Market Structure and the Distributional Implications of Product Bans*

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Abstract

Product bans affect market competition and possibly the demand for the whole product category by changing consumers' perception of product quality. We analyze the ban of Nestlé's Maggi, the largest producer of instant noodles in India, which was banned for alleged non-compliance with health safety standards. Maggi returned to stores after six months when the High Court ruled that the ban was never justified. We document substantial heterogeneity in consumers' responses to the ban across socioeconomic categories. We also show the presence of negative spillovers to competitors. By estimating a structural model of consumer and firm behavior, we are able to identify demand and supply responses to the intervention. Through counterfactuals, the model allows us to examine firms responses and separate changes in competition from changes in preferences.

Keywords: boycott, product ban, instant noodles, distributional impacts

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1 Introduction

Governments can intervene in markets by withdrawing operational permits from specific firms. Such market interventions, which can take the form of product or firm bans, may be motivated by various reasons, including geopolitical considerations.[1] Product bans impact market structure and alter the intensity of competition within local markets. As a result, these interventions can have differential effects on consumer and total welfare in heterogeneous markets.

In this paper, we study the competitive and distributional implications of the ban of Nestlé's Maggi, the largest producer of instant noodles, a large consumer product category in India. We examine how the unexpected exit of Maggi products impacted local competition, consumers, and welfare across markets. We uncover a large disparity in product availability across consumers' socioeconomic categories. We also show that the ban negatively affected the sales of non-banned firms, taking away any potential gains due to reduced competition. Finally, using a structural model, we find that the ban lowered prices but that it also lowered consumers' utility from purchase, which entailed that the ban lowered consumer welfare overall.

We analyze the instant noodles market in India, a USD 379 million market as of 2014.[2] At the time of the ban, Maggi was the largest brand in the market, with a national share of 84 percent in 2014. In our data, 41 percent of households purchased Maggi instant noodles in 2014, and 18 percent did so in any given month. Unsurprisingly, the entire instant noodles category was often referred to as "Maggi noddles" (Pande and Chakravarty, 2003).

In June 2015, various Indian states and soon after the national government banned Nestlé's Maggi instant noodles. To justify the ban, the Indian government cited lab test that reported lead in excess of the allowed limits and an undisclosed flavor enhancer in samples of Maggi instant noodles. Although Maggi rejected these re-

[1] Such bans include HUAWEI in US, Britain, and France, among other. TikTok was banned by India, and there are bans of the app from government devices in Britain, Australia, Canada, the executive arm of the European Union, France and New Zealand's Parliament, and more than two dozen US states (see "Why Countries Are Trying to Ban TikTok," May 23, 2023, The New York Times). Italy, Russia and China have banned ChatGPT, among other. Also, the Securities and Exchange Commission (SEC) recently approved a rule allowing laws that ban foreign firms from participating in U.S. exchanges under certain conditions (see *SEC Clears a Path to Ban Foreign Companies From U.S. Exchanges*, The Wall Street Journal, November 21st, 2021). Other examples constitute bans of product imports/exports from/to specific countries, such as the 1960 U.S. embargo against Cuba, the Arab boycott on Israel (Fershtman and Gandal, 1998), and the 2006 Russian sanctions on Georgia.

[2] Source: Kantar India, the provider of the data used in this article.

sults, and later that same year the High Court of Bombay ruled that the regulator had acted arbitrarily and without evidence that would support its decision, Maggi products were banned and rapidly removed from the shelves.[3]

Our research design combines reduced-form and structural modeling to identify the distributional and competitive effects of the Maggi ban. The reduced form analysis leverages the fact that the ban happened quickly, preventing firms and consumers from anticipating future changes. We examine the presence of demand- and supply-side effects of the ban. On the demand side, we show a large and persistent negative effect of the ban on Maggi's sales. We also show that the sales of Maggi's competitors decreased in the first months after the ban. Although the sales of non-Maggi instant noodles eventually surpassed pre-ban levels, the initial shock shows the presence of negative spillovers to Maggi's competitors. In the long run, we find that Maggi's competitors neither benefited nor suffered from the ban.

Because India is characterized by significant inequality and segregation (Chancel and Piketty, 2017; Adukia et al., 2022), the differential welfare impact of the ban should be particularly relevant to policymakers. We focus on market heterogeneity across income, poverty rates, and the fraction of scheduled castes.[4] We show that the effect of the ban varied depending on socioeconomic classes. We find that consumers in low-income markets had access to less than half the number of products as consumers in high-income markets. This difference remained during and after the Maggi ban.

On the supply-side, we uncover a large increase in advertising expenditures of non-Maggi brands following the ban, as well as a reduction in the number of products and in the number of manufacturers present. Finally, we also document entry and exit by non-Maggi brands in the post-ban period.

Following a court ruling that reversed the ban and that established that the ban had never been justified, Maggi returned to the market six months after the ban was imposed. Maggi reentered markets sequentially due to production constraints. The reentry pattern provides an opportunity to examine how product offerings in local markets are related to local demographics, such as income and demand conditions. We show that once the ban was lifted, Maggi re-entered higher-income markets first. We also find strategic entry by Maggi: Maggi reentered more quickly markets in

[3]See The High Court of Judicature at Bombay (2015) and Section 2 for details.

[4]Scheduled castes, formerly known as "Untouchables," are the social group at the bottom of the caste hierarchy in India and other South Asian countries.

which the number of competitors increased the least relative to the pre-ban period.

We separately identify demand- and supply-side responses to the Maggi ban by constructing and estimating a structural model of consumer and firm behavior. The structural model also overcomes the problem of the absence of a control group. The model permits flexible consumer substitution both across products and between the category of instant noodles and the outside option. We compute counterfactuals that allow us to examine whether the observed responses were driven by competitive forces (e.g., the remaining firms faced less competition after Maggi left the market), a reaction to changes in consumer behavior (e.g., consumers abandoning the entire category rather than just Maggi), or a combination of the two.

Our preliminary findings show that the negative spillovers to the category resulted in lower equilibrium prices than what would have been in the absent of spillovers. However, consumer welfare decreased by 26 percent as a consequence of the ban, and consumers of lower socioeconomic groups suffered the largest decreases (28 percent versus 25 for the highest socioeconomic group). In ongoing work, we explore how the change in market structure induced by the ban also impacted market outcomes above and beyond the impact of spillovers to the category. Finally, also in ongoing work, we explore how alternative policies that would target foreign firms but would not ban them, such as taxes and an advertising ban, would have impacted market outcomes.

This paper is related to recent work that examines the distributional effects of regulatory policies such as soda taxes (Allcott et al., 2019b; Dubois et al., 2020), liquor taxes (Miravete et al., 2020), environmental car subsidies (Durrmeyer, 2022), information disclosure (Luco, 2019), and the entry of public retail pharmacies (Atal et al., 2021), among others. We focus on a regulatory intervention that directly impacted the market structure and had significant spillovers to other firms and consumers.

Another relevant body of work explains differences in consumption patterns across income groups. Recent papers show that these differences are driven by heterogeneous preferences, which explain most of the observed nutritional inequality (Allcott et al., 2019a), and the difference in pricing and product availability across income-segregated areas (Handbury, 2021). In this paper, we study a single product category consumed across all income and social groups in India. Our contribution is to examine how heterogenous consumers react to the ban of a major manufacturer in that product category. Moreover, we are among the first ones to study and characterize consumer packaged goods markets in a developing country.

This paper is also related to the literature that examines how regulation and the release of information about product quality impact consumer behavior (Jin and Leslie, 2003).[5] An important regulatory intervention is product bans, product-harm crises, and recalls. For example, Van Heerde et al. (2007) finds that firms' advertising had a lower impact after the complete recall of the leading peanut-butter brand in Australia (see also, Chen et al., 2009; Liu et al., 2016).[6] Also relevant to our work are papers that study consumer and firms' responses to boycotts (Clerides et al., 2015; Hendel et al., 2017). Also related is Bachmann et al. (2023) that examines spillovers of Volkswagen's Dieselgate to other German carmakers. We contribute to this literature by examining how the ban impacted consumers' choices and quantifying demand spillovers to other firms.

This paper continues as follows. Section 2 describes the context in which the Maggi crisis and ban took place. Section 3 introduces our data sources. Section 4 presents evidence regarding the demand- and supply-side responses to the ban. Section 5 introduces our structural work, and discusses our estimates. Section 6 presents our preliminary quantification of the impact on market outcomes of the demand- and supply-side responses to the Maggi ban. Finally, Section 7 concludes.

