

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

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Abstract

How do firms compete when all firms in an industry set identical prices? Using Nielsen data on India's biscuit manufacturers, we document productivity-based competition on nonprice strategies under industry-wide uniform pricing. Products with one standard deviation higher quantity-based productivity contain, on average, 13% 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) sensitivity in rural markets combined with industry-wide uniform pricing imposes a greater burden on rural consumers. Additional analyses show that firms can reduce this burden by selling different pack sizes in urban and rural areas.

1 | INTRODUCTION

Pricing is central to strategy. Setting the right price is an important firm capability, which allows the firm to appropriate the value created by other firm resources and capabilities (Dutta et al., 2002, 2003). Price plays a critical role in models of productivity-induced efficiencies resulting in price competition (Olley & 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 & Stuart, 1996; Lippman & Rumelt, 2003).

Prices are sticky, changing prices is costly, and firms and managers do not always have the information or the ability to set the right price (DellaVigna & Gentzkow, 2019). For these reasons and other historical, institutional, or idiosyncratic reasons, prices are surprisingly uniform in many settings (e.g., Courty & Nasiry, 2018; Orbach & Einav, 2007; Shiller & Waldfogel, 2011), indicating that in these settings price has a limited role as a market-clearing mechanism.

When prices are sticky, 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 & Paolini, 2019; Cabral & Natividad, 2020; Einav, 2007); airlines compete on service quality and marketing practices, such as frequent flyer programs (Lederman, 2008; Prince & Simon, 2015), particularly when ticket prices are regulated (Douglas & Miller, 1974); hospitals compete on quality when reimbursement prices are administratively set (Gaynor & Town, 2011); supermarkets compete on availability and convenience while prices are largely uniform across stores within a chain (DellaVigna & Gentzkow, 2019; Matsa, 2011); booksellers compete on service and amenities, such as reviews (Clay et al., 2002), particularly when book prices are

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fixed (Canoy et al., 2006); and colleges compete on admission dates (Avery & 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.

We study how firms compete using nonprice strategies 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 either by geography or product. We refer to such pricing as industry-wide uniform pricing. Since our context features industry-wide uniform pricing, the channel through which price-based competition operates directly is entirely foreclosed, allowing 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 & Shivakumar, 1999; Dewenter et al., 2011; Fershtman & Gandal, 1994; Steen & Sørsgard, 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.

The most salient dimension of nonprice competition in our context is pack-size competition, which has received limited attention in prior literature. Granger et al. (1972) show that consumers switch to larger pack sizes if the price per unit information becomes salient. 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 pack sizes are consistent with price discrimination. Koenigsberg et al. (2010) show that small pack sizes allow consumers to match their purchases more closely with desired consumption and firms to set a higher unit price and sell more. Smaller pack sizes can also be profitable if they bring in new consumers or increase consumption (Jain, 2012). 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 size downsizing, 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.

We hypothesize that if firms compete under industry-wide uniform pricing, then more productive firms offer larger pack sizes, more volume (quantity) promotions, higher availability, and greater variety for more productive products. We test these hypotheses in India's biscuit (cookies) industry, a context that features industry-wide uniform pricing. Our study has three parts. First, we examine whether firms compete on 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 exist in our setting, we expect to observe differences in pack size and, therefore, in price per pack size. Consistent with our hypothesis, 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 & 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 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 rural consumers. Consistent with this expectation, demand estimates based on the methodology employed by

DellaVigna and Gentzkow (2019) reveal that consumers in rural areas have twice as large price (per pack size) elasticity and one-third fewer number of products compared with consumers in urban areas. Therefore, we conclude that nonprice strategies such as pack-size competition when combined with industry-wide uniform pricing do not benefit the consumers in rural areas.

Although loosely connected, the three parts of the paper combine to document the use of industry-wide uniform pricing and provide an overall assessment of its impact on the nonprice dimensions to which more productive firms shift competition when prices are inflexible. Our study highlights the important role nonprice strategies can play in generating consumption inequality even when all firms in an industry set identical prices and joins the broader literature on examining consumption inequality using product-level data (e.g., Attanasio & Pistaferri, 2016; Broda et al., 2009; Miravete et al., 2020). Prior literature on uniform pricing examines whether it is optimal to deviate from it (Cho & Rust, 2010; Ho et al., 2018; Shiller & Waldfogel, 2011). Given that prices are inflexible in our setting, we examine whether firms can increase their profits by setting optimal pack sizes for urban and rural markets.

We contribute to a deeper understanding of productivity-based nonprice competition within industries featuring price rigidity (Syverson, 2011) by combining product-level data with firm-level financial data and documenting the relationship between productivity and nonprice strategies, whereas prior studies on uniform pricing rarely observe the supply-side in such detail (DellaVigna & Gentzkow, 2019). 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 multiproduct firms (Bernard et al., 2010). To address this challenge, we use a measure of quantity-based product-level productivity (De Loecker et al., 2016; Dhyne et al., 2017; Foster et al., 2008). Because our data span only 1 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 our paper is that the relationship between productivity and the use of nonprice strategies that we document must not be interpreted as 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 & West, 2013).

2 | DATA AND METHODOLOGY

2.1 | 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. Under India's Legal Metrology Rules in the Consumer Goods Act, firms are required to *display* the maximum resale price (MRP) as well as the net weight or volume on the packaging of every packaged good. The firms are free to set prices for their products but the measure to *display* the price is intended to limit retailer opportunism by promoting price transparency. Although firms are not mandated to set uniform (or any other) prices, many consumer product goods (CPGs) in India exhibit industry-wide uniform pricing (Bhat, 2011).¹ We use Nielsen data for biscuits, the largest CPG category. The data contain product-level 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 quantity and price promotions offered by the manufacturer and the number of retail stores that sell each product are also available.

Each product is identified by a unique stock-keeping unit (SKU) constituting 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 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 A.1, in Supporting Information Appendix A.

We merge Nielsen data with firm financial data obtained from the Centre for Monitoring the Indian Economy Prowess data set used widely in the literature (e.g., De Loecker et al., 2016). We match firm names in the two data sets and limit our econometric analysis to the top 10 matched firms, which account for 88% of the total sales revenue, 86% of sales units, and 87% of the total kilograms of biscuits sold in India. Table A.1, Panel (a) in Supporting Information Appendix A, reports a comparison between the full Nielsen sample and the subsample of the top 10 firms. The top 10 firms produce 4714 products spanning 306 subbrands and 76 brands, accounting for nearly 390,000 product-region-month observations.

