Gianluca Antonecchia

Productivity and Strategies of Multiproduct Firms

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Productiviteit en strategieën
van bedrijven met meerdere producten

Thesis

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"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

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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.

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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).

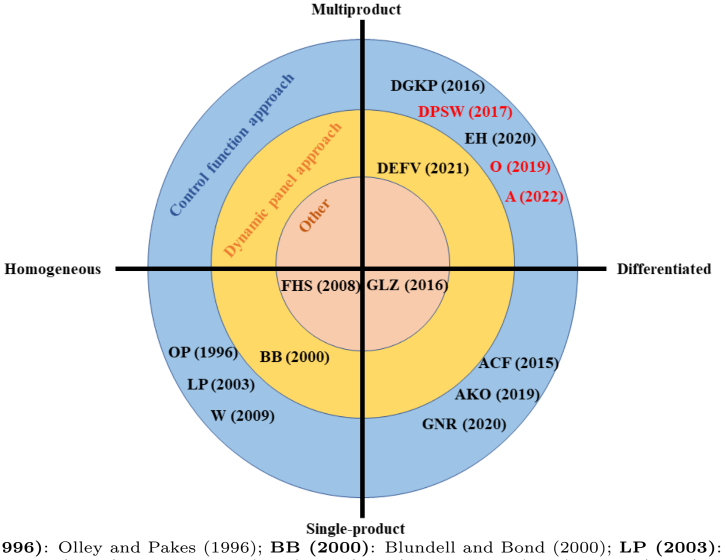
uct firms. First, regardless of whether a firm is multiproduct or not, productivity is unobserved to anyone but the firm, that chooses the amount of inputs based on it (Olley and Pakes, 1996). This *simultaneity bias* alters the OLS estimation of the production function residual. Second, production output — 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 2

How firms compete when they set identical prices? Nonprice strategies in the Indian biscuit industry

2.1 Introduction

Pricing is central to strategy. Setting the prices right is an important firm capability, which allows the firm to appropriate value created by other firm resources and capabilities (Dutta et al., 2003). Accordingly, strategy literature pays considerable attention to how the prices are set, how buyers and sellers negotiate over price, how much value buyers and sellers capture in a transaction, what signal prices send to stakeholders, and how differences in pricing strategies generate sustained performance heterogeneity. Prices play a critical role in models of productivity-induced efficien-

† This chapter is based on the working paper titled "How firms compete when they set identical prices? Nonprice strategies in the Indian biscuit industry" and is joint work with Ajay Bhaskarabhatla. After revision the working paper will be resubmitted at the Journal of Economics and Management Strategy. We thank Thomas Peeters, Enrico Pennings, the participants at MaCCI 2020 (Mannheim), European Workshop on Efficiency and Productivity Analysis 2019 (London), INFORMS Marketing Science Conference 2019 (Rome), Yale China India Insights Conference 2019 (MIT Sloan), Strategic Management Society Conference 2019 (Minneapolis), and seminar participants at ShanghaiTech and Erasmus School of Economics. We thank Nielsen India for sharing the data. Researcher(s) own analyses calculated (or derived) based in part on data from The Nielsen Company (India), Private Limited. The conclusions drawn from the Nielsen data are those of the researcher(s) and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

cies resulting in price competition (Olley and Pakes, 1996). Yet the efficiency of the price system has been debated in various theories of the firm, notably the value-based strategy literature (Brandenburger and Stuart Jr, 1996; Lippman and Rumelt, 2003).

Prices are sticky (Klenow and Malin, 2010; Cavallo and Rigobon, 2016), changing prices is costly (Anderson et al., 2015; Zbaracki and Bergen, 2010), and firms and managers do not always have the information or the ability to set the right price (DellaVigna and Gentzkow, 2019; Dutta et al., 2003, 2002) . For these reasons and other historical, institutional, or idiosyncratic reasons, prices are surprisingly uniform in many settings (e.g., Shiller and Waldfogel, 2011; Orbach and Einav, 2007; Courty and Nasiry, 2018), indicating that in these settings prices have a limited role as a market-clearing mechanism.

When prices are less flexible, firms often compete on nonprice dimensions such as product durability, reliability, and service (Carlton, 1989; Dixit, 1979; Spence, 1977; Stigler, 1968). For example, movies compete on release dates although ticket prices remain uniform (Belleflamme and Paolini, 2019; Cabral and Natividad, 2020; Einav, 2007), airlines compete on service quality and marketing practices such as frequent flyer programs (Lederman, 2008; Prince and Simon, 2015) particularly when ticket prices are regulated (Douglas and Miller, 1974), hospitals compete on quality when reimbursement prices are administratively set (Gaynor and Town, 2011), supermarkets compete on availability and convenience while prices are largely uniform across stores within a chain (DellaVigna and Gentzkow, 2019; Matsa, 2011), booksellers compete on service and amenities such as reviews (Clay et al., 2002) particularly when book prices are fixed (Canoy et al., 2006), and colleges compete on admission dates (Avery and Levin, 2010). In these settings, both price and nonprice forms of competition often coexist to some degree and it is difficult to isolate the role of nonprice competition and examine its implications.

In this chapter, we examine a setting that features nonprice competition under industry-wide uniform pricing, which allows us to study how firms compete exclusively on nonprice dimensions. If price and nonprice competition are perfect substitutes, markets in which firms sell a uniform quantity at varying prices (e.g., firms selling one gallon of milk at different prices) may operate no differently than markets in which firms sell varying quantities at a uniform price (e.g., firms selling different ounces of milk but all firms choosing one dollar as the price). However, price and nonprice competition might not be perfect substitutes because when prices are inflexible and all firms set identical prices, firms may either compete or collude. Prior theoretical studies examining price and nonprice collusion are inconclusive and show that uniformity of prices can either strengthen or weaken the incentive for collusion on nonprice characteristics (Brod and Shivakumar, 1999; Dewenter et al., 2011; Fershtman and Gandal, 1994; Steen and Sørgard, 1999; Sullivan, 2020). Therefore, whether firms compete or partially or fully collude under industry-wide uniform pricing remains an empirical question, which, to our knowledge, has not been examined previously.

Using Nielsen data at the stock-keeping unit (SKU) level, we study India's biscuit (cookies) industry, the largest product category in India's CPG sector with sales of nearly $4 billion in 2014. Firms in the biscuit industry predominantly charge at discrete price points of Rupees (hereafter, Rs.) 5, 10, 15, 20, 25, 30. The products sold at price points 5 and 10 account for 62 percent of the total market share in our dataset from 2014 and it has increased to 75 percent in 2019 (Bose, 2019). Biscuit manufacturers set retail prices and print them on product packaging, as is mandated by law in India, and the 12 million independently owned retailers and one million wholesalers in India play little role in price-setting, leading manufacturers to compete on *retail price points*. Several firms compete at each of these price points, and unlike in other studies involving discrete price points (e.g., Conlon and Rao, 2020), price changes are rare. For example, when the prices of raw materials increased in 2018, firms lowered grams per pack while keeping the price constant. In particular, the best-selling biscuit product in India, Parle-G at Rs. 5, reduced its pack size from 70 to 65 grams in December 2018. Therefore, the channel through which price-based competition operates directly is entirely foreclosed in our context, bringing into principal focus nonprice-based channels of competition.

Our study has three parts. First, we examine whether firms compete on quantities. We focus primarily on pack size competition in this study, but we also examine other nonprice dimensions of competition, namely, pack size promotions, product availability, and product variety. In a world where prices vary, productivity differences among products influence their prices, causing firms to set lower prices for products with higher productivity (e.g., Foster et al., 2008; Syverson, 2011). In our empirical context featuring industry-wide uniform pricing, we examine the extent to which markets are competitive by relating productivity differences to the nonprice strategies that firms adopt. Since prices remain constant but productivity differences can persist in our setting, we expect to observe differences in pack size and, therefore, in price per pack size. We hypothesize that if firms compete under industry-wide uniform pricing, then they offer larger pack sizes, more pack size (quantity) promotions, improved availability, and greater variety for more productive products. Overall, we find evidence of productivity-based competition despite industry-wide uniform pricing.

Second, we examine whether firms' pack size choices are consistent with collusion. We interpret our results on productivity-based pack size variation as evidence of robust competition under industry-wide uniform pricing. Nevertheless, the practice of setting identical prices can facilitate collusion on pack size choices. Therefore, we examine whether the variability in pack sizes between two firms is lower if the pair is more familiar with each other due to multimarket contact and, therefore, can sustain tacit collusion better (Bernheim and Whinston, 1990; Busse, 2000). However, we find no evidence of such collusion on pack sizes using tests proposed by Ciliberto et al. (2019). On the contrary, productivity differences explain differences in pack sizes.

Third, we examine the heterogeneity in the use of nonprice strategies across different markets. In particular, we examine whether the effects of industry-wide uniform pricing are uneven across urban and rural markets. As consumers in urban areas generally exhibit higher levels of income and willingness to pay than consumers in rural areas, setting a uniform price across both types of markets can impose a relatively higher burden on the rural consumers. Consistent with this expectation, demand estimates based on the approach employed by DellaVigna and Gentzkow (2019) reveal that consumers in rural areas have twice as large price (per pack size) elasticity. In a uniform price context, this means that consumers in the rural areas are more sensitive to pack size differences and would consume more if the pack size was larger. However, not only the pack sizes in the rural areas are the same as in the urban areas but consumers have access to only two thirds of the products purchasable in the urban areas. Therefore, nonprice strategies such as pack size competition when combined with industry-wide uniform pricing might not benefit the consumers in rural areas.

Although somewhat loosely connected, the three parts of this chapter combine to document, for the first time to our knowledge, the use of industry-wide uniform pricing. We provide an overall assessment of its impact on nonprice competition by looking at the nonprice strategies the more productive firms use when prices are inflexible. Using Nielsen retail scanner data, recent studies examine the extent to which consumers across income groups pay heterogeneous prices for a homogeneous good, leading to consumption inequality (e.g. Broda et al., 2009; Attanasio and Pistaferri, 2016). Miravete et al. (2020) show uniform pricing rules can generate cross-subsidies among heterogeneous consumers and firms. Our study highlights the important role nonprice strategies can play in generating consumption inequality even when all firms in an industry set identical prices.

We contribute to the study of industries featuring uniform pricing. To our knowledge, industry-wide uniform pricing has not been examined in the previous literature, although it is found in many product categories in the consumer-packaged goods (CPGs) sector in India (Prahalad, 2005; Bhat, 2011; Bose, 2019), and accounts for 40 percent of its CPG sector estimated at $68 billion in 2018 (IBEF, 2019). Similar pricing schemes can also be observed in other countries. For example, “dollar” store chains in the U.S. and “100 yen” store chains in Japan set identical prices for several product categories. Such stores have grown rapidly in numbers, surpassing 30,000 stores in the U.S. alone (Hitt, 2011), but the competitive strategies of the product categories in these stores and of these stores themselves have received little attention.

We also contribute to the literature on productivity by combining product-level data with firm-level financial data and examining the relationship between productivity and nonprice strategies, whereas prior studies on uniform pricing rarely observe the supply-side in such detail (DellaVigna and Gentzkow, 2019). In doing so, we contribute to a deeper understanding of productivity-based nonprice competition within industries featuring price rigidity (Syverson, 2011). A challenge we face in estimating the above relationship is that the traditional, revenue-based measures of productivity for single-product firms introduce biases in our setting involving multi-product firms (Bernard et al., 2010). To address this challenge, we use a measure of quantity-based product-level productivity (Foster et al., 2008; De Loecker et al., 2016; Dhyne et al., 2017). Because our data span only one year, we cannot, as the prior literature does, rely on variation over time at the product-year-level to estimate the output elasticities of the inputs. We adapt the method developed by Levinsohn and Petrin (2003) to estimate productivity in our context where considerable cross-sectional variation exists among products within narrowly defined product markets that differ only in pack size. Our approach controls for biases related to input measurement, simultaneity, and product scope of the firm. The method may be used to estimate production function in other settings where a product is observed across its varieties.

An important limitation of this chapter is that the statistical association between productivity and competition that we document is not causal given recent studies indicate that productivity and competition are correlated (Backus, 2020). Also, although anecdotal evidence in our empirical setting suggests that the convenience of conducting cash transactions at currency price points and reaching relatively poor consumers with small pack sizes are likely the reasons for industry-wide uniform pricing (Bhat, 2011), we do not address how industry-wide uniform pricing emerged in our empirical setting (for a review of potential explanations, see Eckert and West, 2013).

The chapter proceeds as follows. Section 2.2 reviews related literature. In Section 2.3, we describe the dataset, document industry-wide uniform pricing, and discuss the methodology to estimate productivity. In Section 2.4, we present the empirical strategy and the main results on pack size. In Section 2.5, we examine other nonprice strategies. In Section 2.6, we present tests of tacit collusion. In Section 2.7, we conduct a counterfactual analysis in which firms choose optimal pack sizes and conclude in Section 2.8.

2.2 Literature review and research questions

We study how firms compete using nonprice strategies —— namely, competition on pack sizes, promotions, product availability, and product variety —— in an industry where all firms set identical prices that remain constant over time, although these firms face no regulatory constraints to set uniform prices. We refer to such pricing as industry-wide uniform pricing. We observe uniform pricing throughout the industry, that is, not only within a firm across its product and regional markets but also across all the firms within the industry.

Nonprice competition becomes more prominent when prices are inflexible. The related literature on nonprice competition can be divided into three categories. First, most studies examine nonprice competition in industries where prices also vary. For example, Prince and Simon (2015) find that service quality worsens due to a low-cost carrier's entry into the U.S. airline industry. Matsa (2011) finds that product availability improves when Walmart becomes a local competitor. Sahni et al. (2016) show that product promotions such as discounts serve as advertising. Second, prior literature also examines nonprice competition under uniform pricing. For example, Belleflamme and Paolini (2019) study the motion picture industry and find that movies, whose tickets are typically sold at uniform prices, compete on movie release dates with higher budget movies releasing closer to peak demand seasons (see also, Einav, 2007). Cabral and Natividad (2020) note that non-blockbuster movies are released during low-peak demand seasons. Third, prior literature also examines nonprice competition when regulations eliminate price competition. For example, resale price maintenance laws on books in Europe gave rise to fixed book prices, forcing retailers to compete on nonprice dimensions such as the variety of books or retailer service quality (Clay et al., 2002; Winter, 1993). However, the above literature does not feature industry-wide uniform pricing.

The most salient dimension of nonprice competition in our context is the pack size competition. In particular, firms can vary the number of grams of biscuits in the pack at a given price point. Pack size choices received limited attention in prior literature.

In an early study, Granger and Billson (1972) show that consumers switch to larger pack sizes if price per unit information becomes salient to them. Gerstner and Hess (1987) show that pack size can be used to discriminate if consumer segments have varied inventory costs. Cohen (2008) shows that nonlinearities in pricing across multiple package sizes in the paper towel industry are consistent with price discrimination. Koenigsberg et al. (2010) show that small package sizes allow consumers to more closely match their purchases with desired consumption and firms to charge a higher unit price and sell more. Smaller pack sizes can also be profitable if they bring in new consumers or increase consumption (Wansink, 1996; Jain, 2012). Studies also show that pack sizes can influence consumers' perception of the quality of products, with smaller pack sizes being perceived as having higher quality (Yan et al., 2014). Çakır and Balagtas (2014) and Yonezawa and Richards (2016) examine the consequences of package downsizing, that is, the practice of lowering the quantity per pack over time while keeping the shelf price constant or increasing it. Prahalad (2005) notes that smaller pack sizes are more suitable for rural consumers with limited purchasing power. Yet prior studies do not examine pack size competition when firms set identical prices. In a study that features uniform markups rather than industry-wide uniform prices, Miravete et al. (2020) examine the overall impact of uniform markup regulation on liquor prices in Pennsylvania. They study three bottle sizes, 375 ml, 750 ml, and 1.75 L, and show that uniform markup underprices the less-elastic 375 ml products, implicitly subsidizing lower-income consumers who strongly favor this size.

Prior literature on uniform pricing examines whether it is optimal to deviate from it. For example, Ho et al. (2018) find that deviating from uniform pricing and setting a two-tiered uniform pricing for 2D and 3D movies separately is optimal. Shiller and Waldfogel (2011) also find alternatives to uniform pricing more profitable in the market for online music, as do Cho and Rust (2010) in their study of uniform pricing in the US car rental market. By contrast, Chen and Cui (2013) show that uniform pricing can increase profits if consumers value fairness-based pricing. Recent studies find that several U.S. retail chains employ nearly uniform pricing across many product categories. Using data from the three major home-improvement retailers, Adams and Williams (2019) find that price discrimination would not benefit all the retailers. Using the Nielsen data, DellaVigna and Gentzkow (2019) show that, although uniform pricing produces a loss both to the median chain and the rural consumer, it prevents store managers from setting the wrong prices. The findings of Hitsch et al. (2019) confirm the inability of stores to distinguish demand across the local markets. Building on the above literature, we also examine the optimality of industry-wide uniform pricing. Given that pricing seems to be too inflexible to change and remains an industry-wide standard, we examine whether firms can increase their profits by setting optimal pack sizes.

To summarize our research questions, we hypothesize that if firms compete under industry-wide uniform pricing, then they offer larger pack sizes, more pack size (quantity) promotions, improved availability, and greater variety for more productive products. We test these hypotheses and the broader consequences of price inflexibility below.

2.3 Data and methodology

2.3.1 Data construction

We use Nielsen data on India's biscuit industry for the financial year 2014, which begins in April 2014 and ends in March 2015, the first financial year after Nielsen India improved their data collection procedure. India has regulations governing the packaging of goods to promote the comparability of weights and measures across competing products. Under these regulations, firms are required to print on the packaging the maximum resale price (MRP) as well as the net weight or volume for all products. Although Nielsen India collects detailed data on sales and product characteristics for several categories of products in the CPG sector, many of which exhibit industry-wide uniform pricing (Bhat, 2011), our data are limited to the largest category, namely biscuits.[1] Nielsen data contain, for each biscuit product sold in India, monthly sales revenues, and sales quantity as well as the weight of each biscuit pack in grams. Nielsen does not directly report price data. So, we compute it as the ratio of monthly revenue to the number of packs of the product sold monthly. In addition, for each product, data on pack size (quantity) promotions offered by the manufacturer and the number of retail stores that sell each product are also available. We do not, however, have any information on the individual purchases made by consumers in India.

Each product is identified by a unique stock keeping unit (SKU). A product identifies the type of biscuit and its pack size in grams. The data are disaggregated at the regional level into 21 regions, and within each region, further into urban and rural

[1] Bhat (2011) compiles an illustrative but incomplete list of CPG categories sold at five rupees in India: (a) Chocolates; (b) Bathing soaps; (c) Detergent bars; (d) Snacks; (e) Tea and coffee; (f) Shampoos; and (g) Noodles. Bose (2019) documents the continued growth of such pricing strategy across several CPGs in India. Rs. 5 is the largest price point, accounting for 55 percent of the market share in the snacks-related product categories (Singh, 2019).

areas.[2] In all, we observe 41 regional markets in the data, as 20 regions have both urban and rural areas (the exception is the national capital region, Delhi, which is entirely urban).[3] The data are further disaggregated into 12 biscuit *segments* such as cream and marie.[4] In each segment, firms offer their brands of biscuits and often multiple products of a firm share the same brand name. For each brand, where appropriate, we observe additional product characteristics such as flavor (e.g., chocolate, vanilla, or cardamom). Using these characteristics, products within the same brand-segment level can be further divided into subbrands. Within each subbrand, products are similar in all other dimensions except for pack size. We provide an example of the familiar Oreo products in Figure 2.A.1, in the Chapter Appendix.

We merge Nielsen data with firm financial data obtained from Prowess dataset, used widely in the literature (e.g., De Loecker et al., 2016). We match firm names in the two datasets and limit our econometric analysis to the top 10 matched firms, which account for 88 percent of the total sales revenue, 86 percent of sales units, and 87 percent of the total kilograms of biscuits sold in India. Table 2.A.1, Panel (A) in the Chapter Appendix, reports a comparison between the full Nielsen sample and the subsample of top 10 firms. The top 10 firms produce 4,714 products spanning 306 subbrands and 76 brands, accounting for nearly 390,000 product-region-month observations.

2.3.2 Variables and descriptive statistics

We define price per unit (Pu_{irt}) of product i in region r and month t as the ratio of monthly revenue to the number of packs of the product sold monthly.[5] As Table 2.A.1, Panel (B) in the Chapter Appendix reports, products in the sample of top

[2] Nielsen India divides the country into 21 regions, which largely coincide with India's 29 states and 9 union territories. In the following cases, each region is composed of more than one state. North-East includes Arunachal Pradesh, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim, and Tripura. Himachal-JK includes Himachal Pradesh and Jammu & Kashmir. Andhra Pradesh includes Telangana (an independent state since 2014). Delhi, a union territory, is considered as a distinct region.

[3] Nielsen India defines urban areas as places with a minimum population of 5,000, where at least 75 percent of male working population is engaged in non-agricultural sectors, and with a density of population at least 400 persons per square kilometer.

[4] Biscuit market segments are: cream, glucose, marie, milk, non-salt crackers, salt crackers, cookies, arrowroot, wafer, cereal bars, assorted, other. Compared to the former seven segments, the latter five segments have relatively fewer observations and will be gathered in our analysis into a unique segment named *other biscuits*.

[5] Since we do not directly observe price but compute it by diving sales and units, in 28 percent of the observations, Pu_{irt} is not an integer. In such cases, we round price per unit to the nearest integer. For 87 percent of the observations the price per unit is in the range of ±0.25% from the nearest integer value. See Table 2.A.2 in the Chapter Appendix for details on the extent to which rounding occurs at various price points in our data.

Table 2.1 Market share and number of products by segment and main price point

Price per unit (Pu)		Cream	Glucose	Marie	Milk	Nonsalt Cracker	Salt Cracker	Cookies	Others	Total
Rs. 5	%	49.3	49.3	8.4	20.3	33.0	35.3	39.2	18.6	37.3
	N	1485	204	155	99	317	380	623	285	3548
Rs. 10	%	20.7	15.4	31.5	44.6	42.0	36.0	19.2	2.5	24.6
	N	1062	158	277	162	407	395	766	136	3363
Rs. 15	%	2.4	0.1	8.4	0.7	0.2	3.5	2.0	1.8	2.3
	N	178	18	136	38	33	52	248	96	799
Rs. 20	%	6.2	4.2	6.3	5.5	5.8	9.5	14.2	3.4	8.2
	N	397	50	179	63	127	129	637	132	1714
Rs. 25	%	4.1	0.0	3.2	1.3	7.7	2.4	3.2	1.9	3.2
	N	332	9	171	45	79	70	388	154	1248
Rs. 30	%	4.9	0.1	1.2	7.4	1.8	3.2	5.4	6.1	3.5
	N	109	11	49	25	48	51	442	182	917
Total 5-30	%	87.6	69.0	59.0	79.9	90.5	89.9	83.3	34.3	79.2
	N	3563	450	967	432	1011	1077	3104	985	11589

Notes: *Price per unit (Pu)* is defined as the price of a biscuit pack in Indian Rupees. In the second column *%* is the market share in percent and N is the number of SKU. Total 5-30 indicates all the SKUs sold at price points Rs. 5 to 30 in multiples of five. This table is based on the Nielsen full sample from April 2014 to March 2015.Firms in the biscuit industry predominantly charge at discrete price points of Rupees (hereafter, Rs.) 5, 10, 15, 20, 25, 30. The products sold at price points 5 and 10 account for 62 percent of the total market share in our dataset from 2014. In the glucose biscuit segment, 204 different SKUs of biscuits sold at an MRP of Rs. 5 account for 49.3 percent of the segment market share and another 158 SKUs sold at Rs. 10 account for an additional 15.4 percent. Overall, the price points at which biscuits and other CPGs are sold have remained the same for over a decade, despite changes in demand and supply conditions that occur over time.

10 firms have an average Pu_{irt} of Rs. 16.7 and the median is Rs. 10. Table 2.1 shows the total market share and number of SKUs by segment and price. At Rs. 5 price point, 1,485 SKUs of cream biscuits are sold during the 12-month period, accounting for 49.3 percent of the total market share for cream biscuits. Rs. 10 price point accounts for 20.7 percent of the cream biscuit market share. Similar patterns can be observed in other biscuit segments with either Rs. 5 or 10 price point accounting for the largest share of sales across all prices. Also, in the main biscuit segments (i.e., excluding the segment "others") the market share of the products sold at Rs. 5 or its multiples is high and, in most cases, close to 90 percent. Overall, including also the prices above Rs. 30, products sold at multiples of Rs. 5 account for 81.4 percent of total biscuit industry sales.

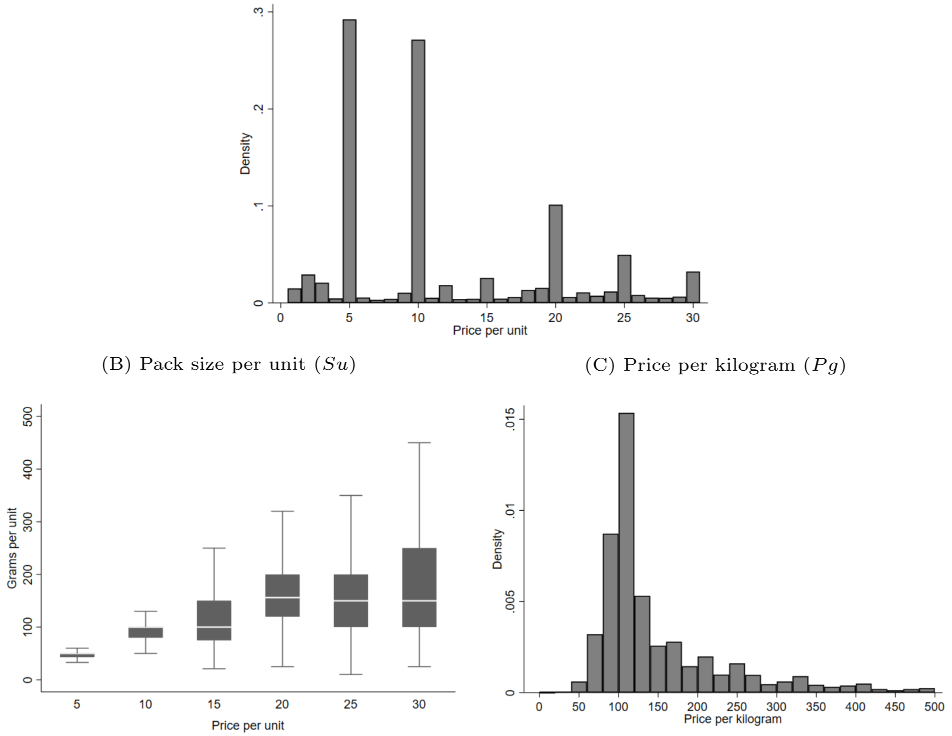
The patterns we document reveal the use of industry-wide uniform pricing at discrete price points. We further document pricing at specific points in Figure 2.1, Panel (A), which shows the distribution of prices in the overall Nielsen sample. The distribution of prices spikes sharply at Rs. 5 and 10 and relatively smaller peaks can be observed at Rs. 20, 25, and 30. At prices other than multiples of five, the frequency of products is noticeably low. Consistent with these patterns, 72 percent of the product-region-month observations are sold at a unit price that is a multiple of 5 (47 percent are sold at Rs. 5 or 10).

Figure 2.1 Price and pack size distributions

(A) Price per unit (Pu)

(B) Pack size per unit (Su)

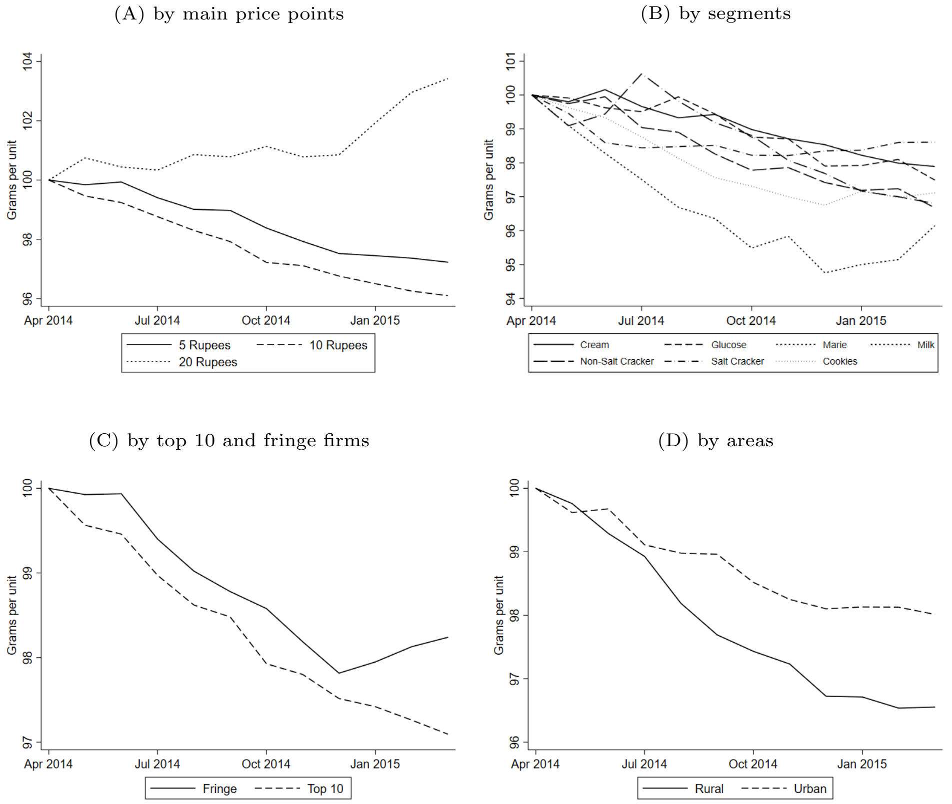
(C) Price per kilogram (Pg)



Notes: Panel (A): *Price per unit (Pu)* is defined as the price of a biscuit pack in Indian Rupees. Panel (B): *Pack size per unit (Su)* is computed as the grams of product contained in the pack. The grey area of the box plot indicates the interquartile range and the white line is the median. Upper and lower bands delimit the distributions within the 1st and 99th percentile. Panel (C): *Price per kilogram (Pg)* is defined as the price of one kilogram of product in Indian Rupees. This figure is based on the Nielsen full sample from April 2014 to March 2015.

Under industry-wide uniform pricing, we expect firms to compete on product pack size at each price point. We define pack size per unit (Su_{irt}) as grams of biscuits contained in one unit pack of product i in region r and month t. Panel (B) of Table 2.A.1 in the Chapter Appendix shows that the products of the top 10 firms have an average pack size of 116 grams and a median of 100 grams. In Figure 2.1, Panel (B), we plot the interquartile range for pack size distribution at various price points from Rs. 5 to 30. At Rs. 5, the average product contains 50 grams and about 80 grams at Rs. 10. The quantity in grams sold in a biscuit pack is not fixed at a price point but varies considerably, as shown in Figure 2.A.2 in the Chapter Appendix, consistent with pack size competition.

Figure 2.2 Pack size per unit (Su) over time



Notes: *Pack size per unit* (Su) is computed as the grams of product contained in the pack, averaged across products within the month-segment-price point. For each segment-price point average pack size takes value 100 in April 2014 (base month). Panel (A): main price points are Rs. 5, 10 and 20. Panel (B): segment "Other" is excluded. Panel (C): top 10 firms are Anmol Bakers, Britannia Inds, Glaxo Smithkline, ITC, Mondelez International, Mrs Bector Food Specialist, Parle Prods, Raja Udyog, Saj Inds, Surya Food & Agro. Panel (D): urban areas include: a) all places with a municipality/ corporation/ cantonment board/ notified town area, etc.; b) all other places with a minimum population of 5,000, where at least 75 percent of male working population engaged in non-agricultural pursuits and the density of population is at least 400 persons per square km. This figure is based on the Nielsen full sample from April 2014 to March 2015.

Large pack size differences within a given price point imply dispersion in price per pack size. We define price per kilogram (Pg_{irt}) of product i in region r and month t as price per unit to pack size scaled to one kilogram. As Table 2.A.1 in the Chapter Appendix, Panel (B) reports, the products of the top 10 firms have an average price per kilogram of Rs. 132 and a median of Rs. 105. We plot the distribution of price per kilogram in Figure 2.1, Panel (C). The distribution is more concentrated compared to the price per unit one, especially at around Rs. 100. Nearly a third of the observations fall between Rs. 90 and 110.

In our context, where unit prices do not vary, if firms keep pack sizes constant over time, they face lower margins due to rising input costs and inflation. Therefore, we expect pack sizes to decline over time, resulting in a declining price per kilogram. In Figure 2.2 we plot the average pack size across price points, segments, firm size, and by urban and rural areas and find a consistent decline over 12 months. In particular, the average pack size has decreased across the main price points, Rs. 5 and 10, by 2.5 and 4 percent respectively (see Panel A), as well as across the main segments (see Panel B). In Table 2.A.3, in the Chapter Appendix, we find that this downward trend in pack size is observed across all the firms, segments, and price points.

2.3.3 Measuring productivity

Our main explanatory variable is productivity. To estimate productivity at the product level, consider a log-additive production function (e.g., Cobb-Douglas) whose coefficients remain constant over the sample period:

$$q_{it} = \omega_{it} + \beta_k k_{it} + \beta_{\mathbf{v}} \mathbf{v_{it}} + \eta_{it} \tag{2.1}$$

where, for each product i and time t, q is log output measured in kilograms of product, k is log capital and $\mathbf{v}$ is a vector of variable inputs in logs. This function assumes product-specific production technology, implying that marginal changes in product i's input to affect only product i and not other products of the firm (De Loecker et al., 2016). Product-specific log productivity (ω) is Hicks-neutral and can be computed as a Solow residual. Because the output is measured in the physical quantity of product, as opposed to sales revenue, productivity is defined as *quantity-based*, as opposed to the *revenue-based* measure.

To compute product-level productivity we must calculate the output elasticities of the production function, β_k and $\beta_{\mathbf{v}}$. Foster et al. (2008) compute output elasticities with respect to capital and variable inputs (labor, materials, and energy) as the average input cost share over the sample. Productivity calculated using this method is known as *cost-based* productivity. This methodology is suitable for single-product firms selling homogeneous goods. However, these assumptions do not suit our context, where products vary across segments significantly and manufacturers produce multiple products.

Dhyne et al. (2017) propose a method to estimate product-level productivity that does not require any assumption on the level of competition and is suitable for multiproduct firms producing heterogeneous products. They estimate a production function for multiproduct firms that uses inputs at the firm level, relaxes the assumption of product-specific production technology, and allows marginal changes in one input to affect all the products of a firm. They control for the biases related to simultaneity and product scope of the production function by adapting the estimator developed by Levinsohn and Petrin (2003) (henceforth, LP). We build on Dhyne et al. (2017) to obtain an *estimation-based* measure of product-level productivity using a production function where variable inputs enter at the product level and capital enters at the firm level.[6]

Given that in our data we observe only one year of firm-level inputs, we cannot use the lagged variables needed to apply the LP estimator. However, for each subbrand b we observe N_b product varieties i that can be sorted in the ascending order of pack size, i.e., the variety with the smallest pack is $i = 1$ and the variety with the largest pack is $i = N_b$. We can write the production function as follows:

$$q_{bi} = \omega_{bi} + \beta_k k_f + \beta_{\mathbf{v}} \mathbf{v_{bi}} + \gamma y_{-bi} + \eta_{bi} \tag{2.2}$$

where, y_{-bi} is log revenues of all other products of the firm which are not product i of subbrand b. Following Dhyne et al. (2017), this term controls for the product scope bias and we expect its coefficient γ to be negative, as an increase in firm revenues, holding product variable inputs and firm-level capital constant, would result in a decrease in the quantity of product i.[7] To estimate the production function we have to allocate firm-level inputs to each product only for the variable inputs, given that capital is firm-specific in Equation (2.2).[8] To address the simultaneity bias we adjust the LP estimator and obtain output elasticities with respect to capital, material, and labor, separately for every segment of the biscuit market. Key assumptions to accommodate the LP estimator are: (i) the demand for the intermediate input m is dependent on firm capital and product productivity, and it is monotonically increasing in ω; (ii) the productivity of variety i differs from the average productivity

[6] In the biscuit industry, we consider raw materials and salaries as product-specific inputs because a marginal change in real raw material expenses or real salaries for product i affects the output of product i but not the output of the other products of the firm. A change in real capital expenditure, instead, being related to machinery, software, or plant space, is more likely to affect more than one product of the firm, and enters the production function at the firm level, as in Dhyne et al. (2017).

[7] Controlling for log quantities of all other products (q_{-bi}) instead of log revenues (y_{-bi}) in Equation (2.2) does not change the estimated output elasticities significantly given our uniform pricing context. However, we prefer controlling for log revenues as multiproduct firms produce heterogeneous products and their aggregation in units is questionable.

[8] To allocate variable inputs of the firm across its products, we assume that the cost of materials and labor used to produce a kilogram of a product does not vary across different pack sizes of the same subbrand. For further details, see input allocation methodology in Appendix M.2.1.1.

Table 2.2 Comparing estimation-based and cost-based production functions

		Cost-based				Estimation-based				
		β_k	β_l	β_m	β_e	β_k	β_l	β_m	γ	N
Cream		0.42	0.04	0.51	0.03	0.36	0.55	0.45	-0.15	1528
Glucose		0.24	0.04	0.67	0.05	0.25	0.58	0.42	0.13	394
Marie		0.31	0.03	0.63	0.03	0.23	0.58	0.42	0.02	391
Milk		0.37	0.05	0.56	0.02	0.52	0.84	0.16	-0.20	230
Non-salt crackers		0.27	0.04	0.65	0.04	0.98	0.76	0.24	-0.04	389
Salt crackers		0.31	0.03	0.61	0.05	0.01	0.79	0.21	-0.04	429
Cookies		0.31	0.04	0.62	0.03	0.61	0.43	0.56	-0.31	1108
	Arrowroot	0.26	0.03	0.68	0.03					53
	Assorted	0.23	0.04	0.69	0.05					143
Other biscuits	Cereal bars	0.59	0.09	0.3	0.02	0.46	0.69	0.60	-0.09	4
	Wafer	0.29	0.04	0.61	0.06					27
	Other	0.28	0.04	0.61	0.06					18
Industry average		0.34	0.04	0.59	0.04	0.43	0.59	0.43	-0.13	4714

Notes: Cost-based and the estimation-based output elasticities are calculated at the segment level. Cost-based output elasticities are calculated as the average input cost share over the sample; estimation-based output elasticities are calculated using a semiparametric estimator based on Levinsohn and Petrin (2003). Both production functions are quantity-based, having kilograms of product sold as dependent variable. Column β_k reports the output elasticity to capital, Column β_l reports the output elasticity to labor, Column β_m reports the output elasticity to materials, Column β_e reports the output elasticity to energy (only for cost-based productivity), Column γ reports the output elasticity to firm's product scope (only for estimation-based productivity). N is the number of observations. This table is based on the sample of top 10 firms from April 2014 to March 2015.

of subbrand b by a zero mean error term. We present the details of our procedure to estimate product-level productivity in Appendix M.2.1.

