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Informative Advertising and Consumer Search: Evidence from a Price Transparency Regulation in Supermarkets

by

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Informative Advertising and Consumer Search: Evidence From a Price Transparency Regulation in Supermarkets^{*}

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Abstract

We exploit a regulation that required Israeli supermarkets to post online the prices of all items in their brick-and-mortar stores to test theories of informative advertising and consumer search. Using data collected before and after the transparency regulation went into effect, multiple complementary control groups and a differences-in-differences research design, we show that prices have declined by 4% to 5% after the regulation, primarily in premium chains. Price dispersion has also dropped as chains adopted a uniform pricing strategy, setting similar prices across stores affiliated with the same chain. To test the mechanisms driving these effects, we show that after the regulation hard-discount supermarket chains heavily used informative-price advertising campaigns, referencing to price surveys conducted by the media. These media-based ads were used more extensively when prices were lower. In contrast, price comparison platforms that became available after the regulation failed to gain traction. Our findings lend strong support to Robert and Stahl (1993), highlighting the pro-competitive role of advertising and the important role of the media.

JEL: D83; L81; L66

Keywords: Transparency; Price Advertising; Supermarkets; Search; Media; Uniform Pricing

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1 Introduction

Economists, at least since Stigler (1961) seminal paper "The Economics of Information", have been studying the role of information in explaining imperfectly competitive market behaviors. Stigler discusses consumer search and firm advertising as two channels through which consumers obtain information, and large literatures have subsequently emerged on both channels.¹ In recent years, numerous studies exploited the rise of e-commerce to empirically explore the role of information in markets, and more specifically to what extent the reduction in search costs associated with the Internet explains the empirical patterns.² Somewhat surprisingly, this ongoing extensive research effort ignored the second channel highlighted by Stigler – that firms themselves could take advantage of the readily available information, and through advertising provide it to consumers. In fact, recent papers emphasized ways that firms can manipulate online information, in order to increase consumer search costs.³ In this paper, we begin addressing this gap in the literature by studying the role of informative advertising in the context of an online price transparency regulation that was implemented in the Israeli retail food market. We take advantage of this regulation to evaluate its effects on prices set in traditional retail stores, and examine how these effects depend on initial market structures, types of stores and products. Importantly, we also examine the roles of advertising and consumer search in driving these changes, providing striking support to predictions derived from Robert and Stahl (1993), thereby demonstrating the pro-competitive effect of advertising.

The public sector has been quite slow to adapt to technological changes and only recently regulators have begun to embrace measures that take advantage of the Internet as a means to disclose and disseminate information. Such regulatory initiatives include laws mandating that public entities must publish information online about their practices,⁴ in addition to price transparency regulations that require firms to disclose real-time prices. For instance, gasoline prices in Germany, Italy, Australia, South Korea and Chile are now available online. In the US, attempts to curb health costs have led to regulation, effective in January 2019, that requires hospitals to disclose online charges for standard procedures.⁵ In Argentina, Uruguay and Mexico, governments require food retailers to post online the prices of many of the products that they sell.⁶ In Israel, which is the

¹Early contributions in the search and advertising literatures include: Diamond (1971), Salop and Stiglitz (1977), Stahl (1989); Nelson (1970), Butters (1977), Robert and Stahl (1993), respectively. See also the surveys on search: Baye et al. (2006), Anderson and Renault (2016), and on advertising: Bagwell (2007) and Renault (2015).

²In general, these studies have not found - as predicted by traditional models of search - that prices and price dispersion in online markets are low compared to traditional markets (e.g., Brynjolfsson and Smith (2000), Baye and Morgan (2004), Jolivet et al. (2014), Einav et al. (2015). Consequently, new search models have been developed (see Baye et al. (2006), Anderson and Renault (2016) for more details).

³For instance, Ellison and Ellison (2009), Ellison and Wolitzky (2012), Spiegler (2011).

⁴These regulations often aim to increase accountability and curtail spending. For instance, the DATA Act requires the U.S. federal government to transform its spending into open data (www.datacoalition.org/issues/data-act). ⁵www.cms.gov/newsroom/press-releases/cms-finalizes-changes-empower-patients-and-reduce-administrative-burden

⁶In 2015, the Argentinian government forced retailers to submit daily prices for a basket of goods to be posted on a website that allows consumers to compare prices (see https://www.precisc.large.gob_ar)

focus of this study, since May 2015 supermarket chains are required to post online the prices of all the items that they sell in their brick-and-mortar stores. Given that sales in brick-and-mortar markets still account for the vast majority of retail sales,⁷ one can expect that the adoption of online price transparency regulations will further expand, making the study of the effects of such regulations of interest to consumers, firms, and policy-makers alike.

Any attempt to reliably identify the impact of transparency on prices must overcome several challenges. First, it is necessary to obtain price data corresponding to the period before the change in transparency, a period for which such data might not be readily available. A second challenge is to control for additional factors, aside from transparency, that might affect pricing decisions (e.g., local competition, costs, seasonality). Because these factors may change over time, it is inherently difficult to attribute changes in prices to a change in transparency over a given time period. Our research design enables us to address these concerns. To address the first challenge, we exploited the fact that the transparency regulation went into effect more than a year after it passed in the parliament, and hired a survey firm to collect prices in physical stores over the course of that year. The price data were collected at several points in time and covered multiple items sold in multiple stores and chains throughout Israel. For the period after the regulation went into effect (the post-transparency period), we collected data from one of the price comparison platforms that began to operate after the transparency regulation became effective. To address the second, and perhaps more concerning challenge, we rely on several distinct complementary control groups which enable us to identify the effects of the transparency regulation. That is, the identification comes from comparing changes in prices of "treatment" items collected by the survey firm in the pre-transparency period and whose prices became transparent only after the regulation, against price changes in four distinct control groups, as follows.

The first control group consists of the same products included in the treatment group, but sold in the online channels of the supermarket chains whose products are used in the analysis. These items constitute a useful control group because their prices were transparent both before and after the transparency regulation became effective. The second control group consists of products that are sold in traditional stores and do not overlap with the products in our treatment group and whose prices are periodically collected by the Israeli Consumer Council (ICC). The prices of these products are often cited in the media and mentioned in chains' ad campaigns as a reliable source of price data. Thus, effectively, the ICC products constitute a set of items whose prices were transparent before and after the transparency regulation went into effect. The third and fourth

⁷According to the US Census Bureau, sales from e-commerce for U.S. retailers were \$ 389.1 billion in 2016 - up 14.4 percent from \$340.2 billion in 2015 - overall accounting for 8% of total retail sales. https://www.census.gov/content/dam/Census/library/publications/2018/econ/e16-estats.pdf In the UK, e-commerce turnover in 2017 was 15.6 billion Eur - 13.65% increase from 2016 - overall accounting for 16.4% of total retail sales. See, https://ecommercenews.eu/ecommerce-in-uk-grew-to-e15-6-billion-in-2017/

control groups consist of products that overlap with the items in the treatment group, but are sold in stores that were exempt from the transparency regulation: drugstores and mom-and-pop grocery stores, respectively. Although each of the control groups might be subject to critique, they complement one another, such that when taken together, they enable us to rule out many alternative explanations for any effects observed. Notably, our analyses yield consistent results across the four control groups, giving us confidence that the results indeed reflect the impact of transparency on prices.

Our first set of results concerns the impact of transparency on price dispersion. We show that prices within chains were diverse before the regulation, and that shortly after prices became transparent price dispersion dropped. In particular, we show that the drop in price dispersion was driven by supermarket chains' decision to adopt a uniform pricing strategy, setting identical prices across the stores affiliated with a single chain. Figure 1 presents a time series of the average number of distinct prices per item in the treatment group and for the first and second control groups, i.e., items that were sold through chains' online channels, and items in the ICC basket. According to the figure, before prices in the treatment group became transparent, the average number of distinct prices in each of the two control groups was smaller than the number of distinct prices in the treatment group. Quickly after the regulation went into effect, the differences between the treatment and the control groups diminished. As we elaborate in Section 4.2 we claim that the decision to adopt uniform pricing was driven by fairness concerns, that were exacerbated once consumers could easily observe the prices of similar items sold at different stores of the same chain.

Next, we examine the impact of transparency on price levels. Our results indicate that, after the regulation took effect, prices of items in the treatment group decreased 4 to 5 percent more than did the prices of items in the various control groups. We also find that prices primarily decreased among chains that are considered more expensive, and that prices declined less in supermarkets that faced fiercer local competition.

The empirical findings regarding price levels and price dispersion suggest that the availability of information facilitated by the transparency regulation was driving these changes. To uncover the particular mechanisms through which information reached the market, we test predictions based on Robert and Stahl (1993), the first model which incorporated optimal search and informative advertising in one framework. Using detailed data on chains' ad expenditures and the specific content of each ad, we show that after prices became transparent hard-discount chains have allocated more resources to ad campaigns that emphasized their low prices. Specifically, their ads referred to price surveys, which were conducted by the media, as a credible information source for their low prices. Such price surveys were easier and cheaper to carry out when prices were transparent. Thus, we highlight the important role of the media, as an intermediary that provides extensive and reliable information about food prices. We further show, consistent with Robert and Stahl (1993), that the use of these media-based ad campaigns increased in periods in which food prices were lower, and that consumer usage of the price-comparison website is limited. Thus, our findings imply that advertising was a key factor for the more competitive environment in the post-transparency period.⁸

Our paper offers four main contributions to the literature. First, to the best of our knowledge, we are the first that empirically examine the roles of both firm advertising and consumer search as information channels. Many studies on the effects of information, and specifically the Internet, considered only the search channel and typically assumed away selection issues with regard to the types of retailers and products under investigation. For instance, Brown and Goolsbee (2002) who study the impact of the Internet and lower search costs on the prices of life-insurance policies. Probably due to endogeneity concerns, fewer studies examined the impact of advertising on prices. For instance, Milyo and Waldfoegel (1999) who investigate how removing a ban on advertising prices of alcohol products affected prices have not considered consumer search. Our findings strongly underscore the important role of informative advertising as an important channel through which information is disseminated, and markets become more competitive.

Second, our findings are valuable to the understanding of the effects of transparency regulation, which policy-makers are considering to adopt. The outcome of such regulations is not obvious given that transparency may also help firms to monitor their rivals' prices and facilitate tacit collusion (e.g., Green and Porter (1984), Rotemberg and Saloner (1986), Campbell et al. (2005)). Unlike the voluminous literature on voluntary disclosure of information (i.e., using the Internet), very few studies examine the impact of mandatory price disclosure regulations. Luco (Forthcoming) is the only paper that we are aware of that uses price data before and after a price transparency regulation required firms to post prices online. He finds that gasoline prices in Chile have increased after prices become transparent, and obtains inconclusive evidence regarding price dispersion.⁹ We study an online transparency regulation in the supermarket industry, an industry that firms are typically larger than gasoline stations, advertise more, and sell thousands of products. We obtain very different results and, among other things, consider how pre-existing local market conditions and price transparency interact.¹⁰

⁸In separate analyses, we also characterize the impact of transparency across different types of products. To do so, we use data from the post-transparency period, instead of limiting the analysis to products for which both preand post-transparency data are available. This enables us to use data on a larger number of products (specifically, 355 products), and a much wider set of stores (589 stores). The findings of these analyses suggest that the prices of more expensive and less popular products decreased to a greater extent compared with those of less expensive and more popular products. We also find that the prices of branded products decreased more than did the prices of "similar" private-label products.

⁹Rossi and Chintagunta (2016) study the impact of mandatory highway signs on gasoline prices in Italy. and Byrne and Roos (Forthcoming) use price data from a post-transparency period to study how gasoline stations coordinate their prices. Also related are Albek et al. (1997) who use prices collected after a transparency regulation to study wholesale prices of ready-mixed concrete in Denmark. Mas (2017) examined the effects of pay transparency regulations, and Jin and Leslie (2003) examine the impact of mandatory disclosure of quality.