2.2 | Variables and descriptive statistics

For each product i sold in region r in month t , we define pack size per unit (Su_{irt}) as grams of biscuits contained in one unit pack, price per unit (Pu_{irt}) as the ratio of monthly revenue to the number of packs of the product sold.⁵ Descriptive statistics related to these variables indicate significant evidence for uniform pricing. In Figure 1, Panel (a), we plot the

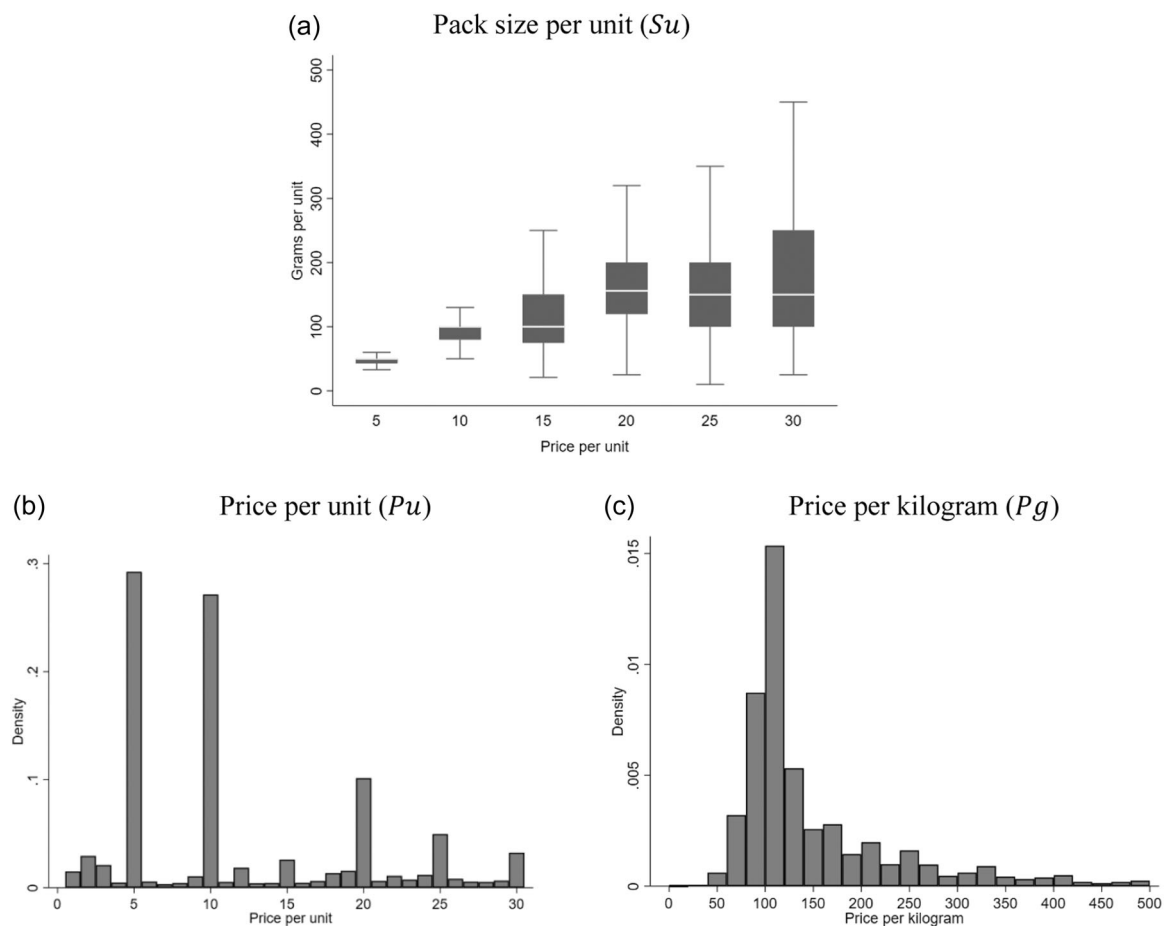


FIGURE 1 Price and pack-size distributions. Panel (a): *Pack size per unit* (Su) is computed as the grams of product contained in the pack. The gray area of the box plot indicates the interquartile range, and the white line is the median. Upper and lower bands delimit the distributions within the 1st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

interquartile range for pack-size distribution at various price points from Rs. 5 to 30. At Rs. 5, the average product contains 50 g and about 80 g at Rs. 10. The quantity in grams sold in a biscuit pack is not fixed at a price point but varies considerably. Prices, however, are sticky. In Figure 1, Panel (b), 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% of the product-region-month observations are sold at a unit price that is a multiple of 5 (47% are sold at Rs. 5 or 10). Unlike in other studies involving discrete price points (Conlon & Rao, 2020), price changes are rare in our setting. Large pack-size differences within a given price point imply dispersion in price per pack size. We define price per kilogram (Pg_{irt}) as price per unit to pack size scaled to 1 kg and plot its distribution in Figure 1, Panel (c). The distribution is more concentrated compared with the price per unit one, especially at around Rs. 100. Nearly a third of the observations fall between Rs. 90 and 110.

We compile evidence of industry-wide uniform pricing in Table 1, which shows the total market share and number of SKUs by segment and price. At Rs. 5 price point, 1485 SKUs of cream biscuits are sold during the 12 months, accounting for 49.3% of the total market share for cream biscuits. Rs. 10 price point accounts for 20.7% of the cream biscuit market share. Similar patterns can be observed in other biscuit segments with either Rs. 5 or 10 price points 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%. Overall,

TABLE 1 Market share and number of products by segment and main price point.

Price per unit (<i>Pu</i>)	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
<i>N</i>	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
<i>N</i>	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
<i>N</i>	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
<i>N</i>	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
<i>N</i>	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
<i>N</i>	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
<i>N</i>	3563	450	967	432	1011	1077	3104	985	11,589

Notes: Price per unit (*Pu*) is defined as the price of a biscuit pack in Indian Rupees. In the first column % is the market share in percent and *N* is the number of stock-keeping units (SKUs). Total 5–30 indicates all the SKUs sold at price points Rs. 5–30 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, and 30. The products sold at price points 5 and 10 account for 62% of the total market share in our data set from 2014. In the glucose biscuit segment, 204 different SKUs of biscuits sold at an MRP of Rs. 5 account for 49.3% of the segment market share and another 158 SKUs sold at Rs. 10 account for an additional 15.4%. Overall, the price points at which biscuits and other consumer product goods are sold have remained the same for over a decade, despite changes in demand and supply conditions that occur over time.

also including the prices above Rs. 30, products sold at multiples of Rs. 5 account for 81.4% of total biscuit industry sales.⁶

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 we plot the average pack size across price points, segments, firm size, and 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%, respectively (Panel a) as well as across the main segments (Panel b). The patterns are similar for the top 10 firms and fringe firms (Panel c) and across rural and urban areas (Panel d).⁷

2.3 | 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:

$$q_{it} = \omega_{it} + \beta_k k_{it} + \beta_v v_{it} + \eta_{it}, \quad (1)$$