Table 2.2 shows the segment-level output elasticities calculated using the estimation-based method and compares them to those calculated using the cost-based method. The elasticities with respect to labor of the estimation-based method are noticeably larger than the cost-based ones. The opposite is observed for the elasticities with respect to materials. Elasticities with respect to capital, instead, are more similar. The coefficient estimate for γ that controls for the product scope of the firm is, as expected, negative in most segments. The correlation between the two measures of productivity is high at 0.57. Our preferred productivity measure is the estimation-based one, as it controls for the product scope of the firm. We use cost-based productivity for examining the robustness of our results.

As we estimate productivity using the kilograms of product sold, one might be worried about a possible mechanical relationship between pack size and the dependent variable in Equation (2). Indeed, the kilograms of product sold is given by the number of packs sold times their size in kilograms. However, productivity is calculated as the difference between the actual and the estimated kilograms, where the latter is a function of the production inputs and depends on pack size as well. Therefore, a higher pack size does not necessarily lead to higher productivity. In addition, we must consider that the number of units sold depends on product size as well, and not necessarily with a positive sign. For example, a higher pack size might be a sign of lower product appeal, resulting in lower unit sales. This seems to be the case of our sample, where the correlation between pack size and unit sales is negative for the products sold at the main price points (see Table 2.A.4 in the Chapter Appendix).

2.4 Pack size competition

2.4.1 Empirical strategy

We want to assess the role of nonprice competition under industry-wide uniform pricing. To do so, ideally one would compare two otherwise identical markets, one exhibiting price competition with fixed quantities and the other exhibiting nonprice competition with fixed prices. Yet, it is difficult to observe such markets that serve as ideal counterfactuals. Our approach, instead, is based on productivity as the driver of competition. Under price competition, product price differences stem from differences in productivity or markup of the products. Specifically, higher productivity leads to lower prices, generating selection on productivity (Syverson, 2011). Similarly, when prices are inflexible, differences in productivity among products can trigger nonprice competition. Our empirical strategy is therefore focused on how productivity affects nonprice strategies. More specifically, we want to assess if more productive products offer larger pack sizes, given that they are sold at a fixed price point. We, therefore, estimate the relationship between product-level productivity and pack size in narrowly defined product and geographic markets using the following specification:

$$log(Su_{irt}) = \alpha_1\omega_i + \alpha_2 X_{irt} + \mu_j + \eta_r + \lambda_f + \delta_t + \pi_c + \epsilon_{irt} \tag{2.3}$$

where the dependent variable $log(Su_{irt})$ is the pack size of product i in region r in month t, measured as the logarithm of grams of biscuit contained in a pack and ω_i is product-specific log productivity calculated for the financial year 2014. We include a vector of covariates X_{irt} as controls for interfirm competition (logarithm of the number of products sold in the segment-region-month-price point by firms other than firm f), intrafirm competition (logarithm of the number of products other than product i sold by firm f within the segment-region-month-price point), intrabrand competition (logarithm of the number of products other than product i sold by firm f within the same brand as product i in the segment-region-month-price point), and product age (logarithm of years since product launch). Additional controls include biscuit segment fixed effects μ_j, region fixed effects η_r, month fixed effects δ_t, and firm fixed effects λ_f. We also control for the price category in which products compete using dummies for specific price points π_c. In particular, we include dummies for Rs. 5, 10, 15, 20, 25, and 30, a dummy for all other multiples of five, and a dummy for all the remaining prices.

2.4.2 Baseline results

In Table 2.3 we report the estimates of Equation (2.3) on the sample of top 10 firms. The coefficient estimate of productivity is positive and significant across almost all the subgroups and shows that products with one standard deviation higher productivity offer, on average, 12.6 percent more quantity in the pack for the same unit price. This finding suggests that productivity can trigger competition on pack size despite the use of industry-wide uniform pricing.[9] Across the main price points — Rs. 5, 10 and 20 — products with one standard deviation higher productivity offer between 19 and 22 percent more quantity in the pack for the same unit price. In all the major segments, with the exception of the glucose segment (Column 6) where the dominance of Parle is indisputable (see Table 2.A.3, in the Chapter Appendix), products with one standard deviation higher productivity offer between 6 and 62 percent more quantity in the pack for the same unit price.

Our results show that other factors drive product pack size within the region-month, such as the number of other products competing and product age. The number of products of competing firms available in the same segment-region-month at the same price point (inter-firm competition) seems to lower pack size, however, the evidence is mixed across price points and segments. The same can be stated for the number of other products within the same firm (intra-firm competition) or within the same brand (intra-brand competition) available in the segment-region-month-price point. The positive coefficient estimates observed in Column 1 lose their significance, across price points and segments. Product age, instead, has a strong positive relationship with pack size. On average, the older the product, the larger the number of grams in the pack. The relationship is similar across price points and segments as shown in Figure 2.2 and Table 2.A.3. Our baseline results indicate that newly introduced products have lower pack size and consequently higher prices per kilogram.

[9] Controlling for the interaction among fixed effects or clustering the standard errors differently does not change the magnitude and significance of the results. The relationship between productivity and pack size remains positive when we use the cost-based productivity measure as defined in Section 2.3.3. In the first column of Table 2.A.5, in the Chapter Appendix, we estimate that products with one standard deviation higher productivity offer, on average, 27 percent more quantity in the pack for the same unit price.

Table 2.3 Competition on pack size

	Pack size per unit (Su)										
	(1) All	(2) Rs. 5	(3) Rs. 10	(4) Rs. 20	(5) Cream	(6) Glucose	(7) Marie	(8) Milk	(9) NS-Cracker	(10) S-Cracker	(11) Cookies
Productivity (ω)	0.126***	0.187***	0.178***	0.223***	0.168***	-0.127**	0.104***	0.061	0.623***	0.373***	0.230***
	(0.011)	(0.022)	(0.016)	(0.019)	(0.016)	(0.056)	(0.024)	(0.107)	(0.043)	(0.031)	(0.022)
Product age	0.098***	0.160***	0.131***	0.083***	0.066***	0.243***	0.122***	0.058*	0.130***	0.107***	0.066***
	(0.014)	(0.021)	(0.012)	(0.020)	(0.017)	(0.060)	(0.029)	(0.029)	(0.030)	(0.032)	(0.023)
Inter-firm competition	-0.047***	-0.021*	0.001	0.002	-0.016	0.023	-0.004	-0.021	0.081***	0.023	0.052**
	(0.012)	(0.013)	(0.009)	(0.013)	(0.013)	(0.029)	(0.018)	(0.021)	(0.027)	(0.023)	(0.025)
Intra-brand competition	0.035***	0.116***	0.036**	0.003	0.058***	0.416***	-0.026	0.047	0.020	0.018	0.006
	(0.013)	(0.020)	(0.015)	(0.014)	(0.010)	(0.101)	(0.054)	(0.097)	(0.033)	(0.030)	(0.022)
Intra-firm competition	0.027**	-0.088***	-0.006	-0.024	0.016	-0.316***	0.043	0.024	-0.081**	0.044	0.028
	(0.013)	(0.021)	(0.015)	(0.018)	(0.014)	(0.103)	(0.056)	(0.105)	(0.034)	(0.034)	(0.029)
Price point FE	Yes	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Segment FE	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.595	0.623	0.602	0.694	0.736	0.565	0.744	0.818	0.725	0.752	0.683
Observations	390413	99438	106913	43910	142793	26412	27476	14376	33463	32639	103537

Notes: OLS estimates, standard errors (in parentheses) clustered at the product level. The dependent variable, *Pack size (Su)*, is measured as the logarithm of grams per unit. *Productivity (ω)* is estimation-based product-level productivity standardized to have zero mean and unitary standard deviation. *Product age* is the logarithm of the years since the product was launched. *Inter-firm competition* is the logarithm of the number of products sold within the same segment-region-month-price point by competing firms, *Intra-firm competition* is the logarithm of the number of other products sold by the firm in the same segment-region-month-price point of the observed product, *Intra-brand competition* is the logarithm of the number of other products sold by the firm under the same brand within the same segment-region-month-price point of the observed product. *Price point FE* include dummies for Rs. 5, 10, 15, 20, 25, and 30, a dummy for all other multiples of five, and a dummy for all the remaining prices. This table is based on the sample of top 10 firms from April 2014 to March 2015. Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

2.4.3 Results for urban and rural markets

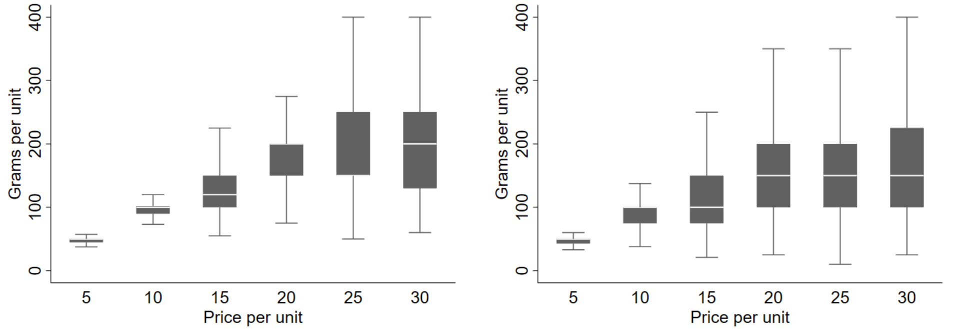
Nielsen distinguishes product sales between urban and rural areas within a state, allowing us to compare the differential use of nonprice strategies such as pack size. In theory, consumer preferences in the two areas are expected to differ and generate different levels of demand because in rural areas consumers are more budget-constrained than in urban areas. Therefore, demand is likely to be more elastic in rural areas compared to urban areas. The uniform pricing context limits a firm's ability to adjust price per unit to meet the demand in both rural and urban areas. As a result, likely the common price each firm sets for the urban and rural areas is somewhere between the willingness-to-pay of the rural and urban consumers. If rural consumers have a lower willingness-to-pay than urban consumers, this can lead to a welfare loss due to a failure of both sides of the market: in the rural areas, people consume less, and producers earn less. However, producers can adjust the price per kilogram of a product by changing the pack size. Panel (I) of Figure 2.3 compares the dispersion in pack size in grams across the main price points for urban and rural areas. For every price point, the median pack size is higher in rural areas than in urban areas. A similar difference can also be seen in Panel (II) of Figure 2.3, which compares the average price per unit between the two areas. In rural areas, a larger share of the market is for products with a price per unit of Rs. 5 than in urban areas, where the average price per unit is Rs. 12.

In Table 2.3 we show that productivity differences among products are mirrored in their pack size: the higher the productivity, the larger the pack. In a uniform pricing context, this result suggests some degree of selection on productivity as, all else equal, consumers would prefer buying larger packs for the same price. This effect might not be similar in urban and rural areas. The size of a product sold in the rural areas might depend on drivers other than productivity, like the distance from the biscuit plant or demand-specific factors. Therefore, we estimate the effect of a one standard deviation change in productivity on the pack size of the product as in Equation (2.3) for urban and rural areas. We divide the sample into products sold in urban and rural areas and report the estimates in Table 2.4. The results show that differences in productivity have a larger effect on pack size in rural areas than in urban areas. A product with a one standard deviation higher productivity offers, on average, 15-16 percent more grams per unit in rural areas (Columns 1 and 2) and 13 percent more grams per unit in urban areas (Columns 3 and 4). This difference is statistically significant at 5 percent (Column 6). In Columns 5 and 6 we also notice that in rural areas the pack size is on average 6-7 percent smaller than in urban areas.

Figure 2.3 Pack size and price distributions in urban and rural areas

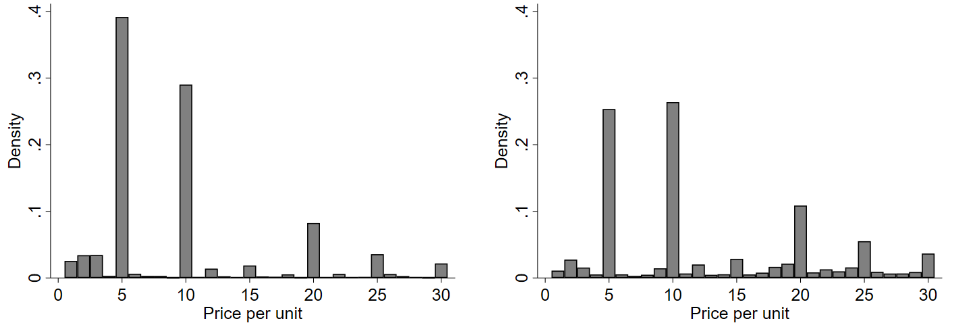
(I) Distribution of pack size per unit (Su) by main price point

(A) Rural (B) Urban



(II) Distribution of price per unit (Pu)

(A) Rural (B) Urban



Notes: *Pack size per unit (Su)* is computed as the grams of product contained in the pack. *Price per unit (Pu)* is defined as the price of a biscuit pack in Indian Rupees. The grey area of the box plot indicates the interquartile range and the white line is the median. Upper and lower bands delimit the distributions within the 1st and 99th percentile. Urban areas include: a) all places with a municipality/ corporation/ cantonment board/ notified town area, etc.; b) all other places with a minimum population of 5,000, where at least 75 percent of male working population engaged in non-agricultural pursuits and the density of population is at least 400 persons per square km. This figure is based on the Nielsen full sample from April 2014 to March 2015.

2.5 Other nonprice strategies

Pack size is one of the nonprice strategies used by biscuit manufacturers to compete. Nielsen data allow us to examine if productivity-induced competition is observed in three other nonprice dimensions: pack size promotions; product availability; and product variety. As with competition on pack size, in all these cases we expect that productivity has a positive effect on these nonprice strategies.

Table 2.4 Competition on pack size in urban and rural areas

	Pack size per unit (Su)					
	(1) Urban	(2) Urban	(3) Rural	(4) Rural	(5) All	(6) All
Productivity (ω)	0.132***	0.129***	0.150***	0.161***	0.126***	0.122***
	(0.011)	(0.011)	(0.016)	(0.015)	(0.011)	(0.011)
Productivity (ω) X Rural						0.021**
						(0.008)
Rural					-0.063***	-0.067***
					(0.012)	(0.013)
Product age		0.096***		0.098***	0.099***	0.099***
		(0.014)		(0.020)	(0.014)	(0.014)
Inter-firm competition		-0.059***		-0.106***	-0.043***	-0.044***
		(0.012)		(0.018)	(0.012)	(0.012)
Intra-brand competition		0.033***		0.072***	0.035***	0.035***
		(0.012)		(0.020)	(0.013)	(0.013)
Intra-firm competition		0.033**		-0.066***	0.030**	0.029**
		(0.013)		(0.021)	(0.013)	(0.013)
Price point FE	Yes	Yes	Yes	Yes	Yes	Yes
Segment FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.560	0.571	0.694	0.709	0.594	0.594
Observations	299891	299891	90522	90522	390413	390413

Notes: OLS estimates, standard errors (in parentheses) clustered at the product level. The dependent variable, *Pack size (Su)*, is measured as the logarithm of grams per unit. *Productivity (ω)* is estimation-based product-level productivity standardized to have zero mean and unitary standard deviation. *Rural* is a dummy taking value one when the product is sold in a rural area and zero when it is sold in a urban area. Urban areas include: a) all places with a municipality/ corporation/ cantonment board/ notified town area, etc.; b) all other places with a minimum population of 5,000, where at least 75 percent of male working population engaged in non-agricultural pursuits and the density of population is at least 400 persons per square km. *Productivity (ω) X Rural* is the interaction variable between *Productivity (ω)* and the dummy *Rural*. *Product age* is the logarithm of the years since the product was launched. *Inter-firm competition* is the logarithm of the number of products sold within the same segment-region-month-price point by competing firms, *Intra-firm competition* is the logarithm of the number of other products sold by the firm in the same segment-region-month-price point of the observed product, *Intra-brand competition* is the logarithm of the number of other products sold by the firm under the same brand within the same segment-region-month-price point of the observed product. *Price point FE* include dummies for Rs. 5, 10, 15, 20, 25, and 30, a dummy for all other multiples of five, and a dummy for all the remaining prices. This table is based on the sample of top 10 firms from April 2014 to March 2015. Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

2.5.1 Pack size promotions

Pack size promotions occur when a package is redesigned to include additional grams of biscuits, and this is advertised as a promotion. For example, some SKUs offer "20% extra" weight and others offer one or more packs for free with the purchase of a standard-size pack (e.g., "buy 2 get 1 free"). Such promotions are printed on the packaging by the manufacturers, eliminating any direct role for the retailers in such promotions. Using the same specification as in Equation (2.3), we test whether more productive products offer more pack size promotions. We employ two alternative dependent variables: i) a dummy variable taking value one when the product is offered on pack size promotion; and ii) the quantity in kilograms of the product offered as pack size promotion. The first measure captures the probability that a product receives pack size promotion, i.e., the *extensive margin*, and the second measure captures the extent of pack size promotion, i.e., the *intensive margin*.

Columns 1 and 2 of Table 2.5 report the results of the relationship between productivity and pack size promotions and shows that productivity is positively related to the extensive margin of pack size promotions. Indeed, the probability that a product is sold with a pack size promotion is 5.4 percent higher if its productivity is one standard deviation higher. Column 1 shows also that in rural areas it is 3.2 percent more likely to find a product with pack size promotion than in urban areas. Conditional on being sold with a pack size promotion, a product with one standard deviation higher productivity increases the extent of the promotion by 28 percent in the urban areas and 4 percent in the rural areas. However, pack size promotions are 106 percent larger in rural areas than in urban areas (Column 2). These results are consistent with competition on pack size promotions under industry-wide uniform pricing.

2.5.2 Product availability

Next, we test whether the availability of a product in a regional market depends on its productivity. As shown in Figure 2.3, the distribution of products sold is less dispersed in rural areas, indicating lower availability of products in rural areas compared to urban areas. Indeed, the number of products sold in rural areas is two-thirds that of the urban areas, indicating that rationing the availability of products in rural areas is a nonprice strategy employed in the biscuit industry.

We use the same specification as in Equation (2.3) and measure product availability using two different dependent variables: i) a dummy variable taking the value one when the product is sold in a regional market; and ii) the percentage of stores that sell the product in the regional market. The first measure of availability takes into consideration all the regional markets, including those in which the product is not sold and, therefore, for which there is no observation. The dummy variable for availability takes the value zero when a product is not available in a regional market. Overall, this measure expresses the probability that a product is available in the regional market, i.e., the *extensive margin*. The other measure is calculated on products that are effectively available and captures the extent to which the product is available, i.e., the *intensive margin*.

Columns 3 and 4 of Table 2.5 report the results of the relationship between productivity and product availability and show that productivity is positively related to both the extensive and intensive margins of product availability in rural areas.

Table 2.5 Competition on other nonprice strategies

	Pack size promotions		Product availability		Product variety	
	(1) Probability	(2) Kilograms for free	(3) Probability	(4) Stores (%)	(5) Number	(6) Std. Dev.
Productivity (ω)	0.054***	0.277**	-0.058***	0.309**	0.094***	0.146***
	(0.007)	(0.133)	(0.004)	(0.135)	(0.032)	(0.055)
Productivity (ω) X Rural	0.003	-0.231**	0.090***	0.139	0.035	0.113**
	(0.005)	(0.096)	(0.005)	(0.118)	(0.027)	(0.049)
Rural	0.032***	1.063***	-0.495***	1.351***	-0.582***	-0.688***
	(0.009)	(0.128)	(0.001)	(0.210)	(0.036)	(0.053)
Product age	-0.157***	-2.481***	-0.066***	-2.575***		
	(0.013)	(0.202)	(0.003)	(0.195)		
Inter-firm competition	0.025***	-0.069	-0.114***	0.456***		
	(0.008)	(0.098)	(0.003)	(0.148)		
Intra-brand competition	0.059***	0.324*	0.008**	0.355		
	(0.012)	(0.192)	(0.004)	(0.220)		
Intra-firm competition	-0.023*	0.074	-0.065***	0.164		
	(0.014)	(0.187)	(0.004)	(0.209)		
Price point FE	Yes	Yes	Yes	Yes	No	No
Segment FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
R2		0.268		0.086	0.147	0.107
Observations	384788	47531	584852	390414	73119	73119

Notes: Probit average marginal effects (column 1 and 3) and OLS (column 2 and 4-6) estimates, standard errors (in parentheses) clustered at the product level. Every nonprice strategy is measured in two different ways. For the pack size promotions strategy the dependent variables are: (1) *Probability* is a dummy taking value one when the product is offered on value promotion; (2) *Kilograms for free* is the logarithm of the kilograms of product given for free as volume promotion. For the product availability strategy the dependent variables are: (3) *Probability* is a dummy taking value one when the product is sold (observed) in a region-month and zero when it is not; (4) *Stores (%)* is the percentage of shops that sell the product in the region-month. For the product variety strategy the dependent variables are: (5) *Number* is the logarithm of the number of different pack sizes of a subbrand in a month-region market; (6) *Std. Dev.* is the logarithm of the standard deviation of the pack size within a subbrand in a month-region market. In column 1-4, *Productivity (ω)* is estimation-based product-level productivity standardized to have zero mean and unitary standard deviation. In column 5-6, *Productivity (ω)* is average productivity of the subbrand, measured as a weighted average of all estimation-based productivities of the products within the subbrand, standardized to have zero mean and unitary standard deviation. *Rural* is a dummy taking value one when the product is sold in a rural area and zero when it is sold in a urban area. Urban areas include: a) all places with a municipality/ corporation/ cantonment board/ notified town area, etc.; b) all other places with a minimum population of 5,000, where at least 75 percent of male working population engaged in non-agricultural pursuits and the density of population is at least 400 persons per square km. *Productivity (ω) X Rural* is the interaction variable between *Productivity (ω)* and the dummy *Rural*. *Product age* is the logarithm of the years since the product was launched. *Inter-firm competition* is the logarithm of the number of products sold within the same segment-region-month-price point by competing firms, *Intra-firm competition* is the logarithm of the number of other products sold by the firm in the same segment-region-month-price point of the observed product, *Intra-brand competition* is the logarithm of the number of other products sold by the firm under the same brand within the same segment-region-month-price point of the observed product. *Price point FE* include dummies for Rs. 5, 10, 15, 20, 25, and 30, a dummy for all other multiples of five, and a dummy for all the remaining prices. This table reports elaborations on the sample of top 10 firms from April 2014 to March 2015. Column 1, 4-6 are estimated on the full subsample. Column 2 is estimated only on the observations that are offered on volume promotion. Column 4 are estimated on the full subsample, incremented by the product-region-month missing observations, i.e. those where the product is not observed as it has zero sales. This table is based on the sample of top 10 firms from April 2014 to March 2015. Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

These effects are driven by the products available in rural areas, as the probability that a product is available in urban areas is negatively related to its productivity (Column 3). Conditional on being sold in a certain region- month, a product with a one standard deviation higher productivity can be found in 0.3 percent more stores

(Column 4). On the intensive margin, productivity has the same effect on product availability in rural areas as in urban areas, where they can be found in 1.35 percent more stores than in urban areas (Column 4). In other words, once a product reaches the rural market it is available in more stores than in the urban areas. These results suggest that, although fewer products compete in the rural areas, their degree of productivity-based competition is not necessarily lower than in the urban areas.

2.5.3 Product variety

Product variety is another important nonprice dimension. On average, a product has 15 other pack size varieties within the subbrand (products within a subbrand differ only by their pack size). We test whether the product variety of a product depends on the average productivity of its subbrand. We measure product variety in two ways: i) as log number of different pack sizes of the product within the subbrand in a region-month market, and; ii) as log standard deviation of the pack size within the subbrand in a region-month market. The average productivity of the subbrand is measured as the weighted average of all estimation-based productivities of the products within the subbrand.

Columns 5 and 6 of Table 2.5 show that productivity is positively related to product variety. One standard deviation higher productivity at the subbrand level increases the number of varieties by 9.4 percent (Column 5) and the standard deviation of the pack size distribution by 14.6 percent (Column 6). Relative to the urban areas, in rural areas the pack size range is 58 percent smaller (Column 5), and the standard deviation of the pack size distribution is 69 percent smaller (Column 6), consistent with our descriptive evidence that product variety is lower in rural areas compared to urban areas.

We find that the above results relating to pack size promotion, product availability, and product variety are robust to using the cost-share-based measure of productivity (see, for details, Table 2.A.5 in the Chapter Appendix).

2.6 Coordination tests on nonprice characteristics

2.6.1 Collusion on pack size

We interpreted the results that more productive products offer larger pack sizes and more pack size promotions for a given price and have higher product availability and variety as evidence of robust nonprice competition. Yet it is possible that firms coordinate on nonprice strategies to limit competition (Brod & Shivakumar, 1999; Dewenter, Haucap, & Wenzel, 2011; Fershtman & Gandal, 1994; Steen & Søgard, 1999, Sullivan, 2020), and particularly so under industry-wide uniform pricing. To investigate whether pack size choices of firms in our data are consistent with potential collusive behavior, we examine the role of multimarket contact. In the spirit of Bernheim and Whinston (1990), we consider multimarket contact as a facilitator of collusion among firms and test whether greater multimarket contact is associated with lower pack size variability between pairs of firms in a market. We define each of the segment-region-price point combinations as a market and compute multimarket contact following Evans and Kessides (1994), MMC^{EK}, as the number of other markets that two firms that meet each other in a focal market also serve in a month. For robustness, we also consider the measure of multimarket contact proposed by Ciliberto and Williams (2014), MMC^{CW}, which equals MMC^{EK} divided by the total number of markets served by one of the firms in the pair.[10]

Following Ciliberto et al. (2019), we conduct two tests to examine whether firms with greater multimarket contact coordinate on nonprice strategies under industry-wide uniform pricing. The first test is based on the hypothesis that pack size differences between firms decrease in multimarket contact. The dependent variable, ΔSu, is computed for every firm pair-market- month as the absolute value of the difference between the pack sizes of the two firms in the pair. The pack size of each firm is defined as the average pack size across all its products within the market-month. We regress pack size difference on multimarket contact controlling for productivity differences between the firms, Herfindahl–Hirschman index, market, month, and firm pair fixed effects. The second test is based on the idea that greater multimarket contact reduces, over time, pack size variability within a firm pair. The dependent variable, CV, is a coefficient of variation in pack size computed for every firm pair-market as the ratio between the standard deviation of an average pack size of the firm pair-month, and its annual mean. The average pack size of the pair is weighted by the share of units sold by each firm. Controlling for yearly averaged productivity differences between the firms in the pair, Herfindahl–Hirschman index, market, and firm pair fixed effects, we regress the coefficient of variation on multimarket contact. We report the results in Table 2.6. The coefficient estimates associated with multimarket contact are not statistically significant in any of the specifications

[10] MMC^{EK} is calculated at the firm pair-market-month level, whereas MMC^{CW} is calculated at the level of firm-market-month, given that the denominator can take the value of either the first or the second firm in the pair. Therefore, we drop one of the firms in each pair when using MMC^{EK} in the tests of collusion, which results in a halving of the regression sample.

Table 2.6 Tests for tacit collusion on pack size

	Pack size difference (ΔSu)			Pack size rigidity (CV)		
	(1)	(2)	(3)	(4)	(5)	(6)
MMC^{EK}	-0.048	-0.025		-0.024	-0.024	
	(0.099)	(0.098)		(0.036)	(0.037)	
MMC^{CW}			0.000			-0.402
			(0.002)			(0.246)
Δ Productivity (ω)		0.246***	0.246***		0.014***	0.014***
		(0.017)	(0.017)		(0.002)	(0.002)
Herfindahl–Hirschman Index	0.008	0.012	0.012	0.094**	0.096**	0.095**
	(0.052)	(0.051)	(0.051)	(0.044)	(0.044)	(0.044)
Region-segment-price point FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	No	No	No
R2	0.487	0.500	0.500	0.434	0.440	0.446
Observations	144330	144330	288836	16708	16708	34054

Notes: OLS estimates, standard errors (in parentheses) clustered at the segment-region-price point level. The table reports two tests of collusion following Ciliberto et al. (2019). Columns 1-3 test tacit collusion on pack size difference (ΔSu), the absolute value of log pack size difference for a firm pair in a region-segment-price point-month. Pack size is measured as the average grams of biscuit included in a pack by a firm across all its products sold within a region-segment-price point-month. MMC^{EK} is from Evans and Kessides (1994): the number of markets (defined as region-segment-price point) that two distinct firms concomitantly serve at the same time. MMC^{CW} is MMC^{EK} divided by the total number of markets served by one of the firms in the pair (Ciliberto and Williams, 2014). Δ Productivity (ω) is the absolute value of the difference in average productivity of a firm pair within a region-segment-price point-month. Columns 4-6 test tacit collusion on pack size rigidity: CV is market-specific coefficient of variation of a firm pair, computed as the ratio between the standard deviation of the pair-specific average pack size in the region-segment-price point over time, and its mean over time. This table is based on the sample of top 10 firms from April 2014 to March 2015. Significance: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

related to the two tests, indicating that the pack size choices are unaffected by the extent of multimarket contact. By contrast, consistent with our previous findings on nonprice competition, pack size differences between pairs of firms are driven by the differences in average productivity levels between firms.

2.6.2 Market splitting and leadership concession

Firms in our context, particularly the big three which account for two-thirds of the market share, can coordinate on splitting the market by segments or regional markets. For example, *Parle*, *Britannia*, and *ITC* can tacitly develop the understanding to dominate the markets for cream, glucose, and salt biscuit segments respectively. Similarly, *Parle* can focus on urban markets whereas *Britannia* and *ITC* focus on rural markets. Such coordination can, in theory, also extend to pack size choices, pack size promotions, product availability, and varieties. For example, in markets where *Parle* is the dominant player and promotes its product, market followers might decide to not compete aggressively by avoiding promotions in exchange for cooperation in other markets. In a recent study, Sullivan (2020) notes that the nonprice

Table 2.7 Coordination on nonprice strategies

	Leader			
	Pack size	Pack Size Promotions	Availability	Variety
	(1) Grams per pack (Su)	(2) Kilograms for free	(3) Stores (%)	(4) Number
Main follower	0.297***	0.166***	0.327***	0.219***
	(0.051)	(0.051)	(0.048)	(0.032)
Second follower	0.176***	0.076**	0.417***	0.220***
	(0.047)	(0.037)	(0.091)	(0.031)
Region-segment-price point FE	Yes	Yes	Yes	Yes
Firm FE, Month FE	Yes	Yes	Yes	Yes
R2	0.758	0.382	0.426	0.675
Observations	13851	13851	13851	13851

Notes: OLS estimates, standard errors (in parentheses) clustered at the segment-region-price point level. Each column indicates a nonprice strategy: (1) *Grams per pack (Su)* is log average grams of biscuit included in a pack by a firm across all its products sold in the segment-region-price point-month; (2) *Kilograms for free* is the kilograms of product given for free as volume promotion; (3) *Stores (%)* is the mean percentage of stores that sell the products of the firm in the segment-region-price point-month; (4) *Number* is log number of different products sold by the firm in the segment-region-price point-month. The dependent variables are the *Leader*'s value of the measure of nonprice competition indicated in each column. The explanatory variables are the *Main follower* and *Second follower*'s value of the measure of nonprice competition indicated in each column. *Leader*, *Main follower* and *Second follower* are defined as the firms with, respectively, the highest, second highest and third highest market share in the segment-region-price point-month. This table is based on the sample of top 10 firms from April 2014 to March 2015. Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

strategies of the two main competitors in the US ice cream market, Ben & Jerry's and Häagen-Dazs, are consistent with tacit collusion. In particular, Ben & Jerry's and Häagen-Dazs developed distinct product styles—chunky and smooth, respectively—and avoided entering each other's product spaces.

On the contrary, in our context we find anecdotal evidence that the big three firms introduce new products constantly and often imitate each other's new product offerings, leading them to sometimes sue each other (Sethi, 2016; Prasad, 2018). An analysis of the extent of product differentiation by market segment and price point shows considerable overlap among the top 10 firms (Figure 2.A.3, in the Chapter Appendix). A similar analysis of flavors within the cream biscuit segment, plotted in Figure 2.A.4, in the Chapter Appendix, further indicates significant overlap, particularly in major flavor markets (chocolate, orange, and cardamom).

We examine whether the nonprice strategies of the big three firms are positively or negatively correlated in a regional market. If the market leader in a segment-region-price point market offers more grams, market followers lowering their grammage would indicate less aggressive competition. On the contrary, if the market leader's competitive actions are reciprocated, then we would see a positive correlation. We limit the sample of firms to the big three and define a market leader as the firm that has the largest market share in a segment-region-month-price point. The other two firms are considered market followers. The identity of the market leader and followers changes significantly over the 41 regional markets and segments in our data. We estimate the correlation between leaders' actions and followers' actions across pack sizes, pack size promotions, product availability, and varieties. The results are shown in Table 2.7. We find positive correlations across all four columns in Table 2.7, indicating that market leaders and followers have similar nonprice strategies within a market. This evidence is not consistent with tacit coordination among the big three firms in the industry, although we cannot rule out that firms are tacitly colluding to maintain industry-wide uniform pricing.

2.7 Revenues and profits with optimal pack size

In this section, we examine how firm profits are affected by the optimal choice of pack sizes. We use a simple demand model, in which firms compete on pack size, to calculate the optimal pack size and show the effect on revenues and profits if these optimal strategies were adopted. Our purpose here is not to build a model that explains our empirical evidence but to conduct counterfactual analyses assuming competition on pack sizes.

2.7.1 Optimal pack size and price elasticity

The method we use is similar to the one employed by DellaVigna and Gentzkow (2019) although they focus on optimal prices and not pack sizes. In the biscuit industry, price per unit Pu_i of product i is bound to a few price points. At a given price point $\overline{Pu}_i$, however, firms can choose an optimal pack size measured in kilograms per unit Su_i^* and, consequently, an optimal price per kilogram Pg_i^*, given that $\overline{Pu}_i = Su_i \cdot Pg_i$. A monopolistically competitive firm f chooses a pack size Su_{ir} for each product i in region r to maximize total profits. The model, described in Appendix M.2.2, follows DellaVigna and Gentzkow (2019) and defines the optimal pack size as:

$$Su_{ir}^* = \frac{\overline{Pu}_{ir}}{cg_{if}} \frac{1 + \theta_{ir}}{\theta_{ir}} \tag{2.4}$$

where θ_{ir} is price elasticity of product i in region r and 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.[11]

[11] 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 compare the observed pack size with the optimal one in Equation (2.4) we need measures of the price elasticities of demand θ_{ir} and of the marginal costs cg_{if}. We estimate price elasticity for each segment-region-price point separately using the following log-linear demand specification, which also controls for firm fixed effects λ_f and month fixed effects δ_t:

$$log(Qg_{irt}) = \theta_{jrc} log(Pg_{irt}) + \lambda_f + \delta_t + \epsilon_{irt} \tag{2.5}$$

where Qg_{irt} is the quantity in kilograms of product, calculated as the number of packs sold times the pack size in kilograms, and Pg_{irt} is the price per kilogram. Because a demand shock for product i might stimulate a price increase, OLS estimates of the coefficient $\hat{\theta}_{jrc}$ may be positively biased. Following Foster et al. (2008), we instrument prices with quantity-based product-level productivity, a supply-side driver of prices embodying information on a firm's cost of production (see, also, Aw and Lee, 2014; Foster et al., 2016). Indeed, productivity is a measure of technical efficiency which is unlikely to be correlated with idiosyncratic product-specific demand shocks in the short run.[12]

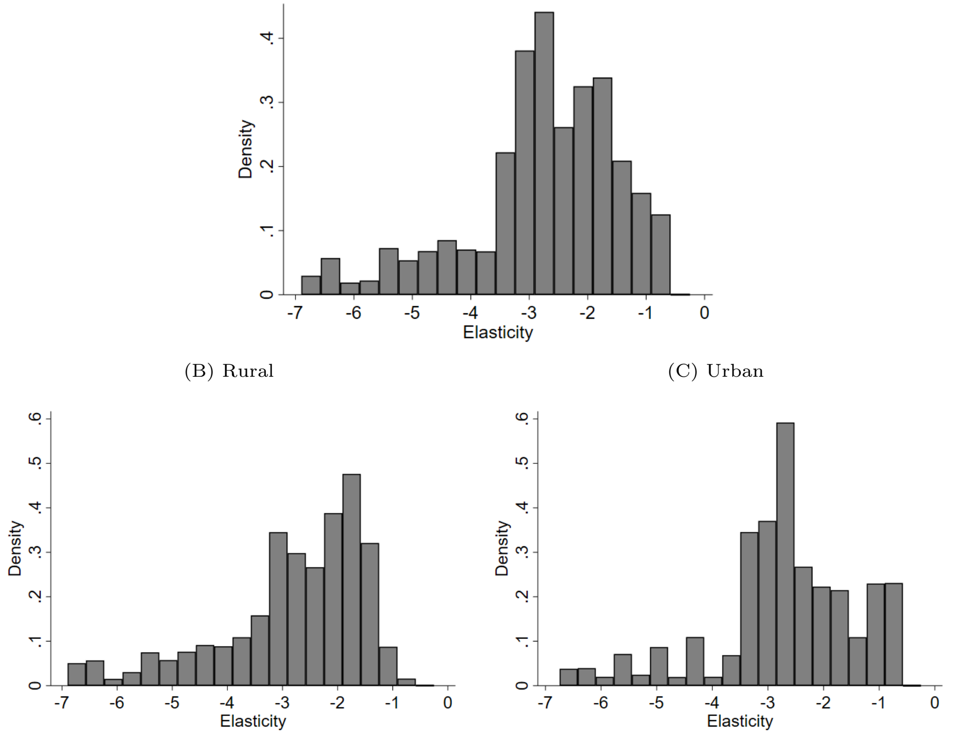
Panel (A) of Figure 2.4 shows the distribution of price elasticities estimated at the segment-region-price point level that are statistically different from zero with a 95 percent probability. These estimates range mostly between -1 and -4 and are consistent with others reported in the literature for food-related items (Coloma, 2011; DellaVigna and Gentzkow, 2019). Consumer preferences in rural areas are different from those in urban areas. Panels (B) and (C) of Figure 2.4 show that the distribution of price elasticity in rural areas has a thicker left tail and lower density in the neighborhood of -1, relative to the urban areas. In the uniform pricing context, a more elastic demand with respect to price per kilogram in the rural areas implies a lager consumer response to pack size differences. In Appendix M.2.2 we show that demand in rural areas is 0.75 percentage points more elastic than in urban areas, consistent with our expectation.

to the fixed costs at the product-region level.

[12] As discussed in Foster et al. (2008), the use of productivity as an instrument can be questioned for two reasons. First, if higher productivity leads to a higher probability of survival when drawing a negative demand shock, then lagged productivity and demand might be negatively correlated for surviving products, violating the instrument exogeneity assumption. However, we observe only one year, and a bad draw in such a short period can be cross subsidized by the other products of the firm. Second, measurement error in estimating productivity can undermine the validity of the instrument. Such measurement error can arise if quantities are not directly observed but instead calculated by dividing sales by prices. Because we directly observe quantities in kilograms of the product sold, measurement error is less of a concern in our study.

