Gianluca Antonecchia

Productivity and Strategies of Multiproduct Firms

Productivity and Strategies of Multiproduct Firms

Productivity and Strategies of Multiproduct Firms

Productiviteit en strategieën
van bedrijven met meerdere producten

Thesis

to obtain the degree of Doctor from
the Erasmus University Rotterdam
by command of the rector magnificus

Prof. dr. A.L. Bredenoord

and in accordance with the decision of the Doctorate Board

The public defence shall be held on
Wednesday November 2nd, 2022 at 10:30

by

GIANLUCA ANTONECCHIA
born in Campobasso, Italy

Erasmus University Rotterdam

Doctoral Committee

Promotor:	Prof. dr. H.P.G. Pennings
Other members:	Prof. dr. M.A. Carree
	Prof. dr. M.P. García-Gómez
	Dr. T.L.P.R. Peeters
Copromotor:	Dr. A.S. Bhaskarabhatla

Tinbergen Institute, Erasmus School of Economics dissertation series number: 801
ISBN: 978-90-5892-649-4
© 2022, Gianluca Antonecchia

Design: PanArt, www.panart.nl
Print: OBT bv, www.obt.eu

All rights reserved. No part of this publication may be reproduced or transmitted in any form or by any means electronic or mechanical, including photocopying, recording, or by any information storage and retrieval system, without permission in writing from the author.

This publication (cover and interior) is printed on FSC® paper Magno Satin MC.

FSC® www.fsc.org MIX Papier van verantwoorde herkomst FSC® C022586

"Why do you speak to me of the stones?
It is only the arch that matters to me."
Polo answers: "Without stones there is no arch."
(Italo Calvino, *Invisible cities*, 1972)

To our ladybug

Acknowledgements

My PhD was a time machine. But it worked in my favor: I have gained five additional years of youth. When I left my permanent job to start a research masters I felt - and indeed was - an "old" PhD. Indeed, I kept losing my hair and my lines have become more evident. But I have felt more and more energetic and passionate about this job, and life in general. This Benjamin Button effect was only possible because I have never been alone in these years. The first two pages of this thesis are dedicated to the people that made my PhD a privilege.

My first thank you is for Ajay Bhaskarabhatla. Supervisor, coauthor and friend. Your ability to keep these three qualities separated made my PhD an experience that I would restart tomorrow. Considering our promising ongoing projects, I hope to keep thanking you for the coming years. My second thank you is for my promoter. Enrico Pennings, despite your many obligations, you have never left me without your help when I needed it. Thanks for pushing your "approved" button so often, especially at the beginning of the PhD. That boosted my confidence in my research and spurred me to present it outside the department.

A large credit for my PhD completion must be attributed to the OSE faculty, especially Kirsten, Zhiling, Thomas, Frank, Bas, Michiel, Jolanda, Niels, Brigitte, Jan, and the secretaries Manuela, Petra, Ylaise, Mads, Astrid, Malva, Cindy, Judith, Carolien, Christine and Arianne. The support that such a vibrant group gave to my research is invaluable. I have loved to go to the office and meet you there.

Other academics have supported the different phases of my PhD. Thank you, Eric Bartelsman for supporting my visibility; Serguey Braguinsky for being my main reference point and a superb host; Eric Verhoogen for transforming a promising idea into a solid project; Benoit Crutzen for helping set my expectations; Anna, Anne, Felix, Sacha, Agnieszka, Vladimir, Carlos and Chen for helping restructure my communication; Hans, Aurelien, Georg, Tom, Pilar and Han for your comments on my research and/or for running one evening per week from the N-building. My long-run gratitude goes to Paolo Onofri for opening the gate of economics to me and Francesco Daveri for inciting me towards productivity.

I have never hidden that what attracts me the most to academia rather than the study is the debate. I shared my best time of these years with many young and talented scholars. Our relationship has gone beyond Erasmus and effortlessly became friendship. In random order I thank Annelot for Sky Radio Christmas, Sanaz for her green thumb, Marcus for being louder than me, Tilbe for daydreaming, Zsolt for drawing, Capozza for the CCCP, David for the choco-coffee, Vahid for beating, Rita for calling me Giacomo, Giorgio for becoming bald together, Eric for 5 kg of cherry tomatoes, Sammy for skating on the Kralingse Plas, Principe for the Strega, Nicola for the carbonara nights and Astrid for Point zero, Megan for caring and the s* biscuits, Mirgiam for punning, Sara for silent night h* night, Nienke for deciding, Merel for being indestructible, Sai for disappearing, Cristian for the Clooneyness and Clarisse for Paul, Esmée for welcoming me on the 8th floor, Matthijs for the octopus by the Tago, Didier por la Victoria, Plato for the fridge, Riccardo for understanding my presentations, Marco for dancing Raffaella Carrà at Casa Azzurri, Max for our lunch at Motore, Yannis for guiding us through Athens, Surabhi for the dal, Takuya for being hungry, the other office mates that I wish I had more time to share with - Dilnoza, Domenico, Diarmaid, Malin, Lisa, Paniz, Kristel, Arjun, Marius, Elisa - and those that I will remember after this page will be printed.

Next to my university fellows, I had the chance to meet new friends that supported my PhD from outside the ivory tower. I want to acknowledge them for building the creative environment that underpinned my PhD. Thanks Iveta, Melanie, Andre and Yves for playing the guitars at candlelight, Roberto for introducing me to Rotterdam, Magda for sailing and Robin for going to pick up the speaker at 3 am, Fabrizio for running in the outskirts, Ruben, Claudia and Renske for uuuh and the violin spider, Anna for Sanremo and Jose for quah, Inge for the 5 cent in the tulips, Louis for being a gentleman even when serving snert, Sury and Hans for knocking on our door at the parties (and joining), Vigyan for starring me, Matt and Harriet for coming to Rotterdam when I leave, Jan Dodd for remembering of me in her youth. Also, thanks to my futsal team WIA for the (little) victories, the (many) injuries and post-match drinks.

In my family we never thank with each other. But Old Fred and Irene do not know this yet. Then, thank you both for bringing the spring back. Finally, I would like to thank the person who made these years a carnival. She knows that I would be somewhere else if I had not met her colorful foulard that morning in Bologna. But I cannot write this without making her blush. So, I do not thank her here. I will do it in person, at home.

Table of contents

Chapter 1

Introduction

"The efficient grow and survive; the inefficient decline and fail."

Boyan Jovanovic (1982)

Firm heterogeneity in productivity — the efficiency with which firms turn inputs into outputs — is extensively documented in both rich and poor countries, even within narrowly defined industries composed of homogeneous products (Bartelsman and Doms, 2000; Syverson, 2011; Maue et al., 2020). In the last two decades the research in industrial organization and macroeconomics has devoted substantial effort to understand the causes and the welfare implications of productivity dispersion (e.g., Hsieh and Klenow, 2009; Aghion et al., 2019). In the large majority of these studies firm productivity is positively correlated with profitability, size, growth, survival and wage (De Loecker and Syverson, 2021). Another common empirical finding connects productivity with firm strategies: highly productive producers set lower prices (e.g., Foster et al., 2008). Recently, thanks to the availability of product-level data, firm heterogeneity in productivity has been further disaggregated into within-firm heterogeneity for multiproduct firms. There is evidence of productivity dispersion also within firms, across their products (Dhyne et al., 2017; Orr, 2019). In my doctoral research I study how differences in product-level productivity influence product-level strategies and market power.

I provide two main contributions to the economic literature. First, I study the production and the strategies of multiproduct firms. Moving the empirical analysis from the firm to the product level is challenging. Firms have traditionally been considered as single-product/market entities. However, firms produce many products, with each product having its own production line and therefore its own productivity (Bernard et al., 2009). Moreover products of the same firm often serve different markets and, by definition, have their own market power and market strategies (Hottman et al., 2016). Product-level analysis of productivity and strategies is also a methodological challenge as variables of interest such as product-level productivity, price elasticity and markup cannot be computed adopting the techniques of firm-level analysis (De Loecker et al., 2016; Dhyne et al., 2017). In addition, detailed product-level data to study productivity and strategies for an entire industry are rare, although increasingly available.

The second major contribution of this thesis is the study of the relationship between productivity and the market strategies of the products. There is evidence on how firm strategies are affected by supply-side factors including productivity (Syverson, 2007), location (Atkin and Donaldson, 2015), innovation (Braguinsky et al., 2020) and managerial style (Malmendier and Tate, 2015). Conversely, product strategies are often considered only as responses to consumer preferences and product demand (e.g., DellaVigna and Gentzkow, 2019; Jaravel, 2019). I consider the market strategy of a product also as an optimal response to its productivity; a supply-side indicator of the efficiency to produce that product. I analyse this relationship combining firm-level data to large product-level data for industries such as the pharmaceuticals and consumer product goods.

Since productivity and market strategies are closely related to growth and resource (mis)allocation, emerging countries represent a relevant setting to study this relationship. India's pharmaceutical and fast-moving consumer goods industries offer essential products whose strategies and market power are directly responsible for the drug and food accessibility of 1.3 billion people. Understanding what drives strategies and market power in these industries at such a detailed level offers the possibility to provide precise policy recommendations (Syverson, 2019; Berry et al., 2019).

1.1 Productivity and strategies of the products

Firm productivity has been identified as a primary supply-side source of firm size and growth (Melitz, 2003; Autor et al., 2020).[1] The mechanism that transforms productivity into firm growth depends on the market strategies of the firm, primarily pricing strategies. Yet models of firm dynamics and industry evolution predict *selection on productivity*: more productive firms set lower prices, gaining market shares and forcing less productive firms to exit (Jovanovic, 1982; Hopenhayn, 1992).[2] Higher productivity implies lower marginal costs that, in a competitive environment, turn into lower prices (Syverson, 2007; Hortaçsu and Syverson, 2007; Foster et al., 2008).[3] In markets with reduced or no price dispersion, productivity heterogeneity among firms can still exist and find nonprice strategy channels — e.g., promotions, pack size, product availability — to influence demand and firm growth (Adams and Williams, 2019).

I investigate the role of productivity differences across products in the definition of their market strategies. In the three core chapters of this thesis, I show that productivity differences exist also among products, within and across firms, and within narrowly defined markets. In the second chapter, I find that productivity differences across products persist even in markets where there are no price differences (uniform pricing), and that they drive firm strategies other than pricing, allowing firms to engage in the so called *nonprice competition.* In the third and fourth chapter, I show that higher productivity is related with lower product wholesale price and market power, but the effect on product demand is highly influenced also by the buyer power of the retailers and the appeal of the product.

1.2 Productivity estimation: the state of the art

In this thesis, productivity is defined as *total factor productivity* (TFP), estimated as the residual of the production function, i.e. the output variation that cannot be explained by observable inputs. Estimating productivity requires the solution of some identification problems that are further complicated when dealing with multiprod-

[1] Research suggests various other candidates as supply-side drivers of firm size and growth: fixed costs and capability (Das et al., 2007; Boehm et al., 2022), product quality (Khandelwal, 2010; Schott, 2004), innovation (Klepper and Thompson, 2006; Braguinsky et al., 2020), scope (Bernard et al., 2010; Hottman et al., 2016), management practices (Bloom and Van Reenen, 2010; Bloom et al., 2013; Syverson, 2007) and expectations (Tanaka et al., 2019; Coibion et al., 2020).

[2] Similarly, models of international trade predict that more productive firms enter into exporting, as they can cover transportation and other costs relative to less productive firms (Melitz, 2003; Mayer et al., 2014; Melitz and Redding, 2014).

[3] This relation is stronger in markets serving homogeneous goods, whereas it is inverted in markets where quality difference among products is high (Kugler and Verhoogen, 2011; Atkin et al., 2019).

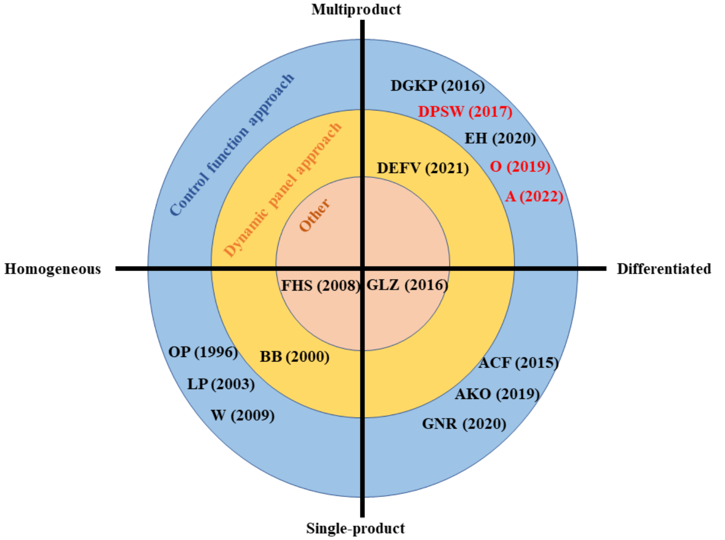
uct firms. First, regardless of whether a firm is multiproduct or not, productivity is unobserved to anyone but the firm, that chooses the amount of inputs based on it (Olley and Pakes, 1996). This *simultaneity bias* alters the OLS estimation of the production function residual. Second, production output — across and within firms — can be homogeneous or differ in quality. Neglecting product differentiation and how prices reflect it can cause distorted productivity estimates (Klette and Griliches, 1996). This *omitted price bias* arises because input and output prices are not commonly available in the data. Third, the number of products is decided by the firm according to the observed productivity (Bernard et al., 2010). This *product scope bias* should be accounted for when estimating the productivity of multiproduct firms.

Based on the methods employed to tackle these biases, I briefly classify some of the most influential (or promising) methodological approaches on productivity estimation. Without the presumption to be exhaustive, Figure 1.1 proposes a visual inspection of this classification. Traditionally the literature assumes that all firms produce one homogeneous product and addresses the simultaneity bias using the so-called *control function approach* (Olley and Pakes, 1996; Levinsohn and Petrin, 2003). This approach links the production function to the mechanisms that drive input demand and is opposed to the *panel data approach* that avoids that structure (and assumptions), exploiting the input variability of the firm over time (Blundell and Bond, 2000). The panel data approach has been recently revived by De Roux et al. (2021) that extend the method to quality-differentiated multiproduct firms. To avoid distortions due to unaccounted product differentiation, Foster et al. (2008) calculate productivity on a sample of homogeneous product producers only. More recent elaboration on the control function approach relaxes some of the assumptions of the pioneering studies and extends the method to product-differentiated firms (Ackerberg et al., 2015; Gandhi et al., 2020).

More recently, thanks to the availability of product-level data, the product scope bias has also been tackled and the control function approach has been accommodated to include multiproduct firms. The omitted price bias has been reduced using output data expressed in units and not in sales, allowing the current literature to distinguish between *revenue-based* and *quantity-based* productivity (*TFPR* and *TFPQ*). For this reason, the measure of productivity in the research on multiproduct firms is almost always TFPQ. To cope with the lack of product-level input data, new methods to allocate firm-level input across products have been proposed.[4] Assuming that productivity and markups do not vary within the firm across products, firm-level inputs

[4] An exception is a dataset of Chilean multiproduct plants including product-specific input cost shares (Garcia-Marin and Voigtländer, 2019).