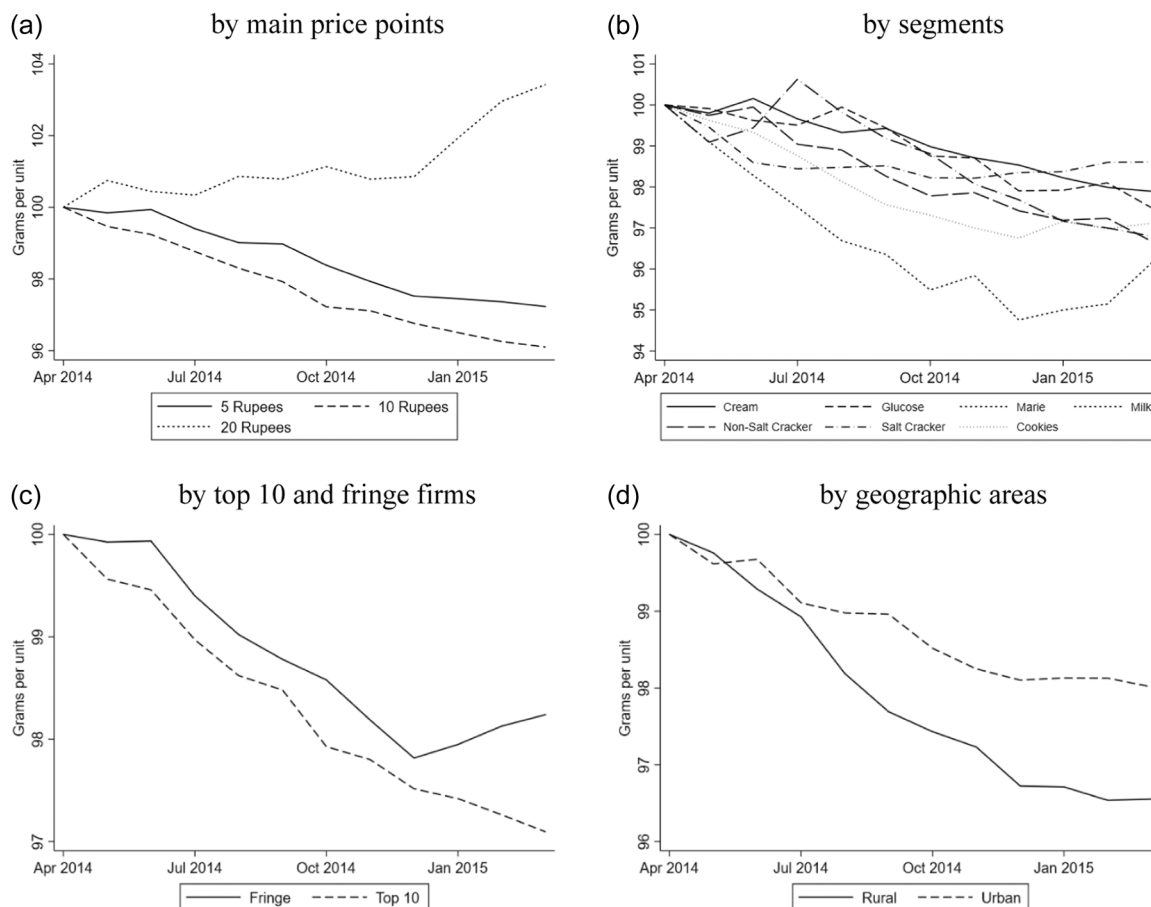


FIGURE 2 Pack size per unit (S_u) over time. Pack size per unit (S_u) is computed as the grams of product contained in the pack, averaged across products within the month-segment-price point. For each segment-price point average pack size takes value 100 in April 2014 (base month). Panel (a): Main price 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, and Surya Food & Agro. Panel (d): Urban areas include (a) all places with a municipality/corporation/cantonment board/notified town area, and so forth; (b) all other places with a minimum population of 5000, where at least 75% of male working population engaged in nonagricultural 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.

where, for each product i and time t , q is the log output measured in kilograms of product, k is the 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 no 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 the product, as opposed to sales revenue, productivity is defined as *quantity-based*, as opposed to *revenue-based* measure.

To compute product-level productivity we must calculate the output elasticities of the production function, β_k and β_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 for multiproduct firms producing heterogeneous products. To do so, they use inputs at the firm level, relax the assumption of product-specific production technology, and allow marginal changes in one input to affect all the products of a firm. The method controls 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.⁸

Given that in our data we observe only 1 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, that is, 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:

$$q_{bi} = \omega_{bi} + \beta_k k_f + \beta_v \mathbf{v}_{bi} + \gamma y_{-bi} + \eta_{bi}, \quad (2)$$

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 .⁹

To estimate the production function, we use firm financial data obtained from the Prowess data set and exploit Nielsen product-level data to apportion firm-level financial data across different products. We use the ratio of product-specific revenues to the overall revenues of the firm and product price to impute the quantity produced (q_{bi}) at the product level. We also allocate firm-level inputs to each product only for the variable inputs (\mathbf{v}_{bi}), given that capital (k_f) is firm-specific in Equation (2).¹⁰ Using the LP estimator adapted to our setting, we obtain output elasticities with respect to capital, material, and labor, separately for every segment of the biscuit market. Our modified LP estimator assumes that: (i) the demand for the intermediate input m is dependent on firm capital and product productivity, and it is monotonically increasing in ω ; and (ii) the productivity of variety i differs from the average productivity of subbrand b by a zero-mean error term. We present the details of our LP procedure in Supporting Information Appendix B.

Table 2 shows segment-level output elasticities calculated using the estimation-based method and compares them to those calculated using the cost-based method. 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.

3 | PACK-SIZE COMPETITION

3.1 | Empirical strategy

We estimate the relationship between product-level productivity and pack size in narrowly defined product and geographic markets using the following specification:

$$\log(Su_{irt}) = \alpha_1 \omega_i + \alpha_2 \mathbf{X}_{irt} + \mu_j + \eta_r + \lambda_f + \delta_t + \pi_c + \epsilon_{irt}, \quad (3)$$

TABLE 2 Cost-based and estimation-based production functions at the segment level.

	Cost-based				Estimation-based				N
	β_k	β_l	β_m	β_e	β_k	β_l	β_m	γ	
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
Nonsalt 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
Other biscuits									
Arrowroot	0.26	0.03	0.68	0.03					53
Assorted	0.23	0.04	0.69	0.05					143
Cereal bars	0.59	0.09	0.30	0.02	0.46	0.69	0.6	-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 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 the top 10 firms from April 2014 to March 2015.

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.