Figure 2.4 Elasticities by segment-region-price point

(A) All areas



Notes: Distributions of the elasticities estimated at the segment-region-price point level using the IV estimator, as from Equaiton (2.5). Products are grouped in 8 segments, 41 regions and 8 price categories. We keep the elasticities whose estimated value is significantly different from zero with a probability of 95 percent. All figures reports estimates on the sample of top 10 firms from April 2014 to March 2015. Panel (A): distribution of all elasticities estimated. Mean=-2.76, median=-2.64, interquartile range=1.44. Panel (B): distribution of all elasticities estimated in rural areas. Mean=-2.82, median=-2.49, interquartile range= 1.54. Panel (C): distribution of all elasticities estimated in urban areas. Mean=-2.71, median=-2.64, interquartile range=1.35

2.7.2 Counterfactual analysis

Once the price elasticities of demand $\hat{\theta}_{jrc}$ are estimated, we need a measure of the marginal costs of the product cg_{if} to estimate the optimal pack size using Equation (2.4). We proxy the marginal costs of the product with the lowest price per kilogram within the subbrand, calculated as the minimum price per kilogram across all its varieties. The optimal pack size is, therefore, computed as:

$$\widehat{Su}^*_{irt} = \frac{\overline{Pu}_{irt}}{\min_{i\epsilon b} Pg_{it}} \frac{1+\hat{\theta}_{jrc}}{\hat{\theta}_{jrc}} \tag{2.6}$$

Using the estimated optimal pack size, we can compute optimal demand, sales revenues and profits at the product-region level.[13] Table 2.8 reports the comparison of sales revenues, and profits between the observed pack size and the optimal pack size for the main price points: Rs. 5, 10 and 20. Among the products varies across segments between -0.5 and -4.8. sold at Rs. 5 the median pack size is 50 grams. The median optimal pack size, as calculated from Equation (6), would be 39 grams (Column 5). As the optimal pack size is lower than the observed one, the median product would have lower demand and, notwithstanding the higher price per kilogram, its sales would decrease by 12 percent (Column 11). However, a lower pack size means lower unit costs, implying a 25 percent increase in product median profits (Column 14). Among the products sold at Rs. 10 or 20 the optimal median pack size is larger than the observed one (13 percent and 8 percent, respectively). This would imply an increase in demand for those products that offsets the contribution of the lower price per kilogram, causing median sales to increase by 27 percent for Rs. 10 price point and 15 percent for Rs. 20 price point. Although unit costs increase with pack size, higher demand would increase product median profits by 20 percent for Rs. 10 price point and 17 percent for Rs. 20 price point.

Next, we compute the optimal pack size separately for urban and rural areas and estimate the difference in product revenues and profits between the optimal and the observed pack size. We show the results of the counterfactual analysis for the main price points in Table 2.8. Among the products sold at Rs. 5 the median pack size is again 50 grams. The median optimal pack size, as calculated from Equation (2.6), would be 39 grams in rural areas and 40 grams in urban areas. As the optimal pack size is lower than the observed one in both rural and urban areas, the median product would receive less demand and its sales would decrease, notwithstanding the higher price per kilogram. The decrease in unit costs given by the reduction in pack size leads to a 19 percent and 17 percent increase in product median profits for rural and urban areas respectively. Among the products sold at Rs. 10, the difference in price elasticities between the two areas causes the optimal median pack size to be larger in the urban areas (111 grams) than in the rural areas (98 grams). This difference in optimal pack size is mirrored in the median optimal product revenues, which are 43 percent higher than the observed revenues in urban areas and only 14 percent higher than the observed revenues in rural areas. The higher optimal pack size causes unit

[13] Following DellaVigna and Gentzkow (2019) we calculate optimal demand for product i in region r as $\widehat{Qg}^*_{ir} = \widehat{G}_{ir}\left(\frac{\overline{Pu}_{ir}}{\widehat{Su}^*_{irt}}\right)^{\hat{\theta}_{jrc}}$, where the product-region scale factor $\widehat{G}_{ir}$ is calculated as $Qg_{ir} \cdot \left(\frac{Su_{ir}}{\overline{Pu}_{ir}}\right)^{\hat{\theta}_{jrc}}$, using yearly averages of the observed quantity sold at the product-region level (Qg_{ir}).

Table 2.8 Product revenues and profits with optimal pack size

$\overline{Pu}$	Su	Su^*			$\frac{Su^*}{Su}$			$\frac{\overline{Pu}Qu^*}{\overline{Pu}Qu}$			$\frac{\Pi^*}{\Pi}$		
(1) All	(2) All	(3) Rural	(4) Urban	(5) All	(6) Rural	(7) Urban	(8) All	(9) Rural	(10) Urban	(11) All	(12) Rural	(13) Urban	(14) All
5	50	39	40	39	0.86	0.92	0.87	0.87	0.90	0.88	1.19	1.17	1.25
10	100	98	111	104	1.08	1.21	1.13	1.14	1.43	1.27	1.21	1.19	1.20
20	150	187	178	180	1.14	1.06	1.08	1.27	1.12	1.15	1.24	1.14	1.17

Notes: This table reports the median value of the distribution of the variables indicated in the top row, for Rs. 5, 10, and 20 price points distinguishing between urban and rural areas. The variables of interest are respectively: actual pack size in grams (Su), optimal pack size in grams (Su^*), ratio between optimal and actual pack size (Su^*/Su), ratio between optimal and actual sales revenues ($\overline{Pu}Qu^*/\overline{Pu}Qu$), ratio between optimal and actual profits (Π^*/Π). Actual pack size, sales revenues and profits are those observed in the sample of top 10 firms from April 2014 to March 2015. Optimal pack size, sales revenues and profits are calculated using IV-estimated price elasticities at the segment-region-price point level and assuming monopolistic competition.

costs to be higher in the urban areas than in the rural areas, implying that the large difference in median optimal revenues between the two areas almost cancel out. Among the products sold at Rs. 20, the optimal median pack size is larger than the observed one for both areas. This leads to an increase in median sales and profits by 24 percent in the rural areas and 14 percent in the urban areas.

2.8 Conclusion

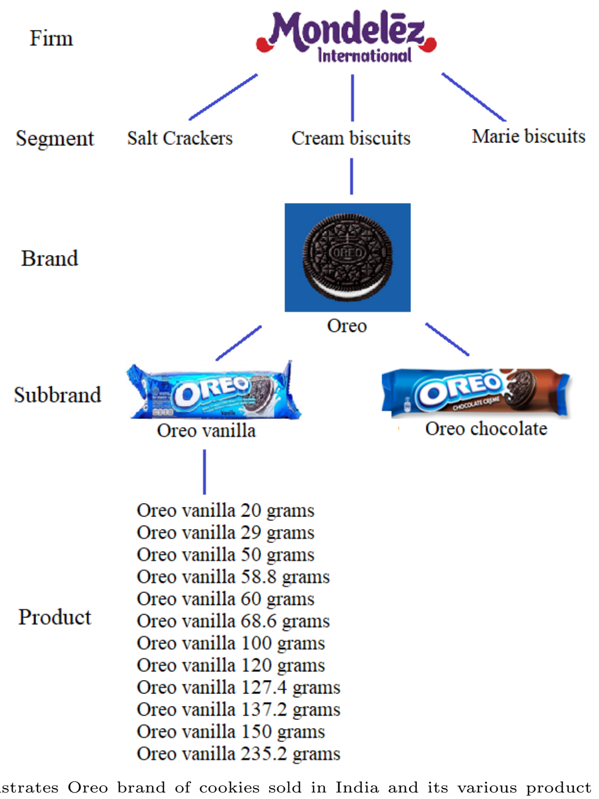
We examined the case of an industry where all firms set identical prices, raising questions about the competitiveness of such an industry structure. We find evidence that despite direct price competition being entirely foreclosed, firms compete on several nonprice dimensions, such as pack size, pack size promotions, availability, and variety. We find that products with one standard deviation higher productivity offer, on average, 13 percent more quantity per pack for the same price. Productivity also positively affects other nonprice strategies such as promotions on pack size, product availability, and product variety.

The use of industry-wide uniform pricing, however, implies that urban and rural consumers with different demand elasticities for pack size pay a common price for a common pack size of a given product, leading to potential welfare losses for the rural consumers. We also 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 set identical prices. However, when small packaging strategies aimed at rural consumers are combined with industry-wide uniform pricing strategies, they do not always benefit the consumers in rural areas.

Our study has several limitations. First, our study employs data for one financial year and one product category, and it does not fully quantify the welfare consequences of industry-wide uniform pricing. Although the pattern of results we obtain does indicate that consumption inequality can arise from nonprice strategies even when all firms set identical prices, we do not quantify the extent of such inequality. Second, although we examine several nonprice strategies, we do not assess their relative importance for competition. Nevertheless, our focus on pack size is reasonable, as prior studies show price and quantity promotion strategies may be less relevant in emerging economies compared to developed economies (e.g., Mathur and Sinitsyn, 2013; Desai et al., 2012). Third, we do not model how retailers influence competition under industry-wide uniform pricing. It is reasonable to do so in our context as retailers play little role in price-setting or promotional strategies. For example, retailers do not offer pack size promotions of their own in our empirical setting. However, future studies examining industry-wide uniform pricing and nonprice strategies in other contexts such as dollar store chains may have to pay attention to the relationship between manufacturers and retailers and distinguish competitive strategies of retailers from those of the manufacturers themselves. Fourth, quality remains an omitted variable in our analyses. For example, one may argue that controlling for product quality might weaken the relationship between productivity and pack size. However, we do not have a useful proxy to measure quality. Also, our measure of quantity-based productivity partly accounts for the differences in input quality. Specifically, we impute variable input allocation across products using output prices, which can reflect product quality (Khandelwal, 2010; Atkin et al., 2019). Finally, we do not examine why prices are inflexible in our empirical context, which requires a much longer panel spanning several years if not decades. These issues remain useful avenues for future studies.

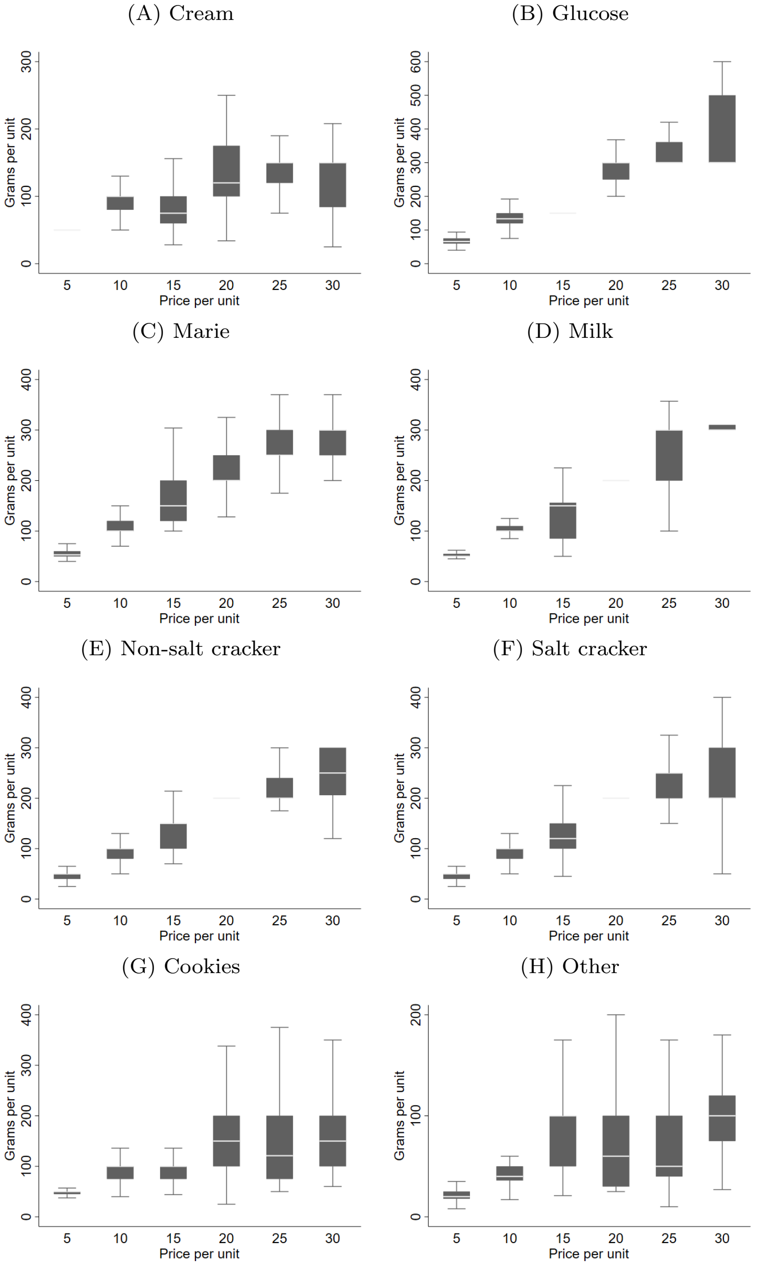
2.A Additional Tables and Figures

Figure 2.A.1 The OREO product family tree



Notes: The figure illustrates Oreo brand of cookies sold in India and its various product varieties. Mondelez's Oreo brand entered India in 2011 and in 2014 it accounts for 6.8 percent of the cream biscuit market share and 1.3 percent of the overall biscuit industry market share. It produces six subbrands: Vanilla, Chocolate, Orange, Roast Almond, Strawberry and Assorted. Vanilla subbrand accounts for 49 percent of the overall share and the prices on average correspond to Rs 5 (20 grams), Rs 10 (50 grams), Rs 200 (100 grams), Rs 30 (150 grams). According to the president of Mondelez India, rural areas contribute 20 percent to the sales of Mondelez, with small pack sizes driving its sales (Bose, 2019).

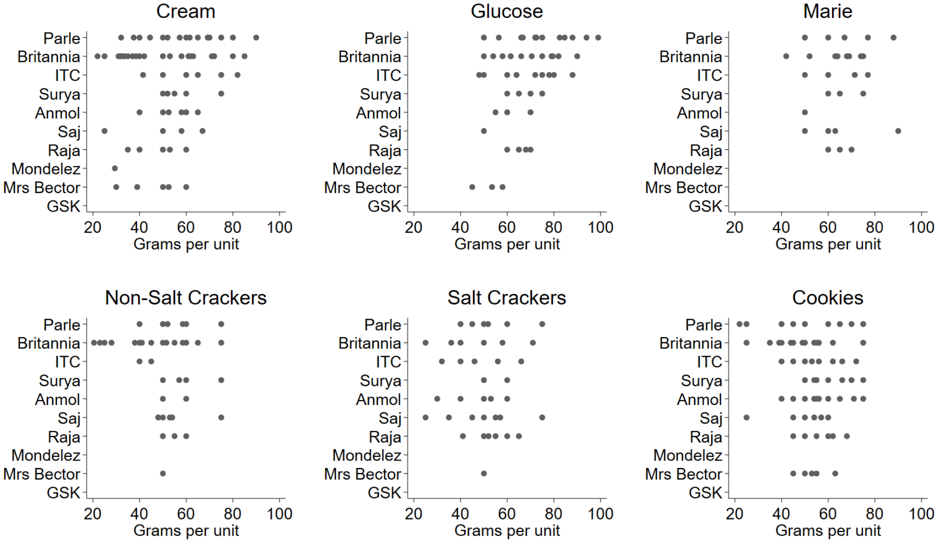
Figure 2.A.2 Distribution of pack size (Su) by main price point and segment



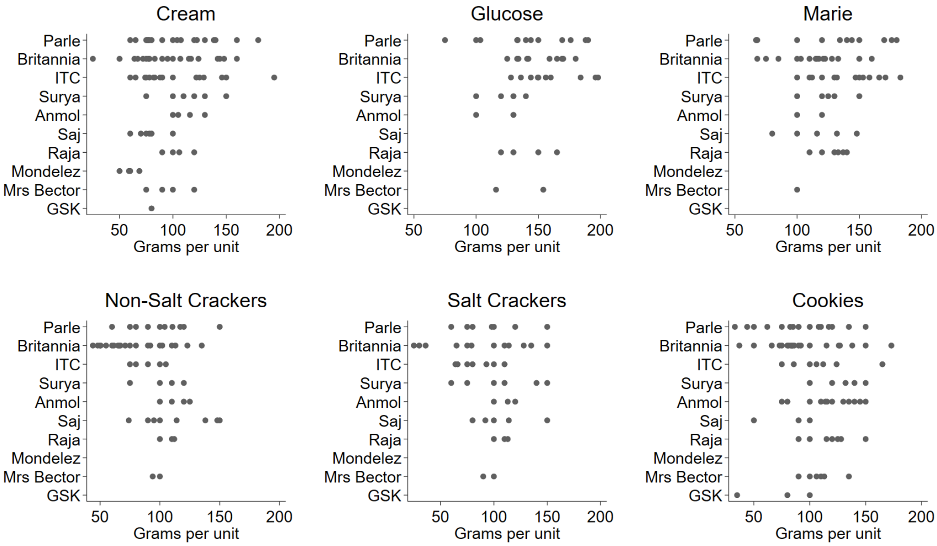
Notes: *Pack size (Su)* is computed as the grams of product contained in the pack. *Price per unit (Pu)* is defined as the price of a biscuit pack in Indian Rupees. The grey area of the box plot indicates the interquartile range and the white line is the median. Upper and lower bands delimit the distributions within the 1th and 99th percentile. The segment *Other* gathers five segments have relatively few observations: arrowroot, wafer, cereal bars, assorted and other. This figure is based on the Nielsen full sample from April 2014 to March 2015.

Figure 2.A.3 Product variety across top 10 firms by segment and main price point

(A) Rupees 5



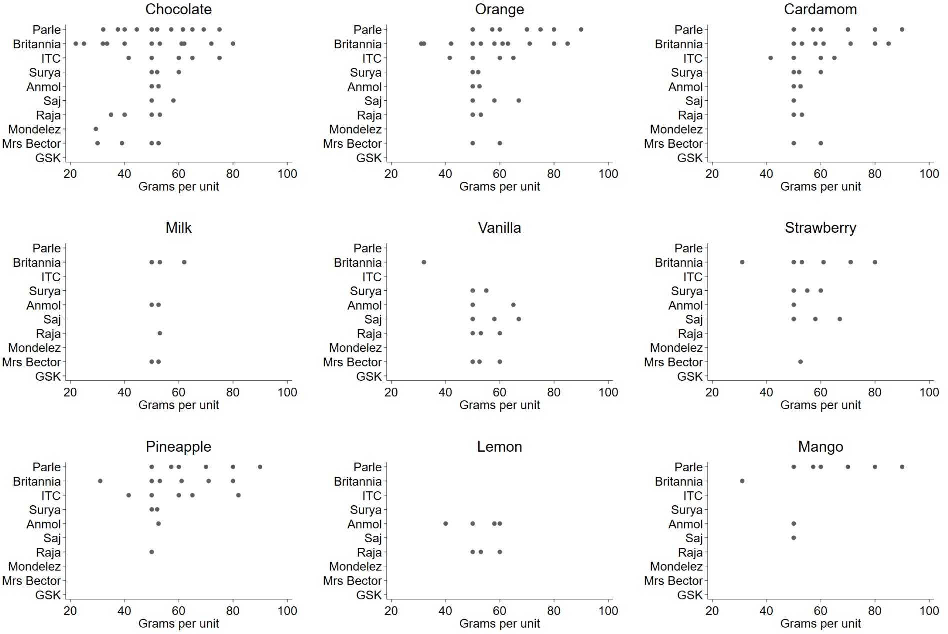
(B) Rupees 10



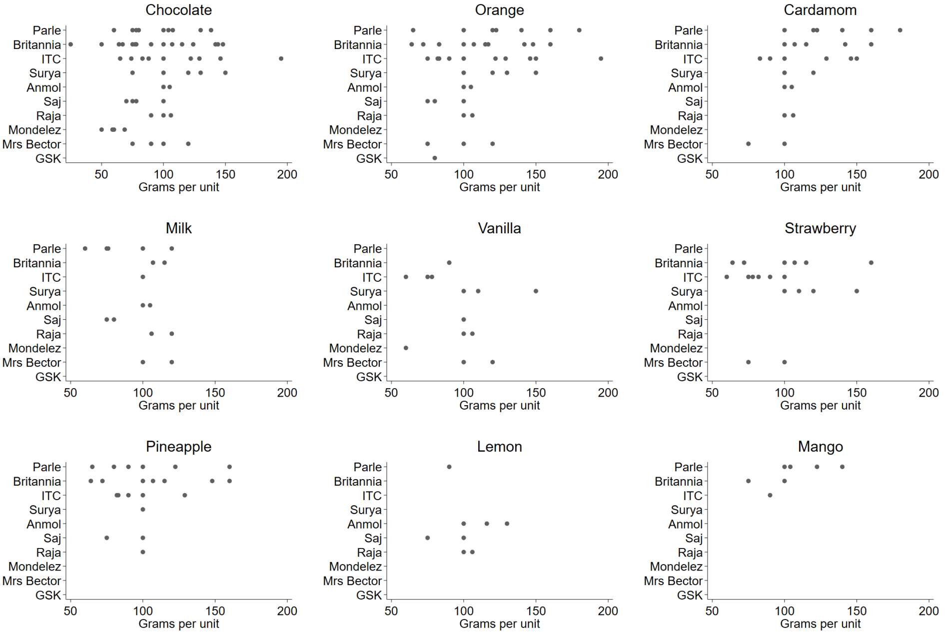
Notes: The dots in the scatter plot correspond to the size in gram of all products offered by top 10 firms and segments, excluding "Milk" and "Other" Panel (a): Products sold at 5 Rupees. Panel (b): Products sold at 10 Rupees.

Figure 2.A.4 Flavour of cream biscuits across top 10 firms by main price point

(A) Rupees 5



(B) Rupees 10



Notes: The dots in the scatter plot correspond to the size in gram of all products offered by top 10 firms and flavours of cream biscuit. Panel (a): Products sold at 5 Rupees. Panel (b): Products sold at 10 Rupees.

Table 2.A.1 Summary statistics

Panel (A) - Observations

	Nielsen	Top 10
Firms (N)	719	10
Segments (N)	12	12
Brands (N)	814	76
Subbrands (N)	1,313	306
Products (N)	15,035	4,714
Product-region-month obs.	694,872	390,414
Sales (Billion Rupees)	238	208
Units sold (Billion)	33.1	28.6
Kilograms sold (Billion)	2.27	1.98

Panel (B) - Distributions

	Top 10			
Firm scope	mean	min	median	max
Segments per firm (N)	8.0	1	8.5	11
Subbrands per firm (N)	30.7	6	21.5	79
Products per firm (N)	473.0	50	357.5	1336
Competition	mean	min	median	max
Firms per segment (N)	6.7	1	8.0	10
Subbrands per segment (N)	29	3	19	108
Products per segment (N)	394.2	4	311.5	1533
Variety	mean	min	median	max
Products per subbrand (N)	15	1	7	215
Main variables	mean	25pp	median	75pp
Price per unit (Rs.) (Pu)	16.7	5	10	20
Price per kilogram (Rs.) (Pg)	132.2	95	105	150
Pack size per unit (Grams) (Su)	116.3	53	100	150

Notes: The firms included in the *Top 10* sample are: Anmol Bakers, Britannia Inds, Glaxo Smithkline, ITC, Mondelez International, Mrs Bector Food Specialist, Parle Prods, Raja Udyog, Saj Inds, Surya Food & Agro. Biscuit market *segments* are: cream, glucose, marie, milk, non-salt crackers, salt crackers, cookies, arrowroot, wafer, cereal bars, assorted, other. *Brand* is the commercial name of the product. *Subbrand* groups all the products that differ only by their pack size. *Product* is identified by a unique SKU that changes across different pack size within the same subbrand. Prices and sales revenues are expressed in Indian Rupees. This table is based on monthly data from April 2014 to March 2015.

Table 2.A.2 Price per unit (Pu): raw and rounded values

Rounded integer	Raw ratio integer	Raw ratio ± 0.25 from the integer	Rounded integer	Raw ratio integer	Raw ratio ± 0.25 from the integer
1	0.98	0.98	26	0.43	0.72
2	0.97	0.98	27	0.35	0.66
3	0.95	0.97	28	0.26	0.58
4	0.41	0.62	29	0.12	0.48
5	0.96	0.99	30	0.70	0.88
6	0.71	0.84	31	0.15	0.49
7	0.55	0.73	32	0.37	0.66
8	0.50	0.70	33	0.25	0.58
9	0.11	0.44	34	0.19	0.54
10	0.88	0.96	35	0.69	0.86
11	0.17	0.51	36	0.30	0.6
12	0.69	0.87	37	0.16	0.54
13	0.40	0.70	38	0.38	0.67
14	0.25	0.57	39	0.14	0.52
15	0.73	0.90	40	0.66	0.86
16	0.39	0.66	41	0.13	0.51
17	0.20	0.53	42	0.31	0.64
18	0.37	0.66	43	0.13	0.52
19	0.15	0.53	44	0.17	0.53
20	0.75	0.91	45	0.59	0.82
21	0.14	0.51	46	0.12	0.54
22	0.41	0.70	47	0.14	0.51
23	0.19	0.53	48	0.22	0.55
24	0.16	0.55	49	0.13	0.53
25	0.71	0.88	50	0.66	0.85
			Total	0.72	0.87

Notes: *Price per unit (Pu)* is calculated as the ratio of product revenues to the number of packs of product sold, rounded to the nearest integer. For every rounded price per unit (*Rounded integer*), the table reports the share of observations whose price per unit has not been rounded, being already an integer after the ratio (*Raw ratio integer*); and the share of observations whose raw price per unit was in the range of + or - 0.25 from the nearest integer (*Raw ratio ± 0.25 from the integer*).

Table 2.A.3 Pack size (Su) change of top 10 firms by main price points

Segment	Firm	Market share 5	Market share 10	Market share 20	Region-areas 5	Region-areas 10	Region-areas 20	Pack size change 5	Pack size change 10	Pack size change 20
Cream	Parle	24.7	11.5	25.2	41	41	41	-1.0	-8.2	13.2
	Britannia	16.2	12.4	17.5	41	40	38	-10.5	-9.1	3.1
	ITC	25.3	26.5	27.5	41	41	40	1.1	-3.5	2.2
	Surya	5.0	12.1	1.0	27	29	24	-0.4	-1.2	21.4
	Anmol	9.1	8.8	9.0	32	29	26	-2.1	-3.0	0.7
	Saj	1.3	0.9	6.0	23	19	24	-8.0	-6.5	-2.6
	Raja	1.8	2.5	1.1	33	33	14	-5.9	-4.1	0.0
	Mondelez	0.9	9.1	4.5	41	41	37	-0.7	-1.5	1.0
	Mrs Bector	1.6	4.0	0.1	18	21	8	-0.2	4.5	0.0
Glucose	Parle	87.6	81.1	85.7	41	41	41	-0.6	-1.5	-1.1
	Britannia	3.7	10.0	5.9	33	41	13	1.2	-6.5	-12.0
	ITC	5.7	5.8	8.1	27	33	26	-0.4	-1.6	3.2
	Surya	0.1	0.3		22	22		-4.3	-0.8	
	Raja	0.1	0.5		19	26		-5.3	-9.3	
	Mrs Bector	0.2	0.1		14	8		-5.1	-4.5	
Marie	Parle	9.7	13.8	0.1	38	41	14	-6.1	-11.5	-8.5
	Britannia	59.0	57.5	65.3	37	41	32	-2.1	-6.1	-5.0
	ITC	13.2	14.1	14.6	15	40	35	-5.1	-10.9	0.4
	Surya	7.8	1.5	0.5	26	27	18	-3.2	0.9	-14.3
	Anmol	0.6	0.6	1.6	19	26	21	0.0	-5.6	-10.7
	Saj	0.6	7.7	4.1	17	23	13	2.3	-2.1	-6.2
	Raja	1.1	0.5	1.0	25	26	9	-8.1	-5.2	5.1
	Mrs Bector		0.1			19			-10.0	
Milk	Parle	4.3	4.0	3.1	35	37	6	-2.0	-3.5	0.0
	Britannia	66.8	67.9	54.9	34	16	33	-3.5	-7.4	-0.6
	ITC		4.5			10			-13.1	
	Anmol		1.1	2.4		16	19		-8.2	-7.4
	Saj	0.2	0.2	18.8	13	15	16	0.0	3.2	-1.3
	Raja		1.7	9.7		14	11		-16.5	-14.5
	GSK	26.4	17.6	2.9	36	36	24	-4.7	-4.5	-18.8
Non-salt Cracker	Parle	26.1	29.5	5.8	41	41	30	-6.0	-9.9	-7.8
	Britannia	29.4	37.6	6.7	41	41	33	-9.7	-6.4	14.6
	ITC	0.6	1.4	6.4	12	17	10	-4.0	-2.3	-6.4
	Surya	21.0	8.3	0.3	26	29	17	-5.9	0.4	0.0
	Anmol	7.0	5.2		29	29		-2.4	-1.0	
	Saj	1.7	2.3	67.1	21	23	22	-2.2	-7.4	-1.0
	Raja	1.1	1.4	1.8	33	33	12	-0.4	-1.4	-13.3
	Mrs Bector	0.1	0.3		15	17		-15.3	-8.9	
Salt Cracker	Parle	29.2	34.6	8.6	41	41	35	-7.0	-11.8	-36.5
	Britannia	2.8	9.3	0.3	41	41	18	-1.6	6.5	17.6
	ITC	2.7	8.1		33	41		-3.1	-2.7	
	Surya	21.2	13.5	0.1	27	28	10	1.7	0.8	0.0
	Anmol	15.2	6.2	39.6	30	28	28	-7.4	-8.3	-10.9
	Saj	1.8	1.7	17.7	21	20	19	8.4	-12.7	-2.8
	Raja	2.1	2.7	6.8	33	32	25	0.0	-1.9	0.0
	Mrs Bector	0.3	1.4	0.1	18	18	7	-13.6	-9.1	-11.7
Cookies	Parle	48.6	12.9	8.7	41	41	41	-5.2	-0.9	-2.5
	Britannia	16.1	49.4	50.2	41	41	41	0.7	-6.9	14.5
	ITC	11.4	7.3	8.8	41	41	41	-3.5	-10.2	-6.8
	Surya	3.8	5.6	9.3	28	27	28	-10.5	-6.6	4.1
	Anmol	6.7	5.3	8.6	30	29	29	-0.8	-0.3	-4.7
	Saj	0.1	0.1	1.1	20	20	22	-5.0	-3.4	-3.0
	Raja	1.7	2.5	2.4	33	30	32	-5.9	-10.9	-8.0
	Mrs Bector	2.4	3.9	2.2	20	28	20	-0.8	-3.1	-5.8
	GSK			0.2			28			5.7

Notes: For every segment, excluding "Other", percent market share, number of region served and percent change in average pack size between April 2014 and March 2015 is reported by top 10 firms and main price points. Top 10 firms are Anmol Bakers, Britannia Inds, Glaxo Smithkline, ITC, Mondelez International, Mrs Bector Food Specialist, Parle Prods, Raja Udyog, Saj Inds, Surya Food & Agro. Main price points are Rupees 5, 10 and 20.

Table 2.A.4 Correlation table

Rs. 5	Units (Qu)	Quantity (Qg)	Pack size (Su)	Productivity (ω)
Units (Qu)	1.000			
Quantity (Qg)	0.969	1.000		
	(0.000)			
Pack size (Su)	-0.305	-0.076	1.000	
	(0.000)	(0.000)		
Productivity (ω)	0.133	0.122	-0.058	1.000
	(0.000)	(0.000)	(0.000)	
Rs. 10	**Units (Qu)**	**Quantity (Qg)**	**Pack size (Su)**	**Productivity (ω)**
Units (Qu)	1.000			
Quantity (Qg)	0.994	1.000		
	(0.000)			
Pack size (Su)	-0.170	-0.062	1.000	
	(0.000)	(0.000)		
Productivity (ω)	-0.016	0.031	0.405	1.000
	(0.000)	(0.000)	(0.000)	
Rs. 20	**Units (Qu)**	**Quantity (Qg)**	**Pack size (Su)**	**Productivity (ω)**
Units (Qu)	1.000			
Quantity (Qg)	0.990	1.000		
	(0.000)			
Pack size (Su)	-0.043	0.099	1.000	
	(0.000)	(0.000)		
Productivity (ω)	0.029	0.113	0.580	1.000
	(0.000)	(0.000)	(0.000)	

Notes: Correlation coefficients reported. *Units (Qu)* is the logarithm of the number of product packs sold; *Quantity (Qg)* is the logarithm of the kilograms of product sold; *Pack size (Su)* is the logarithm of the grams per unit of biscuits; *Productivity (ω)* is estimation-based product-level productivity standardized to have zero mean and unitary standard deviation. This table reports elaborations on the sample of top 10 firms from April 2014 to March 2015.

Table 2.A.5 Nonprice competition under uniform pricing: robustness check using cost share based productivity

	Pack size	Pack size promotions		Product availability		Product variety	
	(1) Grams per unit (Su)	(2) Probability	(3) Kilograms for free	(4) Probability	(5) Stores (%)	(6) Number	(7) Std. dev. pack size
Productivity (ω)	0.267***	0.206***	-0.790***	0.004	-0.077	0.180***	0.252***
	(0.016)	(0.013)	(0.245)	(0.003)	(0.158)	(0.036)	(0.069)
Product age	0.049***	-0.216***	-2.148***	-0.068***	-2.520***		
	(0.013)	(0.013)	(0.215)	(0.004)	(0.199)		
Inter-firm competition	-0.042***	0.024***	-0.004	-0.114***	0.450***		
	(0.012)	(0.008)	(0.105)	(0.003)	(0.151)		
Intra-brand competition	0.009	0.043***	0.295*	0.010***	0.417*		
	(0.011)	(0.012)	(0.176)	(0.004)	(0.222)		
Intra-firm competition	0.032***	-0.020	0.126	-0.067***	0.107		
	(0.012)	(0.013)	(0.174)	(0.004)	(0.207)		
Price point FE	Yes	Yes	Yes	Yes	Yes	No	No
Segment FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.630		0.277		0.089	0.155	0.108
Observations	390413	384788	47531	584852	390414	73119	73119

Notes: OLS (column 1,3 and 5-7) and Probit average marginal effects (column 2 and 4) estimates, standard errors (in parentheses) clustered at the product level. Every column indicates a measure of nonprice competition which serves as a dependent variable: (1) *Grams per unit (Su)* measures the pack size as the logarithm of the grams per unit of biscuits; (2) *Probability* is a dummy taking value one when the product is offered on value promotion; (3) *Kilograms for free* is the logarithm of the kilograms of product given for free as pack size promotion; (4) *Probability* is a dummy taking value one when the product is sold (observed) in a region-month and zero when it is not; (5) *Stores (%)* is the percentage of shops that sell the product in the region-month; (6) *Number* is the logarithm of the number of different pack sizes of a subbrand in a month-region market; (7) *Std. dev. pack size* is the logarithm of the standard deviation of the pack size within a subbrand in a month-region market. *Productivity (ω)* is cost-based product-level productivity standardized to have zero mean and unitary standard deviation. *Product age* is the logarithm of the years since the product was launched. *Inter-firm competition* is the logarithm of the number of products sold within the same segment-region-month-price point by competing firms, *Intra-firm competition* is the logarithm of the number of other products sold by the firm in the same segment-region-month-price point of the observed product, *Intra-brand competition* is the logarithm of the number of other products sold by the firm under the same brand within the same segment-region-month-price point of the observed product. *Price point FE* include dummies for Rupees 5, 10, 15, 20, 25, and 30, a dummy for all other multiples of five, and a dummy for all the remaining prices. This table reports elaborations on the sample of top 10 firms from April 2014 to March 2015. Column 1, 4-6 are estimated on the full subsample. Column 2 is estimated only on the observations that are offered on pack size promotion. Column 4 are estimated on the full subsample, incremented by the product-region-month missing observations, i.e. those where the product is not observed as it has zero sales. This table reports elaborations on the sample of top 10 firms from April 2014 to March 2015.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 2.A.6 Price elasticity estimates

	OLS *log Qg*	First stage *log Pg*	IV *log Qg*			
	(1) All	(2) All	(3) All	(4) Urban	(5) Rural	(6) All
Price per Kilogram (*log Pg*)	0.245**		-0.643***	-0.313**	-1.611***	-0.434***
	(0.099)		(0.175)	(0.171)	(0.191)	(0.167)
Price per Kilogram (*log Pg*) X Rural						-0.745***
						(0.164)
Productivity		-0.248***				
		(0.007)				
Price point FE	Yes	Yes	Yes	Yes	Yes	Yes
Segment FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.137	0.695				
Observations	390414	390414	390414	299892	90522	390414
F-stat			1287.3	1562.3	355.6	167.0

Notes: OLS and IV estimates, standard errors (in parentheses) clustered at the product level. The dependent variable in Column 1,2,5 and 6, $log\ Qg$, is the quantity in kilograms of product sold in a region-month. The dependent variable in Column 3 and 4, $log\ Pg$, is the price per kilogram of the product in a region-month. *Productivity (ω)* is estimation-based product-level productivity standardized to have zero mean and unitary standard deviation. It serves as an instrumental variable for price per kilogram (Pg)in the IV estimates. *Rural* is a dummy taking value one when the product is sold in a rural area and zero when it is sold in a urban area. *Price per kilogram (log Pg) X Rural* is the interaction variable between *Price per kilogram (log Pg)* and the dummy *Rural*. This table is based on the sample of top 10 firms from April 2014 to March 2015.Significance: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 2.A.7 Price elasticity at the segment level

	Quantity in kilograms (*log Qg*)							
	(1) Cream	(2) Glucose	(3) Marie	(4) Milk	(5) NS-Cracker	(6) S-Cracker	(7) Cookies	(8) Other
Price per Kilogram (*log Pg*)	-0.608***	-4.889***	-3.962**	22.338	-1.490**	-3.661***	-1.089***	7.102***
	(0.188)	(1.763)	(1.844)	(29.774)	(0.718)	(0.474)	(0.221)	(1.566)
Price point FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	142793	26412	27476	14376	33463	32639	103538	9717
F-stat	5535.6	111.1	60.5	0.4	288.9	482.4	3966.6	39.7

Notes: IV estimates, standard errors (in parentheses) clustered at the product level. The dependent variable, *Quantity in kilograms (log Qg)*, is the logarithm of kilograms of product sold in a region-month. *Productivity* (ω) is estimation-based product-level productivity standardized to have zero mean and unitary standard deviation. It serves as an instrumental variable for price per kilogram (*Price per kilogram (log Pg)*) in the IV estimates. Each column reports the estimates calculated on a subsample of products sold in specific biscuit segments: cream, glucose, marie, milk, non-salt crackers, salt crackers, cookies, arrowroot, other (including wafer, cereal bars, assorted, other). This table reports elaborations on the sample of top 10 firms from April 2014 to March 2015.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Chapter 3

How do wholesale prices and retail markups affect market shares in the pharmaceutical industry?