¹⁰ Our study is also related to studies on the retail industry in general (Basker (2016), Hitsch et al. (2017)) and in

Third, recent research has been exploring the prevalence of uniform pricing and the reasons why retailers prefer it over price discriminating across locations, as standard theory predicts (e.g., DellaVigna and Gentzkow (2017), Cavallo (2018)). Our findings, showing that Israeli food retailers adopted uniform pricing after prices became transparent strongly suggest that fairness concerns (e.g., Rotemberg (2011)) are a major factor driving retailers' decision to adopt uniform pricing. This finding is interesting also because papers that emphasize fairness (Fehr and Schmidt (1999) often stress that such motivations are likely to be important in bilateral environments while not in competitive market settings. Fourth, recent studies in the macroeconomic literature have explored the potential relationship between online markets and the frequency and magnitude of price changes in traditional markets (Cavallo (2017), Gorodnichenko et al. (2018), Goolsbee and Klenow (2018), Cavallo (2018)). One conjecture is that the combination of uniform pricing and the availability of online prices have contributed to low levels of inflation in recent years in the US. Our findings offer evidence for a causal link between online price transparency and price levels.

The remainder of the paper is organized as follows. In Section 2 we provide the necessary background on the Israeli food retail market. In Section 3 we discuss the data that we use, the empirical methodology and the results. We describe the testable predictions regarding the advertising mechanism and the relevant results in Section 4. robustness and additional results from the post-transparency period are presented in Section 5. Section 6 concludes.

2 Institutional Background

The average household expenditure on food items in Israel in 2015 accounts for 16.3% of disposable income.¹¹ The Israeli retail food market is considered quite concentrated and was ranked 7th among OECD countries according to the CR3 criterion, and 5th according to the CR2 criterion (OECD (2013)). Herein we consider five large Israeli supermarket chains. Shufersal, the largest chain in the country, operated 283 stores at the end of 2014, and Mega, the second largest chain, operated 197 stores at the end of 2014. The other chains we consider operated fewer stores at the end of 2014: Rami Levy, a hard-discount chain, operated 27 large stores; Victory operated 28 stores and Yeinot Bitan operated 67 stores. We selected these supermarket chains because of their substantial collective market share, 63% of supermarkets sales in 2011, and because each of these chains also offers an online grocery service (prices in the online segment are one of the control groups that we use). Online grocery sales in Israel are growing but still account for only a small share of total food sales, about 3% in the relevant period. In addition, sales of private label items are growing but

the supermarket industry in Israel and elsewhere (e.g., Hendel et al. (2017), Eizenberg et al. (2017), Matsa (2011), Pozzi (2013)). Hendel et al. (2017) studied the impact of the Israeli consumers' boycott of cottage cheese in the summer of 2011, while Eizenberg et al. (2017) documents large price dispersion in the Israeli retail food market during 2005 to 2007.

¹¹http://www.cbs.gov.il/statistical/mb158h.pdf

still account for a relatively small fraction of total grocery sales in the Israeli food market, about 5% in $2014.^{12}$

Food prices in Israel had been rising fast between 2005 and 2011.¹³ The steep rise in prices was a main driver behind the social protests that took place in Israel in the summer of 2011. It is often said that, following the social protests, Israeli consumers became more price-conscious and more likely to search for low-priced items. One measure that likely captures the change in the competitive food retail landscape before and after the social protests is the gross profits of the two largest supermarket chains, Shufersal and Mega. In the second quarter of 2011, before the summer protests, the gross profit percentages of Shufersal and Mega were 26.6 percent and 27.5 percent, respectively. In contrast, in the second quarter of 2014, the two chains' gross profit percentages fell to 23 percent and 24.9 percent, respectively. Moreover, during the same time period, the hard-discount chains were able to increase their market shares. Following the change in the competitive landscape and other managerial issues, Mega, the second largest chain, faced increasingly profound financial difficulties. In June 2016, towards the end of our sample (i.e., July 2016), the Israeli antitrust authority allowed Yeinot Bitan, another large chain, to purchase Mega. A direct consequence of Israel's 2011 social protests was the formation of a special committee on food prices (the Kedmi Committee). Following the recommendations of the committee and a long legislation process, in March 2014 the Israeli parliament passed the "Food Act". A primary component of the new legislation was a transparency clause requiring each chain to upload real-time price information on all products sold in all its stores to a publicly available database.¹⁴

During the legislation process of the transparency regulation and soon afterwards, managers of supermarket chains, politicians, and academics have all raised their concerns regarding the effectiveness of the new regulation. The head of the economic committee in the Israeli parliament, MP Professor Avishay Braverman remarked "I am not convinced that transparency will result in good news. I hope that prices will go down in the process, though I doubt it and hope to be

¹²The market description relies on various sources, such as financial reports, reports by government agencies and media coverage. For instance, see the Analysis by the Ministry of Finance of prices in the Israeli retail food: https://mof.gov.il/chiefecon/economyandresearch/doclib/skiracalcalit_20180429.pdf and https://www.storenext.co.il/wp-content/uploads/2016/01/Summary-of-2015-English.pdf.

¹³According to the Kedmi Committee report, the cumulative annual growth rate of food prices between was 5%, compared with 2.1% increase for the period January 2000 to September 2005, and compared with 3.2% in OECD countries for the same period. See page 8 in http://economy.gov.il/publications/publications/documents/kedmireport2012.pdf.

¹⁴The regulation requires each supermarket chain to upload to a designated website files containing information about prices and promotions for each product sold in each store. The files are updated on a daily basis if no price changes have occurred, and within an hour if a price change has occurred during the day. The Ministry of Economy and Industry lists on its website links to the designated website of each of the chains. See, http://economy.gov.il/Trade/ConsumerProtection/Pages/PriceTransparencyRegulations.aspx. In the Online Appendix, we added a translation of the transparency regulations, detailing the structure and the updating protocols of each file that the chains need to submit. The Israeli Food Law has two additional components. These different timing of these changes and the control groups that we use, we don't think that these changes pose a threat to our identification. Foe some more details on the Food Law see https://www.fas.usda.gov/data/ israel-tel-aviv-tidbits-development-israel-s-agriculture-and-food-sector-2

wrong.^{"15} Eyal Ravid, CEO of Victory argued that online transparency would facilitate collusion. Likewise, Itzik Aberkohen, the CEO of Shufersal noted that "there is a concern that transparent prices will be used as a platform to coordinate prices under the law". Finally, in an op-ed, Prof. Yossi Spiegel called on the government "to reconsider the mass experiment that consumers are subjected to."¹⁶

On May 20, 2015, the transparency clause went into effect, and retailers began uploading price data to dedicated websites. Given that the raw price data uploaded by each chain were not easy to use, independent websites began making the data more accessible to consumers. During July and August 2015, websites began providing "beta" versions of price comparison services for food items sold in brick-and-mortar retail food stores across Israel. Information from personal communications indicates that food retailers and suppliers also obtained data from these websites. As of 2016, three websites offered food price comparison services: MySupermarket.co.il, Pricez. co.il and Zapmarket.co.il. Figures 1 and 2 in the online Appendix present photos taken from Mysupermarket.co.il. Figure 1 shows a price comparison of a single item and Figure 2 shows a price comparison of a basket consisting of 42 items. The different websites offer visitors several features such as the option to follow a fixed grocery list and use the same address when they return to the website. Against initial hopes, however, these websites have failed to attract considerable traffic.

3 Data, Empirical Strategy and Results

Identifying causal effects of transparency on prices is a challenging task for several reasons. First, such an endeavor requires an exogenous shock to the level of transparency. In the absence of such a shock, it would be difficult to argue that a change in transparency is the source of observed price changes. Furthermore, if price transparency is endogenously determined by firms, then selection is another valid concern. That is, the firms that choose to advertise their prices, and the products they choose to advertise may not be representative of all firms or all products. This selection issue is likely to bias the analysis of the effect of transparency. Second, given that an exogenous shock to transparency has taken place, identifying the impact of this shock requires data from both before and after the regulation. Collecting post-transparency data is likely to be straightforward; however, obtaining data from a period in which such information was not readily available is likely to be more complex. Third, pricing decisions take into account various factors, such as cost, local competition and seasonality. These factors may very well change alongside changes in transparency. Thus, to identify the impact of transparency on prices one needs to account for potential changes

¹⁵See http://www.globes.co.il/news/article.aspx?did=1000921890. Interestingly, in his academic career, Braverman published an important study on consumer search (Braverman (1980)). ¹⁶See http://www.themarker.com/opinion/1.2506245.

in other determinants of pricing decisions that might have taken place concurrently with the implementation of the transparency regulation. Finally, supermarkets offer a challenging setting for the study of pricing decisions, as they sell thousands of items, which may all be subject to different pricing considerations. Accordingly, to obtain a reasonable estimate of the overall impact of transparency on prices, it is necessary to investigate a large sample of items. Our data and differences-in-differences research design, discussed in detail below, offer a unique opportunity to address these empirical challenges.

In what follows we discuss the various sources for the price data used for the treatment group and the control groups. We also discuss the limitations of these control groups and how, we think, the use of multiple control groups mitigates these concerns. After describing the data, we provide additional details on the estimation and sources of identification.

3.1 Data and descriptive statistics

We collected price data for a treatment group of products, as well as for four control groups of products. We supplemented these price data with rich post-transparency data that correspond to a larger array of products and stores, in addition to data on local competition and on products' characteristics. These data will be primarily used to examine the effects of transparency on price dispersion and price levels (H1-H3). After describing the price data, we discuss the data sources on advertising expenditures and on usage of the price-comparison websites, which we use in subsection 4.1 to examine the potential channels underlying our results (Hypotheses 4-8).

3.1.1 Price data

Treatment group: The treatment group comprises 69 products sold in 61 stores located in 27 different cities and operated by the 5 supermarkets chains under consideration. Figure 3 in the Online Appendix shows the locations of these stores across Israel. The treatment group products belong to several product categories (e.g., dairy products, drinks, prepared meals, household cleaning, health and beauty) and different price levels. Our reliance on such a large set of items and stores mitigates concerns that the price changes are driven by unobserved local trends or changes that are relevant to specific type of products. During the pre-transparency period, we used a market survey firm to collect the prices of these items. The data collection by the market survey firm was carried out during the last week of the following 8 months: July, August, September, October and December 2014, and February, March and April 2015. Post-transparency prices for these products and stores were obtained on a weekly basis from one of the price comparison websites. A potential concern with the data that we use is that we rely on two different data sources for the pre and the post periods. To address this concern, in Section 5.2.1 we rely on the same data source for the pre- and post- time periods and show that the results are qualitatively similar.

Figure 2 presents a time series of the average basket price for each of the five supermarket chains in our data, for the year prior to the regulation and in the year after. As can be observed in the figure, there is a declining trend in prices. In addition, chains' average prices seem to have converged shortly after prices became transparent. The figure can also be used to rank the five chains according to basket price. The prices of the basket at the two largest chains: Mega and Shufersal are higher than at the other chains; in particular, the basket price at Rami Levy, the hard-discount chain, is the cheapest. The patterns observed in the figure might be driven by other factors besides price transparency. To take these factors into account, we collected data on four control groups of products described below.

Control group 1: products sold online. The first control group relies on the fact that each of the chains we consider also offers an online retail service. The prices of products available through these online channels were transparent both before and after the transparency regulation. Unlike prices at brick-and-mortar stores, which were often determined locally and vary across stores (even within a single chain), prices of items sold online by a given chain are determined at the national level and are not dependent on the customer's location. Also, supermarket chains do not offer online grocery services throughout Israel. Since July 2014 we have been collecting on a weekly basis the prices of all the items included in the treatment group but sold online through the websites of each of the five grocery chains. The prices were collected from an online platform that allowed consumers to compare and purchase grocery items from the various chains that offered an online grocery service. Figure 4 in the Online Appendix shows a screen shot from the online platform, where consumers can compare and choose among the online retailers. Figure 3 presents a time series of the total price of a basket of items in the treatment group and a time series of a basket of items in control group 1 (products sold online), starting in July 2014 and ending in July 2016; each data point represents the average across all stores in the respective group. The figure reveals that prices online are generally cheaper than the prices of the same items sold in brick-and-mortar stores. Importantly, we also see that the price gap between online and traditional stores diminished after May 2015, when prices in traditional stores became transparent.

