Productivity, prices and market shares
in multiproduct firms[*]

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Abstract

We examine the relationship between product market shares and prices in the Indian pharmaceutical industry featuring multiproduct firms. Using detailed data on product-level sales and prices coupled with firm-level financial data, we find that in narrowly defined product markets, products sold at higher wholesale prices have a higher revenue-based market share. To disentangle the demand- and supply-side effects of price on market shares we estimate product-level productivity, controlling for the biases related to input measurement, simultaneity, and product scope. We find that product prices are correlated negatively with quantity-based productivity and positively with revenue-based productivity. We use quantity-based productivity to instrument for prices and find that prices and market shares are related negatively. However, the relationship is positive for the market leaders, who offer higher absolute margins to retailers and face a relatively more inelastic demand. Our results suggest that selection on productivity does not always result in lower prices in the presence of manufacturer market power and retailer buyer power.

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*, with a market share of 22.6 percent in January 2016 has a wholesale price of Rs. 206 for ten 625 mg tablets. By contrast, the brand with the second-highest market share of 12 percent has a relatively lower wholesale price of Rs. 63 for ten tablets. The analysis of more than 7800 narrowly defined medicine markets in India from 2011 to 2016 shows that, on average, products with a higher wholesale price have a higher market share (see Table 1). This pattern holds after controlling for the number of rival products, and firm, market, and time fixed effects. The positive relationship between prices and market shares is not only puzzling but, if confirmed, it also points to a public health crisis in one of the world's most populous countries characterized by limited public health infrastructure, low levels of health insurance, and consumers directly purchasing and paying for medicines exclusively from specialist, government-licensed retailers.

This paper examines the relationship between prices and market shares in the Indian pharmaceutical industry featuring multiproduct firms. The positive relationship that we observe can be due to both supply- and demand-side factors. On the demand side, quality difference among products is a common explanation of why higher prices can be correlated with higher market shares. Since we compare drugs in very narrowly defined markets, where different products have common molecules, *effective* quality difference is not responsible for the observed price dispersion.[1] However, we are unable to control for *perceived* quality. In this regard, prior research shows that uninformed consumers pay a higher premium for purchasing branded medicines when generic medicines with the same molecules are available (Bronnenberg et al., 2015). Naturally, if there are more uninformed consumers in the market, brands with higher prices have higher market shares as well. Other frictions on the demand-side such as consumer search costs lead to higher market shares for higher-priced products (Hastings et al., 2017; Chernew et al., 2018).

On the supply side, differences in prices can stem from both differences in productivity (cost structure) and markups. The supply of medicines in India involves a vertical distribution chain that includes pharmaceutical manufacturers in the upstream and wholesalers

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[1] Bennett and Yin (2014) conducted a quality test on the most important antibiotics in India and showed that 96 percent of the drugs sampled comply with Indian Pharmacopoeia quality standards. Moreover, in our final sample analysis we consider only traded companies which are supposed to be more observant (and controlled) about quality aspects.

and retailers of medicines in the downstream. The retailers are represented by a trade association with considerable buyer power, and employ restrictive vertical trade practices such as regulating entry into local markets and boycotting the sales of medicine brands that offer low retailer markups (Bhaskarabhatla et al., 2016). The presence of such retailer buyer power can create incentives for the retailer trade association to promote the sale of brands manufactured by less-productive pharmaceutical manufacturers that offer higher markups while neglecting the more productive manufacturers with lower retailer markups, resulting in allocative inefficiency in production. On the other hand, more productive manufacturers may gain market share by offering higher retailer markups, indicating that the inefficiency on the supply side lies with the buyer power of the downstream intermediaries rather than the manufacturers' market power. Our paper attempts to disentangle these effects.

Using detailed data on product-level sales and wholesale prices coupled with firm-level financial information, we estimate the relationship between prices and market shares among multiproduct firms at the product level. Following Hottman et al. (2016) we identify product cost, markup, appeal and firm scope as the drivers of product market share. We proxy product cost with product *wholesale price*, markup with *retail margin* on the product, appeal with *brand age*, and firm scope with the *number of markets* where it operates. To identify the demand- and supply-side effects of prices on market shares we instrument for wholesale prices using product-level productivity, as suggested by Foster et al. (2008). Productivity, a proxy for technical efficiency in production, is correlated with prices but not with the product market share except through its impact on prices.

Estimates of product-level productivity can be biased due to product-level input allocation, input price differentials, simultaneity bias between inputs and productivity, and product scope bias. Building on the recent advances in the literature (De Loecker et al., 2016; Dhyne et al., 2017), we address these biases and estimate a quantity-based measure of product-level productivity. We also compare our measure with other measures proposed by the literature to examine the robustness of our results.[2]

We find that the positive relationship between prices and market shares described in Table (1) is robust to the inclusion of other determinants of market shares. Similar to Foster et al. (2008), we find that wholesale prices are correlated negatively with quantity-based productivity and positively with revenue-based productivity. Instrumenting for

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[2]Productivity can be distinguished between revenue-based or quantity-based, depending on whether revenue or physical units sold is used as the output variable in the production function.

wholesale price with quantity-based productivity shows that an increase in the price stemming from the supply side (manufacturer cost structure) affects market share negatively on average. When we decompose this effect between market-leading and market-following products, we observe that prices affect leaders' market shares positively and followers' market shares negatively. This result is mainly due to the differences in price elasticities, which are significantly higher for the market followers compared to market leaders. These patterns indicate that market leaders are 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 retailer buyer power.

Our research contributes to the extant literature in several ways. First, we contribute to the empirical literature on the determinants of product demand in imperfectly competitive markets where the power of brand, retailers or trade associations can heavily determine market shares of products. Our results imply that product-level technical efficiency is not sufficient to determine market shares, generating distortions that affect product (and firm) profitability and survival. Product market shares are also driven by non-price demand-related features, involving retailer buyer power and uninformed consumers.

Second, we contribute to the empirical literature on estimating productivity for multi-product firms. Using traditional methods (Levinsohn and Petrin, 2003), as well as recent advances (De Loecker et al., 2016; Dhyne et al., 2017). We estimate productivity at the product-level, where each product is defined at the stock keeping unit (SKU) level. By 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. Our sample of pharmaceutical products allows us to calculate product-level productivity for more than 41,000 SKUs.

Third, the instrumental variable approach we use to identify the supply-side effect on market share includes an analysis of product price heterogeneity. Figure 1 shows product price distribution within the firm (panel a) and within the market (panel b). Studying prices using an average firm-level price measure rather than individual product prices set across hundreds of product markets is a compromising solution which eclipses product-level heterogeneity in prices (Smeets and Warzynski, 2013). We contribute to this area of research, studying the relationship between product-level productivity and wholesale prices. We find the negative correlation between quantity-based productivity and product wholesale price turns into positive when revenue-based productivity is considered. This

result confirms the findings in Foster et al. (2008), pointing at revenue-based productivity, used by the large majority of the literature, as a distorted measure of technical efficiency.

Figure 1: Distribution of product prices

(a) within-firm prices   (b) within-market prices
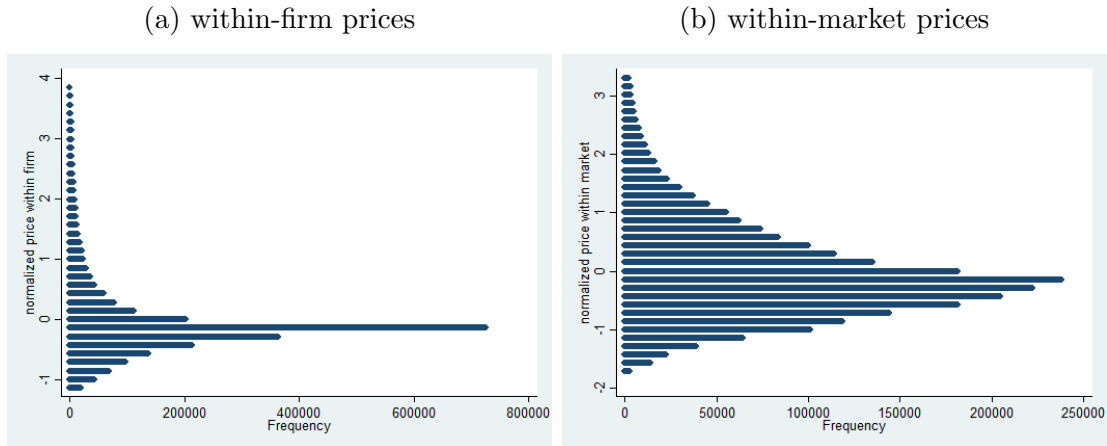
Source: AIOCD dataset

Note: Panel (a): percentiles 1 to 99 of the normalized distribution of product prices to the retailer within the firm (the normalized mean is the average firm price) . Panel (b): percentiles 1 to 99 of the normalized distribution of product prices to the retailer within the market (the normalized mean is the average market price).

Fourth, our paper contributes to an emerging literature that examines the rise in markups in the US in the recent decades and points to an increased market concentration (De Loecker and Eeckhout, 2017). Although our context features markets that are seemingly competitive, we examine the role of retail margins - the difference between retail and wholesale prices - in maintaining the dominant position of market leaders who are also the price leaders. Our findings show that retail margins positively affect the market share of the product, especially if market leaders, suggesting a determinant (and potentially distortive) role of the intermediaries.