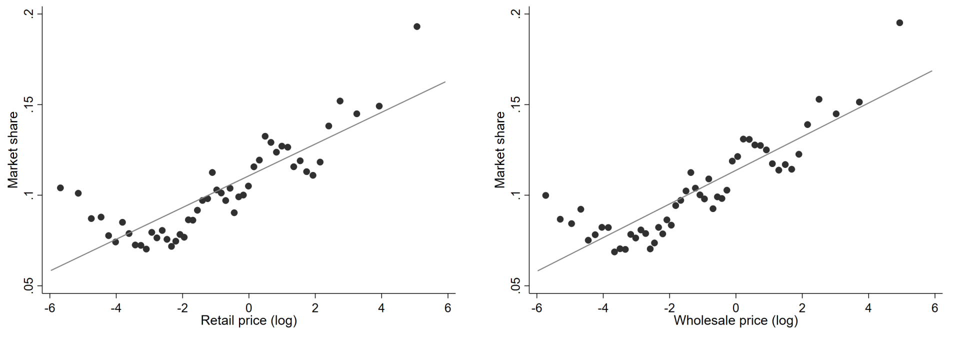
3.1 Introduction

Amoxicillin Clavulanic Acid, an antibiotic launched in October 1993, is one of India's best-selling medicines with more than 200 brands competing in the market. The leading brand in the market, *Augmentin*, charges a wholesale price of 206 Rupees for ten 625 mg tablets. By contrast, for the same number of tablets and dosage strength, the brand with the second-highest market share charges a relatively lower wholesale price of 63 Rupees. An analysis of more than 8000 narrowly defined medicine markets in India, consisting of the combination of an active ingredient (Anatomic Therapeutic Classification, *ATC5*) and dosage form (e.g., tablet), during April 2011 and March 2016 confirms the relationship observed in the Amoxicillin example: on average,

[†] This chapter is based on the working paper titled "How do wholesale prices and retail markups affect market shares in the pharmaceutical industry?" and is joint work with Ajay Bhaskarabhatla. We thank Rajshree Agarwal, Serguey Braguinsky, Bruno Cassiman, Benoit Crutzen, Pilar Gárcia-Gómez, Florin Maican, Gloria Moroni, Melissa Newham, Nina Pavcnik, Amil Petrin, Mark Roberts, Evan Starr, Jo Van Biesebroeck, and the seminar participants at Miami (NAPW), New Delhi (ACEGD), Ghent (Workshop on Firm Heterogeneity), Mannheim (MaCCI), Warwick (RES), Michigan (CAED), Barcelona (EARIE), Rotterdam (ESE and TI), College Park (Seminar at Ed Snider Center), Philadelphia (ISA) and Vienna (EARIE). We thank the Erasmus Trustfonds for financial support and AIOCD for sharing the data.

Figure 3.1 Product market share, retail price and its components

(A) Market share and retail price (B) Market share and wholesale price



Notes: Binned scatterplots. Market share is the product-year share of sales of the market. The *Market* is defined as the set of drugs made of the same active pharmaceutical ingredient (5-digit Anatomical Therapeutic Classification, ATC5) and with the same dosage form (e.g., tablet, injection, syrup). Panel (A): *Retail price* is product retail price normalized by dividing the retail price by product dosage strength and pack size; Panel (B): *Wholesale price* is product wholesale price normalized by dividing the wholesale price by product dosage strength and pack size. This figure is based on AIOCD data.

products with a higher price have a higher market share. Figure 3.1 shows that market share is positively correlated with both wholesale and retail prices.[1]

The positive correlation between prices and market shares might not seem surprising, given the high costs of innovation, the presence of patent monopolies, the prevalence of non-price competition through marketing investments, the inelastic nature of demand for pharmaceutical products, and the mechanical correlation between prices and revenues (Lakdawalla, 2018; Gaynor et al., 2015; Chernew et al., 2018; Berndt, 2002). However, the Indian pharmaceutical context characterized by scores of competing brands, selling mostly off-patent medicines, and consumers directly purchasing medicines as out-of-pocket expenses, suggests intense competition in these markets. Indeed, many scholars suggest low prices and high levels of competition as reasons for not regulating these markets (Berndt and Cockburn, 2014). Nevertheless, if interpreted as causal, this positive relationship between prices and market shares would point to the high cost of purchasing medicines, an overwhelming majority of which are out of patent protection. This would flag a critical issue in one of the world's most populous countries characterized by negligible levels of health insurance and limited public provision of healthcare.

This chapter identifies the causal effect of prices on product market shares in

[1] Table 3.A.1 in the Chapter Appendix shows that this pattern holds even after controlling for alternative specifications, the number of rival products, and firm, market, and year fixed effects.

the Indian pharmaceutical industry. Our objective is to assess to what extent the observed positive correlation depends on the cost structure or on the demand characteristics of the product. This would inform the regulator about the drivers of the medicine demand and the potential effects of a policy. We divide the retail price into wholesale price and retail markup and separately identify their marginal effects on product market share. This comparison between the market power of the manufacturers and the buyer power of the retailers is paramount given the importance of the latter in the pharmaceutical industry. However, to our knowledge, it has not been studied from previous research.

Estimating the causal relationship between prices and market shares poses several challenges. First, the positive correlation observed in Figure 3.1 is likely to be biased because prices and demand are simultaneously determined and other factors that might influence the relationship are omitted. Second, firms in our context produce multiple products, often more than a hundred, complicating efforts to infer product-level costs that influence pricing decisions. In addition, firms producing multiple products adopt pricing strategies that leverage their scope further complicating the assessment of the relationship between prices and market shares. Third, differences in prices can stem either from differences in productivity or markups, and isolating these effects poses additional challenges. While higher productivity leads to lower prices, higher demand, and a higher market share, with inelastic demand, more productive products may not compete on prices, resulting in a positive correlation between prices and market shares. Fourth, the use of vertical price restraints can alter the relationship between prices and market shares (Asker and Bar-Isaac, 2014). The presence of retailer buyer power can create incentives to promote the sale of brands manufactured by less-productive products that offer higher retail markups at the expense of more productive products with lower retail markups. This practice would imply an allocative inefficiency in production. On the other hand, more productive manufacturers may gain market share by offering higher retail markups, indicating that the inefficiency on the supply side lies with the buyer power of the downstream intermediaries rather than the manufacturers' market power. Fifth, if higher prices signal higher quality then unobserved quality differences are a possible explanation for why higher prices can be correlated with higher market shares but quality is not easily observed (Bronnenberg et al., 2015).

Using detailed data on product-level sales, retail and wholesale prices coupled with firm-level financial information, we identify the effect of wholesale prices and retail markups on product market shares in multiproduct firms. Building on Hottman et al. (2016), we model the contributions to product market share of the following drivers: wholesale price, retail markup and product appeal. We estimate the marginal effect of wholesale price on market share addressing the simultaneity bias by using quantity-based product-level productivity as an instrument for wholesale prices. Following Foster et al. (2008), we expect productivity, a proxy for technical efficiency in production, to be correlated with prices but not with the product market share except through its impact on prices. Building on recent advances in productivity estimation for multiproduct firms, we overcome challenges posed by the multiproduct nature of our data. The data allow us to isolate the effect of wholesale prices from that of retail markup on market share, which also can raise endogeneity issues. Following Nevo (2001), we instrument retail markup of the product with firm average retail markup in the non-focal ATC5. To control for product appeal we use firm-market fixed effects and exploit the variation in brand launch dates and product pack size.

We find that the positive relationship between prices and market shares described in Figure 3.1 is robust to the inclusion of other determinants of market shares. However, once prices are instrumented with productivity, the sign of this relationship turns negative: a one-percent increase in relative relative wholesale prices reduces market share by 5.7 percent. This effect is heterogeneous across firm, market and product characteristics: is larger for domestic firms, solid drugs, chronic treatments, single-ingredient medicines. Primarily, the negative effect of wholesale price on market share is halved for the market leaders and market pioneers, products that traditionally enjoy higher market power. Retail markups have, on average, a strong negative effect: a one-percent increase in relative relative retail markup reduces product market share by 1.5 percent. The heterogeneity of this effect across firm, market and product characteristics mimics that of the wholesale price, however, market share increases by 0.2 (0.5) percent for market leaders (pioneers) if they offer a one-percent higher retail margin.

Our theoretical model predicts the marginal effects of wholesale price and retail markup on product market share to be the same, since each market is populated by medicines with identical medical effect. Our results do not match this prediction and imply that retailers display an elasticity of substitution across medicines within the market is almost four times larger than that of the consumers, being the retailers more able to switch across medicines. Product appeal contributes largely to product market share (77 percent of the market share variance), is positively correlated with wholesale prices and retail margins, but does not fully reward productivity. Products in the upper tail of the appeal distribution have relatively lower productivity than those in the center of the appeal distribution. Similar to Foster et al. (2008), we find that wholesale prices are correlated negatively with quantity-based productivity, suggesting that productivity induces price competition. These findings indicate that market leaders are partly insulated from price competition and that selection on productivity does not always result in lower prices, particularly in the presence of manufacturer market power and significant retailer incentives.

This chapter makes two main contributions. First, we identify the effect of price on market share at the product level, using an instrumental variable approach that avoids the restrictions of the most widely adopted structural models. We follow the theoretical framework of Hottman et al. (2016) that distinguishes the components of firm size by modelling the structure of demand and supply. We also build on Foster et al. (2008) for identification by instrumenting for wholesale prices with quantity-based product-level productivity. More broadly this chapter contributes to the empirical literature on productivity estimation. Adapting traditional methods (Levinsohn and Petrin, 2003) and recent advances (De Loecker et al., 2016; Dhyne et al., 2017) to the pharmaceutical context, we estimate productivity at the product-level in multiproduct firms. In our dataset a product is defined at the stock keeping unit (SKU) level, the most disaggregated level possible. Our sample of pharmaceutical products allows us to calculate product-level productivity for almost 41,000 SKUs.[2] Product-level productivity estimation can be biased due to product-level input allocation (Foster et al., 2008; De Loecker et al., 2016); input price differentials (Katayama et al., 2009; De Loecker and Goldberg, 2014), simultaneity of productivity with input choice (Olley and Pakes, 1996; Ackerberg et al., 2015), and with the product scope of the firm (Bernard et al., 2010; Dhyne et al., 2017). We address these biases in estimating quantity-based product-level productivity and compare it to other revenue- and quantity-based measures. The instrumental variable approach we use to identify the effect of prices on market shares requires an analysis of the relationship between product price heterogeneity and productivity (Foster et al., 2008; Goldberg and Hellerstein, 2012).[3] We find that prices are negatively correlated with productivity when quantity-based and positively correlated when revenue-based. This result confirms the findings in Foster et al. (2008), indicating that revenue-based productivity, used extensively in prior literature, is a distorted measure of technical

[2] For comparison, Foster et al. (2008) select eleven seven-digit products manufactured in the US. Bernard et al. (2010) collect 1500 five-digit SIC codes products of the US manufacturing. De Loecker et al. (2016) use data for the entire Indian manufacturing and observe around 2400 products.

[3] Smeets and Warzynski (2013) show that, when firms are multiproduct, the results of a firm-level analysis on prices can be largely biased as average firm-level price measures eclipse product-level heterogeneity in prices.

efficiency. We also document differential effects of retail markups and margins on product demand and revenues. We show that retail margin affects the market share of the market leading products positively, helping to maintain the dominant position of the leaders in markets with highly substitutable products. This chapter connects to the emerging literature on the rise in global (De Loecker and Eeckhout, 2018) and industry-specific markups (Berry et al., 2019). Considering the pharmaceutical industry, our study reduces the research gap on the effect of retail markups on product demand. It also relates to the research on the role of retailers on firm strategy and profits (Dubois and Sæthre, 2020) and, more broadly, to the recent studies documenting the role of intermediaries on competition and welfare (Hastings et al., 2017; Grennan et al., 2018; Craig et al., 2018; Starc and Swanson, 2018).

Second, this chapter contributes to the broader literature on the pricing of pharmaceuticals. Pharmaceutical pricing is a contentious issue globally and poses unique challenges for India as it balances industry, trade, and health policies (Chaudhuri et al., 2006; Duggan et al., 2016). Indian pharmaceutical firms account for a significant share of exports of low-cost generic medicines to countries around the world. Yet, as our study highlights, despite the large number of competitors, Indian pharmaceutical markets exhibit limited price competition. Pharmaceutical manufacturers enjoy market power through branding of largely generic medicines coupled with laws that prevent substitution among them. Physicians prescribe brands rather than generics and retailers limit competition by agreeing to uniform margins of 24 to 30 percent (Bhaskarabhatla et al., 2016). Therefore, despite being more productive, larger pharmaceutical firms charge higher prices to sustain retailer incentives. This chapter offers evidence consistent with this narrative and motivates the need for a deeper examination of the role of the retailers. Responding to the need for more studies on firm productivity in emerging economies (Syverson, 2011) and pharmaceutical markets (Lakdawalla, 2018), we provide evidence on the relationship between market shares, prices and productivity in the Indian pharmaceutical industry. The Indian context has gained attention in the literature, as the country has undergone several important reforms over the last three decades. This chapter contributes an industry case study to the broader literature on India while previous studies examine the impact of trade reforms in India on price and markups (De Loecker et al., 2016; Alfaro and Chari, 2014), product scope (Goldberg et al., 2010a), productivity (Topalova and Khandelwal, 2011; Ahsan, 2013), multiproduct firms (Goldberg et al., 2010b).

The chapter proceeds as follows. In Section 3.2 we present the theoretical model. In Section 3.3 we describe the dataset. In Section 3.4 we discuss the empirical strategy. In Section 3.5 we show and comment the main results. In Section 3.6 we present additional results and robustness checks. Section 3.7 concludes.

3.2 Theoretical framework

In this section, building on Hottman et al. (2016), we model product market share as a function of wholesale price, retail markup, firm scope and product appeal.[4]

We assume that utility at time t, U_t, is a Cobb-Douglas aggregate of physical quantities consumed, Q_{jt}, of a continuum of product markets:

$$U_t = \int_{j \in \Omega_j} \varphi_{jt} \, lnQ_{jt} \, dj \tag{3.1}$$

where j denotes each product market, φ_{jt} is the share of expenditure on product market j at time t, and Ω_j is the set of product markets.

Following Hottman et al. (2016), the aggregate physical quantities consumed across all products of market j, Q_{jt}, and across all products of firm f in market j, Q_{fjt}, are defined as follows:

$$Q_{jt} = \left[\sum_{f \in \Omega_{fj}} (\varphi_{fjt} Q_{fjt})^{\frac{\sigma_j - 1}{\sigma_j}} \right]^{\frac{\sigma_j}{\sigma_j - 1}} \quad , \quad Q_{fjt} = \left[\sum_{i \in \Omega_{ifj}} (\varphi_{it} Q_{it})^{\frac{\sigma_{fj} - 1}{\sigma_{fj}}} \right]^{\frac{\sigma_{fj}}{\sigma_{fj} - 1}}$$

where Q_{it} is the physical output of product i supplied by firm f in market j, Ω_{fj} is the set of firms operating in market j and Ω_{ifj} is the set of products of firm f operating in market j. The elasticity of substitution of the output supplied by the different firms within the market and the elasticity of substitution of the different product of a specific firm within the market are, respectively, σ_j and σ_{fj}. Product i's appeal is φ_{it} and φ_{fjt} is the average appeal of firm f's products within market j:

$$\varphi_{fjt} = \frac{1}{N_{fjt}} \sum_{i \in \Omega_{ifj}} \varphi_{it}$$

where N_{fjt} is the number of products of firm f for market j. The average appeal of firm f across all its products and markets is:

$$\varphi_{ft} = \frac{1}{N_{ft}} \sum_{j \in \Omega_j} \varphi_{fjt} \tag{3.2}$$

[4] Hottman et al. (2016) divide the contribution to firm revenues into firm cost, markups, appeal and firm scope.

where N_{ft} is the number of markets in which firm f operates.

Using the properties of CES demand function, Hottman et al. (2016) show that the demand for the physical output of product i supplied by firm f within product market j, Q_{it} is:

$$Q_{it} = (\varphi_{fjt})^{\sigma_j - 1}(\varphi_{it})^{\sigma_{fj}-1}Y^R_{jt}(P^R_{jt})^{\sigma_j-1}(P^R_{fjt})^{\sigma_{fj}-\sigma_j}(P^R_{it})^{-\sigma_{fj}} \tag{3.3}$$

where Y^R_{jt} is total consumer expenditure in market j, P^R_{jt} is an index of retail price in market j, P^R_{fjt} is an index of retail price of firm f's products within market j and P^R_{it} retail price of product i. Market and firm-market retail price indexes are, respectively:

$$P^R_{jt} = \left[\sum_{f\in\Omega_{fj}}\left(\frac{P^R_{fj}}{\varphi_{fjt}}\right)^{1-\sigma_j}\right]^{\frac{1}{1-\sigma_j}} \quad , \quad P^R_{fjt} = \left[\sum_{f\in\Omega_{ifj}}\left(\frac{P^R_{it}}{\varphi_{it}}\right)^{1-\sigma_{fj}}\right]^{\frac{1}{1-\sigma_{fj}}}$$

where P^R_{it} is retail price of product i

We use the model to define the different sources of market shares heterogeneity across products. Firm revenues from product i, Y^W_{it}, are given by:

$$Y^W_{it} = P^W_{it}Q_{it}$$

where P^W_{it} is the wholesale price of product i. Using Equation (3.3) firm revenues from product i can be rewritten as:

$$Y^W_{it} = P^W_{it}(\varphi_{fjt})^{\sigma_j-1}(\varphi_{it})^{\sigma_{fj}-1}Y^R_{jt}(P^R_{jt})^{\sigma_j-1}(P^R_{fjt})^{\sigma_{fj}-\sigma_j}(P^R_{it})^{-\sigma_{fj}}$$

Retail prices can be divided into two components: wholesale prices P^W and retail markups μ^R. We can, therefore, define the market share of product i as:

$$\frac{Y^W_{it}}{Y^W_{jt}} = \left(\frac{P^W_{jt}}{P^W_{fjt}}\right)^{\sigma_j}\left(\frac{P^W_{fjt}}{P^W_{it}}\right)^{\sigma_{fj}}\left(\frac{P^W_{it}}{P^W_{jt}}\right)\left(\frac{\mu^R_{jt}}{\mu^R_{fjt}}\right)^{\sigma_j}\left(\frac{\mu^R_{fjt}}{\mu^R_{it}}\right)^{\sigma_{fj}}(\varphi_{fjt})^{\sigma_j-1}(\varphi_{it})^{\sigma_{fj}-1}$$

In narrowly defined markets, if we assume the elasticity of substitution of the output supplied by the different firms within the market is equal to the elasticity of substitution of the different products of a specific firm within the market are the same, namely $\sigma_j = \sigma_{fj} = \sigma$.[5] We can rewrite:

$$\frac{Y^W_{it}}{Y^W_{jt}} = \left(\frac{P^W_{it}}{P^W_{jt}}\right)^{1-\sigma} \left(\frac{\mu^R_{it}}{\mu^R_{jt}}\right)^{-\sigma} (\Phi_{it})^{\sigma-1} \tag{3.4}$$

where Φ_{it} indicates total firm-product appeal in the market. Equation 3.4 shows that product market share, $\frac{Y^W_{it}}{Y^W_{jt}}$, is a function of: (i) relative wholesale price of product i, $\frac{P^W_{it}}{P^W_{jt}}$; (ii) relative retail markup of product i, $\frac{\mu^R it}{\mu^R jt}$; (iii) firm-product appeal, Φ_{it}. Given that $\sigma \geq 1$, a higher relative wholesale price or retail markup is expected to reduce product market share, while a positive effect is expected from higher firm-product appeal.

3.3 Data

We use product-level data of all the pharmaceutical firms operating in India from April 2011 to March 2016. Since April marks the beginning of a new financial year in India, we have data for five financial years. Data are compiled by the All India Organization of Chemists and Druggists (AIOCD), the union of Indian pharmacies. For each *product*, identified by a unique stock keeping unit (SKU), we observe both wholesale and retail prices, as well as the number of units sold on India's pharmaceutical market, on a monthly basis. Since we employ these data at the product-year level, for every product we aggregate sales revenues and units across months, and define wholesale and retail prices as the weighted averages of the year.

AIOCD data contain nearly 3.1 million SKU-month observations spanning almost 900 firms, and around 92,000 different SKUs. For each product we observe its Anatomic Therapeutic Classification (*ATC5*), assigned based on the molecular composition of the active ingredient of the drug (e.g., paracetamol), *dosage form* (e.g., tablet), *dosage strength* (e.g., 10 mg) and *pack size* (e.g., number of tablets or syringes). We define a *market* as the combination of ATC5 and dosage form, aggregated over different strengths and pack size. We identify more than 8,000 markets for 2,900 ATC5s. Products within a firm often share a common *brand*, as medicines with common ATC5 but differing dosage forms, strength, and pack size are assigned the same brand. In our data there are more than 54,000 brands.

[5] The narrower the definition of market, the closer the substitutability of goods across firms and within firms in the market. This is indeed the case of our definition of market that includes drugs with the same active ingredients and dosage form. Hottman et al. (2016) prescribe σ_j to be equal or higher than σ_{fj}. In case of equality the model replicates a standard CES system at the product level, but it has no implications for our purpose.

We combine the AIOCD data with Prowess data on firm financials compiled by the Centre for Monitoring Indian Economy (CMIE).[6] The Prowess data contain annual financial information for publicly listed firms traded on the National and the Bombay Stock Exchanges in India. We 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. We manually match firm names between the Prowess and AIOCD data during 2011 and 2015. Among the 899 firms in the AIOCD dataset, we successfully match 119 public firms accounting for almost 130,000 product-year observations, spanning more than 38,000 SKUs. We present descriptive statistics for the combined dataset in Table 3.1. The matched firms represent 42 percent of all SKUs, their sales account for 60 percent of the total industry sales, and produce about 2,300 ATC5s. All the firms in the combined sample are multiproduct firms, manufacturing, on average, 326 different SKUs per firm. These firms are also multiscope firms, operating, on average, in 165 markets and 123 ATC5s.

Within a market the products with the same ATC5 and dosage form can differ by dosage strength (e.g., 500 mg of Metformin vs 1000 mg of Metformin) and pack size (e.g., 10 tablets vs. 15 tablets). To facilitate comparison among prices and quantities of products, we normalize prices (P) and physical units of product (Q) by dosage strength (DS) and pack size (PS) using the formulae:

$$NP = \frac{P}{DS \times PS}$$

$$NQ = Q \times DS \times PS$$

Note that multiplying the normalized price per unit (NP) by normalized quantity (NQ) gives product sales revenue. Since each market sells medicines with specific chemical components and therapeutic use, it is not feasible to compare prices and quantities across products between markets using absolute value measures. Conversely, relative measures like market share (defined as the product share of sales of the market), relative wholesale price (defined as the ratio between normalized wholesale price of a product and the average normalized wholesale price of the market) and relative retail markup (defined as the ratio between product retail markup and the average retail markup of the market) are comparable. Using relative mea-

[6] The CMIE Prowess data are used in other works regarding Indian multiproduct firms, such as Goldberg et al. (2010a); Topalova and Khandelwal (2011); Ahsan (2013); De Loecker et al. (2016) among the others. Another dataset that contains the same financial variables required to conduct our of analysis is the ASI dataset. The latter has the advantage of gathering also small and non-traded Indian firms. However, it does not include the name of the firm, which is the only identifier we have for the firms in the AIOCD dataset. Merging the two datasets is, therefore, not possible.

Table 3.1 Summary statistics of the estimation sample

(A) - Observations

Firms (N)	119
ATC5 (N)	2,315
Markets (N)	5,032
Brands (N)	19,079
Products (N)	38,463
Product-year observations (N)	129,449

(B) - Distributions

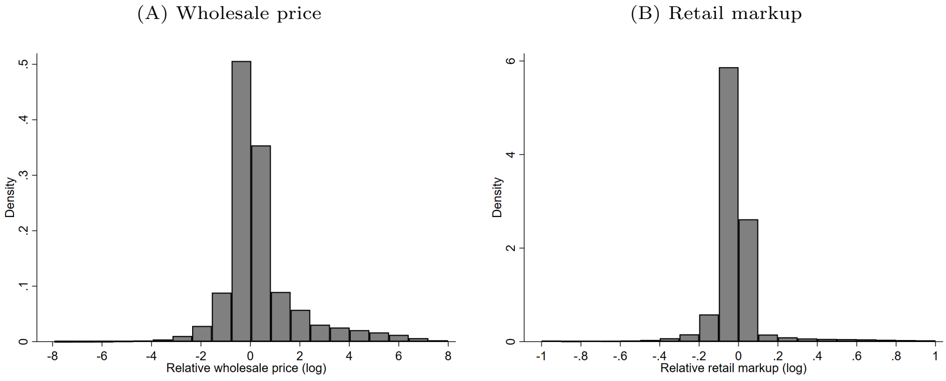
	mean	median	10^{th} perc.	90^{th} perc.
Products per firm (N)	326	158	21	846
ATC5s per firm (N)	123	71	12	308
Markets per firm (N)	165	92	13	428
Sales per product (INR)	17.6 mn	1.9 mn	10.3 th	39.6 mn
Sales per firm (INR)	5.5 bn	1.3 bn	7.6 mn	19.3 bn
Revenue-based market share (%)	11.6	0.8	0.003	41.5
Quantity-based market share (%)	11.5	0.6	0.002	42.2
Wholesale price per unit (INR)	265	51	11	243
Relative wholesale price (log)	0.26	0.00	-0.86	1.63
Retail markup	1.52	1.29	1.24	1.48
Relative retail markup (log)	0.04	-0.00	-0.08	0.08
Retail margin per unit (INR)	90	16	4	79
Relative retail margin (log)	-0.04	-0.02	-0.52	0.42

Notes: The dataset is obtained by combining AIOCD and Prowess, CMIE data. *ATC5* refers to the active pharmaceutical ingredient, *Market* refers to the combination between ATC5 and dosage form (tablet, injection, syrup, etc.), *Brand* refers to the retail name of the drug (irrespective of the strength or dosage), *product* refers to the SKU. *Revenue-based market share* is the ratio between product sales and total market sales. *Quantity-based market share* is the ratio between normalized product units and the total normalized units sold on the market. *Wholesale price per unit* is wholesale price for one unit (pack) of product. *Relative wholesale price* is the ratio between product's normalized wholesale price and the average normalized wholesale price of the market. *Retail markup* is the ratio between retail and wholesale price of the product. *Relative retail markup* is the ratio between product retail markup and the average retail markup of the market. *Retail margin per unit* is the difference between retail and wholesale price of one unit (pack) of product. *Relative retail margin* is the ratio between product's retail margin and the average retail margin of the market. *Sales*, *Wholesale price per unit* and *Retail margin per unit* are expressed in Indian Rupees (INR) where *bn* is billion, *mn* is million, *th* is thousand.

sures we observe significant dispersion in market shares, wholesale prices and retail markups within and across the markets. In Table 3.1, Panel B, we notice that the distribution of market shares is heavily right-skewed, suggesting the presence of large market leaders. The distribution of relative wholesale prices plotted in Figure 3.2, Panel A shows substantial price dispersion within the market, greater than the retail markup dispersion plotted in Figure 3.2, Panel B.

As shown in Equation (3.4), market shares depend not only on wholesale prices but also on retail markups. To illustrate this, we show in Table 3.2 top ten markets by revenue in our data. Although many firms compete in these markets, competition is limited by the presence of products with dominant positions. Indeed, in each

Figure 3.2 Distribution of wholesale price and retail markup within the market



Notes: Distribution of product wholesale price and retail markup relative to the market average. The *Market* is defined as the set of drugs made of the same active pharmaceutical ingredient (5-digit Anatomical Therapeutic Classification, ATC5) and with the same dosage form (e.g., tablet, injection, syrup). Panel (A): *Relative wholesale price* is the logarithm of product normalized wholesale price divided by the average normalized wholesale price of the market (the value is zero when the product wholesale price equals the market average); Panel (B): *Relative retail markup* is the logarithm of product retail markup divided by the average retail markup of the market (the value is zero when the product retail markup equals the market average). This figure is based on AIOCD data.

of these markets more than a hundred different products compete, but the revenue share of the market-leading product is more than ten percent in all markets except Atorvastatin. The dominant position of the market leaders is more evident when we compare their wholesale prices, retail markups and margins with those of the other products in the market. Market leaders charge a higher wholesale price and lower retail markup, measured as the ratio between retail and wholesale price. Despite the lower retail markups, charging higher wholesale prices allows the leaders to provide higher retail margin, measured as the difference between retail and wholesale price.

3.4 Empirical strategy

We estimate the relation between product market share, wholesale price and retail markup using the model solution in Equation (3.4). The estimation equation is the following:

$$\widetilde{Y}_{ifjt} = \alpha_1 \widetilde{P^W}_{ifjt} + \alpha_2 \widetilde{\mu^R}_{ifjt} + \alpha_3 X_{ifjt} + \lambda_{fj} + \delta_t + \epsilon_{ifjt} \tag{3.5}$$

where $\widetilde{Y}_{ifjt}$ is the logarithm of product i's share of revenues of market j. The variable $\widetilde{P^W}_{ifjt}$ is the logarithm of product i's relative wholesale price, defined as the ratio between product's normalized wholesale price and the average normalized wholesale

Table 3.2 Top 10 largest markets. Wholesale prices and markups of market leaders.

	Number market competitors	Leader's market share	Leader's relative wholesale price	Leader's relative retail markup	Leader's relative retail margin
Amoxycillin & Clavulanic Acid (Tablet)	411	13.69	0.96	0.95	1.15
Atorvastatin (Tablet)	332	5.17	1.85	0.81	0.92
Azithromycin (Syrup)	503	18.12	1.23	0.95	1.05
Cefixime (Tablet)	336	21.53	1.03	0.87	1.07
Cefuroxime (Tablet)	246	25.90	1.54	0.89	1.30
Chlorpheniramine & Codeine (Tablet)	101	35.82	1.23	0.94	1.25
Glimepiride & Metformin (Tablet)	274	12.83	1.17	1.01	1.19
Pantoprazole (Tablet)	249	27.88	1.33	0.85	1.22
Rosuvastatin (Tablet)	196	10.44	1.37	1.00	1.49
Telmisartan (Tablet)	224	18.56	1.24	0.98	1.62

Notes: The 10 largest markets in terms of sales are listed in alphabetical order. The *Market* is defined as the set of drugs made of the same active pharmaceutical ingredient (5-digit Anatomical Therapeutic Classification, ATC5) and with the same dosage form (e.g., tablet, injection, syrup). *Number market competitors* is the number of different products competing in the market. *Leader's market share* is the market share of the product with the highest level of sales within the market. *Leader's relative wholesale price* is the ratio between the normalized wholesale price of the market leader and the average normalized wholesale price of the market. *Leader's relative retail markup* is the ratio between the retail markup of the market leader and the average retail markup of the market. *Leader's relative retail margin* is the ratio between the retail margin of the market leader and the average retail margin of the market. The table is based on AIOCD data.

price of the market. Relative retail markup is captured by $\widetilde{\mu^R}_{ifjt}$, the logarithm of the ratio between product retail markup and the average retail markup of the market. The vector X_{ifjt} controls for product characteristics considered demand shifters, such as the age of the brand (the years since the product brand was launched) and the pack size of the product (relative to the average pack size of the market). The vector λ_{fj} captures firm-market fixed effects and δ_t controls for time fixed effects. Assuming that firm appeal in a market is time invariant and that product age is a leading driver of product appeal, the vectors X_{ifjt} and λ_{fj} jointly proxy for product and firm appeal within the market. The error term, ϵ_{ifjt}, is product-year specific.

Estimating (3.5) using OLS introduces an upward bias in α_1, as an idiosyncratic shock in demand might stimulate an increase in price by the manufacturers. To identify price elasticity in a standard demand function for single-product firms, Foster et al. (2008) instrument for prices with a product-level measure of productivity, a supply-side driver of prices containing information on a firm's cost of production. Indeed, productivity is a measure of technical efficiency, directly comparable across products within and across markets. Moreover, it is unlikely to be correlated with idiosyncratic product-specific demand shocks in the short run. We adopt the same methodology and instrument for relative wholesale price with a measure of quantity-based productivity. Unlike Foster et al. (2008), our dependent variable is market share and our firms produce multiple products. We estimate product-level productivity controlling for the "product scope bias" that arises when estimating the production function in multiproduct firms: firm productivity is correlated with product switching, suggesting that firms endogenously select the goods to produce Bernard et al. (2010). We build on Dhyne et al. (2017) to estimate a quantity-based measure of product-level productivity for multiproduct firms (*TFP-QEM*). The production function estimation approach is discussed in Appendix M.3.1. In Figure 3.A.1 in the Chapter Appendix we show the distribution of the estimated product-level productivity and the central moments of the distributions of the output elasticities of the production function adopted.

The use of productivity as an instrument can be questioned for two reasons (Foster et al., 2008). First, if higher productivity leads to higher probability of survival when drawing a negative demand shock. The first issue is mitigated by the fact that our data span for five years, and a bad draw in such a short period can be amortized by cross subsidization of other products of the firm. Second, measurement error in estimating productivity can undermine the usefulness of the instrument. Such measurement error can arise if quantities are not directly observed but instead calculated by dividing sales with prices. Since we observe quantities separately from prices and sales, measurement is not a concern in our study.

For the same reverse causality reason introduced by the wholesale price, also the coefficient α_2 can be upward biased if estimated using OLS. To identify the effect of retail markup on market share we instrument the retail markup with the firm average retail markup in the non-focal ATC5. This measure is likely to be correlated with the product retail markup in the focal ATC5, as the firm might strategically set an average retail markup across all its products, before deciding product-specific markup. This instrument is also supposed to be uncorrelated with idiosyncratic product-specific demand shocks in the short run, because of the multiproduct nature of the firm. This methodology is commonly adopted to identify the price elasticity in a demand function (Nevo, 2001; DellaVigna and Gentzkow, 2019).

3.5 Results

3.5.1 The effect of wholesale price and retail markup on product market share

In contrast with the model prediction, the OLS estimates of Equation (3.5), reported in Table 3.3, confirm the positive relation between market share and wholesale price (Column 1-3). Retail markup, instead, is negatively correlated with market share,

Table 3.3 The effect of wholesale price and retail markup on product market share. Baseline estimates.

	Market share (log)					
	(1) OLS	(2) OLS	(3) OLS	(4) IV P	(5) IV P&M	(6) IV P&M
Relative wholesale price (log)	0.047**	0.015	0.073***	-4.910***	-4.888***	-5.718***
	(0.023)	(0.022)	(0.024)	(0.541)	(0.538)	(0.748)
Relative retail markup (log)		-0.742***	-0.687***		-1.185***	-1.516***
		(0.058)	(0.057)		(0.424)	(0.473)
Brand age (log)			0.614***			-0.074
			(0.056)			(0.138)
Pack size (log)			0.217***			-3.256***
			(0.043)			(0.493)
Market X Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.717	0.719	0.725			
Observations	135941	135941	129449	135941	135931	129441
F-stat				60.7	104.0	100.4

Notes: OLS and IV estimates. The dependent variable *Market share* is the product share of the wholesale sales of the market. The *Market* is defined as the set of drugs made of the same active pharmaceutical ingredient (5-digit Anatomical Therapeutic Classification, ATC5) and with the same dosage form (e.g., tablet, injection, syrup). *Relative wholesale price* is the ratio between product's normalized wholesale price and the average normalized wholesale price of the market. *Relative retail markup* is the ratio between product retail markup and the average retail markup of the market. In IV estimates, *Relative wholesale price* is instrumented with quantity-based product-level productivity (*TFP-QEM*), whereas *Relative retail markup* is instrumented with the firm average retail markup in the non-focal ATC5. In Column (4) only *Relative wholesale price* is instrumented (*IV P*), whereas in Column (5) both *Relative retail markup* and *Relative retail markup* are instrumented (*IV P&M*). *F-stat* is Kleibergen-Paap F statistic. All variables are expressed in logarithms. The table is based on AIOCD and Prowess, CMIE data. Standard errors (in parentheses) clustered at the market level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

consistent with the model prediction (Column 2-3). The OLS estimates remain robust after controlling for brand age, pack size and firm-market fixed effects (Column 3).

We expect the OLS estimates to be biased. Following Foster et al. (2008), we instrument for relative wholesale price with quantity-based product-level productivity (*TFP-QEM*). Using the IV estimator reverses the sign of the effect of wholesale price on market share (Column 4): a one-percent higher wholesale price reduces market share by 4.9 percent. This result confirms that the initially-observed positive relationship between wholesale price and market share was upward biased. Following Nevo (2001), we instrument for relative retail markup with the firm average retail markup in the non-focal ATC5. Instrumenting both wholesale price and retail markup more than doubles the (negative) magnitude of the effect of retail markup on market share (Column 5): a one-percent higher retail markup reduces market share by approximately 1.2 percent. The IV estimates increase slightly in magnitude after controlling for brand age, pack size and firm-market fixed effects (Column 6). The reported F-statistics confirms that the instruments chosen are jointly strongly relevant.[7]

[7] Table 3.8, Column 1 reports the results of the IV first-stage regression for wholesale price. Quantity-based productivity is strongly negatively related to wholesale price. Table 3.8, Column 7 reports the results of the IV first-stage regression for retail markup. Firm average retail markup

Although the 119 pharmaceutical firms in the combined sample account for 60 percent of the total sales in the industry, there are 798 firms in the original AIOCD dataset that are not observed in the Prowess data. Since the Prowess sample consists of publicly traded firms, the non-matched firms are on average smaller in size and scope. Moreover, there are markets which are not covered by the Prowess firms, potentially implying that our results are not representative for the informal and fringe firms that populate India's pharmaceutical industry. However, when we compare the OLS estimates on the combined sample in Table 3.3 with those obtained from the full AIOCD sample in Table 3.A.2 in the Chapter Appendix, we notice that the results are very close.

3.5.2 Subsample analysis

In this section, we examine whether the pattern of results we observe previously are due to the idiosyncrasies of the Indian pharmaceutical industry or the unusual manner in which health care is organized and consumed in India. We divide the observations in our sample across firm, market and product characteristics and estimate Equation (3.5) using the IV method described in Section 3.4.

We begin with subsamples of our data based on firm and market characteristics. We examine whether the elasticities of market share to wholesale price and retail markup are different for domestic and multinational firms. We expect the multinational firms to have higher appeal and lose less demand when they charge higher prices with respect to the domestic firms. We examine this by distinguishing domestic and multinational firms in our dataset and conducting a split-sample analysis of the effect of wholesale price and retail markup on market share in Table 3.4, Column 1-2. The estimates confirm our expectations: the negative effect of a one-percent higher wholesale price for domestic firms (-6.1 percent) is almost double than that for multinational firms (-3.9 percent). The negative effect of retail markup, highly significant for domestic firms, does not apply to multinational firms.

Next, we examine whether the results are specific to some dosage forms than others. Unlike medicines in solid form (such as tablets), injectibles are often consumed with the help of a healthcare professional. We hypothesize that product substitutability across solid and liquid medicines is higher than that of the injectable medicines, implying higher elasticities of market share to wholesale price and retail markup for solid and liquid drugs compared to that for injectable drugs. The estimates reported

in the non-focal ATC5 is strongly positively related to wholesale price. The first-stage estimates confirm that both instruments are individually strongly relevant.

Table 3.4 The effect of wholesale price and retail markup on product market share. Subsample analysis on firm and market characteristics.