Control group 2: ICC products. This control group comprises 38 products sold in hundreds of stores throughout Israel, whose prices are collected by the ICC, the largest consumer organization in Israel. These products do not overlap with the products in our treatment group. We obtained the ICC's monthly reports of the products' prices for the period between July 2014 and July 2015, and for the post-transparency period we obtain the price data from the price comparison website. Importantly, the 61 treatment-group supermarkets, i.e. the stores where the market survey firm visited, are a subset of the stores from which the ICC collected the price data. The prices of the products in the ICC basket are frequently cited in media reports informing consumers about the prices of food items. For instance, a TV program called "Saving Plan", one of the toprated programs in Israel, devoted a weekly segment to updating the public about the ICC's price collection and comparison initiative. In addition to the media reports, supermarket chains often mentioned the ICC reports as a credible reference point when advertising their own low prices. Mega, the second-largest supermarket chain, dedicated about 40% of its advertising budget in 2014 to add mentioning the ICC price comparison initiative. Finally, the ICC website offered a weekly comparison of basket prices across the stores visited. Accordingly, it is reasonable to assume that supermarket chains and consumers are well aware of the price of items collected by the ICC, or in other words, that the prices of these items were already transparent before the regulation went into effect.¹⁷ Figure 4 presents a time series for six items from the treatment group and a time series for six comparable items from the control group 2. In other words, each product in one group has a close substitute in the other group. For instance, a 200- gram jar of Nescafé Taster's Choice instant coffee, included in the ICC group, is matched to a 200- gram jar of Jacobs Kronung Coffee (another quality brand of instant coffee), included in the treatment group. Similarly, we match a 700- ml bottle of Hawaii shampoo in the ICC group to a 700-ml bottle of Crema Nourishing Cream Wash in the treatment group.¹⁸ In this figure, we observe that pre-transparency prices of products in the control group ICC and in the treatment behave quite similarly. Furthermore, after prices became transparent, prices of items in the treatment group declined substantially more than did the items in the ICC group.

Control group 3: products sold at Super-Pharm. The third control group comprises 28 products sold at 32 stores affiliated with Super-Pharm, the largest drugstore chain in Israel. These items provide a useful control group because drugstore chains were exempt from the Food Act and were not available for sale online.¹⁹ The prices at Super-Pharm stores were collected by our RAs at two points before the transparency regulation law came into effect — in late October 2014 and in late April 2015— and at two points in the post-transparency period — in late October 2015 and in late April 2016. Given that drugstores do not sell the full array of products sold in supermarkets, we do not have full overlap between items in the treatment group and the items in the Super-Pharm control group. Control group 4: products sold in mom-and-pop grocery stores. Our fourth control group includes 12 products, whose prices were collected by the Central Bureau of Statistics from both mom-and-pop grocery stores and supermarkets across Israel; the mom-and-pop grocery

¹⁷More details on the items in the ICC control group are described in Ater and Gerlitz (2017). We found further suggestive evidence that the ICC basket prices can serve as a reasonable transparent control group when we examine the change in the ICC basket price after the ICC began collecting the prices of these items. In particular, the price of the basket of ICC items declined substantially few months after the ICC began collecting and advertising these prices. See Figure 5 in the Online Appendix.

¹⁸The choice of these pairs also follows from a more systematic measure of distance across product characteristics. ¹⁹Starting in July 2017, drugstore chains also became subject to the transparency regulation. In Table 1 of the Online Appendix we present regression results demonstrating that prices at Super-Pharm declined soon after its prices became transparent.

stores, like drugstores, were not subject to the transparency regulation. Given the small number of items in the latter group, unavailable information (e.g., on the identity of the specific supermarket chain in which the products were sold at, and the week during the month in which the prices were collected) and confidentiality concerns, we cannot use this group in all of our analyses. Thus, we present results corresponding to this control group only in the robustness section. Table 1 presents summary statistics for the number of products and observations in the treatment group and in the first three control groups. Table XX in the Online Appendix provides more details on the products associated with the treatment and each of the control groups.

Additional data for the price analyses. Most of our analyses rely on the data collected for the treatment and control groups, as elaborated above. After the transparency regulation went into effect, the price collection became less cumbersome; therefore, for this period, we were able to obtain from a price comparison website more expansive and finer-grained data for further investigation. Specifically, we use weekly reports on the prices of nearly 355 products sold in 589 stores of the 5 chains, including the chains' online stores. The 355 products include the treatment group products and other items, such as private-label goods. In addition to obtaining price data, we also constructed measures of local competition. These measures are based on the number of supermarkets operated by rival chains within a certain distance of a given store.

3.1.2 Advertising and Price-comparison websites data

We use the following data on advertising and access to the price comparison websites to explore the roles of advertising and search in driving the changes in prices.

Advertising data. To explore the relationship between advertising and prices, we collected advertising data on the five supermarket chains in our data. These data, we collected from 'Ifat', the leading Israeli company for tracking and monitoring advertising, contain detailed data on advertising content and expenditures for the time period from July 2014 to June 2016. For each ad, we have the following information: the name of the ad campaign, the advertising retail chain; the date that the ad was posted; media channel used (e.g., television, newspapers, radio, Internet), a classification of the ad into promotion/image classification, the expenditure on each ad based on list prices, and the ad itself. We further viewed all the ads and classified the ads based on whether they include a reference to media coverage, such as price surveys carried by a media outlet. We define such ads as "media-based" ads. Figures 5 and 6 in the Online Appendix include examples of newspaper ads that refer to price comparison surveys conducted by the media. Figure 7 in the Online Appendix includes an example of a price ad, yet one that does not mention any particular media source.

Price comparison websites data. To examine the relationship between the use of the price-

comparison websites and the level of prices we obtained from Similarweb, a digital market intelligence company, data on the number of viewers and the total number of pages viewed on each of the three websites that were offering price comparison services during the relevant time period (*MySupermarket.co.il, Pricez.co.il and ZapMarket.co.il*). These data, at the monthly level, cover the time period from July 2014 to July 2016. Data on the number of visitors are available for MySupermarket and for Pricez also in the pre-transparency period. The reason for this is that MySupermarket's main business is in the online grocery segment, and Pricez offered a price comparison service based on consumer reports.

3.2 Identification and estimation

The graphical illustration presented in figures 3 and 4 is encouraging and suggests that the mandatory disclosure of prices resulted in lower prices. Nevertheless, the figures do not account for time and item specific changes that may have occurred over the relevant time period. In this section, we elaborate on our identification strategy, which enables us to argue why these preliminary findings indeed reflect the effects of mandatory disclosure of prices. To identify how the transparency regulation affected price dispersion and price levels, we observe price changes in the treatment group after versus before the regulation took effect, and compare these changes to the corresponding changes in each control group. A significant difference between a change in the treatment group and a change in the control group should be attributable to the effect of the transparency regulation. The nature of this difference can shed light on whether the transparency regulation enhanced competition or promoted collusion. Importantly, each of the control groups helps to mitigate concerns about the validity of the causal interpretation of the estimation. For instance, a difference between the treatment group and control group 1 might actually be a result of an unobserved change that took place in the online segment at the time the transparency regulation took effect. Control group 2 — comprising items that were sold in traditional stores — is not vulnerable to this concern. Similarly, a difference between control group 2 and the treatment group — which includes different products — might be related to differences in the marginal costs of the products that the two groups contain, rather than to changes in transparency. Control groups 1, 3 and 4 are not susceptible to this concern, as they contain the same items as the treatment group. Finally, one might be concerned that our results using control group 3 are biased because the transparency regulation changed the level of competition between supermarket chains and drugstores. Yet, using control group 2 which focuses on different items sold in the same store is less vulnerable to this concern. More generally, the use of the different control groups, and the fact that we obtain similar results using these alternative control groups, provides confidence that our estimates are indeed driven by the transparency regulation rather than by other changes in the market.

3.2.1 Price dispersion

Our first specification focuses on the relationship between transparency and price dispersion. In the regression analysis, to capture changes in price dispersion, we aggregate the price-store-date data to the product-date level, and in some specifications to the product-chain-date level. We use three measures of price dispersion: the number of distinct prices that a given product i is sold for in a given period t, the coefficient of variation of a given product i in a given time period t, and the percentage price range of a given product i in a given time period t. In each regression, we compare the treatment group to a single control group. Formally, we estimate the following equation:

$$y_{it} = \mu_i + \gamma_t + \beta \times After_t \times Treatment_{it} + \epsilon_{it} \tag{1}$$

where the dependent variable is one of the three measures of price dispersion. The After indicator equals one if the time period t in which the product's prices were collected is after May 2015 (when the transparency regulation took effect), and zero otherwise. The Treatment indicator takes the value of one for observations in the treatment group, and zero for observations in the control group.²⁰ The equation also includes fixed effects for the product and for the time period in which the prices were collected. The product fixed effects capture time-invariant characteristics of each item, such as its mean cost of production. The time period fixed effects capture the impact of seasonality on pricing and other regulatory changes that might have affected chains' costs and pricing decisions. We also accommodate the possibility of pricing trends that may vary across items by incorporating linear product-specific time trends. Standard errors are clustered at the product level. The coefficient of interest, β captures the change in price dispersion in the treatment group of items after prices became transparent relative to the corresponding change in dispersion in the control group.

3.2.2 Price levels

To identify the impact of transparency on price levels, we use the following difference-in-differences specification:

$$log(p_{ist}) = \mu_i + \eta_s + \gamma_t + \beta \times After_t \times Treatment_{is} + \epsilon_{ist}$$
⁽²⁾

In this specification an observation is a product-store-date tuple, and the dependent variable is the log(price) of product *i* sold in store *s* in week *t*. To control for other factors that potentially affect prices we also include time period (γ_t) , store (η_s) and item (μ_i) fixed effects. The weekly fixed

 $^{^{20}}$ Since the dispersion of prices might also depend on the number of observations per product-date, we verify that the results are similar if we add as a control variable the number of times that a price of a certain product was recorded in each period.

effects capture the impact of seasonality on pricing and other regulatory changes that might have affected chains' costs and pricing decisions. For instance, the value-added tax in Israel dropped from 18 to 17 percent in October 2015 and the minimum wage in Israel increased in April 2016. These changes have likely affected retail chains' pricing decisions. Yet, such an effect on pricing should be captured by the week fixed effects. The store fixed effects capture time-invariant local competition conditions and the socio-demographic characteristics of local customers. Note that the estimation does not separately include a treatment variable as it is subsumed by the other fixed effects (e.g., the product fixed effects subsume the treatment variable when using the ICC control group and the chain fixed effects subsume the treatment variable when using the Super-Pharm control group). Finally, we cluster the standard errors at the store level.

The main parameter of interest is β which is the coefficient on the interaction between the *After* and the *Treatment* indicators in equation 2. The identifying assumption is that the only systematic difference between the control groups and the treatment group is the amount of price-related information available to consumers before the law took effect. Per our discussion above regarding the use of the different control groups, and given that the treatment and control groups contain a substantial number of products in several categories, with overlapping manufacturers and different retailers, we believe that this is a reasonable assumption.

3.2.3 Additional specifications

To examine whether firms or stores that initially set higher prices were driving the reduction in average prices, we modify Eq. 2 in two ways. First, we interact the After * Treatment variable in Eq. 2 with an indicator for the type of the five supermarket chains (premium/discount). In the appendix we also repeat this analysis with a chain-specific interaction term. Second, we examine how the local market conditions affected price levels in the wake of the transparency regulation. To do so, we interact the After * Treatment variable in Eq. 2 with a measure of local competition that we constructed based on the number of other food retailers operating in the local market. We construct two such measures. One is a binary variable indicating whether a store's local environment is characterized by high versus low competition (i.e., store concentration above versus below the median). The other is a continuous measure of local competition. Notably, in this analysis we explore whether stores that are affiliated with the same supermarket chain but face different local competitive conditions respond differently to the transparency regulation. In this analysis, we compare pricing decisions by same-chain brick-and-mortar stores; therefore, we only use control group 2 (the ICC basket) in this exercise.