2 The Maggi Ban

In 2014 the instant noodles industry in India generated USD 379 million in sales. The largest brand in the country was Nestlé's Maggi, with a national market share of 84%. Maggi's closest rival, Yippee, held a market share of 13%. The popularity of Maggi noodles before 2015 was immense. As an example, *The Economic Times* wrote, "What Xerox is to photocopiers and Colgate to toothpaste, Maggi is to noodles in India" (Pande and Chakravarty, 2003). Similarly, Baviskar (2018) refers to the pop-

[5]In the context of food products, a recent set of papers study product reformulation in the wake of nutritional labeling reforms (Araya et al., 2022; Alé-Chilet and Moshary, 2022; Barahona et al., 2020). Also, Ferrer and Perrone (2023) studies consumer responses to the mad cow disease in France, and Atal et al. (2022) analyzes the impact of quality standards on the pharmaceutical market.

[6]Recalls are a common phenomenon in markets under any regulatory surveillance, such as pharmaceuticals, vehicles, and food. However, recalls or bans of entire brands are less common. Examples of bans include the FDA's ban on flavored refillable e-cigarette products and Zantac (ranitidine), both in 2020, and its ongoing attempt to ban menthol cigarettes.

ularity of Maggi instant noodles as a form of "consumer citizenship" that united social groups across India.

In March 2014, samples of Maggi Noodles tested positive for monosodium glutamate (MSG), a food enhancer, in a state laboratory in Uttar Pradesh. The packet was labeled as having "no added MSG." Although MSG is generally safe for consumption (FDA, 2012), its addition to a food product requires disclosure in packaged products in India. Nestlé denied adding MSG to noodles and argued that MSG might appear naturally in products. As a result, another sample was sent to the Central Food Laboratory in Kolkata. The results of this test arrived a year later in Uttar Pradesh, in May 2015. The results confirmed the presence of MSG and also reported finding seven times the permissible lead content (17.2ppm versus a legal limit of 2.5ppm). When Nestlé was notified, it sent records of its own monitoring process to the Uttar Pradesh food-safety officials. These records did not document irregularities or excess lead content over the relevant period. Because of the one-year delay between the dates when the samples were taken and when the results arrived in Uttar Pradesh, neither Maggi nor the state government ordered a recall because the original batch was no longer on the shelves.[7]

On May 7, 2015, two days after Maggi's response, a local Hindi newspaper reported on the issue starting a nationwide scare. The story made national news on May 16, and by May 18, the hashtag #MaggiBan was trending on Twitter. Meanwhile, Nestlé engaged with regulators and officials to deal with the issue. The company's first public statement came on May 21, when they tweeted that there was no recall of Maggi Noodles. A second statement followed on June 1, announcing that extensive testing had revealed no excess lead in the product. Nestlé's reaction suggests that they were confident in the safety of Maggi noodles and did not anticipate a recall or ban.

However, from June 2 to June 9, most Indian States issued bans on the sale of Maggi instant noodles. On June 5, Nestlé decided to recall the noodles from the market due to an "environment of confusion," but continued to insist on its safety.[8]

[7] *Fortune*, April 26th, 2016. Accessed on July 13th, 2022.

[8] Nestlé's CEO, Paul Bulcke, arrived in India to deal with the crisis. During a press conference in Delhi on June 5 he said: "this is a case where you can be so right and yet so wrong. We were right on factual arguments and yet so wrong on arguing." The press conference again emphasized Nestlé's position during the crisis: Maggi was safe to consume, but unfounded concerns shook consumer and regulator trust, and they were working towards restoring trust (*Fortune*, April 26th, 2016. Accessed on July 13th, 2022). The company recalled 37,000 tons of Maggi instant noodles and incinerated them.

Later that day, the Food Safety and Standards Authority of India (FSSAI) ordered a temporary ban on the manufacture, sale, and distribution of Maggi noodles, pronouncing the product "unsafe and hazardous for consumption." The ban was based on test results from 72 samples of Maggi noodles performed by the different Indian States and Union Territories, 30 of which reported lead content above the legal limit.

Nestlé filed a lawsuit against the FSSAI at the High Court at Bombay. The lawsuit argued that the ban was unfair and illegal and caused substantial financial losses and damage to Nestlé's reputation. According to Nestlé, the 30 test results reporting excess lead came from unaccredited labs and used improper testing methods. At the same time, the FSSAI ignored the 2,700 lab reports submitted by Nestlé from internal and external labs, which indicated that lead levels were under permissible limits.[9] Meanwhile, other countries that imported Maggi instant noodles from India (Singapore, Hong Kong, Australia, the United Kingdom, Canada, and the United States) tested the products and found lead within permissible limits.

On June 30, the High Court at Bombay allowed Nestlé to resume manufacturing Maggi for export. On August 13, the same Court overturned the ban, declared that the FSSAI had acted arbitrarily, and allowed Nestlé India to resume sales of Maggi after clearing the test of samples in three nationally accredited labs.[10,11] Maggi relaunched on November 9th without the label "no added MSG."[12] Coincidentally with Maggi's ban, the local conglomerate Patanjali Ayurveda released its own brand

The cost estimate of the recall was about USD 67.42 million (*Reuters*, September 9, 2015. Accessed on July 13th, 2022).

[9]*Fortune*, April 26th, 2016. Accessed on July 13th, 2022.

[10]The Court's ruling went further and established that the tests used as evidence by the FSSAI were performed at laboratories that were either unaccredited or if accredited, they did not have the accreditation to test for the presence of lead (The High Court of Judicature at Bombay, 2015, page 46). Finally, the Court explicitly established that "Merely stating that the food was unsafe or that the action was in the public interest is not sufficient [...]" (The High Court of Judicature at Bombay, 2015, page 59). The Court argued that the claim that Maggi noodles had lead in excess of permissible levels was not substantiated.

[11]Two days before the High Court at Bombay overturned the ban, on August 11, the Indian government sued Nestlé India for USD 99 million of compensation. The complaint, lodged on behalf of consumers by the National Consumer Disputes Redressal Commission (NCDRC), alleged unfair trade practices and false labeling. It was the first time that the NCDRC acted on this purpose. The Supreme Court of India acquitted Nestlé from this subsequent government suit in January 2019 (*Reuters*, January 3rd, 2019. Accessed on July 17th, 2022.)

[12]Maggi noodles became available for sale in all but eight states where bans were still in place (Bihar, Himachal Pradesh, Mizoram, Nagaland, Odisha, Punjab, Tripura, and Uttarakhand). Nestlé worked with local regulators to lift the bans in the remaining States by the end of November (*Fortune*, April 26th, 2016. Accessed on July 13th, 2022).

of instant noodles, which started selling around the time of Maggi's return to stores.

In summary, the evidence that local and national authorities had when they chose to ban Maggi was, at the very least, conflicted, and, according to the High Court's ruling, it did not support their decision. Although some test results suggested the excess presence of lead in Maggi samples, these tests were performed at laboratories that were not accredited or could not control for environmental and cross-contamination according to the High Court of Bombay. Further, none of the tests performed by national authorities in other countries could replicate the results when using samples produced in India during the relevant time period. This suggests that other motivations may have been at play and influenced the decision to ban Maggi noodles. Although we do not claim that non-health related concerns were the sole reason behind the ban, we believe the evidence suggests that they were at least an important factor driving some of the decisions made by the relevant authorities.[13]

3 Data and Summary Statistics

3.1 Data Sources

This work uses three primary data sources: instant noodle sales data from Kantar India, the Indian National Sample Survey (NSS), and advertising data from Television Audience Measurement (TAM) India. We describe each of them here.

Instant noodle sales data (2013-2017) These data, obtained from Kantar India, record sales (in tons) and revenues (in Rupees) of the most important UPCs of instant noodles. Minor UPCs are grouped together. We have monthly data for the period June 2013 through June 2017 that were aggregated at the state $\times$ population size $\times$ Socioeconomic Classification (SEC) level. *State* corresponds to the Indian

[13]Nestlé has not been the only foreign subject of a ban. In 2006, Coca-Cola and PepsiCo were banned in India following a report by an environmental group claiming their sodas contained high levels of pesticide. Local governments started a partial ban on their products and additional tests showed high pesticide levels. Lawmakers called for a nationwide ban and the Supreme Court requested Coca-Cola to reveal its recipe. Protesters smashed and burned cans and bottles of Coca-Cola and Pepsi. Both companies issued statements emphasizing their commitment to consumer safety and compliance with international norms and national regulations. Source: *The New York Times*, August 7th, 2006. Accessed on July 15th, 2022.

State in which the data were recorded. *Population size* is a categorical variable corresponding to three urban strata of population (0 to 1 million, 1 to 4 million, more than 4 million).[14] *SEC* is a classification of consumers used in India. The classification is based on the head of the household's education level and the household ownership of 11 consumer durable goods. Households are ranked from *A* (highest education level and more consumer durables) to *E*. Kantar records purchases of 80 thousand representative households in India, which it then extrapolates to estimate sales and revenues for all of India. We group *D* and *E*, the two lowest SECs. Following Kantar's aggregation, we define a *market* as a state-population size-SEC unit. This definition is consistent with high levels of segregation in India (Adukia et al., 2022).