Our approach considers productivity as the driver of competition. Specifically, higher productivity leads to lower prices, generating *selection on productivity* (Foster et al., 2008). Therefore, under uniform pricing we expect the differences in productivity to trigger competition on pack size. However, ordinary least squares (OLS) estimates of Equation (3) may not be interpreted as causal because higher competition can simultaneously increase both productivity and pack sizes for a given price per unit, a mechanism that Backus (2020) terms *treatment effect*. In a context where prices change, both selection and treatment mechanisms can explain the stylized fact that more productive firms charge lower prices (De Loecker & Syverson, 2021). However, the latter operates across markets—competition would cause productivity and pack-size distribution to differ across markets—while the former operates within markets—productivity of a product relative to that of another product of the same market drives pack sizes within the market. The fixed effects we employ help with the identification of the effect of productivity on nonprice strategies as they restrict competition to a market containing a set of products that serve the same segment and region and have the same price point. For this reason, our findings are likely the causal effect of productivity on strategies, rather than an association driven by an exogenous competition shock. We, however, do not interpret our results causally because products can compete not only within their segment or price point but also beyond and because consumers can substitute across segments and price points. We do not intend to neglect the possibility that the

treatment effect of competition operates across different segments, price points, or regions and spurs the productivity of the products in markets where the pack size is higher.

As we estimate productivity using the kilograms of product as the output variable, one might be worried about a possible mechanical relationship between pack size and productivity. Indeed, the kilograms of product is given by the number of packs times their pack 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, 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 in our sample, where the correlation between pack size and unit sales is negative for the products sold at the main price points (see Table A.5 in Supporting Information Appendix A).¹¹

3.2 | Baseline results

In Table 3 we report the estimates of Equation (3) using the sample of the 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% more quantity in the pack for the same unit price. This finding suggests that productivity is associated with competition on pack size despite the use of industry-wide uniform pricing.¹² Across the main price points—Rs. 5, 10, and 20—products with one standard deviation higher productivity offer between 19% and 22% more quantity in the pack for the same unit price. In all the major segments, except for the glucose segment (Column 6) where Parle is dominant (see Table A.4, in Supporting Information Appendix A), products with one standard deviation higher productivity offer between 6% and 62% more quantity in the pack for the same unit price. The results remain similar if we exclude 13% of the observations that contain volume or value promotions given by the manufacturers (see Table A.7 in Supporting Information Appendix A), a topic to which we will return in Section 4.

The estimated relationship between productivity and pack size in Table 3 should not be interpreted as causal for reasons explained in Section 3.1, mainly that competition would cause productivity and pack-size distribution to differ across markets. However, to the extent that the level of competition is the same across markets or products compete only within their segment or price point, our results can be interpreted causally. Our results are robust to the inclusion of more fine-grained fixed effects composed of interacting segment, region, and price point fixed effects, corresponding to the narrowest possible definition of a market in our data (segment-region-price point), as reported in Table A.8 in Supporting Information Appendix A.

3.3 | Results for urban and rural markets

In theory, consumer preferences in urban and rural 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 with 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, the common price each firm sets for the urban and rural areas is likely 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 3 compares the dispersion in pack size in grams across the main price points for urban and rural areas. For the main price points, pack-size dispersion is higher in urban areas than in rural areas. A similar difference can also be seen in Panel (II) of Figure 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 a uniform pricing context, 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 rural areas might depend on factors other than productivity, like the distance from the manufacturing plant or demand. Therefore, we estimate the effect of a one standard deviation change in productivity on the pack size of the product as in Equation (3) for urban and rural areas by dividing the sample into products sold in urban and rural areas and report the estimates in Table 4. The results

TABLE 3 Competition on pack size.

	Pack size per unit (S_u)										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	All	Rs. 5	Rs. 10	Rs. 20	Cream	Glucose	Marie	Milk	Nonsalt cracker	Salt cracker	Cookies
Productivity (ω)	0.126*** (0.011)	0.187*** (0.022)	0.178*** (0.016)	0.223*** (0.019)	0.168*** (0.016)	-0.127** (0.056)	0.104*** (0.024)	0.061 (0.11)	0.623*** (0.043)	0.373*** (0.031)	0.230*** (0.022)
Product age	0.098*** (0.014)	0.160*** (0.021)	0.131*** (0.012)	0.083*** (0.02)	0.066*** (0.017)	0.243*** (0.06)	0.122*** (0.029)	0.058* (0.03)	0.130*** (0.03)	0.107*** (0.032)	0.066*** (0.023)
Interfirm competition	-0.047*** (0.012)	-0.021* (0.013)	0.001 (0.009)	0.002 (0.013)	-0.016 (0.013)	0.023 (0.029)	-0.004 (0.018)	-0.021 (0.02)	0.081*** (0.027)	0.023 (0.023)	0.052** (0.025)
Intrabrand competition	0.035*** (0.013)	0.116*** (0.02)	0.036** (0.015)	0.003 (0.014)	0.058*** (0.01)	0.416*** (0.101)	-0.026 (0.054)	0.047 (0.1)	0.02 (0.033)	0.018 (0.03)	0.006 (0.022)
Intrafirm competition	0.027** (0.013)	-0.088*** (0.021)	-0.006 (0.015)	-0.024 (0.018)	0.016 (0.014)	-0.316*** (0.103)	0.043 (0.056)	0.024 (0.105)	-0.081** (0.034)	0.044 (0.034)	0.028 (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
R^2	0.595	0.623	0.602	0.694	0.736	0.565	0.744	0.818	0.725	0.752	0.683
Observations	390,413	99,438	106,913	43,910	142,793	26,412	27,476	14,376	33,463	32,639	103,537

Notes: Ordinary least squares estimates, standard errors (in parentheses) clustered at the product level. The dependent variable, *Pack size* (S_u), 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. *Interfirm competition* is the logarithm of the number of products sold within the same segment-region-month-price point by competing firms, *Intrafirm 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, *Intrabrand 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* includes 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 the top 10 firms from April 2014 to March 2015.

* $p < .1$; ** $p < .05$; *** $p < .01$.

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% more grams per unit in rural areas (Columns 1 and 2) and 13% more grams per unit in urban areas (Columns 3 and 4). This difference is statistically significant at 5% (Column 6). In Columns 5 and 6 we also notice that in rural areas the pack size is on average 6%–7% smaller than in urban areas.

The composition of products sold in urban and rural areas can be different and that might drive our results. To examine this, we divide products into those sold in urban areas, rural areas, and both and estimate the results. The results, shown in Table A.9 in Supporting Information Appendix A, the coefficient estimate of productivity (ω) remains positive and significant across these subsamples. Since the composition of products differs across urban and rural areas, we conclude that manufacturers can indeed set price per pack size differently across these regions. They do so not by changing the price per unit but by selecting different pack sizes and choosing product variety. We have already observed that pack-size dispersion is smaller in rural areas (Figure 3, Panel I) and that unit prices are lower in rural areas (Figure 3, Panel II) because of the smaller pack size (Table 4, Columns 6 and 7). The lower income in rural areas allows consumers to buy products with a smaller unit price. However, these products have a smaller pack size. Since rural consumers are more sensitive to pack-size changes, both consumers and firms could benefit from a different (optimal) pack size. We will return to examine this observation in greater detail in Section 6.

