result of the heterogeneity in the intensive growth dynamics across farms of different sizes.

Quotas thus successfully refrained growing inequalities across surviving farms, by stemming a natural trend that reappeared once they got removed. Panel (b) also confirms that this redistributive motive did not completely impede productivity gains, as less efficient farms kept exiting over the entire period.

Inefficiency

In order to more precisely assess how much quotas have put a brake on an *a priori* efficient reallocation, we propose an *ad hoc* measure. For each year t , we rank farms in the distribution of quantities within each *département* i , which we denote r_i . We then build the following measure:

$$L_{it}^k = \frac{1}{2} \sum_r |s_{rit}^k - s_{ri2018}^k|.$$

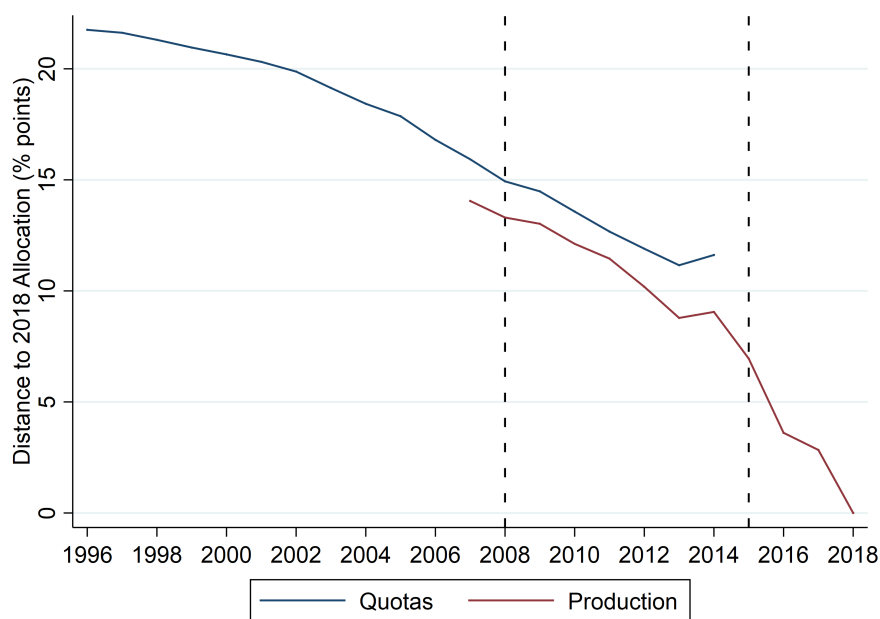
where $s_{rit}^k = k_{rit}/k_{it}$ is the market share of the farm occupying rank r in *département* i at time t , where k alternatively denotes milk quotas q or quantities m depending on the considered measure, and $s_{ri2018}^k = m_{ri2018}/m_{i2018}$. The L_{it} indicator thus measures the distance between the repartition of the production in *département* i at time t and its 2018 unconstrained repartition.

Through a weighted average, we can then aggregate these measures to get their national equivalents:

$$L_t^k = \sum_i L_{it}^k \times s_{it}^k.$$

where $s_{it}^k = k_{it}/k_t$ is the production or quotas share of *département* i at time t in national production. Figure 2.16 shows how the natural reallocation of production across farms seems to have occurred when quotas were totally removed, as the slope becomes steeper in 2015.

Figure 2.16: Reallocation Across Farms



Notes: Distance between quotas and production repartition at the farm level in a given year and its 2018 repartition. More detail above.

6. Disentangling the Restructuring Effects of Farm Size and Spatial Constraint Loosening

So far, we have analyzed the effects of the quota regime and its removal on spatial distribution and inter-farm reallocation. However, we do not have explicitly considered heterogeneity in the timing of liberalization. In fact, in some *départements*, constraints implied by the existence of quotas determined at the *département* level were not binding, even before their increase in 2008. Consequently, in these low-productivity *départements*, constraints on farm sizes are also less important. This heterogeneity allows us to distinguish periods in which liberalization is incomplete, *i.e.* only achieved in such *départements*, and to distinguish the heterogeneous effects of intra- and inter-*département* constraints.

6.1. Discretizing the Inter-*Département* Divergence

Départements are regrouped into six categories depending on their total milk production growth between 1996 and 2018. Table 2.1 presents some descriptive statistics.

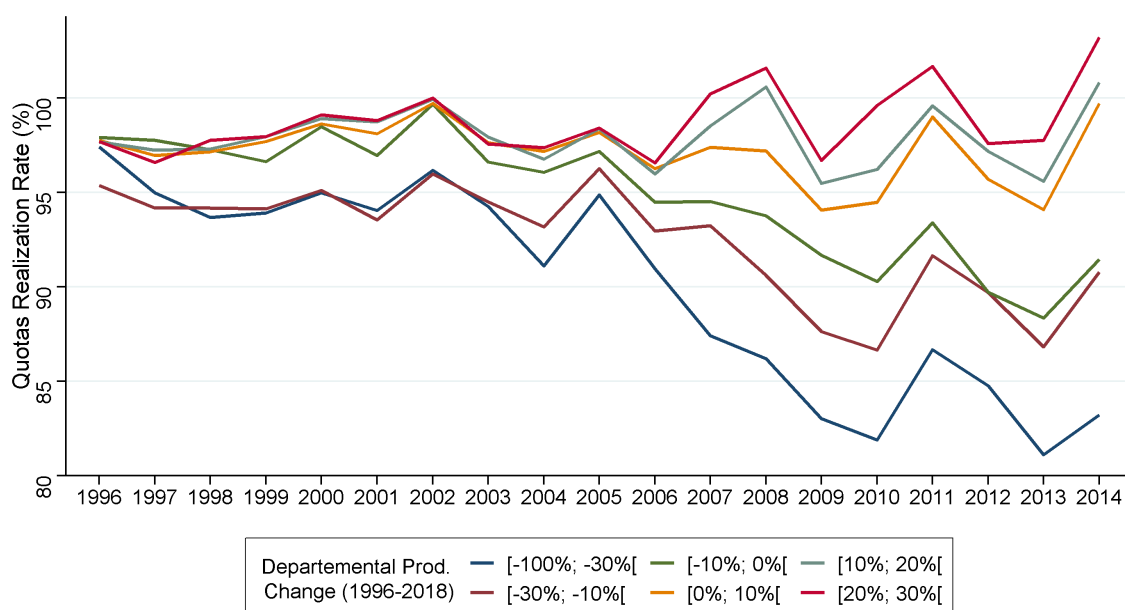
Table 2.1: Descriptive Statistics, by *Département* Growths (1996-2018) Category

Dep. Prod. Change (1996-2018)	Number of dep.	Share of farms (%)		Share of production (%)		Farms av. size (liters)	
		1996	2018	1996	2018	1996	2018
[-110%; -30%[25	8.8	5.2	7.4	4.0	126,351	348,255
[-30%; -10%[15	6.2	5.0	5.1	4.1	124,132	366,788
[-10%; 0%[14	13.2	13.2	12.1	10.8	138,329	374,815
[0%; 10%[16	26.8	28.1	27.2	27.3	152,881	445,630
[10%; 20%[13	28.1	30.1	30.7	33.4	164,776	494,759
[20% ; 30%[7	16.8	16.9	17.3	20.5	155,275	554,394

A large number of *départements* (25 out of 90) experimented severe milk production declines, of more than 30%, leading them to represent only 4% of total milk production in 2018, against 7.4% in 1996. 29 *départements* incurred more moderate losses in milk activity, while production increased between 1996 and 2018 in 36 of them. The 20 *départements* who experimented the biggest growths (more than 10%) represent about 54% of the national production in 2018, against 48% in 1996. In line with our theory, *départements* which grew the most are the ones where farm average sizes were initially the biggest, a pattern which is starkly more pronounced in 2018.

6.2. Spatial Heterogeneity in the Production Constraint Loosening

Figure 2.17: Quotas Realization Rates



Notes: Ratio between *département* effective production and quotas, averaged over the given category.

Under the quota regime, in a *département* whose total production is constrained by quotas, the latter are in priority affected to small farms. This distorts farms' natural growth rates. Conversely, in *départements* for which this constraint is not binding, this distortive effect is weaker, and farms can relatively more freely choose which quantity of milk to produce. When quotas were first implemented in 1984, quotas constraints were mechanically binding in each *département*. In 1996 and over the subsequent years, the coercion degree of these constraints depends on the past dynamics of each *département* production. Figure 2.17 shows that there is substantial cross-*départements* heterogeneity in the timing of these constraints loosening.

Figure 2.17 shows the average annual quotas realization rates of French *départements* - *i.e* the ratio between annual production in a given *département* and its total amount of quotas - regrouped along the previously defined categories. Starting as of 1996, average quota realization rates already exhibit substantial heterogeneity, barely lying around 95% for the *départements* which later experienced the biggest falls (-10 to -100%) in milk activity. Putting it the other way around, it means that *départements* with the lowest realization rates in 1996 essentially are the *départements* which will lose the more over the entire period of analysis. For subsequent developments, this also imply that we can consider these *départements* as being "liberalized" from the very beginning of the period.¹⁹

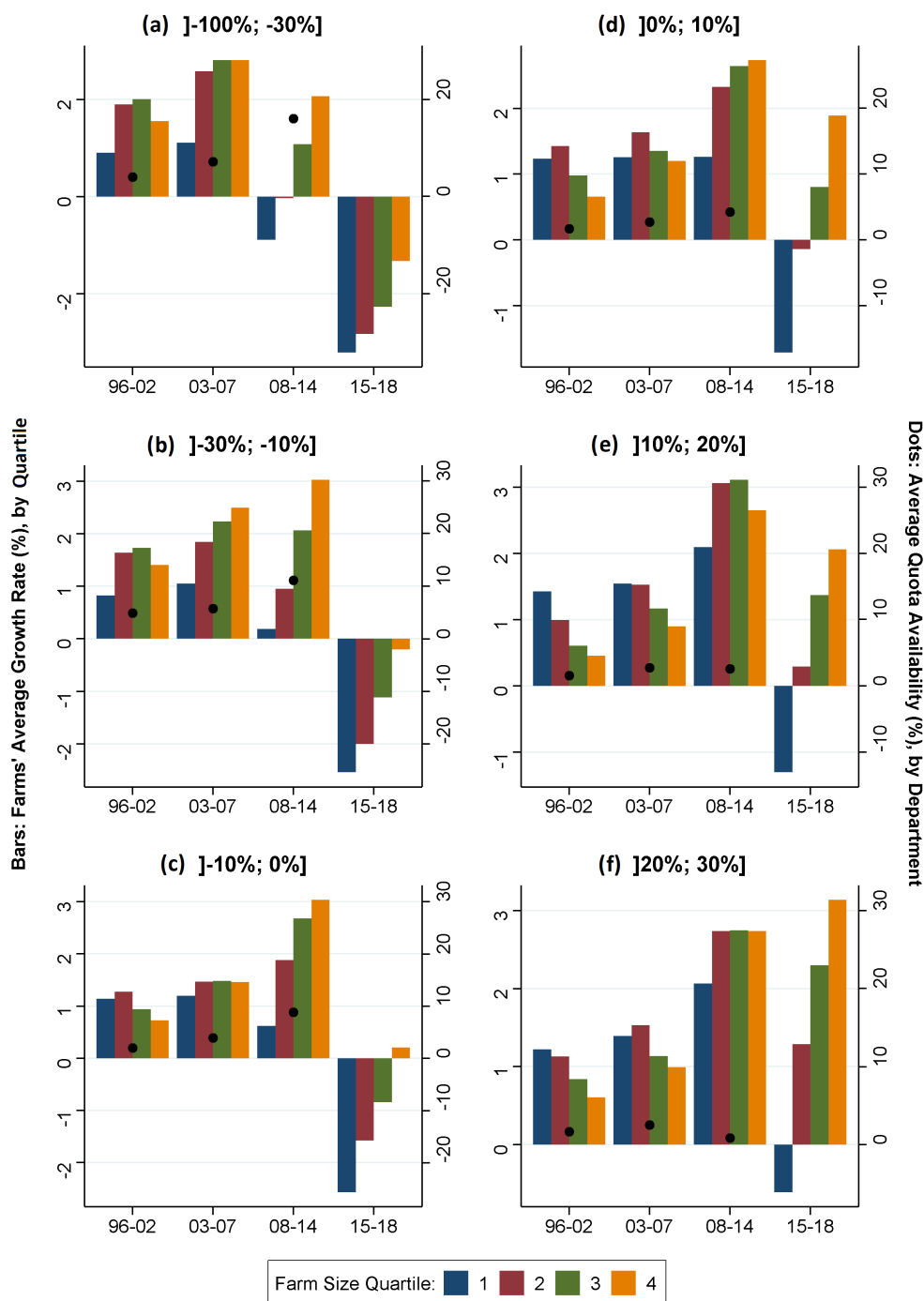
On the contrary, *départements* which suffered relatively less from the quota removal on average fill 98% to 99% of their yearly quotas until 2006. From then, divergences appear and accentuate each year, between *départements* which ultimately incurred falls in milk production and those whose production grew. As a consequence, *départements* experimenting moderate declines ($[-10\%; 0\%]$) or growth ($[0\%; +10\%]$) to a lesser extent see their quotas constraints significantly loosening. Dynamic *départements* which grew by more than 10% see this constraint disappearing only once the quotas were completely removed, in 2015.

6.3. Département-level Liberalization and Inter-Farm Reallocation

Figure 2.18 allows us to analyze the heterogeneous relative farms' intensive growth rates by quartile, depending on the quota realization rates. Indeed, we saw in Figure 2.17, the heterogeneity in the liberalization timings of the various categories of *départements* we built. We chronologically analyze Figure 2.18 in what follows.

¹⁹They may even have been "liberalized" before, which we cannot observe. The trends later described however seem to confirm that the liberalization took place during the period of analysis.

Figure 2.18: Intensive Farm Growth Rates by Quartile and Liberalization



Notes: Bars - Farms average growth rates, conditional on surviving, dropping entrants and exiters, by *département* 1996-2018 production growth and farm size quartile, over the given period. Based on individual quotas (1996-2006) and quantities (2007-2018). Dots - Average quantity of unfilled *département* quotas.

1996-2002 Over this stable quota period, *départements* which ultimately experiment production declines greater than 10% ((a) and (b)) are already liberalized, as around 5% of their quotas are unfilled. In these *départements*, the quotas redistribution scheme is thus not as favorable to the smallest farms as it is in other - more constrained - *départements*.

As a consequence, farms' average growth rates of the first farm quartile are relatively much less upward distorted as they are in these other *départements*. For the most constrained *départements*, average intensive growth rates on the contrary starkly decrease with farm relative sizes.

2003-2007 During the second period of analysis, which follows the quota removal announcement, growth rates are clearly increasing with farm relative sizes in the two categories of liberalized *départements* ((a) and (b)), while remaining distorted in favor of smaller farms in the others.

Overall, in these two first periods of analysis, *départements* exhibiting the lowest productivity levels are gradually liberalized. This liberalization is however not associated with increased competition from more productive *départements* since the latter ones remain fully constrained by the quota regime. Inter-*département* reallocation is thus still wiped out, but within these low productivity markets, intra-*département* production reallocation operates. Relatively more productive farms grow faster than smaller farms, generating the patterns described above. As inter-*départements* relocation is so far mechanically impossible, meaning that only the constraints on farms sizes within the aforementioned *départements* are loosening, these results are fully consistent with theoretical prediction 1.

2008-2014 During this *soft landing* phase, the quotas availability rates increase in the four first *département* categories ((a), (b), (c) and (d)), reaching at least 10% in the three first ones. As a result, market forces *within these départements* are freed, and growth rates become increasingly rising with farms' relative sizes. Conversely, growth rates across quartiles are still distorted by the quotas redistributive scheme in the two categories gathering the most productive *départements* ((e) and (f)).

Moreover, quotas increases over these years strengthen the competition at the national level, as production is allowed to increase in every *département*. Growth rates are as expected more important in more productive *départements* in which production was so far constrained. Productivity gains are eventually allowed, which drives the raw milk market price down. As a result, divergence *between départements* takes place, farms in the least productive ones growing relatively less or even starting to decline for the smallest farms.

2015-2018 In 2015, quotas are completely removed and the French (and European) milk market liberalization is thus total. The increasing and natural relationship between growth rates and farms' relative sizes is now clear in every group of *départements*. Growth rates are now negative for relatively less productive farms in the *overall national distri-*

bution. As relatively less productive farms are increasingly concentrated in relatively less productive *départements*, the latter ones suffer the biggest drops in milk production. Conversely, growth potentials of the biggest farms in the most productive *départements* - refrained during 30 years of production quotas - are finally occurring. These effects align with the joint effects described in theoretical predictions 1 and 2.

7. Research Avenues

In this section, we present further developments we consider for this project, and for which the work presented here would constitute an interesting basis.

7.1. Structural Model

The primarily considered avenue to develop our research project is to develop a more structural model, which would leverage the full granularity of the data we have in hand, at the farm level, manufacturer level, and also farm-manufacturer pair level. The latter dimension was somewhat eluded in the present study but is a key feature that we are able to observe in the data. We consider several strands of the literature that could be, *altogether or alternatively*, leveraged to inspire our structural model.

First, we could build an equilibrium model of trade à la [Eaton and Kortum \(2002\)](#) where several farms and regions with different productivities produce milk and sell them to manufacturers through a farm-to-firm network that we are able to observe in the data. Second, we could follow a more macro but also agricultural literature quantifying misallocation ([Hsieh and Klenow, 2009](#); [Restuccia and Santaaulalia-Llopis, 2017](#); [Aragón et al., 2022b,a](#)). Given the data we have in hand, a production function estimation at the farm and manufacturer level could be performed to retrieve productivity residuals which are at the core of such misallocation quantification. Studying the effects quota introduction and removal, a policy that explicitly affects production allocation, had on misallocation is definitely one of the aims of the present research. A more structural IO literature could also be leveraged, following [Ryan \(2012\)](#) in taking into account and estimating farm and manufacturer fixed costs, which are an important determinant of the milk market structure. Finally, another strand of the literature reviewed by [Macchiavello \(2022\)](#) studies the value of relationships (again, observed in our data), in agricultural and developing country contexts which ultimately resemble ours ([Macchiavello and Morjaria, 2015, 2021](#)).

Building a structural model inspired by one of several of these strands of the literature could guide us in a sounder study of the quota (introduction and removal) disruptive effects, and of the different restructuring margins at work. Doing so, we could use the data we have in hand to (1) estimate the model parameters, and (2) run counterfactual analyses and compute welfare gains. This will be the very next step of the present analysis.

7.2. Causality and Difference-in-Difference Analyses

Moreover, we have long considered and still consider the possibility of conducting appropriate difference-in-difference (henceforth, DID) analyses to study the effects of the quota regime and of its removal. This option is clearly appealing as it would help to have

more causal statements on the exact role of the quota removal onto the *cream-skimming* of the French milk market. However, its practical implementation is relatively difficult as it seems very complicated to properly define control groups in the present setting. First, the quota removal was announced far in advance, and anticipated to a certain extent, as we have shown. Second, if we do exhibit evidence that the actual liberalization occurred at various dates across *départements*, *a priori* calling for a staggered event-study design or a stacked difference-in-difference approach, they are made complicated by the importance of *spillover effects*. Indeed, farmers are in competition within but also between *départements*, and the liberalization of a given *département* potentially affects equilibria in all others. These competition effects essentially depend on the degree of substitutability between *départements*. Throughout our theoretical and empirical analysis, we neglected this dimension, assuming homogeneous raw milk and hence, perfect substitutability. In practice, the degree of substitutability is indeed high, as dairy manufacturers purchasing milk are often part of important groups implanted in various *départements*. Moreover, farmers on the upstream side of the dairy value-added chain are also indirectly competing through the competition prevailing in the dairy product markets further downstream.

An interesting case of reduced substitutability between milk across locations lies in the existence of Protected Designations of Origin (henceforth, PDO). PDOs imply that the labeled products are "produced, processed, and prepared in a specific geographical area, using the recognized know-how of local producers and ingredients from the region concerned". The French dairy industry for instance counts about 40 cheese varieties protected by PDO labels. This implies that milk used to process such cheeses is necessarily produced by local farms, and is thus not substitutable with milk from other *départements*. By definition, farms producing such *protected* milk seem sheltered from the competition of farms located outside the given PDO zone, and may thus have been less affected by the increased *upstream* competition due to the quota removal.