In separate analyses we also examine whether price transparency differently affected the price levels of different categories of products. In this analysis we exploit the fact that changes in price levels only began to be observed in January 2016, several months after the regulation went into effect (see the findings in Section 5.1). The gradual impact of the regulation enables us to do two things. First, we can rely on the prices collected only after the regulation went into effect, and include in our sample a much larger set of items and stores (355 items in 589 stores). Second, we can re-estimate the change in prices attributed to the transparency regulation using a newly defined periods of pre-transparency periods (between August and December 2015) and posttransparency period that lasts from January to July 2016. In particular, we re-estimate Equation 2 with interaction terms capturing different product characteristics, and compare price changes of these items to those of a control group comprising the same products sold online by the same chains (similar to control group 1). For instance, in this set of analyses we compare the price changes of private-label products and branded-products in the same category of products. Further details on the product characteristics that we include in this analysis are described in Section 5.1.

3.3 Results on changes in prices

3.3.1 Price dispersion

The regression results of Equation 1 are shown in Table 2. The table includes the estimates for each of the three measures of price dispersion: the number of unique prices, the coefficient of variation and the percentage price range. Each of the three columns includes not only the point estimate of the parameter of interest but also the average value of the dependent variable. Although the magnitude of the transparency effect varies across dispersion measures and control groups, the results indicate that following the transparency regulation had an economically and statistically significant negative effect on price dispersion. For instance, in columns 1-3 we observe that, after the transparency regulation went into effect, the number of distinct prices charged for a product in a given time period decreased by 8 to 16 distinct prices, depending on the control group that we use. This decrease is quite substantial, given that the average number of distinct prices for a product in the pre-transparency period was between 16 to 19. In Table 2 in the Online Appendix we present the estimation results of a specification that captures the effect on the number of unique prices for each of the chains. The table reveals significant effect for each of the chains, suggesting that no single chain is responsible for the results shown in Table 2.

3.3.2 Price levels

Table 3 presents the regression results of Equation 2, which reflects the effect of mandatory disclosure of prices on price levels. The point estimates of the main parameter of interest are roughly similar across the three control groups and indicate that after the transparency regulation went into effect prices in traditional supermarkets decreased by 4 to 5 percent relative to the prices in the control groups.²¹²²

Table 4 presents the point estimates obtained for a modification of Equation 2 that simultaneously estimates the transparency effect, once we distinguish between premium and discount supermarket chains. The regression results illustrate that the reduction in prices attributed to the transparency regulation took place among the premium chains. For the discount chains we do not find strong evidence that prices decreased after the transparency regulation went into effect. Table 5 in the Online Appendix presents the results when we include a chain-specific interaction variable. We find that the effect of the transparency was large and negative for the chains that set relatively high prices and considerably smaller for the chains that set relatively low prices (see the ranking of the total basket price, shown in figure 2). In fact, for Rami-Levy the hard-discount chain, we do not find evidence that prices have declined. Table 5 presents the results of an analysis that accounts for the possibility that the effect of transparency on prices depends on the degree to which a store faces local competition. Column 1 presents the results of a specification in which competition is captured by a binary variable reflecting whether the market in which the focal store is operating is more (or less) concentrated than the median degree of concentration. Column 2 presents the results of a second specification, which imposes a linear effect of local market concentration on the effect of transparency on prices. The regression results suggest that the changes in prices following the transparency regulation were significantly greater in stores that faced weaker competition.

Our findings regarding price levels and price dispersion strongly suggest that the increased availability of price information in the post-transparency period was driving the changes in prices. Yet, the exact channel that this information was reaching consumers and markets is unclear. By extending the analysis to potential mechanisms we are able to highlight the important roles of the media and informative advertising in driving these changes.

4 Mechanisms

In this section we first examine the role of informative advertising, relying on testable predictions derived from Robert and Stahl (1993). Next, we discuss why fairness concerns explain retailers' decision to adopt a uniform pricing strategy.

 $^{^{21}}$ We also estimated the same equation using subsets of the treatment group and of control group 2 (the ICC group), namely the "comparable baskets" of goods discussed above (see Figure 4). We obtain similar qualitative results (presented in Table 3 in the Online Appendix). We also obtain similar estimates when price promotions are taken into account (see Table 4 in the Online Appendix).

 $^{^{22}}$ Note that the regression analysis assumes equal weights to all the products. As we later show, the prices of more popular products have declined less than less popular products. Accordingly, the impact on consumers' actual spending may have been smaller than the estimates reported in the table.

4.1 The media, informative advertising and prices

Robert and Stahl (1993) were the first to consider optimal consumer search and informative advertising in one framework.²³ They characterize a unique and symmetric price-dispersion equilibrium, for an environment where firms sell a homogeneous good, consumers are aware of firms' existence, and learn about their prices through either costly search or from exposure to ads. Bagwell (2007) notes that their model fits an established industry, where similar products are sold in different stores (like the supermarket industry). Although the model considers firms that sell one good and our setting involves multiproduct firms, we view the media as an intermediary which aggregates price information on multiple items into one "representative" price. In the model, firms simultaneously choose prices and advertising levels, where some consumers are exposed to ads (informed consumers) while other are not (uninformed ads), depending on the level of advertising chosen endogenously by the firms. The model generates the following testable predictions:

Hypothesis 1 (H1): As the cost of informative advertising fall, its use will increase.

As we elaborate below, following the transparency regulation the Israeli media reported on retail food prices more comprehensively and more reliably. As the media coverage expanded, hard-discount chains were able to undertake advertising campaigns that were more effective and reliable. Thus, the transparency regulation reduced the media's cost of covering supermarket prices, and indirectly facilitated the use of informative advertising by chains.²⁴

Hypothesis 2 (H2): In equilibrium, chains that set high prices will not use informative advertising. In contrast, chains that set low prices will use informative advertising.

Hypothesis 3 (H3): In equilibrium, informative advertising by hard-discount chains is higher during periods that prices are lower.

The intuition for H2 follows from the fact that chains that set high prices sell only to uninformed consumers and prefer to set high prices. In contrast, low-price firms want to inform consumers about their prices and will therefore invest in informative advertising. Furthermore, because the marginal benefit of informative advertising is greater during periods that prices are lower (say, holiday seasons), we expect H3 to hold.

Hypothesis 4 (H4): In equilibrium, actual consumer search is limited.

 $^{^{23}}$ Butters (1977) consider advertising and search in his model, but does not model optimal search. Recent theoretical papers that consider both channels are: Janssen and Non (2009), Wang (2017), and Board and Lu (2018).

 $^{^{24}}$ Robert and Stahl derive additional predictions that follows a change in either search costs or advertising costs. However, we cannot directly examine these comparative static results because transparency likely resulted in a reduction in both search and advertising costs. Nevertheless, we note that according to Robert and Stahl (1993) a reduction in either search or advertising cost should have resulted in lower prices and lower price dispersion. For a simplified version of the model, see Renault (2015).

H4 follows from the increase use of informative advertising and from the pricing decision by the high-price non-advertising chains. In equilibrium, these chains set prices at a level that discourages consumers who visit their stores (and who are not exposed to ads) from searching in other stores. At those price levels, these consumers prefer to buy at these stores rather than continue to search. Consumers who are exposed to ads do need to search as they obtain information from the ads they receive. The no-search prediction arises in other standard search cost models for homogeneous goods. Introducing some product or consumer heterogeneity lead to some level of consumer search in equilibrium.

4.1.1 The media

For many years now, the Israeli media has been actively involved in supporting pro-market agendas, criticizing attempts to gain market power and denouncing price increases. News outlets report regularly on consumer issues, typically taking a pro-consumer point of view. Following the social protests in 2011 and the cottage cheese boycott, media coverage of the food market became substantial and influential. In 2012, for instance, TheMarker, a prominent business newspaper in Israel, selected Rami Levy, the man who owns and manages the hard-discount chain Rami Levy (the third largest supermarket chain in Israel) as the most influential figure in Israel in that year. Three years later, on Israel's Independence day in 2015, Rami Levy was awarded the Israel Prize, Israel's most prestigious honor for Israelis who have made a difference to society. The media seems to embrace its role in highlighting market-related concerns: The year 2017, was the first in which a reporter covering consumer issues has won the Israel's Journalists' Association's prestigious lifetime achievement award.

The Israeli media coverage of consumer-related topics also involves comparisons of prices across different supermarket stores. Before the transparency regulation, reporters had to physically visit stores and wander through the aisles to find the price of each product. After the regulation went into effect, the costs of collecting and comparing prices dropped significantly, providing the media with ample opportunities to report on price differences across numerous stores and products, much more than was possible before prices were transparent. For instance, on April 7, 2016, the news site Ynet, the most popular Israeli website in Israel, published a comprehensive price comparison across dozens of supermarket stores throughout the country. The comparison, based on information from Pricez.co.il, included information from 18 geographic regions; for each region, the names and the addresses of the three stores that offered the cheapest basket were reported. The number of items included in the basket varied across regions, ranging between 130 and 210.²⁵ On January 12,

²⁵See http://www.globes.co.il/article.aspx?did=1001108062 and http://www.yediot.co.il/articles/ 0,7340,L-4858377,00.html for additional examples. Price comparisons are also highlighted in local media, in addition to national media: For instance, the local newspaper of Petach Tikva, the fifth largest city in Israel, used a price comparison platform to report on the supermarkets with the cheapest prices in Petach Tikva. See

2016, Channel 2 News, Israel's most popular news program, ran a 4.5-minute item on a new price competition among supermarket chains in the city of Modi'in.²⁶ In this case, too, the reporter used the Pricez mobile app to compare prices across supermarket chains. Another example of the role of the media relates to the merger between two large supermarket chains: Mega and Yeinot Bitan. The merger took place in June 2016, towards the end of our data collection period. In this case, TheMarker, reported prices at the merged chains before versus after the merger, and compared them against the corresponding price differences at another supermarket chain that did not take part in the merger. The Marker used price data from one of the price comparison platforms and repeated this exercise a few weeks after the merger and then again a few months after the merger.²⁷

Media-based advertising and prices 4.1.2

How does the media coverage relate to advertising and to food prices? We argue that the extensive media coverage following the transparency regulation provided retailers, and particularly harddiscount chains that received favorable media coverage, an opportunity to mention it in their ad campaigns. Since supermarkets sell thousands of items in each store, they cannot price advertise all these items. Furthermore, a decision to price advertise a subset of items entails limited information on the prices of other items (Rhodes (2014). Thus, the media coverage serves as an arguably objective, reliable measure for the aggregate price of a large number of items sold in supermarkets. We build on this distinction and classify add that reference to media reports as "media-based advertising". Figure 5 shows an example of such ad used by Rami-Levy, the hard-discount chain. In the analysis, we use this classification and consider the expenditures on media-based ads by each chain as our measure for informative advertising.

Figure 6 presents the expenditures on media-based advertising for the year before and for the year after the transparency regulation came into effect, divided into the hard-discount chain, Rami Levy and the other chains. As can be seen in Figure, after the transparency regulation the expenditures by the hard discount chain, increased significantly whereas the expenditures on media-based add by the other chains significantly dropped. Regression results presented in column 1 of Table 6 confirm these patterns, showing that the expenditures on media-based ads by Rami Levy sharply increased relative to the expenditures by other supermarket chains. As a falsification test, we show in column 2 in that table that after prices became transparent the expenditures on promotional ads (i.e., ads mentioning specific price promotions) by Rami Levy did not increase relative to the expenditures on such add by the other retailers. We also show that the use of mediabased advertising is negatively correlated with the prices in supermarket chains. To capture this,

https://goo.gl/YsVT9a ²⁶www.mako.co.il/news-channel2/Channel-2-Newscast-q1_2016/Article-996f23598873251004.htm. ²⁷See www.themarker.com/advertising/1.3006498 and www.themarker.com/advertising/1.3116830.

we estimated a treatment intensity version of Equation 2, replacing the transparency indicator in the original specification with a standardized measure of expenditures on media-based ads by Rami Levy in a given month. In this specification, we use the online group as our control group and present the results in column 3 in Table 6. The results support H3 and indicate that expenditures on media-based ads are greater during periods in which prices are lower.

4.1.3 Usage of price-comparison websites

We now turn to examine consumer search as another channel through which consumers may have gained information about prices. According to H4 consumers in equilibrium do not actually search.²⁸. Admittedly, it is difficult to show that consumers do not engage at all in search. Nevertheless, we believe we can show that the use of the price-comparison websites that became freely available after the transparency regulation is very limited.