	Market share (log)							
	(1) Domestic	(2) Multinational	(3) Solids	(4) Liquids	(5) Injectables	(6) Before 1995	(7) 1995-2004	(8) After 2005
Relative wholesale price (log)	-6.122***	-3.860***	-8.555***	-5.195***	-2.534***	-4.791***	-7.624***	-8.900***
	(0.872)	(0.974)	(1.204)	(0.850)	(0.742)	(0.933)	(0.947)	(1.784)
Relative retail markup (log)	-1.847***	-0.340	-2.759***	-0.949	1.311	-1.019**	-3.305**	-4.848
	(0.511)	(2.233)	(0.661)	(0.811)	(1.562)	(0.456)	(1.338)	(7.639)
Market X Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	115118	14323	87563	18777	19547	55534	55763	17319
F-stat	103.0	9.0	73.1	61.4	5.2	68.9	28.2	3.9

Notes: IV estimates. The dependent variable *Market share* is the product share of the wholesale sales of the market. The *Market* is defined as the set of drugs made of the same active pharmaceutical ingredient (5-digit Anatomical Therapeutic Classification, ATC5) and with the same dosage form (e.g., tablet, injection, syrup). *Relative wholesale price* is the ratio between product's normalized wholesale price and the average normalized wholesale price of the market. *Relative retail markup* is the ratio between product retail markup and the average retail markup of the market. The logarithms of product pack size and brand age are included in the specification. The subsamples *Multinational* and *Domestic* include, respectively, the drugs produced by multinational companies and domestic companies. The subsamples *Solid*, *Liquid* and *Injectables* include, respectively, drugs whose dosage form is solid (e.g. tablet), liquid (e.g. syrup) and injectable (e.g. syringe). The subsamples *Before 1995*, *1995-2004* and *Since 2005* include ATC5 launched before 1995, between 1995 and 2004, from 2005 onwards, respectively. In all estimates, *Relative wholesale price* is instrumented with quantity-based product-level productivity (*TFP-QEM*), whereas *Relative retail markup* is instrumented with the firm average retail markup in the non-focal ATC5. *F-stat* is Kleibergen-Paap F statistic. All variables are expressed in logarithms. The table is based on AIOCD and Prowess, CMIE data. Standard errors (in parentheses) clustered at the market level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

in Table 3.4, Column 3-5 confirm our hypothesis: a one-percent higher wholesale price for solid and liquid drugs has a negative effect on market share which is, respectively, three and two times larger than that for injectable drugs. The negative effect of retail markup is not significant for liquid and injectable drugs but highly significant and negative for solid drugs.

We also examine the population of medicines in India, which are composed of medicines from different launch periods. It is possible that our results are driven by recently launched medicines that tend to be more expensive. In particular, India agreed to the WTO TRIPS agreement in 1995 and implemented it since 2005. In Table 3.4, Column 6-8 we distinguish between medicines launched before 1995, between 1995 and 2004, and since 2005 and estimate the marginal effect of higher wholesale price and retail markup on market share. We find that the negative effect of higher wholesale prices decreases in the age of the market. In older markets many products have been commercialized for a long time and, despite a larger number of competitors, enjoy higher consumer confidence and retention. Similar effects are observed for the retail markup: the older the market, the smaller the effect of retail markup on market share.

We further examine the robustness of our results to several subsample analyses based on medicine characteristics. The frequency of purchase of medicines can influence the relationship between relative wholesale price and market share. Medicines for chronic diseases such as diabetes are consumed over extended periods of time and are associated with repeated purchases. By contrast, medicines for acute conditions such as flu or fever are characterized by occasional use. In Table 3.5, Column 1-2 we distinguish medicines for their use in acute and chronic treatment and report the estimates of the the marginal effect of wholesale price and retail markup on market share. We find that the estimated wholesale price effect for the chronic medicine subsample is almost three times larger than that for the acute medicine subsample, suggesting that the markets for chronic treatment medicines are relatively more competitive. The estimated retail markup effect for chronic treatment medicines is also large (and negative), while that for the acute treatment medicines is not significant.

A large part of the ATC5 sold in India are combination of multiple active ingredients (e.g., amoxycillin and clavulanic acid). We call these drugs combination medicines and examine whether there are differential effects compared to single-ingredient ones. The results reported in Table 3.5, Column 3-4 indicate that the negative effect of wholesale price on market share is slightly larger for single-ingredient drugs, suggesting that combination medicine markets are relatively less competitive.

Table 3.5 The effect of wholesale price and retail markup on product market share. Subsample analysis on drug characteristics.

	Market share							
	(1) Acute	(2) Chronic	(3) Single	(4) Combination	(5) Non-regulated	(6) Regulated	(7) Over-the-counter	(8) Prescription
Relative wholesale price (log)	-4.675***	-12.681***	-6.418***	-4.615***	-5.232***	-7.738***	-4.169***	-9.124***
	(0.668)	(2.572)	(1.215)	(0.697)	(0.818)	(1.052)	(0.724)	(1.302)
Relative retail markup (log)	-0.618	-15.321***	-1.262**	-2.006***	-1.637***	-1.454*	-0.876	-2.367***
	(0.414)	(5.396)	(0.637)	(0.679)	(0.611)	(0.811)	(0.631)	(0.798)
Market X Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91783	37658	83167	46274	102889	26552	74549	54892
F-stat	102.7	4.9	53.7	57.8	71.1	30.8	52.0	51.2

Notes: IV estimates. The dependent variable *Market share* is the product share of the wholesale sales of the market. The *Market* is defined as the set of drugs made of the same active pharmaceutical ingredient (5-digit Anatomical Therapeutic Classification, ATC5) and with the same dosage form (e.g., tablet, injection, syrup). *Relative wholesale price* is the ratio between product's normalized wholesale price and the average normalized wholesale price of the market. *Relative retail markup* is the ratio between product retail markup and the average retail markup of the market. The logarithms of product pack size and brand age are included in the specification. The subsamples *Acute* and *Chronic* include drugs used for treating, respectively, acute and chronic. The subsamples *Single* and *Combination* include drugs composed by, respectively, a single active ingredient and the combination of two or more active ingredients. The subsamples *Non-regulated* and *Regulated* include drugs in ATC5s that are, respectively, non-regulated and regulated by the Indian government. The subsamples *Over-the-counter* and *Prescription* include drugs that, respectively, do not and do need a medical prescription to be purchased. In all estimates, *Relative wholesale price* is instrumented with quantity-based product-level productivity (*TFP-QEM*), whereas *Relative retail markup* is instrumented with the firm average retail markup in the non-focal ATC5. *F-stat* is Kleibergen-Paap F statistic. All variables are expressed in logarithms. The table is based on AIOCD and Prowess, CMIE data. Standard errors (in parentheses) clustered at the market level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Nevertheless, the effect of retail markup for the two subsamples are very similar.

India adopted a price ceiling regulation in mid-2013 for essential medicines, covering nearly a fifth of the market for pharmaceuticals in India. We estimate the effect of wholesale price and retail markup on market share for unregulated and regulated medicines. The results reported in Table 3.5, Column 5-6 indicate that the negative effect of wholesale price on market share is slightly larger for the regulated drugs, suggesting that non-regulated markets are relatively less competitive in terms of wholesale prices. The effect of retail markup is qualitatively similar for both regulated and unregulated medicines. We also distinguish between medicines that can be purchased over-the-counter and those that require a medical prescription. In Table 3.5, Column 7-8 we compare the estimates of the the marginal effect of wholesale price and retail markup on market share and observe that the effect of both price components for medicines that require a prescription are almost twice as large as the effects estimated for medicine that can be purchased without prescription.

3.5.3 Nonlinear effects for market leaders and pioneers

The results reported in Table 3.3 constitute an average effect in the industry of a change in product price on market share. However, this effect can be different for products with different levels of market power (Frank and Salkever, 1997; Berndt and Aitken, 2011; Reiffen and Ward, 2005). Next, we study how wholesale price and retail markup affect the market shares of market-leading or market pioneering products compared to their competitors.

In each market we identify the leading product as the product with the highest share of sales within each market. We distinguish between market leaders from followers using the binary variable *Leader*, which takes value one when the product is the market leader. In each market we also identify the pioneering product as the product that was launched in the same year as the market. We flag market pioneers using the binary variable *Pioneer*, which takes value one when the product is the market pioneer. We interact each of these binary variables with product wholesale price.

Wholesale price, however, is not the only determinant that can present asymmetric effects for leaders and followers. Higher retail markups can incentivize the retailer to provide a larger availability of a certain product. In such a case, a higher retail markup can boost the market share of the product, despite implying also a higher retail price. If the decrease in sales due to higher retail prices is negligible, then increasing retail markups is a profitable strategy for the firm. We consider whether the market share of products with higher levels of market power,

Table 3.6 The effect of wholesale price and retail markup on product market share. Market leaders and market pioneers.

	Market share (log)			
	(1) OLS	(2) IV	(3) OLS	(4) IV
Relative wholesale price (log)	0.083***	-5.431***	0.076***	-5.770***
	(0.023)	(0.730)	(0.023)	(0.772)
Relative wholesale price (log) × Leader	-0.052	2.585***		
	(0.032)	(0.520)		
Relative wholesale price (log) × Pioneer			-0.001	3.533***
			(0.070)	(0.780)
Relative retail markup (log)	-0.655***	-1.510***	-0.678***	-1.585***
	(0.056)	(0.460)	(0.057)	(0.474)
Relative retail markup (log) × Leader	0.200	0.419		
	(0.146)	(0.615)		
Relative retail markup (log) × Pioneer			0.154	0.582
			(0.215)	(0.756)
Leader	2.547***	1.636***		
	(0.039)	(0.173)		
Pioneer			1.462***	0.477*
			(0.098)	(0.256)
Market × Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R-squared	0.745		0.728	
Observations	129449	129441	129449	129441
F-stat		101.5		99.4

Notes: OLS and IV estimates. The dependent variable *Market share* is the product share of the wholesale sales of the market. The *Market* is defined as the set of drugs made of the same active pharmaceutical ingredient (5-digit Anatomical Therapeutic Classification, ATC5) and with the same dosage form (e.g., tablet, injection, syrup). *Leader* is a binary variable taking value 1 when the product has the highest market share within the market. *Pioneer* is a binary variable taking value 1 when the product was launched in the same year as the market. *Relative wholesale price* is the ratio between product's normalized wholesale price and the average normalized wholesale price of the market. *Relative retail markup* is the ratio between product retail markup and the average retail markup of the market. The logarithms of product pack size and brand age are included in the specification. In IV estimates, *Relative wholesale price* is instrumented with quantity-based product-level productivity (*TFP-QEM*), whereas *Relative retail markup* is instrumented with the firm average retail markup in the non-focal ATC5. *F-stat* is Kleibergen-Paap F statistic. All variables are expressed in logarithms. The table is based on AIOCD and Prowess, CMIE data. Standard errors (in parentheses) clustered at the market level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

such as market leaders and pioneers, depends by retail markup less than that of other products. To test this we interact also retail markups with the leader and the pioneer binary variables defined above.

Table 3.6 shows that the coefficient estimates for the wholesale prices of the leaders have opposite sign compared to the coefficient estimate for the wholesale price of the other products (Column 2). A one-percent higher wholesale price reduces market share by 2.6 percent for market leaders and by 5.4 percent for the other products. These results are in line with the findings of Berndt and Aitken (2011) indicating that market leaders are partly shielded from price competition. We also observe a positive but not significant effect of an increase in retail markups for product leaders (Column 2). Higher retail markup diminishes the demand for the product also for market leaders and is not compensated by the retailer incentive to stock the product and allocate greater selling effort for the products with higher markups. The results on the non-linear effects for market pioneers show similar estimates and have the same implications as the estimates on market leaders (Column 4).

3.6 Additional results and robustness tests

3.6.1 Elasticity of substitution across products

Equation (3.5), used for the baseline estimates, is the log-linearized version of the model solution in Equation (3.4). The coefficient α_1 and α_2 are functions of the elasticity of substitution across products σ as defined in the model: $\alpha_1 = 1 - \sigma$ and $\alpha_2 = -\sigma$. Thus we expect to observe such a relationship between the estimated coefficients: $\widehat{\alpha_1} = 1 + \widehat{\alpha_2}$. Table 3.7 reports the elasticity of substitutions calculated using the wholesale price coefficient ($\sigma = 1 - \widehat{\alpha_1}$), the retail markup coefficient ($\sigma = -\widehat{\alpha_2}$) and their ratio. The average elasticity of substitution calculated using the wholesale price coefficient is 6.7, in line with the estimates in Hottman et al. (2016). However, elasticity of substitution calculated using the retail markup coefficient is substantially lower than expected and is on average 4 times smaller than that calculated using the wholesale price coefficient.

These results suggest two relevant implications. First, considering the narrow definition of market that we adopt (drugs with the same ATC5 and dosage form) the substitutability among products should be perfect. However, due to the preferences of physicians, pharmacists and consumers, a substantial vertical differentiation across products is perceived. Second, the difference between the two estimates of elasticity of substitution can be interpreted as the difference in elasticity of substitution between retailers and consumers. For the same retail markup, retailers substitute products based on their perceived vertical difference across products. On the other hand, for the same wholesale price, the retailers substitute products based on the consumer's perceived vertical difference across products. Our results imply that the elasticity of substitution for the retailers is larger than that for the consumers, as also observed by Bronnenberg et al. (2015).

3.6.2 Product appeal, prices and productivity

In Equation (3.5) we include firm-market fixed effects to capture the time invariant characteristics of the firm within the market. If average product appeal is time invari-

Table 3.7 Elasticities of substitution across subsamples

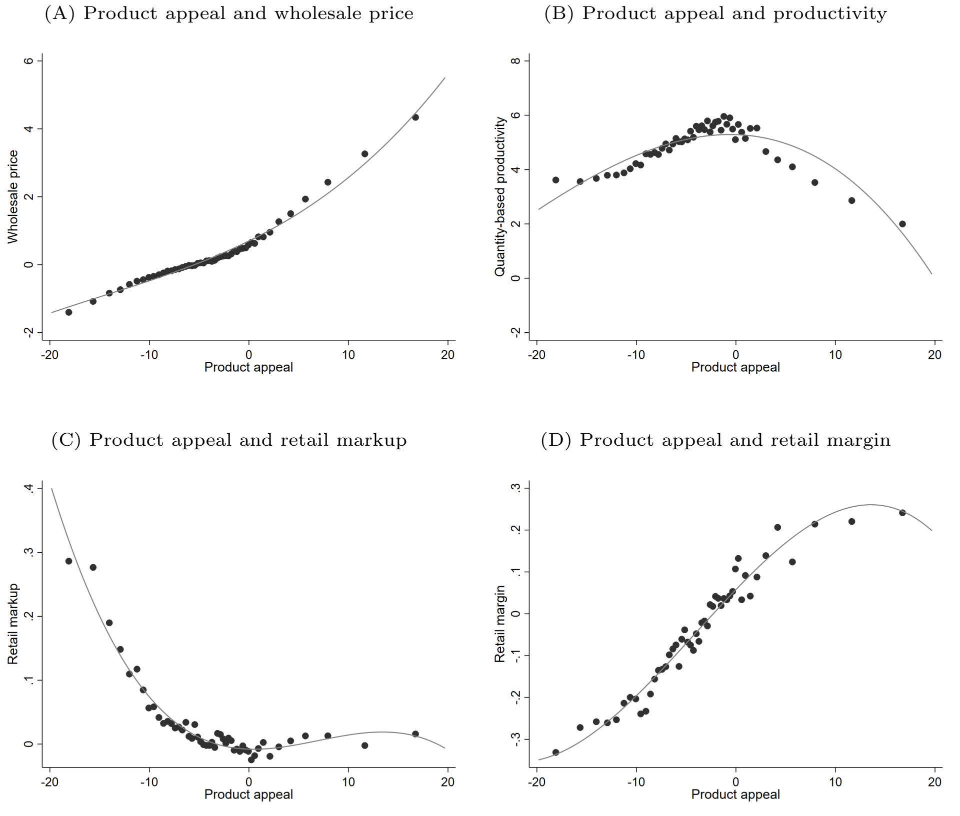
Sample	Elasticity of substitution (σ)		
	$1-\widehat{\alpha_1}$	$-\widehat{\alpha_2}$	$\frac{1-\widehat{\alpha_1}}{-\alpha_2}$
All	6.7	1.5	4.4
Domestic	7.1	1.8	3.9
Multinational	4.9	0.3	14.3
Solids	9.6	2.8	3.5
Liquids	6.2	0.9	6.5
Injectables	3.5	-1.3	-2.7
Before 1995	5.8	1.0	5.7
1995-2004	8.6	3.3	2.6
After 2005	9.9	4.8	2.0
Acute	5.7	0.6	9.2
Chronic	13.7	15.3	0.9
Single	7.4	1.3	5.9
Combination	5.6	2.0	2.8
Non-regulated	6.2	1.6	3.8
Regulated	8.7	1.5	6.0
Over-the-counter	5.2	0.9	5.9
Prescription	10.1	2.4	4.3

Notes: Estimates of average elasticity of substitutions across products of the same market. The *Market* is defined as the set of drugs made of the same active pharmaceutical ingredient (5-digit Anatomical Therapeutic Classification, ATC5) and with the same dosage form (e.g., tablet, injection, syrup). $1-\widehat{\alpha_1}$ is the elasticity of substitution calculated using the estimated market share elasticity to wholesale price as from Table 3.3, Table 3.4 and Table 3.5. $-\widehat{\alpha_2}$ is the elasticity of substitution calculated using the estimated market share elasticity to retail markup as from Table 3.3, Table 3.4 and Table 3.5. The subsamples *Multinational* and *Domestic* include, respectively, the drugs produced by multinational companies and domestic companies. The subsamples *Solid*, *Liquid* and *Injectables* include, respectively, drugs whose dosage form is solid (e.g. tablet), liquid (e.g. syrup) and injectable (e.g. syringe). The subsamples *Before 1995*, *1995-2004* and *Since 2005* include ATC5 launched before 1995, between 1995 and 2004, from 2005 onwards, respectively. The subsamples *Acute* and *Chronic* include drugs used for treating, respectively, acute and chronic. The subsamples *Single* and *Combination* include drugs composed by, respectively, a single active ingredient and the combination of two or more active ingredients. The subsamples *Non-regulated* and *Regulated* include drugs in ATC5s that are, respectively, non-regulated and regulated by the Indian government. The subsamples *Over-the-counter* and *Prescription* include drugs that, respectively, do not and do need a medical prescription to be purchased. The table is based on AIOCD and Prowess, CMIE data.

ant, firm-market fixed effects estimate the average product appeal of the firm in the specific market. In our results, the variation of the estimated firm-market fixed effects explains 77 percent of the variation in product market share, suggesting that the average product appeal of the firm is the principal component of market share.[8] We compare the values in the estimated vector of firm-market fixed effects with the average firm-market values of wholesale price and productivity. Figure 3.3, Panel (A) and (B) show that both wholesale price and productivity are positively related with product appeal. However, while wholesale price increases in product appeal monotonically,

[8] This finding is close to the contribution of product appeal to firm sales variance (approximately 80 percent) estimated by Hottman et al. (2016). The variation of market share explained by appeal is calculated as: $\frac{Cov(\widetilde{Y}_{ifjt},\lambda_{fj})}{Var(\widetilde{Y}_{ifjt})}$.

Figure 3.3 Product appeal, prices and productivity



Notes: Binned scatterplots. Product appeal is measured using the firm-market fixed effects estimated from Equation 3.5 and is time invariant. The *Market* is defined as the set of drugs made of the same active pharmaceutical ingredient (5-digit Anatomical Therapeutic Classification, ATC5) and with the same dosage form (e.g., tablet, injection, syrup). Panel (A): *Wholesale price* is the average relative wholesale price within the firm-market; Panel (B): *Quantity-based productivity* is the firm-market average of product-level productivity (*TFP-QEM*) estimated as from Equation (M.3.1); Panel (C): *Retail markup* is the average relative retail markup within the firm-market; Panel (D): *Retail margin* is the average relative retail margin within the firm-market. All variables on the y-axis are expressed in logarithms. A third-degree polynomial fitted line is plotted. The figure and the table are based on AIOCD and Prowess, CMIE data.

productivity decreases in product appeal for the highest values of the latter. This implies that product appeal, although fully mirrored in the prices, does not reward productivity completely. High values of product appeal do not indicate higher efficiency, but only high prices.

We also compare firm-market fixed effects with the average firm-market values of retail markup and margin. Figure 3.3, Panel (C) shows that retail markup decreases as product appeal increases. At first glance this might look counterintuitive as retailers are missing the possibility to charge higher retail markup for more appealing (and less substitutable) products. However, considering that wholesale prices increase with product appeal, the retail margins remain high even with lower markups and have a positive relationship with product appeal, as shown in Figure 3.3, Panel (D).

3.6.3 Product prices and selection on productivity

In Section 3.5 we used an estimated measure of quantity-based product-level productivity *TFP-QEM* to instrument for relative prices. We test the relevance of the instrument using another five measures of product-level productivity to instrument for relative price. The methodology for calculating the alternative five measures of productivity is discussed in Appendix M.3.3 and summarized in Table 3.A.3 in the Chapter Appendix. The alternative first-stage regressions of in Equation (3.5) are shown in Table 3.8. We control for relative retail markup, brand age, pack size competition and a battery of firm-market and year fixed effects. We find that relative wholesale prices are negatively correlated with the three quantity-based measures (Columns 1-3), but positively correlated with the three revenue-based ones (Columns 4-6). Foster et al. (2008) find a similar pattern of results. They note that the results are driven by the fact that revenue-based productivity incorporates prices by definition although revenue-based productivity is calculated with deflated values. This suggests that a revenue-based measure is not a suitable instrument for prices to identify elasticity in Equation (3.5). Quantity-based productivity, instead, is more appropriate to satisfy the exogeneity condition.

The negative relation between quantity-based productivity and prices is not surprising: more efficient products have lower marginal costs, allowing firms to charge lower prices for them. Indeed, many dynamic models predict that more productive firms set lower prices, forcing less productive firms to exit the industry and gaining market shares (Jovanovic, 1982; Hopenhayn, 1992; Jovanovic and MacDonald, 1994). The ensuing competitive process spurs the reallocation of production inputs from less productive plants and firms to more productive ones, fostering growth (Foster et al., 2016).[9] Also empirical studies of specific industries show that, on average, an increase in the productivity levels within an industry leads to lower prices. For example, using data on ready-mixed concrete, Syverson (2007) shows that when producers have heterogeneous costs and sell one homogeneous product, competitive selection on costs lowers product prices. Our analysis on multiproduct firms shows that higher productivity is associated with lower prices even at the product level.

[9] 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).

Table 3.8 First stages of the baseline specification: the relationship between wholesale price and product-level productivity

	Relative wholesale price (log)						Relative retail markup (log)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Quantity-based productivity (TFP-QEM)	-0.113***						
	(0.014)						
Quantity-based productivity (TFP-QC)		-0.748***					
		(0.043)					
Quantity-based productivity (TFP-QES)			-0.127***				
			(0.024)				
Revenue-based productivity (TFP-RC)				0.251***			
				(0.029)			
Revenue-based productivity (TFP-VE)					0.030***		
					(0.010)		
Revenue-based productivity (TFP-RE)						0.042**	
						(0.018)	
Relative retail markup (log)	-0.526***	-0.216***	-0.502***	-0.478***	-0.459***	-0.499***	
	(0.030)	(0.032)	(0.029)	(0.028)	(0.031)	(0.030)	
Markup non-focal ATC5 (log)							0.226***
							(0.016)
Relative wholesale price (log)							-0.042***
							(0.004)
Market X Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.745	0.885	0.745	0.733	0.759	0.725	0.422
Observations	135941	135934	135947	135934	124978	135947	135931

Notes: OLS estimates. The dependent variable *Relative wholesale price* is the ratio between product's normalized wholesale price and the average normalized wholesale price of the market. The productivity measures are defined as follows. *TFP-RC*: revenue-based productivity calculated using the share of costs following Foster et al. (2008); *TFP-VE*: value added-based productivity calculated following Ahsan (2013); *TFP-RE*: revenue-based productivity calculated following Topalova and Khandelwal (2011); *TFP-QC*: quantity-based productivity calculated using the share of costs following Foster et al. (2008); *TFP-QES*: quantity-based productivity for single-product firms, following De Loecker et al. (2016); *TFP-QEM*: quantity-based productivity for multiproduct firms following Dhyne et al. (2017). The dependent variable *Relative retail markup* is the ratio between product retail markup and the average retail markup of the market. *Markup non-focal ATC5* is firm's average retail markup in the non-focal ATC5. All variables are expressed in logarithms. The table is based on AIOCD and Prowess, CMIE data. Standard errors (in parentheses) clustered at the market level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

3.6.4 Quantity-based market share and demand estimation

In Section 3.5 we observe that market share is positively correlated with wholesale prices when estimated using OLS. Since market shares are calculated using product revenues that include wholesale prices, there is a mechanical positive relation between the two variables. In Table 3.9, Columns 1-4 we remove this issue by estimating the effect of wholesale price and retail markup on *quantity-based* market share. Quantity-based market share is calculated as the product share of normalized quantity sold in the market. Within the market, the products have the same chemical composition, therefore we can sum their normalized quantities sold and obtain a measure of quantity-based market share comparable across different markets. Quantity-based market share is negatively correlated with wholesale prices also when estimated with OLS (Column 1-2). IV estimates confirm the direction of the relation, but the size of the price coefficient increases in absolute value, as expected (Column 3-4).

A comparison with the estimates reported in Table 3.6, whose dependent variable is revenue-based market share, shows that the IV coefficients are very close. These findings suggest that the positive correlation between revenue-based market share and prices does not, on average, imply a higher demand (quantity) for the product. As consumers might perceive higher prices as higher product quality, this result implies that perceived quality is not the main driver of the upward relationship between revenue-based market share and prices.

Demand elasticity is, therefore, another important component of the puzzle. We investigate price elasticity of demand using the same controls as in Equation (3.5) . The dependent variable is the log of normalized units of product sold and the main explanatory variable is log normalized wholesale prices. Table 3.9, Columns 5-8 presents the estimates of wholesale price and retail markup elasticity. The OLS estimates of wholesale price elasticity are close to one, whereas the estimates of retail markup elasticity are 0.76 (Column 5-6). The IV estimates show a higher elasticities for both retail price components. A one-percent higher wholesale price (retail markup) leads to a 6.0 percent (1.6 percent) decrease in the units of drug sold (Columns 7-8). Our results regarding the price elasticity of demand are in line with those in Dubois and Lasio (2018) on anti-ulcer drugs in France, Germany and USA.

Table 3.9 The effect of wholesale price and retail markup on product demand. Quantity-based market shares and demand function estimates.

Dependent variable	Quantity-based market share (log)				Quantity (log)			
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimator	OLS	OLS	IV P	IV P&M	OLS	OLS	IV P	IV P&M
Relative wholesale price (log)	-0.953***	-0.985***	-5.911***	-5.889***				
	(0.023)	(0.022)	(0.541)	(0.538)				
Relative retail markup (log)		-0.746***		-1.190***				
		(0.058)		(0.424)				
Wholesale price (log)					-0.957***	-0.990***	-6.006***	-5.983***
					(0.024)	(0.023)	(0.541)	(0.537)
Retail markup (log)						-0.755***		-1.584***
						(0.054)		(0.338)
Market X Firm FE	Yes	Yes	Yes	Yes	Yes	Yes		
Year FE	Yes	Yes	Yes	Yes	Yes	Yes		
R-squared	0.752	0.754			0.775	0.776		
Observations	135941	135941	135941	135931	135941	135941	135941	135931
F-stat			60.7	104.0			61.8	141.4

Notes: OLS and IV estimates. The dependent variable *Quantity-based market share* is the product share of the normalized units sold in the market. The dependent variable *Quantity* is the normalized units of product sold. The *Market* is defined as the set of drugs made of the same active pharmaceutical ingredient (5-digit Anatomical Therapeutic Classification, ATC5) and with the same dosage form (e.g., tablet, injection, syrup). *Wholesale price* is product wholesale price normalized by dividing the wholesale price by product dosage strength and pack size. *Relative wholesale price* is the ratio between product's normalized wholesale price and the average normalized wholesale price of the market. *Retail markup* is calculated as product retail price divided by product wholesale price. *Relative retail markup* is the ratio between product retail markup and the average retail markup of the market. The logarithms of product pack size and brand age are included in the specification. In IV estimates, *Relative wholesale price* is instrumented with quantity-based product-level productivity (*TFP-QEM*), whereas *Relative retail markup* is instrumented with the firm average retail markup in the non-focal ATC5. In Column (3) and (7) only *Relative wholesale price* is instrumented (*IV P*), whereas in Column (4) and (8) both *Relative retail markup* and *Relative retail markup* are instrumented (*IV P&M*). *F-stat* is Kleibergen-Paap F statistic. All variables are expressed in logarithms. The table is based on AIOCD and Prowess, CMIE data. Standard errors (in parentheses) clustered at the market level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

3.6.5 Retail markup and retail margin

In Section 3.5 we discussed the significant effect of the retail markup in influencing product market share negatively, as predicted by our model. As a robustness test we repeat the exercise with product retail margin, measured as the difference between retail price and wholesale price of the product. Although conceptually similar, retail margin is measured in rupees and depend both on wholesale price and retail markup. Therefore, retail margin can serve as a better proxy for retailer's incentive to stock and allocate greater selling effort to some products (Brekke et al., 2013). Figure 3.4 shows the triangular relationship among wholesale prices, retail markups and retail. As wholesale price increases retail markup declines, allowing anyway increasing retail margin. Retail markups and retail margins are highly positively correlated, but are driven by different economic forces and can have different effects on product market share.

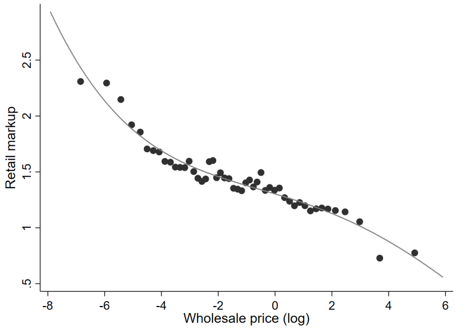
Table 3.10 reports the effects of retail margin on product market share using the same specification as in Equation 3.5, but replacing relative retail markup with relative retail margin. The effect of a marginal change in retail margin reported in Column 2 is half the one observed for the markup in Table 3.3, Column 6. We also compare the coefficient of retail margin with that of retail markup for market leaders and market pioneers. We find that retail margin for market leaders or market pioneers drives product market share positively. A one-percent higher retail margin for the market leader leads to a 0.2 percent higher product market share, whereas the same change for another product would lead to a 0.7 percent lower product market share (Columns 4). A one-percent higher retail margin for the market pioneer leads to a 0.5 percent higher product market share, whereas the same change for another product would lead to a 0.7 percent lower product market share (Columns 6). These results are in line with those in Brekke et al. (2013) on pharmaceutical retail margins in Norway.[10]

The results in Table 3.6 and Table 3.10 provide evidence of how market power influences product market share in narrowly defined markets. If the product has some market power, a wholesale price increase affects market share to a lesser extent. However, the results also suggest that pharmaceutical firms can benefit from allowing higher retail margins. If the retailer buyer power is high, a higher retail price can even increase the demand for the leading products. On the consumer side, both

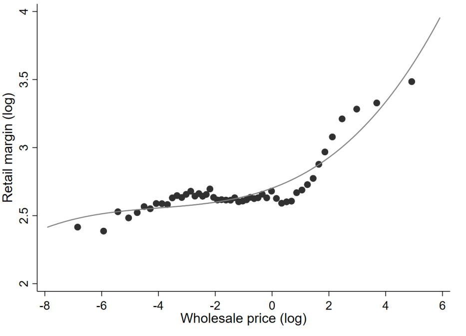
[10] In Table 3.A.4 in the Chapter Appendix we repeat the exercise using the product market share measured with retail price, as in Brekke et al. (2013). We find that retail margin has no effect on product market share by the retailers and that it has a positive effect on the difference between product market share by the retailers and product market share by the wholesalers.

Figure 3.4 Retail markups and retail margins

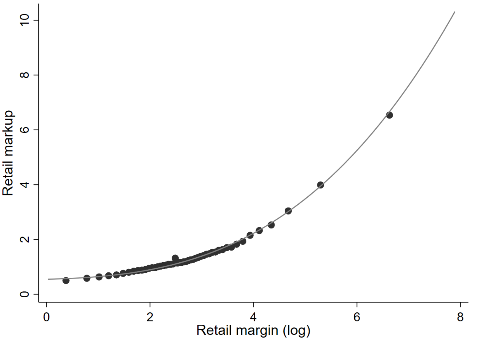
(A) Retail markup and wholesale price



(B) Retail margin and wholesale price



(C) Retail markup and retail margin



Notes: Binned scatterplots. *Wholesale price (log)* is the logarithm of product wholesale price normalized by dividing the wholesale price by product dosage strength and pack size. *Retail markup* is calculated as product retail price divided by product wholesale price. *Retail margin (log)* is calculated as the logarithm of the difference between product retail price and product wholesale price. A third-degree polynomial fitted line is plotted. This figure is based on AIOCD data.

market power and buyer power contribute to a welfare loss. The manufacturers of best selling drugs appear not to lower their prices and the retailers are more willing to provide products that yield them a higher margin. Moreover, consumer-specific factors such as product appeal is a relevant component of market shares in all our estimates. Demand-side factors involving consumers and retailers, and the presence of asymmetries for market leaders seem to be primarily responsible for the positive relation between prices and revenue-based market shares observed.

Table 3.10 The effect of retail margin on product market share.

	Market share (log)					
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
Relative wholesale price (log)	0.073***	-5.821***	0.083***	-5.528***	0.075***	-5.863***
	(0.023)	(0.766)	(0.023)	(0.748)	(0.023)	(0.790)
Relative wholesale price (log) X Leader			-0.037	2.614***		
			(0.032)	(0.528)		
Relative wholesale price (log) X Pioneer					-0.021	3.572***
					(0.070)	(0.793)
Relative retail margin (log)	0.340***	-0.714***	0.326***	-0.720***	0.341***	-0.762***
	(0.026)	(0.235)	(0.025)	(0.232)	(0.027)	(0.237)
Relative retail margin (log) X Leader			-0.407***	0.958**		
			(0.075)	(0.453)		
Relative retail margin (log) X Pioneer					0.186**	1.262***
					(0.091)	(0.334)
Leader			2.566***	1.602***		
			(0.040)	(0.182)		
Pioneer					1.517***	0.469*
					(0.098)	(0.267)
Market X Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.725		0.745		0.729	
Observations	129421	129413	129421	129413	129421	129413
F-stat		123.8		122.5		122.6

Notes: OLS and IV estimates. The dependent variable *Market share* is the product share of the wholesale sales of the market. The *Market* is defined as the set of drugs made of the same active pharmaceutical ingredient (5-digit Anatomical Therapeutic Classification, ATC5) and with the same dosage form (e.g., tablet, injection, syrup). *Leader* is a binary variable taking value 1 when the product has the highest market share within the market. *Pioneer* is a binary variable taking value 1 when the product was launched in the same year as the market. *Relative wholesale price* is the ratio between product's normalized wholesale price and the average normalized wholesale price of the market. *Relative retail margin* is the ratio between product retail margin and the average product retail margin of the market. The logarithms of product pack size and brand age are included in the specification. In IV estimates, *Relative wholesale price* is instrumented with quantity-based product-level productivity (*TFP-QEM*), whereas *Relative retail margin* is instrumented with the firm average retail markup in the non-focal ATC5. *F-stat* is Kleibergen-Paap F statistic. All variables are expressed in logarithms. The table is based on AIOCD and Prowess, CMIE data. Standard errors (in parentheses) clustered at the market level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

3.7 Conclusion

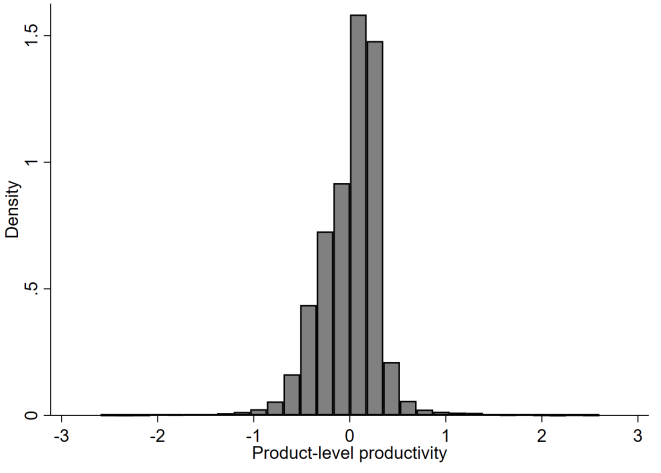
We examine the relationship among wholesale prices, retail markups and product market shares in the pharmaceutical industry. We exploit a rich dataset on Indian pharmaceutical firms containing detailed information on quantities, wholesale and retail price of every drug sold in the country. Using a naive OLS estimation that does not control for simultaneity and omitted variable bias, we find that market share is positively correlated with product prices. In this chapter we split retail price into wholesale prices and retail markups, and identify their relationship with product market shares addressing the aforementioned biases.

Building on Hottman et al. (2016) model of heterogeneous multiproduct firms, we distinguish the principal drivers of product market share into product wholesale price, retail markup and appeal. We control product appeal using firm-market fixed effects, product brand age and pack size and estimate the effect of a change in wholesale price and in retail markup on product market share. We instrument for wholesale prices with a measure of quantity-based product-level productivity, a supply side driver of wholesale prices, uncorrelated with product-specific demand shocks. We instrument for retail markup with the firm average retail markup in the non-focal ATC5, a firm-specific driver of retail markups, uncorrelated with product-specific demand shocks. We find that a one-percent higher wholesale price reduces product market share by 5.7 percent and a one-percent higher retail markup reduces product market share by 1.5 percent. This finding indicates that, on average, higher wholesale prices do not lead to higher market share.

Analysing market leaders and market pioneers separately, however, reveals the significant market power that the leaders possess in the markets we study. The negative effect on market share of a wholesale price increase of the market-leading product is half that of other products, indicating that leaders are partly insulated from price competition in the market. One mechanism that helps leader's insulation from competition seems to be the incentive provided to the retailers in the form of higher margins. These results reveal how retailer's buyer power can foster a win-win relationship between retailers and market leaders. In markets offering close substitute goods, retailers can exploit the informative gap between them and the consumers and widen the difference between the true and the perceived elasticity of substitution from the consumers. In our findings the relatively higher demand for market leaders can depend on both retailer incentives and perceived quality. Since we consider markets with close substitute goods, our 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 the market-leading product to a cheaper alternative. Nevertheless, our results also show that the selection mechanism in the Indian pharmaceutical market does not reward the less productive products. Quantity-based productivity is negatively correlated with product wholesale price, implying that productivity triggers price competition, on average. Indeed, this consideration excludes the market leaders whose price setting decision leverages their interaction with the intermediaries and the consumers.

3.A Additional Tables and Figures

Figure 3.A.1 Product-level productivity estimates



	β_k	β_l	β_m	γ
Mean	0.571	0.205	0.524	-0.059
	(0.417)	(0.357)	(0.336)	(0.399)
Median	0.600	0.163	0.550	-0.016

Notes: The figure plots the standardized distribution of product-level productivity (*TFP-QEM*) estimated as from Equation (M.3.1). The production function is quantity-based and estimated using the LP estimator, adjusted to control for firm's product scope. Output elasticities are estimated at the ATC5 level for 2,323 ATC5s. The table reports means, standard deviations (not standard errors, in brackets) and medians of the ATC5-level output elasticities estimated. Column β_k reports the output elasticity to capital, Column β_l reports the output elasticity to labor, Column β_m reports the output elasticity to materials, Column γ reports the output elasticity to firm's product scope. The figure and the table are based on AIOCD and Prowess, CMIE data.