As such, they could at first sight constitute an interesting candidate for a control group in the type of analyses aforementioned. Indeed, the PDO neutralizes the direct channel through which quotas can affect a farm: increased spatial substitution between milk producers across *départements*. However, quota liberalization also has indirect effects due to product substitution on the downstream side of the market. Suppose we were willing to compare the respective growths of two farms of a similar size, in the same *département*, before and after the quotas. The only difference between these farms in this hypothetical example would here reside in the fact that one is in a PDO zone, producing milk then processed into the given PDO product, while the other is outside this PDO zone, and its milk is processed into yogurts. Performing a DID analysis on such treatment and control groups would nevertheless thus not be informative on the effects of the increased risk of spatial substitution due to quota liberalization, for the following reason. As regions are to some extent specialized in terms of products processed with local milk, the two farms

here are potentially confronted with differentiated demand dynamics once the quotas are removed. These dynamics are governed by the relative efficiency gains in the production of substitutable dairy products permitted by quota removal. In our example, and taking into account that PDO cheeses are more cross-substitutable than PDO cheeses and yogurts are, it is likely that the respective demand dynamics of the given PDO cheese and of yogurts diverged. This is due to the fact that territorial specialization is by definition extreme for PDO products, and much less pronounced for yogurts. As a consequence²⁰, relative efficiency gains permitted by the liberalization - and hence the associated demand dynamics - are likely to be more diverging across different PDO products than between the given PDO products and yogurts. For this reason, PDO farms cannot constitute proper control group candidates. A first look at the data for instance confirmed that some of the PDO cheeses performed very well while others seem to have under-performed after the quota removal.

Note that we ignored this territorial specialization in particular products throughout our analysis, because (i) it is much less pronounced for non-PDO products²¹, and (ii) its effects on trends at the *départements* and farm levels seem to be of a second-order compared to the ones presented here.

²⁰And due to the heterogeneities across territories mentioned throughout our analysis.

²¹PDO milk being limited to 10% of milk produced in France.

8. Conclusion

In this paper, we analyze the impact of production quotas and of their progressive removal on the French milk market. We show that production quotas generated two types of distortions. First, by mechanically fixing *département* production shares at their pre-quota 1984 level, they stopped a natural spatial concentration for about 25 years, a process which restarted right after the beginning of the quota removal process in 2008. Second, the implementation of quotas in France overall encouraged the growth of small farms and conversely constrained the expansion possibilities of bigger farms. We show this redistributive scheme successfully refrained growing inequalities among farms, but it came at the cost of partially distorting the competition-led *cream-skimming* of the French milk market, slowing down the selection process of the most efficient farms by protecting the least efficient ones. We finally document how the inherent catching-up process in farm selection intervened more or less early across regions, depending on the stringency implied by quotas constraints at the *département* level. We also show that most of these empirical observations can be rationalized by a simple model, which would require further developments in order to properly quantify the effects of production quotas on the French dairy market. In particular, we plan to build a structural equilibrium model to assess better the efficiency and distributional effects of such input market liberalization.

Finally, an interesting feature of the dairy market we eluded throughout this paper lies in its organization along a vertical supply chain, with farmers selling milk to manufacturers which in turn process it into various dairy products. Given the high level of concentration at this stage of the chain, the importance of milk transportation costs, and the diverging dynamics in various dairy product demands, farms' trajectories may be dependent on a buyer they did not necessarily choose. We leave for future research the joint exploitation of *farm-to-firm* network and manufacturer production data to study the role played by this (inter)dependence during the market liberalization.

References

- Aragón, F. M., D. Restuccia, and J. P. Rud (2022a). Are small farms really more productive than large farms? *Food Policy* 106, 102168.
- Aragón, F. M., D. Restuccia, and J. P. Rud (2022b). Assessing misallocation in agriculture: plots versus farms. Technical report, National Bureau of Economic Research.
- Bouamra-Mechemache, Z., J.-P. Chavas, T. Cox, and V. Réquillart (2002a). Eu dairy policy reform and future wto negotiations: a spatial equilibrium analysis. *Journal of Agricultural Economics* 53(2), 233–257.
- Bouamra-Mechemache, Z., J.-P. Chavas, T. L. Cox, and V. Réquillart (2002b). Partial market liberalization and the efficiency of policy reform: the case of the european dairy sector. *American Journal of Agricultural Economics* 84(4), 1003–1020.
- Bouamra-Mechemache, Z., R. Jongeneel, and V. Réquillart (2008). Impact of a gradual increase in milk quotas on the eu dairy sector. *European review of agricultural economics* 35(4), 461–491.
- Eaton, J. and S. Kortum (2002). Technology, geography, and trade. *Econometrica* 70(5), 1741–1779.
- Hsieh, C.-T. and P. J. Klenow (2009). Misallocation and manufacturing tfp in china and india. *The Quarterly journal of economics* 124(4), 1403–1448.
- Huettel, S. and R. Jongeneel (2011). How has the eu milk quota affected patterns of herd-size change? *European Review of Agricultural Economics* 38(4), 497–527.
- Lips, M. and P. Rieder (2005). Abolition of raw milk quota in the european union: A cge analysis at the member country level. *Journal of Agricultural Economics* 56(1), 1–17.
- Macchiavello, R. (2022). Relational contracts and development. *Annual Review of Economics* 14, 337–362.
- Macchiavello, R. and A. Morjaria (2015). The value of relationships: evidence from a supply shock to kenyan rose exports. *American Economic Review* 105(9), 2911–2945.
- Macchiavello, R. and A. Morjaria (2021). Competition and relational contracts in the rwanda coffee chain. *The Quarterly Journal of Economics* 136(2), 1089–1143.
- Restuccia, D. and R. Santaaulalia-Llopis (2017). Land misallocation and productivity. *NBER working paper* (w23128).
- Ryan, S. P. (2012). The costs of environmental regulation in a concentrated industry. *Econometrica* 80(3), 1019–1061.

Samson, G. S., C. Gardebroek, and R. A. Jongeneel (2016). Explaining production expansion decisions of dutch dairy farmers. *NJAS-Wageningen Journal of Life Sciences* 76, 87–98.

Witzke, H. P. and A. Tonini (2009). Milk quota expiry impacts and sensitivity analyses using the capsim model. *German Journal of Agricultural Economics* 58(670-2016-45778), 228–237.

Zimmermann, A. and T. Heckelei (2012). Structural change of european dairy farms—a cross-regional analysis. *Journal of Agricultural Economics* 63(3), 576–603.

Chapter 3

Market Power in Input Markets: Theory and Evidence from French Manufacturing

Note: This chapter is co-authored with Monica Morlacco (USC).¹

Abstract

The chapter quantifies buyer power in input trade and evaluates its aggregate effects. We develop an empirical strategy for estimating importers' buyer power from standard trade and production data that does not rely on assumptions about other input markets. Using data on French manufacturing firms, we find an average markdown of 1.49 on imported inputs and of 1.59 on domestically purchased inputs, revealing significant buying power in both markets. We explore the welfare implications of these estimates using an equilibrium model. Like an import tariff, the importers' buyer power forces a trade-off between terms-of-trade gains and losses in consumer surplus.

Keywords: Buyer Power, Markdowns, Market Power, Input Trade

¹We thank Costas Arkolakis, Vittorio Bassi, Lorenzo Caliendo, Joel David, Jan De Loecker, Teresa Fort, Penny Goldberg, Sam Kortum, Clémence Lenoir, Jacques Mairesse, Isabelle Méjean, Michael Peters and Tommaso Porzio for helpful suggestions and fruitful discussions. We also thank Francis Kramarz for making the data available, and Frederic Warzynski and the FIND Group at Aarhus University for critical support during Monica's time at Aarhus BSS. Clément Boullé provided outstanding research assistance. Funding from the Yale Economics Department and the Yale MacMillan Center International Dissertation Research Fellowship is gratefully acknowledged. All errors are our own.

1. Introduction

Large buyers play a prominent role in many sectors of modern economies, and their ability to pressure sellers into lowering prices below competitive levels is a growing concern of antitrust authorities.¹ The exercise of buyer power can impact the economy's overall welfare, as it not only alters the division of surplus between buyers and suppliers but also affects consumers through output and price effects.

Buyer power may be particularly relevant in international trade. In this context, high fixed costs of participation result in a concentration of imports and exports among a few large and dominant firms (Antràs, 2020). Importers' buyer power can serve as a countervailing force against exporters' market power, potentially resulting in lower import prices. However, it can also lead to distortions in import quantities, making the outcomes for imports, consumer prices, and quantities uncertain. Despite the significant role of input trade in a country's economic performance, our understanding of the size and implications of buyer power in imports remains limited, as the international trade literature often assumes that importers act as price takers.

This paper quantifies buyer power in input trade and evaluates its impact on the aggregate economy. Our approach combines a novel empirical strategy to estimate market power in input markets with a tractable equilibrium model to convert the buyer power estimates into welfare calculations. We apply our methodology using data from French manufacturing importers, which provides an ideal case study for our analysis, given France's status as a large open economy and one of the world's largest importers.

We develop an empirical strategy to estimate importer-level markdowns in input trade using standard trade and production data. The starting point is a theoretical framework that encompasses various models of input trade under imperfect competition. In this framework, we define a firm market power in a foreign input market as the gap between the input marginal cost and its price, i.e., the input price markdown. We demonstrate that the average importer markdown across all input markets in which they participate can be calculated as the ratio between the revenue elasticity of the imported inputs and the inputs' share in the total firm revenues. The revenue elasticities can be estimated using trade and revenue data following existing approaches in the industrial organization (IO) literature; the input revenue shares are directly observed in the data.

Our methodology builds upon the production approach to estimating market power pioneered by Hall (1988), De Loecker and Warzynski (2012), and Dobbelaere and Mairesse (2013), which has primarily focused on market power in product or labor markets. This approach has recently gained popularity due to its minimal data requirements and the increasing interest in measuring market power in modern economies. However, it faces two significant challenges. First, the standard approach assumes the existence of a perfectly

¹See, e.g., *American Antitrust Institute (AAI)'s Report on Competition Policy* (2008, Chapter 3).

competitive variable input, often intermediate inputs. Second, it relies on estimates of the output elasticity of variable inputs, which are difficult to obtain without data on output and input prices and quantities, leading to well-known input and output price biases in production function estimation.²

In contrast, our approach and its application to the international trade context overcome both these challenges. Firstly, our methodology can accommodate imperfect competition in nearly any input market, including the market for intermediate inputs. The key insight is that information about an input wedge or markdown can be directly obtained from its revenue elasticity (Bond et al., 2021; Hashemi et al., 2022). Secondly, by focusing on estimates of the revenue elasticity of inputs, we avoid the need to separate output price and quantity, thus bypassing the output price bias. Furthermore, by examining input trade, we can leverage the extensive information on input price and quantity readily available in customs data, which mitigates the input price bias.

One disadvantage of our approach, compared to more standard methods, is that estimating the revenue elasticities of inputs requires imposing additional structure on output markets. Specifically, it necessitates introducing a demand system into the standard production function framework (Pozzi and Schivardi, 2016; De Loecker, 2011). To address this, we combine a CES demand system with a gross output specification of technology. This allows us to establish a sales-generating production function that connects firm-level revenues to input quantities and unobserved demand and productivity factors.

We use a demand estimation procedure to obtain estimates of firm-level demand shifters. This involves analyzing price and quantity data from export records, combined with an instrumental variable (IV) strategy similar to the approach used by Piveteau and Smagghue (2019). By estimating the demand shifters, we can then utilize data on firm-level sales and input quantities to consistently estimate revenue elasticities, using established methods in the production function estimation literature (Akerberg et al., 2015).

Using the universe of trade and production data for the French manufacturing sector, we apply our methodology and uncover evidence of significant buyer power in input trade. Our analysis reveals that the average firm-level markdown across all manufacturing industries is estimated at 1.49. This finding implies that importers have substantial pricing power, with import prices, on average, being 67% below competitive levels.

While high markdowns are observed across all industries, we document substantial heterogeneity among firms and industries. For example, buyer power is particularly high in the "Basic Metals" and "Wearing Apparel" industries, with average markdown estimates of 1.80 and 1.85, respectively. Conversely, the "Chemical" and "Rubber" industries appear relatively more competitive, with markdowns around 1.25. Across firms, large and

²For detailed discussions, see, e.g., De Loecker and Goldberg (2014), De Loecker et al. (2016), Bond et al. (2021), De Ridder et al. (2022).

productive firms have relatively larger wedges than smaller, unproductive ones. By leveraging the granularity of our highly detailed import data, we further demonstrate that firm-level markdowns on imported inputs exhibited a negative correlation with the average level of competition faced by firms across import markets. This evidence lends support to the claim that methodology is effective at capturing, through a firm-level markdown on imported inputs, the extent of buyer power exerted by a given firm in various import markets.

Although not our primary focus, we then apply our methodology to demonstrate that even when domestically sourced, markdowns on intermediate inputs appear relatively high, with an average markdown of around 1.60.³ Overall, our findings suggest that intermediate input markets are far from competitive, contrary to the usual assumption in related literature. Specifically, our results indicate that existing estimates of markups or markdowns, derived under the assumption of no buyer power in material inputs, may be prone to an upward bias. This bias occurs because such estimates may inadvertently capture market power in input markets (Avignon and Guigue, 2022; Treuren, 2022).

In the last part of the paper, we embed the model of firm behavior into a parsimonious macroeconomic framework to quantitatively evaluate the implications of the buyer power of importers for production and welfare in the economy. At the individual firm level, buyer power leads to an inefficient substitution of the inputs in production and to an inefficiently small firm size. At the aggregate level, micro-level input distortions lead to lower imports and overall lower output, as compared to a world where all firms behave as price takers in all input markets.

The main theoretical insight from the macro model is that at the aggregate level, the buyer power of importers acts like a tariff on imports: it induces distortions on domestic production and the volume of trade, but it does so while improving the terms of trade. On the one hand, lower output and higher prices reduce consumer surplus. On the other hand, profits increase due to foreign rent shifting, and so does producer surplus. The overall effect of buyer power on domestic welfare depends on which of these two effects is larger, so it is ultimately an empirical question.

The micro-level estimates from the first part of our paper are sufficient statistics to provide a quantitative assessment of these effects. In baseline calibrations, we find that welfare is always higher in the distorted economy as compared to the efficient counterfactual benchmark. A classical result in the theoretical trade literature is that countries that have market power in imports exploit it in setting their trade policy (Broda et al., 2008). Our results show that even in the absence of import tariffs, when importers are large and have buyer power in input trade they could generate similar effects on aggregate

³The markdowns we estimate in domestic and foreign input markets lie in the same ballpark as markdowns estimated by Treuren (2022) for Dutch manufacturers buying intermediates and by Avignon and Guigue (2022) for French dairy processors buying raw milk.

variables. Moreover, these effects are sizable, in spite of originating from the behavior of individual firms.

These findings have important policy implications. Because the buyer power of importers could increase national welfare, nationalistic governments may face weak incentives to restrain the market power of the largest firms. A lenient national anti-trust policy could substitute for beggar-thy-neighbor trade policies, such as optimal import tariffs, while being less exposed to the risk of retaliation. We leave a more detailed investigation of similar policy interdependencies for future research.

Literature Review In addition to the papers discussed earlier, our work is related to several works in international trade and macroeconomics. While buyer power in international trade has drawn increased attention from economists in recent years (Alvarez et al., 2021; Ignatenko, 2021), there have been only a few attempts to quantify its importance and even fewer attempts to model its aggregate consequences in general equilibrium.⁴ Raff and Schmitt (2009) studied the implications of buyer power of retailers/wholesalers on the effects of trade liberalization, while Bernard and Dhingra (2019) analyzed the effects of changes in the microstructure of import markets on the division of gains from trade. This paper provides a micro-foundation for a new empirical framework for estimating buyer power in input trade from standard trade and production data. We show novel evidence that the buyer power of importers is sizable, using both reduced-form and structural methods. Finally, we study and evaluate the aggregate implications of buyer power in general equilibrium.

The findings in this paper also contribute to the empirical literature on the effects of input trade for aggregate productivity and growth (Amiti and Konings, 2007; Goldberg et al., 2010; Topalova and Khandelwal, 2011; Halpern et al., 2015; Blaum et al., 2018). By providing evidence that foreign input markets are relatively more distorted than domestic ones, this paper shows that opening up to input trade can generate allocative inefficiencies, such that the productivity gains from input trade may be lower than expected.

Finally, the results in this paper relate to the ongoing academic debate about the causes and consequences of the rising market power in modern economies by bringing international trade and offshoring into the picture.⁵

⁴The bulk of theoretical and empirical work in this literature has focused on the relationship between exports and competition. Studies in this literature include Harrison, 1994; Chen et al., 2009; De Loecker and Warzynski, 2012; De Loecker et al., 2016; Arkolakis et al., 2018; Dhingra and Morrow, 2019.

⁵For evidence and discussions about the rise of market power in modern economies, see, among others, De Loecker et al., 2019; Eggertsson et al., 2018; Gutiérrez and Philippon, 2017; Syverson, 2019.

2. A Framework for Estimating Input Market Power

This section introduces an empirical strategy for estimating firm-level measures of market power in input markets using standard production and trade data. Although our empirical application focuses on the market for imported intermediate inputs, the methodology discussed here can be applied to any static input for which data on production and (input) quantities are available. While we start from use a model of single-product firms for simplicity, we will discuss the extension to multi-product firms at the end of the section as they are prevalent in the data.

2.1. Theoretical Framework

We consider an economy populated by a mass of firms, each indexed by i , which combine several inputs to produce quantity Q_i of a final good variety according to the following gross-output technology:

$$Q_i = Q(\mathbf{K}_i, \mathbf{V}_i; \Theta_i). \quad (3.1)$$

The vector $\mathbf{K}_i = \{L_i, K_i\}$ represents the dynamic inputs subject to adjustment costs or time-to-build, such as capital and labor.⁶ The vector $\mathbf{V}_i = \{Z_i, M_i\}$ includes the variable (or static) inputs, such as the quantity Z_i of domestic intermediate input varieties and the quantity M_i of imported intermediate input varieties. Here, we define an imported intermediate input variety as the combination of an Harmonized System (HS) 8-digit product and source country. We denote foreign input varieties as ν , and the set of all such ν sourced by firm i as Σ_i .⁷ We consider well-behaved production technologies and assume that $Q(\cdot)$ is twice continuously differentiable with respect to its arguments.

The vector of state variables of the firm is given by:

$$\Theta_i = (\mathbf{K}_i, e^{\omega_i}, \Sigma_i). \quad (3.2)$$

The state variables include the dynamic inputs for all products (\mathbf{K}_i), a productivity term (e^{ω_i}), assumed log-additive and firm-specific, and the firm *sourcing strategy* for foreign intermediate input varieties (Σ_i).

⁶While labor is typically assumed to be a static input in production in related literature (e.g., De Loecker and Warzynski, 2012; Dobbelaere and Mairesse, 2013; Yeh et al., 2022), there is evidence that labor markets are particularly rigid in France, especially for large firms (50+ employees), which are the object of our analysis (Garicano et al., 2016). We thus prefer to remain agnostic about the nature of the labor input.

⁷Because variety-level information on domestic inputs is not available, we approximate the set of domestic varieties sourced by all firms with a unit continuum.

By including the firm sourcing strategy in the state variable vector, we assume separability between an importer's extensive and intensive margin sourcing decisions. This means that a firm input mix is a dynamic choice determined prior to the amount of input variety being chosen. This assumption captures the high persistence in firm-to-firm relationships, which arises from the high adjustment costs associated with the extensive margin of trade (Antràs, 2020; Monarch, 2021).

00.00.0000

Foreign input varieties are aggregated according to a constant return to scale production function $h_i^M(\cdot)$, namely:

$$M_i = h_i^M ([M_i(\nu)]_{\nu \in \Sigma_i}). \quad (3.3)$$

The input quantity $M_i(\nu) \forall \nu$ is chosen flexibly in each period, given the sourcing strategy Σ_i . Assumptions 2 and 3 are standard in the trade literature (Gopinath and Neiman, 2014; Blaum et al., 2019). Assumption 2 is important for aggregating imported input choices from the variety level to the firm level, which is necessary for matching the model with the data. Assumption 3 allows us to focus on the optimal choice of input quantities given a sourcing set without taking a stand on how such a set is determined.

00.00.0000

Firms choose the flexible inputs to maximize short-run profits. The assumption of profit-maximizing firms is slightly less general than assuming cost minimization, which more common (e.g., De Loecker and Warzynski, 2012).⁸ In the context of estimating market power in input markets, this assumption is valuable as it avoids imposing additional restrictions on the structure of other input markets, as we discuss below.