To make this point, we first rely on a survey conducted by an Israeli consumer organization, asking a representative sample of consumers on their search habits in retail markets. According to survey, only 4% of respondents have accessed the price-comparison website in the year preceding the survey. We also obtain qualitatively similar patterns when we use data, described in subsection 3.1.2, on the usage of the three price-comparison websites. In particular, the average monthly number of unique visitors to Pricez.co.il and Zapmarket.co.il between October 2015 and July 2016 was 21,414, and 16,992 respectively. These figures combined account for about 2% of the number Israeli households. Mysupermarket.co.il, the third price-comparison website, offers as its main business an online grocery service so we cannot disentangle customers who visit MySuperMarket to shop online (e.g., at Shufersal online) from visitors who want to obtain price information in traditional stores. Yet, we note that the average number of total visitors to MySupermarket has marginally declined from 182k in the year preceding the regulation to 176K in the year after. Conversations we had with both Pricez.co.il and Myspurmarket.co.il further indicate that traffic to their price comparison websites is quite negligible.²⁹ To make a living, at least two of the firms running these websites, offer firms such as food retailers and suppliers BI services which are based on the data generated by the the price-comparison websites.

To increase the traffic to these websites, the Ministry of Economy supported a large TV advertising campaign, and announced a competition among price-comparison websites, in which the first and second prizes (175k and 75k New Israeli Shekels) will be given to websites that will more than

 $^{^{28}}$ The no-search prediction is a standard prediction in search models for homogeneous goods. Once heterogeneity is introduced then search takes place also in equilibrium.

 $^{^{29}}$ We also estimated a treatment intensity version of Equation 2, replacing the transparency indicator in the original specification with a standardized measure for the number of pages viewed in a given month on Pricez. We find a negative correlation between prices and the use of these websites, suggesting that consumers look for price information during periods that prices are expected to be lower (like holidays). This correlation, however, does not survive when we also exploit cross-sectional variation at the city level of the use of these. The regression results using are presented in the Online Appendix XX.

300K and 75k monthly users.³⁰ Despite these efforts and initiatives, they have failed to deliver sustained traffic into the price-comparison websites.³¹

4.2 Fairness concerns and uniform pricing

Few recent papers document the practice of uniform pricing in different settings (e.g., Cavallo et al. (2014), DellaVigna and Gentzkow (2017) and Argentesi et al. (2018))). These findings are somewhat nonintuitive given that standard economic models predict that retailers' pricing decisions should take into account local consumers' price elasticities. DellaVigna and Gentzkow (2017) discuss advertising, tacit collusion, fixed costs of managerial decisions and fairness as alternative explanations for uniform pricing.³² They further argue that fixed costs of managerial decisions best explains their findings.

Our setting is useful to shed further light on the reasons why retailers adopt uniform pricing and to underscore the important relationship between transparency, uniform pricing and fairness. In particular, we propose that fairness concerns best explain the effect of transparency on the decision of each chain to adopt a nearly uniform pricing policy. That is, retailers reduced the number of unique prices they set for each product because they were concerned that consumers would find price differences across same-chain stores to be unfair, and that a public outcry would take place if consumers observed that chains were engaging in that practice. Rotemberg (2011) offers a theoretical framework that takes into account fairness into firms' pricing decisions.

There are three reasons why we think fairness is a main factor in our setting. First, fairness was an integral part of the public debate regarding retail food prices in Israel in the relevant time period. Many media reports publicized the fact that prices of similar products sold by different stores affiliated with the same chain tend to differ from one another, and that prices in affluent areas were often cheaper than prices in rural and relatively poor areas. Echoing the critique, shortly before the transparency regulation came into effect, a legislative attempt requiring food retailers to set uniform prices across all their stores almost passed in the Israeli parliament.³³ Retail chains tried to address the public critique by attributing the price differences to higher transportation costs to rural areas and by announcing that they would reduce the price differences.³⁴ Conversations we had with retailers also confirm that the decision to set uniform pricing was driven by the public discontent. Second, the fact that the changes in price dispersion and in the number of

³⁰The Israeli media also promoted the use of the price comparison platforms: in December 2015, the Israeli Internet Association, together with Google and the Israeli Fair Trade Authority, launched a competition for the development of the best food price comparison application. See http://www.globes.co.il/news/article.aspx?did=1001056276 and http://www.globes.co.il/news/article.aspx?did=1001074618.

³¹For more details, see https://www.calcalist.co.il/articles/0,7340,L-3751446,00.html.

 $^{^{32}}$ Interestingly, Stigler (1961) also mentions the practice of uniform pricing and suggests that reduce consumer search is another potential reason for the use of uniform pricing.

³³http://www.ynet.co.il/articles/0,7340,L-4252811,00.html and www.knesset.gov.il/protocols/data/ rtf/kalkala/2012-07-24-02.rtf.

 $^{^{34}\}mathrm{E.g.}, \mathtt{https://www.themarker.com/advertising/1.1613349}.$

unique prices occurred shortly after the regulation (see Section 5.1) came into effect also suggests that these changes were not driven by consumers' usage of the price comparison websites or by coordination among chains. Finally, the fact that already before the transparency regulation the prices that retail chains set in their online channels were nationally uniform, further suggests that chains recognized the reputational costs associated with charging different "transparent" prices in different markets.

5 Additional Results

5.1 Effects of transparency across products

In this section we report additional results using a larger set of products and stores which are available in the post-transparency period. To undertake this analysis we first show that the change in price levels became significant only in the beginning of 2016, few months after prices became transparent. We rely on this finding to perform a modified difference-in-differences analysis explained below. We also note that while we think that these additional results offer valuable insights on the effect of the transparency policy, we are also aware of the potential limitations of relying on post-transparency data and therefore cautiously interpret the results of this analysis.

To examine the pace at which the change in price dispersion and price levels took place, we estimate the monthly effect of price transparency on measures of price dispersion and price levels for each month included in our 2 years sample. We estimated the month-specific effects using modified versions of Equations 1 and 2. Figure 10 in the Online Appendix presents the monthly effects of the transparency regulation on the number of distinct prices (as a measure for price dispersion) and on the (log) price levels. The figure demonstrates that price dispersion diminished quite immediately after the transparency regulation went into effect, whereas the effect of transparency on price levels was essentially indistinguishable from zero for several months. Only at the beginning of 2016 did the effect of transparency on price levels become negative and statistically significant. We exploit this fact and carry out a series of differences-in-differences analyses for the post-transparency period using panel price data on 355 products from 589 stores. In these analyses the comparisons are made between the prices of products sold in traditional stores (the treatment group) and the price of the same products sold online by the same chain (as a control group).

In our first analysis in this series, we evaluate the overall extent to which price levels dropped in 2016. We obtain similar results to the those reported in Table 3. That is, among traditional stores, the price difference between the January-August, 2016 period and the August-December, 2015 period was 3.2% lower compared to the corresponding price difference of the same items sold through the online channel. This finding, shown in column 1 of Table 8, suggests that our initial sample of treatment products is largely representative of the products sold in supermarkets.

Next, we use regression analysis to characterize which products experienced a greater drop in prices during 2016, relative to the control group. First, we divide the 355 products into 10 price deciles based on their mean price and estimate a specific treatment effect for the set of products within each of the mean price deciles. As shown in Figure 7, we find a strong negative relationship between the price level and the corresponding decline in price. That is, more expensive product experienced a greater drop in prices. Next, we examine how the observed price reductions correlate with product popularity. To this end, we assign each product a popularity score which is based on a list of the top 500 selling items at Mysupermarket.co.il.³⁵ We then interact this measure of popularity with a dummy variable indicating whether the item's price corresponds to the period before or after January 2016 and add this interaction variable to the estimated specification. The regression results are shown in column 2 of Table 8. As can be seen in the table, the results suggest that the prices of more popular products declined less than the prices of less-frequently-bought items. One potential explanation for this finding is that in the pre-transparency period consumers paid closer attention to products that they purchased more frequently. As a result, prices for these products were a priori relatively low, and the impact of the transparency regulation on prices was greater for less popular goods. Furthermore, these findings suggest that estimating a quantityweighted regression of the effect of transparency would indicate that the effect of the transparenct policy on consumer surplus is somewhat smaller than the effect we report in Section 3.3.2.

We now turn to evaluate whether price changes differed between private-label and branded products in the same category. To capture this difference, we estimate an equation similar to Equation 2 and also include two interaction terms. One term is an interaction between an indicator for the post-January-2016 period and an indicator for a private-label product. The second term is an interaction between an indicator for the post-January-2016 period and a branded-product indicator. In this specification the sample of products consists only of the 12 categories that contain private label products. The results, presented in column 3, indicate that the prices of branded products dropped significantly more than the prices of private-label products. These findings may suggest that following the transparency regulation, consumers found it easier to compare the prices of branded products than to compare the prices of private-label products, which differ across chains.

Finally, we also examine the prices of products that are likely to have been characterized by a high degree of consumer search, even prior to the transparency regulation. We expect that frequently-searched products are likely to have undergone smaller price reductions following the transparency regulation compared with similar, less search-intensive products. In particular, for a

 $^{^{35}}$ Because more than half of the products in our sample are not included in the top 500 products, we cannot directly match the list with each product. Instead we use a more coarse classification for popularity. The results are robust to different classifications.

given product category, we compare price changes among products that offer the most stringent kosher requirement ("Mehadrin Kosher") with price changes among corresponding products carrying the regular kosher label only. For example, we match a 25-gram package of Osem Bamba peanut snack in the Mehadrin kosher set with a 100-gram package of Osem Bamba peanut snack in the regular kosher set. Ceteris paribus, the majority of Israeli consumers are indifferent between the two kosher options. Yet, certain groups of religious Jewish consumers purchase only goods that fulfill the more stringent kosher requirement, and are thus likely to track their prices. The results, presented in column 4, suggest that the prices of Mehadrin kosher goods decreased significantly less than did those of the corresponding regular kosher products. Overall, these results may suggest that the prices of products that can be characterized by a high degree of search before the transparency regulation decreased less compared with the prices of less-searched-for products.

5.2 Robustness

5.2.1 Measurement errors and grocery stores as a control group

Our regression analysis indicates that after the transparency regulation went into effect, prices of items in the treatment group fell 4-5 percent more than did the prices of items in the different control groups. A potential concern with our results is that they might have been affected by the changes in the sources of data used for the analysis. In particular, the source of data for the treatment group and the ICC control group in the pre-transparency period were a market survey firm and the ICC, respectively. After the regulation, the data for these groups came from a price comparison website.³⁶ Thus, if there are systematic measurement errors associated with one of these methodologies then our results are potentially biased. In particular, if (due to the collection method) the prices recorded in the treatment group during the pre-transparency period were systematically higher than the actual prices, then our results are potentially biased upward (in absolute values).

To address this concern, we obtained data collected by the Israeli Central Bureau of Statistics ("CBS") for the same time period as our main analysis. We obtained data on the prices of 39 items, which are regularly collected by the CBS to construct the Israeli consumer price index. Importantly, the methodology to collect the prices of these items did not change over the relevant time period. The CBS data include, for each item, a product identifier, price, store identifier, city name, the month in which the price was collected, and an indication of whether the store belongs to a supermarket chain or is a mom-and-pop grocery store. For confidentiality, these data do not include a specific address, chain affiliation or exact date. Thus, we cannot directly compare this data set with the other sources of data that we use. Nevertheless, we can use the CBS data to

 $^{^{36}}$ For the Super-Pharm and online control groups the same data sources were used before and after the regulation.

examine how the regulation affected prices in supermarkets (which were subject to the regulation) relative to prices in mom-and-pop grocery stores (which were not subject to the regulation). Out of the 39 products, 27 products are products that are included in the ICC basket. Thus, we first focus on the remaining 12 products, and estimated Equations 1 and 2. The results of these analyses, which are presented in Table 7, indicate that after the transparency regulation went into effect, both price dispersion and price levels decreased to a greater extent in supermarket chains than in mom-and-pop grocery stores. The magnitude of the estimated effect on prices is 1.9%. If we restrict attention to the 8 items, for which there are on average more than 10 observations per month, we obtain an estimated effect of 2.2%. Given that the sample of items used in this analysis is a small subset of the products that we used in the main analysis, we view these results as providing additional support for the findings presented in the main analysis. Using the prices in grocery stores as a control group is also useful because, as we further discuss in Section 5.2.5, it seem unlikely that the owners of these small, independent stores would have responded strategically to the transparency regulation by changing their prices.