Figure 1.1 Productivity: the state of the art



Notes: **OP (1996)**: Olley and Pakes (1996); **BB (2000)**: Blundell and Bond (2000); **LP (2003)**: Levinsohn and Petrin (2003); **FHS (2008)**: Foster et al. (2008); **W (2009)**:Wooldridge (2009); **ACF (2015)**: Ackerberg et al. (2015); **DGKP (2016)**: De Loecker et al. (2016); **GLZ (2016)**: Grieco et al. (2016); **DPSW (2017)**: Dhyne et al. (2017); **AKO (2019)**: Atkin et al. (2019); **O (2019)**: Orr (2019); **GNR (2020)**: Gandhi et al. (2020); **EH (2020)**: Eslava and Haltiwanger (2020); **DEFV (2021)**: De Roux et al. (2021); **A (2022)**: this thesis. In red the studies that estimate product-level productivity.

can be split equally across the products or assigned based on product revenue shares (Foster et al., 2008; De Loecker, 2011). Imposing specific characteristics of the production technology and competition environment, Orr (2019) shows how to estimate product-specific inputs by exploiting the profit maximization conditions and using product-level price and output data available. Without restricting the form of competition, De Loecker et al. (2016) allocate inputs across products by dividing the production function into two components, one depending on product-level inputs and the other not, and solving a system of equations using the conditions implied by the assumption of constant within-firm productivity. Dhyne et al. (2017) circumvent the input allocation problem and estimate product-level TFPQ using only firm-level inputs, controlling for the product scope of the firm. This method does not require assumption on the production technology or competition form and allows for synergies across products within the firm. Building on Dhyne et al. (2017), I estimate product-level TFPQ in the pharmaceutical industry and in the consumer product goods industry. I exploit the characteristics of the submarkets of these industries which are populated by many products with homogeneous characteristics, such as the same chemical components or ingredients.

Despite the numerous innovations in productivity estimation of the last 30 years, there are several gaps that literature is required to fill.[5] I would emphasize two aspects that involve also the productivity estimates in my thesis. First, productivity is largely modelled as TFP, while, recent evidence shows that factor-specific productivity, and particularly labor-augmenting productivity, fits better the data in some cases and has similar implications to the Hicks-neutral productivity (Raval, 2020; Doraszelski and Jaumandreu, 2018). In the highly mechanized manufacturing industries that I study, productivity could also be modelled as capital- or material-specific. Second, estimating TFPQ in multiproduct firms using input expenditure, even if appropriately deflated and corrected for the input price bias, can be severely distorted due to the input price heterogeneity within the firm. Quantity-based inputs at the product level are not available in the data, but even if they were, their aggregation at the firm level would be problematic.

1.3 Thesis outline

Inspired by the literature outlined above, the aim of this thesis is to provide empirical evidence on how firm heterogeneity in productivity influence firms strategy and market power. The rest of this introduction illustrates the overall thesis and summarises the three chapters included. Each of the three chapters is then enclosed as a self-contained paper, with each providing a study of the drivers of firm strategy and market power. Chapter 2 studies how product-level productivity influences the non-price strategies of the firms in markets where all the firms charge the same prices. Chapter 3 investigates the relationship between prices and market shares in the pharmaceutical industry. Chapter 4 studies the sources of market power of the medicines. Chapter 5 concludes the thesis with a review of the three chapters, discussing the contributions to the extant literature and outlining potential extensions for future research. The Methodological Appendix at the bottom of the thesis explains the methods used to estimate the production and demand functions, separately for each chapter.

Chapter 2 and 3 are co-authored by Dr. Ajay Bhaskarabhatla, under the supervision of Prof. Enrico Pennings. Although both Dr. Bhaskarabhatla and I participated in every process of the research, Table 1.1 clarifies the major contribution of each co-author.

In Chapter 2 Dr. Bhaskarabhatla and I study how firms compete when all firms in

[5] For a structured discussion, see De Loecker and Syverson (2021)

Table 1.1 Authors' contribution to the thesis

Chapter	Author	Major contribution
2	G. Antonecchia	Conceptualization, Methodology, Analysis, Writing
	A. Bhaskarabhatla	Conceptualization, Data curation, Writing
3	G. Antonecchia	Methodology, Analysis, Writing
	A. Bhaskarabhatla	Conceptualization, Data curation, Writing
4	G. Antonecchia	Single-authored

Notes: Enrico Pennings provided feedback and supervision to all the chapters.

an industry set identical price (uniform pricing). Using Nielsen data on India's biscuit manufacturers, we document productivity-based competition on nonprice strategies. Products with one standard deviation higher quantity-based productivity contain, on average, 13 percent more quantity per pack for the same price. Productivity also positively correlates with promotions on pack size, availability, and variety. A higher price (per pack size) elasticity in rural markets combined with industry-wide uniform pricing imposes a higher burden on rural consumers. Additional analyses show that firms can reduce this burden by selling different pack sizes in urban and rural areas.

In Chapter 3 Dr. Bhaskarabhatla and I examine how prices influence product market shares in the Indian pharmaceutical industry. Using detailed data on product-level sales and prices for 8000 narrowly defined markets (active ingredient-dosage form), we divide the retail price into wholesale price and retail markup and identify their marginal effects on product market share. We tackle the simultaneity bias instrumenting wholesale price with quantity-based product-level productivity and retail markup with firm average markup in the non-focal markets. We find that a one-percent higher wholesale price reduces market share by 5.7 percent, whereas one-percent higher retail markup reduces market share by 1.5 percent. This implies that elasticity of substitution across medicines with identical medical effect for the retailers is almost four times larger than that of the consumers, being the retailers more able to switch across medicines. We also find that market leaders and market pioneers face less elastic demand and benefit from offering higher retail margins. These results, combined with the evidence that wholesale prices are correlated negatively with product-level productivity, suggest that, although productivity differences induce price competition, they do not necessarily improve access to medicines in the presence of manufacturer market power and substantial incentives for the retailers.

In Chapter 4 I study the sources of market power using product-level data for narrowly-defined markets of the Indian pharmaceutical industry. I measure the market power on the product market separating it from the market power on the input market, and identify the marginal effect of its four components: wholesale markup, productivity, retail markup and appeal. Product market power depends positively on demand-side sources, such as wholesale markup and appeal, and negatively on supply-side sources, such as productivity and retail markup. The sales of the largest firms are concentrated in a small number of *superstar products* that have higher market power, higher productivity and contribute substantially to the aggregate market power and sales concentration.

Chapter 5

Conclusions

"One cannot simply rely on producer-level variation 'canceling out' when looking at aggregate changes. That variation is what creates the aggregate changes."

Chad Syverson (2019)

This doctoral thesis studies how differences in productivity influence the strategies and the market power of multiproduct firms. This conclusion takes stock of the contributions of this thesis in light of the current related literature, outlines the implications of the results and, finally, discusses possibilities for future research.

Chapter 2 examines a unique case of an industry, the Indian biscuit industry, where all firms charge identical prices, raising questions about the competitiveness of such an industry structure. We find strong evidence that, despite the inflexibility of prices, firms compete on several non-price dimensions, pack size being chief among them. The use of industry-wide uniform pricing, however, implies that urban and rural consumers with different demand elasticities pay the same price for the same pack size of a given product, leading to potential welfare losses for the rural consumers. Indeed, we show that firms can increase their profits by optimally choosing pack sizes and potentially setting different pack sizes for urban and rural consumers. Overall, our study shows that selection on productivity and competition can exist even when all firms charge identical prices. While our study examines the consequences of industry-wide uniform pricing, the process through which it emerged and its implications for competition policy remain important questions for future studies.

Chapter 3 and 4 examine the relationship between productivity, prices and market power in the Indian pharmaceutical industry, featuring multiproduct firms. The results show that the selection mechanism in the pharmaceutical markets does not reward less productive products. Quantity-based productivity is negatively correlated with product wholesale price, implying that productivity triggers price competition, on average. Nevertheless, this consideration excludes the top-selling products both of the markets and of the firms. Market leaders and superstar products have higher productivity, prices and market power compared to their competitors. One possible mechanism that helps large products insulate from competition seems to be the incentive provided to the retailers in the form of higher margins. Indeed, in our findings a higher demand corresponds not only to lower prices but also to higher retailer incentives and higher product appeal (perceived quality). These results reveal how retailer's buyer power can foster a win-win relationship between retailers and market leaders. Since we consider markets with close substitute products, these findings imply a welfare loss for the less informed consumers. However, in our data we cannot distinguish if the observed results for the market leaders is the outcome of a retailer-driven strategy to reduce local availability of competing products. In such a case, even the well-informed consumers would have little opportunity to switch from larger products to cheaper alternatives.

The results of Chapter 3 and 4 have implications for the Indian government, the pharmaceutical firms operating in India, the intermediaries (pharmacies and physicians), and the consumers. The Indian government, like a few others, has regulated the prices of some medicines in order to lower prices and improve drug accessibility. There can be several explanations for why medicine prices may be high in India (e.g. dominant positions of manufacturers and retailers, patent protection and inelastic demand). This thesis gives the governments and public institutions a clear setting for understanding how pricing decisions affect the revenues of the pharmaceutical industries and how firm market power and retail buyer power affect medicine affordability. This study also has implications for the pharmaceutical firms operating in India. The pricing decision of a drug depends not only on its cost of production. We show that retail margins and product appeal are relevant drivers of a product market share. Especially the relationship with the retailers can be considered as a vehicle for the market power to be exercised. The intermediaries in the market for medicines are also key stakeholders of our research. The buyer power that they have on the pharmaceutical firms and their key role in the distribution of medicines makes them a prime actor at every negotiation table on pharmaceutical industry regulation.

This research addresses the question about the influence of pharmaceutical retailers (chemists and druggists) to the market power of a drug, but it can be generalized to other intermediaries of the health industry, like insurers and doctors. Finally, the research is of interests for the 1.3 billion Indian people, for whom access to medicines depends on the strategies of the regulator, the manufacturers and the retailers. The large differences in drug prices across medicines treating the same diseases do not fully reflect their productivity differences. We calculate that if, for each medicine market, the price was set at the median price, there would be a decrease in drug expenses by 3.5 billion rupees (about 400 million euros) per year.

Each chapter provides its own contribution to the literature. However, two general contributions can be outlined in the thesis. First, I treat firm production and market strategies as the "aggregate" result of the production and market strategies of its products. Second, I distinguish demand-side from supply-side drivers of price and nonprice strategies, introducing product-level productivity as a source of heterogeneity within and across firms. The findings in the three chapters are synergic to indicate that productivity is a significant driver of product market strategies. In particular, the results indicate that productivity differences across products induce competition via price and nonprice strategies. Products with higher productivity leverage their lower marginal cost to charge lower prices or, in the nonprice competition environment, to offer higher pack size, more discounts, larger availability and product variety. The probability that the one described is the mechanism that links productivity to product strategy is further increased by the results showing the effect of productivity to be larger in more contestable markets — less concentrated, with lower entry barriers, a higher number of competitors, or higher (perceived) substitutability across competitors (Backus, 2020). This evidence, consistent with the hypothesis of selection based on productivity (Foster et al., 2008; Garcia-Marin and Voigtländer, 2019), finds an important exception in the top-selling products. These products, called market *leaders* — top-selling products of the markets — or *superstar* products — top-selling products of the firms —, are not only more productive, but have also lower price elasticity, allowing higher market power and higher prices. This evidence underlines how different the market strategies of large products are and the different effects that they provide to the market outcomes, compared the strategies of the smaller products. These findings contributes to the literature that studies how firm heterogeneity drives aggregate market power and industry concentration focusing on the role of large, superstar firms (De Loecker et al., 2020; Aghion et al., 2019). Corollary to this contribution is the evidence showing how within-firm heterogeneity, if neglected, hides drivers and outcomes of competition that might appear puzzling when observed at a more aggregate level (Syverson, 2019).

Nevertheless, not all the results of the three core chapters provide evidence towards organic conclusions. The role of the retailers, for example, seems to be industry-specific. If in the pharmaceutical industry the retailers are crucial to foster or limit the success of a product, in the consumer goods market they are mostly executors of the strategies of the producers. These results can be explained by the higher buyer power that the pharmacists have compared to the grocery stores, being the former gathered in a famous trade association (Bhaskarabhatla et al., 2016). The role of the retailers is not central in the thesis and will be further investigated in my forthcoming projects, as discussed below. Another contrast among the findings of the three chapters regards the relevance of the product scope of the firm in establishing its market strategies. Besides the key role of product scope in determining productivity, conditional on other firm characteristics, an increase in the number of products offered or markets served does not directly benefit all the products of the firm. In the consumer good industry higher product scope of the firm is correlated with higher product pack size and more volume promotions. In the pharmaceutical industry higher product scope does not influence significantly the market shares of the firm's products and contributes to the average firm market power to a small extent. A deeper understanding of the role of product scope in defining firm strategies is also in my future research plans, considering the attention that it has received by the recent literature (Dhingra and Morrow, 2019; Braguinsky et al., 2020).

Similar to the firm heterogeneity "revolution" that has been moving macroeconomic analysis closer to the micro-based methods of industrial economics, the product heterogeneity approach is tightening the bond between industrial economics and strategic management. This within-firm approach to competition allows researchers to identify more clearly the markets where these firms operate. This helps the policy recommendations to be targeted to specific products and markets in a world where firms are increasingly more multiscope and multimarket and their production and market strategies for different products and locations are confounded. This approach is also useful in the debate on the welfare effects of market power, where good (productivity and innovation) and bad (appeal and rents) components of market power are weighted. Being able to clearly identify the markets where a firm has a dominant position and the sources of that market power is necessary to implement more accurate policies for its limitation. Especially in emerging countries, where market power is directly responsible for product affordability and inequality.

This thesis is an attempt to clarify the relationship between productivity and the market strategies of multiproduct firms. However, many aspects have not been addressed and, in my opinion, require further analytical effort from the literature. Some of these aspects have already been set in the target of industrial economics research and I expect to find them increasingly more in the top rated publications during the coming decade. With my future and ongoing projects, I aim to contribute to this literature by studying four aspects. First, industrial economists need to disclose clearly the mechanism that connects productivity to market power and profitability via *all* the costs. In this thesis, the opposite sign of the relationship productivity-prices for small products and large products marks the difference between small products that need to increase productivity to survive competition and large products that need to increase productivity to grow bigger, shielded from competition. In both cases the relationship between productivity and product market share is positive. However, I am not able to disclose the extent to which productivity affects product profitability because I do not know the costs. Although in both market power and profitability costs are central, in the literature marginal and fixed costs at the product level are rarely and debatably estimated. The ongoing debate on the role of fixed and overhead costs, R&D expenditure and sunk costs on market power will stimulate new contributions to the literature (Syverson, 2019; De Loecker et al., 2020). I will devote my postdoc to study how these costs are related to market power.