Table 3.A.1 The relationship between price and market share

	Market share		Market share (log)			
	(1) All	(2) All	(3) All	(4) All	(5) N10	(6) N10
Retail price (log)	0.009***					
	(0.001)					
Wholesale price (log)		0.009***				
		(0.001)				
Relative retail price (log)			0.022*		0.036***	
			(0.011)		(0.013)	
Relative wholesale price (log)				0.065***		0.084***
				(0.011)		(0.013)
Market FE	No	No	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.009	0.009	0.541	0.541	0.391	0.392
Observations	329280	329280	328746	328746	257099	257099

Notes: OLS estimates. The dependent variable *Market share* is the product share of the wholesale sales of the market. The *Market* is defined as the set of drugs made of the same active pharmaceutical ingredient (5-digit Anatomical Therapeutic Classification, ATC5) and with the same dosage form (e.g., tablet, injection, syrup). *Retail price* is product retail price normalized by dividing the retail price by product dosage strength and pack size; *Relative retail price* is the ratio between product's normalized retail price and the average normalized retail price of the market. *Wholesale price* is product wholesale price normalized by dividing the wholesale price by product dosage strength and pack size; *Relative wholesale price* is the ratio between product's normalized wholesale price and the average normalized wholesale price of the market. All variables are expressed in logarithms. Sample *All* includes all the markets; subsample *N10* includes the markets with ten or more products. The table is based on AIOCD data. Standard errors (in parentheses) clustered at the market level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.A.2 Sample representativeness

	Market share (log)											
	All firms				Domestic firms				Multinational firms			
	(1) AIOCD	(2) CMIE	(3) AIOCD	(4) CMIE	(5) AIOCD	(6) CMIE	(7) AIOCD	(8) CMIE	(9) AIOCD	(10) CMIE	(11) AIOCD	(12) CMIE
Relative wholesale price (log)	0.048**	0.047**	0.027	0.015	0.055***	0.058**	0.035*	0.025	-0.009	-0.026	-0.028	-0.050
	(0.019)	(0.023)	(0.019)	(0.022)	(0.020)	(0.025)	(0.021)	(0.024)	(0.033)	(0.045)	(0.032)	(0.044)
Relative retail markup (log)			-0.670***	-0.742***			-0.644***	-0.722***			-0.903***	-0.978***
			(0.041)	(0.058)			(0.041)	(0.059)			(0.137)	(0.179)
Market X Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.784	0.717	0.785	0.719	0.788	0.718	0.789	0.720	0.722	0.704	0.725	0.707
Observations	322759	135941	322759	135941	291086	121016	291086	121016	31673	14925	31673	14925

Notes: OLS. The dependent variable *Market share* is the product share of the wholesale sales of the market. The *Market* is defined as the set of drugs made of the same active pharmaceutical ingredient (5-digit Anatomical Therapeutic Classification, ATC5) and with the same dosage form (e.g., tablet, injection, syrup). *Relative wholesale price* is the ratio between product's normalized wholesale price and the average normalized wholesale price of the market. *Relative retail markup* is the ratio between product retail markup and the average retail markup of the market. The sample *AIOCD* includes all the observations in the AIOCD data, whereas the sample *CMIE* includes the observations in the AIOCD data matched with those in the CMIE data. The subsamples *Multinational* and *Domestic* include, respectively, the drugs produced by multinational companies and domestic companies. All variables are expressed in logarithms. The table is based on AIOCD and Prowess, CMIE data. Standard errors (in parentheses) clustered at the market level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.A.3 Comparing alternative production function estimates

		Revenue-based	Quantity-based
Cost share -based	Label	TFP-RC	TFP-QC
	Function	$y_{it} = \omega_{it} + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_e e_{it}$	$q_{it} = \omega_{it} + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_e e_{it}$
	Elasticities	$\beta_k = .75; \beta_l = .08; \beta_m = .15; \beta_e = .02$	$\beta_k = .75; \beta_l = .08; \beta_m = .15; \beta_e = .02$
	Literature	Foster et al. (2008)	Foster et al. (2008)
Estimation -based	Label	TFP-VE	TFP-QES
	Function	$va_{it} = \omega_{it} + \beta_k k_{it} + \beta_l l_{it}$	$q_{it} = \omega_{it} + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it}$
	Proxy	e_{it}	m_{it}
	Conditioning	-	$k_{it}; k_{it-1}; l_{it-1}; m_{it-1}; m_{it-2}$
	Elasticities	$\beta_k = .69; \beta_l = .32$	$\beta_k = .52; \beta_l = -.04; \beta_m = .43$
	Literature	Ahsan (2013)	De Loecker et al. (2016)
	Label	TFP-RE	TFP-QEM
	Function	$y_{it} = \omega_{it} + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it}$	$q_{it} = \omega_{it} + \beta_k k_{ft} + \beta_l l_{it} + \beta_m m_{it} + \gamma y_{-it}$
	Proxy	m_{it}	m_{it}
	Conditioning	$k_{it}; k_{it-1}; l_{it-1}; m_{it-1}; m_{it-2}$	$k_{ft}; k_{ft-1}; l_{it-1}; m_{it-1}; m_{it-2}; y_{-it-1}$
	Elasticities	$\beta_k = .71; \beta_l = .11; \beta_m = .23$	$\beta_k = .57; \beta_l = .20; \beta_m = .52; \gamma = -.06$
	Literature	Topalova and Khandelwal (2011)	Dhyne et al. (2017)

Notes: Product-level production function estimates. *Revenue-based* and *Quantity-based* refer to the output measure of the production function: product sales and product physical units sold, respectively. *Cost share-based* and *Estimation-based* refer to the methodology of calculation of output elasticities. The first equals elasticities to the average cost share of the market, the second estimates them at the ATC5 level. The variables indicated in the production functions are expressed in logs: y is sales revenue, q is physical units sold, va is value added calculated as the difference between revenue sales and raw materials, k is capital employed, l is salary, m is raw materials, e is power and fuel expenses. Subscripts i, $-i$, f and t indicate product, all other products but product i, firm and year, respectively. The estimated elasticities reported are the industry average of ATC5-level estimates. The table is based on AIOCD and Prowess, CMIE data.

Table 3.A.4 The effect of retail margin on product market share at the retailers.

	Retail market share (log)		Δ market share (log)	
	(1) OLS	(2) IV	(3) OLS	(4) IV
Relative wholesale price (log)	-0.002	-5.751***	-0.200***	-4.505***
	(0.020)	(0.755)	(0.032)	(0.865)
Relative retail margin (log)	0.586***	-0.209	1.224***	4.909***
	(0.025)	(0.227)	(0.044)	(0.435)
Market X Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R-squared	0.724		0.652	
Observations	129421	129413	46566	46559
F-stat		123.8		111.8

Notes: OLS and IV estimates. The dependent variable *Retail market share* is the product share of the retail sales of the market. The dependent variable Δ *market share* is the difference between retail market share and wholesale market share of the product. The *Market* is defined as the set of drugs made of the same active pharmaceutical ingredient (5-digit Anatomical Therapeutic Classification, ATC5) and with the same dosage form (e.g., tablet, injection, syrup). *Relative wholesale price* is the ratio between product's normalized wholesale price and the average normalized wholesale price of the market. *Relative retail margin* is the ratio between product retail margin and the average product retail margin of the market. The logarithms of product pack size and brand age are included in the specification. In IV estimates, *Relative wholesale price* is instrumented with quantity-based product-level productivity (*TFP-QEM*), whereas *Relative retail margin* is instrumented with the firm average retail markup in the non-focal ATC5. *F-stat* is Kleibergen-Paap F statistic. All variables are expressed in logarithms. The table is based on AIOCD and Prowess, CMIE data. Standard errors (in parentheses) clustered at the market level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Chapter 4

Superstar products and the sources of market power

4.1 Introduction

Increasing markups and industry concentration are two of the global stylized facts that recent literature has pointed out as potential causes for the decrease in both labor shares and growth rates of the last several decades (De Loecker and Eeckhout, 2018; Bajgar et al., 2019). These trends in markups and concentration are interpreted as signs of an increase in firm market power and are principally attributed to sales reallocation towards large and high-markup firms (De Loecker et al., 2020; Autor et al., 2020). In other words, the rise of average market power depends on size and market power heterogeneity across firms. While recent studies have investigated the sources of firm size (Hottman et al., 2016; Braguinsky et al., 2020), little is known about the sources of firm market power. In particular, literature often considers a firm as a monad, neglecting that firms produce many products, each product competing on

[†] This chapter is based on the working paper titled “Superstar products and the sources of market power”. I am grateful to Eric Bartelsman, Filippo Biondi, Ajay Bhaskarabhatla, Benoit Crutzen, Jan Eeckhout, Pilar Gárcia-Gómez, Georg Granic, John Haltiwanger, Matthias Mertens, Gloria Moroni, Scott Orr, Thomas Peeters, Enrico Pennings, Vigyan Ratnoo, Riccardo Silvestrini, Tom Van Ourti and Eric Verhoogen for fruitful comments. I also thank the participants to the virtual seminars and conferences in Rotterdam (ESE, IAAE), Miami (NAPW), Mannheim (MaCCI), Belfast (RES), Boston (ISA), Bergen (EARIE), Maastricht (OSE), Coimbra (CAED), Paris (IMT), Munich (Max Planck). I thank the Thakur Family Foundation for financial support and AIOCD for sharing the data.

a specific market with its own market power. Since firm market power is an aggregate measure of the market power of its products, I study the sources of *product* market power and show that aggregate levels of market power originate *within* the firm.

Industry sales have been increasingly concentrating in a small number of *superstar firms*, which have higher share of industry sales, productivity and markups (Autor et al., 2020).[1] I focus on *within-firm concentration*, which measures the degree to which a small number of products contribute to the total sales of the firm, and observe products with similar superstar characteristics — higher share of firm sales, productivity and market power. Research on multiproduct firms is mostly focused on firm scope and finds that the number of products is a principal driver of firm productivity and growth (Bernard et al., 2010; Hottman et al., 2016). By focusing on within-firm concentration, this chapter shows that firm market power depends not only on the number of products but also on each product's relative weight within the firm.[2]

Market power, defined as the ability of a firm to influence the price of its products, has always been of interest for industrial organization studies. Recently, the new global stylized facts have motivated macroeconomic research to design models that encompass them all (Autor et al., 2020; Aghion et al., 2019). However, these studies do not investigate the sources of firm heterogeneity in market power considering the primitives of supply and demand (Syverson, 2019; Berry et al., 2019). Supply primitives such as marginal, fixed costs and productivity are primary sources of heterogeneity, influencing, for example, firm survival (Hopenhayn, 1992), exports (Melitz, 2003) and size (Bento and Restuccia, 2017). Demand primitives such as price elasticity, product substitutability and firm appeal, have been shown to affect firm's growth, especially in multiproduct firms (Syverson, 2004; Hottman et al., 2016; Neiman and Vavra, 2019). Referring to the multiproduct context, Syverson (2019) advices to focus on within-industry heterogeneity in market power as a key to explain aggregate trends.

I study the sources of market power in the Indian pharmaceutical industry, using detailed product-level data that cover all the drugs sold in the country from 2011 to early-2016. The data reports monthly information on sales value, quantities sold,

[1] Gutiérrez and Philippon (2019) challenge this hypothesis. They find that superstar firms have not become larger and more productive, and that their contribution to productivity growth has almost halved since 2000. They do not deny the existence of superstar firms, but argue that large firms have lobbied to partly shield themselves from competition, opposing the explanation of superstar firms' increased efficiency.

[2] Within-firm concentration is not firm specialization. The latter implies producing only the (few) products in which the firm has some comparative advantage. Within-firm concentration, instead, can be high even when the firm produces a large number of products, as long as those that generate a consistent share of firm sales remain a small number.

and wholesale and retail prices for products in over 8000 narrowly-defined markets, consisting of the combination of an active ingredient (Anatomic Therapeutic Classification, *ATC5*) and dosage form (e.g., tablet). I begin by showing how the relative marker power of two products serving the same market can be proxied by the ratio of their wholesale prices. Then I document how industry sales are concentrated in a few *superstar firms*. These firms, defined as those with more than 1 percent of industry share of sales, represent 3 percent of the firms but generate 71 percent of industry sales.[3] I also document high within-firm concentration. *Superstar products*, defined as the products generating more than 1 percent of the superstar firm's total sales, are 2 percent of superstar firms' products, and yet account for one-third of their total sales and have higher market power, productivity and price elasticity.

Building on the theoretical model in Hottman et al. (2016), I distinguish the components of product market power into: (i) wholesale markup, (ii) productivity, (iii) retail markup, and (iv) appeal. I estimate wholesale markup and productivity from a demand function and a production function, respectively, and proxy retail markup with the ratio between retail and wholesale price and product appeal with the age of the product from its launch. All the variables are expressed in relative terms, using another product in the market as a benchmark. I find that productivity and retail markup — supply-side components — have a negative effect on market power, while wholesale markup and product appeal — demand-side components — affect market power positively.

In the pharmaceutical industry, product entry and exit are related to innovation or perceived quality, which might influence product market power (Berndt and Aitken, 2011). I test whether market-pioneering products and new entrants have different levels of market power and find that products launched when the medicine market was first introduced have 7.3 percent higher market power . I also exploit the price cap regulation implemented in India from July 2013, targeting medicines defined as essential by the World Health Organization, to test whether it affected market power. I find that regulation reduced the average relative market power of the regulated medicines by 18 percent, but did not affect the superstar products significantly.

Since the products in which firm sales are concentrated wield higher market power, reallocation within the firm can be a powerful instrument to increase firm market power. Just like industry concentration in superstar firms increases average market power, similarly, within-firm concentration in superstar products increases firm market power. Using a decompositions built upon Olley and Pakes (1996), I find

[3] Within the markets, concentration is also high. In half of the markets, the sales-leading firm owns at least 56 percent of the market share.

that within-firm concentration contributes substantially to firm market power and industry concentration, i.e. the two factors driving average market power.

This research provides several contributions to the literature. The first is the identification of the components of market power. The hypothesis that market power is primarily driven by market characteristics, like industry concentration (structure-conduct-performance paradigm), has been rejected by the industrial organization mainstream in favor of an economic primitives-based approach (Bresnahan, 1989; Berry et al., 2019). The challenge, however, is that these primitives — price elasticity, productivity, appeal — are not directly observable. The theoretical model in this chapter indicates four components of product market power — wholesale markup, productivity, retail markup and appeal — proxied with variables derived from the data. To the best of my knowledge, there are no empirical studies that identify the effect of such components on product market power. Since these variables are derived from or proxied by economic primitives, they can be considered as predetermined, mitigating endogeneity concerns.[4] My findings are consistent with some mechanisms documented by previous literature. The negative effect of productivity on market power indicates that selection on productivity may be in place (Foster et al., 2008). The negative relationship between retail markups and market power signals that the buyer power of the retailers can counterbalance firm market power (Starc and Swanson, 2018). The positive effect of demand-side components, instead, suggests that consumers value branded, old products more than young ones, despite having the same chemical composition (Bronnenberg et al., 2015, 2020).

The second contribution is methodological. Identifying market power is a challenge for research in industrial economics. Markup is the "natural" proxy of firm's ability to influence the price at which its products are sold (Syverson, 2019). Recent approaches have estimated the markup as a ratio of the output elasticity of a variable input to that input's cost share of revenues (De Loecker et al., 2016, 2020). While this production function approach improves the feasibility of calculating markups, it has other shortcomings in terms of measurement error, generalizability and interpretation (Basu, 2019; Syverson, 2019; Bond et al., 2020). Probably the most relevant drawback concerns how cleanly such a markup estimator identifies the market power of the firm on the market where its products are sold, given that it also captures the market power of the firm on the input market (Morlacco, 2019). In addition, if calculated using the retail price of the products, markups indicate the market power of both the manufacturer and the retailer. Using the production function ap-

[4] Retail markup is not a primitive but can be considered as predetermined due to resale price maintenance practices. Details on the identification strategy can be found in Section 4.4.2.

proach and considering the *relative* markup of two products of the same market, I can identify for each product the relative market power of the manufacturer *on the product market*.[5] Under this approach, the relative marker power of two products is proxied by the ratio of their wholesale prices.[6]

Another contribution of this research is to the literature on competition in the pharmaceutical industry. Due to the indispensable nature of pharmaceutical products and associated regulation, the drivers of medicine price and sales can differ from those in other markets (Berndt, 2002; Lakdawalla, 2018). In the United States, the use of generic drugs is concentrated in older markets, where competition is more intense (Conti and Berndt, 2020). I show that market power increases with product age and that the market power of the first products launched in a market persists over time. I also measure how much market power differences across products can be attributed to the retailers. Intermediaries are crucial to access the healthcare and pharmaceutical markets, especially in emerging countries. Differences in bargaining power drive the large price heterogeneity across retailers in Brazil (Linde et al., 2019), while in India the resale price maintenance practice has increased the profits of retailers (Bhaskarabhatla, 2020). The Indian pharmaceutical industry accounts for a significant world share of exports of low-cost generic medicines and has been the setting of several studies concerning innovation, regulation and competition (Chaudhuri et al., 2006; Duggan et al., 2016). As this chapter shows, despite a large number of competitors, the Indian pharmaceutical industry is concentrated in a small number of firms, selling mostly off-patent medicines. This chapter adds evidence to the global debate on pharmaceutical market regulation (Berndt and Cockburn, 2014), suggesting that it might help reduce the market power of the drugs on average, but not particularly that of superstar products.

The chapter proceeds as follows. In Section 4.2, I present the data and the construction of the main variables. In Section 4.3, I define the superstar products and show stylized facts on market power and within-firm concentration. In Section 4.4, I present the theoretical model and the empirical strategy to estimate the effect of the components of market power. In Section 4.5, I comment on the results of

[5] I assume constant returns to scale out of the raw material used, which is particularly credible in the pharmaceutical industry where medicines have fixed chemical components, but can also be extended to other industries with standardized, homogeneous or regulated product inputs.

[6] If for every product the market power is calculated relative to the same benchmark product, the relative market power of all the products within the market are comparable and a firm-level relative market power indicator can be calculated aggregating (and appropriately weighing) product-level relative market power. In this way, firm relative market power is the result of the market power of all its products on their specific markets relative to their competitors, and not an average firm market power that does not consider that the firm competes in each of the markets within its scope.

the estimates and test their robustness. In Section 4.6, I study the market power of pioneer and entrant products and analyse the effects of the price cap regulation. In Section 4.7, I discuss the policy implication of the findings for industry concentration and firm market power, before concluding in Section 4.8.

4.2 Data and main variables

4.2.1 Product-firm-level data

I use product-level data of all the pharmaceutical firms operating in India from April 2011 to March 2016. Since April marks the beginning of a new financial year in India, I have data for five financial years. Data are compiled by the All India Organization of Chemists and Druggists (AIOCD), the union of the Indian pharmacies. For each *product*, identified by a unique stock-keeping unit (SKU), I observe both wholesale and retail prices, as well as the number of units sold on India's pharmaceutical market every month. AIOCD data contain nearly 3.1 million SKU-month observations spanning almost 900 firms, and around 92,000 different SKUs. For each product, I observe its *ATC5* (the molecular composition of the active ingredient of the drug) and *dosage form* (e.g., injection, tablet, etc.), *dosage strength* (e.g., 10 mg, 100 ml, etc.) and *pack size* (number of tablets, syringes, etc.). I define a *market* as the combination of ATC5 and dosage form, aggregated over different strengths and pack sizes.

Within a market, the products with the same ATC5 and dosage form can differ by dosage strength (e.g., 500 mg of Metformin vs 1000 mg of Metformin) and pack size (e.g., 10 tablets vs. 15 tablets). To facilitate comparison among prices and quantities of products within the same market, I normalize prices (P) and quantity of product (Q) of each product i to the median dosage strength (DS_j^{med}) and pack size (PS_j^{med}) of market j using the formulae:

$$P_{ij} = \frac{P_{ij}^u \cdot DS_j^{med} \cdot PS_j^{med}}{DS_{ij} \cdot PS_{ij}}$$

$$Q_{ij} = \frac{Q_{ij}^u \cdot DS_{ij} \cdot PS_{ij}}{DS_j^{med} \cdot PS_j^{med}}$$

where P_{ij}^u and Q_{ij}^u are the price and quantity of one unit (pack) of product i sold belonging to market j. The same AIOCD dataset is used in Chapter 3 of this thesis and described in greater detail in Chapter 3.3. Descriptive statistics of the dataset are summarized in Table 4.A.1, in the Chapter Appendix.

4.2.2 From markup to market power

The literature considers markup as the best measure of market power for firms and products (Syverson, 2019; De Loecker et al., 2020). Following the production function approach in De Loecker et al. (2016), the markup (μ) of product i in month t is:

$$\mu_{it} = \beta_{it}^{V} \frac{P_{it}^{R} Q_{it}}{P_{it}^{V} V_{it}} \tag{4.1}$$

where P^R is retail price, Q is quantity sold, V is the amount of variable input used to produce product i, P^V is the price of that variable input and β^V is output elasticity of that variable input. Product markup incorporates both the retailer and the manufacturer markups. To distinghish the contribution of each markup to the total product markup, I decompose the formula of markup as follows:

$$\mu_{it} = \beta_{it}^{V} \frac{P_{it}^{W} Q_{it}}{P_{it}^{V} V_{it}} \frac{P_{it}^{R}}{P_{it}^{W}} = \mu_{it}^{W} \mu_{it}^{R} \tag{4.2}$$

where P^W is product wholesale price. In Equation (4.2) the first part, $\beta_{it}^{V} \frac{P_{it}^{W} Q_{it}}{P_{it}^{V} V_{it}}$, is the manufacturer markup (μ_{it}^{W}) and the second part, $\frac{P_{it}^{R}}{P_{it}^{W}}$, is the retail markup ($\mu_{it}^{R}$).

I focus on the variable input raw materials (M) and assume that raw materials have constant returns to scale. This assumption is reasonable in the pharmaceutical industry, since all the products sold within a market j have an identical chemical composition and the amount of raw materials (bulk drugs) used to produce one milligram of a drug, is the same across all products within the market, whatever its pack size or dosage strength. The absence of scale returns in raw materials implies that both the marginal and the average product of a firm within the market use the same amount of raw materials. If I consider two products, i and h, of the same market j, they have the same output elasticity of raw materials, i.e. raw materials needed to produce an additional unit of the drug: $\beta_{ijt}^{M} = \beta_{hjt}^{M} = \beta_{j}^{M}$. The two products also need the same amount of raw materials to produce the average drug: $\frac{Q_{ijt}}{M_{ijt}} = \frac{Q_{hjt}}{M_{hjt}}$. Therefore, I can write the manufacturer markup of product i relative to the manufacturer markup of product h as follows:

$$\frac{\mu_{ijt}^{W}}{\mu_{hjt}^{W}} = \frac{P_{ijt}^{W}}{P_{hjt}^{W}} \frac{P_{hjt}^{M}}{P_{ijt}^{M}} \tag{4.3}$$

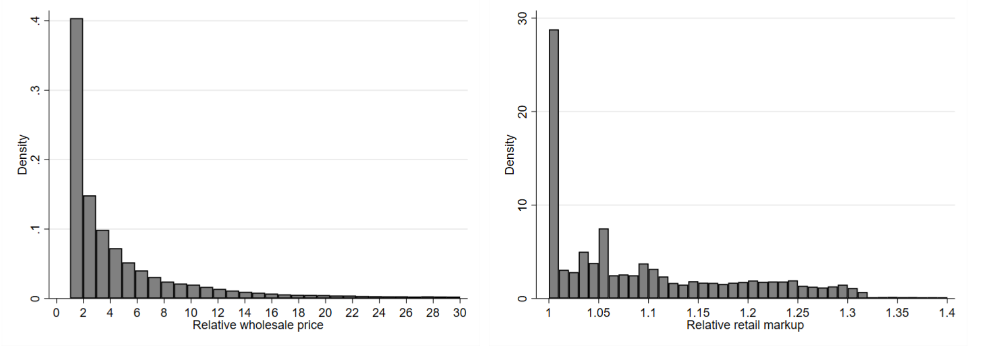
Equation (4.3) shows that the manufacturer's relative markup of a drug depends on its relative wholesale prices and the relative price of the raw materials employed in its production. The latter term is key for interpreting the markup as an indicator of manufacturer's market power. Syverson (2019) notes that the markup formula in Equation (4.1) shows firm market power in both the *product market* and the *factor market*. A lower relative price of the raw materials in Equation (4.3) might reflect a higher manufacturer's relative market power in the market of raw materials. In case two products belong to the same firm, the price of their raw materials is the same and their manufacturer's relative markup will depend only on their relative wholesale prices. In such a case, the manufacturer's relative markup of the product fully represents the relative market power of the manufacturer on the product market. When two products belong to two different firms, the relative market power of the manufacturer in the product market is captured by the relative wholesale price of the product, while the relative market power of the manufacturer in the factor market is captured by the relative price of the raw materials. For this reason, I take the relative wholesale price of the product as a measure of the relative manufacturer's market power in the product market.

Since each market sells medicines with specific chemical components and therapeutic use, it is not accurate to compare the market power of two products in different markets using their absolute value of product markups. Within-market relative wholesale prices are comparable across markets, and identify the relative market power of a product. For every product in the market, I define its market power relative to the product with the lowest wholesale price in the market. The distribution of manufacturer's relative market power of products, henceforth only relative market power, is plotted in Figure 4.1, Panel (A) and shows substantial dispersion across products. Nearly 36 percent of the products have a manufacturer's market power less than double that of the product with the lowest market power and another 28 percent of the products have a relative market power of the manufacturer between 2 and 5.

Retailer's markup, likewise, might reflect both retailer's market power on the product market as well as retailer's buyer power on the wholesale market. The conceptual difference compared to the manufacturer's market power is that each product is wholesaled by a unique manufacturer, but not retailed by a unique retailer. If therefore manufacturer's market power can be attributed to a specific firm, retailer's market power is an average of retailers' market power. Retail market power is not the object of this research. However, retail markup is a complement of manufacturer's market power and will be further considered in the analysis. The distribution of retail markups relative to the product with the lowest retail markup in the market is plotted in Figure 4.1, Panel (B). Relative retail markups take value from 1.10 to 1.44

Figure 4.1 Relative market power and retail markup of the product

(A) Relative market power (B) Relative retail markup



Notes: Panel (A): distribution of relative market power, intended as manufacturer's relative market power of a product. Relative market power is calculated as the wholesale price of the product relative to the lowest wholesale price of a product within the market; Panel (B): distribution of relative retail markup. Relative retail markup is calculated as the retail markup relative to the lowest retail markup of a product within the market. The figure is based on AIOCD data.

and are almost uniformly distributed between 1 and 1.3, except for the 12 percent of products having relative retail markups equal to 1.

An important clarification must be made on the product and raw materials quality. Within a medicine market, where all the products are made of the same raw materials, differences in the price of raw materials across products may also depend on the quality of raw materials.[7] Assuming that all drugs within a market comply with the quality standards prescribed by the Indian authorities, the differences in quality of raw materials can be ruled out from the drivers of raw materials price differences.[8] Perceived quality, instead, is a price component that does not affect input prices (Bronnenberg et al., 2015, 2020). Differences in perceived quality of the final product and its raw materials can exist only at the consumer level but concur to the product market power formation via either wholesale and retail relative price.

[7] The O-Ring theory is the main reference in price-quality pass-through from raw materials to final products. Kremer (1993) and Kugler and Verhoogen (2011), respectively, model and show that more expensive inputs lead to more expensive products.

[8] Quality of medicines in emerging markets is an important health policy issue (Bate et al., 2011). 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.

Table 4.1 Top products, concentration and market power

	Top N products of the firm					
	Share of firm sales			Relative market power		
	Top 1	Top 3	Top 5	Top 1	Top 3	Top 5
All firms	0.21	0.44	0.58	2.40	1.66	1.42
Firm scope quartile I	0.49	0.86	0.97	2.22	1.49	1.35
Firm scope quartile II	0.23	0.49	0.64	2.32	1.55	1.30
Firm scope quartile III	0.17	0.37	0.49	2.22	1.65	1.43
Firm scope quartile IV	0.10	0.23	0.32	2.83	1.91	1.57
Domestic firms	0.21	0.44	0.57	2.40	1.66	1.42
Multinational firms	0.21	0.46	0.60	2.42	1.73	1.45
Non-superstar firms	0.22	0.45	0.59	2.35	1.63	1.38
Superstar firms	0.06	0.13	0.18	3.52	2.40	2.13

Notes: *Top 1* corresponds to the product with the highest level of sales within the firm. *Top 3* corresponds to the 3 products with the highest level of sales within the firm. *Top 5* corresponds to the 5 products with the highest level of sales within the firm. *Firm scope* is the number of products of the firm and is divided into 4 quartiles with thresholds 16, 35 and 72 products. Superstar firms are the firms generating 1 percent or more of total industry sales. The table is based on AIOCD data.

4.3 Stylized facts

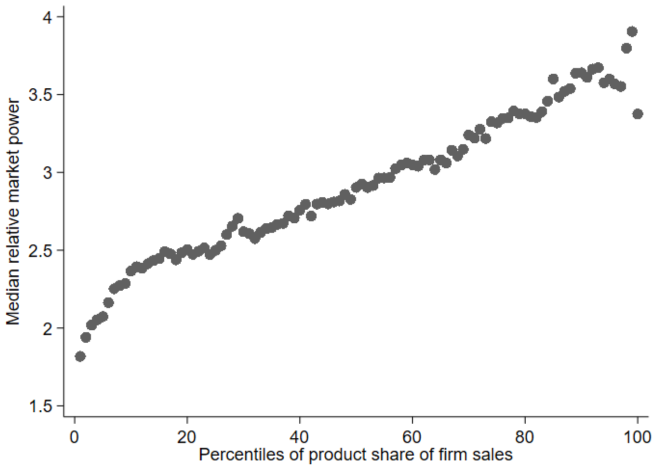
4.3.1 Superstar firms, within-firm concentration and market power

The Indian pharmaceutical industry is highly concentrated. It is served by almost 900 firms, but only 27 of them are large and generate more than 1 percent of the industry share of sales. I refer to these firms as *superstar firms*, which account for 40 percent of the medicines sold and 71 percent of the industry sales.[9] Within the firm the distribution of product share of sales is heavily skewed, implying high within-firm concentration. The median share of firm sales derived by firm's top-selling products is reported in Table 4.1. For half of the firms the product with the highest share of sales generates at least 21 percent of firm sales and the top 5 products generate at least 58 percent of firm sales.[10]

[9] The average superstar firm produces 712 products and serves 377 markets, compared to the average non-superstar firm that produces 51 products and serves 35 markets. Superstar firms are mostly domestic companies, e.g. Sun Pharmaceutical and Cipla (whose industry share of sales is around 5 percent each). Only one-fourth are foreign multinational companies, e.g. Abbott or GlaxoSmithKline. The list of superstar firms and their industry share of sales are reported in Table 4.A.2 in the Chapter Appendix.

[10] Another measure to quantify within-firm concentration is the Herfindahl-Hirschman Index (HHI), constructed using the square of product share of firm sales. The average within-firm HHI index is 0.18. If firm share of sales were equally distributed across their products, the HHI would have been 0.09. Within-firm HHI (monthly average) is plotted in Figure 4.A.1 in the Chapter Appendix by quartiles of firm scope and can be compared to the HHI in a counterfactual where firm share of sales are equally distributed across the products. The concentration index is naturally higher for firms with lower product scope but their size, compared to their counterfactual, increases with the

Figure 4.2 Relative market power by percentiles of share of firm sales



Notes: Percentiles of share of firm sales are derived from the distribution of the product share of firm sales. Median relative market power is the median value of relative market power for the products belonging to the corresponding percentile of share of firm sales. The figure is based on AIOCD data.

Are products generating higher shares of firm sales also generating higher firm market power? Table 4.1 reports the ratio between the average market power of the top 1, 3 and 5 products of the firm and the average market power of the remaining products. The market power of the best-selling products of the firm is on average 2.4 higher than that of the other products of the firm, while the average market power of the five best-selling products of the firm is on average 1.42 higher than that of the other products of the firm. For superstar firms, the market power of the best-selling products relative to the other products of the firm is higher than that of non-superstar firms. Overall, products with a higher share of sales within the firm tend to have higher market power. In Figure 4.2 the median market power by percentiles of product share of firm sales is plotted. Median market power increases in product share of firm sales: very steeply for the first decile and almost linearly afterwards.

4.3.2 Economic primitives and superstar products

The literature observes that market power and concentration derive from demand and supply primitives (Berry et al., 2019; Syverson, 2019). Primitives can be defined as the sources of product heterogeneity; they make a product intrinsically different

product scope. Average HHI index is 1.7, 3.5, 4.3 and 6.3 times the counterfactual HHI index for product scope first, second, third and fourth quartile, respectively.

from another and are not observed in the data. Productivity (supply-side primitive) and price elasticity (demand-side primitive) are considered among the principal drivers of firm size and market power (Hopenhayn, 1992; Melitz, 2003; Hottman et al., 2016). I observe how these two primitives are related to market power and concentration within the firm, using the measures of productivity and price elasticity estimated as reported in Appendices M.4.1 and M.4.2, respectively. I estimate quantity-based product-level productivity building on the multiproduct production function in Dhyne et al. (2017).[11] I estimate product-level price elasticity using a relative demand function: the demand of a product relative to the demand of another product within the same market.[12] To estimate these primitives additional data are needed. I merge the AIOCD data with Prowess data on firm financials compiled by the Centre for Monitoring Indian Economy (CMIE). This dataset has already been introduced in Chapter 3.3. I manually match firm names between the Prowess and AIOCD data during the five financial years. Descriptive statistics of the combined dataset are summarized in Table 4.A.1, in the Chapter Appendix.[13]

Table 4.2, Panel (A), reports the median productivity of the product by quartiles of market power and share of firm sales. Overall, products generating a higher share of firm sales have higher productivity, while higher market power is rather related to lower productivity. The latter evidence might depend on the definition of relative market power as the relative wholesale price within the market. As observed in

[11] Dhyne et al. (2017) propose a product-level production function where inputs enter at the firm-level. The production function that I consider has product-specific raw materials and is estimated using the LP estimator (Levinsohn and Petrin, 2003). This approach controls for biases related to input measurement, simultaneity, and scope of the firm and can be applied to estimate multiproduct production function in markets with many competitors. This method preserves the assumption of invertibility of the intermediate input demand function as in Levinsohn and Petrin (2003), without adding further assumptions on the functional form as in Dhyne et al. (2017). See Appendix M.4.1 for details and Figure 4.A.2 in the Chapter Appendix for the productivity estimates.

[12] Pairing each product with every other product in the market, I estimate product-level price elasticity without the need of an exogenous instrument for price (Nevo, 2001; Foster et al., 2008; DellaVigna and Gentzkow, 2019). Concerns about the simultaneity between prices and quantities in estimating product-level demand function are limited, considering that this approach includes all the prices of the other products in the market and controls for any exogenous shock that might affect product cross-elasticities. The consistency of the estimates is guaranteed by the use of pairwise observations of all the products in a market across 60 months. See Appendix M.4.2 for details and Figure 4.A.3 in the Chapter Appendix for the elasticity estimates.

[13] Among the 899 firms in the AIOCD dataset, I successfully combine 113 public firms accounting for 561,460 product-month observations, spanning almost 15,734 SKUs. These matched firms produce 17 percent of all SKUs, their sales account for 26 percent of the total industry sales, and produce nearly 832 ATC5s. All the firms in the merged sample are multiproduct, manufacturing, on average, 246 different SKUs, and operating, on average, in 163 markets. The combined dataset AIOCD+CMIE includes around half of the products of the combined dataset in Chapter 3. The reason is that some of the products of the matched firms show scarce variability of their inputs or prices over time and prevent accurate estimates of product-level productivity or product-level elasticity.

Table 4.2 Productivity and elasticity by quartiles of market power and product share of firm sales

Panel (A): Median productivity

		Quartiles of market power				
		I	II	III	IV	Total
Quartiles of firm share	I	0.09	0.04	-0.01	0.05	0.05
	II	0.20	0.11	0.03	0.13	0.12
	III	0.14	0.14	0.14	0.08	0.14
	IV	0.12	0.24	0.27	0.24	0.23
	Total	0.14	0.11	0.08	0.10	0.11

Panel (B): Median elasticity

		Quartiles of market power				
		I	II	III	IV	Total
Quartiles of firm share	I	-2.22	-2.25	-2.27	-2.04	-2.21
	II	-2.17	-2.17	-2.26	-2.12	-2.18
	III	-2.29	-2.18	-2.16	-1.94	-2.13
	IV	-2.39	-2.13	-2.01	-1.93	-2.05
	Total	-2.22	-2.20	-2.20	-2.02	-2.15

Notes: Productivity is the standardized quantity-based product-level productivity estimated as from in Equation (M.4.1) using the LP estimator, adjusted to control for firm scope ($TFPQ-E$). Price elasticity is product-level price elasticity estimated as from Equation (M.4.13) (*relative elasticity*). Quartiles of market power are derived from the distribution of product market power of the manufacturer (wholesale price) relative to the product with the lowest manufacturer's market power within the market. Quartiles of firm share are derived from the distribution of the product share of firm sales. Reported values correspond to the median productivity and price elasticity by quartiles of market power and product share of firm sales. The table is based on AIOCD and Prowess, CMIE data.

Chapter 3, in the Indian pharmaceutical industry the relationship between prices and productivity is negative on average and positive for the market best-selling products. My findings are similar, signalling selection on productivity (Foster et al., 2008) for the products that are not in the highest quartile of share of firm sales. Table 4.2, Panel (B), reports the median price elasticity of the product by quartiles of market power and share of firm sales. Overall, price elasticity is higher when either market power or share of sales is higher. However, while price elasticity increases in the share of firm sales gradually, it is mostly flat from the first to the third quartile of market power and increases sharply only in the top quartile.

Products with a higher share of firm sales are positively related to their market power, productivity and price elasticity. The products that generate more than 1 percent of the firm total sales, which I define as *top products*, represent 20 percent of the industry products and generate 45 percent of the industry sales. I also define the top products of superstar firms as *superstar products*. Superstar products represent 2 percent of the superstar firms' products and generate 32 percent of the superstar firms' sales.[14]

[14] An example from the Cefixime Tablet market, a popular antibiotic medication used to treat bac-

Market power and productivity distributions plotted in Figure 4.3, Panel (A) and (B), show that top products have both higher market power and productivity than non-top products. The gap increases when top products are also superstar products. Price elasticity, plotted in Figure 4.3, Panel (C), is higher for superstar products than for non-top products in non-superstar firms, but does not differ from that of top products in non-superstar firms and non-top products of superstar firms. The visual inspection of Figure 4.3, is confirmed in Table 4.A.3, in the Chapter Appendix, where the correlation of the type of product with market power, productivity and price elasticity is reported controlling for firm, market and month fixed effects.

4.4 Theoretical and empirical framework

4.4.1 A model for the components of market power

In this section, building on Hottman et al. (2016), I model product relative market power as a function of wholesale markup, productivity, retail markup and product appeal. The same theoretical framework is used in Chapter 3.2 to model product market share. In this Chapter I focus on the pricing rule of the product, without introducing any further assumption in the demand structure described above.