Market Power in Imported Input Markets

To account for the market power of importers in this general framework, we depart from the standard assumption that importers act as price-takers and instead allow them to negotiate with foreign exporters over the price of intermediate input varieties. We present a formal model of importer-exporter bargaining in Appendix 3.C, which is based on contemporary work by Alvarez et al. (2021). The model we consider is a flexible extension of more common pricing models in the trade literature, as it encompasses both the competitive benchmark and the monopsony limit as special cases. In this section, we provide a brief summary of the most important elements of the model.

Importers and exporters exchange an intermediate input and bargain over its price, so as to maximize their joint profit or generalized Nash product. The price is determined based on the bargaining power and each party's gains from trade. The quantity of the

⁸Specifically, when firms choose inputs to minimize costs, they condition on an output level that is not necessarily profit-maximizing. Vice-versa, when firms maximize profits, they select both inputs and final output optimally.

input exchanged is determined by the demand function at the negotiated price. The buyer market power is due to two factors: the upward-sloping export supply function and the oligopsony power of each importer, which is proportional to their share of the total exporter's input supply.

It can be shown that one can fully summarize the outcome of the bargaining game from the importer's perspective using an inverse supply schedule that maps the importer's demand to a negotiated price. Specifically, this can be written as:

$$W_i^M(\nu) = W_i^M(M_i(\nu)), \quad (3.4)$$

where the function $W_i^M(\cdot)$ is specific to each importer-exporter match due to factors such as the exporter's bargaining power and productivity, and bilateral outside options. The inverse supply elasticity $\Psi_i^M(\nu) \equiv \frac{d \ln W_i^M(\nu)}{d \ln M_i(\nu)} \geq 0$ characterizes the mapping in (3.4), and it is non-negative and increasing in the importer's share of the foreign exporter's output.

The mapping in (3.4) encompasses perfect competition as a special case. Specifically, when importers are atomistic, their share of the foreign exporter's output is small, and the inverse elasticity approaches zero ($\Psi_i^M(\nu) \rightarrow 0$). In this case, importers act as price takers in the foreign input market. Conversely, the elasticity is positive for non-atomistic importers because they internalize their impact on aggregate input supply and price when choosing their optimal input demand. They will distort their input demand to negotiate lower prices.

Equilibrium Let $\mathcal{L}_i = R_i - \int_{\Sigma_i} W_i^M(\nu) M_i(\nu) d\nu - E_i^Z$ denote the Lagrangian associated with the firm short-run profit maximization problem, where $W_i^M(\nu)$ is the price of input variety ν paid by firm i and E_i^Z denotes total expenditure on domestic intermediate inputs. The buyer chooses the optimal quantity of input variety ν to maximize \mathcal{L}_i subject to the input price schedule in (3.4). The first-order condition (FOC) of the problem yields:

$$W_i^M(\nu) = \frac{MR_i^M(\nu)}{\psi_i^M(\nu)}, \quad (3.5)$$

where $MR_i^M(\nu) \equiv \partial R_i / \partial M_i(\nu)$ is the marginal revenues generated by input variety ν , or the input's shadow value. Thus, the first-order condition states that the input price $W_i^M(\nu)$ can be expressed as a wedge $\psi_i^M(\nu)$ below the input's marginal revenues.

The wedge $\psi_i^M(\nu)$ captures the importer i 's input price markdown, a standard measure of input market power. This markdown is defined as $\psi_i^M(\nu) \equiv 1 + \Psi_i^M(\nu) \geq 1$, where $\Psi_i^M(\nu)$ is the input's inverse supply elasticity from equation (3.4). When importers act as price takers in foreign input markets, i.e., when $\Psi_i^M(\nu) = 0$, $\psi_i^M(\nu) = 1$, which means that the input price equals its marginal revenues. Vice versa, when importers have buyer power in input trade, i.e., when $\Psi_i^M(\nu) > 0$, $\psi_i^M(\nu) > 1$ such that the input price is below

marginal revenues.

With a bit of algebra, we can rewrite equation (3.5) as:

$$\psi_i^M(\nu) = \frac{\theta_i^{M,r}(\nu)}{\alpha_i^M(\nu)}, \quad (3.6)$$

This equation expresses the markdown of firm i for foreign input variety ν as the ratio between the revenue elasticity of variety ν , denoted by $\theta_i^{M,r}(\nu) \equiv \frac{\partial R_i}{\partial M_i(\nu)} \frac{M_i(\nu)}{R_i}$, and its revenue share, denoted by $\alpha_i^M(\nu) \equiv \frac{W_i^M(\nu)M_i(\nu)}{R_i}$.

Equation (3.6) is similar to standard markup expressions used in the literature to estimate markups (e.g., De Loecker and Warzynski, 2012), but with two differences. First, the elasticity on the right-hand side of equation (3.6) is the *revenue* elasticity of the input, instead of the *output* elasticity. Second, the markdown is defined at the firm-variety level, rather than just the firm level. This makes it challenging to obtain data on revenue elasticities of input varieties, as this information is typically only available at the firm level. However, we can use Assumption 2 to overcome this measurement issue.

From Theory to Measurement

Let us denote by $\theta_i^{M,r} \equiv \frac{\partial R_i}{\partial M_i} \frac{M_i}{R_i}$ the elasticity of revenues with respect to the foreign input quantity index M_i , and by $\alpha_i^M \equiv \frac{\int_{\Sigma_i} W_i^M(\nu)M_i(\nu)d\nu}{R_i}$ the revenue share of foreign input expenditures. We derive the following result.

Lemma 1 *The average markdown of firm i in foreign input markets can be written as:*

$$\bar{\psi}_i^M = \frac{\theta_i^{M,r}}{\alpha_i^M}, \quad (3.7)$$

where $\bar{\psi}_i^M \equiv \int_{\Sigma_i} \gamma_i^M(\nu)\psi_i^M(\nu)d\nu$ is the weighted average of variety-level markdowns $\psi_i^M(\nu)$, with weights equal to the share of variety ν in total firm i 's expenditure on imported inputs, i.e. $\gamma_i^M(\nu) \equiv \frac{W_i^M(\nu)M_i(\nu)}{E_i^M}$.

Proof See Appendix 3.B1..

Lemma 1 demonstrates that one can estimate the average firm-level markdown of firm i across foreign input markets, which is a theory-consistent measure of buyer power at the importer level, given data on the revenue shares of imported inputs (α_i^M) and estimates of the revenue elasticity of foreign intermediate inputs ($\theta_i^{M,r}$).

Given that we can estimate firm-level revenue elasticities from revenue and input quantity data, and revenue shares are directly observed, Lemma 1 implies that we can gain insights into the market power of importers in input trade solely by analyzing standard firm-level data, without requiring further knowledge of the import environment. This

can be done starting with a general model of production and input trade that imposes minimal assumptions on output and input markets.

Discussion

Before we discuss how we estimate the revenue elasticities, we establish a connection between our framework and the existing literature on firm-level markdown estimation.

In the empirical labor literature, measures of the employers' markdowns have been estimated using the "double-ratio estimand" approach (Dobbelaere and Mairesse (2013)). This approach shares similarities with the one described above but with two key distinctions. Firstly, it assumes firms behave as cost minimizers rather than profit maximizers. Secondly, it assumes the existence of at least one input market where firms act as price takers. Under cost minimization and price-taking buyer behavior in a generic input market X , the average markdown of firm i in market M can be expressed as:

$$\bar{\psi}_i^M = \frac{\theta_i^M}{\alpha_i^M} \left(\frac{\theta_i^X}{\alpha_i^X} \right)^{-1}, \quad (3.8)$$

Here, θ_i^V , $V = \{M, X\}$ represents the output elasticity of variable input V , defined as $\theta_i^V \equiv \frac{dQ_i}{dV_i} \frac{V_i}{Q_i}$. The variable input X is assumed to be perfectly competitive.

The expression in (3.8) has been widely used in empirical research to estimate labor markdowns, such as in Dobbelaere and Mairesse (2013), Dobbelaere and Kiyota (2018), and Yeh et al. (2022), among others. However, this standard approach has two limitations. First, it requires knowledge of output elasticities θ_{it}^V , $V = \{M, X\}$. Estimating output elasticities using standard production data, where revenue serves as the measure of output, is notoriously challenging due to well-known biases in input and output prices in production function estimation.⁹ A second limitation of the standard approach is its assumption of price-taking behavior by firms in at least one input market, typically the market for intermediate inputs. However, given our focus on market power in intermediate input markets and the absence of a clear candidate for a competitive input market, the "double-ratio estimand" approach may not be suitable for this study.

Although more restrictive than cost minimization, assuming that firms maximize profits enables us to infer an importer's buyer power by analyzing firm behavior in a single input market, without having to impose restrictions on the market structure of other input markets where the firm operates. The key insight is that if firm-level markups are not necessary, information about an input's wedge or markdown can be directly obtained

⁹Studies that discuss the so-called *output price bias* in production function estimation include, but are not limited to, Klette and Griliches (1996), De Loecker (2011), De Loecker and Goldberg (2014), De Loecker et al. (2016). More recently, Bond et al. (2021) highlights the issues when proxying output elasticity by revenue elasticity in the production function approach to markup estimation, while Hashemi et al. (2022) shows that using the revenue elasticity for a variable input recovers input wedges, rather than output wedges.

from its revenue elasticity (Bond et al., 2021; Hashemi et al., 2022).

However, our approach requires estimating revenue elasticities alongside markdowns, with both advantages and disadvantages. The main advantage is that unlike output elasticities, identifying and estimating revenue elasticities does not require data on the physical units of output, avoiding the issue of output price bias. The main disadvantage is that the revenue function depends on the underlying demand system and market structure, necessitating imposing some structure on the output market that would not be necessary otherwise.

2.2. Estimating the Revenue Elasticities of Inputs

We consider the following functional-form specification of the production function in (3.1):

$$Q_{it} = e^{(\omega_{it} + \epsilon_{it})} K_{it}^{\beta_k} L_{it}^{\beta_l} X_{it}^{\beta_x} \quad (3.9)$$

$$X_{it} = (M_{it}^\rho + Z_{it}^\rho)^{\frac{1}{\rho}}, \quad (3.10)$$

where X_i is an intermediate input composite, which is a constant elasticity of substitution (CES) composite of foreign-produced (M_i) and domestically-produced (Z_i) intermediates, with substitution elasticity equal to $1/(1-\rho) > 1$. The coefficients β_j , $j = \{k, l, x\}$ are the Cobb-Douglas elasticities of capital, labor, and intermediates, respectively. The vector of parameters $\{\beta, \rho\}$ is assumed to be common at the two-digit manufacturing sector level and constant over the sample period, as is standard in the literature. In addition to the various inputs, production depends on a firm-specific productivity shifter (ω_{it}), which captures the productivity component known by the firm, and ϵ_{it} , which captures measurement error and idiosyncratic shocks to production.

Taking logs on both sides of equation (3.9), and using the Taylor's formula for a second-order expansion of equation (3.10) around $\rho = 0$, one could write the firm's production function as:¹⁰

$$q_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_z z_{it} + \beta_{mm} m_{it}^2 + \beta_{zz} z_{it}^2 + \beta_{mz} m_{it} z_{it} + \omega_{it} + \epsilon_{it}, \quad (3.11)$$

where lower-case variables denote the logs of the corresponding upper-case variables.

We define a firm's (log) revenue as $r_{it} = q_{it} + p_{it}$, where p_{it} is the log price of the firm's

¹⁰Following Kmenta (1967), the second-order Taylor expansion of (3.10) around $\rho = 0$ reads:

$$\begin{aligned} x_{it} &= m_{it} + z_{it} + \frac{\rho}{2} m_{it}^2 + \frac{\rho}{2} z_{it}^2 + \rho m_{it} z_{it} + \epsilon_{it} \\ &= \gamma_m m_{it} + \gamma_z z_{it} + \gamma_{mm} m_{it}^2 + \gamma_{zz} z_{it}^2 + \gamma_{mz} m_{it} z_{it} + \epsilon_{it}, \end{aligned}$$

which is a Translog function of order 2. The β coefficients in equation (3.11) are then defined as $\beta_i \equiv \beta_x \gamma_i$ for $i = \{m, z, mm, zz, mz\}$.

output. To determine the price p_{it} , we incorporate a demand system for the firm's final good variety into the production framework. Specifically, we follow [De Loecker \(2011\)](#) in adopting a standard CES demand system:

$$q_{it} = -\sigma_s(p_{it} - p_{st}) + q_{st} + \eta_{it}. \quad (3.12)$$

Here, p_{st} and q_{st} represent the (log) average price and quantity in industry s , and η_{it} is an idiosyncratic demand shifter observed by the firm but unobserved by the econometrician. The parameter σ_s denotes the substitution elasticity across varieties of the final good. In the single-product case, each firm produces a single variety and, in equilibrium, the quantity produced equals the quantity demanded.

Using equations (3.11) and (3.12), we obtain an expression for firm-level (log) revenues as:

$$r_{it} = \tilde{\beta}_k k_{it} + \tilde{\beta}_l l_{it} + \tilde{\beta}_m m_{it} + \tilde{\beta}_z z_{it} + \tilde{\beta}_{mm} m_{it}^2 + \tilde{\beta}_{zz} z_{it}^2 + \tilde{\beta}_{mz} m_{it} z_{it} + \delta_{st} + \omega_{it}^* + \eta_{it} + \epsilon_{it}, \quad (3.13)$$

where $\tilde{\beta}_x = (1 - \sigma_s) \beta_x$, for $x = \{k, l, m, z, mm, zz, mz\}$ are reduced-form parameters that combine technology and demand parameters, and where the term δ_{st} subsumes the market-level demand shifters. Just like the production function coefficients, the unobserved productivity and demand term enters the estimating equation scaled by the relevant demand parameter, e.g., $\omega_{it}^* \equiv (1 - \sigma_s) \omega_{it}$. Since we are not interested in separately identifying demand and technology parameter, we ignore this distinction and drop the asterisk notation hereafter.

Given equation (3.13), the revenue elasticity of foreign inputs can be found as:

$$\theta_{it}^{M,r} = \tilde{\beta}_m + 2\tilde{\beta}_{mm} m_{it} + \tilde{\beta}_{mz} z_{it}, \quad (3.14)$$

which is a function of data (m_{it}, z_{it}) and parameters $\{\tilde{\beta}_m, \tilde{\beta}_{mm}, \tilde{\beta}_{mz}\}$ and which can be estimated alongside the revenue equation (3.13).

Obtaining consistent estimates of the parameters of equation (3.13) requires dealing with several sources of bias. First and foremost, unobserved demand (η_{it}) and productivity shocks (ω_{it}) lead to well-known simultaneity biases ([Foster et al., 2008](#); [Akerberg et al., 2015](#)). An additional issue in estimating equation (3.13) is that it requires information on firm-level input quantities, which are not directly available for all inputs. In the following three paragraphs, we discuss our approach to dealing with these biases.

Estimating Firm-level Demand Shifters

Our initial objective is to estimate the firms' idiosyncratic demand shifters η_{it} based on equation (3.12). Estimating these demand shifters relies on demand estimation, which

necessitates data on the quantity and price of final goods sold by the firms. However, in our data context, we can only observe information on the price and quantity of goods the firm exports.

In this section, we outline our approach to estimating firm-level export demand shifters using customs data. These demand shifters will serve as a proxy for the average firm-level demand shifters in output markets. To fully utilize the richness of our customs data, we first recover demand shifters at the firm-product-destination-year level and then aggregate them at the firm level.

Considering the multi-product, multi-country nature of the data, we introduce additional notation in the demand system described in equation (3.12). We use c to represent the destination country and p to denote the product variety sold by firm i in destination c . The price of product p sold by firm i in destination country c , accounting for iceberg trade costs and expressed in local currency, is denoted as p^{ipct} . This price is related to the observed FOB (Free on Board) price in the home currency (p_{ipct}) by the equation $p^{ipct} = p_{ipct} + \ln \tau_{pct} - e_{ct}$, where τ_{pct} represents the iceberg trade cost of shipping good p from France to destination d , and e_{ct} denotes the logarithm of the bilateral exchange rate, indicating the foreign currency price of one unit of domestic currency (euro in our application).

We denote with η_{ipct} the firm-product-country specific demand shifter, which reflects factors such as vertical quality differences among firm-level varieties of an exported good or demand idiosyncrasies across foreign importers that may influence the sale of a product at a given price. We decompose η_{ipct} as $\eta_{ipct} = \eta_{it} + \eta'_{ipct}$, where η_{it} is a firm-level average, and η'_{ipct} is a deviation of the demand shifter of firm i selling product p in c from the firm-level average shifter. We consider η_{it} as a measure of the demand shifter in the revenue function in (3.20).

We allow the demand function to vary across broad product chapters, denoted by s , as defined in the official in the HS Product Classification, and estimate the following equation for each product p in chapter s :¹¹

$$q_{ipct} = -\sigma_s p_{ipct} + \delta_{pct} + \eta_{ipct} \quad (3.15)$$

where q_{ipct} is the (log) quantity of the variety sold by i in the destination market, and $\delta_{pct} \equiv -\sigma_s (\ln \tau_{pct} - e_{ct}) + (\sigma_s - 1) \ln P_{pct} + \ln Q_{pct}$ is a product-destination-time term capturing aggregate shifters, including the price index of good p in destination c at year t , the aggregate expenditure, the iceberg trade cost and exchange rate.

Estimating equation (3.15) is complicated by a well-known simultaneity problem: positive shocks to market appeal lead producers to raise prices, which can result in p_{ipct} and

¹¹Examples of broad product categories in the HS classification include “Animal and Animal Products” (HS2 codes 01-05), “Textiles” (HS2 codes 53-60), and “Machinery and Electrical” (HS2 codes 84-85).

η_{ipct} being positively correlated (Foster et al., 2008). Therefore, estimating demand elasticity using plain ordinary least squares (OLS) would underestimate it. To address this endogeneity problem, we use an instrumental variable (IV) approach and instrument for p_{ipct} using an import-weighted exchange rate at the firm level as a supply-side (cost) shifter. The basic idea is that real exchange rate shocks affecting a firm's imports represent cost shocks that are passed through to final prices and are orthogonal to destination-specific demand shifters. Using this instrumental variable strategy, we obtain consistent estimates of the demand parameters, despite the endogeneity of p_{ipct} .

To obtain estimates of firm-level demand shifters η_{it} , we first obtain the residual $\hat{\eta}_{ipct}$ from the IV estimation of equation (3.15). We then obtain an estimate of the average firm-level shifter η_{it} as a weighted average of these residuals, where weights are given by the export share of the variety at time t . A similar IV strategy has been used by Piveteau and Smagghue (2019) to obtain quality measures at the firm-product-country-year level. We closely follow their approach when adapting equation (3.15) to our data, and we refer readers to their study for a more detailed discussion of the instrument's validity in estimating demand using similar data. Appendix 3.D includes the details of the estimation procedure.

Unobserved Productivity

To control for unobserved productivity ω_{it} in the estimation of the revenue function (3.13), we consider the control function approach in Akerberg et al. (2015). The idea behind this approach is to write the firms' unobserved productivity as a function of observable variables by inverting the equilibrium demand function for a flexible variable input.

We consider firm-level expenditure on services as the flexible input of interest. In the French data, expenditures on services primarily include subcontracting costs, leasing fees, rents and rental charges, maintenance and repair, insurance premiums, the remuneration of intermediaries and fees, advertising costs and banking services; it is one of the variables that most strongly correlates with contemporaneous output growth (Wong, 2019), thus satisfying the flexibility condition. We denote as s_{it}^e the (observed) expenditure on services, and with s_{it} the corresponding (unobserved) physical measure.

Since expenditures on services largely reflect firms' operating expenses not directly related to the production of goods sold, we assume that services do not affect the production of output directly, but only through their impact on productivity. We thus write $\omega_{it} = \omega(s_{it}, \phi_{it})$ where ϕ_{it} is an exogenous idiosyncratic productivity term, known by the firm but unknown to the econometrician. We also assume that $s_{it} = s(s_{it}^e, \phi_{it})$, with $s'_{\phi} > 0$, which says that the total amount of services available to the firm is an increasing function not only of expenditures, but also of productivity ϕ_{it} . In this sense, we can think

of ϕ_{it} as capturing the efficiency with which firms are able to deploy services (De Ridder, 2019). Our last assumption is that firms take the price of services as given, such that nominal expenditure measures do not confound unobserved price differences across firms, conditional on a firm's location and industry.

We consider the following optimal service expenditure function:

$$s_{it}^e = h(\phi_{it}, \mathbf{X}_{it}, G_{it}, \eta_{it}), \quad (3.16)$$

where G_{it} is a vector of variables that can affect firms' service prices, which includes location, sector, and year fixed effects. Equation (3.16) allows operating expenses to vary with the firm inputs $\mathbf{X}_{it} = (k_{it}, l_{it}, m_{it}, z_{it})$. Finally, we also allow the idiosyncratic demand shocks to affect a firm demand of services.