Fifth, we provide evidence about the functioning of an imperfectly competitive industry in an emerging country. Indian firms have gained attention recently because India has undergone several important reforms over the last three decades.[3] Using a sample of multiproduct firms from India, Goldberg et al. (2010b) show that multiproduct firms are

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[3]Firms in developing countries are, in general, the target of academic studies because they face political constraints or innovations which are particularly useful for policy evaluation analysis (Pavcnik, 2002; Van Biesebroeck, 2005; Lileeva and Trefler, 2010). Moreover, countries at different stages of development exhibit nonnegligible differences in firm size, firm performance and resource allocation (Hsieh and Klenow, 2009; Bartelsman et al., 2013; De and Nagaraj, 2014).

larger, more productive, and perform better. Recent studies examine the impact of trade reforms in India on price and markups (De Loecker et al., 2016), product scope (Goldberg et al., 2010a), productivity (Topalova and Khandelwal, 2011; Ahsan, 2013). Other scholars studying the liberalization of the Indian economy found insignificant effects on productivity growth (Bollard et al., 2013), but significant effects on the reallocation of market shares towards the bigger firms (Alfaro and Chari, 2014).

The paper proceeds as follows: in Section 2 we present the dataset and in Section 3 we identify the determinants of market share and discuss the empirical strategy. In Section 4 we introduce the methodology to estimate product-level productivity in multiproduct firms. Section 5 shows and comments the main results and Section 6 concludes.

2   Data

We use new product-level data of the universe of multiproduct firms operating in the Indian pharmaceutical industry between April 2011 and March 2016. Data are provided by the All India Organization of Chemists and Druggists (AIOCD). A unique feature of our data is that we observe both wholesale and retail prices for each stock keeping unit (SKU) of the medicine, as well as the sales of each SKU of each firm collected for 60 consecutive months starting in April 2011. The data contain nearly 3.1 million SKU-month observations spanning 917 firms and almost 95 thousand SKUs. The sample allows defining product *markets* based on the molecular composition (four-digit therapeutic category) of the drug. We can identify more than 2900 markets. Within a market we further distinguish *submarkets* based on the dosage form of the drug (like injection, tablet, etc.). We can identify more than 8100 submarkets. Within a firm we also group the products into *brands* based on the commercial name of the drug. One brand can gather many products having different dosage form, strength and pack size. In the Indian pharmaceutical industry there are more than 51000 brands. We present an overview of AIOCD dataset in Table 2. Almost 99% of the firms in the Indian pharmaceutical industry are multiproduct firms, manufacturing, on average, 101 different SKUs. Indian pharmaceutical firms are mainly multiscope firms, operating, on average, in 47 markets and 61 submarkets, showing a large propensity to change their product mix - introducing or dropping a (new) product - or market mix - entering or quitting a (new) market.

We merge AIOCD product-level data with Prowess data on firm financials compiled

by the Centre for Monitoring Indian Economy (CMIE).[4] The CMIE Prowess data include yearly information on the standalone financial statement and other identifying information on the firms (name, industry, location, age) of all Indian companies traded on the National Stock Exchange and the Bombay Stock Exchange. The merged dataset contains over one million product-month observations, spanning almost 43 thousand SKUs produced by 125 firms (Table 2, second column). These firms are larger than the average and represent 14% of the initial AIOCD sample, their products cover 46% of all SKUs, and their sales account for 60% of the total sales. These firms operate in nearly 2500 markets. Every firm in the merged sample produces on average almost 300 different SKUs, and operates in 124 different markets.

The additional information provided by the CMIE dataset implies a cost in the representativeness of the sample that we use for our estimations. Traded companies are typically larger and show different entry and exit dynamics. The entry rate of firms in the pharmaceutical industry is high (15%) and relevantly above the exit rate (6%), giving us the idea of a very dynamic environment.[5] Moreover, traded firms show a higher propensity for product and market switching than AIOCD companies.

In the pharmaceutical industry the products sold in every submarket are homogeneous in the sense that they have all the same chemical composition. Drugs in every submarket also have the same quality as the bulk drugs used to produce the final goods are standard chemical elements. The only sources of differentiation among products in the same submarket are the pack size (measured in units, e.g., the number of single tablets in the pack) and the dosage strength (measured in weight or capacity, e.g., Metformin has dosages of 500, 850 or 1000 mg). To facilitate comparison among product prices per units (P) and physical units of product (Q) sold within the submarket, we normalize these measures (NI for $P, Q \in I$) for dosage strength (DS) and pack size (PS) using the formula:

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

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

Note that multiplying the normalized price per unit (NP) by normalized quantity

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[4]The CMIE data was used in other works of the field: Ahsan (2013); De Loecker et al. (2016); Goldberg et al. (2010a); Topalova and Khandelwal (2011) among the others.

[5]Goldberg et al. (2010b) show that in Indian manufacturing industry, entering in a product-level market is more common than exiting, because high sunk costs make firms reluctant to withdraw production lines.

(NQ) gives product sales revenues. Comparability of quantities and prices between submarkets are not possible, but relative measures like quantity-based market share, intended as the ratio between normalized quantity of a product and the sum of all normalized quantities sold in the same submarket, and relative price, intended as the ratio between normalized price of a product and the highest normalized price for a product in the same submarket. We observe a large dispersion of market shares and prices within and across the submarkets (Table 2, Panel b).

3   Methodology

In Table 1 we show that in the Indian pharmaceutical industry the relation between revenue-based submarket shares and wholesale prices is positive and significant. The economic theory predicts this relation to be negative, implying a trade-off in firm's profit-maximizing price-setting decision: increasing prices but losing market shares, or lowering prices but gaining market shares (Klemperer, 1995).[6] We aim to understand the forces that drive this relation, taking into account the others determinants of market shares that can affect the estimates. In this section we first identify and discuss the determinants of product market share, distinguishing the role of the agents interacting in the pharmaceutical industry: manufacturing firms, retailers and consumers. We then propose a reduced form model to empirically disentangle the effect of demand- and supply-side factors, using instrumental variables to solve for possible endogeneity. We extend the model to capture potential asymmetric effects of market-leading and market-following products on submarket shares. Finally, we adopt the same specification to estimate the price elasticity of demand.

3.1   Market shares in multiproduct firms

A correct estimation of the effect of a price change on product market share needs to control for other product-, firm- and market-level variables that influence the relationship. Hottman et al. (2016) propose an equilibrium model that distinguishes the determinants of the market share of multiproduct firms into four main components: costs, markups, appeal and scope. The same variables can be considered at the product level and identified

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[6]In the Appendix we show that if price elasticity is higher than one in absolute value a marginal increase in the product price results in a decrease in revenue-based market share.

as the determinants of the market share of the product.

To introduce these controls in the specification for product market share we proxy them with product-level variables: i) cost is product *wholesale price*; ii) markup is *retail margin* on the product; iii) appeal is *brand age*; iv) firm scope is the *number of markets* where the firm operates.

These variables can be seen as the contribution to product market share of the three agents operating in the pharmaceutical industry: manufacturing firms, retailers and consumers. The behaviour of both consumers and intermediaries, indeed, can help explain the positive relationship between manufacturer prices and market share. On the consumer side, the literature documented cases of lack of information in the pharmaceutical industry (Bronnenberg et al., 2015) implying higher and inelastic demand for branded and higher priced medicines. The theory of switching costs Klemperer (1995) can help understanding why consumers might have a strict preference on a good regardless of what the price is. This mechanism can help clarifying why we don't find a loss in market share when consumers face an increase in prices.

Intermediaries can play a role in maintaining the dominance of a product in its market, despite a relatively higher price. Indeed, manufacturers may incentivize intermediaries to promote their products offering higher retail margins. Since pharmaceutical retailers in India are represented by a trade association, it is possible for them to coordinate the distribution of a specific product across the country. Linking the availability of a product to its retail margin may also affect the demand for that product as consumers' switching costs may depend on product availability.

In theory, products with a higher market share are those charging lower prices as relatively more productive. The presence of uninformed consumers and coordinated retailers, however, may affect the selection process of a product in the market, distorting the 'true' demand for the product. Therefore, it is also possible that the market-leading products selected through this process are relatively more expensive because relatively less productive.

We can, then, divide the determinants of product market share by the manufacturer into demand-side ones (brand appeal and retail margin) and supply-side ones (product wholesale price and firm scope).

3.2 Empirical strategy

We estimate the relation between product market share and wholesale prices in the pharmaceutical industry, including the other determinants of market share pointed out by Hottman et al. (2016). The estimation equation is the following:

$$share_{ifjt} = \alpha_0 + \alpha_1 price_{ifjt} + \alpha_2 margin_{ifjt} + \alpha_3 scope_{ft} +$$
$$+ \alpha_4 age_{ifjt} + \alpha_5 competition_{jt} + \eta_j + \mu_f + \delta_t + \epsilon_{it} \tag{1}$$

where $share_{ifjt}$ is submarket j shares of revenues of product i produced by firm f, or submarket j shares of normalized physical units of product i produced by firm f. The variable $price_{ifjt}$ can be either: (i) product i's log normalized price to retailer; (ii) product i's normalized relative price to retailer. Retail margin is the percent difference between normalized wholesale price and normalized retail price for product i ($margin_{ifjt}$). Firm scope is the number of products produced by firm f in logs ($scope_{ft}$). Brand appeal is captured by the years since the product brand was launched (age_{ifjt}). We also control for market competition using the number of competing products in the market in logs ($competition_{jt}$), and for demand shift, including submarket (η_j), firm (muf) and yearly (δ_t) fixed effects, which adjust for any firm-, therapeutic category- and industry-specific demand variation, respectively. The error term (ϵ_{it}) is product-year specific.