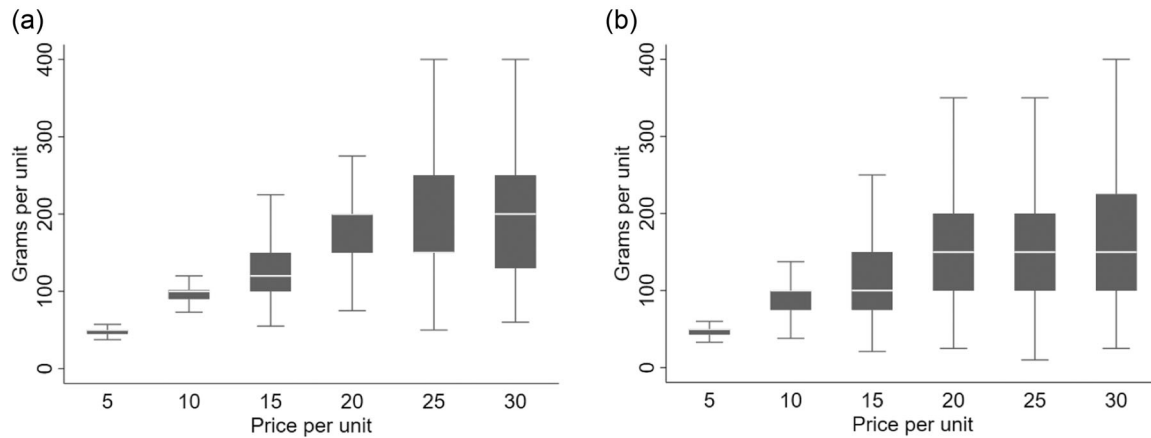
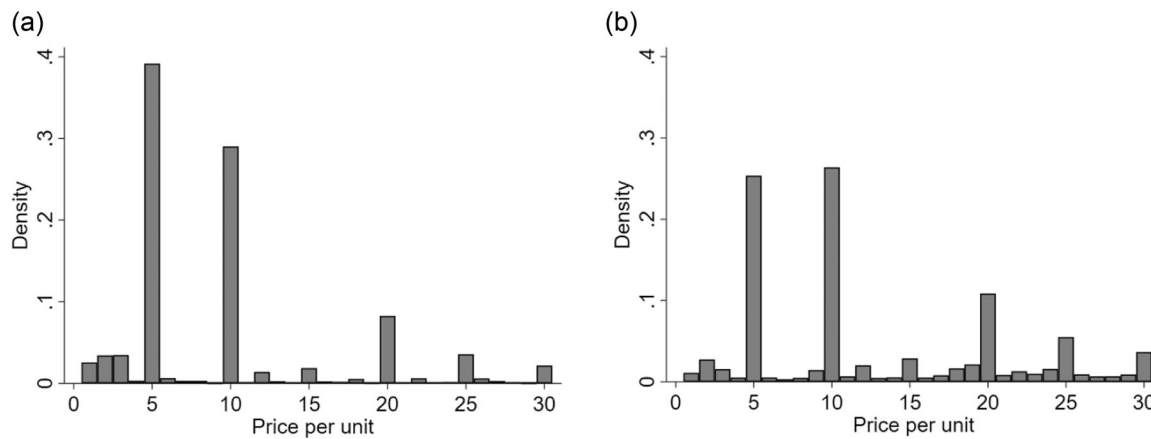
(I) Distribution of pack size per unit (S_u) by main price point(II) Distribution of price per unit (P_u)

FIGURE 3 Pack-size and price distributions in (a) urban and (b) rural areas. *Pack size per unit* (S_u) is computed as the grams of product contained in the pack. *Price per unit* (P_u) is defined as the price of a biscuit pack in Indian Rupees. The gray 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, and so forth; (b) all other places with a minimum population of 5000, where at least 75% of male working population engaged in nonagricultural 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.

4 | OTHER NONPRICE STRATEGIES

Next, we examine if productivity-induced competition is observed in three other nonprice dimensions besides pack size: pack-size promotions, product availability, and product variety. As with competition on pack size, in all these cases we expect that productivity is positively related to these nonprice strategies.

4.1 | Pack-size promotions

Pack-size promotions are additional grams of biscuits given as quantity promotion. For example, firms offer “20% extra” grams of a product or “buy 2 get 1 free” promotions. Such promotions are printed on the packaging by the manufacturers, largely eliminating any direct role for the retailers in such promotions. Retailers do not offer volume promotions separately, as that would require repackaging. Manufacturers rarely offer price rebates. Specifically, less than 1% of the observations in our data correspond to price rebates (value promotions) while more than 12% correspond to volume promotions.¹³

TABLE 4 Competition on pack size in urban and rural areas.

	Pack size per unit (S_u)					
	(1) Urban	(2) Urban	(3) Rural	(4) Rural	(5) All	(6) All
Productivity (ω)	0.132*** (0.011)	0.129*** (0.011)	0.150*** (0.016)	0.161*** (0.015)	0.126*** (0.011)	0.122*** (0.011)
Productivity (ω) \times Rural						0.021** (0.008)
Rural					-0.063*** (0.012)	-0.067*** (0.013)
Product age		0.096*** (0.014)		0.098*** (0.02)	0.099*** (0.014)	0.099*** (0.014)
Interfirm competition		-0.059*** (0.012)		-0.106*** (0.018)	-0.043*** (0.012)	-0.044*** (0.012)
Intrabrand competition		0.033*** (0.012)		0.072*** (0.02)	0.035*** (0.013)	0.035*** (0.013)
Intrafirm competition		0.033** (0.013)		-0.066*** (0.021)	0.030** (0.013)	0.029** (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
R^2	0.56	0.571	0.694	0.709	0.594	0.594
Observations	299,891	299,891	90,522	90,522	390,413	390,413

Notes: Ordinary least squares estimates, standard errors (in parentheses) clustered at the product level. The dependent variable, *Pack size* (S_u), 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 an urban area. Urban areas include (a) all places with a municipality/corporation/cantonment board/notified town area, and so forth; (b) all other places with a minimum population of 5000, where at least 75% of male working population engaged in nonagricultural pursuits and the density of population is at least 400 persons per square km. *Productivity* (ω) \times *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. *Interfirm competition* is the logarithm of the number of products sold within the same segment-region-month-price point by competing firms, *Intrafirm 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, *Intrabrand 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* includes 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 the top 10 firms from April 2014 to March 2015.

* $p < .1$; ** $p < .05$; *** $p < .01$.