To obtain a control function for unobserved productivity ϕ_{it} , we invert the function in (3.16) under the assumption that ϕ_{it} is the only unobserved variable affecting operating expenses.¹² The control function can thus be written as $\phi_{it} = h^{-1}(s_{it}^e, \mathbf{X}_{it}, G_{it}, \eta_{it})$, such that, given $\omega_{it} = \omega(s_{it}, \phi_{it})$ and $s_{it} = s(s_{it}^e, \phi_{it})$, we can write:

$$\omega_{it} = \tilde{h}(s_{it}^e, \mathbf{X}_{it}, G_{it}, \eta_{it}). \quad (3.17)$$

Input Price Biases

When firm-level inputs are measured as deflated expenditures, standard techniques for estimating equation (3.13) may lead to an input price bias (De Loecker and Goldberg, 2014).

We alleviate concerns about the foreign input price bias by constructing a physical measure of the imported input relying on a firm-level deflator built from import data. We first use a fixed effect strategy on variety-level import prices to construct a measure \hat{w}_{it}^m of average firm deviation from the industry-level price of different imported inputs. We then construct the firm-level import price deflator as

$$\tilde{w}_{it}^m = w_{st}^m + \hat{w}_{it}^w, \quad (3.18)$$

where w_{st}^m is the observed industry deflator for imported intermediates. Finally, we construct a physical measure of the imported input by deflating total expenditures on the imported inputs by the firm-level deflator in (3.18). In doing so, differences in imported input prices among firms are accounted for, thus alleviating concerns about the foreign input price bias.

The remaining concern is thus with domestic intermediate inputs, due to the lack of

¹²Note that, even if demand shocks η_{it} are unobserved, we can control for them using our estimates from demand estimation.

price and quantity data and the possibility of unobserved price differences across firms that are not captured by industry-wide deflators. The presence of a domestic input price bias in our analysis would be problematic for our focus on buyer power in import markets to the extent that it biases the measure z_{it} and the coefficients $\tilde{\beta}_m$, $\tilde{\beta}_{mm}$, and $\tilde{\beta}_{mz}$. De Loecker et al. (2016) propose approaches based on control functions to address input price bias, essentially suggesting to alleviate concerns about unobserved differences in buyer power or quality by controlling for (relevant) market shares or prices. We refer to De Loecker et al. (2016) for a more formal explanation. Our baseline approach includes firm-level average wages per worker (a proxy for labor quality) in the input price bias control function. They are good proxies for other input quality, as they positively correlate with input quality in a large class of theoretical models. Additionally, we include indicators for the firm 4-digit sector and region to control for variation in input prices across sectors and locations.¹³

Formally, it implies the following input price bias control function:

$$b_{it}(\cdot; \tilde{\beta}^b) = b\left(1, X_{it} \times X_{it}^b; \tilde{\beta}^b\right) + \gamma_{it} \quad (3.19)$$

where inputs contained in X_{it} enter only interacted with the control variables in X_{it}^b (solely featuring the average wage in our baseline estimation) in order not to perturb the production function specification. $\tilde{\beta}^b$ contains the corresponding coefficients and γ_{it} contains 4-digit sector and location fixed effects which enter linearly.

Estimation

Putting pieces together, the estimating equation reads:

$$r_{it} = f(\mathbf{X}_{it}; \tilde{\beta}) + \omega_{it} + \eta_{it} + \epsilon_{it}, \quad (3.20)$$

where $f(\mathbf{X}_{it}; \tilde{\beta}) \equiv \tilde{\beta}_k k_{it} + \tilde{\beta}_l l_{it} + \tilde{\beta}_m m_{it} + \tilde{\beta}_z z_{it} + \tilde{\beta}_{mm} m_{it}^2 + \tilde{\beta}_{zz} z_{it}^2 + \tilde{\beta}_{mz} m_{it} z_{it}$ is the production function, $w_{it} \equiv h(s_{it}^e, \mathbf{X}_{it}, G_{it}, \eta_{it})$ is the TFP shock, and where we subsumed the market-level shifter δ_{st} which will be controlled in the estimation by time fixed effects. To estimate (3.20), we follow the two-step GMM procedure described in Akerberg et al. (2015).

In the first stage, we run OLS on a non-parametric function of the dependent variable on all the included terms:

$$r_{it} = \phi_t(s_{it}^e, \mathbf{X}_{it}, G_{it}, \eta_{it}) + \epsilon_{it}, \quad (3.21)$$

¹³We do not include output (here export) price controls in the baseline as we aim here to estimate a revenue function. We do not include market share controls as we cannot observe relevant market shares for domestic input markets. The market shares we can build, defined at the industry or industry-location level, lack relevance and create a spurious correlation with firm-level domestic input measures. Ignoring convergence issues for some industries, robustness checks including such controls however deliver results similar to baseline results.

where the function ϕ_t is approximated by a third order polynomial. The goal of this first stage is only to separate anticipated revenue \hat{r}_{it} from a term $\hat{\epsilon}_{it}$ made of unanticipated shocks and/or measurement errors: $r_{it} \equiv \hat{r}_{it} + \hat{\epsilon}_{it}$.

The second stage then identifies the revenue function coefficients from a GMM procedure. The first-order Markov law of motion for productivity is described by:

$$\omega_{it} = g(\omega_{it-1}) + \xi_{it}, \quad (3.22)$$

where we approximate $g(\omega_{it-1})$ by a second order polynomial in s_{it-1}^e , \mathbf{X}_{it-1} , and η_{it-1} , while fixed effects contained in G_{it-1} enter linearly. Using (3.19), (3.20) and (3.21) we express ω_{it} as:

$$\omega_{it}(\cdot, \tilde{\beta}, \tilde{\beta}^b) = \hat{r}_{it} - f(\cdot; \tilde{\beta}) - b_{it}(\cdot; \tilde{\beta}^b) - \eta_{it}. \quad (3.23)$$

We can now substitute (3.23) in (3.22) to derive an expression for the innovation in the productivity shock $\xi_{it}(\tilde{\beta})$ as a function of observables and unknown parameters $\tilde{\beta}$. Given $\xi_{it}(\tilde{\beta})$, we can write the moments identifying conditions as:

$$\mathbb{E} \left(\xi_{it}(\tilde{\beta}) \mathbf{Z}_{it} \right) = 0, \quad (3.24)$$

where \mathbf{Z}_{it} includes terms in $g(\cdot)$, a second-order polynomial in k_{it} , and interactions of k_{it} with all lagged inputs. The identifying restrictions, standard in the production function estimation literature (e.g. Levinsohn and Petrin, 2003; Akerberg et al., 2015), is that the innovation term ξ_{it} is uncorrelated with current levels of the dynamic inputs (here k_{it}), and lagged level of the static inputs (here l_{it} , m_{it} and z_{it}).¹⁴

We estimate the revenue function by 2-digit sector over the sample period 1996-2007. We then compute the revenue elasticities of the foreign intermediate input as in equation (3.14). We then use these elasticities to compute our measures of the input market power of importers using the expression in (3.7). When doing so, and similarly to Treuren (2022), we use anticipated revenue from the first stage in the input wedge construction. This reflects the fact that firms by definition optimize on planned revenue, not unanticipated revenue. Formally, revenue shares used in equation (3.7) are thus based on planned revenue as computed from $\hat{R}_{it} = R_{it}/\hat{\epsilon}_{it}$.¹⁵

¹⁴Assuming instead that labor, on which we do not want to take a specific stand, is a dynamic input does not affect the results.

¹⁵While theory-consistent, this adjustment has a limited impact in practice.

3. Data

To conduct the empirical analysis, we employed two longitudinal datasets covering the production and trade activity of all French manufacturing firms from 1996 to 2007.¹⁶ The first dataset contains complete production accounts for each firm, which includes information on the value of output and inputs, such as labor, capital, and materials. We obtained this dataset from the FICUS database of the French Institute of National Statistics (INSEE). Additionally, we used industry-level deflators for output, capital, and material inputs from the STAN Industrial dataset to supplement the production data.

The second dataset is sourced from official records of the French Customs Administration, providing comprehensive information on the import and export flows of French firms. The trade flows are reported at the firm-product-country level, with products defined at the 8-digit (CN8) level of aggregation. One significant advantage of customs data is that they include details on the value and quantity of imports and exports, which makes it possible to calculate import and export prices as unit values. We refer to [Bergounhon et al. \(2018\)](#) for an extensive description of this dataset.

Sample Selection

The methodology involves two steps. Firstly, we estimate demand shifters at the firm level using the demand estimation approach described in Section 2.2. and Appendix 3.D. For this exercise, we use import and export data and conduct demand estimation at the firm-product-country-year level. Import data are leveraged to build shift-share cost instruments for prices, based on exchange rate movements and the firm import sourcing mix. The estimating sample thus comprises firms that engage in import and export activities during a particular year. Table A.1 presents the relevant summary statistics for this sample, while Appendix 3.E2. provides more detail on the basic cleanings we implement.

Secondly, we combine firm-level demand shifters from demand estimation with firm-level production and import data to estimate revenue elasticities from equation (3.20). The estimating sample thus comprises firms engaging in import and export activities during a particular year which are matched with production data. To align with homogeneity requirements implied by the revenue function estimation exercise (done at the 2-digit industry level) and our focus on input trade, we restrict attention to firms whose imports represent more than 5% of their revenues. Table A.2 presents relevant summary statistics for the sample retained for revenue function estimation, while Appendix 3.E2. provides more detail on the exact selection procedure.

These firms constitute approximately 46% of all manufacturing firms in France and contribute to 80% of total manufacturing value added. The French data confirms a

¹⁶For a detailed description of these data sources, we refer to [Blaum et al. \(2018\)](#)

significant size premium for importing and exporting firms, consistent with extensive empirical research on firms and trade. The firms retained for revenue function estimation heavily rely on foreign intermediates for their production, with imported inputs accounting for around 40% of the total material expenditure and 20% of revenues. The final sample comprises approximately 16,000 firms annually, spread across 18 two-digit manufacturing sectors.

4. Results

This section presents the estimation results. We first discuss the results of the demand (shifters) estimation exercise and then those of revenue function estimation.¹⁷

4.1. Demand Shifters

We estimate demand in the pooled sample of firms and by broad HS chapters. Table 3.1 presents the demand estimates for the pooled sample. As expected, the coefficient from OLS estimation is biased towards zero compared to the corresponding IV estimate. The IV methodology identifies a price elasticity of around 4, consistent with the results in Piveteau and Smagghue (2019) who used similar data on French exports.¹⁸ The first-stage and reduced-form price coefficients in columns (3) and (4) exhibit expected and statistically significant correlation signs. Our instrument, which is interpreted as a positive cost shifter, is found to be significantly and positively (negatively) correlated with output prices (quantities). The validity of the instrument is confirmed by the Kleibergen-Paap F-statistic, which exceeds the rule-of-thumb threshold of 10.

We report the demand estimates by broad product chapters in Table A.3 in the Appendix. Similar to the results from the pooled sample, the IV procedure identifies price elasticities ranging from 2.1 to 5.5 for most industries considered.

Given the demand elasticity estimates from Table A.3, we recover estimates of firm-year level demand shifters (η_{it}) using the methodology described in Section 2.2.¹⁹ Table A.5 demonstrates how these firm-level demand shifters positively correlate with export prices, quantities, and values. Furthermore, Table A.6 confirms that such positive correlations persist even when considering firm-level variables, such as employment (l_{it}), wage bill (wl_{it}), and revenue (r_{it}), which are only partially influenced by the firm's exporting

¹⁷For now, all standard errors displayed in this section are step-specific standard errors. We will ultimately compute standard errors from bootstrapping the entire procedure.

¹⁸The main differences between our study and theirs are as follows: (1) we focus solely on manufacturing firms, while their research includes retailers and wholesalers; (2) they examine a slightly longer sample period that extends to 2010.

¹⁹In a first step, we estimate demand shifters at the firm-product-destination country level. We then purge the residuals from product-country-year (PCY) fixed effects, and Table A.4 shows that prices (p_{ipct}), quantities (q_{ipct}), and exports (exp_{ipct}) significantly and positively correlate with these residuals.

Table 3.1: Demand Estimation - Pooled

	OLS	IV	First Stage	Reduced Form
	q_{ipct}	q_{ipct}	p_{ipct}	q_{ipct}
p_{ipct}	-0.869*** (0.017)	-4.076*** (1.523)		
$\overline{RE}_{it}^{imp_{t-1}}$			0.266*** (0.076)	-1.086*** (0.352)
$Entry_{ipct}$	-0.966*** (0.015)	-0.957*** (0.017)	0.003 (0.003)	-0.968*** (0.015)
$\overline{GDP}_{it}^{imp}$	0.015 (0.013)	0.042** (0.019)	0.007** (0.004)	0.0127 (0.013)
$\overline{GDP}_{it}^{exp}$	0.199*** (0.027)	0.236*** (0.040)	0.012** (0.005)	0.186*** (0.027)
Observations	1,199,857	1,199,857	1,199,857	1,199,857
Kleibergen-Paap F-stat		12.45		

Notes: Firm \times prod \times dest \times spell and prod \times dest \times year fixed effects are included in all regressions. Standard errors in parentheses are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

activity. The strong correlation with firm-level revenue is reassuring, as we aim to control for these firm-level demand shifters when estimating the revenue function.

4.2. Revenue Elasticities

Table 3.2 presents the estimates of the revenue elasticity of foreign- and domestically-produced intermediates, calculated using the equation in (3.14). To ensure clarity, we report only the median estimate of the revenue elasticities across firms within each two-digit industry. The complete table of estimates, including the vector of parameters $\tilde{\beta}$, along with the estimates' standard errors and standard deviations, is available in Table A.7 in the Appendix.

On average, the median revenue elasticity across firms for foreign-produced intermediates is estimated to be around 0.25 in each 2-digit industry, while the median revenue elasticity for domestically-produced intermediates is around 0.40. The revenue elasticity of the labor and capital coefficients are estimated to be 0.05 and 0.30, respectively, as indicated by the respective coefficients in Table A.7. All coefficients are estimated precisely.

4.3. Market Power in Input Markets

Table 3.3 presents the mean and median estimated markdowns based on the revenue elasticities reported in Table 3.2 for each two-digit industry. Table A.8 provides additional deciles and more detailed distribution information. Both tables also report estimates for domestically-produced inputs. Across all manufacturing industries, the average firm-level

Table 3.2: Revenue Function Estimates

	Sector	θ_m	θ_z	Obs.
15	Food Products and Beverages	0.233	0.465	6,096
17	Textiles	0.281	0.326	5,238
18	Wearing Apparel	0.332	0.282	3,527
19	Leather	0.298	0.335	1,609
20	Wood	0.181	0.441	2,027
21	Pulp	0.227	0.371	2,694
22	Printing and Publishing	0.272	0.265	1,891
24	Chemicals	0.206	0.399	5,986
25	Rubber	0.195	0.380	5,574
26	Non-metallic mineral Products	0.207	0.307	1,925
27	Basic Metals	0.285	0.356	1,805
28	Fabricated Metal Products	0.209	0.319	7,175
29	Machinery and Equipment	0.210	0.347	6,906
31	Electrical machinery & App.	0.210	0.358	2,447
32	Radio and Communication	0.214	0.342	1,453
33	Medical	0.178	0.301	3,161
34	Motor Vehicles	0.222	0.422	1,838
35	Other Transport Equipment	0.257	0.390	724

Notes: Median θ and (revenue) by industry are displayed, where θ are computed following Equation (3.14). Associated standard deviations are in parentheses.

markdown in the market for foreign intermediates is 1.50, indicating substantial price-setting power for importers. The average and median markdowns significantly deviate from competitive levels in every manufacturing industry, with variation in heterogeneity across industries and firms. For instance, “Basic Metals” (1.80) and “Wearing Apparel” (1.85) industries show high markdowns, while “Chemical” (1.24) and “Rubber” (1.29) industries appear to be more competitive.

The market for domestically-produced intermediates also exhibits high markdowns, with an average estimated markdown of 1.60 across two-digit industries. We find a positive correlation between the average industry markdowns in the two input markets. The distribution of markdowns in the foreign input market is substantially skewed, with firms in the 90th percentile charging a markdown almost three times as high as those in the 10th percentile. In contrast, the distribution is relatively normal in the domestic input market. These findings align with the significant skewness in import behavior documented in Table A.2.

4.4. Validation

The econometric framework used in this study identifies market power in input markets by examining distortions, or “wedges”, in the profit-minimizing behavior of industries and firms. In this context, foreign and domestic intermediates are defined as firm aggregates, which allows for the use of production function estimation techniques to obtain consistent estimates of the wedges. However, this level of aggregation may introduce concerns about

Table 3.3: Average and Median Markdowns

Sector	ψ_i^M		ψ_i^Z	
	Mean	Median	Mean	Median
15 Food Products and Beverages	1.63	1.56	1.36	1.24
17 Textiles	1.52	1.40	1.79	1.60
18 Wearing Apparel	1.85	1.60	1.90	1.54
19 Leather	1.54	1.46	1.72	1.57
20 Wood	1.16	1.10	1.63	1.49
21 Pulp	1.19	1.15	1.44	1.38
22 Printing and Publishing	2.30	2.11	1.74	1.27
24 Chemicals	1.24	1.17	1.60	1.42
25 Rubber	1.29	1.22	1.51	1.41
26 Non-metallic mineral Products	1.58	1.46	1.82	1.51
27 Basic Metals	1.80	1.62	1.43	1.31
28 Fabricated Metal Products	1.66	1.55	1.63	1.42
29 Machinery and Equipment	1.46	1.36	1.41	1.27
31 Electrical machinery & App.	1.23	1.14	1.52	1.38
32 Radio and Communication	1.29	1.19	1.67	1.45
33 Medical	1.22	1.12	1.61	1.35
34 Motor Vehicles	1.44	1.26	1.59	1.44
35 Other Transport Equipment	1.52	1.34	1.77	1.57

Notes: The table shows relevant moments of the markdown distribution in each two-digit industry, for the imported and domestic intermediates, respectively. The distribution is trimmed at the 3rd and 97th percentiles.

confounding factors that could affect the results.

The literature on trade and industrial organization offers several potential confounding factors, with the unobserved fixed cost of sourcing and input-augmenting productivity being the most important. For instance, if low-cost country sourcing is more expensive, larger and more productive firms might spend less on shipments of the same size (Antràs et al., 2017), leading the econometric framework to attribute differences in sourcing costs to differences in pricing power across firms. Additionally, if the production technology features input-augmenting productivity, then we could wrongly attribute the wedges to input market power (Raval, 2022).

Table 3.4 provides robust evidence that the size and variation in the wedges are large and economically important, even after sourcing costs and differences in technology are controlled for. Moreover, evidence across firms lends support to the interpretation of the wedges as due to input market power.

First, in all regressions, markdowns are found to be positively correlated with firm size, as measured by firm employment l_{it} .

Second, the validation exercise also aims to leverage the granularity of import data, exploiting differences in competition intensity faced by French firms in their import markets. Regressions in column (1) include, as all columns, industry-year fixed effects, an indicator for the firm multinational status, and for the average GDP per Capita ($\overline{GDP}_{it}^{imp}$) in the firm source markets, but does not include sourcing mix controls. As a result, markdowns

negatively and significantly correlate with the average number of French importers in the firm sourcing markets, yet with a low magnitude, in Panel (a), but also negatively correlate with the average HHI in the firm sourcing markets, in Panel (b). This is potentially due to spurious correlations driven by firm selection in the different import markets. As the extensive margin of imports is a crucial determinant of input expenditures, it is indeed necessary to hold the sourcing strategy fixed when comparing the estimated wedges across firms.

Columns (2) to (9) thus aim to leverage variation in the average competition faced by firms across import markets, but controlling for the firm selection in a particular sourcing strategy, following [Blaum et al. \(2019\)](#). A sourcing strategy is defined as a given set of import markets (resp. ranked in terms of import values), where the market definition varies across our different specifications. A market is defined as a CN4 category in column (2) (resp. (3)), a CN4 category-country in column (4) (resp. (5)), a CN4 category-year in column (6) (resp. (7)) or a CN4 category-country-year triplet in column (8) (resp. (9)).²⁰ The identification thus stems from variations (i) in the *intensive margin* of imports, *i.e.* in the weight of each import market in the firm sourcing mix, and (ii) in the *competition* faced by firms across different CN8 products, holding the extensive margin of imports, *i.e.* the sourcing strategy, fixed. Columns (2) to (5) leverage such variation both in the cross-section and panel dimensions, while columns (6) to (9) only leverage variation in the cross-section.²¹

With stringent enough sourcing strategy definitions, as in columns (4) to (9), mark-downs are found to be negatively correlated with the average competition faced by the firm in its import markets, as measured by the number of competing French importers sourcing the same products from the same markets or the Herfindahl index (HHI). In the last two columns, and even though the drastically shrunk sample size suggests caution, the effect of firm size and of the average competition faced by a firm on its import markets are of a comparable magnitude.