Indian National Sample Survey (NSS, 2011-2012) The 2011-2012 NSS survey on consumer expenditure contains detailed information on demographic and economic characteristics. We aggregate NSS data at the market level to match with the Kantar dataset.

Advertising data (2013–2017) These data, obtained from TAM India, track TV, radio, and printed ads for every product. We have monthly data for every product in the instant noodles category for June 2013 to June 2017. TAM calculates the total expenditure for each ad campaign. The data include the language of the ads, and the state where radio and printed ads appeared. We assign TV advertising expenditure to states based on the within-state language share among radio and printed ads.

Other data sources. We hand-collected ingredients data on the main instant noodles products. We also obtained wholesale onion and wheat prices from the Ministry of Agriculture and Farmers Welfare, and production plants location from the firms' websites.

3.2 Descriptive Statistics by SEC.

We provide summary statistics of the data and highlight patterns that motivate the analyses we perform later in this paper. Table 1 reports summary statistics of demo-

[14] Kantar also provides a rural stratum. Because rural markets tend to be small and very heterogeneous even when compared with other rural markets, we focus our analysis on urban areas.

Table 1: Descriptive Statistics by SEC

Mean	A	B	C	D/E
Population (million)	2.4	1.9	2.8	1.9
Total Monthly Per Capita Expenditure (Rs)	4978.1	2897.2	2128.5	2101.2
Food Monthly Per Capita Expenditure (Rs)	1402.3	1065.2	891.5	991.1
Share of Food Expenditure (%)	28.9	37.3	42.2	47.8
Fraction Below Poverty Line (%)	2.3	12.4	30.5	49.1
Fraction Scheduled Castes (%)	5.7	10.7	15.1	21.6
Number of Children in Household	1.0	1.3	1.3	1.2
N	28,635	20,894	15,717	10,248

Note: The table shows the average of the variable in the rows across markets by socio-economic classification (SECs) categories. Variables other than population are weighted by market population. Source: NSS.

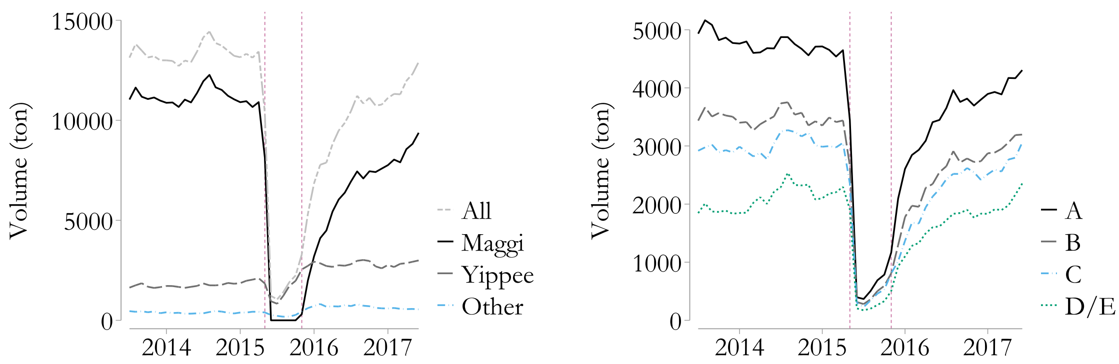
graphic and socioeconomic variables, and illustrates the heterogeneity across SEC categories. The table reports the mean of each variable across markets by SEC. The statistics show that markets have similar population sizes on average across SECs. As expected, A markets have the highest total and food expenditure per capita, and the lower share of total expenditure spent on food. A markets also contain very few households below the poverty line (2.3%) and that belong to scheduled castes (5.7%). At the other end, half of the population in D/E markets live below the poverty line, and 21.6% of them belong to scheduled castes. Also, the number of children per household is lower for higher SECs than for lower ones.

4 Consumer and Firm Responses to the ban

In this section, we provide evidence of how consumers and firms responsed to the ban. We exploit the variation induced by the ban to identify how the demand for Maggi, for its rivals, and for the whole instant noodles category was impacted by the ban.[15] In most analyses, we divide the time period in three: before the ban, during the ban, and after the ban, when Maggi returned to the stores. We also examine how demand and supply changed across locations and were related to

[15]Section 2 provides evidence that neither Nestlé nor consumers expected the ban even a few days before it took place.

Figure 1: Monthly Volume Sold over Time



(a) Volume by Brand

(b) Total Volume by SEC

Note: The dashed vertical lines show the start (June 2015) and the end (November 2015) of the ban.

local socioeconomic and demographic characteristics of each market.

4.1 Total effect on the volume of instant noodles purchased

Aggregate Impact. We first examine how the ban on Maggi products impacted the instant noodles category. Consumers may have reacted to the Maggi ban by either switching to other brands or leaving the instant noodles category altogether. Our data shows evidence for both effects and their persistence over time.

Figure 1a plots the sales of instant noodles by brand between June 2013 and June 2017, two years before and two years after the ban. The two dotted vertical lines correspond to the start (June) and end (November) of the ban. The figure shows that the ban had a large and long-lasting impact on the different brands and on the instant noodles category, and that Maggi's sales recovered slowly starting in November 2015 but did not reach pre-ban levels during our sample period. At the same time, non-Maggi brands suffered a decrease in sales following the ban's implementation, despite not being subject to it. This shows that there were negative spillovers of the ban to Maggi's competitors that were bigger than the competitive effect of Maggi's absence. The negative effect lasted roughly until August 2015, when sales of non-Maggi brands started to rise and eventually surpassed pre-ban levels. The panel also shows that the total sales of the noodles category plummeted with the ban. To determine whether the relatively small substitution to non-Maggi

Table 2: Total Sales

	Dep. Var.: Ln Volume						
	Brand level			Pooled			
	Maggi	Non-Maggi		Non-Maggi		All	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ban		-0.390***		-0.518***		-1.918***	
		(0.042)		(0.044)		(0.050)	
Post-Ban	-0.566***	0.092***		0.306***		-0.375***	
	(0.029)	(0.029)		(0.040)		(0.028)	
Ban + Post-Ban			0.013		0.166***		-0.532***
			(0.028)		(0.038)		(0.028)
Brand F.E.	–	Yes	Yes	–	–	–	–
N	32353	36852	36852	23501	23501	41730	41730
R-Squared	0.53	0.44	0.44	0.49	0.47	0.53	0.50
Mean Volume Pre-ban	12.36	2.91	2.91	4.37	4.37	12.94	12.94

Notes: An observation is a state × population size × SEC × month × flavor (masala) × package size combination. Columns (1)–(3) disaggregate the observations further at the brand level. All specifications include state, population size, SEC, flavor (masala), package size, and month-of-the-year fixed effects. Volume is measured in tons. Standard errors clustered at the market level are in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

brands was due to low substitution patterns across brands or to persistent negative spillovers we need the model that we present in the following section.

In order to examine further the differences across time periods, we regress log volume sold on dummy variables that indicate each time period while controlling for market and product characteristics, and month-of-year fixed effects. We define the ban period as June–October 2015, and the post-ban period as November 2015–June 2017.

The columns of Table 2 present the results for Maggi, non-Maggi brands, and all brands. Column (1) shows that sales of Maggi decreased by 43 percent ($e^{-0.566} - 1$) during the post-ban period relative to the pre-ban period. Columns (2)–(3) repeat this exercise but look at sales of non-Maggi brands. The estimates show that sales of these brands decreased by around 32 percent during the ban and increased by 9 percent during the post-ban period (relative to the pre-ban period). Thus, there were negative spillovers of the ban to Maggi's rivals but they subsided over time. Moreover, the negative effect of the ban on sales for the *average* non-Maggi brand nets out with the positive effect in the post ban, as Column (3) shows. Columns (4)–(5) pool the data from non-Maggi brands. They show that aggregated non-Maggi consumption decreased during the ban, increased in the post ban, and—in contrast to the effect on the average brand— increased in the combined ban and post-ban period. This different effect at the aggregate level indicates a change in brand composition. Column (6) shows that pooled total sales decreased both during the ban and the post-ban periods. Column (7) indicates that consumers reduced their consumption of instant noodles in the combined ban and post-ban period by 41 percent.

Heterogeneity by SEC. Next, we show there was substantial heterogeneity in instant noodles consumption across SEC groups during our sample period. We show the plot of the total volume purchased by SEC category in Figure 1b. The total volume of instant noodles sold is a good indicator of welfare changes in the market. The figure shows three facts. First, consumers in higher-socioeconomic markets bought more instant noodles overall than other socioeconomic groups (this claim is also true for per capita purchases). Second, following the ban's implementation, consumption dropped sharply across all income categories. This decrease in consumption shows that the substitution to other brands was only partial and that most consumers stopped purchasing instant noodles altogether. Third, even though sales of instant noodles recovered following Maggi's reentry, total sales did not reach their pre-ban level in the two years that followed.