Second, the literature should investigate deeper the sources of market power over time (Pakes, 2020). In my thesis I investigate the sources of market power in a static setting, looking at product heterogeneity across only five years. This approach is sufficient to identify the characteristics that distinguish a superstar from a fringe product, but not to understand what makes a product a superstar. Key to unravel this mechanism will be data availability that cover product history and firm innovation. In the spirit of Braguinsky et al. (2020), I will investigate the importance of product differentiation, identifying the technological leaps that allow a product to become a superstar and the spillover effects provided to the firm. Innovation is also crucial to understand the dynamics of firm productivity. Product and technological innovations have been identified among the main components of firm upgrading, an aspect that is particularly important for the developing countries (Verhoogen, 2021). In ongoing research, I look at patent expiration to identify shocks that allow firms to innovate their technological capacity and product scope.

Third, the role of the retailers in determining the success of a product is understudied. If producer strategies are a developed field of research, retail strategies are often undistinguished from those of the producers. In the thesis I show how retailers can be susceptible to incentives and discriminate across products. I also show that often competition operates via nonprice channels. New studies on retail strategies, especially nonprice, can help understand the drivers of product survival or product growth. Using Nielsen retail scanner data, I will study the strategies of the dollar stores in the United States focusing on product heterogeneity and geographic market characteristics. Another relevant aspect of the thesis is the relationship between the suppliers and the buyers, which is well grounded in the industrial organization literature (Galbraith, 1954). However, only recently the empirical evidence has considered productivity in the light of the balance between producer market power and retail buyer power (Hortaçsu and Syverson, 2007; Atalay et al., 2014). The newly available product-level data on both supply and demand side (retail scanner data) will allow forthcoming research to address relevant questions on causes and outcomes of the bargaining between producers and retailers. How retail buyer power influence the nonprice strategies of the producers is another aspect that requires further academic attention, especially in the pharmaceutical industry where this process is directly connected to medicine accessibility (Ellison and Snyder, 2010; Dafny et al., 2022). In ongoing research, I am studying how retailers induce supplier competition on volume discounts, a phenomenon that is increasingly observed, not only in the pharmaceutical industry.

The last aspect linked to this thesis that requires, in my opinion, further research is methodological and embraces all the previous points discussed. We must find new methods to address the issues related to production and demand function estimation for multiproduct firms — e.g., input allocation bias and product cross-subsidization — and markup and market power measurement — e.g., market power on the input market and demand-production approach duality. In this thesis I elaborate on the most recent approaches to estimate economic primitives, such as productivity and price elasticity, at the product level (De Loecker et al., 2016; Berry et al., 2019; Bond et al., 2020). I show how to calculate relative markups using both the production and the demand function approach and how to separate the market power on the input market from the market power on the product market. In ongoing research, I compare demand and production function approaches to markup estimation at the product level. Additional research avenues have been opened by the availability of longer panel data on product-level production. These data, combined with detailed information on product demand — collected by the online platforms, for example — is among the most promising areas of economic research.

Bibliography

Ackerberg, D. A., Caves, K., and Frazer, G. (2015). Identification properties of recent production function estimators. *Econometrica*, 83(6):2411–2451.

Adams, B. and Williams, K. R. (2019). Zone pricing in retail oligopoly. *American Economic Journal: Microeconomics*, 11(1):124–56.

Aghion, P., Bergeaud, A., Boppart, T., Klenow, P. J., and Li, H. (2019). A theory of falling growth and rising rents. *NBER Working Paper*.

Ahsan, R. N. (2013). Input tariffs, speed of contract enforcement, and the productivity of firms in india. *Journal of International Economics*, 90(1):181–192.

Alfaro, L. and Chari, A. (2014). Deregulation, misallocation, and size: Evidence from india. *The Journal of Law and Economics*, 57(4):897–936.

Anderson, E., Jaimovich, N., and Simester, D. (2015). Price stickiness: Empirical evidence of the menu cost channel. *Review of Economics and Statistics*, 97(4):813–826.

Asker, J. and Bar-Isaac, H. (2014). Raising retailers' profits: On vertical practices and the exclusion of rivals. *The American Economic Review*, 104(2):672—686.

Atalay, E., Hortaçsu, A., and Syverson, C. (2014). Vertical integration and input flows. *American Economic Review*, 104(4):1120–48.

Atkin, D. and Donaldson, D. (2015). Who's getting globalized? the size and implications of intra-national trade costs. *NBER Working Paper*.

Atkin, D., Khandelwal, A. K., and Osman, A. (2019). Measuring productivity: Lessons from tailored surveys and productivity benchmarking. *AEA Papers and Proceedings*, 109:444–49.

Attanasio, O. P. and Pistaferri, L. (2016). Consumption inequality. *Journal of Economic Perspectives*, 30(2):3–28.

Autor, D., Dorn, D., Katz, L. F., Patterson, C., and Van Reenen, J. (2020). The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics*, Forthcoming.

Avery, C. and Levin, J. (2010). Early admissions at selective colleges. *American Economic Review*, 100(5):2125–56.

Aw, B. Y. and Lee, Y. (2014). A model of demand, productivity and foreign location decision among taiwanese firms. *Journal of International Economics*, 92(2):304–316.

Backus, M. (2020). Why is productivity correlated with competition? *Econometrica*, 88(6):2415–2444.

Bajgar, M., Berlingieri, G., Calligaris, S., Criscuolo, C., and Timmis, J. (2019). Industry concentration in europe and north america. *OECD Working Paper*.

Bartelsman, E. J. and Doms, M. (2000). Understanding productivity: Lessons from longitudinal microdata. *Journal of Economic literature*, 38(3):569–594.

Basu, S. (2019). Are price-cost markups rising in the united states? a discussion of the evidence. *Journal of Economic Perspectives*, 33(3):3–22.

Bate, R., Jin, G. Z., and Mathur, A. (2011). Does price reveal poor-quality drugs? evidence from 17 countries. *Journal of Health Economics*, 30(6):1150–1163.

Belleflamme, P. and Paolini, D. (2019). Strategic attractiveness and release decisions for cultural goods. *Journal of Economics & Management Strategy*, 28(2):198–224.

Bennett, D. and Yin, W. (2014). The market for high-quality medicine. *NBER Working Paper*.

Bento, P. and Restuccia, D. (2017). Misallocation, establishment size, and productivity. *American Economic Journal: Macroeconomics*, 9(3):267–303.

Bernard, A. B., Redding, S. J., and Schott, P. K. (2009). Products and productivity. *The Scandinavian Journal of Economics*, 111(4):681–709.

Bernard, A. B., Redding, S. J., and Schott, P. K. (2010). Multiple-product firms and product switching. *The American Economic Review*, 100(1):70.

Berndt, E. R. (2002). Pharmaceuticals in us health care: determinants of quantity and price. *Journal of Economic Perspectives*, 16(4):45–66.

Berndt, E. R. and Aitken, M. L. (2011). Brand loyalty, generic entry and price competition in pharmaceuticals in the quarter century after the 1984 waxman-hatch legislation. *International Journal of the Economics of Business*, 18(2):177–201.

Berndt, E. R. and Cockburn, I. M. (2014). The hidden cost of low prices: limited access to new drugs in india. *Health Affairs*, 33(9):1567–1575.

Bernheim, B. D. and Whinston, M. D. (1990). Multimarket contact and collusive behavior. *RAND Journal of Economics*, pages 1–26.

Berry, S., Gaynor, M., and Scott Morton, F. (2019). Do increasing markups matter? lessons from empirical industrial organization. *Journal of Economic Perspectives*, 33(3):44–68.

Bhaskarabhatla, A. (2020). Maximum resale price maintenance and retailer cartel profits: evidence from the indian pharmaceutical industry. *Antitrust Law Journal*, Forthcoming.

Bhaskarabhatla, A., Chatterjee, C., Anurag, P., and Pennings, E. (2017). Mitigating regulatory impact: the case of partial price controls on metformin in india. *Health policy and planning*, 32(2):194–204.

Bhaskarabhatla, A., Chatterjee, C., and Karreman, B. (2016). Hit where it hurts: Cartel policing using targeted sales and supply embargoes. *The Journal of Law and Economics*, 59(4):805–846.

Bhat, H. (2011). All for rupees five. *Business Line*, June 01.

Bloom, N., Eifert, B., Mahajan, A., McKenzie, D., and Roberts, J. (2013). Does management matter? evidence from india. *The Quarterly Journal of Economics*, 128(1):1–51.

Bloom, N. and Van Reenen, J. (2010). Why do management practices differ across firms and countries? *The Journal of Economic Perspectives*, 24(1):203–224.

Blundell, R. and Bond, S. (2000). Gmm estimation with persistent panel data: an application to production functions. *Econometric Reviews*, 19(3):321–340.

Boehm, J., Dhingra, S., and Morrow, J. (2022). The comparative advantage of firms. *Journal of Political Economy*.

Bond, S., Hashemi, A., Kaplan, G., and Zoch, P. (2020). Some unpleasant markup arithmetic: Production function elasticities and their estimation from production data. *NBER Working Paper*.

Bose, I. (2019). How small sizes are packing a punch in retail. *Financial Express*, July 28.

Braguinsky, S., Ohyama, A., Okazaki, T., and Syverson, C. (2020). Product innovation, product diversification, and firm growth: Evidence from japan's early industrialization. *NBER Working Paper*.

Brandenburger, A. M. and Stuart Jr, H. W. (1996). Value-based business strategy. *Journal of Economics & Management Strategy*, 5(1):5–24.

Brekke, K. R., Holmås, T. H., and Straume, O. R. (2013). Margins and market shares: pharmacy incentives for generic substitution. *European Economic Review*, 61:116–131.

Bresnahan, T. F. (1989). Empirical studies of industries with market power. *Handbook of industrial organization*, 2:1011–1057.

Brod, A. and Shivakumar, R. (1999). Advantageous semi-collusion. *The Journal of Industrial Economics*, 47(2):221–230.

Broda, C., Leibtag, E., and Weinstein, D. E. (2009). The role of prices in measuring the poor's living standards. *Journal of Economic Perspectives*, 23(2):77–97.

Bronnenberg, B., Dube, J.-P., Gentzkow, M., and Shapiro, J. (2015). Do pharmacists buy bayer? informed shoppers and the brand premium. *Quarterly Journal of Economics*, 130(4):1669–1726.

Bronnenberg, B. J., Dubé, J.-P., and Sanders, R. E. (2020). Consumer misinformation and the brand premium: a private label blind taste test. *Marketing Science*.

Busse, M. R. (2000). Multimarket contact and price coordination in the cellular telephone industry. *Journal of Economics & Management Strategy*, 9(3):287–320.

Cabral, L. and Natividad, G. (2020). Movie release strategy: Theory and evidence from international distribution. *Journal of Economics & Management Strategy*.

Çakır, M. and Balagtas, J. V. (2014). Consumer response to package downsizing: evidence from the chicago ice cream market. *Journal of Retailing*, 90(1):1–12.

Canoy, M., Van Ours, J. C., and Van Der Ploeg, F. (2006). The economics of books. *Handbook of the Economics of Art and Culture*, 1:721–761.

Carlton, D. W. (1989). The theory and the facts of how markets clear: is industrial organization valuable for understanding macroeconomics? *Handbook of Industrial Organization*, 1:909–946.

Cavallo, A. and Rigobon, R. (2016). The billion prices project: Using online prices for measurement and research. *Journal of Economic Perspectives*, 30(2):151–78.

Chaudhuri, S., Goldberg, P. K., and Gia, P. (2006). Estimating the effects of global patent protection in pharmaceuticals: a case study of quinolones in india. *American Economic Review*, 96(5):1477–1514.

Chen, Y. and Cui, T. H. (2013). The benefit of uniform price for branded variants. *Marketing Science*, 32(1):36–50.

Chernew, M., Cooper, Z., Larsen-Hallock, E., and Morton, F. S. (2018). Are health care services shoppable? evidence from the consumption of lower-limb mri scans. *NBER Working Paper*.

Cho, S. and Rust, J. (2010). The flat rental puzzle. *The Review of Economic Studies*, 77(2):560–594.

Ciliberto, F., Watkins, E., and Williams, J. W. (2019). Collusive pricing patterns in the US airline industry. *International Journal of Industrial Organization*, 62:136–157.

Ciliberto, F. and Williams, J. W. (2014). Does multimarket contact facilitate tacit collusion? inference on conduct parameters in the airline industry. *RAND Journal of Economics*, 45(4):764–791.

Clay, K., Krishnan, R., Wolff, E., and Fernandes, D. (2002). Retail strategies on the web: Price and non–price competition in the online book industry. *The Journal of Industrial Economics*, 50(3):351–367.

Cohen, A. (2008). Package size and price discrimination in the paper towel market. *International Journal of Industrial Organization*, 26(2):502–516.

Coibion, O., Gorodnichenko, Y., and Ropele, T. (2020). Inflation expectations and firm decisions: New causal evidence. *The Quarterly Journal of Economics*, 135(1):165–219.

Coloma, G. (2011). Market delineation and merger simulation: a proposed methodology with an application to the argentine biscuit market. *Journal of Competition Law and Economics*, 7(1):113–131.

Conlon, C. T. and Rao, N. L. (2020). Discrete prices and the incidence and efficiency of excise taxes. *American Economic Journal: Economic Policy*.

Conti, R. M. and Berndt, E. R. (2020). Four facts concerning competition in us generic prescription drug markets. *International Journal of the Economics of Business*, 27(1):27–48.

Courty, P. and Nasiry, J. (2018). Loss aversion and the uniform pricing puzzle for media and entertainment products. *Economic Theory*, 66(1):105–140.

Craig, S. V., Ericson, K. M., and Starc, A. (2018). How important is price variation between health insurers? *NBER Working Paper*.

Dafny, L., Ho, K., and Kong, E. (2022). How do copayment coupons affect branded drug prices and quantities purchased? *NBER Working Paper*.

Das, S., Roberts, M. J., and Tybout, J. R. (2007). Market entry costs, producer heterogeneity, and export dynamics. *Econometrica*, 75(3):837–873.

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. and Eeckhout, J. (2018). Global market power. *NBER Working Paper*.

De Loecker, J., Eeckhout, J., and Unger, G. (2020). The rise of market power and the macroeconomic implications. *The Quarterly Journal of Economics*.

De Loecker, J. and Goldberg, P. K. (2014). Firm performance in a global market. *Annuual Review of Economics*, 6(1):201–227.

De Loecker, J., Goldberg, P. K., Khandelwal, A. K., and Pavcnik, N. (2016). Prices, markups, and trade reform. *Econometrica*, 84(2):445–510.

De Loecker, J. and Syverson, C. (2021). An industrial organization perspective on productivity. In *Handbook of Industrial Organization*, volume 4, pages 141–223. Elsevier.

De Roux, N., Eslava, M., Franco, S., and Verhoogen, E. (2021). Estimating production functions in differentiated-product industries with quantity information and external instruments. *NBER Working Paper*.

DellaVigna, S. and Gentzkow, M. (2019). Uniform pricing in us retail chains. *The Quarterly Journal of Economics*, 134(4):2011–2084.

Desai, P., Mathur, S., and Srinivasan, K. (2012). Quantity discounts in emerging and developed markets. *Working Paper. Carnegie Mellon University*.