The results presented in [Table 3.4](#) thus show the ability of our methodology to capture in a sufficient statistic, namely the firm-level markdown, the overall ability of a given firm to exert buyer power in different import markets.

²⁰We rely on a CN4 (instead of a more stringent CN6 or CN8) definition of a product category as the sample size rapidly shrinks when adding sourcing strategy fixed effects.

²¹Columns (2) to (5) (as well as Column (1) thus accordingly rely on the harmonized CN8 nomenclature defined in [Bergounhon et al. \(2018\)](#).

Table 3.4: Markdowns and Average Competition in Import Markets

Outcome var: ψ_i^M	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel (a): Number of French Importers									
\bar{N}_{it}^{imp}	-0.015*** (0.004)	-0.007 (0.010)	-0.012 (0.011)	-0.066** (0.030)	-0.063** (0.033)	-0.048*** (0.016)	-0.046*** (0.017)	-0.136** (0.059)	-0.150** (0.060)
l_{it}	0.035*** (0.003)	0.095*** (0.011)	0.094*** (0.012)	0.110*** (0.027)	0.105*** (0.030)	0.114*** (0.018)	0.116*** (0.019)	0.204*** (0.043)	0.207*** (0.045)
Panel (b): Herfindahl Index (HHI)									
\bar{HHI}_{it}^{imp}	-0.024*** (0.005)	-0.002 (0.012)	0.001 (0.013)	0.066** (0.029)	0.076*** (0.028)	0.029 (0.018)	0.028 (0.018)	0.125*** (0.045)	0.130*** (0.045)
l_{it}	0.035*** (0.003)	0.094*** (0.011)	0.093*** (0.012)	0.110*** (0.027)	0.105*** (0.029)	0.106*** (0.016)	0.106*** (0.017)	0.166*** (0.041)	0.168*** (0.043)
Sourcing Strat. FE	No	P	P ^r	PC	PC ^r	PT	P ^r T	PCT	PC ^r T
Observations	38,091	6,054	5,046	2,125	1,697	2,001	1,870	257	232

Notes: \bar{N}_{it}^{imp} is a weighted average of the number of French importing firms across import markets of firm i in year t , where a market is defined by a product-country combination. \bar{HHI}_{it}^{imp} is a weighted average of HHI across import markets of firm i in year t , where a market is defined by a product-country combination. All variables are in log. Products are defined based on the harmonized nomenclature for columns (1)-(5), and the CN8 contemporaneous nomenclature for columns (6)-(9). l_{it} is the employment (average number of workers) of firm i in year t . Sourcing strategies are defined in terms of the presence of firms on CN4 product (P), or CN4 product-country (PC) markets, interacted with year (T) for col (6)-(9). Firms sharing the same (ranked, denoted with the subscript r) sourcing strategy have the same set of import markets (ranked similarly in terms of value). All regressions include Industry-Year fixed effects, an MNF indicator, and $\overline{GDP}_{it}^{imp}$ controls. Sample reduced to observations (firm-year) for which products switching nc4 categories over time represent less than 2% of imports. Standard errors in parentheses are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

5. Buyer Power and the Aggregate Economy

Having established the sizable buyer power of French importers in input trade, we next aim to measure its impact on aggregate variables. We do this by constructing the most straightforward model that enables us to answer this question within the context of French manufacturing.

We consider the standard heterogeneous firms model of production in Melitz (2003) and expand it to incorporate imperfect competition in input trade. To concentrate on this source of aggregate distortions, we assume that domestic input markets are perfectly competitive. Hereafter, we will use capital letters to represent aggregate variables and lowercase letters to denote firm-level variables.

5.1. Environment

The economy consists of two symmetrical countries: the Home country (France) and a Foreign country (Rest of the World). We focus on the equilibrium in the Home country, where a representative consumer consumes differentiated varieties of a final good and supplies a fixed amount of labor L at a fixed unit wage of W^L . The consumer also earns income from owning claims to the profits of domestic firms.

We denote total consumption as Q and write it as:

$$Q = \left(\int_{i \in M} q_i^\rho di \right)^{\frac{1}{\rho}}, \quad (3.25)$$

where q_i denotes the quantity consumed of variety i of the final good, and $0 < \rho < 1$ is a preference parameter capturing the substitutability between any two varieties, which can be summarized by an elasticity of $\sigma = \frac{1}{1-\rho} > 1$. We use the final good Q as the numeraire, such that the associated price index is given by $P = \left(\int_{i \in N} p_i^{-\frac{\rho}{1-\rho}} di \right)^{-\frac{1-\rho}{\rho}} = 1$.

In the context of this analysis, we focus on an equilibrium where entry is restricted, such that the measure N of varieties produced in equilibrium remains fixed and exogenous.²²

The consumer problem is to choose the optimal amount of consumption $\{q_i\}_{i \in N}$ that maximizes (3.25) subject to a budget constraint. Consumer optimization leads to a standard CES demand for variety i , given by:

$$q_i = p_i^{-\frac{1}{1-\rho}} Q. \quad (3.26)$$

Firms Each of the N differentiated varieties of the final good is produced locally by domestic firms combining domestic labor with foreign intermediate inputs. This means that international trade is allowed for intermediate inputs but not for final goods, such that international trade is necessarily unbalanced.²³

The production function can be written as:

$$q_i = \phi_i m_i^\beta l_i^{1-\beta}, \quad (3.27)$$

where $\phi_i \equiv e^{\omega_i}$ represents the firm-level total factor productivity (TFP), m_i denotes the quantity of foreign inputs used by firm i in the production process, and l_i represents the labor input.²⁴

Foreign Intermediate Inputs We assume that each firm i utilizes a differentiated variety of the foreign intermediate input m_i . These input varieties are supplied by a

²²It is important to note that, due to the assumption of fixed entry, the profits of the firms only capture a measure of static (accounting) profits.

²³Importantly, the fact that intermediates are imported in this model implies that aggregate income does not align with total revenues. Instead, aggregate income (and welfare) coincides with domestic value added, which can be expressed as $Y = VA = Q - \int_{i \in N} W_i^M m_i di$, where the second term in the right-hand side denotes total imports.

²⁴Even though we refer to l as labor, the latter can be thought of as a constant return to scale aggregator of l_v for $v = 1, \dots, N$ primary factors, including labor, capital, and domestic intermediate inputs.

competitive fringe of (unmodeled) foreign firms, given the following supply function:

$$W_i^M = \left(\frac{m_i + M_{-i}}{\bar{m}_i + M_{-i}} \right)^\eta. \quad (3.28)$$

Here, $M_{-i} \in [0, \infty)$ denotes total demand by foreign competitors of firm i , \bar{m}_i is a normalizing factor for firm-level prices, and $\eta > 0$ represents the (constant) elasticity of the intermediate input price to total supply. We assume that the competitors' demand M_{-i} is taken as given by the firm, such that total input demand $M_i \equiv m_i + M_{-i}$ satisfies $\partial M_i / \partial m_i = 1$.

The assumption of horizontal differentiation among input varieties implies that the supply function in Equation (3.28) is specific to each firm. Foreign input producers can supply any quantity of the foreign input to firm i , subject to the constraint given by Equation (3.28).²⁵

Equation (3.28) simplifies the reality of foreign intermediate markets significantly. It is the counterpart to equation (3.3), but it ignores the heterogeneity in the sourcing strategy across firms by assuming the same supply structure for all firms. Moreover, by treating foreign input producers as price-takers, we avoid the need to model the complex bargaining game between domestic buyers and foreign suppliers. The advantage of considering a supply equation as in (3.28) is that we will be able to analytically characterize the effect of buyer power distortions on aggregate variables.

5.2. Firm-Level Equilibrium

Firms differ along two exogenous dimensions: productivity (ϕ_i) and foreign market conditions (M_{-i}). To allow for imperfect competition in foreign input markets, we assume that firms internalize that input prices W_i^M are endogenous to the total quantity M_i . In other words, firms consider the supply function in equation (3.28) when choosing optimal input demand.

We then assume that firms compete in monopolistic competition in final good markets while they act as price takers in the domestic labor market, where they can hire labor at a unit wage W^L , which they take as given.

Given (ϕ_i, M_{-i}) , the problem for firm i is to choose inputs to maximize profits, subject to final demand, upstream supply, and technology. Formally:

$$\max_{l, m} p_i q_i - W_i^M m_i - W^L l_i, \quad (3.29)$$

where W_i^M , p_i and q_i are as in (3.28), in (3.26) and (3.27), respectively.

²⁵This allows us to disregard the general equilibrium effects of firm i 's behavior on the demand of other domestic firms.

Solving the problem in (3.29) yields the following first-order condition for the two inputs:

$$\beta \frac{p_i q_i}{W_i^M m_i} = \frac{\psi_i}{\rho} \quad (3.30)$$

$$(1 - \beta) \frac{p_i q_i}{W^L l_i} = \frac{1}{\rho} \quad (3.31)$$

where the term ρ^{-1} captures the firm-level markup over the final good variety, which is constant by the assumptions of monopolistic competition and CES demand, and ψ_i is the firm-level markdown on foreign intermediate inputs. Given the assumptions on input supply, the latter can be found as:

$$\psi_i = 1 + \eta s_i^M \geq 1, \quad (3.32)$$

where $s_i^M = \frac{m_i}{m_i + M_{-i}} \in (0, 1)$ is the buyer share in the market for foreign inputs. The previous expression shows that the source of firm i 's buyer power in foreign input markets is oligopsony. Given the upward-sloping input supply, the firm will decide to optimally curb input demand to extract rents from foreign firms, provided it accounts for a sizable share of total input demand, i.e., provided that $s_i^M > 0$.

Given the FOC in (3.30) and (3.31), the impact of buyer power in foreign markets on the firm-level equilibrium can be summarized by the following system of equations:

$$m_i \propto \phi_i^{\frac{\rho}{1-\rho}} \psi_i^{-\frac{1-\rho(1-\beta)}{1-\rho+\eta(1-\rho(1-\beta))}} \quad (3.33)$$

$$\frac{l_i}{m_i} \propto \psi_i^{\frac{1-\rho}{1-\rho+\eta(1-\rho(1-\beta))}} \quad (3.34)$$

$$q_i \propto \phi_i^{\frac{1}{1-\rho}} \psi_i^{-\frac{\beta}{1-\rho+\eta(1-\rho(1-\beta))}}. \quad (3.35)$$

This system shows that buyer power in foreign markets generates three sources of inefficiency at the firm level. First, it reduces demand for the foreign input (equation (3.33)). Second, it leads firms to substitute inefficiently between foreign and domestic inputs (equation (3.34)). Third, it reduces firm-level output, leading to higher final good prices (equation (3.35)). The wedge ψ_i summarizes the firm-level distortions resulting from buyer power and is thus a sufficient statistic for its effect on firm-level variables.

5.3. Aggregation

The simple model allows for an analytical characterization of the aggregate equilibrium. Assuming a joint distribution $\mu(\phi, \psi) = \mu_\phi(\phi)\mu_\psi(\psi)$ of productivity and buyer power levels over a subset of $(0, \infty) \times (1, \infty)$, the aggregate demand C can be expressed as follows:

$$C = \Theta \cdot \tilde{\phi}^{\frac{1}{1-\beta}} \tilde{\psi}^{-\frac{\beta(1-\rho)}{(1-\beta)\Phi}} \cdot L, \quad (3.36)$$

Here, $\Theta \equiv \chi^{\frac{(1-\rho)(1-\beta\kappa)}{(\rho-\kappa)(1-\beta)}} \left(\frac{1}{\rho}\right)^{-\frac{\beta}{1-\beta}} \left(\frac{1}{\beta}\right)^{-\frac{\beta}{1-\beta}}$ is a constant, $\tilde{\phi} \equiv \left[\int_0^\infty \phi^{\frac{\rho}{1-\rho}} \mu_\phi(\phi) d\phi\right]^{\frac{1-\rho}{\rho}}$ and $\tilde{\psi} = \left[\int_1^\infty \psi^{-\frac{\beta\rho}{\Phi}} \mu_\psi(\psi) d\psi\right]^{-\frac{\Phi}{\beta\rho}} > 1$ are weighted averages of firm productivity and buyer power levels respectively. Equation (3.36) clearly demonstrates how buyer power impacts aggregate output. As the average buyer power $\tilde{\psi}$ increases, the aggregate output decreases.

Additionally, the term $\tilde{\psi}^{-\frac{\beta(1-\rho)}{(1-\beta)\Phi}}$ completely summarizes aggregate output and consumption distortions in this simple model where productivity and buyer power are jointly independent. Results would change, but remain similarly tractable, if the two distributions were correlated rather than independent. However, assuming independent distributions allows for a transparent characterization of the aggregate distortions.

The following expressions can be derived for all aggregate variables: aggregate imports of intermediate inputs E^M , aggregate labor income $W^L L$, aggregate profits Π , and welfare, which in this model can be measured as domestic value added: $W = W^L L + \Pi$. We derive the following expressions:²⁶

$$\frac{E^M}{E^{M,EFF}} = \tilde{\psi}^{-\frac{\beta(1-\rho)}{(1-\beta)\Phi}} \hat{\psi}^{-1} \quad \frac{W^L L}{(W^L L)^{EFF}} = \tilde{\psi}^{-\frac{\beta(1-\rho)}{(1-\beta)\Phi}} \quad (3.37)$$

$$\frac{\Pi}{\Pi^{EFF}} = \left[1 + \frac{\beta\rho}{1-\rho} \left(1 - \hat{\psi}^{-1}\right)\right] \tilde{\psi}^{-\frac{\beta(1-\rho)}{(1-\beta)\Phi}} \quad \frac{W}{W^{EFF}} = \frac{1 - \beta\rho \hat{\psi}^{-1}}{1 - \beta\rho} \tilde{\psi}^{-\frac{\beta(1-\rho)}{(1-\beta)\Phi}}.$$

Together with $\tilde{\psi}$, the term $\hat{\psi} \equiv \frac{\int_1^\infty \psi^{-\frac{\beta\rho}{\Phi}} \mu_\psi(\psi) d\psi}{\int_1^\infty \psi^{-\frac{\beta\rho+\Phi}{\Phi}} \mu_\psi(\psi) d\psi} > 1$ is a second index of buyer power affecting aggregate variables. While $\tilde{\psi}$ captures the distorting effect of buyer power on output, $\hat{\psi}$ captures the distorting effect of buyer power on foreign input markets.

The output distortions lead to lower labor income and consumer surplus, as shown by the top right equation in (3.37). On the contrary, the effect on profits (bottom left equation) and producer surplus depends both on output and import distortions: the larger the import distortions, i.e., the larger $\hat{\psi}$, the larger the profits due to sizable rent transfers from foreign countries; the higher the output distortions, i.e., the larger $\tilde{\psi}$, the lower the profits due to lower demand. The former effect always dominates for profit-maximizing firms, such that producer surplus always increases with buyer power.

The contrasting role of buyer power in consumer and producer surplus results in ambiguous welfare consequences. As the bottom right equation shows, welfare increases with $\hat{\psi}$, but decreases with $\tilde{\psi}$. Which of these effects prevails is ultimately an empirical question.

²⁶The derivations are to be added in the Appendix.

5.4. Calibration

To quantify the aggregate effect of buyer power on the domestic economy, we require estimates of the parameters η , β , and ρ , along with a distribution for ψ .

Inverse Supply Elasticity. The parameter η is the inverse supply elasticity of foreign inputs. Values of $\eta > 0$ indicate that suppliers' marginal costs increase with downstream demand. The value of η can be determined from equation (3.32), which shows that η governs the relationship between firm-level buyer power ψ_i and i 's share as a buyer in foreign input market $s_i^M = \frac{m_i}{M_i}$, where $\eta = \frac{\psi_i - 1}{s_i^M}$.

For our baseline result, we choose the value of η that matches the observed ratio between the average median wedge $\bar{\psi}^M$ across sectors and the average buyer share s_i^M observed in French import data.²⁷ This exercise results in a value of $\eta = 2.61$, which is consistent with the estimates of import supply elasticities by Soderbery (2018).²⁸

Demand Elasticity. The parameter ρ governs both the demand elasticity and firm-level markups, which are assumed to be constant in the model. We calibrate this parameter using the estimates of the demand elasticity in Table 3.1. These estimates imply a value of $\rho = 0.73$.

Output Elasticities and Buyer Power. We calibrate the value of β using the estimates of the revenue elasticities from Table 3.2 and the demand elasticities from Table 3.1. Revenue and output elasticities are related by the following relationship: $\theta^{M,r} = \beta^M / \mu$, where $\mu = \rho^{-1}$ is the firm-level markup. Similarly, the values of ψ_i are set equal to the estimated distribution of firm-level foreign input wedges, i.e., $\psi_i = \psi_i^M$ for all i .

5.5. Results

Table 3.5 summarizes the calibrated parameters and the main results.²⁹ Losses in aggregate output and labor income range from about 3% to 5%. Buyer power has the largest effect on total imports, which we estimate between 36 and 60% below competitive levels. Profits are higher in the distorted than in the efficient economy. The lower bound estimates yield profits 11% higher in the distorted economy than in the competitive one, while the upper bound estimate is 19%. Finally, welfare always increases in the distorted economy, by about 1.4 to 2.4%. The welfare gains stem from a terms-of-trade effect induced by the largest importers' buyer power: in spite of lower output and lower volumes of trade, the gain in import prices relative to export prices is such that the economy as a whole is better off in the distorted economy.

²⁷On average, the quantity share of the French buyer i in foreign export market ν is observed to be 0.15, with a median value of 0.002 and a standard deviation equal to 0.28.

²⁸Soderbery (2018) uses UN Comtrade data over the period 1991-2007 to estimate values of the export supply elasticity by HS4 manufacturing product and import country. Their estimates for η range from 0.15 to 5+.

²⁹Figures displayed in Table 3.5 have to be updated in accordance with the input wedge estimates from Section 4. Table 3.5 is for now based on the wedges estimated in Morlacco (2019).

Table 3.5: Aggregate Effects of Buyer Power in Input Trade

Panel (a): Parameter Estimates (Baseline)			
PARAMETER	β	ρ	η
VALUE	0.16	0.73	2.61
SOURCE	ESTIMATED	CALIBRATED	CALIBRATED

Panel (b): Changes in Aggregate Variables		
	Lower Bound	Upper Bound
Output ($\Delta\%$)	-2.97	-4.86
Imports ($\Delta\%$)	-35.97	-59.53
Labor Income($\Delta\%$)	-2.97	-4.86
Profits ($\Delta\%$)	11.37	18.91
Welfare ($\Delta\%$)	1.40	2.38

Notes: Panel (a) reports the baseline estimates of the main parameters. See the respective source tables and the main text for more detail. Panel (b) shows the changes in the main variables of interest when moving from a counterfactual economy where all buyers are price takers to the economy where firms have buyer power. A negative value should be interpreted as the value is lower in the distorted economy, and vice versa for positive values. Lower bound estimates (first column in panel (b)) are those obtained when we set equal to one the wedge of firms whose raw value is estimated below one in Section 4.3. Upper bound estimates (second column in panel (b)) are obtained when we exclude from the sample all the firms whose estimated ψ_i^M is below one.

5.6. Discussion

The theoretical model offers valuable insights into the role of importers' buyer power in an economy. Like an optimal tariff on imports, the buyer power of importers can benefit a country through terms-of-trade effects that can more than compensate for smaller trade volumes and losses in consumer surplus (Kaldor, 1940). A classical result in the theoretical trade literature suggests that countries with market power in imports exploit it in setting their trade policy (Broda et al., 2008). The results in this Section show that even in the absence of import tariffs, importers with large buyer power in input trade can generate similar effects on aggregate variables. Table 3.5 provides evidence that these effects are significant, despite being the result of individual firm behavior.

The analysis also shows that while welfare may increase, gains may be unequally distributed across economic agents. In settings where labor is owned by consumers and firms by producers, only the latter benefit, while consumers are unambiguously worse off. This type of firm behavior could have implications for income inequality within a country.

However, the large sensitivity of welfare estimates to key parameters suggests caution in interpreting specific welfare numbers since the model is stylized. A more rigorous quantification exercise would require including trade costs, asymmetries between the Home and Foreign countries, and more realistic assumptions on the joint distribution of productivity and buyer power. These are straightforward extensions of the current model but have been omitted to ensure transparency of the main results.