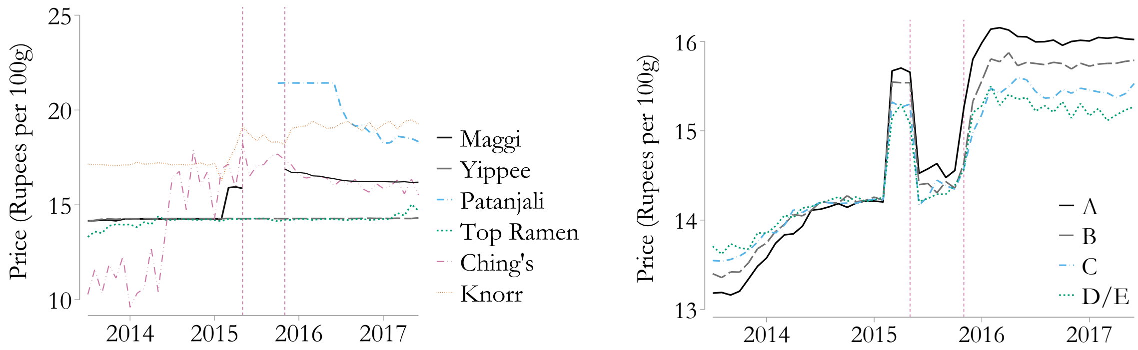
To further examine differences in sales across socioeconomic categories, we regress log volume sold on indicators for the different time periods, and their interactions with a Low Income dummy variable (SECs C and D/E). The regressions control for market and product characteristics and month-of-year fixed effects. We define the ban period as June–October 2015, and the post-ban period as November 2015–June 2017. Table 3 shows the results. Column (1) shows that the decrease in Maggi sales was larger in higher-income markets. Columns (2)–(3) shows no statistically significant differences across income groups for non-Maggi and pooled non-Maggi brands. Column (4) shows that the heterogeneous effects for Maggi result in significant and larger decreases also of aggregated instant noodles sales in higher-income markets. That is, consumers in higher socioeconomic markets decreased their purchase of instant noodles more relative to lower socioeconomic markets.

Table 3: Total Sales — Heterogeneous Effects

	Dep. Var.: Ln Volume			
	Maggi	Non-Maggi	Non-Maggi (Pooled)	All (Pooled)
	(1)	(2)	(3)	(4)
Ban		-0.378***	-0.523***	-2.047***
		(0.057)	(0.057)	(0.060)
Ban * Low Income		-0.036	0.013	0.353***
		(0.080)	(0.084)	(0.092)
Post-Ban	-0.597***	0.095**	0.288***	-0.412***
	(0.034)	(0.040)	(0.053)	(0.034)
Post-Ban * Low Income	0.091*	-0.011	0.047	0.101**
	(0.053)	(0.056)	(0.071)	(0.047)
Brand F.E.	–	Yes	–	–
N	32353	36852	23501	41730
R-Squared	0.53	0.44	0.49	0.53
Mean Volume Pre-ban	12.36	2.91	4.37	12.94

Notes: An observation is a state $\times$ population size $\times$ SEC $\times$ month $\times$ flavor (masala) $\times$ package size combination. Column (2) disaggregates observations further at the brand level. All specifications include state, population size, SEC, flavor, package size, and month-of-the-year fixed effects. Volume is measured in tons. Standard errors clustered at the market level are in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Figure 2: Prices over Time



(a) Average price by Brand (Masala ≤70g) **(b)** Price Index

Note: The two dotted vertical lines correspond to the start (June) and end (November) of the ban.

4.2 Supply-Side Responses

We now turn to analyze how the firms changed their strategic decision variables with the ban and with Maggi's subsequent reentry.

Prices. The first strategic variable we examine is price. Figure 2a shows average prices for the largest brands over time for the most popular package size (masala 70 grams or less). The plot shows that Maggi's average price increased in March 2015, only three months before the ban. According to industry insiders, Maggi's price increase was triggered by rising input costs.[16] Most of Maggi's rivals also increased their prices before the ban. In addition, Maggi's price increased further after the ban. In contrast, Yippee's average price was stable throughout our sample period.

Figure 2b shows an industry price index by socioecomomic category, calculated by dividing total sales by total volume. Thus, the panel includes brand compositional changes. The panel shows that the market price during the ban decreased, a result of consumers switching brands as we will see below, and that prices increased after the ban.

In Table 4 we examine whether prices differentially changed across time periods and brands, using a similar econometric specification as in Table 2. The specification also adds a pre-ban dummy variable that indicates the period until February 2015 to capture the price increase of that month, which was unrelated to the ban. Thus,

[16]The source is personal correspondence with high-level managers.

Table 4: Prices

	Dep. Var.: Ln Prices						
	Maggi		Non-Maggi		All		All (Pooled)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ban			0.014***	0.016***	0.001	0.001	-0.069***
			(0.004)	(0.005)	(0.004)	(0.004)	(0.006)
Ban * Low Income				-0.008		-0.001	0.013*
				(0.006)		(0.006)	(0.007)
Post-Ban	0.026***	0.023***	0.029***	0.029***	0.026***	0.024***	0.024***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)
Post-Ban * Low Income		0.011**		0.001		0.004	0.003
		(0.005)		(0.004)		(0.003)	(0.005)
Pre-Ban	-0.077***	-0.077***	-0.015***	-0.015***	-0.053***	-0.053***	-0.065***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)
Brand F.E.	–	–	Yes	Yes	Yes	Yes	–
N	32353	32353	36852	36852	69205	69205	41730
R-Squared	0.51	0.51	0.62	0.62	0.55	0.55	0.35
Mean Baseline Price	14.07	15.23	14.32	14.32	14.80	14.80	15.07

Note: An observation is a state × population size × SEC × month × brand × flavor (masala) × package size. All specifications include state, population size, SEC, brand, flavor, package size, and month-of-the-year fixed effects. Column (7) aggregates observations by brand and it does not include brand fixed effects. The pre-ban dummy variable indicates the period before March 2015 so that the omitted time period variable is March–May 2015. Standard errors clustered at the market level in parentheses * $p<0.10$, ** $p<0.05$, *** $p<0.01$

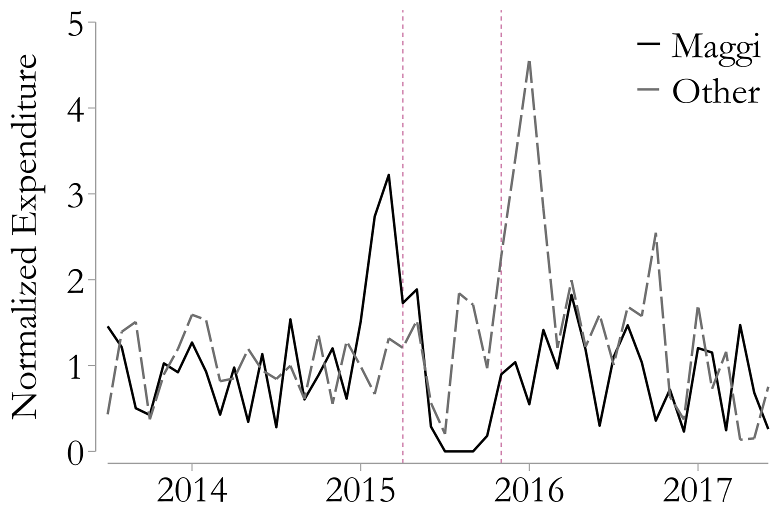
the omitted time period in the regressions is March–May 2015. Columns (1) and (2) of the table restrict attention to prices of Maggi products. Column (1) shows that these prices increased by 2.6 percent in the post-ban period relative to prices just before the ban. Column (2) shows that price differences for Maggi products across SECs widened after the ban. Columns (3) and (4) repeat this exercise for non-Maggi prices and show that during the ban, prices were 1.4 percent higher than before the ban, and this figure increased to 2.9 percent higher after the ban was lifted. Columns (5) and (6) show similar results for Maggi and non-Maggi brands pooled together. Finally, Column (7) shows results for products pooling brands together. The fact that the Ban coefficient becomes larger and significant between Columns (6) and (7) shows that the price decrease during the ban observed in Figure 2b was a result of brand compositional changes.

The pricing patterns during and after the ban are puzzling. In the absence of demand spillovers, models of competition in differentiated-product industries would predict that Maggi's exit would have triggered upward pricing pressure on Yippee and other brands. Yet, Yippee, the second largest brand, kept its prices stable throughout the sample period. One potential explanation is that negative demand spillovers may have counteracted the upward pricing pressure, which is something we explore in the counterfactuals.

Advertising. Another important strategic variable is advertising. Figure 3 presents the total advertising expenditures of Maggi (we normalized the pre-ban average to 1) and all its competitors in the instant noodles market. The vertical lines indicate the start and end of the ban (May and November 2015). In February 2015, Maggi increased its advertising expenditures coincidentally with the rise in prices caused by the cost increases described above. During the ban, Maggi's advertising expenditures dropped to zero while its competitors maintained their pre-ban levels. Upon Maggi's return to the market, its competitors increased their advertising expenditures by more than 50 percent of the pre-ban levels on average. Maggi also increased its advertising expenditures in the months just after the ban but at a more moderate rate.