Dewenter, R., Haucap, J., and Wenzel, T. (2011). Semi-collusion in media markets. *International Review of Law and Economics*, 31(2):92–98.

Dhingra, S. and Morrow, J. (2019). Monopolistic competition and optimum product diversity under firm heterogeneity. *Journal of Political Economy*, 127(1):196–232.

Dhyne, E., Petrin, A., Smeets, V., and Warzynski, F. (2017). Multi product firms, import competition, and the evolution of firm-product technical efficiencies. *NBER Working Paper*.

Dixit, A. (1979). Quality and quantity competition. *The Review of Economic Studies*, 46(4):587–599.

Doraszelski, U. and Jaumandreu, J. (2018). Measuring the bias of technological change. *Journal of Political Economy*, 126(3):1027–1084.

Douglas, G. W. and Miller, J. C. (1974). Quality competition, industry equilibrium, and efficiency in the price-constrained airline market. *The American Economic Review*, 64(4):657–669.

Dubois, P. and Lasio, L. (2018). Identifying industry margins with price constraints: Structural estimation on pharmaceuticals. *American Economic Review*, 108(12):3685–3724.

Dubois, P. and Sæthre, M. (2020). On the effect of parallel trade on manufacturers' and retailers' profits in the pharmaceutical sector. *Econometrica*, 88(6):2503–2545.

Duggan, M., Garthwaite, C., and Goyal, A. (2016). The market impacts of pharmaceutical product patents in developing countries: Evidence from india. *American Economic Review*, 106(1):99–135.

Dutta, S., Bergen, M., Levy, D., Ritson, M., and Zbaracki, M. (2002). Pricing as a strategic capability. *MIT Sloan Management Review*, 43(3 (April 15, 2002)):61–66.

Dutta, S., Zbaracki, M. J., and Bergen, M. (2003). Pricing process as a capability: A resource-based perspective. *Strategic Management Journal*, 24(7):615–630.

Eckert, A. and West, D. S. (2013). Proliferation of brewers' brands and price uniformity in canadian beer markets. *Review of Industrial Organization*, 42(1):63–83.

Einav, L. (2007). Seasonality in the us motion picture industry. *RAND Journal of Economics*, 38(1):127–145.

Ellison, S. F. and Snyder, C. M. (2010). Countervailing power in wholesale pharmaceuticals. *The Journal of Industrial Economics*, 58(1):32–53.

Eslava, M. and Haltiwanger, J. C. (2020). The size and life-cycle growth of plants: The role of productivity, demand and wedges. *NBER Working Paper*.

Evans, W. N. and Kessides, I. N. (1994). Living by the "golden rule": Multimarket contact in the us airline industry. *The Quarterly Journal of Economics*, 109(2):341–366.

Fershtman, C. and Gandal, N. (1994). Disadvantageous semicollusion. *International Journal of Industrial Organization*, 12(2):141–154.

Foster, L., Grim, C., and Haltiwanger, J. (2016). Reallocation in the great recession: cleansing or not? *Journal of Labor Economics*, 34(S1):S293–S331.

Foster, L., Haltiwanger, J., and Syverson, C. (2008). Reallocation, firm turnover, and efficiency: Selection on productivity or profitability? *The American Economic Review*, 98(1):394–425.

Frank, R. G. and Salkever, D. S. (1997). Generic entry and the pricing of pharmaceuticals. *Journal of Economics & Management Strategy*, 6(1):75–90.

Galbraith, J. K. (1954). Countervailing power. *The American economic review*, 44(2):1–6.

Gandhi, A., Navarro, S., and Rivers, D. A. (2020). On the identification of gross output production functions. *Journal of Political Economy*, 128(8):2973–3016.

Garcia-Marin, A. and Voigtländer, N. (2019). Exporting and plant-level efficiency gains: It's in the measure. *Journal of Political Economy*, 127(4):1777–1825.

Gaynor, M., Ho, K., and Town, R. J. (2015). The industrial organization of health-care markets. *Journal of Economic Literature*, 53(2):235–84.

Gaynor, M. and Town, R. J. (2011). Competition in health care markets. *Handbook of health economics*, 2:499–637.

Gerstner, E. and Hess, J. D. (1987). Why do hot dogs come in packs of 10 and buns in 8s or 12s? a demand-side investigation. *Journal of Business*, pages 491–517.

Goldberg, P. and Hellerstein, R. (2012). A structural approach to identifying the sources of local currency price stability. *Review of Economic Studies*, 80(1):175–210.

Goldberg, P. K., Khandelwal, A. K., Pavcnik, N., and Topalova, P. (2010a). Imported intermediate inputs and domestic product growth: Evidence from india. *The Quarterly Journal of Economics*, 125(4):1727–1767.

Goldberg, P. K., Khandelwal, A. K., Pavcnik, N., and Topalova, P. (2010b). Multiproduct firms and product turnover in the developing world: Evidence from india. *The Review of Economics and Statistics*, 92(4):1042–1049.

Granger, C. W. and Billson, A. (1972). Consumers' attitudes toward package size and price. *Journal of Marketing Research*, 9(3):239–248.

Grennan, M., Myers, K., Swanson, A., and Chatterji, A. (2018). Physician-industry interactions: Persuasion and welfare. *NBER Working Paper*.

Grieco, P. L., Li, S., and Zhang, H. (2016). Production function estimation with unobserved input price dispersion. *International Economic Review*, 57(2):665–690.

Gutiérrez, G. and Philippon, T. (2019). Fading stars. In *AEA Papers and Proceedings*, volume 109, pages 312–16.

Hastings, J., Hortaçsu, A., and Syverson, C. (2017). Sales force and competition in financial product markets: the case of mexico's social security privatization. *Econometrica*, 85(6):1723–1761.

Hitsch, G. J., Hortacsu, A., and Lin, X. (2019). Prices and promotions in us retail markets: Evidence from big data. *NBER Working Paper*.

Hitt, J. (2011). The dollar store economy. *New York Times*, August 18.

Ho, J. Y., Liang, Y., Weinberg, C. B., and Yan, J. (2018). An empirical study of uniform and differential pricing in the movie theatrical market. *Journal of Marketing Research*, 55(3):414–431.

Hopenhayn, H. A. (1992). Entry, exit, and firm dynamics in long run equilibrium. *Econometrica: Journal of the Econometric Society*, pages 1127–1150.

Hortaçsu, A. and Syverson, C. (2007). Cementing relationships: Vertical integration, foreclosure, productivity, and prices. *Journal of Political Economy*, 115(2):250–301.

Hottman, C. J., Redding, S. J., and Weinstein, D. E. (2016). Quantifying the sources of firm heterogeneity. *The Quarterly Journal of Economics*, 131(3):1291–1364.

Hsieh, C.-T. and Klenow, P. J. (2009). Misallocation and manufacturing TFP in China and India. *The Quarterly Journal of Economics*, 124(4):1403–1448.

IBEF (2019). Fast moving consumer goods (fmcg). *India Brand Equity Foundation Industry Report.*

Jain, S. (2012). Marketing of vice goods: A strategic analysis of the package size decision. *Marketing Science*, 31(1):36–51.

Jaravel, X. (2019). The unequal gains from product innovations: Evidence from the us retail sector. *The Quarterly Journal of Economics*, 134(2):715–783.

Jovanovic, B. (1982). Selection and the evolution of industry. *Econometrica: Journal of the Econometric Society*, pages 649–670.

Jovanovic, B. and MacDonald, G. M. (1994). The life cycle of a competitive industry. *Journal of Political Economy*, 102(2):322–347.

Katayama, H., Lu, S., and Tybout, J. R. (2009). Firm-level productivity studies: illusions and a solution. *International Journal of Industrial Organization*, 27(3):403–413.

Khandelwal, A. (2010). The long and short (of) quality ladders. *The Review of Economic Studies*, 77(4):1450–1476.

Klenow, P. J. and Malin, B. A. (2010). Microeconomic evidence on price-setting. In *Handbook of Monetary Economics*, volume 3, pages 231–284. Elsevier.

Klepper, S. and Thompson, P. (2006). Submarkets and the evolution of market structure. *The RAND Journal of Economics*, 37(4):861–886.

Klette, T. J. and Griliches, Z. (1996). The inconsistency of common scale estimators when output prices are unobserved and endogenous. *Journal of applied econometrics*, 11(4):343–361.

Koenigsberg, O., Kohli, R., and Montoya, R. (2010). Package size decisions. *Management Science*, 56(3):485–494.

Kremer, M. (1993). The o-ring theory of economic development. *The Quarterly Journal of Economics*, 108(3):551–575.

Kugler, M. and Verhoogen, E. (2011). Prices, plant size, and product quality. *The Review of Economic Studies*, 79(1):307–339.

Lakdawalla, D. N. (2018). Economics of the pharmaceutical industry. *Journal of Economic Literature*, 56(2):397–449.

Lederman, M. (2008). Are frequent-flyer programs a cause of the "hub premium"? *Journal of Economics & Management Strategy*, 17(1):35–66.

Levinsohn, J. and Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *The Review of Economic Studies*, 70(2):317–341.

Linde, S., Norton, B., and Siebert, R. (2019). The effect of bargaining power determinants on pharmaceutical prices.

Lippman, S. A. and Rumelt, R. P. (2003). A bargaining perspective on resource advantage. *Strategic management journal*, 24(11):1069–1086.

Malmendier, U. and Tate, G. (2015). Behavioral ceos: The role of managerial overconfidence. *Journal of Economic Perspectives*, 29(4):37–60.

Mathur, S. and Sinitsyn, M. (2013). Price promotions in emerging markets. *International Journal of Industrial Organization*, 31(5):404–416.

Matsa, D. A. (2011). Competition and product quality in the supermarket industry. *The Quarterly Journal of Economics*, 126(3):1539–1591.

Maue, C. C., Burke, M., and Emerick, K. J. (2020). Productivity dispersion and persistence among the world's most numerous firms. *NBER Working Paper*.

Mayer, T., Melitz, M. J., and Ottaviano, G. I. (2014). Market size, competition, and the product mix of exporters. *The American Economic Review*, 104(2):495–536.

Melitz, M. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, 71(6):1695–1725.

Melitz, M. J. and Redding, S. J. (2014). Heterogeneous firms and trade. *Handbook of International Economics,*, 4:1–54.

Miravete, E. J., Seim, K., and Thurk, J. (2020). One markup to rule them all: Taxation by liquor pricing regulation. *American Economic Journal: Microeconomics*, 12(1):1–41.

Morlacco, M. (2019). Market power in input markets: Theory and evidence from french manufacturing. *Unpublished, March*, 20:2019.

Neiman, B. and Vavra, J. S. (2019). The rise of niche consumption. *NBER Working Paper*.

Nevo, A. (2001). Measuring market power in the ready-to-eat cereal industry. *Econometrica*, 69(2):307–342.

Olley, G. S. and Pakes, A. (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, 64(6):1263–1297.

Orbach, B. Y. and Einav, L. (2007). Uniform prices for differentiated goods: The case of the movie-theater industry. *International Review of Law and Economics*, 27(2):129–153.

Orr, S. (2019). Within-firm productivity dispersion: Estimates and implications. *University of British Columbia Working Paper*.

Pakes, A. (2020). A helicopter tour of some underlying issues in empirical industrial organization. *NBER Working Paper*.

Prahalad, C. K. (2005). *Fortune at the bottom of the pyramid*. Wharton School Publishing.

Prasad, S. (2018). Parle caught with its hand in the cookie jar, alleges britannia. *Mirror*, April 13.

Prince, J. T. and Simon, D. H. (2015). Do incumbents improve service quality in response to entry? evidence from airlines' on-time performance. *Management Science*, 61(2):372–390.

Raval, D. (2020). Testing the production approach to markup estimation. *Available at SSRN 3324849*.

Reiffen, D. and Ward, M. R. (2005). Generic drug industry dynamics. *Review of Economics and statistics*, 87(1):37–49.

Sahni, N. S., Zou, D., and Chintagunta, P. K. (2016). Do targeted discount offers serve as advertising? evidence from 70 field experiments. *Management Science*, 63(8):2688–2705.

Schott, P. K. (2004). Across-product versus within-product specialization in international trade. *The Quarterly Journal of Economics*, 119(2):647–678.

Sethi, A. (2016). Britannia drags itc to delhi high court, files counter suit. *Bloomberg Quint*, Sept 8.

Shiller, B. and Waldfogel, J. (2011). Music for a song: an empirical look at uniform pricing and its alternatives. *The Journal of Industrial Economics*, 59(4):630–660.

Singh, N. (2019). Rs 5 packs a punch in fast-moving snacks. *Times of India*, April 12.

Smeets, V. and Warzynski, F. (2013). Estimating productivity with multi-product firms, pricing heterogeneity and the role of international trade. *Journal of International Economics*, 90(2):237–244.

Spence, M. (1977). Nonprice competition. *The American Economic Review*, 67(1):255–259.

Starc, A. and Swanson, A. (2018). Preferred pharmacy networks and drug costs. *NBER Working Paper*.

Steen, F. and Sørgard, L. (1999). Semicollusion in the norwegian cement market. *European Economic Review*, 43(9):1775–1796.

Stigler, G. J. (1968). Price and non-price competition. *Journal of Political Economy*, 76(1):149–154.

Sullivan, C. (2020). Split apart: Differentiation, diversion, and coordination in the market for superpremium ice cream. *AEA Papers and Proceedings*, 110:573–78.

Syverson, C. (2004). Product substitutability and productivity dispersion. *Review of Economics and Statistics*, 86(2):534–550.

Syverson, C. (2007). Prices, spatial competition and heterogeneous producers: an empirical test. *The Journal of Industrial Economics*, 55(2):197–222.

Syverson, C. (2011). What determines productivity? *Journal of Economic literature*, 49(2):326–365.

Syverson, C. (2019). Macroeconomics and market power: Context, implications, and open questions. *Journal of Economic Perspectives*, 33(3):23–43.

Tanaka, M., Bloom, N., David, J. M., and Koga, M. (2019). Firm performance and macro forecast accuracy. *Journal of Monetary Economics*.

Topalova, P. and Khandelwal, A. (2011). Trade liberalization and firm productivity: The case of india. *Review of economics and statistics*, 93(3):995–1009.

Verhoogen, E. (2021). Firm-level upgrading in developing countries. *NBER Working Paper*.

Wansink, B. (1996). Can package size accelerate usage volume? *Journal of Marketing*, 60(3):1–14.

Winter, R. A. (1993). Vertical control and price versus nonprice competition. *The Quarterly Journal of Economics*, 108(1):61–76.

Wooldridge, J. M. (2009). On estimating firm-level production functions using proxy variables to control for unobservables. *Economics letters*, 104(3):112–114.

Yan, D., Sengupta, J., and Wyer Jr, R. S. (2014). Package size and perceived quality: The intervening role of unit price perceptions. *Journal of Consumer Psychology*, 24(1):4–17.

Yonezawa, K. and Richards, T. J. (2016). Competitive package size decisions. *Journal of Retailing*, 92(4):445–469.