Estimating (1) using OLS might give a positive bias to price coefficient, as an idiosyncratic shock in demand would imply an increase in price by the producers. To identify price elasticity of physical quantity sold Foster et al. (2008) instrument for prices with a measure of physical (quantity-based) productivity, a supply-side price driver which contains information on firm's cost. Indeed, productivity is a measure of technical efficiency, directly comparable across plants in the same submarket. Moreover, it should not be correlated with idiosyncratic product-specific demand shocks in the short run. We adopt the same idea and instrument for our measures of wholesale prices with a measure of quantity-based productivity, calculated addressing all the potential biases concerning productivity in multiproduct firms. In the following section we document how we calculate product-level productivity in the pharmaceutical industry.

3.3 Market leaders, followers and the level of retail margins

Equation (1) captures the industry average effect of a change in product price. However, this effect can be asymmetric across products with a different market power. Frank and Salkever (1997) show that branded drugs' prices increase after the entry of generic producers in the market and how the latter started competing on prices, instead. Other works suggest that price competition applies to generic drugs and only limitedly to branded drugs (Berndt and Aitken, 2011; Reiffen and Ward, 2005) .

We identify the market-leading product as the drug with the highest share of sales within each submarket, and market followers as the remainder products. We restrict the sample to submarkets with 5 or more products competing. We discriminate between market leaders and followers using the dummy variables *Lead* (taking value 1 when the product is market leader) and *Foll* (taking value 1 when the product is market follower). We interact these dummies with the wholesale price of the drug. The estimation equation is the following:

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\begin{aligned}
share_{ifjt} = \alpha_0 + \alpha_{11}Lead \times price_{ifjt} + \alpha_{11}Foll \times price_{ifjt} + \alpha_2 margin_{ifjt}+ \\
+\alpha_3 scope_{ft} + \alpha_4 age_{ifjt} + \alpha_5 competition_{jt} + \eta_j + \mu_f + \delta_t + \epsilon_{it}
\end{aligned}
\tag{2}
$$

where the other variables are the same as in Equation (1).

Wholesale price, however, is not the only determinant that can present asymmetric effects for leaders and followers. Higher margins can incentivize the retailer to provide a larger availability of a certain product. In such a case, higher retail margins can boost the product market share, despite they imply also higher consumer prices. If the decrease in sales due to higher consumer prices is negligible, then increasing retail margins is a profitable strategy for the firm.

We consider whether products with higher levels of retail margins affect market shares positively and if there is any asymmetry in this relationship across products with different market power. To test this hypothesis we interact retail margin (in logs) with the market-leader and market-follower dummies defined above. We consider the levels of retail margins and not the percentage (already included in the equation), as a marginal increase in the latter can be of a negligible interest for both the retailer and the consumer, in case the wholesale price of the product is low.

Adding the level of retail margins into the equation potentially introduces a source of

bias as it can respond to a product-specific demand increase, likewise the wholesale prices. To identify the effect of the level of retail margins we instrument it with firm percent retail margins across all its products. This variable is likely to be a relevant driver of product retail margin as the firm might strategically set an average percent retail margin across all its products, before deciding product-specific margins. 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. These characteristics make firm percent average retail margins a potentially suitable instrument.

3.4   Units sold and demand elasticity

In Table (1) we observe that quantity-based market share is negatively correlated with wholesale prices, consistently with the theory of trade-off between prices and market shares. This finding indicates that the positive correlation between revenue-based market share and prices does not, on average, imply a higher demand 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. Estimating the effect of prices on quantity-based product sales is, then, particularly relevant. We will use the same specification as in Equation (1) to model quantity-based market share and we test for asymmetric effects across market leaders and followers, with the methodology described in the previous subsection.

Demand elasticity is another important component of the puzzle. To observe a positive relationship between revenue-based market share and relative prices, elasticity should be smaller than one in absolute values (see Appendix). We investigate on price elasticity of demand using the same specification as in Equation (1) and we test for asymmetric effects across market leaders and followers, as described above. The dependent variable of the function will therefore be the log of normalized units of product sold and the main explanatory variable, normalized wholesale prices, will be taken in logs as well.

4 Product-level productivity in multiproduct firms

4.1 Instrumenting for prices: product-level productivity

Product-level productivity, intended as the efficiency with which firms turn inputs into outputs for each good they produce, is a key element of our analysis as it serves as an instrument for contrasting endogeneity between market share and wholesale prices. Although productivity differences among firms within an industry (even if narrowly defined) are well-documented (Bartelsman and Doms, 2000; Syverson, 2011), yet little empirical work examines the relation between prices and productivity and its impact on market shares (Goldberg and Hellerstein, 2012). Our identification strategy relies specifically on the possibility that productivity is correlated with prices, but exogenous - conditional on prices - with respect to market shares, and that this statement holds at the product level.

For this purpose we estimate product-level productivity in multiproduct firms. Indeed, although the choice of single-product industries simplifies the estimation of productivity and modeling competition, there is a growing recognition of the heterogeneity in products within standard industry classifications and their implications for market structure (Klepper and Thompson, 2006). The share of manufacturing firms that produce more than one good is large (Bernard et al., 2010; Goldberg et al., 2010b; Dhyne et al., 2017). Recent studies find that the choice of products mix is endogenous to the firm's productivity and, as a consequence, the usual firm-level and industry-level aggregate productivity measures that do not account for the product mix are biased (Bernard et al., 2009, 2010). With few exceptions, however, the literature on productivity treats firms as single-product producers, leaving aside issues like the choice of the firm product mix and price strategy in every market where the firm competes.[7] We compute six measures of product level productivity for multiproduct firms building on the main and most up-to-date methodologies.

We consider a product-level log-additive production function (e.g. Cobb-Douglas) whose coefficients remain constant over the sample period:

$$x_{it} = tfp_{it} + \alpha k_{it} + \beta \mathbf{v}_{it} \tag{3}$$

where, for each product i and each year t, x is log output, k is log capital employed and

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[7]Among the exceptions: (a) theoretical model incorporating the product mix of multiproduct firms can be found in Bernard et al. (2009, 2010); Mayer et al. (2014); (b) applied works are Foster et al. (2008); De Loecker et al. (2016); Mayer et al. (2016).

v is a vector of variable inputs in logs. Product-specific log productivity (tfp) is Hicks-neutral and can be computed as a Solow residual. According to the nature of the output, the literature divides production functions in *revenue-based*, if output is measured in sales revenues y, and *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; b) we do not observe productivity (neither at the firm nor at the product level). The first aspect can lead to two potential biases: a1) an *input allocation bias*, related to the possible mismeasurement in the process of addressing shares of firm-level inputs to each product; a2) an *input price bias*, related to the differences in purchase prices of the same input across different markets and qualities. Unobserved (to the econometrician) productivity, instead, can lead to two other potential biases: b1) a *simultaneity bias*, as the amount of inputs is chosen based on firm or product productivity; b2) a *product scope bias*, as the number of products is decided by the firm according to observed productivity. In the next two subsections, we discuss how we address these potential biases.

4.2   Product's input measurement

4.2.1   Product's input allocation: the 'reference firm'

The most influential papers in the literature deal with input allocation either apportioning firm-level input values or introducing a method to avoid the problem. Foster et al. (2008) apportion product's share of plant inputs using product's share of plant sales.[8] De Loecker et al. (2016) avoid product's input allocation by estimating productivity using only single product firms.[9] Dhyne et al. (2017) implement a technique to estimate product-level productivity using only firm-level inputs. We exploit specific features of the

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[8]The method is valid under perfect competition or assuming constant markups across firm products. Since they 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.

[9]They assume that a single-product firm uses the same technology of a multi-product 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.

pharmaceutical industry to make assumptions and impute the values of product variable inputs.

The pharmaceutical industry is composed of a large number of submarkets selling homogeneous goods. The unit cost of variable inputs - that is, raw materials, labor, and energy - can be assumed to be the same in the single submarket. Since the chemical composition of each drug is unique, we can assume that the cost of raw materials (bulk-drugs) used to produce a unit of the drug does not vary across all firms of the same submarket. The Indian pharmaceutical industry, which overwhelmingly produces out-of-patent medicines, is arguably more labor intensive than its counterparts in the developed world, where R&D and innovation-related staff play an important role. Since the skills to be employed in the pharmaceutical industry is standardized at the submarket level, and given the highly automated production process, we assume that the cost of labor used to produce a unit of the drug does not vary across all firms of the same submarket. We make the same assumption for energy, whose unit cost is the same for all firms of the same submarket. To identify the cost per unit produced of each variable input we select a firm for each submarket, the one 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 submarket.