Finally, the study has implications for trade policy. The analysis suggests mixed incentives for governments and anti-trust authorities in open economies to restrain the market power of the largest firms. Under most parameter calibrations, buyer power in input trade generates gains in national welfare, at the expense of foreign countries. Therefore, a rationale for lenient anti-trust conduct may be found in beggar-thy-neighbor trade policies, while being less exposed to the risk of retaliation. In similar settings, anti-trust policies would require a globally coordinated policy response to prevent large multi-national buyers from accumulating excessive market power.

6. Conclusion

This paper presents micro-level estimates of buyer power in input trade and analyzes its aggregate implications. We develop a methodology to estimate buyer power in input trade using only firm-level data, without requiring knowledge of the import environment. Our methodology starts with a general model of production and input trade that imposes minimal assumptions on output and input markets. Although our empirical analysis focuses on imported intermediate inputs, the methodology can be applied to any static input with available data on production and input quantities.

Applying our methodology to the universe of trade and production data for the French manufacturing sector, we find evidence of substantial buyer power in input trade. The average firm-level markdown in input trade is 1.49, indicating significant price-setting power on the importers' side, with substantial heterogeneity in markdowns across industries and firms. Larger and more productive firms have relatively larger wedges than smaller, unproductive ones. Using our highly disaggregated import data, we validate our buyer power measures by showing that firm-level markdowns on imported inputs positively correlate with the average concentration faced by firms across their import markets.

We develop a macro model with heterogeneous firms to link the micro-level wedges to aggregate variables. We show that buyer power in input trade generates aggregate distortions while producing a terms-of-trade improvement, similar to an import tariff. Thus, our results suggest that even without trade policy instruments, significant terms-of-trade gains for the economy can result from individual importers' behavior in foreign markets.

Our paper enhances our understanding of the role of buyers in modern economies, specifically in the context of international trade. Despite increasing attention to buyer power, there has been limited focus on the global trade context. Our findings have broader implications for the relationship between globalization and market structure in advanced economies. As participation in international trade increases, the market power of large firms can grow, leading to a decline in overall competition in the economy. Additionally, our results suggest that national governments and anti-trust authorities may have no incentive to prevent excessive market power buildup, as it can result in a net increase in domestic welfare.

These observations contribute to the ongoing debate about the causes of the increase in market concentration and the decline in business dynamism in advanced economies, which includes the impact of international trade and offshoring (See, e.g., [De Loecker et al. \(2019\)](#); [Van Reenen \(2018\)](#); [Syverson \(2019\)](#); [Eggertsson et al. \(2018\)](#); [Akcigit and Ates \(2019\)](#)).

A promising area for future research would be to conduct an explicit analysis of the role of globalization in the observed increase in concentration and market power in large economies.

References

- Akerberg, D. A., K. Caves, and G. Frazer (2015). Identification properties of recent production function estimators. *Econometrica* 83(6), 2411–2451.
- Akcigit, U. and S. T. Ates (2019). What happened to us business dynamism? Technical report, National Bureau of Economic Research.
- Alviarez, V., M. Fioretti, A. K. Kikkawa, and M. Morlacco (2021). Two-sided market power in firm-to-firm trade. *mimeo*.
- Amiti, M., O. Itskhoki, and J. Konings (2014). Importers, exporters, and exchange rate disconnect. *The American Economic Review* 104(7), 1942–1978.
- Amiti, M. and J. Konings (2007). Trade liberalization, intermediate inputs, and productivity: evidence from indonesia. *The American Economic Review* 97(5), 1611–1638.
- Antràs, P. (2020, October 2020). Conceptual aspects of global value chains. *World Bank Economic Review* 34(3), 551–574.
- Antràs, P., T. C. Fort, and F. Tintelnot (2017, 2017). The margins of global sourcing: Theory and evidence from u.s. firms. *The American Economic Review* 107(9).
- Arkolakis, C., A. Costinot, D. Donaldson, and A. Rodríguez-Clare (2018). The elusive pro-competitive effects of trade. *The Review of Economic Studies* 86(1), 46–80.
- Avignon, R. and E. Guigue (2022). Markups and markdowns in the french dairy market. Technical report, mimeo.
- Bas, M. and V. Strauss-Kahn (2015). Input-trade liberalization, export prices and quality upgrading. *Journal of International Economics* 95(2), 250–262.
- Bastos, P., J. Silva, and E. Verhoogen (2018). Export destinations and input prices. *The American Economic Review* 108(2), 353–92.
- Bergounhon, F., C. Lenoir, and I. Mejean (2018). A guideline to french firm-level trade data. *Unpublished manuscript*.
- Bernard, A. B., E. A. Bøler, R. Massari, J.-D. Reyes, and D. Taglioni (2017). Exporter dynamics and partial-year effects. *American Economic Review* 107(10), 3211–3228.
- Bernard, A. B. and S. Dhingra (2019). Importers, exporters and the division of the gains from trade.
- Berthou, A. and V. Vicard (2015). Firms' export dynamics: Experience versus size. *The World Economy* 38(7), 1130–1158.

- Blaum, J., C. Lelarge, and M. Peters (2018). The gains from input trade in firm-based models of importing. *American Economic Journal: Macroeconomics*.
- Blaum, J., C. Lelarge, and M. Peters (2019). Firm size, quality bias and import demand. *Journal of International Economics* 120, 59–83.
- Bond, S., A. Hashemi, G. Kaplan, and P. Zoch (2021). Some unpleasant markup arithmetic: Production function elasticities and their estimation from production data. *Journal of Monetary Economics* 121, 1–14.
- Broda, C., N. Limao, and D. E. Weinstein (2008). Optimal tariffs and market power: the evidence. *American Economic Review* 98(5), 2032–65.
- Chen, N., J. Imbs, and A. Scott (2009). The dynamics of trade and competition. *Journal of International Economics* 77(1), 50–62.
- De Loecker, J. (2011). Product differentiation, multiproduct firms, and estimating the impact of trade liberalization on productivity. *Econometrica* 79(5), 1407–1451.
- De Loecker, J., J. Eeckhout, and G. Unger (2019). The rise of market power and the macroeconomic implications.
- De Loecker, J. and P. K. Goldberg (2014). Firm performance in a global market. *Annu. Rev. Econ.* 6(1), 201–227.
- De Loecker, J., P. K. Goldberg, A. K. Khandelwal, and N. Pavcnik (2016). Prices, markups, and trade reform. *Econometrica* 84(2), 445–510.
- De Loecker, J. and F. Warzynski (2012). Markups and firm-level export status. *The American Economic Review* 102(6), 2437–2471.
- De Ridder, M. (2019). Market power and innovation in the intangible economy. *mimeo*.
- De Ridder, M., B. Grassi, G. Morzenti, et al. (2022). The hitchhiker’s guide to markup estimation. *mimeo*.
- Dhingra, S. and J. Morrow (2019). Monopolistic competition and optimum product diversity under firm heterogeneity. *Journal of Political Economy* 127(1), 196–232.
- Dobbelaere, S. and K. Kiyota (2018). Labor market imperfections, markups and productivity in multinationals and exporters. *Labour Economics* 53, 198–212.
- Dobbelaere, S. and J. Mairesse (2013). Panel data estimates of the production function and product and labor market imperfections. *Journal of Applied Econometrics* 28(1), 1–46.

- Eggertsson, G. B., J. A. Robbins, and E. G. Wold (2018). Kaldor and piketty's facts: the rise of monopoly power in the united states. Technical report, National Bureau of Economic Research.
- Fitzgerald, D. and S. Haller (2018). Exporters and shocks. *Journal of International Economics* 113, 154–171.
- Fontagné, L., P. Martin, and G. Orefice (2018). The international elasticity puzzle is worse than you think. *Journal of International Economics* 115, 115–129.
- Foster, L., J. Haltiwanger, and C. Syverson (2008). Reallocation, firm turnover, and efficiency: Selection on productivity or profitability? *The American Economic Review* 98(1), 394–425.
- Garicano, L., C. Lelarge, and J. Van Reenen (2016). Firm size distortions and the productivity distribution: Evidence from france. *The American Economic Review* 106(11), 3439–3479.
- Goldberg, P. K., A. K. Khandelwal, N. Pavcnik, and P. Topalova (2010). Imported intermediate inputs and domestic product growth: Evidence from india. *The Quarterly Journal of Economics* 125(4), 1727–1767.
- Gopinath, G. and B. Neiman (2014). Trade adjustment and productivity in large crises. *The American Economic Review* 104(3), 793–831.
- Gutiérrez, G. and T. Philippon (2017). Declining competition and investment in the us. Technical report, National Bureau of Economic Research.
- Hall, R. E. (1988). The relation between price and marginal cost in us industry. *Journal of Political Economy* 96(5), 921–947.
- Halpern, L., M. Koren, and A. Szeidl (2015). Imported inputs and productivity. *The American Economic Review* 105(12), 3660–3703.
- Harrison, A. E. (1994). Productivity, imperfect competition and trade reform. theory and evidence. *Journal of International Economics* 36(1-2), 53–73.
- Hashemi, A., I. Kirov, and J. Traina (2022). The production approach to markup estimation often measures input distortions. *Economics Letters* 217, 110673.
- Horn, H. and A. Wolinsky (1988). Bilateral Monopolies and Incentives for Merger Author. *RAND Journal of Economics* 19(3), 408–419.
- Ignatenko, A. (2021). Countervailing power of firms in international trade. Technical report, mimeo.

- Kaldor, N. (1940). A note on tariffs and the terms of trade. *Economica* 7(28), 377–380.
- Klette, T. J. and Z. Griliches (1996). The inconsistency of common scale estimators when output prices are unobserved and endogenous. *Journal of Applied Econometrics* 11(4), 343–361.
- Kmenta, J. (1967). On estimation of the ces production function. *International Economic Review* 8(2), 180–189.
- Levinsohn, J. and A. Petrin (2003). Estimating production functions using inputs to control for unobservables. *The Review of Economic Studies* 70(2), 317–341.
- Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica* 71(6), 1695–1725.
- Monarch, R. (2021). *It's Not You, It's Me: Prices, quality, and switching in us-china trade relationships.* *The Review of Economics and Statistics*, 1–49.
- Morlacco, M. (2019). Market power in input markets: Theory and evidence from french manufacturing. *Unpublished, March 20, 2019.*
- Pierce, J. and P. Schott (2009). Concording us harmonized system codes over time. *Journal of Official Statistics.*
- Piveteau, P. and G. Smagghue (2019). Estimating firm product quality using trade data. *Journal of International Economics* 118, 217–232.
- Pozzi, A. and F. Schivardi (2016). Demand or productivity: What determines firm growth? *The RAND Journal of Economics* 47(3), 608–630.
- Raff, H. and N. Schmitt (2009). Buyer power in international markets. *Journal of International Economics* 79(2), 222–229.
- Rauch, J. E. (1999). Networks versus markets in international trade. *Journal of international Economics* 48(1), 7–35.
- Raval, D. (2022). Testing the production approach to markup estimation. *Review of Economic Studies.*
- Soderbery, A. (2018). Trade elasticities, heterogeneity, and optimal tariffs. *Journal of International Economics* 114, 44–62.
- Syverson, C. (2019). Macroeconomics and market power: Facts, potential explanations and open questions.

- Topalova, P. and A. Khandelwal (2011). Trade liberalization and firm productivity: The case of india. *The Review of Economics and Statistics* 93(3), 995–1009.
- Treuren, L. (2022). *Wage Markups and Buyer Power in Intermediate Input Markets*. KU Leuven, Department of Economics.
- Van Beveren, I., A. B. Bernard, and H. Vandebussche (2012). ConCORDING EU trade and production data over time. Technical report, National Bureau of Economic Research.
- Van Reenen, J. (2018). Increasing differences between firms: Market power and the macro-economy.
- Wong, H. C. (2019). Understanding high-wage and low-wage firms. *mimeo*.
- Yeh, C., C. Macaluso, and B. Hershbein (2022). Monopsony in the US labor market. *American Economic Review* 112(7), 2099–2138.

Appendix - Chapter 3

Appendix 3.A Additional Tables and Figures

Table A.1: Descriptive Statistics - Demand Estimation

	Mean	p10	p25	p50	p75	p90
<i>(1) Full sample: N = 4,436,635</i>						
# Source countries by firm	9.53	0	2	7	14	23
# Observations by exporting spell	3.61	2	2	3	4	8
# Varieties by export market	3.16	1	1	1	3	6
<i>(2) Selected Sample: N = 1,322,508</i>						
# Source countries by firm	14.98	1	6	12	21	31
# Observations by exporting spell	8.06	4	6	8	11	11
# Varieties by export market	4.68	2	2	3	5	9
<i>(3) Estimating sample: N = 1,199,857</i>						
# Source countries by firm	16.72	4	8	14	22	33
# Observations by exporting spell	7.58	4	6	8	10	11
# Varieties by export market	4.49	2	2	3	5	8

Notes: An observation is an export flow at the firm, nc8 product, destination, year combination. An exporting spell is a set of consecutive export flows for a firm-destination-nc8 product triplet. An export market is a nc8 product-destination-year triplet, and a variety a firm-nc8 product pair. Sample (1) comprises firms importing and exporting in a given year. Sample (2) restricts Sample (1) to exporting spells shorter than 7 years. Sample (3) restricts Sample (2) to observations which are not firm×prod×dest×spell and prod×dest×year singletons.

Table A.2: Descriptive Statistics - Revenue Function Estimation Sample

	Mean	p10	p25	Median	p75	p90
<i>(1) Full Sample N=139,789</i>						
<i>Revenue Shares of Inputs</i>						
Labor - α^L	0.25	0.10	0.16	0.23	0.32	0.41
Capital - α^K	0.37	0.06	0.13	0.26	0.48	0.76
Imported Materials - α^M	0.15	0.01	0.03	0.09	0.21	0.36
Domestic Materials - α^Z	0.30	0.08	0.16	0.27	0.39	0.52
<i>Extensive and Intensive Margin of Imports</i>						
# Sourcing countries	6.77	1	3	5	9	14
# Sourcing markets	33.59	2	5	15	36	77
Imported Share of Intermediates	0.32	0.02	0.09	0.25	0.51	0.74
<i>(2) Selected Sample N=87,098</i>						
<i>Revenue Shares of Inputs</i>						
Labor - α^L	0.23	0.10	0.15	0.22	0.30	0.37
Capital - α^K	0.36	0.06	0.13	0.27	0.49	0.76
Imported Materials - α^Z	0.19	0.07	0.09	0.16	0.26	0.38
Domestic Materials - α^M	0.27	0.10	0.16	0.25	0.36	0.47
<i>Extensive and Intensive Margin of Imports</i>						
# Sourcing countries	8.26	2	4	7	11	16
# Sourcing markets	44.71	5	10	23	49	97
Imported Share of Intermediates	0.42	0.16	0.24	0.39	0.59	0.75
<i>(3) Estimating sample: N=62,077</i>						
<i>Revenue Shares of Inputs</i>						
Labor - α^L	0.23	0.10	0.15	0.22	0.29	0.36
Capital - α^K	0.37	0.06	0.13	0.28	0.50	0.76
Imported Materials - α^M	0.20	0.07	0.10	0.17	0.27	0.38
Domestic Materials - α^Z	0.27	0.10	0.16	0.25	0.35	0.46
<i>Extensive and Intensive Margin of Imports</i>						
# Sourcing countries	8.89	3	5	7	11	17
# Sourcing markets	49.51	6	12	26	55	107
Imported Share of Intermediates	0.43	0.18	0.26	0.41	0.59	0.74

Notes: Observations are at the firm-year level. Sample (1) is restricted to importers and exporters kept in demand estimation. Sample (2) restricts Sample (1) according to the selection procedure described in Section 3.E2.. Sample (3) restricts Sample (2) to firm-year observations for which a lag for a given firm is present.

Table A.3: Price-elasticity estimates ($-\hat{\sigma}_s$) for different product categories.

	OLS	IV (Single FS)	obs.
Animal Products	-1.014*** (0.035)	-3.479* (2.045)	31,097
Vegetable Products	-0.915*** (0.034)	-3.624** (1.457)	14,555
Foodstuffs	-0.972*** (0.015)	-3.085*** (0.926)	95,686
Mineral Products	-0.961*** (0.047)	-5.526*** (1.078)	8,359
Chemicals & Allied	-0.926*** (0.008)	-4.509*** (0.500)	189,848
Plastics, Rubbers	-0.979*** (0.011)	-4.108*** (0.653)	108,043
Skins, Leather	-0.691*** (0.030)	-3.609*** (0.966)	16,255
Wood, Wood Products	-0.877*** (0.014)	-0.978 (0.726)	68,880
Textiles	-0.732*** (0.010)	-5.032*** (0.287)	246,854
Footwear, Headgear	-0.365*** (0.038)	-9.379*** (1.236)	14,078
Stone, Glass	-0.955*** (0.021)	-2.235* (1.223)	28,322
Metals	-0.824*** (0.010)	-2.161*** (0.687)	107,337
Machinery, Electrical	-0.929*** (0.007)	-2.375*** (0.476)	179,498
Transportation	-0.956*** (0.019)	-4.353*** (1.278)	36,403
Miscellaneous	-0.813*** (0.014)	-3.135*** (0.724)	54,642

Notes: Estimates in column *OLS* are estimated by OLS separately for each industry. Estimates in column *IV (single FS)* are obtained by estimating a single first stage and a second stage where the price-elasticity is allowed to vary across industries. Controls for weighted average GDP per capita in export and import markets ($\overline{GDP}_{it}^{exp}$, $\overline{GDP}_{it}^{imp}$), for partial-year effect ($Entry_{ipct}$), and firm \times prod \times dest \times spell and prod \times dest \times year fixed effects are included in all regressions. See 3.D and Piveteau and Smagghue (2019) for more details on the methodology. *** p<0.01, ** p<0.05, * p<0.1.