Zbaracki, M. J. and Bergen, M. (2010). When truces collapse: A longitudinal study of price-adjustment routines. *Organization Science*, 21(5):955–972.

Appendix M

Methodological Appendix

M.1 Estimating production and demand functions

This appendix serves as a methodological reference to the thesis. Each of the following sections contains the methodological appendix of one of the three core chapters. In each chapter a production function is estimated to calculate productivity and a demand function is estimated to calculate price elasticity. Although the methodologies adopted to estimate them vary across the chapters, they are often built on the same references, models and assumptions. Therefore, being each of the three chapters enclosed as a self-contained paper, repetitions regarding the methodology can be found in the main text. In the following sections of this appendix the methodological parts that are excluded from the main text find place.

While the level of estimation of the demand function changes across chapters, the production function — and the productivity included in the thesis title — is always estimated at the product level. The rapid literature excursus on production function estimation in Chapter 1.2 introduces the biases addressed when estimating product-level productivity in this thesis. As discussed in De Loecker et al. (2016), to estimate product-level productivity correctly we must deal with the difficulty of measuring product-level inputs. It can lead to two potential biases: the *input allocation bias* - related to the possible mismeasurement in the process of addressing shares of firm-level inputs to each product - and the *input price bias* - related to the differences in purchase prices of the same input across different markets and qualities. Prior literature deals with input allocation either by apportioning firm-level input values or by introducing a method to mitigate the problem. Foster et al. (2008) apportion product's share of plant inputs using product's share of plant sales.[1] De Loecker et al. (2016) address input allocation bias by estimating productivity using only single product firms.[2] Dhyne et al. (2017) implement a technique to estimate product-level productivity using only firm-level inputs. We exploit specific features of the biscuit and pharmaceutical industry to make assumptions and impute the values of variable inputs for each product.

Besides the biases related to input allocation and prices, estimating output elasticities in multiproduct firms at the product level encounters specific problems of identification. Unobserved (to the econometrician) productivity can lead to two other potential biases: i) a *simultaneity bias*, as the amount of inputs is chosen based on firm or product productivity; ii) a *product scope bias*, as the number of products is decided by the firm according to observed productivity. The method proposed by Levinsohn and Petrin (2003) addresses the simultaneity bias, but does not consider the product mix of the firm. Bernard et al. (2010) show that product switching is correlated to firm productivity and suggest that firms endogenously select the products they will produce. De Loecker et al. (2016) propose a method to control for product-mix in the estimation of productivity in single-product firms.[3] Dhyne et al. (2017), propose a new approach to estimate productivity at the product level, which accounts for the firm product scope. Unlike studies that consider the production function of a multiproduct firm as the sum of single product production functions, Dhyne et al. (2017) implement a multiproduct production function. They calculate product-level productivity as the residual of a production function, whose output elasticities are estimated using firm-level (and not product-level) inputs. They consider a quantity-based loglinear Cobb-Douglas production function, specified as follows:

$$q_{it} = \omega_{it} + \alpha k_{ft} + \beta_l l_{ft} + \beta_m m_{ft} + \gamma y_{-it} \tag{M.1.1}$$

where, for each product i, firm f and year t, q is log quantity sold in physical units, k is log capital employed, l is log salaries, m is log raw materials and y_{-i}

[1] The method is valid under perfect competition or assuming constant markups across firm products. Since Foster et al. (2008) select 11 four-digit industries producing homogeneous goods (concrete, gasoline, coffee among them) and highly product-specialized plants (at least 50 percent of plant's revenues are obtained from the product of interest), these assumptions are appropriate.

[2] De Loecker et al. (2016) assume that a single-product firm uses the same technology of a multiproduct firm to produce the same good. In a second stage, they use a system of equations based on firm-level productivity to allocate the inputs of multiproduct firms across products. They assume product share of firm's input to be the same across all different inputs.

[3] De Loecker et al. (2016) use a sample of firms that have been single-product at least for one year in the time span. Their purpose is, actually, not to control for the product scope bias, but for a selection bias regarding the nature of firms which decide to change their product-mix.

is log revenues of all other products except from i produced by the firm. Adding this latter measure to the production inputs Dhyne et al. (2017) "extend the single product setting" calculating a production function which gives "the maximal amount of output achievable of one of the goods the firm produces holding inputs and the levels of other goods produced constant". Product-specific log productivity (ω) is Hicks-neutral and can be computed as a Solow residual.

In each of the following appendices I present how we address the aforementioned biases and describe the changes introduced to the standard LP estimator to estimate product-level productivity.

M.2 Methodological Appendix Chapter 2

M.2.1 Product-level productivity in multiproduct firms

In this appendix subsection we present how we address the biases related to product-level input measurement and describe the changes introduced to the standard LP estimator to estimate productivity using Equation (2.2).

M.2.1.1 Input allocation

We exploit specific features of the biscuit industry to make assumptions and impute the values of variable inputs for each product. The methodology that we adopt does not require us to apportion capital across products as capital enters production function at the firm level.

All product varieties within the same subbrand sell the same biscuit, but in different pack sizes. The unit cost of variable inputs - that is, raw materials and labor - can be assumed to be the same across all products within the single subbrand. As the composition of the biscuit within the subbrand is unique, we can assume that the cost of raw materials (ingredients) used to produce a gram of the biscuit does not vary across all products of the same subbrand. Moreover, as workers' skills employed to produce the same biscuit are standardized and given the highly automated production process, we assume that the cost of labor used to produce a gram of the biscuit does not vary across all products of the same subbrand.

To impute the cost of each variable input for each product within a subbrand we first calculate the input expenditure for the subbrand using the subbrand's revenue shares of the firm, $\frac{y_{bf}}{y_f}$:

$$\mathbf{v}_{bf} = \mathbf{v}_f \frac{y_{bf}}{y_f} \tag{M.2.1}$$

Second, we split input expenditure for the subbrand across all its products (i) using product's kilogram share of the subbrand, $\frac{q_{ibf}}{q_{bf}}$:

$$\mathbf{v}_{bi} = \mathbf{v}_{bf} \frac{q_{bfi}}{q_{bf}} \tag{M.2.2}$$

When imputing product-specific inputs we must consider that the differences in price across products may depend on the differences in their quality, which in turn may imply different levels of input quality and input costs. Prior literature has shown that higher input expenditures lead to more expensive products (Kugler and Verhoogen, 2011) and that indicators of quality can be linked to the differences in output prices (Khandelwal, 2010), although they might also reflect consumer preferences and markups (De Loecker and Goldberg, 2014). Atkin et al. (2019) show that revenue-based productivity, incorporating the output prices, might be a more reliable measure of productivity than the quantity-based one, as it includes information on product quality. To partly include an indicator of quality, in Equation (M.2.1) we use the revenue shares to apportion firm-level variable inputs into subbrands.

Differences in input prices and quality can exist also across firms. However, our analysis considers only the ten largest firms (out of an industry of more than 700 firms), which are publicly listed and expected to have similar quality in both raw materials and labor. In particular, materials employed by large firms are ingredients often purchased on in commodity markets and the workers are similar in their skills across firms. Following De Loecker et al. (2016), we also assume that input prices do not depend on input quantities.

M.2.1.2 The LP estimator controlling for product scope

In the biscuit industry, the same subbrand b produced by firm f can be sold in different pack sizes with different SKUs. They are product varieties i of the same biscuit. On average, a subbrand has 15 different product varieties and a firm produces 31 subbrands. As all firms in our sample are multiproduct, to obtain unbiased estimates of the output elasticities we must control for the product scope bias.

Building on Dhyne et al. (2017), whose approach is summarized in Appendix M.1, we propose a hybrid product-level production function, in which variable inputs enter at the product level and capital enters at the firm level. Instead of observing the product across time, we observe the biscuit across its product variety. In principle, we might assume that the productivity of all the product varieties of a subbrand are the same, or alternatively, that there is a unique subbrand-level productivity. However, every variety has some specificity, which can be related to the production line — i.e., different packaging machines with different productivities — or the distribution process — i.e., different sales managers or transportation procedures. This unexpected discrepancy in productivity among varieties of the same subbrand is the source of heterogeneity that we exploit with the methodology that follows.[4]

The production function can be written as:

$$q_{bi} = \beta_k k_f + \beta_l l_{bi} + \beta_m m_{bi} + \gamma y_{-bi} + \omega_{bi} + \eta_{bi} \tag{M.2.3}$$

where, for each subbrand b and each product variety i, q log output measured in kilograms of product, k is log capital, l is log salaries , m is log materials and y_{-bi} is log revenues of all other products produced by the firm which are not product variety i of subbrand b. Product-specific log productivity (ω) is Hicks-neutral and can be computed as a Solow residual.

To use the LP estimator we must adapt the assumptions to the new setting: (i) the demand for the intermediate input m is dependent on firm capital and product productivity, and it is monotonically increasing in ω and, thus, can be inverted:

$$m_{bi} = \theta(k_f, \omega_{bi}) \rightarrow \omega_{bi} = \theta^{-1}(k_f, m_{bi}) \tag{M.2.4}$$

(ii) the productivity of variety i differs from the average productivity of subbrand b by a zero mean error term, ξ_{bp}:

$$\omega_{bi} = \omega_b + \xi_{bi} \tag{M.2.5}$$

where $\omega_b = \sum_i s_{bi}\omega_{bi}$ is the productivity average of all subbrand b's varieties (weighted by their respective market share, s_{bi}) and ξ_{bi} independent of subbrand productivity ($E[\xi_{bi}|\omega_b] = 0$). For every subbrand the firm observes as many productivities as varieties, although it expects the productivity of each variety to be the same: $E[\omega_{bi}|\omega_b] = \omega_b$. We can therefore rewrite:

$$\omega_{bi} = E[\omega_{bi}|\omega_b] + \xi_{bi} \tag{M.2.6}$$

We assume that the difference in observed productivity between two varieties of the same subbrand is smaller the closer their pack size. The reason for this assumption is that varieties with similar size have also similar production lines and distribution processes. Within the subbrand, then, we sort the product varieties according to their pack size. In such a case if a subbrand has 10 varieties, the variety

[4] We can interpret the differences in productivity across varieties of the same subbrand as measurement errors in subbrand-level productivity.

whose unit weight is higher will be identified as $i = 1$ and the variety whose unit weight is lower will be identified as $i = 10$. For variety $i-1$, then, Equation (M.2.5) becomes :

$$\omega_{bi-1} = \omega_b + \xi_{bi-1} \tag{M.2.7}$$

The error terms of variety $i-1$ is closer to the error terms of variety i than error terms of varieties $i-2$: $|\xi_{bi} - \xi_{bi-1}| \leq |\xi_{bi} - \xi_{bi-2}|$. For a continuum of product varieties of brand b, the difference in productivity between two successive varieties is close to zero: $\xi_{bi} - \xi_{bi-1} \simeq 0$.

From Equation (M.2.7) we have that $\omega_b = \omega_{bi-1} - \xi_{bi-1}$. Plugging this result into Equation (M.2.5) we have:

$$\omega_{bi} = \omega_{bi-1} + \psi_{bi} \tag{M.2.8}$$

where $\psi_{bi} = \xi_{bi} - \xi_{bi-1}$, which is expected to be zero conditional on the productivity of variety $i-1$: $E[\psi_{bi}|\omega_b] = 0$. We can therefore rewrite (M.2.6) as:

$$\omega_{bi} = E[\omega_{bi}|\omega_{bi-1}] + \psi_{bi} \tag{M.2.9}$$

where ψ_{bi} is an innovation to product variety i's productivity, uncorrelated with k_f but not necessarily with l_{bi}. The assumption implies that productivity is more similar between two products with a closer pack size (e.g., 150 grams and 125 grams per pack), than between two products with a larger difference in size (e.g., 150 grams and 25 grams per pack).

Under these assumptions we can rewrite the production function as:

$$q_{bi} = \beta_l l_{bi} + \phi(k_f, m_{bi}) + \gamma y_{-bi} + \eta_{bi} \tag{M.2.10}$$

where, as in the firm-level case:

$$\phi(k_f, m_{bi}) = \beta_0 + \beta_k k_f + \beta_m m_{bi} + \theta^{-1}(k_f, m_{bi}) \tag{M.2.11}$$

We proceed with the two stages of the LP approach that will produce consistent estimates of β_k, β_k, β_m and γ that we plug in Equation (M.2.3) to calculate product-level productivity as a Solow residual.

M.2.2 Optimal pack size and price elasticity estimates

M.2.2.1 Optimal pack size following the approach in DellaVigna and Gentzkow (2019)

A monopolistically competitive firm f chooses a pack size Su_{ir} for each product i in region r to maximize total profits. Each firm faces a residual demand for product i that takes a constant elasticity form:

$$Qg_{ir} = G_{ir} Pg_{ir}^{\theta_{ir}} = G_{ir} \left(\frac{\overline{Pu}_{ir}}{Su_{ir}} \right)^{\theta_{ir}} \tag{M.2.12}$$

where Qg_{ir} is the quantity in kilograms of product sold, G_{ir} is a scale term, and θ_{ir} is price elasticity of product i in region r. Total cost TC_{ir} consists of a product-region fixed cost FC_{ir} and a marginal cost cg_{if} that is the same for every kilogram of product i sold by the firm and does not vary across regions for firm f: $TC_{ir} = FC_{ir} + cg_{if} \cdot Qg_{ir}$. The firm maximizes its profits by setting the optimal pack size of product i in region r:

$$\max_{Su_{ir}} \sum_{i,r} (\overline{Pu}_{ir} - cg_{if} \cdot Su_{ir}) \frac{Qg_{ir}}{Su_{ir}} - \sum_{i,r} FC_{ir} \tag{M.2.13}$$

For the first order conditions to be satisfied, the optimal pack size is:

$$Su_{ir}^{*} = \frac{\overline{Pu}_{ir}}{cg_{if}} \frac{1 + \theta_{ir}}{\theta_{ir}} \tag{M.2.14}$$

Alternatively, the optimal price per kilogram is:

$$Pg_{ir}^{*} = cg_{if} \frac{\theta_{ir}}{1 + \theta_{ir}} \tag{M.2.15}$$

It is reasonable to assume constant marginal costs of a product across regions as a product is usually produced in one plant and sold in many regions. The cost of shipping a product from the region where the production plant is located to the region where the product is sold can be assigned to the fixed costs at the product-region level.

M.2.2.2 Price elasticity estimates

To test the goodness of our identification strategy, we also estimate price elasticity at the industry level and report the OLS and IV results in Table 2.A.6, in the Chapter Appendix, Column 1-3. OLS estimates are not negative, contrary to what the theory predicts. IV estimates, obtained using our estimation-based productivity as an instrument, instead, show a negative and significant coefficient, more in line with the theory. The F-statistic and first-stage regression show that the instrument is relevant for Consumer preferences in rural areas might be different from those in urban areas. We estimate price elasticity of demand separately for urban and rural areas and report the results in Table 2.A.6, in the Chapter Appendix, Column 4-6. IV estimates show that in urban areas demand is noticeably less elastic than in rural areas (Column 4 and 5). In Column 6 we compute the difference in elasticity between the two areas, interacting productivity with a dummy that takes value one when the product is observed in rural areas. Demand in rural areas is 0.75 percentage points more elastic than in urban areas, suggesting rural consumers are more sensitivity to pack size relative to urban consumers. In Table 2.A.7, in the Chapter Appendix, we show that our segment-specific price elasticity estimates lie mostly between -0.6 (cream biscuits) and -4.9 (glucose biscuits). Our estimates are in line with those calculated using Nielsen data by Coloma (2011) for the Argentinian biscuit industry, where the aggregate elasticity is around -0.7 and varies across segments between -0.5 and -4.8.