Following the model in Chapter 3.2, the physical output of product i of market j at time t has the following function:

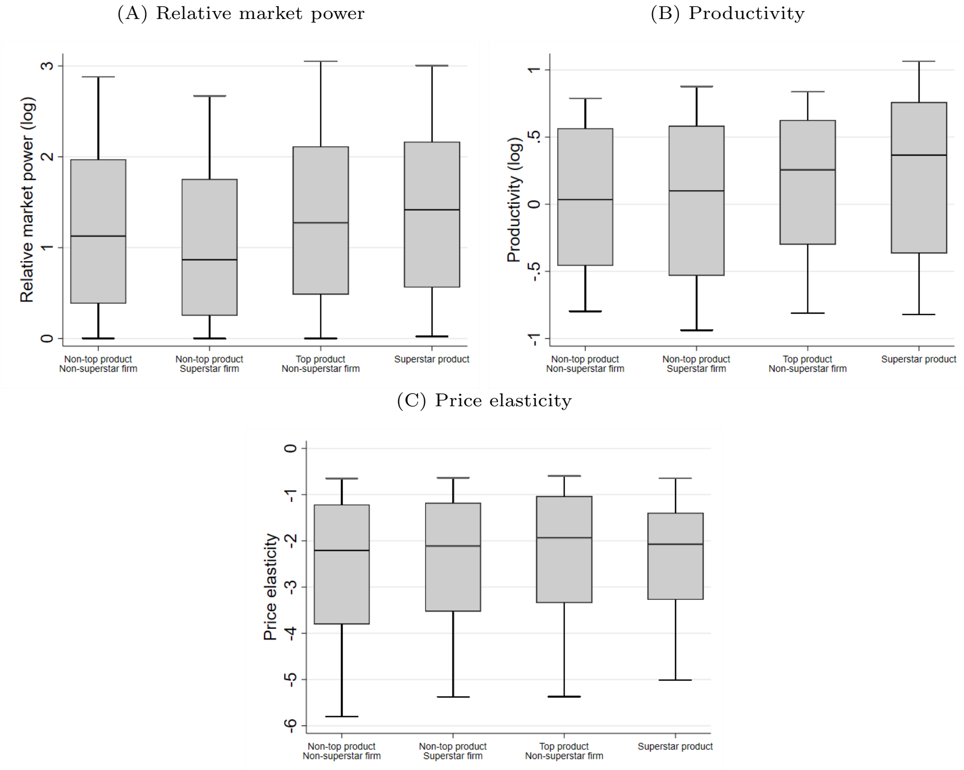
$$Q_{it} = \frac{Y_{jt}^{W}}{P_{jt}^{W}} \left(\frac{P_{it}^{W}}{P_{jt}^{W}}\right)^{-\sigma_j} \left(\frac{\mu_{it}^{R}}{\mu_{jt}^{R}}\right)^{-\sigma_j} (\Phi_{it})^{\sigma_j - 1} \tag{4.4}$$

where Y_{jt} is total market revenues, P_{it}^{W} is product wholesale price, P_{jt}^{W} is market wholesale price index, μ_{it}^{W} is product retail markup, μ_{jt}^{R} market retail markup index, and Φ_{it} is total firm-product appeal in the market. How these variables affect quantity produced depends on the elasticity of substitution σ_j.[15] Quantity is therefore

terial infections and among the top five largest markets in India's pharmaceutical industry with more than 300 products competing. The market leader (21 percent of market share) is Taxim 200 mg 10 Tablet produced by Alkem Laboratories. Taxim 200 MG 10 Tablet is a top product since it generates 4 percent of its firm total sales, but also a superstar product, since Alkem Laboratories is a superstar firm. Another popular product is Milixim 200 mg 10 Tablet, by Glenmark Pharmaceuticals, a superstar firm, for which this product generates 0.8 percent total sales. Milixim 200 mg 10 Tablet is not a superstar product, but a non-top product of a superstar firm. Formic 200 mg 10 Tablet by Elder Pharmaceuticals is a drug in the top 10 of the Cefixime tablet market. It is not a superstar product, but a top product of a non-superstar firm, generating 5 percent of its total sales.

[15] The assumption regarding the elasticity of substitution introduced in Chapter 3.2 — equality between elasticity of substitution of the output supplied by the different firms within the market and that of the different products of a specific firm within the market — holds here as well.

Figure 4.3 Market power, productivity and price elasticity by type of product



Notes: *Top product* is a product generating 1 percent or more of total firm sales. *Superstar firm* is a firm generating 1 percent or more of total industry sales. *Superstar product* is a product generating 1 percent or more of total superstar firm sales. *Relative market power* is the normalized wholesale price of the product, relative to the lowest normalized wholesale price within the market. *Productivity* is the standardized quantity-based product-level productivity estimated as from in Equation (M.4.1) using the LP estimator, adjusted to control for firm's product scope ($TFPQ$–E). *Price elasticity* is product-level price elasticity estimated as from Equation (M.4.13) (*relative elasticity*). The figure is based on AIOCD and Prowess, CMIE data.

a function of the size of the market, $\frac{Y^W_{jt}}{P^W_{jt}}$, relative wholesale price of product i, $\frac{P^W_{it}}{P^W_{jt}}$, the relative retail markup of product i, $\frac{\mu^R_{it}}{\mu^R_{jt}}$, and firm-product appeal, Φ_{it}.

The firm sets an optimal price for each of its products i by maximizing the profits, subject to a production cost whose variable component is $\alpha_{it}(Q_{it})^{1+\delta_j}$, where α_{it} is a cost shifter and δ_j is the elasticity of marginal cost with respect to output.[16] Whether the firms compete a la Cournot or a la Bertrand, the pricing rule is the following:

$$P^W_{it} = \mu^W_{it}(1+\delta_j)\alpha_{it}(Q_{it})^{\delta_j} \tag{4.5}$$

[16] If firms are small relative to the aggregate economy the firm's profit maximizing problem is separable across markets.

where μ_{it}^{W} is the manufacturer markup, a function of price elasticity of demand:[17]

$$\mu_{it}^{W} = \frac{\theta_{ijt}}{1+\theta_{ijt}} \tag{4.6}$$

Plugging Equation (4.4) into Equation (4.5) I can rewrite the optimal price as a follows:

$$P_{it}^{W} = \left(\mu_{it}^{W}(1+\delta_j)\alpha_{it} \left[Y_{jt}^{W} \left(P_{jt}^{W}\right)^{\sigma_j - 1} \left(\frac{\mu_{it}^{R}}{\mu_{jt}^{R}} \right)^{-\sigma_j} \left(\Phi_{it}\right)^{\sigma_j - 1} \right]^{\delta_j} \right)^{\frac{1}{1+\sigma_j\delta_j}} \tag{4.7}$$

As noticed in Section 4.2.2, for the pharmaceutical industry, the relative market power of products could be captured by their relative wholesale prices. The wholesale price of product i relative to the wholesale price of product h serving the same market j can be written as follows:

$$\frac{P_{it}^{W}}{P_{ht}^{W}} = \left(\frac{\mu_{it}^{W}}{\mu_{ht}^{W}} \right)^{\frac{1}{1+\sigma_j\delta_j}} \left(\frac{\alpha_{it}}{\alpha_{ht}} \right)^{\frac{1}{1+\sigma_j\delta_j}} \left(\frac{\mu_{it}^{R}}{\mu_{ht}^{R}} \right)^{-\frac{\delta_j\sigma_j}{1+\sigma_j\delta_j}} \left(\frac{\Phi_{it}}{\Phi_{ht}} \right)^{\frac{\delta_j\sigma_j - \delta_j}{1+\sigma_j\delta_j}} \tag{4.8}$$

Given that $\sigma_j \geq 1$ and $0 \leq \delta_j \leq 1$, the relative market power of products is a function of relative manufacturer markup (+), relative cost shifter (+), relative retail markup (−), and relative product appeal (+).

4.4.2 Empirical strategy

Equation (4.8) describes the equilibrium price set by the manufacturers relative to other products of the same market. As noticed in Section 4.2.2, this is also a measure of relative market power of the product. Equation (4.8) can be log-linearized and rewritten in a reduced form, whose coefficients can be estimated using a linear regression. To do so, I proxy the variables of the theoretical model with those in the dataset. Wholesale markup is calculated by introducing the price elasticities, estimated as discussed in Appendix M.4.2, in Equation (4.6). Productivity is probably considered the principal source of cost heterogeneity within and across firms, therefore this measure,

[17] The role of the elasticity of substitution σ in determining the price elasticity changes according to the type of competition and can depend on the market share of the firm. Since in this chapter I can calculate price elasticities, I do not need to impose additional restrictions on this model. It is important to notice that substitutability among products in the same pharmaceutical market is almost perfect, being all composed of the same chemical elements. If perceived substitutability across products is close to the effective one, the price elasticity of demand would equal the elasticity of substitution. However, previous studies notice that this is not the case in the pharmaceutical market (Bronnenberg et al., 2015).

estimated as discussed in Appendix M.4.1, serves as a proxy for the cost shifter. Retail markup is calculated as the ratio between retail price and wholesale price. Firm-product appeal is proxied by product age and firm fixed effects. All the variables are expressed at the product level and in relative terms, using as a benchmark the lowest value in the same market, and later transformed in logarithms.[18] The specification for relative market power ($\widetilde{\pi}$) of product i of firm f in market j is the following:

$$\widetilde{\pi}_{ifjt} = \alpha_0 + \alpha_1 \widetilde{\mu^W}_{ifj} + \alpha_2 \widetilde{\omega}_{ifjt} + \alpha_3 \widetilde{\mu^R}_{ifjt} + \alpha_4 \widetilde{age}_{ifjt} + \phi_f + \eta_j + \delta_t + \epsilon_{ifjt} \tag{4.9}$$

where $\widetilde{\mu^W}$ is wholesale markup, $\widetilde{\omega}$ is productivity, $\widetilde{\mu^R}$ is retail markup, $\widetilde{age}$ is the number of years between the product launch and the observation in the dataset. Firm (ϕ_f), market (η_j) and month (δ_t) fixed effects are also included in the specification. Coefficient estimates represent the percent change of relative market power due to a one percent change of relative markup (α_1), productivity (α_2), retail markup (α_3) and product appeal (α_4).[19]

I estimate Equation (4.9) using OLS since the variables that I use to proxy the four components of market power are predetermined with respect to market power. Wholesale markup (μ^W_{ifj}) is derived from a time-invariant measure of price elasticity. It can be considered as a "long-run" wholesale markup that the firm observes before setting the price. The short-run elasticity and wholesale markup can be both smaller or larger than the long-run ones, and so monthly price, composing the dependent variable (Nevo, 2001; DellaVigna and Gentzkow, 2019).[20] Like price elasticity, productivity (ω_{ifjt}) is an economic primitive, but proxies for the product marginal costs driving the prices (Foster et al., 2008; Aw and Lee, 2014). In addition, the measure of productivity adopted is quantity-based and product price does not influence its estimation.

In the Indian pharmaceutical industry retail markup (μ^R_{ifjt}) is the outcome of a bargaining process between each wholesaler and the unique trade association of retailers. The adoption of maximum resale price maintenance generates price com-

[18] For example, the transformation of variable Z_i is $\widetilde{Z}_i = ln\left(\frac{Z_i}{\min_{i\in j} Z_i}\right)$. Choosing another benchmark product would only shift the estimated constant.

[19] Coefficient estimates can also be interpreted as deviations from the state where all the products are homogeneous. In the "homogeneous state" all the relative values of a variable take value one $\left(\frac{Z_i}{\min_{i\in j} Z_i} = 1\right)$ and the observed percentage deviation of the relative variable from the homogeneous case is $ln\left(\frac{Z_i}{\min_{i\in j} Z_i}\right) - ln(1)$.

[20] Biases due to measurement errors in estimating price elasticity might lead to biased coefficient estimates. However, by expanding the number of observations, the methodology proposed in Appendix M.4.2 is less vulnerable to idiosyncratic measurement errors. Systematic product-specific measurement errors are, instead, captured by the product-level constants.

petition among wholesalers to guarantee a higher retail margin and receive non-price benefits, such as preference in the distribution, or avoid retailer's boycott (Bhaskarabhatla et al., 2016; Bhaskarabhatla, 2020). Although, by definition, retail markup is mechanically correlated with wholesale price, the former can be considered to be predetermined, i.e. wholesale prices are set given the retail markups. In addition, the retail markup effect on market power that the specification captures is not within-product, but cross-product: products with higher retail markup are expected to have lower market power, ceteris paribus.[21]

Product age (age_{ifjt}) does not suffer from reverse causality, however, the probability of survival of a product might be affected by product wholesale price, implying that the sample is selected based on market power. The direction of this bias is uncertain as a product could exit because its prices are too high — the product is not competitive — or too low — the product is not profitable. Indeed, using the estimation sample I find that price is not a significant driver of product exit (results available upon request). This supports the view that the market power selection bias is null, either because not present or because resulting from counterbalancing forces.

In a second step, I test whether the four components of market power have different marginal effects for superstar products. Introducing a dummy variable indicating superstar products would raise endogeneity issues, as a product can become a superstar due to its higher market power. Splitting the sample into superstar and non-superstar products causes problems of estimation consistency. Given that it is very unlikely to find two or more superstar products in the same market, all the variability would be captured by market fixed effects.[22] Top products, instead, are more likely to be found in the same market. Since a top product of a superstar firm is a superstar product, by controlling for superstar firms in a subsample of top products I can compare the effect of the components of market power of superstar products with that of the top products of non-superstar firms.

[21] The bias due to this mechanical relation is analysed in a robustness check in Section 4.5.3.2. Retail markup is substituted with retail margin, intended as the difference between retail and wholesale price, which is also mechanically related (negatively) to market power. The results show that the bias due to the mechanical relation is limited, as the coefficient estimate is positive and significant.

[22] In such a case market fixed effects would be very similar to a product fixed effect and the estimates would capture changes within the product and not across products. Excluding market fixed effects would compare products across different markets (different medicines for different treatments) without considering the differences in each market's average market power.

Table 4.3 The components of market power

	Relative market power				
	(1)	(2)	(3)	(4)	(5)
Wholesale markup	0.005				0.024
	(0.019)				(0.018)
Productivity		-0.429***			-0.570***
		(0.116)			(0.116)
Retail markup			-0.583***		-0.591***
			(0.023)		(0.023)
Product age				0.037***	0.044***
				(0.012)	(0.011)
Market FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.551	0.552	0.576	0.551	0.579
Observations	561460	561460	561460	561460	561460

Notes: OLS estimates. *Relative market power* is the normalized wholesale price of the product, relative to the lowest normalized wholesale price within the market. *Wholesale markup* is calculated using price elasticity estimated as from Equation (M.4.13) (*relative elasticity*). *Productivity* is the standardized quantity-based product-level productivity estimated as from Equation (M.4.1) using the LP estimator, adjusted to control for firm scope ($TFPQ-E$). *Retail markup* is the ratio between retail and wholesale price. *Product age* is the number of years from product launch date to its observation in the dataset. All the variables above are expressed in relative terms, using as a benchmark the product in the same market with the lowest value of the variable, and later transformed in logarithms. *Market* refers to the combination between ATC5 and dosage form. The table is based on AIOCD and Prowess, CMIE data. Standard errors (in parentheses) clustered at the market level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.5 Results

4.5.1 The components of market power

The baseline estimates of Equation (4.9) are reported in Table 4.3. All coefficient estimates have the signs hypothesized in the model. Wholesale markup is positively related to market power, although not significantly. A one percent higher relative productivity decreases the relative market power by 0.57 percent. As already pointed out in Section 4.3, in presence of selection on productivity the relationship between prices and productivity is negative (Foster et al., 2008). A one percent change in relative retail markups decreases the relative market power by 0.59 percent. There are two possible explanations for this result. The first is that when retail markup is higher, the wholesale price is set lower to counterbalance the market power of the retailer and keep the retail price of the product competitive. The second is that when the retail margin — the *difference* between retail and wholesale price — is set, a lower retail markup is needed when the product price is high. In both cases, this result indicates that the buyer power of the retailers can counterbalance firm market power (Starc and Swanson, 2018). The market power of the products with a one percent higher relative age in the market is 0.04 percent higher. These results confirm the findings in other studies and suggest that consumer value branded, old products more than young ones, despite having the same chemical composition (Bronnenberg et al., 2015, 2020). Overall, an increase in the demand-side components has a positive effect on market power (wholesale markup and age), while supply-side components have a negative effect (productivity and retail markup).

4.5.2 The market power of superstar products

The components of market power might have different effects depending on how important a product is within the firm. In Section 4.3 I documented that superstar products have higher relative market power, productivity and price elasticity. In this subsection I test whether marginal differences in the sources of market power affect superstar products to the same extent as other products and report the results in Table 4.4.

By adding a dummy variable for superstar products in Equation (4.9), the estimates show that superstars have 22.4 percent higher relative market power on average (Column 1), almost three times the effect of top products in non-superstar firms (Column 2). These results are informative of a positive correlation between relative market power and the dummy superstar product, but suffer from reverse causality, as a product can become a superstar due to its higher market power. Considering only the sample of top products, the coefficient estimate of superstar firm indicates that being a superstar product does not cause an increase in market power (Column 3). In addition, the coefficient estimate of wholesale markup, productivity and retail markup are in line with those estimated on the full sample. Product age, instead, is not a relevant component of market power among top products.[23]

These estimates, however, might still be biased: if the market powers of the top products of a firm are highly correlated, the high market power of top products affects the probability of the firm being a superstar. I instrument the dummy superstar firm with the firm scope, intended as its number of products sold in all the markets. Firm scope is supposed to affect the size of a firm, and so its probability to be a superstar, but not the market power of a specific product of a firm, if not via the firm size (Hottman et al., 2016; Braguinsky et al., 2020). Instrumenting the dummy superstar firms with firm scope confirms that the effect of being a superstar among top products does not increase market power significantly (Column 4).[24]

[23] Table 4.A.4 in the Chapter Appendix, Columns 1 and 2, compare the components of market power in the sample of top and non-top products. The coefficient estimates of wholesale markup and productivity across the two samples are very close. For top products, retail markup has half of the effect and product age coefficient estimate is non-significant.

[24] Table 4.A.4 in the Chapter Appendix, Column 4 and 5 show that firm scope is not relevant for product market power, while it significantly (and positively) affects the probability of being a superstar firm. These results, together with the F-statistic value, suggest that firm scope is a valid instrument for superstar firms.

Table 4.4 The market power of superstar products

	Relative market power							
	(1) All	(2) All	(3) Top	(4) Top	(5) Top	(6) Top	(7) Top	(8) Top
Wholesale markup	0.025	0.025	0.134	0.137	0.078	0.068	0.074	0.077
	(0.018)	(0.018)	(0.086)	(0.086)	(0.099)	(0.099)	(0.097)	(0.098)
Wholesale markup × Superstar firm					-0.041			
					(0.433)			
Productivity	-0.600***	-0.508***	-0.754***	-0.725***	-0.747***	-0.670***	-0.748***	-0.760***
	(0.116)	(0.107)	(0.228)	(0.236)	(0.236)	(0.231)	(0.237)	(0.236)
Productivity × Superstar firm						-0.639		
						(0.460)		
Retail markup	-0.588***	-0.626***	-0.451***	-0.450***	-0.285***	-0.282***	-0.298***	-0.283***
	(0.023)	(0.023)	(0.089)	(0.089)	(0.064)	(0.065)	(0.062)	(0.064)
Retail markup × Superstar firm							0.324	
							(0.418)	
Product age	0.043***	0.041***	0.031	0.029	0.026	0.024	0.026	0.051
	(0.011)	(0.011)	(0.029)	(0.029)	(0.028)	(0.028)	(0.028)	(0.033)
Product Age × Superstar firm								-0.110
								(0.072)
Superstar product	0.224***	0.166***						
	(0.042)	(0.049)						
Top product		0.074***						
		(0.026)						
Superstar firm		-0.100***	-0.024	0.023				
		(0.019)	(0.069)	(0.108)				
Market FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	No	No	No	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.579	0.568	0.687					
Observations	561460	561460	43521	43521	43521	43521	43521	43521
F-stat				292	58	114	24	193

Notes: OLS and IV estimates. *Relative market power* is the normalized wholesale price of the product, relative to the lowest normalized wholesale price within the market. *Wholesale markup* is calculated using price elasticity estimated as from Equation (M.4.13) (*relative elasticity*). *Productivity* is the standardized quantity-based product-level productivity estimated as from Equation (M.4.1) using the LP estimator, adjusted to control for firm scope ($TFPQ-E$). *Retail markup* is the ratio between retail and wholesale price. *Product age* is the number of years from product launch date to its observation in the dataset. All the variables above are expressed in relative terms, using as a benchmark the product in the same market with the lowest value of the variable, and later transformed in logarithms. *Top product* is a product generating 1 percent or more of total firm sales. *Superstar firm* is a firm generating 1 percent or more of total industry sales. *Superstar product* is a product generating 1 percent or more of total superstar firm sales. *Market* refers to the combination between ATC5 and dosage form. Columns 1-3 are estimated using OLS. Columns 4-8 are estimated using IV: superstar firm is instrumented with the firm scope. The table is based on AIOCD and Prowess, CMIE data. Standard errors (in parentheses) clustered at the market level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

To estimate the effect of marginal differences in the components of market power for superstar products, each of the four components of market power is interacted with the variable superstar firm, appropriately instrumented with firm scope.[25] The results show that when a product is a superstar, wholesale markup, productivity, retail markup and age have the same marginal effect on market power as they have when the product is a top product of a non-superstar firm.

4.5.3 Heterogeneity and robustness of the results

4.5.3.1 Market characteristics and subsample analysis

In this section, I test whether the results are driven by some peculiarity of the market to which products belong to, or if they are generalizable to the whole industry. I divide the observations in the sample across market and product characteristics and estimate Equation (4.9). The results are reported in Table 4.5.

First, I test whether the results are specific to some dosage forms than others (Column 1-3). Unlike medicines in solid form (such as tablets), injectable drugs are often consumed with the help of a healthcare professional. Overall, the results for the solid form (shared by almost 70 percent of the medicines) remain qualitatively similar to the full sample estimates. For liquid products, the effect of wholesale markup is higher and top products do not have higher market power. For injectable products, the negative effect of productivity is four times larger and superstar products do not show a significantly higher market power.

India's pharmaceutical industry is composed of medicine markets from different launch periods. In particular, India agreed to the WTO TRIPS agreement, regulating intellectual property protection, in 1995 and implemented it starting from 2005. I distinguish between markets launched before 1995, between 1995 and 2004, and since 2005 and estimate Equation (4.9) across these subsamples (Column 4-6). I find that product age is not significant in markets launched before 1994 and that productivity has no significant effects on markets launched after 2005. In addition, superstar products have no market-power advantage compared to other products in markets launched after 2005. These findings suggest that product age matters especially in newly established markets, in which patent protection limits productivity-based competition.

[25] The variable superstar firm non-interacted is captured by the firm fixed effects. The estimates of the marginal effect of the components of market power for superstar products, without instrumenting the dummy superstar firm are reported in Table 4.A.4 in the Chapter Appendix, Column 3. Estimates are largely similar to those reported in Table 4.4,except for the marginal effect of wholesale markup.

Table 4.5 The market power of superstar products: subsample analysis on market characteristics

	Relative market power											
	Dosage form			Market launch			Therapy		Drug composition		Accessibility	
	(1) Solids	(2) Liquids	(3) Injectables	(4) Before 1995	(5) 1995-2004	(6) After 2005	(7) Acute	(8) Chronic	(9) Single	(10) Combination	(11) Over-the-counter	(12) Prescription
Wholesale markup	0.009	0.081*	0.028	0.042	-0.000	0.003	0.045**	-0.022	0.033	0.001	0.049*	-0.001
	(0.020)	(0.043)	(0.059)	(0.026)	(0.028)	(0.040)	(0.022)	(0.028)	(0.021)	(0.032)	(0.026)	(0.024)
Productivity	-0.316***	-0.073	-2.035***	-0.570***	-0.727***	-0.350	-0.694***	-0.385**	-0.589***	-0.613***	-0.599***	-0.656***
	(0.097)	(0.143)	(0.287)	(0.179)	(0.170)	(0.258)	(0.138)	(0.178)	(0.150)	(0.180)	(0.136)	(0.183)
Retail markup	-0.595***	-0.596***	-0.534***	-0.605***	-0.566***	-0.445***	-0.586***	-0.581***	-0.584***	-0.589***	-0.556***	-0.600***
	(0.022)	(0.042)	(0.080)	(0.023)	(0.046)	(0.103)	(0.023)	(0.075)	(0.030)	(0.028)	(0.028)	(0.030)
Product age	0.050***	0.059**	-0.008	0.015	0.059***	0.099***	0.041***	0.052***	0.038***	0.050***	0.033**	0.050***
	(0.013)	(0.027)	(0.029)	(0.016)	(0.017)	(0.027)	(0.014)	(0.018)	(0.015)	(0.015)	(0.015)	(0.016)
Superstar product	0.245***	0.412***	0.091	0.267***	0.222***	0.018	0.288***	0.082*	0.173***	0.295***	0.188***	0.238***
	(0.047)	(0.134)	(0.112)	(0.060)	(0.062)	(0.118)	(0.054)	(0.048)	(0.050)	(0.071)	(0.066)	(0.054)
Market FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.598	0.614	0.493	0.560	0.560	0.686	0.572	0.572	0.556	0.629	0.560	0.595
Observations	390875	66906	89583	238854	241736	79146	378316	183144	363058	198402	271821	289639

Notes: OLS estimates. *Relative market power* is the normalized wholesale price of the product, relative to the lowest normalized wholesale price within the market. *Wholesale markup* is calculated using price elasticity estimated as from Equation (M.4.13) (*relative elasticity*). *Productivity* is the standardized quantity-based product-level productivity estimated as from Equation (M.4.1) using the LP estimator, adjusted to control for firm's product scope ($TFPQ-E$). *Retail markup* is the ratio between retail and wholesale price. *Product age* is the number of years from product launch date to its observation in the dataset. All the variables above are expressed in relative terms, using as a benchmark the product in the same market with the lowest value of the variable, and later transformed in logarithms. *Top product* is a product generating 1 percent or more of total firm sales. *Superstar firm* is a firm generating 1 percent or more of total industry sales. *Superstar product* is a product generating 1 percent or more of total superstar firm sales. The subsamples *Solid*, *Liquid* and *Injectables* include, respectively, drugs whose dosage form is solid (e.g. tablet), liquid (e.g. syrup) and injectable (e.g. syringe). The subsamples *Before 1995*, *1995-2004* and *Since 2005* include, respectively, drug ATC5 launched before 1995, between 1995 and 2004, from 2005 onwards. The subsamples *Acute* and *Chronic* include drugs used for treating, respectively, acute and chronic. The subsamples *Single* and *Combination* include drugs composed by, respectively, a single ingredient and the combination of two or more ingredients. The subsamples *Over-the-counter* and *Prescription* include drugs that, respectively, do not and do need a medical prescription to be purchased. *Market* refers to the combination between ATC5 and dosage form. The table is based on AIOCD and Prowess, CMIE data. Standard errors (in parentheses) clustered at the market level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The frequency of purchase of a drug might affect the market power of products in the market. Medicines for chronic diseases are associated with repeat purchases, while medicines for acute conditions are characterized by occasional use. I differentiate the products by their usage in the treatment of acute and chronic diseases and find that wholesale markup has a positive and significant effect for products in markets of acute disease treatment but not for products in markets of chronic disease treatment (Column 7-8).

Within a market, the medicines are composed using a fixed "recipe" which can require single or multiple ingredients. I examine whether there are differential effects in market power for single-ingredient and combination medicines. The pattern of results I obtained in Section 4.5 remains qualitatively similar for single-ingredient and combination medicines (Column 9-10). I also distinguish between over-the-counter and prescription medicines and find that wholesale markup is a positive and significant component of the market power of over-the-counter medicines, while no effect is observed for prescription medicines (Column 11-12). These results suggest the role of doctors in increasing the steep of the demand curve of drugs.

4.5.3.2 Alternative measures and sensitivity analysis

In this subsection I test the robustness of the results by proxying the components of market power with alternative variables that are expected to capture the same effects. The marginal effects of the alternative proxies are also estimated in the subsample of top products, in interaction with the dummy superstar firms, to estimate the effects for superstar products. The results are reported in Table 4.6.

In the baseline estimates, wholesale markup is calculated using the relative elasticity estimated as shown in Appendix M.4.2. I substitute this measure with the wholesale markup calculated using the biased elasticity estimated as from Equation (M.4.10). The coefficient estimate of this biased measure of wholesale markup is positive and non-significant (Column 1) and does not differ for superstar products (Column 2), similar to the results obtained using unbiased elasticity. The number of observations is lower than in the estimates obtained using unbiased elasticity, as the upward bias causes many products to have an elasticity higher than -1 and negative market power. These observations are excluded from the estimates.

In the baseline estimates, productivity is calculated using an estimation-based method. I substitute this measure with the cost-based productivity calculated following Foster et al. (2008). The effect of productivity remains negative and significant, but its size almost doubles (Column 3) and is not statistically different for superstar

Table 4.6 The market power of superstar products: sensitivity analysis

	Relative market power							
	(1) All	(2) Top	(3) All	(4) Top	(5) All	(6) Top	(7) All	(8) Top
Wholesale markup (biased elasticity)	0.011	0.026						
	(0.008)	(0.025)						
Wholesale markup (relative elasticity) × Superstar firm		0.022						
		(0.093)						
Productivity (TFPQ-C)			-1.244***	-1.025***				
			(0.034)	(0.076)				
Productivity (TFPQ-C) × Superstar firm				0.008				
				(0.188)				
Retail margin					0.397***	0.371***		
					(0.023)	(0.030)		
Retail margin × Superstar firm						-0.039		
						(0.068)		
Brand age							0.046***	0.049
							(0.015)	(0.033)
Brand Age × Superstar firm								0.037
								(0.075)
Wholesale markup (relative elasticity)			0.011	0.036	-0.031**	0.023	0.025	0.074
			(0.009)	(0.056)	(0.014)	(0.064)	(0.018)	(0.098)
Productivity (TFPQ-E)	-0.340***	0.031			-0.253***	-0.516***	-0.601***	-0.770***
	(0.085)	(0.163)			(0.069)	(0.148)	(0.115)	-0.283***
Retail markup	-0.451***	-0.222***	-0.222***	-0.158***			-0.587***	-0.283***
	(0.036)	(0.060)	(0.016)	(0.038)			(0.023)	(0.064)
Product age	0.059***	0.053**	0.053***	0.066***	0.030***	0.017		
	(0.012)	(0.023)	(0.008)	(0.018)	(0.009)	(0.019)		
Superstar product	0.187**		0.034		0.237***		0.219***	
	(0.081)		(0.021)		(0.036)		(0.042)	
Market FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.640		0.767		0.683		0.579	
Observations	293367	23250	561423	43515	561341	43515	561460	43521
F-stat		31		75		150		246

Notes: OLS and IV estimates. *Relative market power* is the normalized wholesale price of the product, relative to the lowest normalized wholesale price within the market. *Wholesale markup (relative elasticity)* is calculated using price elasticity estimated as from Equation (M.4.13) (*relative elasticity*). *Wholesale markup (biased elasticity)* is calculated using price elasticities estimated as from Equation (M.4.10) (*biased elasticity*). *Productivity (TFPQ-E)* is the standardized quantity-based product-level productivity estimated as from Equation (M.4.1) using the LP estimator, adjusted to control for firm's product scope ($TFPQ-E$). *Productivity (TFPQ-C)* is the standardized quantity-based product-level productivity calculate following Foster et al. (2008), whose output elasticities are computed using the product share of costs imputed to every production input ($TFPQ-C$). *Retail markup* is the ratio between retail and wholesale price. *Retail margin* is the difference between retail and wholesale price. *Product age* is the number of years from product launch date to its observation in the dataset. *Brand age* is the number of years from brand launch date to its observation in the dataset. All the variables above are expressed in relative terms, using as a benchmark the product in the same market with the lowest value of the variable, and later transformed in logarithms. *Superstar product* is a product generating 1 percent or more of total superstar firm sales. *Market* refers to the combination between ATC5 and dosage form. Columns 1, 3, 5 and 7 are estimated using OLS. Columns 2, 4, 6 and 8 are estimated using IV: superstar firm is instrumented with the firm scope. The table is based on AIOCD and Prowess, CMIE data. Standard errors (in parentheses) clustered at the market level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

products (Column 4). This can be due to the use of product share of firm sales in the input allocation methodology of cost-based productivity. Cost-based productivity incorporates the prices and the size of the products, biasing the coefficient estimates. The non-significant coefficient estimate of the dummy superstar product in Column 3, supports this interpretation. This result suggests that using the estimation-based is more appropriate in this exercise.

In the baseline estimates, retail markup is calculated as the ratio between retail and wholesale price of the product. I substitute this measure with the retail margin, i.e. the difference between retail and wholesale price. The coefficient estimate of retail margin has opposite sign compared to that of retail markup in the baseline estimates (Column 5). Granting higher retail margins, for a given retail markup, requires higher wholesale prices. This strategy is beneficial for both wholesalers and retailers. This result reveals that the concerns of mechanical correlation between market power and retail markup in the baseline estimates are limited. The effect of retail margin on the market power of superstar products is the same as for top products of non-superstar firms (Column 6).

In the baseline estimates, product appeal is proxied by the age of the product. I substitute it with the age of the brand since the product observed might have cannibalized its within-brand predecessor and exploited its product appeal. The coefficient estimate of brand age is very similar to that of product age in the baseline estimates (Column 7), as well as when considering only the subsample of top products (Column 8).

The results regarding the market power of superstar products reported in Section 4.5.2 are also robust to the change in the definition of top products, superstar firms and superstar products. In Table 4.A.5, in the Chapter Appendix top products are defined as the top 15 products by sales within the firm and superstar firms are defined as the top 15 firms by sales within the industry. Table 4.A.5 reports similar coefficients to those in Table 4.4 .

4.6 Additional results: market entry and regulation

4.6.1 The market power of pioneers and entrants

Product appeal is acknowledged as an important driver of product and firm growth (Hottman et al., 2016; Neiman and Vavra, 2019). In the estimates in Section 4.4 I proxy product appeal with product age, i.e. the number of years from the product launch to its observation in the sample, and find that it indeed affects positively the market power. In this subsection I test whether the age effect is linear and, since in the pharmaceutical industry product dynamics (entry and exit) is related to innovation, I also test if the products that have been in the market from the very beginning (market *pioneers*) benefit of some first-mover advantage. Indeed, the pioneers are more likely to introduce product innovations and maintain market power over the years. I also test if the market power of a new entrant is lower than that of the other products already in the market and if it changes in case it belongs to a superstar firm. The results are reported in Table 4.7.

I define a product as *Young* when it was launched less than 5 years before its observation, and *Old* when it was launched more than than 10 years before its observation. Old products have 5.4 percent higher market power (Column 1) and a larger positive effect of product age (Column 2) compared to the products in the market for less than 10 years. In other words, staying in the market for one additional year yields a higher market power when the product is older.

The dummy variable *Pioneer* takes value one when the launch year of the product is the same as the launch year of the market, i.e. the year when the first product of a new drug ATC5 was launched. A pioneer product has 7.3 percent higher relative market power on average (Column 3). Being a superstar product, a top product or belonging to a superstar firm, does not increase a pioneer's market power (Column 4-5).

To test whether new products entering the market have different market power, I define the dummy *Entrant* which takes value one only in the first year after the product launch. Entrants have the same market power compared to other young products (Column 6) and it does not change if the entrant belongs to a superstar firm, a firm with a top product in the same market, a firm with other products in the market (Column 7-9).

4.6.2 Price regulation and the market power of superstars

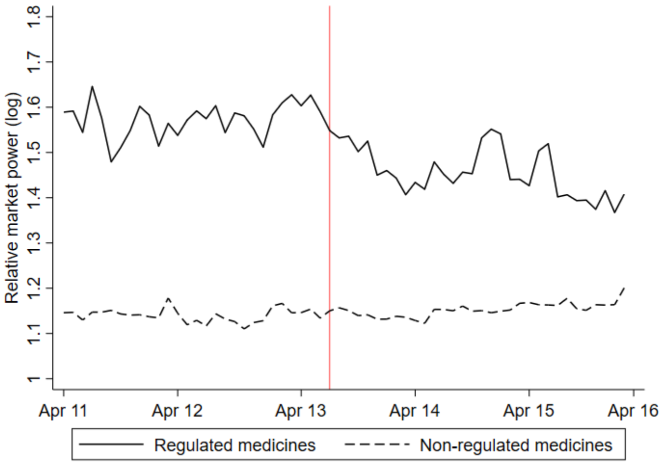
Starting from July 2013, India adopted a price ceiling regulation for essential medicines, covering nearly one-fifth of the market. In this section I test whether the regulation reduced the market power of the targeted drugs and if its effect has been asymmetric for the superstar products, i.e. those with higher market power.

Table 4.7 The market power of pioneers and entrants

	Relative market power								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Wholesale markup	0.027	0.024	0.023	0.024	0.024	0.027	0.027	0.026	0.026
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Productivity	-0.537***	-0.573***	-0.575***	-0.603***	-0.613***	-0.536***	-0.536***	-0.572***	-0.542***
	(0.116)	(0.116)	(0.115)	(0.116)	(0.116)	(0.117)	(0.117)	(0.117)	(0.116)
Retail markup	-0.591***	-0.590***	-0.590***	-0.588***	-0.587***	-0.591***	-0.591***	-0.587***	-0.590***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Product age		0.028**	0.039***	0.038***	0.038***				
		(0.012)	(0.011)	(0.011)	(0.011)				
Young product	0.015					0.015	0.015	0.018	0.015
	(0.014)					(0.013)	(0.013)	(0.014)	(0.013)
Old product	0.054***					0.054***	0.054***	0.050***	0.053***
	(0.016)					(0.016)	(0.016)	(0.016)	(0.016)
Young product × Product age		0.017*							
		(0.010)							
Old product × Product age		0.022**							
		(0.009)							
Pioneer			0.073***	0.068**	0.059				
			(0.027)	(0.027)	(0.062)				
Superstar product				0.221***	0.177***				
				(0.048)	(0.055)				
Top product					0.047*				
					(0.028)				
Pioneer × Superstar product				-0.023	-0.001				
				(0.083)	(0.123)				
Pioneer × Top product					-0.026				
					(0.092)				
Pioneer × Superstar firm					0.011				
					(0.065)				
Entrant						0.013	0.016	0.015	0.020
						(0.022)	(0.029)	(0.023)	(0.048)
Entrant × Superstar firm							-0.005		
							(0.033)		
Firm with top product								0.117***	
								(0.024)	
Entrant × Firm with top product								-0.012	
								(0.055)	
Firm with other products									0.039**
									(0.018)
Entrant × Firm with other products									-0.008
									(0.049)
Market FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.578	0.579	0.579	0.579	0.579	0.578	0.578	0.579	0.578
Observations	561460	561460	561460	561460	561460	561460	561460	561460	561460

Notes: OLS estimates. *Relative market power* is the normalized wholesale price of the product, relative to the lowest normalized wholesale price within the market. *Wholesale markup* is calculated using price elasticity estimated as from Equation (M.4.13) (*relative elasticity*). *Productivity* is the standardized quantity-based product-level productivity estimated as from Equation (M.4.1) using the LP estimator, adjusted to control for firm's product scope ($TFPQ - E$). *Retail markup* is the ratio between retail and wholesale price. *Product age* is the number of years from product launch date to its observation in the dataset. All the variables above are expressed in relative terms, using as a benchmark the product in the same market with the lowest value of the variable, and later transformed in logarithms. *Pioneer* is a product launched in the same year as the market. *Entrant* is a product observed within the first year after its launch. *Top product* is a product generating 1 percent or more of total firm sales. *Superstar firm* is a firm generating 1 percent or more of total industry sales. *Superstar product* is a product generating 1 percent or more of total superstar firm sales. *Market* refers to the combination between ATC5 and dosage form. The table is based on AIOCD and Prowess, CMIE data. Standard errors (in parentheses) clustered at the market level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 4.4 Price cap regulation: market power before and after the policy



Notes: *Relative market power* is the normalized wholesale price of the product, relative to the lowest normalized wholesale price within the market. Price regulation starts in July 2013 to limit the price of essential medicines in India. The figure is based on AIOCD data.