The imputation of unit variable input cost for all products in each submarket leverages on the reference firms $(\bar{f})$. First, we calculate its input expenditure in the referenced submarket $(\bar{j})$ using the submarket's revenue shares of the firm $(s_{\bar{j}\bar{f}t})$:[10]

$$\mathbf{v}_{\bar{j}\bar{f}t} = \mathbf{v}_{\bar{f}t} s_{\bar{j}\bar{f}t} \tag{4}$$

Second, we split reference firm's input expenditure in the referenced submarket $(\mathbf{v}_{\bar{j}\bar{f}t})$ across all its products (i) using product's share of physical units produced in the submarket by the firm $(s^q_{i\bar{j}\bar{f}t})$:[11]

$$\mathbf{v}_{i\bar{j}\bar{f}t} = \mathbf{v}_{\bar{j}\bar{f}t} s^q_{i\bar{j}\bar{f}t} \tag{5}$$

This makes possible to obtain a measure of unit input cost for all products of the reference firm in the submarket $(\mathbf{v}^*_{i\bar{j}\bar{f}t})$, dividing the input cost of each reference firm's product in

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[10]To do so we have to assume that the reference firm has constant markup over all inputs in the referenced submarket.

[11]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.

the referenced submarket by the physical quantity of product sold ($q_{i\bar{j}\bar{f}t}$).

$$\mathbf{v}_{i\bar{j}\bar{f}t}^* = \frac{\mathbf{v}_{i\bar{j}\bar{f}t}}{q_{i\bar{j}\bar{f}t}} \tag{6}$$

Since we assumed the unit cost of variable inputs to be the same in the submarket, we can impute the input cost for all products of all other firms (f) in the submarket ($\bar{j}$) multiplying reference firm's unit input cost to every product's physical units produced in the submarket ($q_{i\bar{j}ft}$).

$$\mathbf{v}_{i\bar{j}ft} = \mathbf{v}_{i\bar{j}\bar{f}t}^* q_{i\bar{j}ft} \tag{7}$$

To impute product-level capital we simply apportion firm-level capital employed among the different products of the firm using product's share of firm sales as in Foster et al. (2008). Anyway, the productivity measure we will finally adopt to instrument for the prices in equation (1) does not require to apportion firm-level capital employed.

4.2.2 Product's input price

In general, product price variation within an industry may depend on the difference in the quality of the goods, which in turn may imply different inputs quality, and different input unit costs. The pharmaceutical industry produces homogeneous goods at the same submarket level. Since every drug sold in the submarket is composed of a fixed chemical composition, product quality variation can be excluded as well as difference in variable input quality within the same submarket. The bulk-drugs to obtain the final drugs are standardized; the workers in the chain of one product do not need to be more skilled than the other workers in the same submarket; energy has no quality variation within the submarket.

Another cause of input prices variation across comparable products is the existence of local input markets with different prices for the same good. We can exclude how this source of price variation affects inputs of products of the same submarket. The market for intermediate inputs such as bulk drugs is organized at the international level as it involves chemical elements. In addition, workers for the same role have the same bargaining power in India, the energy market is nationwide (at least).

Specific features of Indian pharmaceutical industry, however, do not help to infer about the difference in price of the capital goods employed for producing each single product.

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We stick to the O-Ring theory by (Kremer, 1993) and to Kugler and Verhoogen (2011), which model and show, respectively, that more expensive inputs lead to more expensive products. Product's share of firm sales, that we use for apportioning firm-level employed capital among the different products incorporates this information.

An important assumption we make on input prices is that they do not depend on input quantities.[12] 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% of the reference firms have the highest sales share in the referenced submarket, implying that less than 13% of the reference firms are top purchasers on their input markets.

4.3   Estimating product-level productivity

4.3.1   Addressing (or avoiding) the simultaneity bias

To calculate productivity as a Solow residual using equation (3) we must be able to measure the output elasticities, α and β. This can be done in two different ways: a) equaling elasticities to average input cost share over the sample (cost share-based method); b) estimating the elasticities by estimating the production function (estimation-based method). The first method follows the theoretical framework of cost minimization of the firm; 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. Respective to the output indicator, we calculate two measures of cost share-based productivity, one revenue-based ($TFPt$) and one quantity-based ($TFPQt$) as in Foster et al. (2008). The first row of Table 3 shows the elasticities of the cost share-based production functions.

The estimation-based method, instead, faces the problem of simultaneity bias, which arises as input quantities are decided according to observed or expected productivity (Olley and Pakes, 1996). Using the estimator proposed by Levinsohn and Petrin (2003) - henceforth LP estimator - we estimate four measures of estimation-based productivity, two revenue-based ($TFPVAlp$ and $TFPRlp$) and two quantity-based ($TFPQRlp$ and

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

TFPQKlp). This method is commonly used in the empirical literature on Indian firms (Ahsan, 2013; Topalova and Khandelwal, 2011). The second and third rows of Table 3 show the elasticities of the estimation-based product-level production functions.

4.3.2 Addressing the product scope bias

Although widely used, the LP method is not sufficient to eliminate all the sources of bias as it 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 goods to produce. The product scope bias, thus, arises when estimating the production function in multiproduct firms. Given the wide heterogeneity in prices at the product level, the estimation of productivity turns out to be non-negligibly biased (De Loecker and Goldberg, 2014). Although the implications of these unsolved issues affect the measurement of firm-level productivity for all multiproduct firms, the empirical research on this field is still scant. Only recently, De Loecker et al. (2016) included a control for product-mix in the estimation of productivity in single-product firms.[13] Dhyne et al. (2014) and Dhyne et al. (2017), instead, offered some econometric approach to deal with price heterogeneity at the product level, proposing a specification which accounts for the firm product scope. As far as we are concerned, Dhyne et al. (2017) is the only empirical study addressing the product scope bias in estimating prodct-level productivity by multiproduct firms.[14]

Dhyne et al. (2017) incorporate the product scope of the firm in an estimation-based method for measuring output elasticities at the product level which uses only firm-level input measures. In general the production function of the firm is considered as a sum of single product production function (De Loecker et al., 2016). Dhyne et al. (2017) implement a multiproduct production function re-elaborating the contribution of Diewert (1973). They consider a loglinear Cobb-Douglas production function, specified as follows:

$$q_{it} = tfp_{it} + \alpha k_{ft} + \beta_l l_{ft} + \beta_m m_{ft} + \gamma y_{-it} \tag{8}$$

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[13]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.

[14]Both Foster et al. (2008) and De Loecker et al. (2016) calculate product-level productivity using a sample of single-product firms.

where, for each product p, each firm f and each year t, q is log quantity sold in physical units, k is log capital, l is log labour, m is log raw materials and y_{-p} is log revenues of all other products 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." Moreover, their method avoids the procedure of apportioning firm-level inputs to each product. We follow their idea estimating 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 , however, variable inputs can be considered to be product-related, as raw materials and labour can only be used to produce a specific product (or at least be reallocated in the short run to other product of the same submarket). Firm capital expenditure, instead, is more likely to involve many products, complicating the exercise of identifying the exact contribution of firm capital to each product. We propose the following hybrid production function, in which variable inputs enter at the product level and capital enters at the firm level:

$$q_{it} = tfp_{it} + \alpha k_{ft} + \beta_l l_{it} + \beta_m m_{it} + \gamma y_{-it} \tag{9}$$

To contrast the simultaneity bias, we adopt the standard LP estimator using materials as a proxy. 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). We expect coefficient γ to be negative, as an increase in firm revenues, holding product variable inputs and firm-level capital constant, would result into a decrease in the quantity of the product under exam.

5 Results

5.1 Quantity-based and revenue-based productivity

The measures of product-level productivity calculated are collected in Table 3, distinguished by revenue- or quantity-based and cost share- or estimation based. All coefficients of the production function are calculated at the market level. The two cost share-based measures of productivity *TFPt* and *TFPQt* have the same equation (same input elastic-

ities), they just differ for the output variable: revenues for *TFPt* and physical units for *TFPQt*. The two revenue-estimation-based measures of productivity differ according to the inclusion of raw materials in the output (subtracted to the revenues) or among the inputs. For *TFPVAlp* we estimate a product value-added function, where energy costs serve as the proxy variable, as in (Ahsan, 2013). For *TFPRlp* we estimate a product sales function where raw material costs serve as the proxy variable, as in Dhyne et al. (2017), Table A3. The estimated elasticities of capital and labor are significantly lower for the latter measure. The quantity-based measures are both functions of product units, but differ from each other thanks to the control variables. *TFPQRlp* includes labour and raw materials among the inputs, where the latter also serves as a proxy variable, as in De Loecker et al. (2016). *TFPQKlp*, instead, uses firm-level capital input and addresses the product scope bias by including a measure of firm's scope among the explanatory variables, as in Dhyne et al. (2017), Table 3. The estimated elasticities of capital, labor and materials are very close for the latter measure. The negative coefficient for firm product scope (γ) confirms the expectations.

Table 4 shows a postitive and significant correlation between each of the revenue-based measures of productivity. The same happens for quantity-based measures. The correlation between revenue- and quantity based productivity, instead, depends on the type. Cost share-based measures are positively correlated each other, just like TFPRlp and TFPQRlp (both derived from an output function using the same input specification). A significant correlation is also found between both price measures and all six measures of product-level productivity. Interestingly, prices are positively correlated with the three revenue-based measures, but negatively correlated with the three quantity-based ones. Foster et al. (2008) find the same correlation signs and attribute the reason to the fact that, although calculated with deflated values, revenue-based productivity incorporates prices by definition. This suggests a revenue-based measure is not a suitable instrument for prices to identify elasticity in (1). Quantity-based productivity, instead, is more appropriate to satisfy the exogeneity condition.