M.3 Methodological Appendix Chapter 3

M.3.1 Multiproduct production function estimation

Product-level productivity serves as an instrument for addressing endogeneity in estimating the impact of wholesale prices on market shares. Building on Dhyne et al. (2017), whose approach is summarized in Appendix M.1, we estimate the output elasticities of a hybrid production function, which is single-product with respect to the variable inputs and multiproduct with respect to the capital. For the pharmaceutical industry, indeed, both raw materials and salaries can be considered as product-specific. Given that the chemical composition of each drug is fixed, a marginal increase in real raw materials expenditure for product i affects the output of product i only, and not also the output of other products of the firm. The same can be assumed for salaries. Given the highly automated production process of the pharmaceutical industry, a marginal increase in real salaries of the workers producing product i affects the output of product i only, and not also the output of other products of the firm. An increase in real capital expenditure, instead, being related to machinery, software, or plant infrastructure, is more likely to affect more than one product of the firm, and can enter the production function at the firm level, as in Dhyne et al. (2017). We propose the following production function, in which variable inputs enter at the product level and capital enters at the firm level:

$$q_{it} = \omega_{it} + \beta_k k_{ft} + \beta_l l_{it} + \beta_m m_{it} + \gamma y_{-it} \tag{M.3.1}$$

To estimate Equation (M.3.1) we need product-specific raw materials and salaries, which we do not observe. This issue is tackled by assuming that in the pharmaceutical industry, variable inputs within a market have the same quality across products. Consequently, we assume that the unit cost of a variable input is the same across all the products of a market. Exploiting this and other commonly employed assumptions for the purpose, we apportion the amount of firm-level variable inputs into firm-product-level inputs. We provide details related to input allocation in Appendix M.3.2.1.

To address the simultaneity bias, we adopt the estimator proposed by Levinsohn and Petrin (2003) (henceforth, LP) using materials as a proxy.[5] We estimate the output elasticities at the ATC5 level and obtain a quantity-based measure of product-level productivity for multiproduct firms (*TFP-QEM*). In Figure 3.A.1 we show the distribution of product-level productivity and the central moments of the distributions of the output elasticities. On average the output elasticity with respect to capital is 0.57, with respect to labor is 0.20, with respect to materials is 0.52. The coefficient γ is negative on average, -0.06, as expected, since an increase in firm revenues, holding product variable inputs and firm-level capital constant, would result in a decrease in the quantity of the focal product.

M.3.2 Product-level productivity: biases and solutions

In this appendix subsection we present how we address the biases related to product-level input measurement and describe the changes introduced to the standard LP estimator to estimate productivity using Equation (M.3.1).

M.3.2.1 Product's input allocation: the 'reference firm'

We exploit specific features of the pharmaceutical industry to make assumptions and impute the values of product variable inputs.

The pharmaceutical industry is composed of a large number of markets within which drugs have the same therapeutic category, i.e. are used to treat the same diseases. The unit cost of variable inputs - raw materials and labor - can be assumed to be the same across all products within the market. Since the chemical composition of the drugs within a market is unique, we assume that the cost of raw materials (bulk drugs) used to produce one unit of the drug does not vary across firms. The Indian pharmaceutical industry, which overwhelmingly produces out-of-patent medicines, is arguably more labor intensive than its counterparts in the developed world, where

[5] Since the introduction of y_{-it} causes problems of endogeneity, we include its lagged value among the conditioning variables of the GMM estimation in the second stage of LP procedure, as suggested by Dhyne et al. (2017). Find the adjustment operated to the LP estimator in Appendix M.3.2.3.

R&D and innovation-related staff play an important role. Given the highly automated production process, the working skills required to produce a drug are common across firms. Therefore, we assume that the cost of labor used to produce one unit of drug does not vary across firms within the market. To identify the cost per unit produced of each variable input, for each market we select the firm charging the lowest (normalized) price for the drug, which we assume to produce at the marginal cost. We refer to it as the 'reference firm' of the market.

To impute the expenditure in variable input for all the products of a market, we leverage on the reference firms ($\bar{f}$). First, we calculate its input expenditure in the referenced market ($\bar{j}$) using the market's revenue shares of the reference firm, $\frac{y_{\bar{f}\bar{j}t}}{y_{\bar{f}t}}$:[6]

$$\mathbf{v}_{\bar{f}\bar{j}t} = \mathbf{v}_{\bar{f}t}\frac{y_{\bar{j}\bar{f}\bar{j}t}}{y_{\bar{f}t}} \tag{M.3.2}$$

Second, we split reference firm's input expenditure in the referenced market ($\mathbf{v}_{\bar{j}\bar{f}t}$) across all its products (i) using product's share of physical units produced in the market by the firm, $\frac{q_{i\bar{f}\bar{j}t}}{q_{\bar{f}\bar{j}t}}$:[7]

$$\mathbf{v}_{i\bar{f}\bar{j}t} = \mathbf{v}_{\bar{f}\bar{j}t}\frac{q_{i\bar{f}\bar{j}t}}{q_{\bar{f}\bar{j}t}} \tag{M.3.3}$$

Since we assumed the unit cost of variable inputs to be the same for all the products within the market, we can impute the input cost for all products of all other firms (f) in the referenced market ($\bar{j}$) by proportionally rescaling reference firm's product input cost for every product's physical units produced in the market ($q_{if\bar{j}t}$).

$$\mathbf{v}_{if\bar{j}t} = \mathbf{v}_{i\bar{f}\bar{j}t}\frac{q_{if\bar{j}t}}{q_{i\bar{f}\bar{j}t}} \tag{M.3.4}$$

We use firm-level input data from the Prowess dataset. The measure of capital that we adopt is the variable "capital employed" included in the data. It is measured as the sum of equity capital, non-reevaluated reserves and borrowings. We use this measure of capital as the fixed asset variables in Prowess have many missing values. Labor is defined as the amount of salaries and wages of the firm, as employment variables are not reliable enough. Materials are measured as the raw material expenditure of the firm, excluding consumption of stores and spares. Variable inputs are deflated by pharmaceutical 4-digit NIC wholesale price index. Following Ahsan

[6] To do so we have to assume that the reference firm has constant markup over all products in the referenced market.

[7] Units produced are normalized to take into account both the selling size of the good (quantity of drugs in the pack) and the dosage strength.

(2013), capital is deflated using an investment deflator, computed as the average of the wholesale price index for two industries: "manufacture of general purpose machinery" and "manufacture of special purpose machinery".

M.3.2.2 Product's input price

Product price dispersion within an industry may depend on the difference in quality among the products, which in turn may stem from different input quality, and different input costs. Since the bulk drugs used to obtain the final drugs have the same chemical composition and the workers in the chain of one product do not need to be more skilled than the other workers in the same market, we assume that input quality and input prices are the same across all products within a market. In principle in the pharmaceutical industry within the market, products should be materially and qualitatively homogeneous, as every drug has the same ATC5 and dosage form. In a cross country study, Bate et al. (2011) test the quality of drug samples and observe the drugs failing the test are priced lower than those which comply with standardized quality measures. However, they also show that price differences alone is insufficient to identify the quality of drugs. Bennett and Yin (2014) conduct a quality test on the most important antibiotics in India and show that 96 percent of the drugs sampled comply with Indian Pharmacopoeia quality standards. Yet, in the narrowly defined medicine markets that we compare, the magnitude of *actual* quality differences documented in previous studies alone cannot explain the sizeable dispersion in prices observed in our data (Figure 3.2). Moreover, in our estimation sample we consider only traded firms which are supposed to be more observant (and controlled) about quality aspects. We, therefore, consider product quality dispersion within the market a limited problem for our input price assumption.

The productivity measure we adopt to instrument for the prices in Equation (3.5) does not require to allocate firm-level capital across the products. However, in Section 3.6.3 we propose five other measures of productivity. No specific features of Indian pharmaceutical industry, help us make assumptions about the difference in price of the capital goods employed for a product. In that case, to impute product-level capital we simply apportion firm-level capital among the different products of the firm using product's share of firm sales as in Foster et al. (2008). We stick to the O-Ring theory by Kremer (1993) and to Kugler and Verhoogen (2011), which model and show that more expensive inputs lead to more expensive products. Product's share of firm sales, that we use for apportioning firm-level capital among the products, embeds this information.

An important assumption we make on input prices is that they do not depend on input quantities.[8] If this assumption is violated because the input market power of the reference firm - from which we calculate the unit cost of inputs - is high thanks to a high share of input purchased, our imputation method can generate problems. To help to validate this assumption, we verified that only 13 percent of the reference firms have the highest sales share in the referenced market, implying that less than 13 percent of the reference firms are top purchasers on their input markets.

M.3.2.3 The LP estimator controlling for product scope

Dhyne et al. (2017) propose that all kind of inputs used by a multiproduct firm can create a synergy, allowing the firm to reach a higher point on the production possibility curve with the same amount of inputs. In the pharmaceutical industry, however, variable inputs can be considered product-specific. Firm capital expenditure, instead, is more likely to involve many products. To contrast the simultaneity bias, we estimate Equation (M.3.1):

$$q_{it} = \beta_k k_{ft} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it} + \gamma y_{-it} + \eta_{it}$$

adopting the LP technique, using materials as a proxy. Similar to Dhyne et al. (2017), we must modify the standard LP estimator as follows.

The same assumptions as LP must hold at the product level: (i) the demand for the intermediate input m is dependent on the two state variables and it is monotonically increasing in ω and, thus, can be inverted:[9]

$$m_{it} = \theta(k_{ft}, \omega_{it}) \rightarrow \omega_{it} = \theta^{-1}(k_{ft}, m_{it}) \tag{M.3.5}$$

(ii) the law of motion of productivity, i.e. a first order Markov-chain process:

$$\omega_{it} = E[\omega_{it} | \omega_{it-1}] + \psi_{it} \tag{M.3.6}$$

where ψ_{it} is an innovation to productivity, uncorrelated with k_{ft} but not necessarily with l_{it}.

We can rewrite the production function as:

$$q_{it} = \beta_l l_{it} + \phi(k_{ft}, m_{it}) + \gamma y_{-it} + \eta_{it} \tag{M.3.7}$$

[8] The same assumption is also maintained by De Loecker et al. (2016).

[9] Contrary to Dhyne et al. (2017) the equation is invertible as the materials are measured at the product level, creating a one-to-one relationship with product-level productivity.

where, as in the firm-level case:

$$\phi(k_{ft}, m_{it}) = \beta_0 + \beta_k k_{ft} + \beta_m m_{it} + \theta^{-1}(k_{ft}, m_{it}) \tag{M.3.8}$$

We proceed with the two stages of the LP approach that will produce consistent estimates of β_k, β_k, β_m and γ that we plug in Equation (M.3.1) to calculate product-level productivity (*TFP-QEM*) as a Solow residual.

M.3.3 Alternative measures of product-level productivity

In this subsection, we examine the robustness of our results to alternative measures of productivity. To estimate productivity at the product level, prior literature usually considers a log-additive production function (e.g. Cobb-Douglas) whose coefficients remain constant over the sample period:

$$x_{it} = \omega_{it} + \beta_k k_{it} + \boldsymbol{\beta_v} \mathbf{v}_{it} \tag{M.3.9}$$

where, for each product i and year t, x is log output, k is log capital and v is a vector of variable inputs in logs. Product-specific log productivity (ω) is Hicks-neutral. The production functions is either *revenue-based*, if output is measured in sales revenues y, or *quantity-based*, if output is measured in quantity of physical units sold q.

Estimating productivity of multiproduct firms at the product level encounters specific problems of feasibility involving variable existence, selection and identification. As discussed in De Loecker et al. (2016), the estimation of a product-level, log-additive production function needs to take into consideration two main aspects: a) we do not observe product-level inputs, but only firm-level ones; and b) we do not observe productivity (neither at the firm nor at the product level). We discuss our approach to addressing (a) in Appendix M.3.2.1. Concerns related to (b) can lead to two potential biases: i) a *product scope bias*, as the number of products is decided by the firm according to the observed productivity; and ii) a *simultaneity bias*, as the amount of inputs is chosen based on firm or product productivity. We previously discussed the product scope bias and the measure of productivity we proposed in Appendix M.3.1 addresses it.

The simultaneity bias concerns the computation of output elasticities, β_k and $\boldsymbol{\beta_v}$. This can be addressed in two different ways: a) equalling elasticities to average input cost share over the sample (cost share-based method); or b) estimating the elasticities econometrically (estimation-based method). The first method follows the theoretical framework of cost minimization of the firm and the second one follows assumptions on the nature of productivity shocks and firm's information set. While the cost share-based method is easy to construct, it is only valid under the assumption of perfect competition and constant returns to scale. The estimation-based method, instead, addresses the simultaneity bias, which arises as input quantities are chosen according to observed or expected (by the firm) productivity (Olley and Pakes, 1996). We use the LP estimator for our estimation-based method.

The productivity measure used for obtaining the results in Section 3.5, *TFP-QEM*, addresses all the biases that might occur when estimating productivity. Other measures of productivity could be adopted, although they fail to address at least one of the aforementioned biases. We compute five additional measures of product-level productivity, and compare them to our preferred measure in Table 3.A.3 in the Chapter Appendix, distinguishing between revenue- or quantity-based and cost share- or estimation based. All input elasticities are calculated at the ATC5 level and their industry-level average is reported. The two cost-share-based measures of productivity *TFP-RC* and *TFP-QC* are computed using the same equation (same input elasticities), but they differ in terms of the output variable: revenues for *TFP-RC* and physical units for *TFP-QC*, as in Foster et al. (2008). The two revenue-estimation-based measures of productivity differ by either including raw materials in the output (value added-based), *TFP-VE*, as in Ahsan (2013) or in the inputs, *TFP-RE*, as in Topalova and Khandelwal (2011). The quantity-based version of *TFP-RE* is *TFP-QES*, suitable for single-product firms, as in De Loecker et al. (2016).