Product Variety and Access. The instant noodles market is characterized by multiple flavors and package sizes. Thus, another strategic decision is the number of

Figure 3: Advertising Expenditures



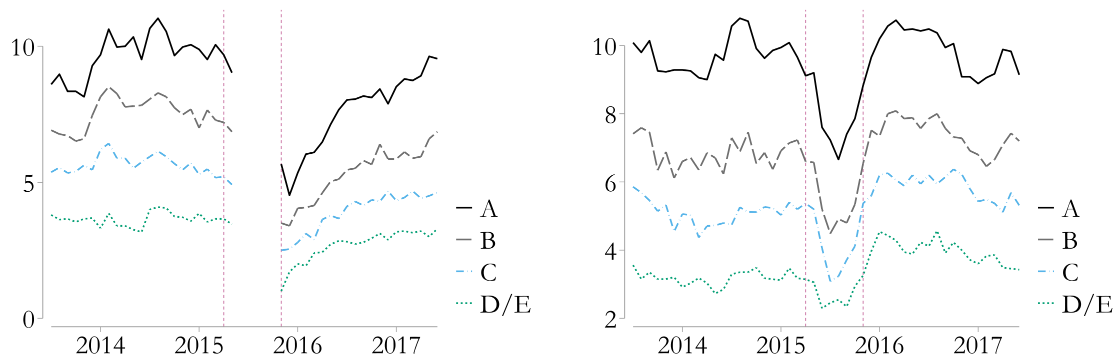
Note: The two dotted vertical lines correspond to the start (June) and end (November) of the ban.

products available in each market. This is important because product variety has welfare implications for consumers and the ban evidently resulted in less products. Figure 4 plots the average number of UPCs across SECs for Maggi and non-Maggi brands over time. The figure shows that consumers in higher-income markets had access to more products than consumers in lower-income markets, of Maggi and non-Maggi brands, and throughout the sample period.[17] For example, before the ban, A SEC consumers had access to 19.3 UPCs on average (Maggi and non-Maggi), but D/E consumers had access to only 6.7. Further, the figure shows that the number of non-Maggi UPCs also decreased during the Maggi ban, consistent with the presence of negative spillovers to the category.

In Table 5 we examine the effect of the ban and the post-ban period on the number of UPCs sold in a market, and whether the effect varies by SEC category. The table shows Poisson regressions results where the dependent variable is the number of UPCs in a market and the independent variables are ban and post-ban dummies interacted with a low income dummy (C and D/E SEC categories). Columns (1)–

[17]This result remains valid when one plots the number of brands offered in each market instead of the number of UPCs. While the number of brands available in A markets ranges between 6 and 8 on average, this number ranges between 2 and 4 for D/E markets. Also, these results show that there is less variety in lower income markets because the large income segregation that exists in India makes it less likely for consumers to switch neighborhoods to buy food products (Adukia et al., 2022).

Figure 4: Total Number of UPCs



(a) Maggi

(b) Not Maggi

Note: The figure shows the average total number of UPCs for every market by SEC for Maggi and non-Maggi brands. The dashed vertical lines correspond to the start (June 2015) and end (November 2015) of the ban.

(6) show results at the market-brand level. These columns show less within-brand variety during and after the ban, which means a smaller number of UPCs for the average brand; and a negative impact on low-income markets, albeit less severe than the one on higher-income markets.

Columns (7)–(8) of Table 5 show results at the market level only (pooling all UPCs together). Column (7) shows that the total number of UPCs increased for non Maggi brands, and that there was more variety for low income markets. This result is driven by entry of new brands (e.g., Patanjali), a fact which was not captured in the within brand analysis. Column (8) shows that variety lowers when pooling Maggi and non-Maggi brands together because the decrease in Maggi UPCs is higher than the increase in non- Maggi UPCs.

Maggi's Reentry after the Ban. The last aspect of the supply-side responses we examine is the reentry of Maggi after the ban was revoked by the Bombay High Court. Figure 5 presents a non-parametric Kaplan-Meier estimator of the hazard of reentry over markets over time. Each line in the plot shows the share of markets in which Maggi had entered in the months after the ban for each SEC. The figure shows that reentry took up to 10 months.[18] This finding shows that Maggi's return was slow in the extensive margin (reentry) as well as in the intensive margin (the

[18]The figure omits two instances of reentry 20 months after November 2015.

Table 5: Product Variety and Income Heterogeneity. Poisson regressions.

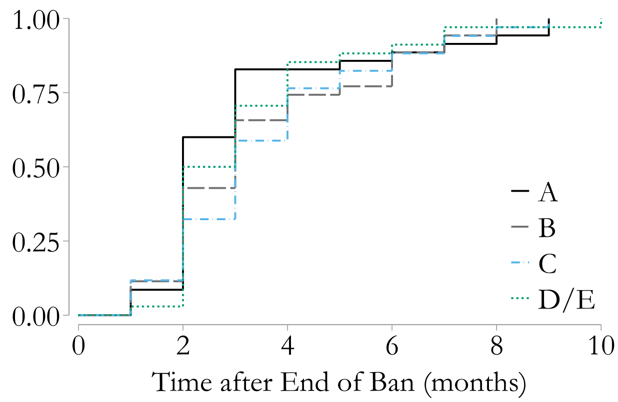
	Dep. Var.: No. of UPCs (within-brand)						No. of UPCs (pooled)	
	Maggi		Non-Maggi		All		Non-Maggi	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ban			-0.231***	-0.235***	-0.270***	-0.312***	-0.321***	-1.044***
			(0.013)	(0.015)	(0.012)	(0.015)	(0.024)	(0.028)
Ban * Low Income				0.008		0.131***	-0.004	-0.039
				(0.028)		(0.026)	(0.040)	(0.040)
Post-Ban	-0.274***	-0.258***	-0.079***	-0.105***	-0.168***	-0.185***	0.049**	-0.140***
	(0.011)	(0.014)	(0.010)	(0.013)	(0.008)	(0.010)	(0.020)	(0.012)
Post-Ban * Low Income		-0.047**		0.074***		0.048***	0.131***	0.038
		(0.023)		(0.021)		(0.015)	(0.033)	(0.023)
Brand F.E.	–	–	Yes	Yes	Yes	Yes	–	–
N	5651	5651	23513	23513	29164	29164	6663	6710
Pseudo R-Sq	0.21	0.21	0.18	0.18	0.34	0.34	0.28	0.38
Mean No. UPCs Pre-ban	6.60	6.60	1.98	1.98	3.11	3.11	6.24	12.75

Note: Poisson regression results. An observation is a state $\times$ population size $\times$ SEC $\times$ month $\times$ brand. All specifications include state, population size, SEC, brand, and month-of-the-year fixed effects. Column (7) and (8) aggregate observations by brand and they do not include brand fixed effects. Standard errors clustered at the market level in parentheses * $p<0.10$, ** $p<0.05$, *** $p<0.01$

number of UPCs in a market) as we showed before. Also, the figure shows that reentry happened faster in higher income SEC markets.

Next, we estimate Cox survival models in order to analyze how various market or firm variables affected the hazard of reentry while controlling for market characteristics that can act as confounders. Table 6 presents the estimation results. All specifications control for state and population size, and for the log market average sales during the pre-ban period as a proxy for market size. Columns (1)–(4) alternatively include a dummy for low income markets (C and D/E SECs), the fraction of population under the poverty line, the share of schedule castes, and market SEC categories fixed effects as explanatory variables. The estimates in Columns (1)–(4) show that proxies for socioeconomic status that could capture different dimensions of inequality, such as population below poverty line or social composition (Scheduled Castes versus other), negatively affect reentry timing. Moreover, potential differences in profits do not seem to explain the effects associated with socioeconomic status given that all the models control for pre-ban log sales as a proxy for market size.

Figure 5: Probability of Maggi's reentry



Note: The plot shows a non-parametric Kaplan-Meier survival estimator of the probability of a market reentry by Maggi after the end of the ban by SECs. Time equals 0 in November 2015.

Finally, the timing of Maggi's reentry could have been determined by the competitive pressure in each local market or its competitors' actions during the ban. We check for such strategic effects in Columns (5) and (6). Column (5) adds the number of brands at reentry, and Column (6) the difference between the number of brands at reentry and the number of brands before the ban. The latter variable measures net entry: its median is 1.07 and 80 percent of its values are positive. Both coefficient estimates are negative and statistically significant, which suggests the presence of deterrent effects on Maggi's reentry.

Summary of evidence. The findings reported above provide evidence of the impacts of the Maggi ban. Yet, this evidence is not enough to determine the welfare impact of the ban, and how demand- and supply-side responses to the ban varied across heterogeneous markets. For this reason, in the next section we propose and estimate a structural model of demand and supply that we later use to examine how consumers of instant noodles and Maggi's rivals reacted to the ban.