We also use the CBS data on the 27 products that are included in the ICC control group, and examine the changes in the prices of these items at grocery stores and at supermarket chains. Interestingly, the level of transparency of these groups has bot changed before and after the regulation. The products in the ICC group were transparent before and after regulation and the prices in the grocery stores were non-transparent before and after the regulation. Accordingly, we do not expect to find a significant change in the price difference between these two groups after the regulation became effective. Indeed, we do not find an effect (p-value = 0.64). We find a similar non-significant result if we again restrict attention to products for which we have more than 10 observations per month.

5.2.2 Different sampling frequencies

Another implication of using different data sources before and after the regulation concerns the frequencies that the different data were collected. For instance, in the pre-transparency period, prices of items in the ICC control group were also collected in the same month, though not necessarily on the same day or week. In contrast, in the post-transparency period, these data were collected on the same day. This difference may mechanically lead to a higher number of unique prices in the pre-transparency period for the ICC group compared to the number of unique prices in the post-transparency period.³⁷ To address this concern, we experimented with different specifications, in which we simulate the post-transparency period to be at the monthly level. For instance, for the post-transparency period we used price data for the treatment group only from the last week

 $^{^{37}}$ For the treatment group, the prices in the pre-transparency period were collected in the last week of a given month and typically on the same day.

of the month (like in the pre-transparency period). Moreover, in the specification using the ICC control group, we use price data from a randomly chosen week in the post-transparency period. In other words, we make the pre- and post periods comparable in terms of their data-collection frequencies. Likewise, for the online control group we use price data collected in the last week of the month, similar to the treatment group. The results for these different specifications, and for three different measures of price dispersion, are shown in Table 7 in the Online Appendix. In all specifications, the qualitative results are unchanged.

5.2.3 Parallel time trends

The identifying assumption in a differences-in-differences research design is that the control and treatment groups share the same time trend. Given the multiplicity of control groups used here, we find it useful to graphically demonstrate that the control groups shares a similar time trend with the treatment group. To this end, we estimated specifications using log(price) as the dependent variables and also add month-specific effects for each specification (treatment group vs. control group). The results are plotted in Figure 8 of the Online Appendix. The figure demonstrates that the treatment group time trend follow a similar time trend as the corresponding control group time trend. Formally, we cannot reject the null hypothesis that the two time trends follow the same pattern when using the online control group. We obtain similar qualitative results when using the ICC control group.

5.2.4 Placebo tests

A potential threat to identification when using a differences-in-differences research design is the possibility that the estimated effects are not driven by the treatment, but rather by other unobserved factors. To address this concern, we conducted a placebo test by considering a sample that started on July 2014 and ended on July 2015, just before the price comparison websites offered their services. We then re-estimated the regression in which (log) price level is used as the dependent variable (Equation 2), defining a fictitious date for the "effective" date of the transparency regulation. Since the treatment group was sampled eight times in the (actual) pre-transparency period, and given that we want the placebo pre-regulation period and the placebo post-regulation period to incorporate at least two data pulls each, we are left with at most five possible points in time at which to set the fictitious regulation dates. We conducted the test for both the online and the ICC control groups. The results, which show no significant effect of the fictitious regulation, are presented in Table 8 of the Online Appendix. These results mitigate the concern that another event that occurred prior to the implementation of the regulation explains our findings.

5.2.5 Strategic responses by prices in the control groups

Another potential concern with the interpretation of our findings is that prices of items in the control groups may have reacted to the transparency regulation. For instance, if prices set by Super Pharm (control group 3) or in chains' online channel declined as a response to the decline in prices in brick-and-mortar stores, then our results might be biased. Note, however, that this would be imply that our estimates using these control groups are a lower bound to the actual impact of transparency.

Furthermore, if following the transparency regulation, Super-Pharm stores decided to target price-insensitive consumers by raising prices, then our results may overstate the impact of the regulation. While we believe that it is unlikely that Super-Pharm would raise its prices in the wake of a regulation enabling consumers to more easily compare prices across different retailers, it is not theoretically impossible. To address this concern, we classified Super-Pharm stores in our sample as 'close' or 'far', according to their proximity to a supermarket store. We then checked whether the price changes in 'close' Super-Pharm stores differed from the price changes in 'far' stores. Arguably, if the above concern holds, we should expect prices in the former to rise more compared with prices in the latter. The estimation results, presented in Table 9 in the Online Appendix, provide no evidence for such a relationship. Second, as mentioned in Section 5.2.1, we use prices of items sold in individual grocery stores as an additional control group and find qualitatively similar results. This analysis further suggests that our main results are not driven by a strategic response by Super-Pharm. With regards to the concern about online prices, we also note that prices in traditional stores have declined also in areas where online grocery services is very limited, further mitigating this concern.

5.2.6 Anticipation of the policy change

One might be concerned that because the Food Act was enacted about a year before the transparency regulation came into effect, supermarket chains might have lowered their prices before the actual implementation of the regulation. We believe this concern is unfounded for several reasons. First, the abrupt change in price dispersion that takes place shortly after the policy came into effect strongly suggests that chains responded shortly after the regulation became effective (not months before it was effective). Second, from a profit-maximizing perspective it is not obvious why chains should set lower prices well before prices become transparent. Finally, if chains did set lower prices well before the regulation came into effect then our estimates are potentially biased downward.

6 Discussion and Concluding Remarks

Since the beginning of 2017 alone, several large retail chains, including Macy's, JC Penney, Sears and Payless ShoeSource have announced the closing of hundreds of brick-and-mortar stores and the layoffs of many thousands of employees.³⁸ This dismal trend of the retail market is often attributed to the highly competitive digital age and the strength of online giants such as Amazon. One important traditional retail market which seems relatively immune to this trend is the grocery market, probably due to the unique characteristics of the products sold in grocery stores.

Amazon decision's to purchase Whole Foods on June 2017 for \$13.7 billion seems to suggest that blending the online channel and the traditional retail food world can offer substantial complementary benefits. For instance, it might result in traditional food stores voluntarily displaying their prices online. Alternatively, government policies may require food retailers to post their prices online. Will this information result in higher or lower food prices? Economic theory offers mixed predictions. On the one hand, the availability of price information is essential for the efficient functioning of markets. On the other hand, several recent papers have shown that firms may manipulate information to make it harder for consumers to find cheap alternatives. How will then the rapid growth of the online market affect the traditional retail food market? What are the implications of price transparency regulations on price levels, price dispersion and price discrimination strategies?

In this paper, we study the impact of a price transparency regulation of food items sold in Israeli traditional brick-and-mortar stores. The retail food industry is a meaningful domain in which to begin to unpack the economic effects of online price transparency, given that consumers spend about one-sixth of their disposable income on food. While the impact of price information is at the core of IO, to our knowledge, thus far hardly no studies were able to examine this issue empirically, and those that have were typically limited in scope: they had to assume away selection issues and have not considered firms' advertising response. Our analysis addresses this gap, using a large set of price data from the Israeli supermarket industry in the period surrounding the implementation of a mandatory transparency regulation. We first show that brick-and-mortar supermarket stores reduced the number of distinct prices that they set for each item offered, and that price levels decreased. The decrease was particularly pronounced in stores affiliated with more pricey chains or stores that faced weaker competition in their local markets. We further highlight the important role of the media and media-based advertising in generating these price reductions. We show that hard discount chains extensively relied in their ad campaigns on price surveys conducted by the media as an objective and reliable source of information. These ad campaigns were used especially

³⁸See https://goo.gl/R8pyTJ

during time periods in which prices were lower. Remarkably, our findings provide strong support to the theoretical model by Robert and Stahl (1993) who were the first to incorporate optima consumer search and advertising into one framework. We are not aware of previous empirical studies that jointly examine the effects of search cost and advertising.

Our estimates suggest that the magnitude of the effect of transparency on prices is not trivial. Relying on the 5% price reduction estimate, we can use back-of-the envelope calculations to assess consumer savings and firms' revenue losses from the increased transparency. In particular, we find that chains lost about 46 million dollars in revenue each month, and average household saved about \$27 per month (about 1.5% of the median wage in Israel in 2015).³⁹. While our findings may support the adoption of similar transparency policies, we also stress that our analysis focuses on a relatively short time period, and that the results regarding the change in prices may change in the long run.

Information disclosure requirements have the potential to affect additional other decisions made by the firms. For instance, transparency can also potentially improve retailers' bargaining power vis-a-vis suppliers. In addition, transparency may affect the frequency at which retailers adjust their prices or their price promotion strategies. Retailers may also take transparency into account when making advertising decisions: For example, loss-leader campaigns may be a useful means of attracting consumers who do not have access to prices of other items in the store; they may be less effective, however, when prices are transparent. We leave these issues for future research.

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³⁹http://www.cbs.gov.il/statistical/mb158h.pdf

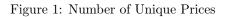
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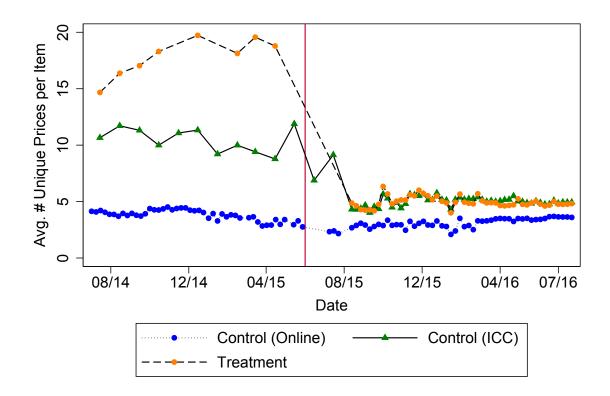
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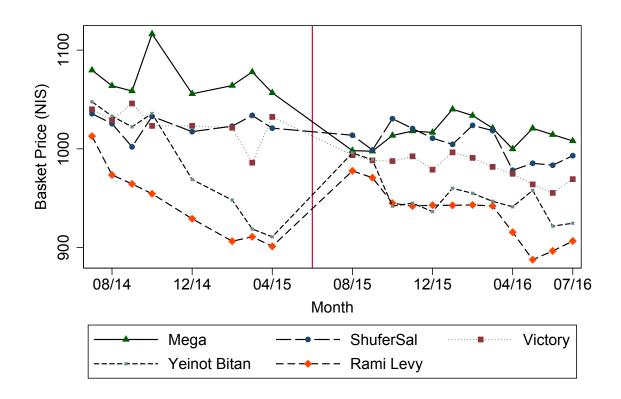
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The figure shows a time series of the average number of unique prices for the treatment group of items, the online control group and the ICC control group. The vertical line denotes the date in which the transparency regulation came into effect. According to the figure, the number of unique prices per item in the treatment group fell significantly after the regulation.

Figure 2: Retailer-Specific Basket Price



The figure shows a time series of the total basket price for each of the five food retailers. The vertical line denotes the date in which the transparency regulation came into effect. A basket consists of 58 items. Monthly basket price is the sum of items average price, where the average is taken over the retailers' stores. Missing price are imputed. The figure suggests that both price dispersion and price levels have decreased after prices became transparent.