Figure 4.4 reports the monthly average relative market power (in logarithms) by regulated and non-regulated drugs. Both regulated and unregulated drugs show a common trend in market power before the policy implementation, with the regulated ones wielding a constantly higher market power. The gap in market power starts reducing after July 2013, due to a gradual but evident reduction of the average market power of the regulated drugs.

Using a difference-in-difference method I estimate the effect of the regulation on the market power in the pharmaceutical industry. For this purpose, the dummy variable *Regulated* — taking value one when the drug is targeted by the policy — and its interaction with a period dummy — taking value one in the months from July 2013 onwards — are introduced in Equation (4.9). Since superstar products have higher market power, they might have been hit more severely than other regulated products by the policy. To test this hypothesis, I also interact the treatment and the period dummies with the dummies indicating if the product is a superstar or top product and if it belongs to a superstar firm.

The results of the effect of the regulation are reported in Table 4.8. Regardless of the regulation, the drugs hit by the regulation had, on average, 11.7 percent higher market power. The effect of the regulation was to reduce the market power of these drugs by 18.3 percent (Column 1). If the regulated product is a top product, then the negative effect of the regulation on market power is 13.5 percent

Table 4.8 The effect of price regulation on market power

	Relative market power			
	(1)	(2)	(3)	(4)
Wholesale markup	0.024	0.024	0.024	0.025
	(0.018)	(0.018)	(0.018)	(0.018)
Productivity	-0.576***	-0.606***	-0.575***	-0.613***
	(0.116)	(0.116)	(0.116)	(0.116)
Retail markup	-0.594***	-0.592***	-0.593***	-0.590***
	(0.023)	(0.023)	(0.023)	(0.023)
Product age	0.043***	0.040***	0.043***	0.040***
	(0.011)	(0.011)	(0.011)	(0.011)
Regulated	0.117**	0.125**	0.121*	0.138**
	(0.057)	(0.056)	(0.067)	(0.064)
Regulated × After July 2013	-0.183***	-0.197***	-0.151***	-0.179***
	(0.047)	(0.046)	(0.058)	(0.058)
Top product		0.088***		0.044
		(0.029)		(0.033)
Regulated × Top product		-0.111		-0.109
		(0.070)		(0.074)
Top product × After July 2013		0.020		0.020
		(0.026)		(0.029)
Regulated × After July 2013 × Top product		0.135**		0.156***
		(0.060)		(0.058)
Regulated × Superstar firm			-0.008	-0.023
			(0.041)	(0.040)
Superstar firm × After July 2013			0.014	0.017
			(0.015)	(0.016)
Regulated × After July 2013 × Superstar firm			-0.049	-0.022
			(0.041)	(0.041)
Superstar product				0.219***
				(0.065)
Regulated × Superstar product				-0.074
				(0.110)
Superstar product × After July 2013				-0.002
				(0.053)
Regulated × After July 2013 × Superstar product				-0.133
				(0.115)
Market FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
R-squared	0.580	0.580	0.580	0.581
Observations	561460	561460	561460	561460

Notes: OLS estimates. *Relative market power* is the normalized wholesale price of the product, relative to the lowest normalized wholesale price within the market. *Wholesale markup* is calculated using price elasticity estimated as from Equation (M.4.13) (*relative elasticity*). *Productivity* is the standardized quantity-based product-level productivity estimated as from Equation (M.4.1) using the LP estimator, adjusted to control for firm's product scope ($TFPQ - E$). *Retail markup* is the ratio between retail and wholesale price. *Product age* is the number of years from product launch date to its observation in the dataset. All the variables above are expressed in relative terms, using as a benchmark the product in the same market with the lowest value of the variable, and later transformed in logarithms. *Regulated* is the treatment variable taking value one for the drugs targeted by the regulation. *Top product* is a product generating 1 percent or more of total firm sales. *Superstar firm* is a firm generating 1 percent or more of total industry sales. *Superstar product* is a product generating 1 percent or more of total superstar firm sales. *Market* refers to the combination between ATC5 and dosage form. The table is based on AIOCD and Prowess, CMIE data. Standard errors (in parentheses) clustered at the market level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

smaller than the effect obtained for the other regulated products, meaning that the overall effect of the regulation for the top products is statistically non-significant (Column 2). No significant difference, instead, is observed in the effect of the regulation for products in superstar firms (Column 3). Despite the superstar products having higher market power, the effect of the regulation was the same as for other top products, i.e. non-significant (Column 4).

The price cap regulation reduced the market power of the regulated products, but not uniformly. In particular, top and superstar products were able to largely shield from this negative effect. In Figure 4.A.4, in the Chapter Appendix, one can observe how the trend of market power for non-top products declined after the implementation of the regulation, while the trends for top and superstar products, after a steep decline in the first few months after the regulation, surged steeply again to their pre-regulation trends. Previous literature on India's pharmaceutical industry regulation can help us explain this effect. Bhaskarabhatla et al. (2017) observe a price increase for the regulated drugs in the market of Metformin during the period preceding the regulation. Since the ceiling price would have been determined by the simple average of the price of the top brands in each market (with at least a 1 percent market share), their findings suggest that firms coordinated to increase the level of price, before the regulation started. Moreover, the pre-regulation price increase is significantly higher for products with higher market share. In Figure 4.A.4, in the Chapter Appendix, the pre-regulation increase in market power is clear for top and superstar products, making the coordination hypothesis a plausible explanation for these findings as well.

The estimates of the regulation effect on each of the components of market power are reported in Table 4.A.6 in the Chapter Appendix. The negative effect of retail markup on product market power is reduced by the regulation, possibly to counterbalance the reduction in market power of the regulated drugs. Also the positive effect of product age on market power is reduced by the regulation. This result suggests that when the medicine is under regulation the role of product appeal in determining product market power is lower.

4.7 Policy implications

Sales reallocation towards superstar firms has increased industry concentration. Since superstar firms have higher market power, average market power has also risen (Autor et al., 2020; De Loecker et al., 2020). Industry average market power is, therefore, generated by the heterogeneity in market power across firms and the level of industry concentration. In the previous sections I studied the relationship between market power and concentration from a more disaggregated level: product market power and within-firm concentration. In this section I quantify the contribution of within-firm concentration to the drivers of industry average market power: firm market power and industry concentration.

I have shown that products in which firm sales are concentrated (top and superstar products) have higher market power. In the same way as an increase in industry concentration raises aggregate market power via the between-firm channel, an increase in within-firm concentration would contribute positively to aggregate market power via the within-firm channel.[26] Quantifying the extent of this contribution is the first objective of this section. The second is to measure the contribution of within-firm concentration to industry concentration. In both exercises, the contribution of within-firm concentration is compared with that of firm scope, considered a principal driver of firm market power (Bernard et al., 2010; Aghion et al., 2019) and firm size (Goldberg et al., 2010b; Hottman et al., 2016).

4.7.1 Within-firm concentration and firm market power

Product relative market power can be aggregated to compute the relative market power of the firm. Since a firm does not exercise the same market power across all the markets/products, it might have larger market power if it produces only one product instead of many. Total firm relative market power can be measured as the average relative market power of all the products of the firm, weighted by the product share of firm sales. If I refer to π_{ifjt} as the relative wholesale price of product i of firm f sold on market j in month t, and to s_{ifjt} as the product share of firm sales, I can write firm market power as: $\pi_{ft} = \sum_i s_{ifjt}\pi_{ifjt}$.

Following Olley and Pakes (1996) I can decompose the manufacturer's market power into the unweighed average of market power across all firm's products and the sample covariance between relative market power and product sales:

$$\pi_{ft} = \overline{\pi}_{ft} + \sum_i \Delta s_{ifjt}\Delta\pi_{ifjt} \tag{4.10}$$

where $\Delta s_{ifjt} = s_{ifjt} - \overline{s}_{ft}$ and $\Delta\pi_{ifjt} = \pi_{ifjt} - \overline{\pi}_{ft}$, and $\overline{\pi}_{ft}$ and $\overline{s}_{ft}$ represent unweighed mean relative market power and market shares, respectively, across all firm f's products. The larger the last term in Equation (4.10), the more the share of firm output

[26] Being the top and superstar products also more productive on average, an increase in within-firm concentration would benefit also firm productivity.

that goes to products with higher market power, and the higher is firm market power.

The unweighed mean relative market power $\overline{\pi}_{ft}$ can be further decomposed into the unweighed average of market power across all firm's markets and the sample covariance between relative market power and firm scope. Consider firm scope as the number of products offered within market j by firm f and define n_{fjt} as the share of firm products offered in market j. Also define $\overline{\pi}_{fjt}$ as unweighed mean relative market power across all firm f's products offered in market j. I can rewrite $\overline{\pi}_{ft}$ as:

$$\overline{\pi}_{ft} = \overline{\overline{\pi}}_{ft} + \sum_j \Delta n_{fjt} \Delta \overline{\pi}_{fjt} \tag{4.11}$$

where $\Delta n_{fjt} = n_{fjt} - \overline{n}_{ft}$ and $\Delta \overline{\pi}_{fjt} = \overline{\pi}_{fjt} - \overline{\overline{\pi}}_{ft}$, and $\overline{\overline{\pi}}_{ft}$ and $\overline{n}_{ft}$ represent unweighed mean relative market power and product shares, respectively, across all firm f's markets. The larger the last term in Equation (4.11), the higher the share of firm scope that goes to markets with higher market power, and the higher is firm market power.

I can finally plug Equation (4.11) into Equation (4.10) and rewrite firm market power as:

$$\pi_{ft} = \overline{\overline{\pi}}_{ft} + \sum_j \Delta n_{fjt} \Delta \overline{\pi}_{fjt} + \sum_i \Delta s_{ifjt} \Delta \pi_{ifjt} \tag{4.12}$$

where the last two terms represent the contribution to firm market power of firm scope, $\sum_j \Delta n_{fjt} \Delta \overline{\pi}_{fjt}$, and within-firm concentration, $\sum_i \Delta s_{ifjt} \Delta \pi_{ifjt}$.

In Table 4.9 I show that much of the firm market power is due to average firm market power and that the contribution of firm scope and within-firm concentration is overall similar and totals 13 percent of the manufacturer's market power. Both contributions are quite stable over the years and increase in firm scope. The firms in the highest quartile for number of products receive a noticeably larger contribution from scope and within-firm concentration compared to the firms in lower quartiles. Scope and concentration provide similar contributions to the domestic firm market power, while for multinational firms the contribution of scope is twice the size as that of the within-firm concentration. Superstar firms receive a contribution from firm scope and concentration which is, respectively, double and eightfold that received by non-superstar firms. Overall, depending on the type of firm, within-firm sales reallocation towards larger products (having higher market power) would produce a larger effect on firm market power than launching an additional product. This is the case of superstar firms, where a product with a 1 percent share of sales higher than the firm average contributes to firm market power 1.3 times more than offering 1 percent more products than the firm average in a market.

Table 4.9 The decomposition of firm market power

	π_{ft}	$\overline{\overline{\pi}}_{ft}$	$\sum_j \Delta n_{fjt} \Delta \overline{\pi}_{fjt}$	$\sum_i \Delta s_{ifjt} \Delta \pi_{ifjt}$
All firms	1.34	1.16	0.09	0.08
Firm scope quartile I	1.44	1.43	0.05	-0.05
Firm scope quartile II	1.48	1.42	0.06	-0.00
Firm scope quartile III	1.40	1.32	0.06	0.01
Firm scope quartile IV	1.32	1.10	0.11	0.11
Domestic firms	1.35	1.17	0.09	0.09
Multinational firms	1.26	1.11	0.10	0.05
Non-superstar firms	1.36	1.27	0.07	0.02
Superstar firms	1.32	1.00	0.14	0.18

Notes: *Market* refers to the combination between ATC5 and dosage form. π_{ft} is the mean of relative market power of all the products of the firm, weighted by the product share of firm sales; $\overline{\overline{\pi}}_{ft}$ is the unweighed mean relative market power across all firm's markets; $\sum_j \Delta n_{fjt} \Delta \overline{\pi}_{fjt}$ is the sample covariance between relative market power and the firm scope; $\sum_i \Delta s_{ifjt} \Delta \pi_{ifjt}$ is the sample covariance between relative market power and the within-firm concentration. *Relative market power* is the normalized wholesale price of the product, relative to the lowest normalized wholesale price within the market. *Firm scope* is the number of products of the firm and is divided into 4 quartiles with thresholds 16, 35 and 72 products. *Superstar firms* are the firms generating 1 percent or more of total industry sales. The table is based on AIOCD data.

4.7.2 From within-firm concentration to industry concentration

Industry concentration, defined as the degree to which the sales of a small number of firms count for the total sales of the industry, has increased over the last years in the Western world (Bajgar et al., 2019). I have previously observed that India's pharmaceutical industry sales are concentrated in a small number of superstar firms. The average Herfindahl-Hirschman Index (HHI) of the industry in the time considered is 2.24 percent. This value is not per se high if one does not consider the number of firms (900) competing in the industry. The counterfactual HHI value in the case where all the firms have an equal share of sales would be almost 20 times lower.[27] To quantify the distinct contribution to industry concentration of firm scope and within-firm concentration, I decompose industry Herfindahl-Hirschman Index (HHI_t) as follows:

$$HHI_t = \sum_f (s_{ft})^2 = \sum_f (N_{ft} \dot{s}_{ft})^2 + \sum_f N_{ft}^2 (\overline{s}_{ft}^2 - \dot{s}_{ft}^2) \tag{4.13}$$

where $\overline{s}_{ft}$ and $\dot{s}_{ft}$ are the mean and the median shares of industry sales of the products of firm f, respectively, and N_{ft} is its number of products of the firm. The first component is the firm scope contribution and the second component is the within-firm concentration contribution to industry concentration. For example,

[27] HHI depends on the number of firms in the industry. For a given equal distribution, HHI is lower when more firms are in the industry.

Table 4.10 Industry sales decomposition

	HHI_t	$\sum_f (N_{ft}\dot{s}_{it})^2$	$\sum_f N_{ft}^2(\bar{s}_{it}^2 - \dot{s}_{it}^2)$
All firms	2.24	0.15	2.10
Domestic firms	1.71	0.12	1.59
Multinational firms	0.55	0.03	0.52
Non-superstar firms	0.11	0.01	0.10
Superstar firms	2.13	0.14	2.00

Notes: HHI_t is the HHI index of industry concentration, $\sum_f (N_{ft}\dot{s}_{it})^2$ is the contribution of firm scope to industry concentration and $\sum_f N_{ft}^2(\bar{s}_{it}^2 - \dot{s}_{it}^2)$ is the contribution of within-firm concentration to industry concentration. *Superstar firms* are the firms generating 1 percent or more of total industry sales. The table is based on AIOCD data.

within-firm concentration is null when all products in the firm have the same share ($\bar{s}_{ft} = \dot{s}_{ft}$). In such a case the only contribution to industry concentration will come from the firm scope component. The higher the difference between mean and median sales, the higher contribution of within-firm concentration. In Table 4.10 I report the results of the decomposition. Within-firm concentration contributes for 2.10 percent points to the 2.24 of industry HHI, while firm scope contributes for 15 percent points. HHI depends on three-fourths on domestic firms and one-fourth on multinational firms. Within-firm concentration in superstar firms generate almost almost 90 percent (2.00 percent points) of the HHI value.

Within-firm concentration is, therefore, a relevant contributor to both firm market power and industry concentration. It counts as much as firm scope for what matters firm market power and 14 times as much as firm scope for what matters industry concentration.

4.8 Conclusion

Recent research has observed that the global rise of market power can be attributed to firm heterogeneity in market power and increasing industry concentration. Superstar firms, wielding higher market power, gained market share via sales reallocation, generating higher industry concentration and aggregate market power. This chapter studies market power and concentration from a disaggregated within-firm perspective, using product-level data of the Indian pharmaceutical industry. I distinguish four components of product market power — wholesale markup, productivity, retail markup and appeal — and identify their marginal contribution to product market power. I find that higher productivity leads to lower market power also for top-selling products, indicating that selection on productivity may be operating (Foster et al., 2008). This mechanism is welfare-enhancing as consumers would benefit from lower prices when firms become more efficient. Also the negative relationship found between retail markups and wholesale prices goes in the same direction, signalling that the buyer power of the retailers can counterbalance firm market power (Starc and Swanson, 2018). The positive effect of wholesale markup and appeal (demand-side components), instead, suggests that consumers value branded, old products more than young ones, despite having the same chemical composition (Bronnenberg et al., 2015, 2020). Superstar products, i.e. products that generate more than one percent of superstar firms' sales, have higher market power. Nonetheless, their market power depends on the four components to the same extent as top-selling products of non-superstar firms.

This chapter shows how the market power of a firm originates within the firm, at the product level, and its drivers are the economic primitives of product demand and supply. Just like industry concentration is crucial to understand aggregate market power, within-firm concentration is crucial to understand firm market power. Within-firm concentration provides an important contribution to firm market power (as much as firm scope) and industry concentration (14 times as much as firm scope). These findings have important implications for an understudied aspect of growth-enhancing reallocation: within-firm reallocation. Similar to the implications of between-firm reallocation towards the superstar firms, increasing within-firm concentration towards superstar products would contribute positively to firm market power.

This research also shows that if high concentration and firm market power are responsible for high prices in the pharmaceutical industry, a price cap regulation, limiting the market power of specific products, can improve access to medicines. In developing countries, where medicine affordability is a pressing problem, institutional infrastructures implementing this kind of policies are necessary. However, the results also show that superstar products, despite having a higher market share, were not affected by the regulation to a larger extent as one would expect, but were rather able to keep a higher market power also after the regulation. Superstar products might have been better at lobbying or strategically reacting to the regulation, abilities which are proper to the superstar firms, according to Gutiérrez and Philippon (2019).

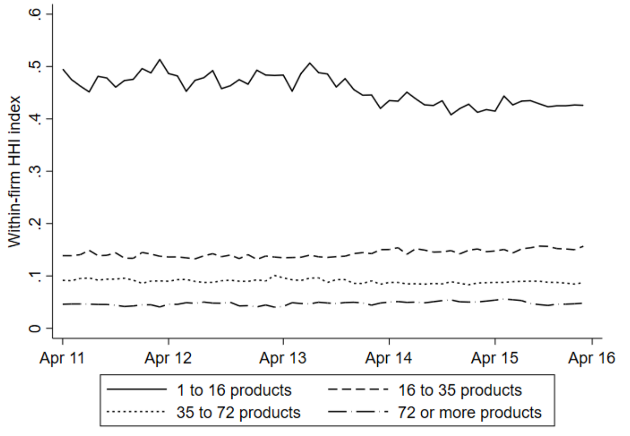
This study has limitations that should be considered for the interpretation of the results and their policy implication. First, the findings of a product-level analysis on the Indian pharmaceutical industry may not be generalizable to other industries in other countries. Even compared to the pharmaceutical industries of other countries, Indian context is very particular: many firms and products competing, mostly off-patent drugs produced, a unique trade association of retailers, negligible insurance coverage for the consumers. However, this context is very common across other emerging and developing countries, not only in the pharmaceutical industry. In all industries small and superstar domestic firms compete with multinational superstar firms on many markets and with many products. Shifting the focus from within-industry to within-firm market power and considering wholesale markup, productivity, retail markup and product appeal as its main components would reveal new potential channels for explaining the global rise of market power. In addition, a single industry product-level study has the advantage of being methodologically more accurate. Markup is not always a good proxy of market power. The relative production function approach used in this study identifies relative market power at the product level and can be aggregated to compute the market power of the firm. Compared to the macroeconomic literature, industry studies like this have the advantage of using assumptions that are more reliable and define the "market" more precisely.

Further limitations depend on the sample used for the econometric analysis, in which superstar firms are largely more represented than in reality. This selection bias, however, does not affect the estimates regarding the effect of the components of superstar products' market power, since they are compared to both the other products of superstar firms and the top products of non-superstar firms. In addition, despite the use of a panel of products, data cover only five years and the results cannot have implications for the dynamics of the pharmaceutical industry. Since only 10 percent of the products in the data are observed since their launch, the estimates capture the effect on market power heterogeneity across products, more than the evolution of product market power. A dynamic study on the determinants of product market power is another blank page of the economic literature but can be conducted using the same tools used in this chapter (Pakes, 2020).

In this research I show how important is to consider the firm as a multiproduct entity, not only looking at its scope but also at the distribution of sales across the products. The results show that firms are very concentrated and that the large product heterogeneity that composes one firm can be reduced to a bunch of very important products. It seems like a paradox: studying multiproduct firms to conclude that they are more single-product than they look.

4.A Additional Tables and Figures

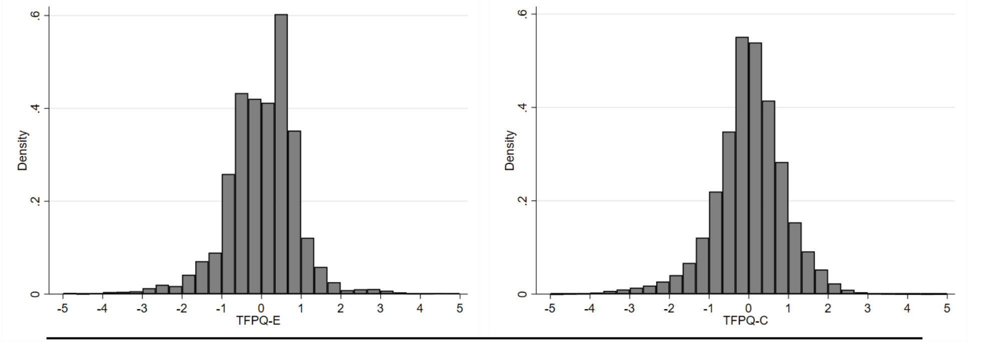
Figure 4.A.1 Within firm concentration



Notes: Within-firm HHI is Herfindahl-Hirschman Index calculated as the sum of the squares of product sales within the firm-month and its monthly average is plotted by quartiles of firm scope. The figure is based on AIOCD data.

Figure 4.A.2 Productivity estimates

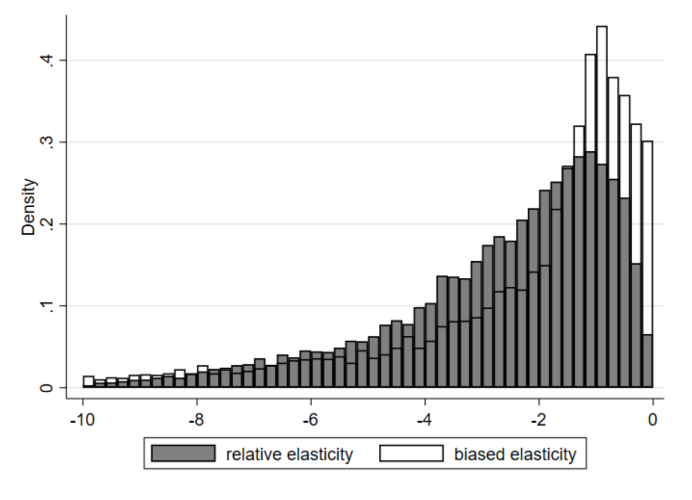
(A) Estimation-based (TFPQ-E) (B) Cost-based (TFPQ-C)



	Estimation-based (TFPQ-E)				Cost-based (TFPQ-C)			
	β^k	β^l	β^m	γ	β^k	β^l	β^m	β^e
Mean	0.584	0.106	0.647	-0.023	0.817	0.056	0.115	0.012
	(0.400)	(0.600)	(0.300)	(0.773)	(0.087)	(0.033)	(0.058)	(0.001)
Median	0.634	0.040	0.703	-0.009	0.826	0.051	0.107	0.010

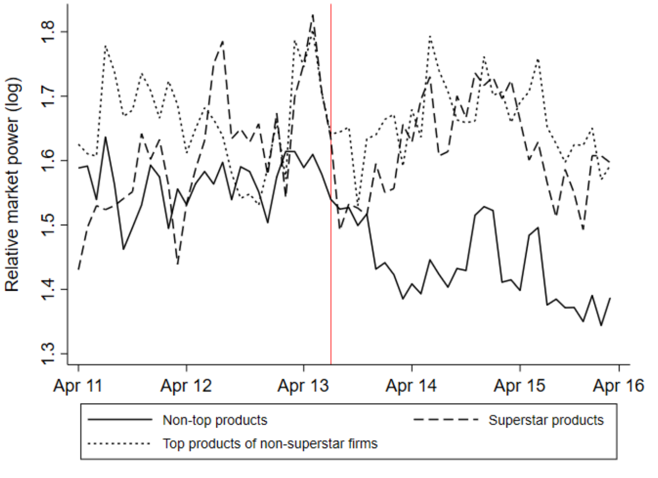
Notes: The figure plots the standardized distributions of the quantity-based product-level productivities estimated. Panel (A): Output elasticities in Equation (M.4.1) are estimated using the LP estimator, adjusted to control for firm's product scope; Panel (B): Output elasticities are computed using the product share of costs imputed to every production input. The table reports means, standard deviations (not standard errors, in brackets) and medians of the ATC5-level output elasticities estimated. Output elasticities are computed at the ATC5 level for 832 ATC5s. Column β^k reports the output elasticity to capital, Column β^l reports the output elasticity to labor, Column β^m reports the output elasticity to materials, Column γ reports the output elasticity to firm's product scope, Column β^e reports the output elasticity to energy consumption. The figure and table are based on AIOCD and Prowess, CMIE data. Standard errors (in parentheses) clustered at the market level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 4.A.3 Demand elasticity estimates



Notes: Figure compares the distribution of the product-level price elasticities estimated as from Equation (M.4.13) (*relative elasticity*) with the price elasticities estimated as from Equation (M.4.10) (*biased elasticity*). Distributions trimmed at values 0 and -10. The figure is based on AIOCD data.

Figure 4.A.4 Price cap regulation: the market power of regulated products



Notes: *Relative market power* is the normalized wholesale price of the product, relative to the lowest normalized wholesale price within the market. *Top product* is a product generating 1 percent or more of total firm sales. *Superstar firm* is a firm generating 1 percent or more of total industry sales. *Superstar product* is a product generating 1 percent or more of total superstar firm sales. Price regulation starts in July 2013 to limit the price of essential medicines in India. The figure is based on AIOCD data.

Table 4.A.1 Summary statistics

Panel (A) - Observations

	AIOCD	AIOCD+CMIE
Firms (N)	899	113
ATC5 (N)	2,956	832
Markets (N)	8,047	1,420
Brands (N)	54,023	8,489
Products (N)	92,907	15,734
Months (N)	60	60
Product-month observations (N)	3,087,502	561,460

Panel (B) - Distributions

	AIOCD		AIOCD+CMIE	
	mean	median	mean	median
Products per firm (N)	80.2	34	246.1	100
ATC5s per firm (N)	39.2	20	125.9	72
Markets per firm (N)	50.3	25	163.2	97
Wholesale sales per product (INR)	1.3 mn	130.7 th	1.8 mn	335.4 th
Wholesale sales per firm (INR)	104 mn	2.2 mn	439 mn	103 mn
Product share of market sales (%)	11.6	0.6	6.6	0.9
Product share of firm sales (%)	1.2	0.1	0.4	0.05
Wholesale price per unit (INR)	191	48	204	53
Retail markup	1.44	1.30	1.55	1.30

Notes: *ATC5* refers to the active pharmaceutical ingredient, *Market* refers to the combination between ATC5 and dosage form (tablet, injection, syrup, etc.), *Brand* refers to the retail name of the drug (irrespective of the strength or dosage), *Product* refers to the SKU. *Product share of market sales* is the ratio between product sales and total market sales. *Product share of firm sales* is the ratio between product sales and total firm sales. *Wholesale price per unit* is wholesale price for one unit (pack) of product. *Retail margin* is the difference between retail and wholesale price of one unit of product. *Retail markup* is the ratio between retail and wholesale one unit of product. *Wholesale sales* and *Wholesale prices* are expressed in Indian Rupees (INR) where *mn* is million, *th* is thousand. The table is based on AIOCD data.

Table 4.A.2 Superstar firms and share of industry sales

Company	Firm share of industry sales
Abbott	5.59
Alembic	1.36
Alkem Laboratories	3.06
Aristo Pharmaceuticals	2.37
Cipla	4.99
Dr. Reddys Laboratories	2.35
Emcure Pharmaceuticals	1.67
FDC	1.06
Glaxosmithkline Pharmaceuticals	4.22
Glenmark Pharmaceuticals	2.13
Intas Pharmaceuticals	2.55
Ipca Laboratories	1.29
Lupin	3.23
Macleods Pharmaceuticals	2.68
Mankind Pharmaceuticals	3.54
Micro Labs	1.94
Novartis India	1.25
Novo Nordisk India	1.03
Pfizer	3.01
Ranbaxy Laboratories	3.46
Sanofi India	2.55
Sun Pharma Laboratories	5.15
Torrent Pharmaceuticals	2.27
USV	1.84
Wockhardt	1.29
Zuventus Healthcare	1.02
Zydus Cadila	3.97

Notes: *Superstar firm* is a firm generating 1 percent or more of total industry sales. The table is based on AIOCD data.

Table 4.A.3 Correlation among type of products and market power, productivity and price elasticity

	Relative market power (log)			Productivity (log)			Price elasticity		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Superstar product	0.246***	0.202***	0.279***	0.096***	0.051***	0.100***	0.084	-0.207	0.052
	(0.048)	(0.054)	(0.048)	(0.010)	(0.010)	(0.009)	(0.119)	(0.136)	(0.120)
Top product		0.044			0.046***			0.295***	
		(0.029)			(0.006)			(0.075)	
Superstar firm			-0.091***			-0.107***			0.151***
			(0.017)			(0.005)			(0.040)
Firm FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Market FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	561460	561460	561460	561460	561460	561460	561460	561460	561460

Notes: *Top product* is a product generating 1 percent or more of total firm sales. *Superstar firm* is a firm generating 1 percent or more of total industry sales. *Superstar product* is a product generating 1 percent or more of total superstar firm sales. *Relative market power* is the normalized wholesale price of the product, relative to the lowest normalized wholesale price within the market. *Productivity* is the standardized quantity-based product-level productivity estimated as from in Equation (M.4.1) using the LP estimator, adjusted to control for firm's product scope ($TFPQ-E$). *Price elasticity* is product-level price elasticity estimated as from Equation (M.4.13) (*relative elasticity*). *Market* refers to the combination between ATC5 and dosage form. The table is based on AIOCD and Prowess, CMIE data. Standard errors (in parentheses) clustered at the market level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.A.4 The market power of superstar products: validity of the instrument

	Relative market power				Superstar firm
	(1) No-Top	(2) Top	(3) Top	(4) Top	(5) Top
Wholesale markup	0.019	0.074	0.123	0.137	-0.034
	(0.018)	(0.097)	(0.105)	(0.086)	(0.031)
Wholesale markup × Superstar firm			-0.511***		
			(0.192)		
Productivity	-0.616***	-0.748***	-0.787***	-0.725***	0.004
	(0.124)	(0.236)	(0.249)	(0.237)	(0.088)
Productivity × Superstar firm			0.328		
			(0.357)		
Retail markup	-0.580***	-0.285***	-0.293***	-0.449***	0.053**
	(0.023)	(0.064)	(0.065)	(0.089)	(0.024)
Retail markup × Superstar firm			0.144		
			(0.180)		
Product age	0.041***	0.026	0.038	0.029	-0.006
	(0.011)	(0.028)	(0.030)	(0.029)	(0.010)
Product Age × Superstar firm			-0.047		
			(0.043)		
Firm scope				0.006	0.254***
				(0.027)	(0.015)
Market FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	No	No
Month FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.579	0.726	0.727	0.687	0.775
Observations	517939	43521	43521	43521	43521

Notes: *Relative market power* is the normalized wholesale price of the product, relative to the lowest normalized wholesale price within the market. *Wholesale markup* is calculated using price elasticity estimated as from Equation (M.4.13) (*relative elasticity*). *Productivity* is the standardized quantity-based product-level productivity estimated as from Equation (M.4.1) using the LP estimator, adjusted to control for firm's product scope ($TFPQ-E$). *Retail markup* is the ratio between retail and wholesale price. *Product age* is the number of years from product launch date to its observation in the dataset. All the variables above are expressed in relative terms, using as a benchmark the product in the same market with the lowest value of the variable, and later transformed in logarithms. *Firm scope* is the logarithm of the number of products of a firm. *Top product* is a product generating 1 percent or more of total firm sales. *Superstar firm* is a firm generating 1 percent or more of total industry sales. *Superstar products* are top products of superstar firms. *Market* refers to the combination between ATC5 and dosage form. The table is based on AIOCD and Prowess, CMIE data. Standard errors (in parentheses) clustered at the market level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.A.5 The market power of top 15 products of top 15 firms

	Relative market power							
	(1) All	(2) All	(3) Top 15	(4) Top 15	(5) Top 15	(6) Top 15	(7) Top 15	(8) Top 15
Wholesale markup	0.024	0.025	0.083	0.090	0.024	-0.043	-0.042	-0.046
	(0.018)	(0.018)	(0.095)	(0.094)	(0.156)	(0.110)	(0.110)	(0.112)
Wholesale markup × Top 15 firm					-0.611			
					(0.653)			
Productivity	-0.581***	-0.453***	-0.642**	-0.596**	-0.569**	-0.525**	-0.571**	-0.591**
	(0.115)	(0.097)	(0.266)	(0.273)	(0.284)	(0.256)	(0.287)	(0.287)
Productivity × Top 15 firm						-0.533		
						(0.690)		
Retail markup	-0.590***	-0.624***	-0.612***	-0.610***	-0.371***	-0.372***	-0.389***	-0.371***
	(0.023)	(0.023)	(0.089)	(0.087)	(0.061)	(0.062)	(0.057)	(0.061)
Retail markup × Top 15 firm							0.537	
							(0.467)	
Product age	0.044***	0.041***	0.031	0.028	0.033	0.032	0.033	0.065*
	(0.011)	(0.011)	(0.028)	(0.027)	(0.022)	(0.023)	(0.023)	(0.033)
Product Age × Top 15 firm								-0.200*
								(0.115)
Top 15 product × Top 15 firm	0.139***	0.062						
	(0.052)	(0.057)						
Top 15 product		0.093***						
		(0.029)						
Top 15 firm		-0.099***	0.002	0.126				
		(0.017)	(0.067)	(0.196)				
Market FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	No	No	No	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.579	0.568	0.714					
Observations	561460	561460	28807	28807	28807	28807	28807	28807
F-stat				70	21	23	16	75

Notes: *Relative market power* is the normalized wholesale price of the product, relative to the lowest normalized wholesale price within the market. *Wholesale markup* is calculated using price elasticity estimated as from Equation (M.4.13) (*relative elasticity*). *Productivity* is the standardized quantity-based product-level productivity estimated as from Equation (M.4.1) using the LP estimator, adjusted to control for firm's product scope ($TFPQ-E$). *Retail markup* is the ratio between retail and wholesale price. *Product age* is the number of years from product launch date to its observation in the dataset. All the variables above are expressed in relative terms, using as a benchmark the product in the same market with the lowest value of the variable, and later transformed in logarithms. *Top 15 product* is a product ranked among the top 15 by firm sales. *Top 15 firm* is a firm ranked among the top 15 by industry sales. *Market* refers to the combination between ATC5 and dosage form. Columns 1-3 are estimated using OLS. Columns 4-8 are estimated using IV: superstar firm is instrumented with the firm scope. The table is based on AIOCD and Prowess, CMIE data. Standard errors (in parentheses) clustered at the market level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.A.6 The effect of price regulation on the sources of market power

	Relative market power			
	(1)	(2)	(3)	(4)
Wholesale markup	0.019	0.024	0.024	0.024
	(0.020)	(0.018)	(0.018)	(0.018)
Wholesale markup × Regulated	0.096*			
	(0.054)			
Wholesale markup × After July 2013	-0.009			
	(0.024)			
Wholesale markup × Regulated × After July 2013	-0.074			
	(0.049)			
Productivity	-0.576***	-0.510***	-0.576***	-0.575***
	(0.115)	(0.139)	(0.115)	(0.115)
Productivity × Regulated		-0.249		
		(0.217)		
Productivity × After July 2013		-0.043		
		(0.168)		
Productivity × Regulated × After July 2013		0.047		
		(0.241)		
Retail markup	-0.594***	-0.595***	-0.576***	-0.593***
	(0.023)	(0.023)	(0.033)	(0.023)
Retail markup × Regulated			-0.012	
			(0.043)	
Retail markup × After July 2013			-0.052*	
			(0.031)	
Retail markup × Regulated × After July 2013			0.091**	
			(0.042)	
Product age	0.042***	0.043***	0.043***	0.059***
	(0.011)	(0.011)	(0.011)	(0.015)
Product Age × Regulated				-0.016
				(0.027)
Product Age × After July 2013				-0.017
				(0.018)
Product Age × Regulated × After July 2013				-0.047*
				(0.025)
Regulated	0.082	0.165**	0.119**	0.139*
	(0.059)	(0.065)	(0.059)	(0.073)
Regulated × After July 2013	-0.155***	-0.190***	-0.201***	-0.112**
	(0.051)	(0.044)	(0.050)	(0.049)
Market FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
R-squared	0.580	0.580	0.580	0.580
Observations	561460	561460	561460	561460

Notes: *Relative market power* is the normalized wholesale price of the product, relative to the lowest normalized wholesale price within the market. *Wholesale markup* is calculated using price elasticity estimated as from Equation (M.4.13) (*relative elasticity*). *Productivity* is the standardized quantity-based product-level productivity estimated as from Equation (M.4.1) using the LP estimator, adjusted to control for firm's product scope ($TFPQ-E$). *Retail markup* is the ratio between retail and wholesale price. *Product age* is the number of years from product launch date to its observation in the dataset. All the variables above are expressed in relative terms, using as a benchmark the product in the same market with the lowest value of the variable, and later transformed in logarithms. *Regulated* is the treatment variable taking value one for the drugs targeted by the regulation. *Market* refers to the combination between ATC5 and dosage form. The table is based on AIOCD and Prowess, CMIE data. Standard errors (in parentheses) clustered at the market level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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:

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

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:

$$x_{it} = \omega_{it} + \beta_k k_{it} + \boldsymbol{\beta_v} \mathbf{v}_{it} \qquad \text{(M.3.9)}$$

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 $\Delta q^h_{ijt} = q_{ijt} - q_{hjt}$, 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

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- Tinbergen Institute, *Research on productivity, trade and growth*, 2018
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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:

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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.

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