5.2   First stage: which productivity is a suitable instrument?

We estimate (1) using a measure of product-level productivity to instrument for prices. The first-stage regression of the 2SLS estimator (equivalent to IV in results) has wholesale prices as the dependent variable and productivity as an explanatory, and informs about

the relevance of the instrument. This relation, moreover, can also give some information about product price-setting of the firm and the role of technical efficiency in this decision. We calculate the first-stage regression for all the six measure that we estimated using both relative prices (Table 5) and log normalized prices (Table 6) as the dependent variable. Including the other determinants of market share in the equation - retail margins, firm scope, brand appeal and competition - the opposite direction of the coefficient of revenue- and quantity- based product-level productivity is confirmed.

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. Yet 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).[15] The industry-specific empirical analysis focused on the relation between productivity and prices 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 standardized product, competitive selection on costs lowers product prices. Our analysis on multiproduct firms shows that the relationship higher productivity-lower prices can be valid also at the product level. Important is to notice that price variation can only limitedly be imputed to perceived quality differentials among products or input price variations within the submarket.

5.3 The determinants of market share

Estimating equation 1 with OLS (Table 7) confirms the positive relation between revenue-based market share and prices, that remains robust to the inclusion of other determinants of market share. Results also confirm the negative relation between quantity-based market share and prices presented in Table 1. Results remain stable also restricting the sample to more competitive markets (Column 2, 3, 5, and 6). Percent retail margin is negatively correlated with market share, in line to what one would expect in perfect competition, as an increase in margin increases price to retailers, i.e. the prices that makes the demand

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[15]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).

for the good. Firm scope's coefficient is not significant, as the inclusion on firm-specific fixed effects absorbs much of its variation. Excluding firm fixed effects (not shown in the table) the coefficient of firm scope turns positive, suggesting that market share is associated with the ability of the firm to produce more goods. Brand age proxies brand appeal is positively and significantly related to market share. Hypothesis of uninformed consumers or switching costs may find an evidence in this result. A comparison among coefficients shows that the correlation of these determinants is similar for both quantity- and revenue-based market share. Only the coefficient of prices has opposed sign.

Given that the OLS estimates are supposed to be biased, following Foster et al. (2008), we instrument for the price variable with a measure of quantity-based productivity calculated in Section 4. We opt for using the only measure that addresses product scope bias: *TFPQKlp*, but the results with the other two are similar. Table 8 shows the results of the IV regression. The reported F-statistics confirms that the instrument chosen is strongly relevant.

Instrumenting for wholesale prices with quantity-based productivity reverses the sign of its effect on revenue-based market share. This result suggests that the initially observed positive relation between prices and revenue-based market shares is not due to distortions on the supply side, as a higher technical efficiency drives prices downwards. The signs of the other explanatories confirm OLS estimates. The results remains consistent also across different price definitions and in submarkets including more than 10 different products.

The coefficient of prices in the quantity-based market share specification was already negative using OLS. IV estimates confirm the direction of the relation, but the size of the coefficient increases in absolute value, as expected.

5.4   Market power and buyer power

Table 9 shows the results of Equation (2) estimates, which identify the asymmetric effect of a price change across market-leading and market-following products in submarket with 5 or more products competing. The table shows that price of leaders and price of followers have opposed signs. A price increase of the leading product affects positively both the revenue-based and the quantity-based market share. In case the product is a market follower, the same increase in price would cause a decrease in market share. These results are in line with the findings of Berndt and Aitken (2011) indicating that market leaders

are not involved into price competition. The findings are robust to different definition of prices and market share. This latter result is of interest: a price increase of the leading product not only increases its revenue-based market share, but also its quantity-based market share. This is consistent with Bronnenberg et al. (2015) which suggest that the higher prices of the leaders can be perceived as higher quality by the consumers, boosting the product demand.

Table 10 shows the estimates of change in market share caused by an increase in the level of retail margin (in logs). For both revenue- and quantity-based measures of market share the OLS coefficient of the level of retail margin is positive and significant (Columns 1 and 4). A 1 percent increase in retail margin increases revenue-(quantity-)based market share by 0.9 (0.8) percentage points. IV estimates (Columns 2 and 5) present this coefficient to be non-statistically different from zero. The coefficients of the interaction terms of retail margins with market-leader and market-follower dummies (Columns 3 and 6) results to be statistically significant only in the first case. An increase in retail margin for a market-follower does not impact on market share. Introducing the level of retail margin does not affects the other coefficients of the estimate. In theory an increase in retail margin should diminish the demand for the product as its retail price, ceteris paribus, is higher. However, higher margin incentivize the retailer to provide a larger availability of the product. This seems to be the rationale behind the null average effect of the retail margin on both quantity- and revenue-based market share.

The results in Table 9 provide evidence of how market power drives product demand even in strictly homogeneous markets. If the product has some market power, prices affect market shares positively. The results in Table 10, instead, suggest that pharmaceutical firms can benefit from the retailer buyer power. In such a case, a higher retail price can even increase product demand for the leading products.

On the consumer side, both market power and buyer power contribute to a general loss. Producer of best seller drugs are not competing to lower their prices and the retailers are more willing to provide products that yield them a higher margin. Moreover, consumer-specific factors, like brand appeal, is a relevant determinant of market shares in all estimates. Demand-side factors involving consumers and retailers, and the presence of asymmetries for market leaders are, therefore, primarily responsible for the positive relation between prices and revenue-based market shares observed.

5.5 Demand elasticity estimates

Table 11 presents the estimates of price elasticity in the pharmaceutical industry. The OLS method estimates a negative and lower-than-unit elasticity. This is consistent with the algebraic implication of the observed positive relationship between revenue-based market share and wholesale prices. However, as for the market share case, this estimation can be upward biased. Again, we instrument normalized prices with quantity-based productivity and obtain a higher price elasticity. The IV results say that a 1 percent increase in prices leads to a decrease 5.6 percent in drug units sold. These estimates hold also in a sample of markets featuring 10 or more competitors.

Also regarding price elasticity we observe asymmetric effects of market-leading products with respect to market-following products (Table 12). Price elasticity is always significantly higher for market followers in both OLS and IV estimates. Also the marginal effect of an increase in retail margin (i.e., retail margin elasticity of demand) has opposite direction, depending on whether the product is market leader or follower. A 1 percent increase in the level of retail margin decreases demand by 0.8 percent for the market followers and increases it by 0.4 percent for the market leaders.

6 Conclusion

This paper examines the relationship between prices and market shares in multiproduct firms. We exploit a rich dataset on Indian pharmaceutical firms containing detailed information on quantities, wholesale and retail price of every drug sold in India. Without imposing assumptions on the market structure and competition among products, we estimate the demand curve that pharmaceutical products face in terms of market share in their therapeutic category market. We observe that market share is positively and robustly correlated with wholesale prices. This puzzling direction of the relationship suffers, however, from estimation biases stemming from the simultaneous formation process of prices and quantities sold. Our approach, then, uses a measure of quantity-based product-level productivity to identify the effect on market share triggered by the supply side (an increase in wholesale price) from the effect activated by the demand side, like an increase in retailer markups, or firm appeal or brand appeal.

To measure quantity-based product-level productivity in the multiproduct firms of the

pharmaceutical industry, we address all the biases arising when estimating the production function at the product level. Building on the most up-to-dated advances in the literature and exploiting peculiar characteristics of the pharmaceutical industry, we introduce a new method for estimating the input elasticities of the production function which accounts also for the product scope of the firm.

We compare the productivity measure that we obtain to other measure of product-level productivity (both quantity- and revenue-based) calculated using the most recently introduced methodologies, and find that it is negatively correlated with prices as well all other quantity-based measures. Conversely, the measures of revenue-based productivity are positively correlated with prices: the same evidence found by Foster et al. (2008).

We show that product wholesale price, once instrumented with a quantity-based measure of productivity, turns to have a negative and significant effect on revenue-based market share. The positive relation between prices and revenue-based market shares that we observe in the OLS estimation is, thus, not an outcome of a supply-side distortions: within narrowly defined market, more productive products have lower wholesale prices.

After distinguishing between market-leading and market-following products, we find that the positive relationship between revenue-based market share and wholesale prices persist for the product with the highest submarket share. Compared to market followers, these products have also a lower price elasticity and benefit from granting higher levels of margins to the retailers. More than wholesale prices, demand-side factors like brand appeal and retail margins are, therefore, the upward drivers of the market shares.

The IV analysis is based on data of listed firms, which are larger and more productive than the average. Thus, these results are not representative of the entire pharmaceutical industry. However, they suggest the relevance of the retailer buyer power in the pharmaceutical industry. In addition, this paper shows that the market power of the leading products not only affects price elasticity, but is also strengthened by the ability of keeping brand appeal within the consumers and the possibility of allowing the retailers to obtain higher margins.