Table A.4: Firm-Prod-Dest-Year Level Demand Shifters and Export Variables

	P_{ipct}	Q_{ipct}	exp_{ipct}	P_{ipct}	Q_{ipct}	exp_{ipct}
$\hat{\eta}_{ipct}$	0.179*** (0.001)	-0.046*** (0.002)	0.133*** (0.002)	0.171*** (0.001)	0.285*** (0.002)	0.457*** (0.002)
Fixed Effects	No	No	No	PCY	PCY	PCY
Observations	3,681,030	3,681,030	3,681,030	3,681,030	3,681,030	3,681,030
R2	0.415	0.009	0.108	0.871	0.575	0.653

Notes: Observations are at the firm \times prod \times dest \times year level. Standard errors in parentheses are clustered at the firm-year level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.5: Firm-Level Demand Shifters and Export Variables

	p_{it}	q_{it}	exp_{it}	p_{it}	q_{it}	exp_{it}
$\hat{\eta}_{it}$	0.193*** (0.004)	0.394*** (0.009)	0.587*** (0.007)	0.131*** (0.003)	0.248*** (0.006)	0.379*** (0.005)
Fixed Effects	No	No	No	IY	IY	IY
Observations	212,726	212,726	212,726	212,726	212,726	212,726
R2	0.043	0.074	0.283	0.900	0.900	0.905

Notes: Observations are at the firm \times year level. Standard errors in parentheses are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.6: Firm-Level Demand Shifters and Balance Sheet Variables

	l_{it}	wl_{it}	r_{it}	l_{it}	wl_{it}	r_{it}
$\hat{\eta}_{it}$	0.192*** (0.003)	0.218*** (0.004)	0.226*** (0.004)	0.023*** (0.001)	0.025*** (0.001)	0.037*** (0.001)
Fixed Effects	No	No	No	IY	IY	IY
Observations	212,726	212,726	212,726	212,726	212,726	212,726
R2	0.101	0.113	0.109	0.962	0.962	0.962

Notes: Observations are at the firm \times year level. Standard errors in parentheses are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.7: Revenue Function Estimates

Sector	$\hat{\beta}_k$	$\hat{\beta}_l$	$\hat{\beta}_m$	$\hat{\beta}_z$	$\hat{\beta}_{mm}$	$\hat{\beta}_{zz}$	$\hat{\beta}_{mz}$	θ_m	θ_z	Obs.
15 Food Products and Beverages	0.033 (0.003)	0.273 (0.005)	0.049 (0.032)	0.320 (0.033)	0.043 (0.004)	0.037 (0.003)	-0.069 (0.007)	0.233 (0.399)	0.465 (0.575)	6,096
17 Textiles	0.028 (0.003)	0.333 (0.006)	0.218 (0.052)	0.129 (0.05)	0.041 (0.005)	0.046 (0.005)	-0.077 (0.009)	0.281 (0.452)	0.326 (0.482)	5,238
18 Wearing Apparel	0.033 (0.005)	0.330 (0.008)	0.246 (0.053)	0.176 (0.055)	0.020 (0.005)	0.021 (0.006)	-0.033 (0.01)	0.332 (0.422)	0.282 (0.36)	3,527
19 Leather	-0.003 (0.007)	0.376 (0.01)	0.027 (0.072)	0.308 (0.066)	0.046 (0.006)	0.037 (0.006)	-0.073 (0.011)	0.298 (0.504)	0.335 (0.472)	1,609
20 Wood	0.044 (0.006)	0.305 (0.009)	-0.017 (0.045)	0.339 (0.059)	0.040 (0.004)	0.034 (0.004)	-0.063 (0.008)	0.181 (0.358)	0.441 (0.549)	2,027
21 Pulp	0.052 (0.005)	0.334 (0.007)	0.089 (0.044)	0.175 (0.05)	0.056 (0.004)	0.056 (0.004)	-0.101 (0.008)	0.227 (0.448)	0.371 (0.546)	2,694
22 Printing and Publishing	0.057 (0.007)	0.429 (0.012)	0.069 (0.085)	0.432 (0.073)	0.023 (0.009)	0.009 (0.01)	-0.031 (0.019)	0.272 (0.36)	0.265 (0.319)	1,891
24 Chemicals	0.044 (0.003)	0.328 (0.006)	0.103 (0.03)	0.361 (0.031)	0.046 (0.003)	0.041 (0.003)	-0.083 (0.006)	0.206 (0.397)	0.399 (0.539)	5,986
25 Rubber	0.030 (0.002)	0.392 (0.005)	0.179 (0.036)	0.195 (0.036)	0.044 (0.003)	0.047 (0.003)	-0.084 (0.006)	0.195 (0.384)	0.380 (0.512)	5,574
26 Non-metallic mineral Products	0.087 (0.006)	0.376 (0.011)	0.224 (0.057)	0.362 (0.06)	0.019 (0.006)	0.017 (0.007)	-0.039 (0.013)	0.207 (0.292)	0.307 (0.372)	1,925
27 Basic Metals	0.074 (0.007)	0.273 (0.01)	0.308 (0.052)	0.201 (0.048)	0.048 (0.006)	0.051 (0.006)	-0.094 (0.011)	0.285 (0.495)	0.356 (0.521)	1,805
28 Fabricated Metal Products	0.060 (0.003)	0.378 (0.005)	0.205 (0.036)	0.099 (0.035)	0.022 (0.003)	0.029 (0.003)	-0.043 (0.006)	0.209 (0.299)	0.319 (0.402)	7,175
29 Machinery and Equipment	0.035 (0.003)	0.393 (0.006)	0.241 (0.028)	0.232 (0.031)	0.034 (0.003)	0.036 (0.003)	-0.067 (0.006)	0.210 (0.359)	0.347 (0.457)	6,906
31 Electrical machinery & App.	0.042 (0.005)	0.372 (0.009)	0.126 (0.044)	0.361 (0.043)	0.038 (0.004)	0.033 (0.004)	-0.068 (0.008)	0.210 (0.367)	0.358 (0.481)	2,447
32 Radio and Communication	0.074 (0.007)	0.351 (0.014)	0.104 (0.061)	0.413 (0.07)	0.037 (0.006)	0.029 (0.006)	-0.064 (0.012)	0.214 (0.372)	0.342 (0.467)	1,453
33 Medical	0.049 (0.005)	0.446 (0.009)	0.144 (0.047)	0.326 (0.049)	0.029 (0.004)	0.024 (0.004)	-0.053 (0.007)	0.178 (0.313)	0.301 (0.395)	3,161
34 Motor Vehicles	0.054 (0.006)	0.275 (0.01)	0.272 (0.038)	0.312 (0.041)	0.039 (0.004)	0.042 (0.004)	-0.079 (0.007)	0.222 (0.426)	0.422 (0.557)	1,838
35 Other Transport Equipment	0.058 (0.013)	0.323 (0.019)	0.423 (0.099)	0.410 (0.102)	0.026 (0.009)	0.029 (0.009)	-0.062 (0.018)	0.257 (0.388)	0.390 (0.505)	724

Notes: $\hat{\beta}$ coefficients from the revenue function estimation by industry. Associated standard errors are in parentheses. Median θ and (revenue) by industry are displayed, where θ are computed following Equation (3.14). Associated standard deviations are in parentheses.

Table A.8: Quantile Distribution of Markdowns

Sector	ψ_i^M						ψ_i^Z					
	Mean	p10	p25	Median	p75	p90	Mean	p10	p25	Median	p75	p90
15 Food Products and Beverages	1.63	0.93	1.17	1.56	2.02	2.46	1.36	0.86	1.00	1.24	1.60	2.05
17 Textiles	1.52	0.91	1.09	1.40	1.82	2.33	1.79	1.00	1.24	1.60	2.14	2.88
18 Wearing Apparel	1.85	0.87	1.11	1.60	2.32	3.31	1.90	0.77	1.02	1.54	2.36	3.60
19 Leather	1.54	0.89	1.12	1.46	1.88	2.34	1.72	0.98	1.20	1.57	2.09	2.68
20 Wood	1.16	0.70	0.87	1.10	1.38	1.68	1.63	1.03	1.20	1.49	1.88	2.51
21 Pulp	1.19	0.84	0.96	1.15	1.37	1.62	1.44	1.01	1.15	1.38	1.66	1.98
22 Printing and Publishing	2.30	1.06	1.43	2.11	3.04	3.84	1.74	0.76	0.94	1.27	1.98	3.37
24 Chemicals	1.24	0.78	0.94	1.17	1.47	1.82	1.60	0.97	1.14	1.42	1.88	2.55
25 Rubber	1.29	0.81	0.99	1.22	1.53	1.85	1.51	0.96	1.13	1.41	1.78	2.23
26 Non-metallic mineral Products	1.58	0.78	0.99	1.46	2.06	2.61	1.82	0.88	1.10	1.51	2.22	3.26
27 Basic Metals	1.80	0.97	1.20	1.62	2.25	2.89	1.43	0.83	1.01	1.31	1.73	2.16
28 Fabricated Metal Products	1.66	0.81	1.06	1.55	2.17	2.69	1.63	0.91	1.10	1.42	1.93	2.64
29 Machinery and Equipment	1.46	0.79	0.99	1.36	1.82	2.28	1.41	0.86	1.02	1.27	1.65	2.17
31 Electrical machinery & App.	1.23	0.73	0.89	1.14	1.49	1.86	1.52	0.93	1.11	1.38	1.80	2.33
32 Radio and Communication	1.29	0.71	0.89	1.19	1.61	2.02	1.67	0.84	1.08	1.45	2.01	2.88
33 Medical	1.22	0.65	0.81	1.12	1.54	1.95	1.61	0.83	1.02	1.35	1.93	2.76
34 Motor Vehicles	1.44	0.59	0.85	1.26	1.88	2.57	1.59	0.65	0.96	1.44	2.01	2.76
35 Other Transport Equipment	1.52	0.75	0.94	1.34	1.98	2.64	1.77	0.91	1.11	1.57	2.16	2.97
All	1.49	0.80	1.00	1.34	1.82	2.39	1.59	0.89	1.08	1.39	1.86	2.53

Notes: Mean and distribution quantiles by industry and for the pooled sample (All), after trimming at the 3rd and 97th percentiles.

Appendix 3.B Theory Appendix

3.B1. Proof of Lemma 1

From the firm profit-maximization problem (at the individual variety level):

$$W_i^M(\nu)\psi_i^M(\nu) = \frac{\partial R_i}{\partial M_i(\nu)}, \quad (3.1)$$

where the terms are defined as in Section 3. Multiplying both sides of equation (3.1) by $\frac{M_i(\nu)}{R_i}$ and rearranging, we get:

$$\frac{E_i^M}{R_i} \cdot \frac{W_i^M(\nu)M_i(\nu)}{E_i^M} \psi_i^M(\nu) = \frac{\partial R_i}{\partial M_i} \frac{M_i}{R_i} \cdot \frac{\partial M_i}{\partial M_i(\nu)} \frac{M_i(\nu)}{M_i}, \quad \forall \nu \quad (3.2)$$

$$\alpha_i^M \cdot \int_{\nu} \gamma_i^M(\nu) \psi_i^M(\nu) d\nu = \theta_i^{M,r} \cdot \int_{\nu} \frac{\partial M_i}{\partial M_i(\nu)} \frac{M_i(\nu)}{M_i} d\nu, \quad \forall \nu, \quad (3.3)$$

where the last line follows from taking integrals over the set of foreign varieties in both sides of the equation, and where $\alpha_i^M \equiv \frac{E_i^M}{R_i}$ and $\theta_i^{M,r} \equiv \frac{\partial R_i}{\partial M_i} \frac{M_i}{R_i}$ are defined as in the main text. We then note that by Assumption 2, specifically by the fact that the foreign input aggregator is constant returns, we can substitute $\int_{\nu} \frac{\partial M_i}{\partial M_i(\nu)} \frac{M_i(\nu)}{M_i} d\nu = 1$.

We thus define $\bar{\psi}_i^M \equiv \int_{\nu} \gamma_i^M(\nu) \psi_i^M(\nu) d\nu$ as the weighted average of input market power of firm i in each individual market, where weights are the total expenditure share of variety ν , namely, $\gamma_i^M(\nu) \equiv \frac{W_i^M(\nu)M_i(\nu)}{E_i^M}$. Substituting in (3.3), we find:

$$\bar{\psi}_i^M = \frac{\theta_i^{M,r}}{\alpha_i^M},$$

which is the main equation of Lemma 1.

Appendix 3.C Price Bargaining in Buyer-Supplier Relationships

This appendix provides a formal economic model that rationalizes the use of a reduced-form input price function in Section 2. to capture bargaining in markets of intermediate inputs. The model builds on the two-sided bargaining framework developed by [Alvarez et al. \(2021\)](#).

We consider a partial equilibrium model of bargaining in firm-to-firm trade. In the model, imported (denoted by i) and exporters (denoted by j) exchange an intermediate input variety and bargain over the terms of trade. To ease exposition, we assume single-

product exporters, such that j denotes both the exporter and the traded variety.

We let Σ_i denote the set of foreign varieties sourced by French importer i , or the importer's *sourcing strategy*. Importer i imperfectly substitutes across foreign input varieties. The foreign intermediate input's quantity and price are defined as:

$$M_i = \left(\sum_{j \in \Sigma_i} \varsigma_{ji} M_{ji}^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}} \quad \text{and} \quad W_{ji}^M = \left(\sum_{j \in \Sigma_i} \varsigma_{ji}^{\rho} (W_{ji}^M)^{1-\rho} \right)^{\frac{1}{1-\rho}} \quad (3.4)$$

where $\rho > 1$ is the (constant) elasticity of substitution between varieties sourced by importer i , ς_{ji} is a demand shifter for variety j of the foreign input, and the remaining variables are defined as in the main text.

Firm i produces its final output Q_i combining the foreign intermediate input with other domestic inputs, as in Section 3. We let C_i denote the firm's unit cost, and we denote by $\gamma \in (0, 1]$ the elasticity of firm i 's unit cost with respect to the foreign input price:

$$\gamma = \frac{d \ln C_i}{d \ln W_i^M} \in (0, 1]. \quad (3.5)$$

In the downstream market, firm i competes in monopolistic competition and faces some iso-elastic demand with associated elasticity

$$\nu = -\frac{d \ln Q_i}{d \ln P_i} > 1, \quad (3.6)$$

where the price P_i is given by the standard formula $P_i = \frac{\nu}{\nu-1} C_i$.³⁰

On the exporter side, we write exporter j 's total supply of variety j as $M_j = M_{ji} + M_{j(-i)}$, where $M_{j(-i)}$ is total j 's demand by downstream importers other than firm i . We let C_j denote exporter j 's marginal cost, and let

$$\frac{1-\theta}{\theta} = \frac{d \ln C_j}{d \ln M_j} > 0 \quad (3.7)$$

denote the marginal cost's elasticity to the total input supply. The parameter $\theta \in (0, 1]$ governs the returns to scale of exporter j 's production. When $\theta \in (0, 1)$, the marginal costs are increasing in total output, which means that upstream production exhibits decreasing returns; conversely, when $\theta = 1$, the exporter's marginal costs are constant, which means that production exhibits constant returns.

Importer i and exporter j engage in bilateral negotiations to determine W_{ji}^M . The outside options of i and j are taken to be the profits when the $i-j$ link is terminated: exporters will make fewer sales, while importers will have higher costs (love-of-variety

³⁰Note that the assumption of CES demand and monopolistic competition is without loss of generality for the purpose of the main result. We discuss below how the main formula of interest would generalize in the case of a more general demand function.

technology). During negotiations, both the network of firm-to-firm trade and the other nodes' prices are taken as given. We thus leverage the Nash-in-Nash solution concept: the price negotiated between i and j is the pairwise Nash bargaining solution given that all other pairs reach agreement (Horn and Wolinsky, 1988). The negotiated price W_{ji}^M solves:

$$\max_{W_{ji}^M} (\pi_j(W_{ji}^M) - \tilde{\pi}_{j(-i)})^{1-\phi_{ij}} (\pi_i(W_{ji}^M) - \tilde{\pi}_{i(-j)})^{\phi_{ij}}, \quad (3.8)$$

where $\pi_j(W_{ji}^M)$ and $\pi_i(W_{ji}^M)$ are the profits to the exporter j and the importer i if the negotiations succeed, and $\tilde{\pi}_{j(-i)}$ and $\tilde{\pi}_{i(-j)}$ are the disagreement payoffs. The parameter $\phi_{ij} \in (0, 1)$ captures exogenous determinants of the firms' bargaining ability that might influence the outcome of the negotiation process. In our notation, a higher ϕ_{ij} denotes higher relative bargaining power of importer i .

Let $s_{ji} = \frac{W_{ji}^M M_{ji}}{\sum_{j \in \Sigma_i} W_{ji}^M M_{ji}}$ denote the share of exporter j 's sales over importer i 's total imports, while $x_{ji} = \frac{M_{ji}}{M_j}$ denotes the share of units of good purchased by importer i over the total units supplied by exporter j . Note that neither of these shares maps exactly to the share s_{ji}^M defined in Section 3. Taking the FOC with respect to (3.8) and rearranging terms, it is possible to write the bilateral price p_{ij} as a markup μ_{ij} over the exporter's marginal cost c_j :

$$W_{ji}^M = \mu_{ji} C_j. \quad (3.9)$$

The bilateral markup is found to be equal to

$$\mu_{ij} = (1 - \omega_{ij}) \cdot \mu_{ji}^{oligopoly} + \omega_{ij} \cdot \mu_{ji}^{oligopsony}, \quad (3.10)$$

which is a weighted average between an "oligopoly markup" $\mu_{ji}^{oligopoly} \equiv \frac{\varepsilon_{ji}}{\varepsilon_{ji}-1}$, with $\varepsilon_{ji} = \rho(1 - s_{ji}) + \tilde{\nu}s_{ji}$, increasing in the exporter's share s_{ij} , and an oligopsony mark-down $\mu_{ji}^{oligopsony} \equiv \theta \left(\frac{1-(1-x_{ji})^{\frac{1}{\theta}}}{x_{ji}} \right)$, decreasing in the importer share of variety j , x_{ji} . The weighting factor ω_{ij} is defined as $\omega_{ij} \equiv \frac{\tilde{\phi}_{ij}\lambda_{ij}}{\tilde{\phi}_{ij}\lambda_{ij} + \varepsilon_{ij}-1} \in (0, 1)$, which is increasing in $\tilde{\phi}_{ij}\lambda_{ij}$ – the product of the relative bargaining parameter ($\tilde{\phi}_{ij}$) and a term, λ_{ij} , which is proportional to the (endogenous) buyer's outside option. The larger $\tilde{\phi}_{ij}\lambda_{ij}$, the larger ω_{ij} , the closer is the bilateral markup μ_{ij} to the oligopsony markup.

We now proceed to characterize the relationship between the bilateral price W_{ji}^M and the quantity purchased by buyer i , M_i . Given equations (3.9)-(3.10), it is possible to show that the inverse supply elasticity of the foreign input variety j can be approximated as:

$$\Psi_{ji}^M \equiv \frac{d \ln W_{ji}^M}{d \ln M_{ji}} \simeq \beta_{ji}^1 + \beta_{ji}^2 x_{ji} \quad (3.11)$$

where β_{ji}^k , $k = 1, 2$ are constants that depends on market conditions upstream and

downstream which the buyer takes as given. In particular, $\beta_{ji}^1 \equiv \Gamma_{ij}^s \frac{d \ln s_{ji}}{d \ln M_{ji}} > 0$ and $\beta_{ji}^2 \equiv (\theta^2 + \frac{1}{\theta} - 2)$, which is positive for values of θ within reasonable ranges. Therefore, we get that the inverse supply elasticity is positive ($\Psi_{ji}^M > 0$), and increasing in the buyer's share x_{ji} .

Given this discussion, it immediately follows that when production upstream features decreasing returns scale (increasing marginal costs), input prices are a (buyer-specific) function of the importer's demand:

$$W_{ji}^M = W_i^M(M_{ji}; \mathbf{A}_i), \quad (3.12)$$

where \mathbf{A}_i is a vector capturing demand and technology conditions, which the buyer takes as given.

Appendix 3.D Demand Estimation

3.D1. Instrument Choice

We consider a CES demand system at the product category-destination level, where a product category is denoted by k and broadly corresponds to a two-digit industry. The demand function of firm i selling product p (in category k) in country c is:

$$q_{ipct} = -\sigma_k p_{ipct} + \sigma_k p_{pct} + q_{qct} + \eta_{ipct}, \quad (3.13)$$

where p_{ipct} is the price charged by firm i , expressed in foreign currency units, and p_{pct} and q_{pct} are the market-level price and demand, respectively.

It is well-known that estimation of (versions of) equation (3.13) is complicated by a classic simultaneity problem: positive shocks to market appeal lead producers to raise prices, making p_{ipct} and η_{ipct} positively correlated (Foster, Haltiwanger, and Syverson, 2008). In the presence of such endogeneity concerns, identification of demand can be obtained through cost shifters that are excluded from equation (3.13) and that are orthogonal to η_{ipct} .

We consider a supply-side model to think about these cost shifters. We let the price of the firm be a markup over marginal cost, i.e., $P_{ipct} = MC_{ipt} \cdot \mu_{ipct} \cdot E_{ct}^{-1}$, where MC_{ipt} is the euro-denominated marginal cost of firm i producing product p , μ_{ipct} is a markup, and E_{ct}^{-1} is the bilateral exchange rate between country c and France, measured as a unit of producer currency for one unit of foreign currency. In our data, we only observe free-on-board prices, which we can write as:

$$P_{ipct}^* = MC_{ipt} \cdot \mu_{ipct}. \quad (3.14)$$

We consider the same production technology as in equations (3.9)-(3.10). The only difference is that here we consider prices in nominal terms: we let W_i^Z denote the euro price of domestically-produced inputs, while $W_i^M E_m$ is the euro price of foreign-produced inputs, where E_m is the exchange rate measured as a unit of producer currency for one unit of foreign currency.³¹ It can be shown that the total variable cost function associated with this production structure is given by:

$$TVC_{ip}(Q_{ip}|\Sigma_i) = \frac{C_i^*}{\underbrace{\Phi_{ip}^{\beta_x} \exp(\omega_{ip})}_{MC_{ip}}} Q_{ip}, \quad (3.15)$$

where $C_i^* \equiv \left(\frac{W^L}{\beta_l}\right)^{\beta_l} \left(\frac{R}{\beta_k}\right)^{\beta_k} \left(\frac{W_i^Z \psi_i^Z}{\beta_x}\right)^{\beta_x}$ is the cost index for a non-importing firm, and $\Phi_{ip} = \left[1 + \left(E_m \frac{W_i^M}{W_i^Z} \cdot \frac{\psi_{ip}^M}{\psi_{ip}^Z}\right)^{\frac{\rho}{\rho-1}}\right]^{\frac{1-\rho}{\rho}}$ is the cost-reducing effect from importing intermediate goods, where $\frac{\psi_i^M}{\psi_i^Z}$ is the relative buyer power of firms in the foreign input market. With this cost structure, the marginal cost is $MC_{ip} = \frac{C_i^*}{\Phi_{ip}^{\beta_x} \exp(\omega_{ip})}$. We let φ_{ip} denote the fraction of total variable cost for producing p spent on imported intermediate inputs. It can be now shown that the partial elasticity of this marginal cost with respect to the exchange rate E_m equals the expenditure share of the firm on imported intermediate inputs, i.e.:

$$\frac{d \ln MC_{ip}}{d \ln E_m} = \varphi_{ip}. \quad (3.16)$$

We consider the import-weighted exchange rate as an instrument for the price P_{ipct} in estimating the demand function in (3.13). Equation (3.13) shows that this exchange rate has explanatory power over prices, especially for large importers. Further, changes in the (import-weighted) exchange rate are unlikely to be correlated with any short-run firm-specific demand shocks embodied in η_{ipct} . Hence they appear quite suitable as instruments for export prices.