M.4 Methodological Appendix Chapter 4

M.4.1 Product-level productivity in multiproduct firms

M.4.1.1 Multiproduct production function estimation

I build on Dhyne et al. (2017), whose approach is summarized in Appendix M.1, to obtain an *estimation-based* measure of product-level productivity using a production function where raw materials enter at the product level and labor and capital enter at the firm level. This relaxes the assumption of product-specific labor input imposed in the production function estimation of Chapter 3.[10] I esti-

[10] In the pharmaceutical industry, I consider raw materials as product-specific inputs because the chemical composition of each drug is fixed and a marginal change in real raw material expenses for product i affects the output of product i, but not the output of the other products of the firm. Changes in real capital expenditure or salaries, instead, might be related to machinery, software or plant space, as well as workers or managerial skills, and are more likely to affect more than one product of the firm. Therefore, capital and labor inputs are assumed to be firm-specific.

mate the following production function:

$$q_{it} = \omega_{it} + \beta^k k_{ft} + \beta^l l_{ft} + \beta^m m_{it} + \gamma y_{-it} + \eta_{it} \tag{M.4.1}$$

where l is log salaries, m is log raw materials and y_{-it} is log revenues of all other products of the firm except product i. Following Dhyne et al. (2017), this term controls for the product scope bias and I expect its coefficient γ to be negative, as an increase in firm revenues, holding constant the other inputs, would result in a decrease in the quantity of product i.[11]

To estimate Equation (M.4.1) I merge the AIOCD data with Prowess, CMIE data on firm financials.[12] In the CMIE data I observe capital and salaries at the firm level, as they appear in Equation (M.4.1). To estimate the production function I also impute product-specific raw materials, which is observed only at the firm level.[13] To address the simultaneity bias I adjust the estimator proposed by Levinsohn and Petrin (2003) (henceforth, LP) and obtain output elasticities of capital, material and labor, separately for every ATC5 of the pharmaceutical industry.[14]

In Figure 4.A.2 in the Chapter Appendix, Panel (A) I show the distribution of the estimation-based product-level productivity (*TFPQ-E*) and the central moments of the distributions of the output elasticities. On average the output elasticity of capital is 0.58, of labor is 0.11, of materials is 0.65. Coefficient γ estimate is negative on average, -0.02, as expected, since an increase in firm revenues, holding product variable inputs and firm-level capital constant, would result in a decrease in the quantity of the focal product. In Figure 4.A.2 in the Chapter Appendix, Panel (B) I compare this *estimation-based* productivity with the *cost-based* productivity estimated following Foster et al. (2008), where the output elasticities of the inputs sum to one by assumption (*TFPQ-C*).[15] This method provides higher output elasticities

[11] Controlling for log quantities of all other products (q_{-it}) instead of log revenues (y_{-it}) in Equation (M.4.1) does not change the estimated output elasticities significantly. However, I prefer the controlling for log revenues since multiproduct firms produce heterogeneous products and their aggregation in units is questionable.

[12] The CMIE Prowess data are used in the productivity estimation literature (e.g., Ahsan, 2013; De Loecker et al., 2016). The Prowess data contain annual financial information for publicly listed firms traded on the National and the Bombay Stock Exchanges in India. I identify the sample of firms in the category "Manufacture of pharmaceuticals, medicinal chemical and botanical products" (division 21) of the National Industry Classification (NIC) 2008.

[13] To allocate raw materials of the firm across its products, I assume that the cost of materials used to produce one milligram/millilitre of a product does not vary across different products of the same market. For further details, see input allocation methodology in Appendix M.4.1.2.

[14] In Appendix M.4.1.3 I present how the assumptions underpinning the LP estimator can be accommodated to allow the original estimator to identify the output elasticities.

[15] Output elasticities of capital and variable inputs (labor, materials and energy) are computed as the average input cost share over the sample. This methodology is suitable for single-product firms selling homogeneous goods, which is not this case.

of capital and lower output elasticities of the variable inputs. The estimation-based productivity is preferable, as it controls for the product scope of the firm. I use cost-based productivity for examining the robustness the results. In the following two subsections we present how we address the biases related to product-level input measurement and describe the changes introduced to the standard LP estimator to estimate productivity using Equation (M.4.1).

M.4.1.2 Input allocation

We exploit specific features of the pharmaceutical industry to make assumptions and impute the values of raw material input for each product. The methodology that I adopt does not require us to apportion capital and salaries across products as both enter the production function at the firm level.

All products within the same market are composed of the same chemical elements but have different pack sizes and strengths. The unit cost of raw materials can be assumed to be the same across all products within the market. Since the chemical composition of the drugs within a market is unique, I assume that the cost of raw materials (bulk drugs) used to produce one unit of the drug does not vary across the firms serving the same market. To impute the cost of raw materials for each product, I select for each market the firm charging the lowest (normalized) price for the drug, which I assume to produce at the marginal cost. I refer to it as the 'reference firm' ($\bar{f}$) of the market.

The allocation of firm-level raw materials across products in market j is the following. Once found the 'reference firm', I calculate its expenditure in raw material for market j using the market's revenue shares of the reference firm, $\frac{Y_{\bar{f}jt}}{Y_{\bar{f}t}}$:[16]

$$M_{\bar{f}jt} = M_{\bar{f}t} \frac{Y_{\bar{f}jt}}{Y_{\bar{f}t}} \tag{M.4.2}$$

Second, I split reference firm's input expenditure in the market ($M_{\bar{j}\bar{f}t}$) across all its products using product's share of (normalized) physical units produced in the market by the firm, $\frac{Q_{i\bar{f}jt}}{Q_{\bar{f}jt}}$:

$$M_{i\bar{f}jt} = M_{\bar{f}jt} \frac{Q_{i\bar{f}jt}}{Q_{\bar{f}jt}} \tag{M.4.3}$$

Since I assumed the unit cost of variable inputs to be the same for all the products

[16] To do so I have to assume that the reference firm has constant markup over all products in the market.

within the market, I can impute the input cost for all products of all other firms (f) in market j by proportionally rescaling reference firm's product input cost for every product's physical units produced in the market (Q_{ifjt}).

$$M_{ifjt} = M_{i\bar{f}jt}\frac{Q_{ifjt}}{Q_{i\bar{f}jt}} \tag{M.4.4}$$

I use firm-level input data from the Prowess dataset. The measure of capital that I adopt is the variable "capital employed" included in the data. It is measured as the sum of equity capital, non-reevaluated reserves and borrowings. I use this measure of capital as the fixed asset variables in Prowess have many missing values. Labor is defined as the amount of salaries and wages of the firm, as employment variables are not reliable enough. Materials are measured as the raw material expenditure of the firm, excluding consumption of stores and spares. Variable inputs are deflated using the pharmaceutical 4-digit NIC wholesale price index. Following Ahsan (2013), capital is deflated using an investment deflator, computed as the average of the wholesale price index for two industries: "manufacture of general-purpose machinery" and "manufacture of special-purpose machinery".

When imputing product-specific inputs we must consider that the differences in price across products may depend on the differences in their quality, which in turn may imply different levels of input quality and input costs. Prior literature has shown that higher input expenditures lead to more expensive products (Kugler and Verhoogen, 2011) and that indicators of quality can be linked to the differences in output prices (Khandelwal, 2010), although they might also reflect consumer preferences and markups (De Loecker and Goldberg, 2014). Since the bulk drugs used to obtain the final drugs have the same chemical composition, I assume that the quality and prices of raw material are the same across all products within a market. In a cross country study, Bate et al. (2011) test the quality of drug samples and observe the drugs failing the test are priced lower than those which comply with standardized quality measures. However, they also show that price differences alone are insufficient to identify the quality of drugs. Bennett and Yin (2014) conduct a quality test on the most important antibiotics in India and show that 96 percent of the drugs sampled comply with the Indian Pharmacopoeia quality standards. Moreover, in the estimation sample I consider only traded firms that are supposed to be more observant (and controlled) about quality aspects. We, therefore, consider product quality dispersion within the market a limited problem for the raw material allocation.

Following De Loecker et al. (2016), we also assume that raw material prices do not depend on quantities. If this assumption is violated and the market power of the reference firm on the input market is high thanks to a high share of raw materials purchased, this imputation method can generate problems. To validate this assumption, I verified that only 13 percent of the reference firms have the highest sales share in the referenced market and might obtain lower prices on the market of raw materials.

M.4.1.3 The LP estimator controlling for product scope

In the pharmaceutical industry raw materials can be considered product-specific. Firm capital expenditure and salaries, instead, are more likely to involve many products. To contrast the simultaneity bias, I estimate Equation (M.4.1):

$$q_{it} = \omega_{it} + \beta^k k_{ft} + \beta^l l_{ft} + \beta^m m_{it} + \gamma y_{-it} + \eta_{it}$$

adopting the LP technique, using materials as a proxy. Similar to Dhyne et al. (2017), I must modify the standard LP estimator as follows.

The same assumptions as LP must hold at the product level: (i) the demand for the intermediate input m is dependent on the two-state variables and it is monotonically increasing in ω and, thus, can be inverted:[17]

$$m_{it} = \theta(k_{ft}, \omega_{it}) \rightarrow \omega_{it} = \theta^{-1}(k_{ft}, m_{it}) \tag{M.4.5}$$

(ii) the law of motion of productivity, i.e. a first order Markov-chain process:

$$\omega_{it} = E[\omega_{it} | \omega_{it-1}] + \psi_{it} \tag{M.4.6}$$

where ψ_{it} is an innovation to productivity, uncorrelated with k_{ft} but not necessarily with l_{ft}.

I can rewrite the production function as:

$$q_{it} = \beta^l l_{ft} + \phi(k_{ft}, m_{it}) + \gamma y_{-it} + \eta_{it} \tag{M.4.7}$$

where, as in the firm-level case:

$$\phi(k_{ft}, m_{it}) = \beta^0 + \beta^k k_{ft} + \beta^m m_{it} + \theta^{-1}(k_{ft}, m_{it}) \tag{M.4.8}$$

We proceed with the two stages of the LP approach that will produce consistent estimates of β_k, β_k, β_m and γ that we plug in Equation (M.4.1) to calculate product-level productivity ($TFPQ$-E) as a Solow residual.

[17] Contrary to Dhyne et al. (2017) the equation is invertible as the materials are measured at the product level, creating a one-to-one relationship with product-level productivity.

M.4.2 Relative demand estimation and price elasticity

Price elasticity is a demand primitive and is used to derive product markup following a demand approach. A monopolistically competitive firm f chooses a normalized price P_{ij} for each product i in market j to maximize total profits. Every firm faces a residual demand for each of its products i that takes a constant elasticity form:

$$Q_{ij} = G_{ij} P_{ij}^{\theta_{ij}} \tag{M.4.9}$$

where Q_{ij} is the normalized quantity of product sold, G_{ij} is a scale term, and θ_{ij} price elasticity of product i in market j.

A standard approach in the literature is to estimate price elasticity from a linear log-demand function:

$$log(Q_{ijt}) = \alpha_0 + \theta_{ij} log(P_{ijt}) + \epsilon_{ijt} \tag{M.4.10}$$

where θ_{ij} is product-specific elasticity and can be estimated using product-level panel data. Estimating Equation (M.4.10) using OLS might introduce an upward bias in θ_{ij}, as an idiosyncratic shock in demand might stimulate a price increase.[18] Using monthly-level data, as in this case, reduces the bias, since price changes can be observed with higher frequency. However, in the dataset there are at most 60 observations per product, which can lead to inconsistent estimates. I propose an alternative approach to address OLS estimation bias and inconsistency. I estimate price elasticity using the *relative* residual demand of the product. Considering two products, i and h, belonging to the same market j, I can write relative residual demand of product i with respect to product h as:

$$log\left(\frac{Q_{ij}}{Q_{hj}}\right) = log\left(\frac{G_{ij}}{G_{hj}}\right) + \theta_{ij} log(P_{ij}) - \theta_{hj} log(P_{hj}) \tag{M.4.11}$$

Indicating as q and p the logs of Q and P, and $\Delta q_{ijt}^{h} = q_{ijt} - q_{hjt}$, I can es-

[18] This problem can be addressed using the instrumental variable approach, provided that one finds a variable that is correlated with the prices, but not with the error term. Foster et al. (2008) identifies price elasticity for single-product firms using their productivity. Chapter 3 finds this method useful to estimate the average price elasticity of the market, but it can be problematic for estimating product-level elasticity as the variability of the instrument, calculated at the product-year level, is reduced by far. In addition, it restricts the sample to the firms for which a value of productivity can be calculated, which are usually the biggest and more productive ones. In estimating product-level price elasticities, prices are often instrumented using the prices of the product in other areas (Nevo, 2001; DellaVigna and Gentzkow, 2019). In the dataset I use I do not observe area-disaggregated data .

timate θ_{ij} using the following equation:

$$\Delta q^h_{ijt} = \alpha^h_{ij} + \theta_{ij} p_{ijt} + \beta^h_{ij} p_{hjt} + \epsilon^h_{ijt} \tag{M.4.12}$$

where α^h_{ij} estimates the relative scale terms, $log\left(\frac{G_{ij}}{G_{hj}}\right)$, and β^h_{ij} the opposite value of price elasticity of product h, $-\theta_{hj}$. Similarly, the demand function of product i relative to any other product of the same market j can be estimated as Equation (M.4.12), identifying the elasticity of both products. Pairing product i with all the other products $-i$ in market j allows me to estimate price elasticity of product i and the elasticity of all the other products in the market using a vectorial specification. Indicating as Δq_{ijt} the vector with all Δq^{-i}_{ijt}, and p_{jt} the vector with all p_{-ijt}, I can estimate price elasticity of product i, θ_{ij}, from the following equation:

$$\Delta q_{ijt} = \alpha_{ij} + \theta_{ij} p_{ijt} + \beta_{ij} p_{jt} + \epsilon_{ijt} \tag{M.4.13}$$

where α_{ij} is a vector including the constant and product fixed effects of all other products $-i$ belonging to market j and β_{ij} is a vector composed by opposite value of price elasticity of all other products $-i$.

An example can be useful. Market j has 3 products ($N_j = 3$): i, h and g. From Equation (M.4.10), the relative demand of product i with respect to all the other products in the market can be estimated as follows:

$$\begin{bmatrix} \Delta q^h_{ijt} \\ \Delta q^g_{ijt} \end{bmatrix} = \begin{bmatrix} \alpha^h_{ij} \\ \alpha^g_{ij} \end{bmatrix} + \theta_{ij} p_{ijt} + \begin{bmatrix} -\theta_{hj} \\ -\theta_{gj} \end{bmatrix} \begin{bmatrix} p_{hjt} \\ p_{gjt} \end{bmatrix} + \begin{bmatrix} \epsilon^h_{ijt} \\ \epsilon^g_{ijt} \end{bmatrix}$$

where α^h_{ij} and α^g_{ij} are captured, respectively, by h and g fixed effects; $-\theta_{hj}$ and $-\theta_{gj}$ are estimated interacting p_{hjt} and p_{gjt} with h and g fixed effects, respectively.

This method allows price elasticity θ_{ij} to be estimated using $(N_j - 1) \times T$ observations, instead of T as in the standard approach in Equation (M.4.10) and its estimation consistency increases in the number of products in the market.[19] In addition, this method estimates price elasticity θ_{ij} also when product i is the second product in the pair - in the example above, when the relative demand of product h or g has to be estimated. Each product's elasticity is estimated N_j times, however when the product is not the first in the pair θ_{ij} is estimated using T observations. Although less consistent, these elasticities are informative of the residual demand of a competitor product and might want to be considered. I can use all the N_j elasticities estimated for each product and define an average product-level price elasticity

[19] The average number of products in a market of the Indian pharmaceutical industry is 10 and for some popular markets it goes above one thousand.

weighted using the number of observations used in the estimation. This weighting procedure guarantees a higher weight to the more consistently estimated elasticity but uses the information of all the other elasticities.