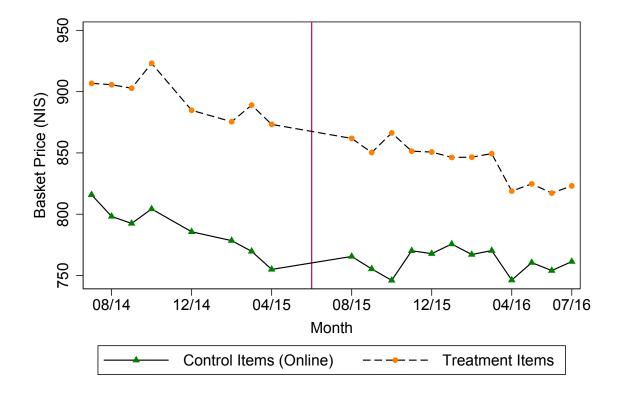
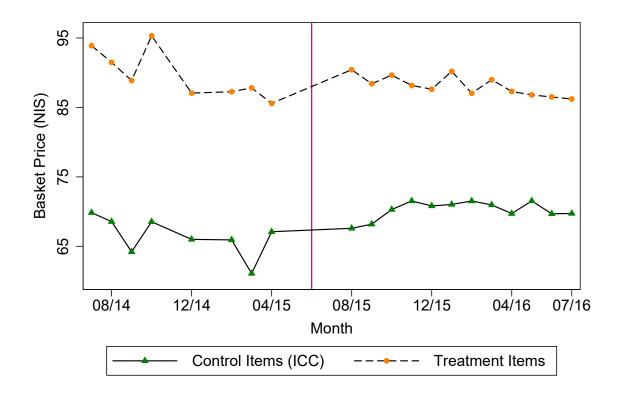


Figure 3: Basket Price in the Online Control and the Treatment Groups

The figure shows a time series of the total basket price, divided into the online (control group) channel and the brick-and-mortar (treatment group) channel. The vertical line denotes the date in which the transparency regulation came into effect. In each channel, prices are averaged across stores and chains and missing prices are imputed. The figure shows that throughout the period the online basket is cheaper than the same basket purchased in the traditional channel. Yet, the difference between the two channels diminishes after the prices in traditional stores become transparent. Similar patterns are observed when we use log(price) instead of price levels.

Figure 4: Comparable Basket Price

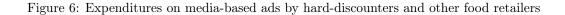


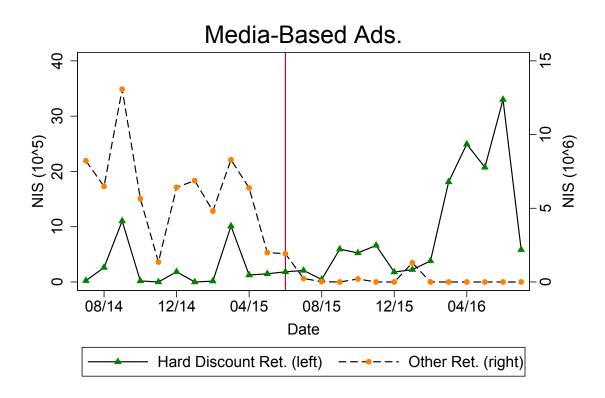
The figure shows a time series of the total basket price for two baskets. One basket consists of six ICC control items and the other consists of six close substitutes items from the treatment group. For instance, a 200- gram jar of Nescafé Taster's Choice instant coffee, included in the ICC group, is matched to a 200- gram jar of Jacobs Kronung Coffee (another quality brand of instant coffee), included in the treatment group. Similarly, we match a 700- ml bottle of Hawaii shampoo in the ICC group to a 700-ml bottle of Crema Nourishing Cream Wash in the treatment group. The figure shows that before prices in the treatment group became transparent, the two baskets exhibited similar patterns, and after prices became transparent the difference between the expenditures on the two baskets diminished.



Figure 5: An example of media-based advertising

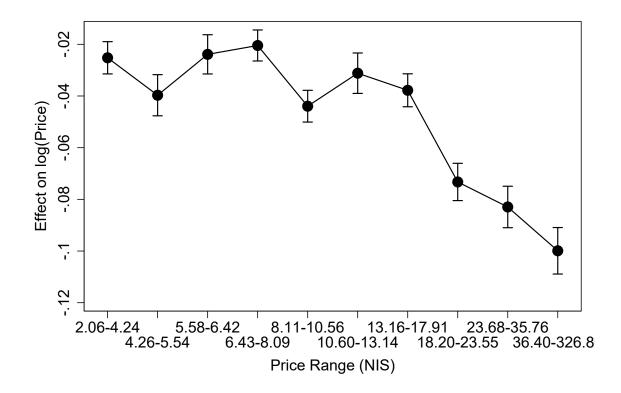
The figure shows an example of an ad by the hard-discount chain Rami Levy in which the chain stresses it offers the cheapest basket in Israel. The ad specifically refers to two price-comparison surveys conducted by the media, One by the newspaper Yediot Aharonot (reported on September 4, 2015) and a second by TV channel 2.





The figure shows on the left vertical axis the monthly expenditures on media-based ads by Rami Levy, the largest hard discount chain in Israel and on the right vertical axis the monthly expenditures on media-based ads by the other supermarket chains. The vertical line corresponds to the date in which the transparency regulation became effective. The Figure shows that after the transparency regulation, expenditures on media-based ads increased for the hard discount chain and decrease for other chains.

Figure 7: The effects of transparency on prices, by price ranges



The figure shows the relationship between the average price of a group of products and the estimated reduction in prices of that group of products. In particular, we use the post-transparency price data and divide the products into 10 deciles based on the mean price. Each dot in the figure corresponds to one decile and as shown there is a clear negative relationship between the average price and the price reduction. That is, more expensive products experienced a larger price drop.

Data Source				
Supermarkets	# Stores	# Items	# Data Pulls	N
Treatment group	61	69	58	159,214
Online	5	69	66	30,865
ICC	61	38	63	115,749
Drugstore	32	28	4	2,789
The table presents information on the number of stores, items and periods for which prices	the number of s	stores, items a	und periods for wi	hich prices
have been collected in the treatment and each of the control groups. For instance, the	ent and each of	the control gr	oups. For instanc	e, the
115,749 prices of the 38 items in the ICC control group were collected in 61 stores at 63	the ICC control	group were o	collected in 61 sto	ores at 63
different weeks.				

Table 1: Descriptive Statistics

		# Unique Prices	rices	Stan	dard Devi	Standard Deviation/Avg.	Percentag	ge Range (10	Percentage Range $(100 * \frac{P_{max} - P_{mix}}{P_{max}})$
	(1)	(2)	(3)	(4)	(5)	(9)	(2)	(8)	(6)
After*Treatment	-10.881^{**} (0.549)	-8.103^{**} (0.812)	-15.920^{**} (1.700)	-0.101^{**} (0.011)	-0.053^{**} (0.012)	-0.083^{**} (0.024)	-27.396^{**} (1.679)	-12.481^{**} (2.436)	-32.962^{**} (6.300)
Week F.E.	>	>		>	>			>	>
Item F.E.	>	>	>	>	>	>	>	>	>
Lin. Item Time Trend	>	>	>	>	>	>	>	>	>
Control Group	Online	ICC	Super Pharm	Online	ICC	Super Pharm	Online	ICC	Super Pharm
Dep. Var. Average Value	16.265	17.317	19.097	0.211	0.211	0.209	55.006	55.642	57.742
R^2	0.785	0.804	0.833	0.392	0.627	0.471	0.488	0.736	0.635
N	9636	6176	1525	9345	6120	1510	9636	6176	1525

Table 2: The Effect of Price Transparency on Price Dispersion

The unit of observation in columns 2, 5 & 8 is item i in date t

Time period covered 7/2014 - 6/2016

Errors are clustered by item

(drugstores, online and ICC). We use prices collected in the year before the transparency regulation for the pre-transparency period, and prices collected in the year after the regulation as our post-transparency regulation. To get a sense of the magnitude of the change in price dispersion following the transparency regulation, we also report the average value of the corresponding dependent variable. For all the measures of price dispersion and for each of the control groups, we find that price dispersion has * p < 0.05, ** p < 0.01The Table presents the regression results of Equation 1 using three different measures of price dispersion as the dependent variable, and each of the three control groups significantly dropped after prices became transparent.

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Table 3:

	(1)	(2)	(3)
	log(Price) log(Price)	$\log(Price)$	$\log(Price)$
$After^{*}Treatment$	-0.051^{**}	-0.052^{**}	-0.040^{**}
	(0.008)	(0.005)	(0.014)
Store F.E.	>	>	>
Date F.E.	>	>	>
Item F.E.	>	>	>
Linear Item Specific Time Trend	>	>	>
Control Group	Online	ICC	Super Pharm
R^{2}	0.937	0.961	0.909
Ν	186810	278228	58358
The unit of observation is item i in store j in time-period t	e j in time-peri	od t	

Time period covered 7/2014 - 6/2016

Errors are clustered by store

* p < 0.05, ** p < 0.01The table presents the regression results of Equation 2, using prices collected during the year before the regulation as the pre-transparency period, and prices collected during the year after the regulation as the post-transparency period. Each column corresponds to a different control group. The results indicate that prices have declined by 4% - 5% after the prices in traditional stores became transparent.

	(1)		(3)
	$\log(Price)$	log(Price)	log(Price)
Premium: After*Treatment	-0.061^{**}	-0.058**	-0.045^{**}
	(0.008)	(0.006)	(0.014)
Discount: After*Treatment	-0.015	-0.026^{**}	0.011
	(0.009)	(0.007)	(0.015)
P-Val: Premium Retailers = Discount Retailers	0.000	0.000	0.000
Store F.E.	>	>	>
Date F.E.	>	>	>
Item F.E.	>	>	>
Linear Item Specific Time Trend	>	>	>
Control Group	Online	ICC	Super Pharm
R^2 –	0.937	0.961	0.909
Ν	186810	278228	58358
The unit of observation is item i in store j in date t			
Time noniced conversed $7/901A = 6/9016$			

Table 4: The Effect of Price Transparency on Prices in Different Retailers.

Time period covered 7/2014 - 6/2016

Errors are clustered by stores

* p < 0.05, ** p < 0.01The Table presents the regression results of a version of Equation 2 in which the post-transparency indicator is interacted with a supermarket type dummy (premium/discount). As shown in the table, the regression results (for each of the control groups) suggest that prices have significantly declined for the large, premium chains and have not changed for the discount chains. We obtain qualitatively results when performing this analysis at the chain-specific level.

	(1)	(2)
	log(Price)	$\log(Price)$
After*Treatment - Low Comp.	-0.059**	
1	(0.006)	
After*Treatment - High Comp.:	-0.044^{**}	
	(0.006)	
After*Treatment		-0.039^{**}
		(0.001)
After*Treatment*Concentration		-0.040^{*}
		(0.015)
Store F.E.	>	>
Date F.E.	>	>
Item F.E.	>	>
Linear Item Specific Time Trend	>	>
Control Group	ICC	ICC
P-Val: Low $Comp = High Comp$.002	
R^2	0.962	0.962
Ν	259557	259557

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Table 5:

The unit of observation is item i in store j in date t

Time period covered 7/2014 - 6/2016

Errors are clustered by stores

* p < 0.05, ** p < 0.01In this table we present the regression results of a version of Equation 2 in which we interact the post-transparency indicator with a measure of the local competition faced by the super-market store. In column 1, the local competition measure is a binary variable for high or low competition, and in column 2 we use a continuous measure of local competition. Be-cause we want to compare price changes across stores that belong to the same chain but that face different local competition, we use only the ICC control group. The results suggest that prices in stores that faced weaker local competition have declined more than stores that faced stronger local competition.

	% Media-Based Ads.	% Media-Based Ads. % Promotional Ads. log(Price)	log(Price)
	(1)	(2)	(3)
Hard Discount * After	48.846^{***}	5.928	
	(9.429)	(10.272)	
Hard Discount Media-Based Ads. Exp.	~	~	-0.013^{***}
			(0.004)
R^2	0.789	0.725	0.937
Ν	191	191	186810
The unit of observation is item i in store j in date t	ate t		

Table 6: Media-based ads and prices

The unit of obsetvation is near i in score j in taw Time period covered 7/2014 - 6/2016

Using online control

All specifications include date FE, item FE, store FE and item-specific linear time trend

Channel variables intensities are standardized

Errors are clustered by stores

* p < 0.1, ** p < 0.05, *** p < 0.01

on media-based ads increased significantly after the transparency regulation. As a falsification test, in column 2 we lation. The unit of observation is week \times hard discount dummy. The observations that refer to non hard-discount chains are aggregated for all retailers and assume the value zero. The dependent variable in column 1 is the weekly share of ads expenditure spent on media-based ads. The results show that spending by the hard-discount chains examine the change in promotional ads over the same time period. We do not find evidence that expenditures on The regression results support (H3) and suggest that media-based ads were more heavily used in time periods in promotional ads by hard-discount chains increased. These results support (H1) and (H2). In column 3 we present regression results examining the relationship between price levels and the use of informative advertising . We esti-Column 1 presents regression results concerning the change in informative advertising after the transparency regumate a treatment intensity version of Equation 2, using the prices of items in the online channel as a control group. The intensity considered is the monthly expenditure on media-based ads by the hard discount retailer (Rami Levy). which prices were set lower.