5 Demand Model, Estimation, and Results

The evidence presented above shows the impact of the ban on consumers and firms, substantial heterogeneity in access to products, and in responses to the ban across

Table 6: Maggi's Reentry Hazard: Cox Survival Models

	(1)	(2)	(3)	(4)	(5)	(6)
Low Income (C/D/E)	-0.301***					
	(0.112)					
Share Below Poverty Line		-0.722**				
		(0.298)				
Share of Scheduled Castes			-1.176*			
			(0.675)			
B				-0.296*	-0.406**	-0.231
				(0.175)	(0.190)	(0.191)
C				-0.529***	-0.806***	-0.499**
				(0.176)	(0.185)	(0.199)
D/E				-0.362***	-0.777***	-0.343**
				(0.135)	(0.205)	(0.154)
No. of Brands at Reentry					-0.201***	
					(0.065)	
Δ No. of Brands						-0.196***
						(0.057)
State F.E., Population F.E.	Yes	Yes	Yes	Yes	Yes	Yes
ln pre-ban sales	Yes	Yes	Yes	Yes	Yes	Yes
N	140	140	140	140	140	140

Note: The table shows the estimation results of Cox models of the Maggi's reentry hazard. SEC A is the omitted category in specifications with SEC fixed effects. Robust standard errors are in parentheses. *** $p<0.01$, **$p<0.05$, * $p<0.1$.

SECs. The evidence also showed that fewer firms served consumers in lower-income markets before the ban and offered fewer products. Yet, the main shortcoming of the previous analysis is that it confounds demand and supply responses. For example, if consumers substituted to non-Maggi brands and to the outside option, non-Maggi brands could also have responded. Thus, we need a model to disentangle the effects of the demand- and supply-side responses to the ban. We introduce such a model in this section and present preliminary estimates of it.

Our strategy consists of separately estimating demand and supply of instant noodles using data from 2014 to 2017. This approach allows us to identify the demand parameters based on the exogenous variation in the choice set caused by the ban, which changed the availability of both Maggi and non-Maggi products. Then, using these estimates, we perform counterfactual analyses that allow us to examine how demand- and supply-side responses to the ban impacted market outcomes. These exercises aim to calculate the impact on the willingness to pay for any instant noodles (the negative spillovers) and the distributional effects of the ban across heterogeneous markets.

Model. We model the demand using a random coefficients logit model (Berry et al., 1995; Nevo, 2001, among others). In this setting, consumers maximize their (indirect) utility, which depends on product characteristics such as price, brand, flavor, package size, and idiosyncratic shocks. We assume that the indirect utility of consumer i of purchasing product j in market m and month t is

$$u_{i,j,m,t}(p_{j,m,t}, X_{j,t}, \xi_{j,m,t}, \varepsilon_{i,j,m,t}; \alpha_i, \beta_i) = \alpha_i p_{j,m,t} + X'_{j,t}\beta_i + \xi_{j,m,t} + \varepsilon_{i,j,m,t}, \qquad (1)$$

where $p_{j,m,t}$ and $X_{j,t}$ represent price and non-price characteristics of product j, respectively.[19] $\xi_{j,m,t}$ is a demand shock, and $\varepsilon_{i,j,m,t}$ is an *i.i.d.* extreme value (logit) distributed shock. In the specifications we show below, we include market, time, and product fixed effects and introduce random coefficients on price and the constant, which allow for flexible substitution patterns across products in the choice set but also with the outside option. Finally, we also include measures of own and rival advertising in $X_{j,t}$. We consider both prices and advertising to be endogenous. To address this endogeneity, as well as to identify the random coefficients, we construct different sets of instruments that we describe below.

[19] Market m is a state-population size-SEC combination.

Instruments. We consider two sets of instruments in our specifications. First, we construct cost shifters related to the cost of shipping products from manufacturing facilities to markets (e.g., the interaction of distance, fuel prices, and a wheat price index). Second, we create local differentiation instruments following Gandhi and Houde (2019). These include continuous and binary characteristics (e.g., calories and the presence of an ingredient, respectively), and their interactions. Because this set of instruments is large, and to address collinearity issues, we use a Principal Components approach and keep the first 15 components that explain 96 percent of the underlying variance. Finally, we use these instruments in the first step of a two-step GMM process to construct approximated optimal GMM instruments. We then use these approximated optimal instruments in the second step of the GMM process.

Estimation and Results. We estimate the model using `pyBLP` (Conlon and Gortmaker, 2020). We report estimates of multiple specifications in Table 7. The specifications vary depending on which covariates include random coefficients, whether the coefficients are specified as a function of observed demographics in addition to an unobserved component, and whether advertising is included in the specification of demand and in which way it is included. The specifications reported in columns (1) to (6) consider our entire sample and, when advertising is included in estimation, it enters in levels and it corresponds to contemporaneous advertising (i.e., advertising in the same month). Specifications (7) to (10) consider a reduced sample in which we drop the first month of data because advertising, when included, considers accumulated advertising over the previous and concurrent month. Advertising in column (8) enters in levels while in columns (9) and (10) we follow Dubois et al. (2017) and include the inverse hyperbolic sine function of advertising (own and rival).[20] When considering cumulative advertising, we multiply the previous month advertising by 0.656 to reflect its lower effect than concurrent advertising on concurrent demand.[21] Column (10) includes further the adjustment term suggested by Ackerberg and Rysman (2005) to deal with congestion in logit models, a term that will be necessary in the next section.

[20] This specification allows us to capture diminishing returns of advertising on consumers who have been previously exposed to advertising.

[21] We assume a weekly decay factor of 0.9 as in Dubois et al. (2017). Because our data is monthly, we consider a monthly discount factor of 0.9^4 for the previous month.

In column (1) of the table we include a constant and a random coefficient in the specification of the price coefficient. Across all specifications we find that this constant is stable and that the coefficient on unobserved heterogeneity is relatively small. In column (2) we maintain this specification and include concurrent advertising for the same product and by rival brands. We find that own advertising increases demand, while rival advertising decreases it. In column (3) we drop advertising but include a random coefficient in the constant term to rationalize substitution to the outside option.

Starting in column (4), we add observed demographics in the specifications of the random coefficients. In column (4) we add the share of total expenditure spent on food, while in column (5) we incorporate the number of children in the household. While incorporating the number of children in the household may be intuitive, as it is related to how much noodles a household consumes, incorporating the share of food expenditure is less obvious. We do this because the NSS data does not have information about households' income but only about their expenditure. However, as we documented in Section 2, the share of food expenditure of households in D/E markets is higher than that of households in higher-income markets. Thus, we use the share of food expenditure as a proxy for income. Across all specifications, we find that households that spend a higher share of their total expenditure on food tend to be more price sensitive than those who spend less. On the other hand, though in the first specifications we find that larger households are less price sensitive than smaller households, we do not find heterogeneity along this dimension in the last specifications. We also find that larger households substitute less to the outside option, while households with a higher food expenditure share substitute more to it.

Finally, in columns (7) to (10) we restrict the sample dropping the first month. We do this because in columns (8) and (9) we use cumulative advertising over the last two months instead of concurrent, which forces us to drop the first month of data. Column (7), therefore, replicates column (5) but with one less month of data. Similarly, column (8) replicates column (6) with one less month of data. In columns (9) and (10) we measure advertising using the inverse hyperbolic sine function. In all cases the estimates are similar to those we reported in earlier columns. Column (10) also includes the Ackerberg and Rysman (2005) adjustment term and shows that though there is some congestion in the product space, this congestion is not large.[22] In the remaining of the paper we use this as our preferred specification.