Estimating elasticity from the relative demand also reduces the upward bias of the OLS estimator that the standard *non-relative* demand suffers from. In Equation (M.4.10) an idiosyncratic shock in demand for product i might come from a change in the price of other products $-i$ or from a taste shock for product i. In the relative demand elasticity approach, the prices of the other products are included in the specification and a competitor product's price change is no longer captured by the error term. Even a taste shock for product i can be controlled for in the model, in case the other products react to that taste shock changing their price.

Figure 4.A.3 in the Chapter Appendix plots the distribution of the weighted average elasticity as defined above (*relative elasticity*) in comparison with the distribution of the price elasticity estimated using the standard specification as in Equation (M.4.10) (*biased elasticity*). Relative elasticity has a mean of -2.7 and a median of -2.2. The biased elasticities are more concentrated around zero and an additional 40 percent of the distribution lies above zero.

Summary

This doctoral thesis studies how differences in productivity influence the strategies and market power of multiproduct firms. This relationship is investigated using firm-product-level data from India's pharmaceutical and fast-moving consumer goods industries, where product strategies and market power directly determine drug and food accessibility for 1.3 billion people.

The three core chapters show that productivity differences exist among products both within the firm and across firms within narrowly defined markets. In the first chapter, I find that productivity differences across products persist also in markets where there are no price differences (uniform pricing), and that they drive firm strategies other than pricing, such as product pack size, discounts, availability and variety. In the second and third chapters, I show that higher productivity is related with lower product wholesale price and market power, except for the top-selling products that have higher productivity, prices and market power compared to their competitors.

Overall, there is evidence that productivity triggers price and nonprice competition. However, consumers do not necessarily benefit from it since their demand is strongly influenced by the intermediation of the retailers and a misperception about product quality.

Samenvatting

Dit proefschrift onderzoekt hoe verschillen in productiviteit de strategieën en marktmacht van bedrijven met meerdere producten beïnvloedt. Deze relatie wordt onderzocht aan de hand van data op bedrijf-product-niveau van de Indiase farmaceutische en fast-moving consumer goods industrie, waarin productstrategieën en marktmacht rechtstreeks bepalend zijn voor de toegankelijkheid van geneesmiddelen en eten voor 1,3 miljard mensen.

De drie kernhoofdstukken laten zien dat er productiviteitsverschillen bestaan tussen producten zowel binnen het bedrijf als tussen bedrijven binnen nauwgedefinieerde markten. In het eerste hoofdstuk toon ik aan dat productiviteitsverschillen tussen producten ook blijven bestaan in markten waar er geen prijsverschillen zijn (uniforme prijsstelling), en dat deze leiden tot andere bedrijfsstrategieën dan prijsstelling, zoals productverpakkingsgrootte, kortingen, beschikbaarheid en verscheidenheid. In het tweede en derde hoofdstuk, toon ik aan dat hogere productiviteit gerelateerd is aan een lagere groothandelsprijs en lagere marktmacht, met uitzonderingen van de bestverkopende producten die een hogere productiviteit, prijs en marktmacht hebben in vergelijking met hun concurrenten.

Over het algemeen zijn er aanwijzingen dat productiviteit prijs- en niet-prijsconcurrentie veroorzaakt. Consumenten hebben er echter niet per se profijt van, aangezien hun vraag sterk wordt beïnvloed door de tussenkomst van de detailhandelaren en een misvatting over de productkwaliteit.

About the author

Gianluca Antonecchia is a PhD candidate at Erasmus School of Economics and Tinbergen Institute under the supervision of Enrico Pennings and Ajay Bhaskarabhatla. He joined the department of Applied Economics in October 2017, after completing his Research Masters at University College London. Prior to that, he worked as an Economist at Prometeia (Bologna).

Gianluca's main research field is Industrial Organization. He is interested in productivity, market power and innovation. His doctoral work examines how productivity differences across products influence firm strategies in emerging countries and markets such as pharmaceuticals and consumer product goods. In his ongoing research he examines the spread of product innovation, the drivers of market power and the effects of retail buyer power. He has also ongoing projects on firm financing and consumption inequality.

Gianluca presented his research at international conferences and workshops. He was awarded a research grant from the Thakur Family Foundation to study the Indian pharmaceutical industry. He also received a grant from the Erasmus Trustfonds to visit the Ed Snider Center for Enterprise and Markets at the University of Maryland during spring 2022. He will continue his academic career at the Department of Economics at KU Leuven as a postdoctoral scholar.

Portfolio

Working Papers

- "How firms compete when they set identical prices? Nonprice strategies in the Indian biscuit industry." with A. Bhaskarabhatla — **R&R** at the *Journal of Economics & Management Strategy*
- "Heterogeneous expectations, forecast accuracy and firms' credit demand." — **R&R** at the *European Economic Review*
- "How do Wholesale Prices and Retail Markups Affect Market Shares in the Pharmaceutical Industry?" with A. Bhaskarabhatla
- "Superstar products and the sources of market power."

Research in Progress

- "Product innovation and firm upgrading in the pharmaceutical industry" with A. Bhaskarabhatla, S. Ghai & E. Verhoogen
- "Supplier concentration, retailer incentive and volume discounts" with A. Bhaskarabhatla
- "Basket composition and consumption inequality in India" with A. Bhaskarabhatla

Teaching activity

- Co-lecturer, *Strategy Economics* (BSc), Erasmus University Rotterdam, 2020-2022
- Co-lecturer, *Strategic Firm Behaviour* (MSc), Erasmus University Rotterdam, 2017-2021
- Lecturer, *Applied Urban Econometrics* (MSc), Erasmus University Rotterdam, 2018-19
- Co-lecturer, *Data Processing for Economics* (BSc), University of Bologna, 2015-16
- Co-lecturer, *International Economics* (MSc), University of Bologna, 2014
- Teaching Assistant, *Macroeconomics* (BSc), University of Bologna, 2014-16

Other activities

- Thesis supervision (bachelor and master), 2017-2022
- Organizer of the seminars in Organisation, Strategy and Entrepreneurship, 2018-2021
- Member of the PhD council at Erasmus School of Economics, 2018-19

Presentations

- 2022: Seminar IMT Business School (IMT Paris - virtual), Seminar Max Plank Institute (Munich - virtual), Seminar Ed Snider Center (University of Maryland), ISA (Philadelphia), EARIE (Vienna)
- 2021: ACEGD (ISI New Delhi - virtual), CAED (Coimbra), EARIE (Bergen - virtual), IAAE (Rotterdam - virtual), ISA (Boston - virtual), RES (Belfast - virtual), MaCCI (Mannheim - virtual), OSE Strategy Seminar (University of Maastricht - virtual), PhD Jamboree (Tinbergen Institute - virtual), OSE Strategy Seminar (Erasmus University Rotterdam - virtual)
- 2020: Brown Bag Seminar (Erasmus University Rotterdam - virtual), NAPW (Miami - virtual), MaCCI (Mannheim), OSE Strategy Seminar (Erasmus University Rotterdam), PhD Seminar (Tinbergen Institute)
- 2019: EARIE (Barcelona), Workshop on Revenue Management (Erasmus University Rotterdam), EWEPA (London), ISMS (Rome), CAED (Ann Arbor), RES (Warwick), MaCCI (Mannheim), Workshop on Firm Heterogeneity in Technological Change (University of Ghent), Brown Bag Seminar (Erasmus University Rotterdam), OSE Strategy Seminar (Erasmus University Rotterdam)
- 2018: EARIE (Athens), NAPW (Miami), GdRE Symposium of Money, Banking and Finance (Aix-en-Provence), OSE Strategy Seminar (Erasmus University Rotterdam), PhD Seminar (Tinbergen Institute)

Scholarships and Grants

- Research grant ($50,000) from Thakur Foundation, University of Rotterdam, 2021-22
- Research visit grant (€2,000) from Erasmus Trustfonds, University of Rotterdam, 2022
- Tutorship, University of Bologna, 2012-13
- Erasmus Programme scholarship, University of Liège, 2009-10

Education

- **Research visit**, University of Maryland, April-June 2022
- **MRes** in Economics, University College of London, 2016-2017
- **MSc** in Economics, University of Bologna, 2011-2013
- **Erasmus Exchange Programme**, University of Liege, 2009-10
- **BSc** in Political Science, University of Roma Tre, 2007-2010

Advanced Education

- Tinbergen Institute, *Research on productivity, trade and growth*, 2018
- CeMMAP London, *Partial identification in practice*, 2017
- University of Bari, *Dynamic panel data*, 2014

Previous Experience

- **Economist** at Prometeia, Bologna, 2013-16

The Tinbergen Institute is the Institute for Economic Research, which was founded in 1987 by the Faculties of Economics and Econometrics of the Erasmus University Rotterdam, University of Amsterdam and Vrije Universiteit Amsterdam. The Institute is named after the late Professor Jan Tinbergen, Dutch Nobel Prize laureate in economics in 1969. The Tinbergen Institute is located in Amsterdam and Rotterdam. For a full list of PhD theses that appeared in the series we refer to List of PhD Theses – Tinbergen.nl. The following books recently appeared in the Tinbergen Institute Research Series:

751 Y. SUN, *Consumer Search and Quality*
752 I. KERKEMEZOS, *On the Dynamics of (Anti) Competitive Behaviour in the Airline Industry*
753 G.W. GOY, *Modern Challenges to Monetary Policy*
754 A.C. VAN VLODROP, *Essays on Modeling Time-Varying Parameters*
755 J. SUN, *Tell Me How To Vote, Understanding the Role of Media in Modern Elections*
756 J.H. THIEL, *Competition, Dynamic Pricing and Advice in Frictional Markets: Theory and Evidence from the Dutch Market for Mortgages*
757 A. NEGRIU, *On the Economics of Institutions and Technology: a Computational Approach*
758 F. GRESNIGT, *Identifying and Predicting Financial Earth Quakes using Hawkes Processes*
759 A. EMIRMAHMUTOGLU, *Misperceptions of Uncertainty and Their Applications to Prevention*
760 A. RUSU, *Essays in Public Economics*
761 M.A. COTOFAN, *Essays in Applied Microeconomics: Non-Monetary Incentives, Skill Formation, and Work Preferences*
762 B.P.J. ANDRÉE, *Theory and Application of Dynamic Spatial Time Series Models*
763 P. PELZL, *Macro Questions, Micro Data: The Effects of External Shocks on Firms*
764 D.M. KUNST, *Essays on Technological Change, Skill Premia and Development*
765 A.J. HUMMEL, *Tax Policy in Imperfect Labor Markets*
766 T. KLEIN, *Essays in Competition Economics*
767 M. VIGH, *Climbing the Socioeconomic Ladder: Essays on Sanitation and Schooling*
768 YAN XU, *Eliciting Preferences and Private Information: Tell Me What You Like and What You Think*
769 S. RELLSTAB, *Balancing Paid Work and Unpaid Care over the Life-Cycle*
770 Z. DENG, *Empirical Studies in Health and Development Economics*
771 L. KONG, *Identification Robust Testing in Linear Factor Models*
772 I. NEAMŢU, *Unintended Consequences of Post-Crisis Banking Reforms*
773 B. KLEIN TEESELINK, *From Mice to Men: Field Studies in Behavioral Economics*
774 B. TEREICK, *Making Crowds Wiser: The Role of Incentives, Individual Biases, and Improved Aggregation*

775 A. CASTELEIN, *Models for Individual Responses*

776 D. KOLESNYK, *Consumer Disclosures on Social Media Platforms: A Global Investigation*

777 M.A. ROLA-JANICKA, *Essays on Financial Instability and Political Economy of Regulation*

778 J.J. KLINGEN, *Natural Experiments in Environmental and Transport Economics*

779 E.M. ARTMANN, *Educational Choices and Family Outcomes*

780 F.J. OSTERMEIJER, *Economic Analyses of Cars in the City*

781 T. ÖZDEN, *Adaptive Learning and Monetary Policy in DSGE Models*

782 D. WANG, *Empirical Studies in Financial Stability and Natural Capital*

783 L.S. STEPHAN, *Estimating Diffusion and Adoption Parameters in Networks New Estimation Approaches for the Latent-Diffusion-Observed-Adoption Model*

784 S.R. MAYER, *Essays in Financial Economics*

785 A.R.S. WOERNER, *Behavioral and Financial Change – Essays in Market Design*

786 M. WIEGAND, *Essays in Development Economics*

787 L.M. TREUREN, *Essays in Industrial Economics - Labor market imperfections, cartel stability, and public interest cartels*

788 D.K. BRANDS, *Economic Policies and Mobility Behaviour*

789 H.T.T. NGUYEN, *Words Matter? Gender Disparities in Speeches, Evaluation and Competitive Performance*

790 C.A.P BURIK, *The Genetic Lottery. Essays on Genetics, Income, and Inequality*

791 S.W.J. OLIJSLAGERS, *The Economics of Climate Change: on the Role of Risk and Preferences*

792 C.W.A. VAN DER KRAATS, *On Inequalities in Well-Being and Human Capital Formation*

793 Y. YUE, *Essays on Risk and Econometrics*

794 E.F. JANSSENS, *Estimation and Identification in Macroeconomic Models with Incomplete Markets*

795 P.B. KASTELEIN, *Essays in Household Finance: Pension Funding, Housing and Consumption over the Life Cycle*

796 J.O. OORSCHOT, *Extremes in Statistics and Econometrics*

797 S.D.T. HOEY, *Economics on Ice: Research on Peer Effects, Rehiring Decisions and Worker Absenteeism*

798 J. VIDIELLA-MARTIN, *Levelling the Playing Field: Inequalities in early life conditions and policy responses*

799 Y. XIAO, *Fertility, parental investments and intergenerational mobility*

800 X. YU, *Decision Making under Different Circumstances: Uncertainty, Urgency, and Health Threat*

Productivity and firm strategies are primarily related to economic growth and resource (mis)allocation. Traditionally, they are studied at the firm level, neglecting that firms produce many products that have their own productivity, strategies and market power. This doctoral thesis studies how differences in productivity influence the strategies and market power of multiproduct firms. This relationship is investigated using firm-product-level data from India's pharmaceutical and fast-moving consumer goods industries, where product strategies and market power directly determine drug and food accessibility for 1.3 billion people. The three core chapters show that productivity differences exist among highly substitutable products, triggering price and nonprice competition.

Gianluca Antonecchia is a PhD candidate at Erasmus School of Economics and Tinbergen Institute under the supervision of Enrico Pennings and Ajay Bhaskarabhatla. He joined the department of Applied Economics in October 2017, after completing his Research Masters at University College London. Prior to that, he worked as an Economist at Prometeia (Bologna). Gianluca's main research field is Industrial Organization. He is interested in productivity, market power and innovation. He will be joining the Department of Economics at KU Leuven as a postdoctoral scholar.

tinbergen institute

Tinbergen Institute

Erasmus University Rotterdam
Erasmus School of Economics

W: www.eur.nl/ese
www.tinbergen.nl