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Tables

Table 1: Market share and wholesale prices

	Revenue-based market share			Quantity-based market share		
	(1) All	(2) N5	(3) N10	(4) All	(5) N5	(6) N10
Relative PTR	0.029***	0.006***	0.007***	-0.086***	-0.068***	-0.044***
	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)
Observations	328746	289164	257099	328746	289164	257099
R-squared	0.678	0.233	0.173	0.657	0.217	0.152

Source: AIOCD and Prowess, CMIE.

Notes: OLS estimates. The dependent variable is the market share. *Revenue-based market share* is calculated as the share of sales of the product in the submarket. *Quantity-based market share* is calculated as the product share of units sold in the submarket. *Relative PTR* is the ratio between product's normalized PTR and the highest normalized PTR in the submarket. Time, firm and submarket fixed effects are included. Set *All* includes all the submarkets, *N5* includes the submarkets with 5 or more products, set *N10* includes the submarkets with 10 or more products.

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

Table 2: Sample statistics

Panel a

	AIOCD	AIOCD + CMIE
Firms (N)	917	125
Markets (N)	2,959	2,499
Submarkets (N)	8,105	5,716
Brands (N)	51,580	21,527
Products (N)	94,892	42,955
Product-year observations	329,280	139,923
Product-month observations	3,130,367	1,342,031
Exiting firms (%)	6.0	2.7
Entering firms (%)	15.6	4.9
Firms changing product mix (%)	87.3	93.7
Firms changing market mix (%)	77.0	87.8

Panel b

	AIOCD				AIOCD + CMIE			
	mean	med	min	max	mean	med	min	max
Products per firm (N)	101	44	1	2451	298	136	1	2451
Markets per firm (N)	47	24	1	731	47	123	1	731
Submarkets per firm (N)	61	31	1	1103	163	89	1	1103
Products per market (N)	24	7	1	3422	13	5	1	395
Products per submarket (N)	10	2	1	1792	6	2	1	185
Sales per product (IRs)	11.3 m	665 t	1	3.2 b	15.6 b	1.5 m	1	2.3 b
Sales per firm (IRs)	1.2 b	24.2 m	23.2	45.2 b	4.6 b	890 m	156	45.2 b
Sales per market (IRs)	272 m	45.9 m	3	15.0 b	174 m	32.5 m	3	6.7 b
Sales per submarket (IRs)	109 m	9.6 m	3	9.5 b	78.0 m	9.9 m	1	5.9 b
Product revenue submarket share (%)	10.4	0.3	1e-07	100	11.7	0.7	1e-07	100
Product unit submarket share (%)	10.4	0.4	6e-07	100	11.7	0.7	7e-07	100
PTR per unit (IRs)	191	45.2	0.01	264 t	269	50	0.01	264 t
Relative PTR (%)	30.8	13.8	3e-06	100	32.6	16.4	3e-06	100

Source: AIOCD and Prowess, CMIE.

Notes: The dataset AIOCD + CMIE is the data obtained merging AIOCD and CMIE datasets. *market* refers to the therapeutic category, *submarket* refers to the combination between therapeutic category and format of the drug (tablet, injection, syrup, etc.), *brand* refers to the retail name of the drug (irrespective of the strength or dosage), *product* refers to the SKU. *Exiting* and *entering firms* are the firms which appear or disappear in the dataset. *Product mix* changes when a firm starts producing or stops producing a stock keeping unit, *market mix* changes when a firm enters a therapeutic category with a new drug or exits a therapeutic category ceasing producing drugs for that market. *Sales* and *PTR* are expressed in Indian Rupees (IRs) where *b* is billion, *m* is million, *t* is thousand. *Product revenue submarket share* is the ratio between product sales and total submarket sales. *Product unit submarket share* is the ratio between normalized product units and the total normalized units sold on the submarket. *PTR per unit* is price to retailer for one unit of product. *Relative PTR* is the ratio between normalized product PTR and the highest normalized product PTR in the submarket.

Table 3: TFP estimates

		Revenue-based	Quantity-based
Cost share -based	Label	TFPt	TFPQt
	Function	$y_{it} = tfp_{it} + \alpha k_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_e e_{it}$	$q_{it} = tfp_{it} + \alpha k_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_e e_{it}$
	Elasticities	$\alpha = .75; \beta_l = .08; \beta_m = .16; \beta_e = .02$	$\alpha = .75; \beta_l = .08; \beta_m = .16; \beta_e = .02$
	References	Foster et al. (2008)	Foster et al. (2008)
Estimation -based	Label	TFPVAlp	TFPQRlp
	Function	$va_{it} = tfp_{it} + \alpha k_{it} + \beta_l l_{it}$	$q_{it} = tfp_{it} + \alpha k_{it} + \beta_l l_{it} + \beta_m m_{it}$
	Proxy	e_{it}	m_{it}
	Conditioning	-	$k_{it}; k_{it-1}; l_{it-1}; m_{it-1}; m_{it-2}$
	Elasticities	$\alpha = .79; \beta_l = .23$	$\alpha = .39; \beta_l = .09; \beta_m = .34$
	References	Ahsan (2013)	De Loecker et al. (2016)
	Label	TFPRlp	TFPQKlp
	Function	$y_{it} = tfp_{it} + \alpha k_{it} + \beta_l l_{it} + \beta_m m_{it}$	$q_{it} = tfp_{it} + \alpha k_{ft} + \beta_l l_{it} + \beta_m m_{it} + \gamma y_{-it}$
	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	$\alpha = .55; \beta_l = .13; \beta_m = .20$	$\alpha = .35; \beta_l = .15; \beta_m = .34; \gamma = -.19$
	References	Dhyne et al. (2017), Tab.A3	Dhyne et al. (2017), Tab.3

Source: AIOCD and Prowess, CMIE.
Notes: *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 market level using Levinsohn and Petrin method. The variables indicated in the production functions are expressed in logs: y is revenue sales, 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. The estimated elasticities reported are the industry average of market-wise estimates.

Table 4: Correlation table

	NPTR	RPTR	Q	TFPt	TFPVAlp	TFPRlp	TFPQt	TFPQlp	TFPQKlp
NPTR	1.000								
RPTR	0.196	1.000							
	(0.000)								
Q	-0.017	-0.033	1.000						
	(0.000)	(0.000)							
TFPt	0.013	0.015	0.005	1.000					
	(0.000)	(0.000)	(0.054)						
TFPVAlp	0.003	0.059	0.001	0.047	1.000				
	(0.301)	(0.000)	(0.762)	(0.000)					
TFPRlp	0.030	0.056	0.012	0.044	0.046	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
TFPQt	-0.459	-0.285	0.120	0.234	-0.006	-0.061	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.044)	(0.000)			
TFPQlp	-0.138	-0.074	0.038	0.010	-0.007	0.103	0.257	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.021)	(0.000)	(0.000)		
TFPQKlp	-0.036	-0.013	0.020	0.012	0.007	-0.016	0.061	-0.022	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.016)	(0.000)	(0.000)	(0.000)	

Source: AIOCD and Prowess, CMIE.

Notes: *NPTR* is normalized price to retailers (PTR), top and bottom 1% values are truncated. *RPTR* is normalized relative PTR: the ratio between normalized product PTR and the highest normalized product PTR in the submarket. *Q* is a normalized measure of product units sold. The TFP measures (in logs) are defined as follows. *TFPt*: revenue-based TFP calculated using the share of costs (Foster et al. (2008) call it "traditional TFP"); *TFPVAlp*: value added-based TFP, based on Ahsan (2013); *TFPRlp*: revenue-based TFP calculated using Levinsohn and Petrin (2003); *TFPQt*: quantity-based TFP calculated using the share of costs (Foster et al. (2008) call it "quantity TFP"); *TFPQlp*: quantity-based TFP, based on De Loecker et al. (2016); *TFPQKlp*: quantity-based TFP calculated, based on Dhyne et al. (2017). See Table 3 for details.
Significance levels in parentheses.

Table 5: First stage: relative wholesale price and productivity

	Revenue-based productivity			Quantity-based productivity		
	(1) TFPt	(2) TFPVAlp	(3) TFPRlp	(4) TFPQt	(5) TFPQlp	(6) TFPQKlp
TFP (log)	0.043***	0.006***	0.006***	-0.099***	-0.017***	-0.012***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Retail margin (%)	-0.002***	-0.002***	-0.002***	-0.000	-0.002***	-0.002***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Rivals brands (log)	-0.194***	-0.194***	-0.194***	-0.206***	-0.196***	-0.198***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Firm scope (log)	0.002	-0.002	-0.000	0.040***	0.003	-0.001
	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.008)
Brand age (log)	-0.013***	-0.016***	-0.016***	-0.009***	-0.009***	-0.007***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Observations	131764	121417	131775	131764	131775	131770
R-squared	0.650	0.646	0.644	0.740	0.655	0.651

Source: AIOCD and Prowess, CMIE.
Notes: OLS estimates. The dependent variable is *Relative PTR*, the ratio between product's normalized PTR and the highest normalized PTR in the submarket. The TFP measures (in logs) are defined as follows. *TFPt*: revenue-based TFP calculated using the share of costs (Foster et al., 2008); *TFPVAlp*: value added-based TFP calculated using Levinsohn and Petrin (2003) like in (Ahsan, 2013); *TFPRlp*: revenue-based TFP calculated using Levinsohn and Petrin (2003); *TFPQt*: quantity-based TFP calculated using the share of costs (Foster et al., 2008); *TFPQlp*: quantity-based TFP calculated using Levinsohn and Petrin (2003) like in De Loecker et al. (2016); *TFPQKlp*: quantity-based TFP calculated using Levinsohn and Petrin (2003) like in Dhyne et al. (2017). See Table 3 for details.
Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: First stage: normalized wholesale price and productivity