Table 7: Demand estimates

	Full sample (concurrent levels of advertising)						Reduced sample (cumulative advertising)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Price coefficient										
Constant	-0.154	-0.162	-0.155	-0.293	-0.150	-0.152	-0.138	-0.164	-0.152	-0.133
	(0.011)	(0.012)	(0.011)	(0.142)	(0.020)	(0.015)	(0.019)	(0.023)	(0.021)	(0.018)
Share of food expenditure				-0.169	-0.045	-0.218	-0.062	-0.289	-0.055	-0.091
				(0.093)	(0.030)	(0.038)	(0.029)	(0.042)	(0.032)	(0.034)
Number of children					0.288	0.588	0.219	1.414	0.460	-0.825
					(0.148)	(0.153)	(0.107)	(0.528)	(0.528)	(3.499)
σ_P	3.59E-04	2.08E-03	1.27E-06	1.40E-01	5.90E-08	1.32E-04	6.13E-03	2.47E-06	0.008	0.006
	(0.073)	(0.073)	(0.059)	(0.071)	(0.008)	(0.005)	(0.008)	(0.009)	(0.007)	(0.013)
Advertising										
Own		0.637				0.636		1.471	0.552	0.552
		(0.050)				(0.051)		(0.073)	(0.028)	(0.028)
Rival		-0.750				-0.725		-0.791	-0.259	-0.259
		(0.059)				(0.060)		(0.069)	(0.052)	(0.054)
Congestion										
$ln(J_{m,t})$										-0.092
										(0.030)
Constant										
Share of food expenditure				3.401	13.140	-14.750	12.800	-7.595	12.800	9.093
				(2.149)	(0.948)	(1.853)	(0.968)	(1.769)	(1.846)	(5.814)
Number of children					-9.108	-6.950	-5.084	-28.050	-42.970	-37.410
					(8.232)	(5.451)	(6.114)	(14.010)	(20.980)	(2.159)
σ_0			1.356	1.890	5.41E-06	6.21E-06	0.054	6.76E-06	0.055	0.121
			(0.273)	(0.943)	(0.119)	(0.082)	(0.121)	(0.160)	(0.113)	(0.234)

Note: All specifications include state-population level-SEC fixed effects, time fixed effects, and product fixed effects. Columns (8)–(10) differ in that advertising is measured in levels in column (8) and using the inverse hyperbolic sine function in columns (9) and (10). Column (10) includes the Ackerberg and Rysman (2005) correction term. Standard errors are clustered at the market level (state-population-SEC).

To examine how our preferred specification performs, Figure 6 reports the cumulative distribution function of the own price elasticities implied by the estimates reported in column (10). The figure shows that consumers in lower-income markets tend to be more price sensitive than consumers in higher-income markets. Overall, the median own price elasticity is -2.49 but this elasticity varies from -2.41 for A markets, to -2.49 in SEC B markets, -2.54 in C , and -2.65 in D/E markets.

Second, we examine how the full model performs relative to the (unreported) IV-Logit model, which restricts substitution patterns. To make this comparison, we choose a market-month (a state-population-SEC-month combination) and compute

[22] In the specification we use, the Ackerberg and Rysman (2005) full congestion model would correspond to a parameter equal to -1, while the logit model would correspond to an estimate of 0.

the diversion ratios across products within that market-month (we omit diversion from one product to itself as it is -1) in this market for both the full model and the IV-Logit model. We then divide the diversion to one product by the maximum diversion from each product to the reference product, which allows us to ensure that scale differences in diversion ratios do not impact the exercise and that variation in diversion is preserved. We report these ratios of diversion in Figure 7. The figure on the left corresponds to the full model and the figure on the right to the IV-Logit model. The ratios vary, as shown in the colored scale, between 0.93 and 1. The figure shows that the estimates of the full model allow for more variation in diversion ratios than the estimates of the IV-Logit model (with ratios that vary between 0.99 and 1), consistent with the full model allowing us to break the independence of irrelevant alternatives property of the IV-Logit model.

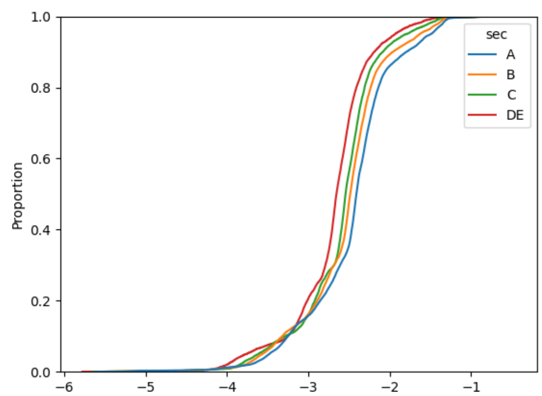


Figure 6: Own-price elasticities implied by the Random Coefficients Logit model (Column 10 in Table 7).

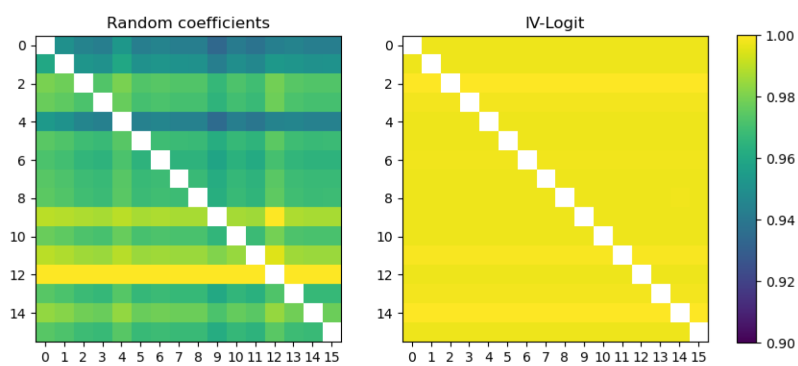


Figure 7: Implied variation in diversion rations for the Random Coefficients Logit model and the IV-Logit model

6 Counterfactuals: How did the Maggi ban impact market outcomes?

The Maggi ban resulted in the exit of the largest producer in the Indian instant noodles market. Because the Indian authorities argued that the ban was necessary for health-safety concerns, consumers and firms reacted. In this section, we use our estimated demand model, together with a conduct assumption about how firms compete, to quantify the ban's overall effect on market outcomes. Specifically, we assume firms compete à la Bertrand-Nash in prices. The exercises we describe in this section can be grouped into two categories. First, we examine how negative spillovers and Maggi's exit impacted market outcomes. Second, we examine whether alternative policies, such as firm-specific taxes and an advertising ban to foreign firms, could have generated the long-run outcomes we observe, without banning Maggi from the market. In this preliminary version, we report the outcome of only one of these exercises as the remaining are ongoing. We use our preferred specification of the demand function (Column (10) in Table 7) to perform these exercises.

6.1 The impact of negative spillovers and Maggi's exit on market outcomes

Recall that two mechanisms were at play in determining how market outcomes changed when the ban took place and Maggi left the market. First, in the absence of spillovers, Maggi's exit would have resulted in an upward pricing pressure due to the additional market power of non-Maggi firms. Second, the negative spillovers to the category shifted in demand for instant noodles downward, leading to downward pricing pressure. We begin this section evaluating the impact of negative spillovers on market outcomes, and then we turn to examining how the change in market structure affected outcomes.

The impact of spillovers on market outcomes In the first step, we simulate a scenario in which Nestlé Maggi abandoned the product category, but there were no spillovers. We implement this counterfactual taking advantage of our decomposition of the demand shock $\xi_{j,m,t}$. Specifically, when we estimated the demand model, we specified this demand shifter as $\xi_{j,m,t} \equiv \xi_j + \xi_m + \xi_t + \Delta\xi_{j,m,t}$ where j is a product, m a market, and t a month. In the estimation we absorbed these fixed effects, and constructed our moment condition using $\Delta\xi_{j,m,t}$. This allowed us to recover estimates for these fixed effects that we now use in our simulation. To implement this counterfactual, we replace the estimated ξ_t during the ban and post-ban period by their pre-ban mean, thus removing the effect that the ban had on the entire category. We then compute equilibrium prices and market shares using the estimates of marginal costs and $\Delta\xi_{j,m,t}$ during the ban and post-ban period. This exercise is attractive because market structure remains fixed, thus allowing to identify the role of spillovers.[23]

We present the results of this counterfactual in Figure 8 (overall effect over time), Figure 9 (results by SEC), and Table 8.

In Figure 8 we report an observed and counterfactual weighted price index. This price index is constructed by first multiplying the equilibrium price of each product by its equilibrium share, adding over all products within the market, and dividing this sum by the total share of the inside options within a market. The figure reports the monthly averages across markets.

Figure 8 shows that the impact of demand spillovers is important. Specifically, if no spillovers had taken place, share-weighted prices would have been higher than the observed ones. The same is reported in Figure 9 but disaggregated by SEC. These findings show that the downward pricing pressure induced by the negative spillovers was important. However, the evolution of the share-weighted price index is not informative about consumer welfare. We turn to this below.