Using the same specification as in Equation (3), we test whether more productive products offer more pack-size promotions.¹⁴ 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, that is, the extensive margin, and the second measure captures the extent of pack-size promotion, that is, the intensive margin. The results reported in Columns 1 and 2 of Table 5 show 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% higher if its productivity is one standard deviation higher. Column 1 shows also that in rural areas it is 3.2% 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% in the urban areas and 4% in the

TABLE 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*** (0.007)	0.277** (0.133)	-0.058*** (0.004)	0.309** (0.135)	0.094*** (0.032)	0.146*** (0.055)
Productivity (ω) \times Rural	0.003 (0.005)	-0.231** (0.096)	0.090*** (0.005)	0.139 (0.118)	0.035 (0.027)	0.113** (0.049)
Rural	0.032*** (0.009)	1.063*** (0.128)	-0.495*** (0.001)	1.351*** (0.21)	-0.582*** (0.036)	-0.688*** (0.053)
Product age	-0.157*** (0.013)	-2.481*** (0.202)	-0.066*** (0.003)	-2.575*** (0.195)		
Interfirm competition	0.025*** (0.008)	-0.069 (0.098)	-0.114*** (0.003)	0.456*** (0.148)		
Intrabrand competition	0.059*** (0.012)	0.324* (0.192)	0.008** (0.004)	0.355 (0.22)		
Intrafirm competition	-0.023* (0.014)	0.074 (0.187)	-0.065*** (0.004)	0.164 (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
R ²		0.268		0.086	0.147	0.107
Observations	384,788	47,531	584,852	390,414	73,119	73,119

Notes: Probit average marginal effects (Columns 1 and 3) and ordinary least squares (Columns 2 and 4–6) estimates, standard errors (in parentheses) clustered at the product level in Columns 1–4 and at the subbrand level in Columns 5 and 6. 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 volume 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 Columns 1–4, *Productivity (ω)* is estimation-based product-level productivity standardized to have zero mean and unitary standard deviation. In Columns 5 and 6, *Productivity (ω)* is the 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 an urban area. Urban areas include (a) all places with a municipality/corporation/cantonment board/notified town area, and so forth; (b) all other places with a minimum population of 5000, where at least 75% of male working population engaged in nonagricultural pursuits and the density of population is at least 400 persons per square km. *Productivity (ω) \times 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. *Interfirm competition* is the logarithm of the number of products sold within the same segment-region-month-price point by competing firms, *Intrafirm 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, *Intrabrand 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* includes 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 the top 10 firms from April 2014 to March 2015. Columns 1 and 4 are estimated on the full product-region-month subsample. Column 2 is estimated only on the observations that are offered on volume promotion. Column 3 is estimated on the full product-region-month subsample, incremented by the product-region-month missing observations, that is, those where the product is not observed as it has zero sales. Columns 5 and 6 are estimated on the full subbrand-region-month subsample. $*p < .1$; $**p < .05$; $***p < .01$.

rural areas. However, pack-size promotions are 106% 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.

4.2 | Product availability

Next, we test whether the availability of a product in a regional market depends on its productivity. As shown in Figure 3, the distribution of products sold is less dispersed in rural areas, indicating lower availability of products in rural areas compared with urban areas. Also, 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 (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. The other measure is calculated on products that are available and captures the extent to which the product is available.

Columns 3 and 4 of Table 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. 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% 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% 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.

4.3 | Product variety

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

5 | COORDINATION TESTS ON NONPRICE CHARACTERISTICS

5.1 | 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

et al., 2011; Fershtman & Gandal, 1994; Steen & Sørsgard, 1999; Sullivan, 2020), and particularly so under industry-wide uniform pricing. To investigate whether the 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.¹⁵

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 differences 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 6. The coefficient estimates associated with multimarket contact are not statistically significant in any of the specifications 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 on average productivity levels between firms.

5.2 | 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 strategies of the two main competitors in the US ice cream market, Ben & Jerry's and Haagen-Dazs, are consistent with tacit collusion. Ben & Jerry's and Haagen-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 (Prasad, 2018; Sethi, 2016). An analysis of the extent of product differentiation by market segment and price point shows considerable overlap among the top 10 firms (Figure A.3, in Supporting Information Appendix A). A similar analysis of flavors within the cream biscuit segment, plotted in Figure A.4, in Supporting Information Appendix A, 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

TABLE 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 (0.1)	-0.025 (0.098)		-0.024 (0.036)	-0.024 (0.037)	
MMC ^{CW}			0.000 (0.002)			-0.402 (0.246)
Δ Productivity (ω)		0.246*** (0.017)	0.246*** (0.017)		0.014*** (0.002)	0.014*** (0.002)
Herfindahl–Hirschman index	0.008 (0.05)	0.012 (0.051)	0.012 (0.051)	0.094** (0.044)	0.096** (0.044)	0.095** (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
R ²	0.487	0.5	0.5	0.434	0.44	0.446
Observations	144,330	144,330	288,836	16,708	16,708	34,054

Notes: Ordinary least squares 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 & Williams, 2014). Δ Productivity (ω) is the absolute value of the difference on 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 the top 10 firms from April 2014 to March 2015.

* $p < .1$; ** $p < .05$; *** $p < .01$.

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 7. We find positive correlations across all four columns in Table 7, indicating that market leaders and followers have similar nonprice strategies within a market. Admittedly simple, 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.

6 | 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.

6.1 | 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,

TABLE 7 Coordination on nonprice strategies.

	Leader			
	Pack size (1) Grams per pack (S_u)	Pack-size promotions (2) Kilograms for free	Availability (3) Stores (%)	Variety (4) Number
Main follower	0.297*** (0.051)	0.166*** (0.051)	0.327*** (0.048)	0.219*** (0.032)
Second follower	0.176*** (0.047)	0.076** (0.037)	0.417*** (0.091)	0.220*** (0.031)
Region-segment-price point FE	Yes	Yes	Yes	Yes
Firm FE, month FE	Yes	Yes	Yes	Yes
R^2	0.758	0.382	0.426	0.675
Observations	13,851	13,851	13,851	13,851

Notes: Ordinary least squares estimates, standard errors (in parentheses) clustered at the segment-region-price point level. Each column indicates a nonprice strategy: (1) *Grams per pack (S_u)* is the 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 the top 10 firms from April 2014 to March 2015.

* $p < .1$; ** $p < .05$; *** $p < .01$.

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 Supporting Information Appendix C, follows DellaVigna and Gentzkow (2019) and defines the optimal pack size as

$$Su_{ir}^* = \frac{\overline{Pu}_{ir}}{cg_{if}} \frac{1 + \theta_{ir}}{\theta_{ir}}, \quad (4)$$

where θ_{ir} is the 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 .¹⁶

To compare the observed pack size with the optimal one in Equation (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 :

$$\log(Qg_{irt}) = \theta_{jrc} \log(Pg_{irt}) + \lambda_f + \delta_t + \epsilon_{irt}, \quad (5)$$

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 & 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.¹⁷ To test the validity of our identification strategy, we also estimate price elasticity at the industry level and report the OLS and IV results in Table A.10, in Supporting Information Appendix A, Columns 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.¹⁸ The Kleibergen–Paap F statistic and first-stage regression show that the instrument is relevant for the endogenous variable, indicating that productivity is negatively correlated with price per kilogram.