	Revenue-based productivity			Quantity-based productivity		
	(1) TFPt	(2) TFPVAlp	(3) TFPRlp	(4) TFPQt	(5) TFPQlp	(6) TFPQKlp
TFP (log)	0.372***	0.036***	0.052***	-0.873***	-0.158***	-0.117***
	(0.011)	(0.005)	(0.013)	(0.007)	(0.016)	(0.006)
Retail margin (%)	-0.024***	-0.028***	-0.025***	-0.008***	-0.026***	-0.027***
	(0.005)	(0.007)	(0.005)	(0.002)	(0.006)	(0.006)
Rivals brands (log)	0.057**	0.062**	0.051**	-0.049***	0.033	0.022
	(0.023)	(0.024)	(0.023)	(0.011)	(0.021)	(0.022)
Firm scope (log)	0.062	0.022	0.040	0.398***	0.072*	0.034
	(0.043)	(0.041)	(0.040)	(0.052)	(0.039)	(0.039)
Brand age (log)	-0.078***	-0.102***	-0.104***	-0.042***	-0.035***	-0.019*
	(0.011)	(0.012)	(0.012)	(0.004)	(0.012)	(0.011)
Observations	131764	121417	131775	131764	131775	131770
R-squared	0.844	0.844	0.837	0.958	0.852	0.848

Source: AIOCD and Prowess, CMIE.
Notes: OLS estimates. The dependent variable is *Normalized PTR (log)*, the product price to retailers divided by the pack size (in units) and dosage strength (measured in weight or capacity). The TFP measures (in logs) are defined as follows. *TFPt*: revenue-based TFP calculated using the share of costs (Foster et al., 2008); *TFPVAlp*: value added-based TFP calculated using Levinsohn and Petrin (2003) like in (Ahsan, 2013); *TFPRlp*: revenue-based TFP calculated using Levinsohn and Petrin (2003); *TFPQt*: quantity-based TFP calculated using the share of costs (Foster et al., 2008); *TFPQlp*: quantity-based TFP calculated using Levinsohn and Petrin (2003) like in De Loecker et al. (2016); *TFPQKlp*: quantity-based TFP calculated using Levinsohn and Petrin (2003) like in Dhyne et al. (2017). See Table 3 for details.
Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: The determinants of submarket shares

	Revenue-based market share			Quantity-based market share		
	(1) All	(2) N5	(3) N10	(4) All	(5) N5	(6) N10
Relative PTR	0.018***	0.008***	0.009***	-0.102***	-0.070***	-0.044***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Retail margin (%)	-0.000**	-0.000**	-0.000*	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rivals brands (log)	-0.145***	-0.039***	-0.022***	-0.165***	-0.048***	-0.028***
	(0.003)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)
Firm scope (log)	-0.002	-0.002	-0.001	-0.003	-0.002	-0.002*
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Brand age (log)	0.029***	0.024***	0.019***	0.027***	0.023***	0.018***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	310627	273562	243132	310627	273562	243132
R-squared	0.691	0.256	0.198	0.674	0.238	0.173

Source: AIOCD and Prowess, CMIE.
Notes: OLS estimates. The dependent variable is the market share. *Revenue-based market share* is calculated as the share of sales of the product in the submarket. *Quantity-based market share* is calculated as the product share of units sold in the submarket. *Relative PTR* is the ratio between product's normalized PTR and the highest normalized PTR in the submarket. Time, firm and submarket fixed effects are included. Set *All* includes all the submarkets, *N5* includes the submarkets with 5 or more products, set *N10* includes the submarkets with 10 or more products.
Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: The determinants of submarket shares
Instrumenting wholesale prices with quantity-based TFP (TFPQKlp)

	Revenue-based market share				Quantity-based market share			
	(1) All	(2) N10	(3) All	(4) N10	(5) All	(6) N10	(7) All	(8) N10
Relative PTR	-1.074*** (0.050)	-0.701*** (0.035)			-1.269*** (0.055)	-0.828*** (0.038)		
Norm. PTR (log)			-0.113*** (0.005)	-0.065*** (0.003)			-0.134*** (0.005)	-0.077*** (0.003)
Retail margin (%)	-0.003*** (0.001)	-0.002*** (0.001)	-0.004*** (0.001)	-0.003*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)
Rivals brands (log)	-0.361*** (0.013)	-0.130*** (0.007)	-0.146*** (0.005)	-0.029*** (0.003)	-0.397*** (0.014)	-0.147*** (0.007)	-0.144*** (0.005)	-0.027*** (0.003)
Firm scope (log)	-0.005 (0.010)	0.003 (0.006)	0.000 (0.006)	0.001 (0.004)	-0.004 (0.011)	0.005 (0.007)	0.002 (0.007)	0.003 (0.004)
Brand age (log)	0.017*** (0.002)	0.016*** (0.001)	0.022*** (0.002)	0.019*** (0.001)	0.014*** (0.002)	0.014*** (0.002)	0.021*** (0.002)	0.018*** (0.001)
Observations	131770	100867	131770	100867	131770	100867	131770	100867
F-stat	529.5	1701.1	768.4	3429.6	529.5	1701.1	768.4	3429.6

Source: AIOCD and Prowess, CMIE.

Notes: IV estimates. Price variables are instrumented with quantity-based productivity based on Dhyne et al. (2017) (*TFPQKlp*). See Table 3 for more details. *Revenue-based market share* is calculated as the share of sales of the product in the submarket. *Quantity-based market share* is calculated as the product share of units sold in the submarket. *Relative PTR* is the ratio between product's normalized PTR and the highest normalized PTR in the submarket. *Normalized PTR (log)* is the product price to retailers divided by the pack size (in units) and dosage strength (measured in weight or capacity). *All* includes all the submarkets, *N10* includes the submarkets with 10 or more products. *F-stat* is Kleibergen-Paap F statistic.
Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: The determinants of submarket shares
Market leaders and market followers

	Revenue-based market share				Qevenue-based market share			
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV
Rel. PTR X Lead.	0.549***	0.792***			0.332***	0.448***		
	(0.006)	(0.116)			(0.008)	(0.110)		
Rel. PTR X Foll.	-0.034***	-0.490***			-0.101***	-0.695***		
	(0.001)	(0.031)			(0.002)	(0.035)		
Norm. PTR X Lead.			0.053***	0.045***			0.025***	0.014*
			(0.001)	(0.008)			(0.001)	(0.008)
Norm. PTR X Foll.			-0.003***	-0.040***			-0.019***	-0.061***
			(0.000)	(0.003)			(0.001)	(0.003)
Retail margin (%)	-0.000**	-0.001***	-0.000**	-0.001***	-0.000	-0.001	-0.000	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Rivals brands (log)	-0.030***	-0.081***	-0.027***	-0.023***	-0.041***	-0.116***	-0.029***	-0.025***
	(0.001)	(0.008)	(0.001)	(0.003)	(0.001)	(0.009)	(0.001)	(0.003)
Firm scope (log)	0.000	0.002	0.001	0.005	-0.001	0.003	0.001	0.006
	(0.001)	(0.005)	(0.001)	(0.003)	(0.001)	(0.007)	(0.001)	(0.004)
Brand age (log)	0.018***	0.007***	0.014***	0.007***	0.018***	0.006***	0.015***	0.007***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	273562	115505	273562	115505	273562	115505	273562	115505
R-squared	0.523		0.627		0.370		0.458	
F-stat		35.1		29.7		35.1		29.7

Source: AIOCD and Prowess, CMIE.
Notes: IV estimates. Price variables are instrumented with quantity-based productivity based on Dhyne et al. (2017) (*TFPQKlp*). See Table 3 for more details. *Revenue-based market share* is calculated as the share of sales of the product in the submarket. *Quantity-based market share* is calculated as the product share of units sold in the submarket. *Relative PTR X Leader* and *Normalized PTR X Leader* are the interaction between price variables and a dummy taking value 1 when the product has the highest submarket share of sales. *Relative PTR X Follower* and *Normalized PTR X Follower* are the interaction between price variables and a dummy taking value 1 when the product has not the highest submarket share of sales. All estimates are conducted on submarkets with 5 or more products.
Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: The effect of the level of retail margin on submarket shares
Market leaders and market followers

	Revenue-based market share			Quantity-based market share		
	(1) OLS	(2) IV	(3) IV	(4) OLS	(5) IV	(6) IV
Rel. PTR	0.005***	-0.898***	-0.484***	-0.072***	-1.062***	-0.700***
	(0.002)	(0.042)	(0.024)	(0.002)	(0.046)	(0.031)
Retailer margin (log)	0.009***	-0.012		0.008***	-0.013	
	(0.000)	(0.009)		(0.001)	(0.010)	
Ret. margin X Lead.			0.121***			0.103***
			(0.006)			(0.007)
Ret. margin X Foll.			-0.008			-0.011
			(0.005)			(0.007)
Retail margin (%)	-0.001**	-0.002***	-0.001**	-0.000	-0.001	-0.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Rivals brands (log)	-0.040***	-0.189***	-0.106***	-0.049***	-0.214***	-0.140***
	(0.001)	(0.009)	(0.005)	(0.001)	(0.009)	(0.006)
Firm scope (log)	-0.002*	-0.002	-0.000	-0.002*	-0.001	0.001
	(0.001)	(0.008)	(0.005)	(0.001)	(0.010)	(0.007)
Brand age (log)	0.024***	0.017***	0.008***	0.023***	0.014***	0.006***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Observations	273515	115489	115489	273515	115489	115489
R-squared	0.258			0.240		
F-stat		118.5	81.5		118.5	81.5

Source: AIOCD and Prowess, CMIE.