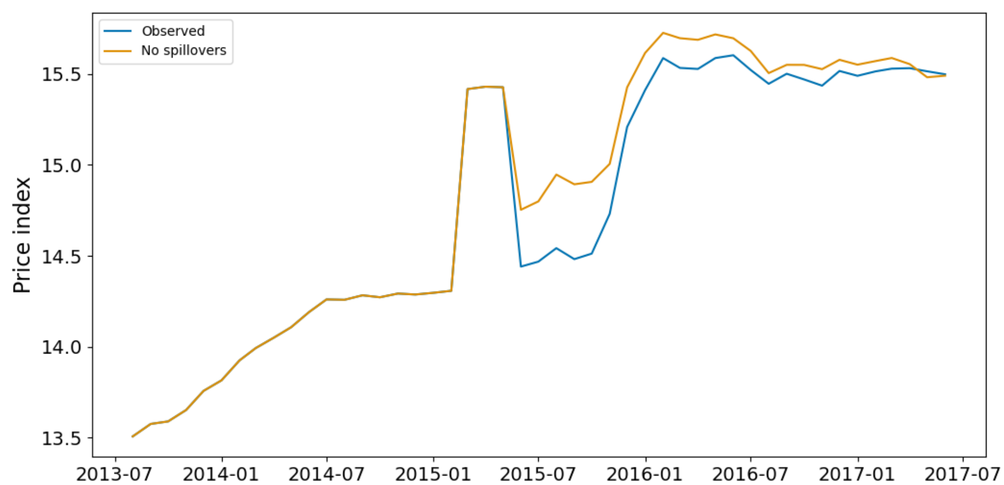
Figure 10a and Figure 10b quantify the impact of the spillovers on consumer welfare. First, the figures show that even though share-weighted prices were lower under the observed equilibrium than what they would have been in the absence of spillovers (as reported in Figure 8 and Figure 9), consumer welfare decreased during the ban and post-ban period. Because market structure is held constant across these exercises, these losses are entirely driven by the presence of negative spillovers to the category. Although the effect decreases over time, the presence of spillovers means that during the ban and post-ban periods consumers considered instant noo-

[23]In the counterfactuals, we do not compare counterfactual equilibria to the data but to what the model implies for the equilibrium observed in the data. In practice, differences between what the model implies for the observed equilibrium and the data are negligible, but still exist. Thus, by comparing counterfactuals to the simulated status quo, simulation error is no longer a concern when interpreting our findings.

dles to be a worse product relative to the outside option than what they did during the pre-ban period.

Next, Figure 10b shows that most of the decrease in consumer surplus (in million Rupee) is due to the effect on high-income markets. This reflects that high-income markets were markets that used to buy more instant noodles before the ban. To consider how welfare changed within an SEC category, we compute monthly averages in percentage changes in consumer surplus between the counterfactual equilibrium without spillovers and the observed one. Table 8 reports total damages (in million Rupees) and mean percentage changes, during the ban and post-ban periods, across SEC. Overall, though only 9 percent of consumer surplus losses can be associated with the lowest-income markets, these markets tend to suffer the larger losses in percentage terms.

Figure 8: The impact of negative spillovers on share-weighted prices



The impact of Maggi's exit on market outcomes In ongoing work we examine how Maggi's exit impacted market outcomes, in addition to the impact of spillovers. To do this, we take the observe market structure and add the most popular Maggi product to those markets that Maggi left because of the ban. We evaluate the impact of Maggi's exit both with and without spillovers. Finally, we also fix adverting covariates at their pre-ban means.[**This work is in progress and we will add the results as soon as we have them.**]

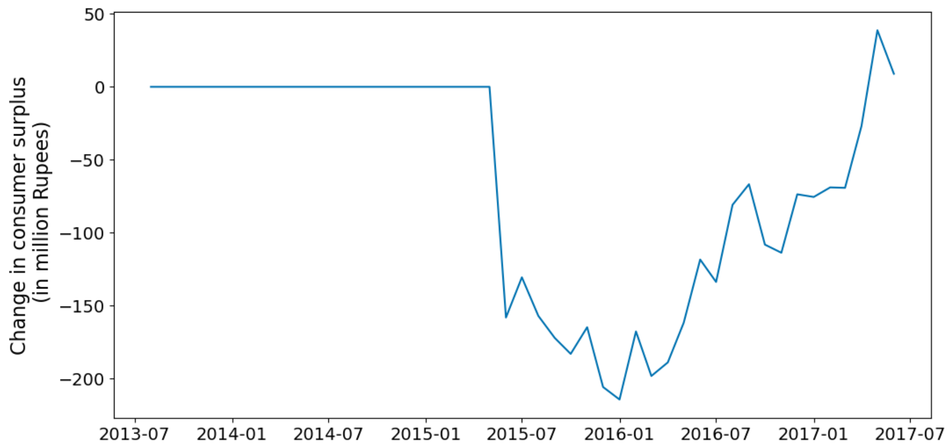
Figure 9: Monthly average price indexes by SEC

Table 8: Counterfactuals: The impact of spillovers

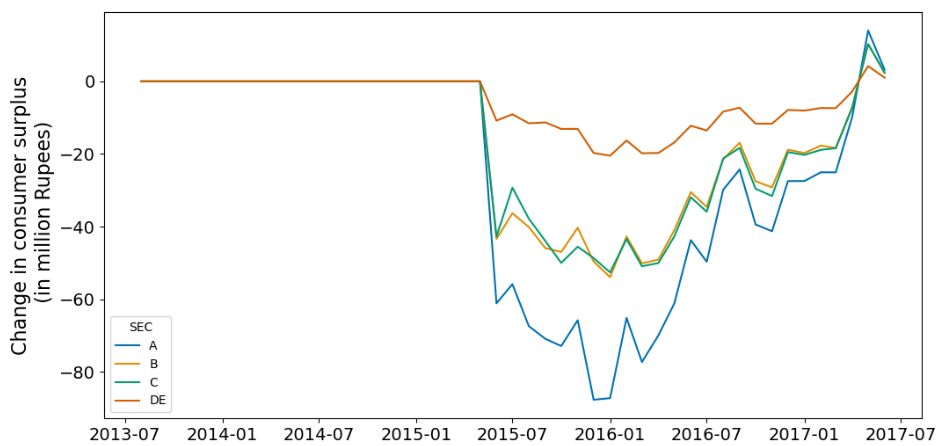
	Consumer surplus losses	
SEC	Million Rupees (total)	Percentage (mean)
A	-1,168.07	-24.87
B	-768.52	-24.83
C	-777.65	-25.76
DE	-274.37	-27.65
Overall	-2988.62	-25.69

Note: The table reports total change in consumer surplus in million Rupees, and the average percentage change in consumer surplus over the ban and post-ban period, by SEC and overall markets. The numbers correspond to losses in the status quo relative to the no-spillover counterfactual.

Figure 10: Impact of spillovers on consumer surplus



(a) Overall effect



(b) By SEC

Computation of these counterfactual exercises is more complex than for the first case. Indeed, we must compute equilibrium prices and shares for an unobserved market structure, with and without spillovers. This means that to solve the first-order conditions of the firms, we need to specify ξ for each observation during this time period. When examining a case without spillovers, we proceed as we described above (replacing ξ_t by its pre-ban mean), but we construct the unobserved demand shock as a function of the market and product fixed effects that correspond to each observation. Thus, we draw pairs of estimated marginal costs and $\Delta\xi_j$ from the pre-ban product-specific joint distribution of these covariates. In the results that follow, we draw 20 pairs of these for each observation, construct ξ for each of them, calculate equilibrium prices for each set of draws, and report the mean effects as well as the corresponding confidence interval.[24] Further, because in this counterfactual we introduce products to the observed market structure, the model would tend to over-estimate welfare costs associated with the ban. For this reason, we use the demand specification reported in Column (10) in Table 7 which includes the Ackerberg and Rysman (2005) adjustment term.

6.2 Alternative policies that target foreign firms

In this subsection we describe two policies that the Indian government could have implemented instead of banning Maggi. The objective of this section is to examine whether it was possible to achieve the same long-term outcomes that we observe in the data without imposing the cost of Maggi's exit on consumers and on the instant noodles product category.

Firm-specific taxes as an alternative to a ban. We examine how taxation could have been used to induce changes in market structure similar to those induced by the ban. To do this, we take Maggi's market share and the industry HHI before the ban and find the Maggi-specific tax that generates Maggi's share and the industry HHI that we observe at the end of our sample period. [TBA]

[24]Note that these counterfactuals are different from the one described above, in which we could exploit the estimated marginal cost and $\hat{\Delta\xi}$ for each product. In this second set of counterfactuals we need to draw these from the estimated joint distribution of these variables during the pre-ban period. For this reason, we take multiple draws per product–market–month and present average results and the corresponding confidence interval.

A ban of advertising by foreign firms Finally, we examine how banning advertising by foreign firms would have impacted market outcomes. In this case, we do not impose that the long-term outcomes must match those in the data but rather compute market outcomes when foreign firms are not allowed to do advertising. [TBA]

7 Conclusions

[TBA]

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Appendix

A Additional Context

Aside from public statements and a dedicated space on their website for information about Maggi safety, Nestlé undertook three major marketing campaigns between the ban and the reentry of Maggi noodles. The first one, which started on August 24th, was a series of ads with the hashtag #WeMissYouToo depicting consumers in various situations compromised by the absence of Maggi noodles. On November 5th, a few days before reentry, another series of ads featured a simple message about safety with the hashtag #LetYourMomKnow. The announcing tweet stated: "Your Maggi is safe, has always been. #LetYourMomKnow." Nestlé chose to return on the first day of Diwali (November 9th), one of the major Hindu festivals. Nestlé also reached an agreement with the e-commerce company Snapdeal to sell 60,000 Maggi welcome kits online on the same day, which sold out in 5 minutes.[25] Finally, on November 30th, a series of ads featured consumers relieved to consume Maggi again, with the hashtag #WelcomeBackMaggi.

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