Panel (a) of Figure 4 shows the distribution of price elasticities estimated at the segment-region-price point level that are statistically different from zero with a 95% 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 & Gentzkow, 2019). Consumer preferences in rural areas are different from those in urban areas. Panels (b) and (c) of Figure 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 the price per kilogram in rural areas implies a larger consumer response to pack-size differences.¹⁹

6.2 | 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 (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

$$\hat{S}u_{ir}^* = \frac{\overline{Pu_{ir}}}{\min_{i \in b} Pg_i} \frac{1 + \hat{\theta}_{jrc}}{\hat{\theta}_{jrc}}. \quad (6)$$

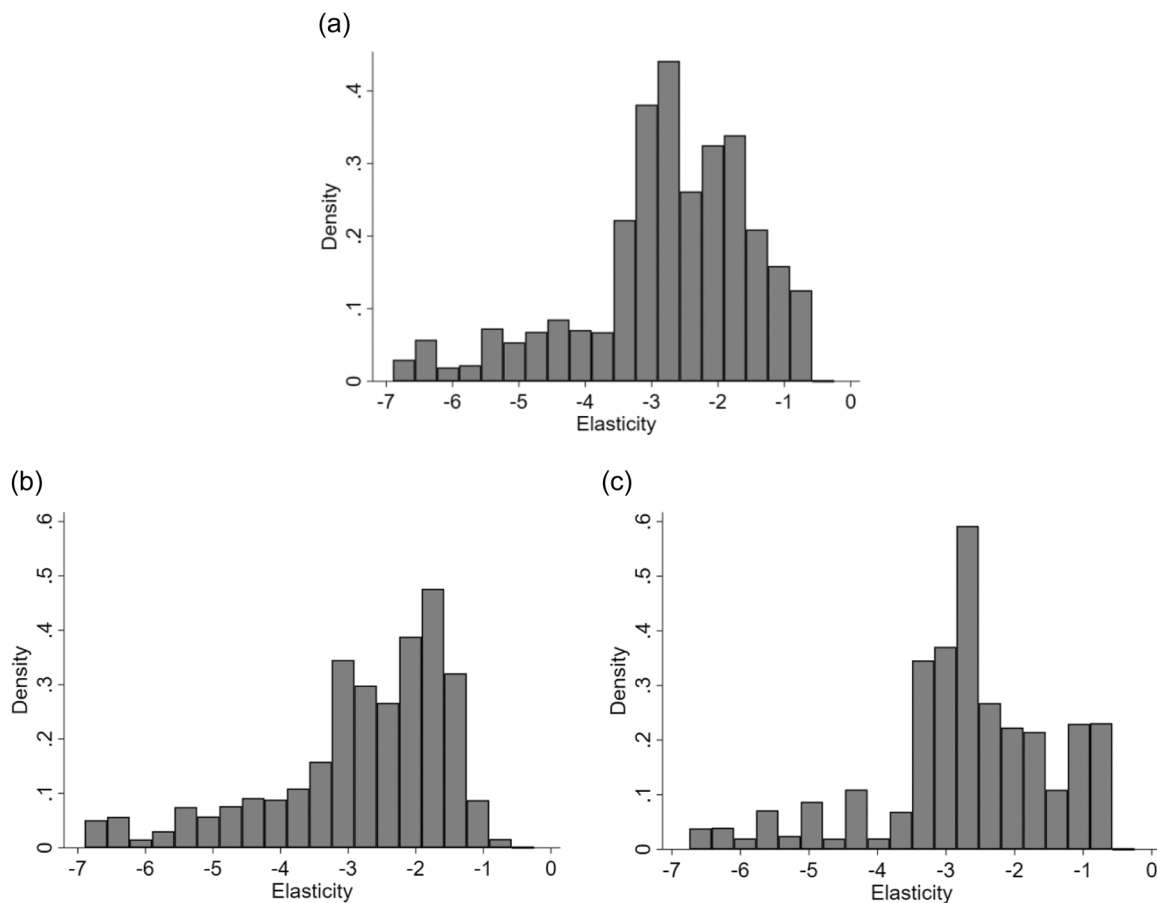


FIGURE 4 Elasticities by segment-region-price point. Distributions of the elasticities are estimated at the segment-region-price point level using the IV estimator, as from Equation (5). Products are grouped into 8 segments, 41 regions, and 8 price categories. We keep the elasticities whose estimated value is significantly different from zero with a probability of 95%. All figures report estimates on the sample of the 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.

TABLE 8 Product revenues and profits with optimal pack size.

$\bar{P}u$ (1) All	Su (2) All	Su^*			$\frac{Su^*}{Su}$			$\frac{\bar{P}u Qu^*}{\bar{P}u Qu}$			$\frac{\Pi^*}{\Pi}$		
		(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 ($\bar{P}u Qu^*/\bar{P}u Qu$), and ratio between optimal and actual profits (Π^*/Π). Actual pack size, sales revenues, and profits are those observed in the sample of the 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.

Using the estimated optimal pack size, we can compute optimal demand, sales revenues, and profits at the product-region level.²⁰ Table 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 g. The median optimal pack size, as calculated from Equation (6), would be 39 g (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% (Column 11). However, a lower pack size means lower unit costs, implying a 25% 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% and 8%, 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% for Rs. 10 price point and 15% for Rs. 20 price point. Although unit costs increase with pack size, higher demand would increase product median profits by 20% for Rs. 10 price point and 17% 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 8. Among the products sold at Rs. 5 the median pack size is again 50 g. The median optimal pack size, as calculated from Equation (6), would be 39 g in rural areas and 40 g 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% and 17% 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 g) than in the rural areas (98 g). This difference in optimal pack size is mirrored in the median optimal product revenues, which are 43% higher than the observed revenues in urban areas and only 14% higher than the observed revenues in rural areas. The higher optimal pack size causes unit costs to be higher in the urban areas than in the rural areas, resulting in little difference in median optimal profits between the two areas. 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% in rural areas and 14% in urban areas.

7 | CONCLUSION

We examined the case of an industry where all firms set identical prices, raising questions about the competitiveness of such a market 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% 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 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, which requires a more structural approach (Berry & Haile, 2021). 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 with developed economies (e.g., Desai et al., 2012; Mathur & Sinitsyn, 2013).