Notes: OLS estimates in Columns 1 and 4, IV estimates in Columns 2,3,5 and 6. *Revenue-based market share* is calculated as the share of sales of the product in the submarket. *Quantity-based market share* is calculated as the product share of units sold in the submarket. *Relative PTR* is the ratio between product's normalized PTR and the highest normalized PTR in the submarket. *Retailer margin (log)* is the difference between MRP and PTR for a unit of product. *Retailer margin X Leader* is the interaction between *Retailer margin (log)* and a dummy taking value 1 when the product has the highest submarket share of sales. *Retail margin X Follower* is the interaction between *Retailer margin (log)* and a dummy taking value 1 when the product has not the highest submarket share of sales. In IV estimates *Relative PTR* is instrumented with quantity-based productivity based on Dhyne et al. (2017) (*TFPQKlp*) and *Retailer margin (log)* with firm percent average retail margin. All estimates are conducted on submarkets with 5 or more products.
Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Wholesale price elasticity of demand

	Norm. units (log)					
	(1) OLS All	(2) OLS All	(3) IV All	(4) OLS N10	(5) OLS N10	(6) IV N10
Norm. PTR (log)	-0.934***	-0.904***	-5.624***	-0.916***	-0.887***	-5.782***
	(0.006)	(0.007)	(0.146)	(0.007)	(0.007)	(0.161)
Retail margin (%)		-0.028***	-0.162***		-0.032**	-0.215***
		(0.010)	(0.036)		(0.015)	(0.062)
Rivals brands (log)		-0.372***	-0.107		-0.169***	0.181
		(0.025)	(0.114)		(0.033)	(0.142)
Firm scope (log)		0.250***	0.341		0.263***	0.472*
		(0.040)	(0.220)		(0.045)	(0.257)
Brand age (log)		0.849***	0.556***		0.881***	0.658***
		(0.014)	(0.058)		(0.015)	(0.063)
Observations	328746	310627	131770	257099	243132	100867
R-squared	0.615	0.629		0.582	0.596	
F-stat			768.4			3429.6

Source: AIOCD and Prowess, CMIE.

Notes: OLS estimates in Columns 1,2,4 and 5, IV estimates in Columns 3 and 6. The dependent variable is *Normalized units (log)* calculated as the logarithm of normalized product units sold. *Normalized PTR (log)* is the product price to retailers divided by the pack size (in units) and dosage strength (measured in weight or capacity). In IV estimates *Normalized PTR (log)* is instrumented with quantity-based productivity based on Dhyne et al. (2017). *All* includes all the submarkets, *N10* includes the submarkets with 10 or more products. Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Wholesale price and retail margin elasticity of demand
Market leaders and market followers

	Norm. units (log)					
	(1) OLS	(2) OLS	(3) IV	(4) OLS	(5) IV	(6) IV
Norm. PTR (log)				-0.937*** (0.007)	-5.782*** (0.156)	-5.374*** (0.140)
Norm. PTR X Lead.	-0.467*** (0.008)	-0.475*** (0.008)	-4.461*** (0.163)			
Norm. PTR X Foll.	-0.949*** (0.006)	-0.921*** (0.007)	-5.233*** (0.131)			
Retailer margin (log)				0.597*** (0.016)	-0.815*** (0.261)	
Ret. margin X Lead.						0.488** (0.238)
Ret. margin X Foll.						-0.807*** (0.244)
Retail margin (%)		-0.027*** (0.009)	-0.145*** (0.033)	-0.045*** (0.016)	-0.131*** (0.035)	-0.118*** (0.032)
Rivals brands (log)		-0.135*** (0.029)	0.111 (0.138)	-0.275*** (0.029)	-0.102 (0.156)	0.089 (0.145)
Firm scope (log)		0.254*** (0.042)	0.377* (0.220)	0.220*** (0.042)	0.357 (0.250)	0.365 (0.232)
Brand age (log)		0.787*** (0.014)	0.487*** (0.056)	0.881*** (0.014)	0.598*** (0.062)	0.481*** (0.058)
Observations	289164	273562	115505	273515	115489	115489
R-squared	0.613	0.625		0.614		
F-stat			29.7		134.7	91.0

Notes: OLS estimates in Columns 1, 2 and 4, IV estimates in Columns 3, 5 and 6. The dependent variable is *Normalized units (log)* calculated as the logarithm of normalized product units sold. *Normalized PTR (log)* is the product price to retailers divided by the pack size (in units) and dosage strength (measured in weight or capacity). *Normalized PTR X Leader* is the interaction between price variables and a dummy taking value 1 when the product has the highest submarket share of sales. *Normalized PTR X Follower* is the interaction between price variables and a dummy taking value 1 when the product has not the highest submarket share of sales. *Retailer margin (log)* is the difference between MRP and PTR for a unit of product. *Retailer margin X Leader* is the interaction between *Retailer margin (log)* and a dummy taking value 1 when the product has the highest submarket share of sales. *Retail margin X Follower* is the interaction between *Retailer margin (log)* and a dummy taking value 1 when the product has not the highest submarket share of sales. In IV estimates *Relative PTR* is instrumented with quantity-based productivity based on Dhyne et al. (2017) (*TFPQKlp*) and *Retailer margin (log)* with firm percent average retail margin. All estimates are conducted on submarkets with 5 or more products.
Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A   The effect of a price change on market share

Define revenue-based market share of product k in market j as:

$$MS_{kfjt} = \frac{y_{kfjt}}{y_{jt}} = \frac{p_{kfjt}q_{kfjt}}{\sum_{i \in j} p_{ifjt}q_{ifjt}}$$

with $i \in [1, ..., k, ..., n]$

Define relative price and quantity of product i in market j with respect to product n:

$$p_{ifjt}^* = \frac{p_{ifjt}}{p_{nfjt}}; q_{ifjt}^* = \frac{q_{ifjt}}{q_{nfjt}}$$

and rewrite the market share of product k as:

$$MS_{kfjt} = \frac{p_{kfjt}^* q_{kfjt}^*}{\sum_{i \in j} p_{ifjt}^* q_{ifjt}^*}$$

Quantities sold of product k depend on a change in p_{kfjt}^*, but also quantities of product i, competing with product k, depend on p_{kfjt}^*: $q_{ifjt}^*(p_{kfjt}^*)$; as well as price of product i: $p_{ifjt}^*(p_{kfjt}^*)$. The change in market share of an increase in price for product k is then given by:

$$\frac{\partial MS_{kfjt}}{\partial p_{kfjt}^*} = \frac{\partial \frac{p_{kfjt}^* q_{kfjt}^*}{\sum_{i \in j} p_{ifjt}^* q_{ifjt}^*}}{\partial p_{kfjt}^*} = \frac{\partial \frac{p_{kfjt}^* q_{kfjt}^*(p_{kfjt}^*)}{\sum_{i \in j} p_{ifjt}^*(p_{kfjt}^*) q_{ifjt}^*(p_{kfjt}^*)}}{\partial p_{kfjt}^*}$$

For N competitors in market j a change in price of product k introduces a change in market share of product k by:

$$\frac{\partial MS_{kfjt}}{\partial p_{kfjt}^*} = \sum_{i \neq k \in j} q_{ifjt}^* p_{ifjt}^* (1 + \epsilon_{kk} - \epsilon_{ik}) - \sum_{i \neq k, n \in j} q_{ifjt}^* p_{kfjt}^* \frac{\partial p_{ifjt}^*}{\partial p_{kfjt}^*}$$

where ϵ_{kk} is price elasticity of product k and ϵ_{ik} is cross price elasticity of product i to price of product k:

$$\epsilon_{kk} = \frac{\partial q_{kfjt}}{\partial p_{kfjt}^*} \frac{p_{kfjt}^*}{q_{kfjt}}; \epsilon_{ik} = \frac{\partial q_{ifjt}}{\partial p_{kfjt}^*} \frac{p_{kfjt}^*}{q_{ifjt}}$$

Market share is expected to be decreasing in prices as the latter term ($q_{ifjt}^* p_{kfjt}^* \frac{\partial p_{ifjt}^*}{\partial p_{kfjt}^*}$) is always non-negative, since the other producers will react to an increase in prices of k increasing or not changing price of i. The first term ($q_{ifjt}^* p_{ifjt}^* (1 + \epsilon_{kk} - \epsilon_{ik})$) is expected to be negative as well since cross price elasticity ϵ_{ik}) must be positive and elasticity ϵ_{kk}) negative and higher than one in absolute value.[16]

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[16]Foster et al. (2008) find that in all NACE2 manufacturing sectors the value of elasticity exceeds one in absolute value.