3.D2. Implementation

We bring (3.13) to the data closely following the methodology of [Piveteau and Smaghiue \(2019\)](#), who use similar data. q_{ipct} and p_{ipct} are observed, while σ_k and η_{ipct} have to be estimated. q_{pct} will be wiped out by including destination-product-year fixed effects in the regression.

To deal with price endogeneity, merely coming from simultaneity, we instrument prices

³¹We denote by m a generic source of imported intermediates, and hence E_m can be thought of as an import-weighted exchange rate faced by the firms. The generalization of the model to multiple import source countries is straightforward; in the data, we measure E_m as an import-weighted exchange rate at the firm-level, as well as split imports by source countries ([Amiti et al., 2014](#))

with a variable consisting of the interaction between firm importing shares by country and real exchange rates. As pointed out by Piveteau and Smagghue (2019), this instrumental strategy leverages two sources of variations at the firm level: the set of countries a firm imports from and the share of these imports in the production cost of the firm. More formally, the import-weighted log real exchange rates are defined as:

$$\overline{rer}_{it}^{imp_{t-1}} = \sum_c \omega_{cft-1}^{imp} \times e_{ct}$$

where ω_{cft-1} is the import share of firm f from source country c , and e_{ct} is the log of the real exchange rate from France to country c at time t . The import weights are defined in year $t - 1$ to keep us safe from endogeneity issues.³²

The final instrument is obtained by interacting the import-weighted exchange rate with the share of these imports in the firm operating costs of the firm at time $t - 1$:

$$\overline{RER}_{it}^{imp_{t-1}} = \overline{rer}_{it}^{imp_{t-1}} \times \frac{m_{ft-1}}{OC_{ft-1}}$$

where m_{ft-1} and OC_{ft-1} respectively are the total imports and the operating costs of firm f at date $t - 1$. This adjustment accounts for the firm-level exposure to RER shocks depending on the importance of imports in firm's f input mix.

3.D3. Identification Discussion

We quickly summarize threats to exogeneity and identification and how to address them, as detailed by Piveteau and Smagghue (2019), to whom we refer for a more exhaustive argumentation. First, the instrument is built from import shares, that are potentially endogenous to demand shifters, which Piveteau and Smagghue (2019) label as quality Bas and Strauss-Kahn (2015); Bastos et al. (2018). Spell fixed effects are introduced to capture time-invariant differences across firms so that the identification ultimately is in the time series. We define a spell as a sequence of consecutive years during which a firm-product-destination triplet is exported. Moreover, we use lagged import weights when defining our instrument. Another potential threat to identification comes from the dual impact of exchange rate variations on firm performance for firms that are both importing and exporting in a similar market. We introduce destination-product-year fixed effect to eliminate such a concern. Furthermore, exchange rate variations can *directly* (and not through

³²We here depart from Piveteau and Smagghue (2019) in a few ways. First, we do not deviate real exchange rates from their trends, which blurs the expected relationship between prices and the instrument. Second, we build our import weights including all goods imported by the firm and not only differentiated goods (based on Rauch (1999)), in order to have a well-defined instrument taking into account shocks to all imported products, even more substitutable ones. Finally, we define weights at year $t - 1$ instead of relying on weights at the initial period at which the importing spells started, so that the weights used are closer to current weights. Our results are robust to these alternative definitions.

the firm import mix) imply quality adjustments. We wipe out such potential effects by adding two control variables to the estimation, namely the import- and export-weighted average GDP per capita of the firm, defined as:

$$\overline{GDP}_{it}^{exp} = \sum_c \omega_{cft}^{exp} \log(gdp_{ct})$$

$$\overline{GDP}_{it}^{imp} = \sum_c \omega_{cft}^{imp} \log(gdp_{ct})$$

Another threat to identification results from endogenous selection in trade activities. As firms can adjust through the extensive margin when they face an adverse shock, *i.e.* stop exporting, the estimation procedure can underestimate intensive margin adjustments to exchange rate movements. We account for this selection bias by limiting our sample to long exporting spells (more than 6 years) with the purpose of keeping in the sample firms which are away from exit thresholds, following [Fitzgerald and Haller \(2018\)](#); [Fontagné et al. \(2018\)](#). Finally, we add a dummy variable, $entry_{ipct}$, equal to one in the first year of an export spell, to account for the well-documented partial-year effect that could contaminate our results [Berthou and Vicard \(2015\)](#); [Bernard et al. \(2017\)](#).

3.D4. Specification

Again following [Piveteau and Smagghue \(2019\)](#), our specification proceeds in two steps. In the first step, we regress the exported price of the firm on the instrument, the fixed effects mentioned above, and the GDP per Capita controls. This writes:

$$p_{ipct} = \beta_0 \overline{RER}_{it}^{imp_{t-1}} + \beta_1 entry_{ipct} + \beta_2 \overline{GDP}_{it}^{exp} + \beta_3 \overline{GDP}_{it}^{imp} + \delta_{ipcs} + \delta_{pct} + u_{ipct}$$

where s characterizes a spell number for a firm f , destination c , and product p triplet.

Using predicted values of exporting prices from this first stage, we then estimate Equation (3.13) in the second stage:

$$q_{ipct} = -\sigma_k \overline{RER}_{it}^{imp_{t-1}} + \alpha_1 entry_{ipct} + \alpha_2 \overline{GDP}_{it}^{exp} + \alpha_3 \overline{GDP}_{it}^{imp} + \gamma_{ipcs} + \gamma_{pct} + \epsilon_{ipct}$$

in which γ_{ipcs} and γ_{pct} are firm-product-country-spell and product-country-year fixed effects. This last equation is identical to the structural demand defined in (3.13) except that we now impose the demand shifters η_{ipct} to take the following form:

$$\eta_{ipct} = \hat{\alpha}_1 entry_{ipct} + \hat{\alpha}_2 \overline{GDP}_{it}^{exp} + \hat{\alpha}_3 \overline{GDP}_{it}^{imp} + \hat{\gamma}_{ipcs} + \hat{\epsilon}_{ipct}$$

The firm-level demand shifter is then obtained at the firm-level weighted average of

the estimated η_{ipct} where weights are given by the firm export share by market:

$$\eta_{it} = \sum p, c \omega_{ipct}^{imp} \eta_{ipct}.$$

Appendix 3.E Data Appendix

3.E1. Data Preparation

Export Data

We follow [Piveteau and Smagghue \(2019\)](#) in cleaning the export data before demand estimation, and this section fully reproduces for the sake of practicality Appendix A in their paper.

We perform two main operations to prepare the final sample. First, we harmonize the product codes to obtain consistent categories across time. Then, we clean the dataset to take into account the existence of measurement errors in trade data.

Harmonization of product codes The product classification used by custom authorities is regularly updated to follow changes in product characteristics. We need to account for these changes to maintain a coherent set of product categories across time. To achieve this, we follow the procedure from [Van Beveren et al. \(2012\)](#) who apply the methodology from [Pierce and Schott \(2009\)](#) to European statistics. This allows us to obtain consistent product categories from 1997 to 2007.

Choice of units for quantity information Data on quantities are known to be subject to measurement errors, which could lead to spurious relationships between quantities and prices (computed by dividing values with quantities). Moreover, the customs statistics from France allow exporters to declare the quantities in two different units: the weight or a supplementary unit that is product specific and more relevant to describe the quantities of certain types of goods. Therefore, we decide to use the supplementary unit when at least 80% of the firms in the category are providing this unit. Otherwise, we use the weight of the good as quantity.

Data Cleaning After harmonizing quantities within product categories, we can compute prices as the export value divided by quantity. Then, because of the potential measurement errors in prices, we drop prices that display large variations from one year to another. In particular, given our identification strategy, we perform the following procedure:

- We declare a price p_{ipct} as abnormal when $\log p_{ipct} - \log p_{ipct-1}$ is larger than one or lower than minus one.

- We declare a price p_{ipct} as missing when the quantity for that observation is missing.
- We drop from the sample the entirety of an exporting spell that contains at least one abnormal or missing price.

By performing this cleaning procedure, we ensure that each exporting spell contained in our sample displays reasonable price changes across the years.

Import Data

As we use import values, and not quantities, for the instrument construction in demand estimation, we do not perform any particular cleaning on import data besides the basic ones recommended by [Bergounhon et al. \(2018\)](#). Product harmonization on the import side is not needed for demand or for revenue function estimation. It is however required for post-estimation analyses presented in Section 4.4., where the identification in Columns (4) and (5) of Table 3.4 for instance partly comes from variation in competition intensity within a product market over time. We use the harmonizing algorithm of [Bergounhon et al. \(2018\)](#).

3.E2. Sample Selection

Demand Estimation

The demand estimation exercise mechanically reduces the sample to firms that are observed both importing and exporting in the data. As described in Section 3.D, we keep exporting spells longer than 6 years for demand estimation, following [Piveteau and Smagghue \(2019\)](#). Demand shifters are then extrapolated on the entire (cleaned) sample.

Revenue Function Estimation

The revenue function estimation exercise requires a more severe sample selection. To comply with a revenue function estimation at the industry level and our focus on input trade, we restrict attention to firms that are homogeneous in terms of their input mix and heavily rely on imported inputs. To that end, we drop firms with labor and domestic input shares in revenues below 1% or above 99%. To deal with the large skewness of the import-to-revenue share distribution, especially on the left side, we implement more severe trimming regarding import shares. We first drop firms whose imported-input-to-domestically-purchased-input ratio is below the 3% or above the 97% percentiles of the corresponding distribution for a given industry-year cell. Finally, we drop firms with an import-to-revenue share below 5%, restricting attention to firms for which the importing activity represents a significant part of their input mix.

Table A.9: Number of Observations and Firms - Revenue Function Estimation Sample

Sector	<i>(1) Full Sample</i>		<i>(2) Selected Sample</i>		<i>(3) Estimating sample</i>	
	# obs.	# firms	# obs.	# firms	# obs.	# firms
15 Food Products and Beverages	16,093	2,600	8,471	1,691	6,096	1,306
17 Textiles	9,204	1,501	7,110	1,279	5,238	1,041
18 Wearing Apparel	7,378	1,524	5,329	1,231	3,527	922
19 Leather	2,728	495	2,208	424	1,609	346
20 Wood	5,202	968	3,000	677	2,028	490
21 Pulp	4,721	718	3,545	602	2,694	505
22 Printing and Publishing	6,242	1,320	2,965	758	1,891	498
24 Chemicals	11,441	1,716	7,940	1,378	5,986	1,136
25 Rubber	11,514	1,826	7,672	1,434	5,574	1,161
26 Non-metallic mineral Products	4,381	775	2,679	529	1,925	431
27 Basic Metals	3,524	515	2,426	426	1,805	357
28 Fabricated Metal Products	19,244	3,583	10,462	22,238	7,175	1,61
29 Machinery and Equipment	16,523	2,708	9,729	1,913	6,906	1,436
31 Electrical machinery & App.	4,967	801	3,307	605	2,447	503
32 Radio and Communication	3,396	625	2,124	454	1,453	356
33 Medical	7,95	1,385	4,596	951	3,161	726
34 Motor Vehicles	3,388	539	2,449	437	1,838	370
35 Other Transport Equipment	1,893	379	1,086	249	724	183
All	139,789	23,978	87,098	17,276	62,077	13,387

Notes: Observations are at the firm-year level. Sample (1) is restricted to importers and exporters kept in demand estimation. Sample (2) restricts Sample (1) according to the selection procedure described in Section 3.E2.. Sample (3) restricts Sample (2) to firm-year observations for which a lag for a given firm is present.

General Conclusion

This dissertation aims to better understand the role of market power and competition frictions between suppliers and buyers in intertwined global and national value chains. This research leverages empirical and theoretical tools applied to the French dairy industry and to French importing manufacturing firms.

The first chapter suggests a new methodology to separately estimate firm buyer and seller power, a task that is important for policy-making but challenging, and apply it to French dairy processors. These firms exert buyer power when purchasing raw milk, and seller power when marketing dairy products. The analysis is based on plant-level data on dairy firms, with observations on prices and quantities of raw-milk input by origin and output by product from 2003 to 2018. Total margins are estimated relying on a production function approach. The existence of a commodity, (i) substitutable as an input or as an output, and (ii) exchanged on global markets where firms are price-takers, then allows separately estimating firm-origin markdowns and firm-product markups. The methodology can also be useful in other contexts, with more limited data. Markdown estimates imply that dairy firms on average purchase raw milk at a price 16% below its marginal contribution to their profits, while markup estimates indicate that firms sell dairy products at a price exceeding their marginal costs by 41%. This chapter also analyzes how shocks to local farmer costs and international commodity prices pass through the supply chain. Processors partially absorb such shocks by adjusting markups and markdowns, thus smoothing variations in farmer revenues. It further implies that 65% of subsidies are currently diverted from farmers due to processor buyer power.

The second chapter aims to tackle the following question: How do input market fragmentation and liberalization affect production allocation? To answer this question, this chapter analyzes the impact of production quotas and their progressive removal in the French milk market, showing that production quotas generated two types of distortions. First, by mechanically fixing production shares across French *départements* at their pre-quota (1984) level, quotas stopped a natural spatial concentration for about 25 years, a process that restarted right after the start of the progressive quota removal in 2008. Second, the design of the quota system spurred the growth of small farms while constraining the expansion possibilities of larger farms. This redistributive scheme thus successfully refrained inequalities among farms growing until then, yet at the cost of distorting the

competition-led cream-skimming of farms. Results finally show how the catching-up process in farm selection following the quota removal intervened more or less early across *départements*, depending on the stringency implied by quota constraints at the local level. These observations are rationalized with a simple model of perfect competition between heterogeneous farms. At the farm level, the effect of the liberalization ultimately depends on (i) the efficiency gains the farm can achieve with the liberalization and (ii) its location in a *département* sheltered from competition or constrained by quotas.

The third chapter quantifies buyer power in input trade and aims at evaluating its aggregate effects. The developed empirical strategy for estimating importer buyer power from standard trade and production data does not rely on assumptions about other input markets. The results show that French manufacturing firms exert an average markdown of 1.49 on imported inputs and of 1.59 on domestically purchased inputs, revealing their significant buyer power in both markets. The welfare implications of these estimates are then explored using a general equilibrium model.

Title : Pouvoir de Marché et Frictions dans les Chaînes de Valeur

Mots clés : Pouvoir de Marché, Frictions, Chaînes de Valeur

Résumé : Cette thèse vise à mieux comprendre le rôle du pouvoir de marché et de la concurrence imparfaite dans les relations entre fournisseurs et acheteurs opérant dans des chaînes de valeur mondiales et nationales entrelacées. Cette recherche s'appuie sur des outils empiriques et théoriques, appliqués à l'industrie laitière française et aux industriels importateurs français. Le Chapitre 1 propose une nouvelle méthodologie pour estimer séparément le pouvoir de marché à l'achat et à la vente, appliquée aux transformateurs de produits laitiers en France. Ces entreprises exercent du pouvoir de marché à l'achat lorsqu'elles achètent du lait cru et à la vente lorsqu'elles commercialisent des produits laitiers. L'analyse est basée sur des données individuelles d'entreprises, où les prix et les quantités de lait cru par origine côté achat et par produit côté vente sont observés de 2003 à 2018. Les marges totales sont estimées via une approche « fonction de production ». L'existence d'un produit de base (i) substituable en tant qu'intrant ou en tant que produit, et (ii) échangé sur les marchés mondiaux où les transformateurs laitiers français sont preneurs de prix, permet ensuite d'estimer séparément les marges de chaque entreprise à l'achat, par origine, et à la vente, par produit. Les résultats indiquent que les entreprises laitières achètent en moyenne le lait cru à un prix inférieur de 16% à sa contribution marginale à leurs bénéfices, et vendent les produits laitiers à un prix supérieur de 41% à leurs coûts marginaux. Une analyse de la transmission des chocs de coûts des agriculteurs et des transformateurs sur la chaîne d'approvisionnement révèle que ces chocs sont partiellement absorbés par les transformateurs. En ajustant leurs marges, les transformateurs lissent les variations de revenu des agriculteurs mais détournent en moyenne 65% de leurs subventions.

Le Chapitre 2 analyse l'impact des quotas de production et de leur suppression progressive sur le marché du lait en France, montrant que les quotas ont généré deux types de distorsions. Premièrement, en fixant mécaniquement les parts de production des départements français à leurs niveaux pré-quotas (1984), les quotas ont stoppé une concentration spatiale naturelle pendant environ 25 ans, un processus qui a repris après le début du retrait progressif des quotas en 2008. Deuxièmement, le système de quotas a favorisé la croissance des petites exploitations mais limité l'expansion des plus grandes, freinant ainsi des inégalités jusqu'alors croissantes entre fermes, mais au prix d'une distorsion de l'écémage concurrentiel des exploitations laitières. Enfin, le processus de rattrapage dans la sélection des exploitations post-quotas est intervenu plus ou moins tôt dans les départements, en fonction de la contrainte imposée par les quotas au niveau local. Ces observations sont rationalisées à l'aide d'un modèle de concurrence parfaite entre exploitations hétérogènes. Le Chapitre 3 quantifie le pouvoir de marché des entreprises à l'achat d'intrants et évalue ses effets agrégés. Le chapitre présente une stratégie empirique visant à estimer le pouvoir de marché à l'achat de produits intermédiaires importés ou achetés localement, sans imposer d'hypothèses sur d'autres marchés d'intrants, et utilisant des données standard de commerce international et de production. Ce chapitre montre que les entreprises manufacturières françaises exercent une marge moyenne à l'achat de 1,49 sur les intrants importés et de 1,59 sur les intrants achetés localement, révélant un pouvoir de marché à l'achat significatif sur les deux types d'intrants. Les conséquences en termes de bien-être sont ensuite explorées avec un modèle d'équilibre.

Title : Market Power and Frictions in Supply Chains

Keywords : Market Power, Frictions, Supply Chains

Abstract : This dissertation aims to better understand the role of market power and competition frictions between suppliers and buyers in intertwined global and national supply chains. This research leverages empirical and theoretical tools applied to the French dairy industry and French manufacturing importers. Chapter 1 suggests a new methodology to separately estimate firm buyer and seller power, which is important for policy-making but challenging, and apply it to French dairy processors. These firms exert buyer power when purchasing raw milk, and seller power when marketing dairy products. The analysis is based on plant-level data on dairy firms, with observations on prices and quantities of raw-milk input by origin and output by product from 2003 to 2018. Total margins are estimated relying on a production function approach. The existence of a commodity, (i) substitutable as an input or as an output, and (ii) exchanged on global markets where firms are price-takers, then allows separately estimating firm-origin markdowns and firm-product markups. The methodology can also be useful in other contexts, with more limited data. Markdown estimates imply that dairy firms on average purchase raw milk at a price 16% below its marginal contribution to their profits, while markup estimates indicate that firms sell dairy products at a price exceeding their marginal costs by 41%. This chapter also analyzes how exogenous farmer and processor cost shocks pass through the supply chain. Processors partially absorb such shocks by adjusting markups and markdowns, thus smoothing variations in farmer revenues. It further implies that 65% of subsidies are currently diverted from farmers due to processor buyer power.

Chapter 2 analyzes the impact of production quotas and their progressive removal in the French milk market, showing that production quotas generated two types of distortions. First, by mechanically fixing production shares across French départements at their pre-quota (1984) level, quotas stopped a natural spatial concentration for about 25 years, a process that restarted right after the start of the progressive quota removal in 2008. Second, the design of the quota system spurred the growth of small farms while constraining the expansion possibilities of larger farms. This redistributive scheme thus successfully refrained inequalities among farms growing until then, yet at the cost of distorting the competition-led cream-skimming of farms. Results finally show how the catching-up process in farm selection following the quota removal intervened more or less early across départements, depending on the stringency implied by quota constraints at the local level. These observations are rationalized with a simple model of perfect competition between heterogeneous farms.

Chapter 3 quantifies buyer power in input trade and evaluates its aggregate effects. The developed empirical strategy for estimating importer buyer power from standard trade and production data does not rely on assumptions about other input markets. The results show that French manufacturing firms exert an average markdown of 1.49 on imported inputs and of 1.59 on domestically purchased inputs, revealing their significant buyer power in both markets. The welfare implications are then explored using an equilibrium model.