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. While anecdotal evidence indicates that retailers in India use MRPs as focal points for collusion and do not deviate from them by offering price rebates (Bhaskarabhatla, 2020; Knittel & Stango, 2003; Mukherjee & Patel, 2005), we do not have information on the extent to which price rebates are given by retailers to consumers aside from the price promotions of the manufacturers. 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 the 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 (Atkin et al., 2019; Khandelwal, 2010). Finally, we do not examine why prices are inflexible in our empirical context. A quantitative analysis of the reasons why firms set identical prices in many product categories in India requires a much longer Nielsen panel predating the period when firms adopted uniform pricing at convenient currency price points. We are unable to do so because of data limitations but speculate on potential reasons why firms set identical prices. The anecdotal evidence indicates that firms set identical prices at convenient and affordable currency price points because it reduces transaction costs and costs of negotiation (Bhushan & Pande, 2010):

Affordability, along with convenience of coinage and single-serve usage, is making thousands of middle-class consumers buy Rs. 5 packs of anything from snacks, biscuits and chocolates to detergents bars, mobile calling cards and shaving blades. Today, Rs. 5 is perhaps the most-in-demand price point.

Although our study focuses on India, pricing schemes that focus on price points can also be observed in other countries. For example, “dollar” store chains in the United States 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 United States alone (Hitt, 2011), but the competitive strategies of the product categories in these stores and of these stores themselves have received little scholarly attention. This remains a topic for future research.

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DATA AVAILABILITY STATEMENT

Data are subject to third-party restrictions. The data that support the findings of this study are available from Nielsen India. Restrictions apply to the availability of these data, which were used under license for this study. We will provide all the codes for replicating the results, but we are not allowed to share the original data, which can be requested from Nielsen India

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ENDNOTES

- 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 a pricing strategy across several CPGs in India. Rs. 5 is the largest price point, accounting for 55% of the market share in the snacks-related product categories (Singh, 2019). Bhushan and Pande (2010) compile anecdotal evidence by interviewing executives from companies, such as Unilever and Pepsi Co. Unilever notes “Currency price points such as Rs. 5 and 10 are an important element to provide value to consumers and make our brands affordable and accessible.” An industry analyst identifies Rs. 5 price point as “the emerging market within the emerging market of India.” Marketing director of foods at PepsiCo India says, “We do everything we can to protect the Rs. 5 price point.”
- 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).
- ³ Nielsen India defines urban areas as places with a minimum population of 5000, where at least 75% of the male working population is engaged in nonagricultural sectors, and with a density of population at least 400 persons per square kilometer.
- ⁴ Biscuit market segments are cream, glucose, marie, milk, nonsalt crackers, salt crackers, cookies, arrowroot, wafer, cereal bars, assorted, and others. Compared with the former seven segments, the latter five segments have relatively fewer observations and will be categorized in our analysis as a unique segment named *other biscuits*.
- ⁵ Since we do not directly observe price but compute it by dividing sales and units, in 28% of the observations, Pu_{irt} is not an integer. In such cases, we round price per unit to the nearest integer. For 87% of these observations, the price per unit is in the range of $\pm 0.25\%$ from the nearest integer value. See Table A.2 in Supporting Information Appendix A for details on the extent to which rounding occurs at various price points in our data.
- ⁶ The quantity in grams sold in a pack is not fixed at a price point but varies considerably also within the segments, as shown in Figure A.2, in Supporting Information Appendix A, consistent with pack-size competition. To examine the extent of price dispersion at a given pack size, we estimate the probability that a product with a certain price point belongs to the modal and the second modal pack size. Our results, shown in Table A.3 in Supporting Information Appendix A, confirm limited price dispersion within a modal pack size suggesting that price plays little role in pack-size dispersion.
- ⁷ In Table A.4, in Supporting Information Appendix A, we find that this downward trend in pack size is observed across all the firms, segments, and price points.
- ⁸ 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, 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).
- ⁹ Controlling for log quantities of all other products (q_{-bi}) instead of log revenues (y_{-bi}) in Equation (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.
- ¹⁰ To impute product-level quantity we assume the product share of revenues to be the same in both Nielsen sales and Prowess production data. As noted in Supporting Information Appendix B.1, 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 Supporting Information Appendix B.2.
- ¹¹ In addition, we estimate the production function under the assumption that the productivity of each product variety (i.e., pack size) within the same subbrand differs by a zero-mean error term from the average subbrand productivity. Therefore, the pack-size strategy of the firm within a subbrand depends on the productivity of the subbrand compared with the productivity of its competitors, and not of the other varieties of the same subbrand of the firm.

- ¹² 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 3.3 (see Table A.6, in Supporting Information Appendix A).
- ¹³ An important limitation of our work is that we do not have data on price rebates offered by retailers. Nevertheless, we find anecdotal evidence to indicate that MRPs printed on the packaging are the final prices consumers pay because MRPs serve as a convenient focal point for collusion and retailers do not deviate from the currency price points at which firms compete (Bhaskarabhatla, 2020; Knittel & Stango, 2003). For example, Mukherjee and Patel (2005) note: “Over the years, the market determined price has taken a back seat and MRP is ruling the Indian market. This is because the retailers do not compete with each other but make a local cartel in each pocket across the country. They sell their products at the MRP irrespective of the price that they buy the product for. In addition, the smaller traders/shopkeepers unions across market places in the country maintain intangible relationships and understanding among themselves to keep the price at MRP level and thereby, avoid any competition that would lead to a market determined pricing structure. Customers are forced to pay the maximum price for the products, which is much higher than the cost of production. Here, to sum up, the (MRP maintenance) mechanism to safeguard the customers against black marketers and uneven pricing is actually forcing the consumers to pay the higher price and not the market determined price.”
- ¹⁴ Productivity is estimated using a measure of physical output that includes both the kilograms of product sold and those given for free as a volume promotion.
- ¹⁵ 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.
- ¹⁶ 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.
- ¹⁷ 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 1 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.
- ¹⁸ In Table A.11, in Supporting Information Appendix A, 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 .
- ¹⁹ We estimate industry-level price elasticity of demand separately for urban and rural areas and report the results in Table A.10, in Supporting Information Appendix A, Columns 4–6. IV estimates show that in urban areas demand is noticeably less elastic than in rural areas (Columns 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.
- ²⁰ Following DellaVigna and Gentzkow (2019) we calculate optimal demand for product i in region r as $\hat{Q}_{g_{ir}}^* = \hat{G}_{ir} \left(\frac{\hat{P}_{u_{ir}}}{\hat{S}_{u_{ir}}} \right)^{\hat{\theta}_{jrc}}$, where the product-region scale factor \hat{G}_{ir} is calculated as $Q_{g_{ir}} \cdot \left(\frac{S_{u_{ir}}}{P_{u_{ir}}} \right)^{\hat{\theta}_{jrc}}$, using yearly averages of the observed quantity sold at the product-region level ($Q_{g_{ir}}$).

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Additional supporting information can be found online in the Supporting Information section at the end of this article.

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