	(1)	(2)	(3)	(4)
	# Unique Price	Standard Deviation/Avg.	Standard Deviation/Avg. Percentage Range (100 * $\frac{P_{max} - P_{min}}{P_{max}}$)	$\log(Price)$
$After^*Treatment$	-1.465^{**} (0.288)	-0.042^{**} (0.004)	-9.407^{**} (0.726)	-0.022^{**} (0.007)
Date F.E.	>	>	>	>
Item F.E.	>	>	~	>
Linear Item Specific Time Trend	>	>	~	>
Control Group	Grocery Stores	Grocery Stores	Grocery Stores	Grocery Stores
Dep. Var. Average Value	9.856	0.164	38.853	2
R^2	0.832	0.905	0.778	0.975
N	400	400	400	9472

Table 7: The Effect of Price Transparency on Price and Price Dispersion using CBS Data

The unit of observation in column 4 is item i in store j in month tTime period covered 7/2014 - 6/2016

Errors are clustered by month in columns 1-3 and by store in column 4

* p < 0.05, ** p < 0.01

The table contains the regression results using small grocery stores, which were subject to the transparency regulation, as an additional control group, In this analysis, we rely on price data obtained from the Israeli Central Bureau of Statistics on 12 items. We repeat the analysis featured in Tables 2 and 3 using the three measures of price dispersion (columns 1-3) and the price level (column 4). The results indicate that both price dispersion and price levels have significantly declined.

	Baseline Spec.	Popularity	Private Label	Private Label Mehadrin Kosher
	(1)	(2)	(3)	(4)
After*Treatment	-0.032^{**} (0.009)			
After*Treatment (property turned off)	~	-0.046^{**}	-0.030^{**}	-0.033^{**}
		(0.009)	(0.010)	(0.00)
After*Treatment (property turned on)		-0.003	-0.010	0.047^{**}
		(0.00)	(0.010)	(0.011)
P-Val: Property $On = Property Off$		0.000	0.000	0.000
Store F.E.	>	>	>	>
Date F.E.	>	>	>	>
Item F.E.	>	>	>	>
Linear Item Specific Time Trend	>	>	>	>
R^2	0.983	0.983	0.978	0.983
N	4981472	4981472	1005062	4981472

Table 8: The effect of Price Transparency on Prices of different Types of Products

Time period covered 8/2015 - 6/2016

Data set is based on 355 items and 589 stores Errors are clustered by stores

* p < 0.05, ** p < 0.01

The table presents regression results using only data from the post-transparency period, focusing on the changes in the prices of 355 items sold in 589 stores affiliated with the five supermarket chains used in the main analysis. In this analysis, the control group is the prices of the same items sold through the online channel of each the chains. The post-transparency period begins in January 2016. In column 1, we estimate Equation 1 and find results qualitatively similar to the ones shown in Table 3. In column 2, we examine the change in prices of items that are classified based on their popularity. In column 3 we examine the change in prices of private label and branded products including only categories with private label products. In column 5 we examine changes in the prices of items that either follow the more stringent kosher (Mehadrin Kosher) requirements or items that offer standard kosher items including only categories with Mehadrin Kosher products.

Online Appendix to "Informative Advertising and Consumer Search: Evidence From a Price Transparency Regulation in Supermarkets"

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Tel-Aviv University Ben-Gurion University

January 17, 2019

This appendix contains additional regression results and figures that are referred to from the main text.

- Tables -
 - Table 1 reports the regression results for effect of price transparency on prices in drugstores, where disclosure was mandated on July 1, 2017.
 - Table 2 reports the regression results of a chain-specific effect of transparency on price dispersion.
 - Table 5 reports the regression results for the differential effect of price transparency on prices set at the five supermarket chains.
 - Table 3 reports the regression results of price transparency on prices, including a fourth column that focuses on 6 pairs of matched- items, each pair consists from an ICC control item and close substitute item from the treatment group.
 - Table 4 reports the regression results of price transparency using promotional prices the dependent variable instead of list prices, as shown in the main text.
 - Table 6 reports the regression results of the effect of price transparency on advertising expenditures by food retailers.
 - Table 7 the effect of price transparency on price dispersion using similar data sampling frequencies before and after the regulation.
 - Table 8 reports placebo tests using pre-transparency data only, and focusing on five fictitious dates for the beginning date of the transparency implementation.

- Table 9 examines strategic response by Super-Pharm to the transparency regulation by allowing the effect on Super-Pharm's prices to depend on the distance of a Super-Pharm store from the nearest supermarket
- Figures -
 - Figures 1 2 present photos taken from Mysupermarket.co.il, a price comparison website. Figure 1 demonstrates a price comparison for a single item - Nature Valley bar 6-pack - sold by different retailers. Figure 2 shows a price comparison for a basket of 42 items.
 - Figure 3 shows a map that marks the locations of the 27 cities in which the 61 treatment group stores are located.
 - Figure 4 presents a screenshot from Mysupermarket.co.il in which consumers observe prices offered by the online retailers and can choose their preferred retailer to make an online grocery order.
 - Figure 5 shows data on prices for the period after the Israeli Consumer Council began collecting prices in March 2014.
 - Figure 6 includes another example of media-based ad, in which a supermarket chain mentions a price comparison survey that was conducted and reported by the media.
 Figure 7 shows an example of an ad that advertises specific prices of several items, without a reference to the media
 - Figure 8 presents the pre-transparency regulation monthly F.E. for log(price) as the outcome variables using both online and ICC control groups.
 - Figure .. includes the list of products used in the treatment and different control groups.
 - Figure 9 a translation from Hebrew of the transparency regulation.
 - Figure 10 shows evidence that the effect on price levels materialized at the beginning of 2016, several months after prices became transparent.

	(1) # Unique Price	(2) Standard Deviation/Avg.	(2) (3) (3) Standard Deviation/Avg. Percentage Range $(100 * \frac{P_{max} - P_{min}}{P_{max}})$	(4) log(Price)
After*Treatment	-2.861^{*} (1.226)	-0.030 (0.048)	-12.880 (8.845)	-0.069^{**} (0.013)
Date F.E.	>			>
Item F.E.	>	>	>	>
Linear Item Specific Time Trend	>	>	>	>
Control Group	Non-Prescription Drugs	Non-Prescription Drugs	Non-Prescription Drugs	Non-Prescription Drugs
Dep. Var. Average Value	8.000	0.173	41.585	
R^2	0.906	0.845	0.818	0.734
Ν	157	157	157	7867

Table 1: Effect on Price and Price Dispersion in Drugstores

The unit of observation in columns 2-4 is item i in month t

Panel consists of 5 monthly observations - $10/16,\,02/17,\,04/17,\,07/17$ and 08/17

Errors are clustered by store in columns 1-3 and by item in column 4

* p < 0.05, ** p < 0.01

The table includes the results from a supplementary analysis that exploits a follow up transparency regulation (effective starting on July 1, 2017) which required drug stores to post their prices online. This regulation excludes the prices of non-prescription drugs, which we use as a control group. The price data for all the items during the period before July 1, 2017 and for the non-prescription drugs after July 1, 2017 were collected by RAs. After July 1 2017, we use a price-comparison website to obtain the prices for other products sold in drugstores. Similar to the results described in the main text, the table demonstrates that following the price transparency regulation, price dispersion and price levels decrease.

	(1)	(2)	(3)
	# Unique Prices	# Unique Prices	# Unique Prices
Mega: After*Treatment	-3.431^{**}	-1.667^{**}	-5.644^{**}
)	(0.107)	(0.183)	(1.183)
Shufersal: After*Treatment	-3.858^{**}	-1.975^{**}	-7.905^{**}
	(0.147)	(0.189)	(1.232)
Victory: After*Treatment	-2.622^{**}	-1.132^{**}	-2.780^{*}
	(0.095)	(0.198)	(1.249)
Yeinot Bitan: After*Treatment	-3.009**	-1.305^{**}	-3.085*
	(0.086)	(0.189)	(1.252)
Rami Levi: After*Treatment	-3.313^{**}	-1.881**	-4.198^{**}
	(0.094)	(0.198)	(1.266)
Week F.E.	>	>	>
Item F.E.	>	>	>
Lin. Item Time Trend	>	>	>
Control Group	Online	ICC	Super Pharm
R^2 -	0.681	0.599	-0.793
Ν	37685	25978	6120

Table 2: The Effect of Price Transparency on the Number of Unique Prices at the Retailer-Specific Level

Time period covered 7/2014 - 6/2016

Errors are clustered by items

* p < 0.05, ** p < 0.01The table presents regression results of Equation 1 in the main text, where each column corresponds to a different control group. To account for the size heterogeneity between retailers, each regression controls also for the number of observations that the dependent variable is based on. The results indicate that the reduction in the number of unique prices took place in all chains.

	•			
	(1) $\log(Price)$	$ \begin{array}{c} (1) & (2) \\ \log(\text{Price}) & \log(\text{Price}) \end{array} $	(3) log(Price)	(4) log(Price)
After*Treatment	-0.051^{**} (0.008)	-0.052^{**} (0.005)	-0.040^{**} (0.014)	-0.034^{**} (0.006)
Store F.E.	>	>	>	>
Date F.E.	>	>	>	>
Item F.E.	>	>	>	>
Linear Item Specific Time Trend	>	>	>	>
Control Group	Online	ICC	Super Pharm	ICC Comparable
R^2	0.937	0.961	0.909	0.982
Ν	186810	278228	58358	32988
The unit of observation is item i in store j in date t	e j in date t			
Time period covered $7/2014$ - $6/2016$				
Errors are clustered by stores				
* $p < 0.05$, ** $p < 0.01$				

Table 3: Mandatory Disclosure Effect on Price

	(1)	(2)	
	log(Special Frice)	log(Special Frice) log(Special Frice)	log(Special Frice)
After*Treatment	-0.061^{**}	-0.044^{**}	-0.048^{**}
	(0.007)	(0.006)	(0.014)
Store F.E.	>	>	>
Date F.E.	>	>	>
Item F.E.	>	>	>
Linear Item Specific Time Trend	>	>	>
Control Group	Online	ICC	Super Pharm
R^2	0.928	0.950	0.900
N	186810	278228	58358

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Table 4:

Time period covered 7/2014 - 6/2016

Errors are clustered by stores

* p < 0.05, ** p < 0.01The table replicates Table 3 in the main text but uses the (log) of promotional price rather than the (log) of list price as the dependent variable. These promotional prices refer to various promotions, such as quantity discounts or offers that are available only to club members. The table reveals similar qualitative result - a price reduction of 4.3-6.1%, depending on the control group being used.

$ \begin{array}{llllllllllllllllllllllllllllllllllll$		(1) log(Price)	(2) log(Price)	(3) $\log(Price)$
Shuffersal: After*Treatment $\begin{array}{cccccccccccccccccccccccccccccccccccc$	Mega: After*Treatment	-0.084**	-0.047**	-0.060**
Shuffersal: After*Treatment -0.048^{**} -0.053^{**} -0.035^{**} -0.035^{**} Nictory: After*Treatment 0.062^{***} -0.044^{***} -0.052 0.044^{***} -0.052 Yeinot Bitan: After*Treatment 0.020 (0.007) (0.026) (0.016) Rami Levi: After*Treatment -0.025 -0.048^{***} -0.006 (0.016) Rami Levi: After*Treatment -0.009 -0.002 (0.016) (0.016) Bani Levi: After*Treatment -0.009 -0.002 0.021 (0.015) Store F.E. \checkmark)	(0.008)	(0.005)	(0.014)
Victory:After*Treatment (0.06) (0.015) (0.015) Yeinot Bitan:After*Treatment -0.062^* -0.044^{**} -0.052 Yeinot Bitan:After*Treatment -0.025 -0.048^{**} -0.006 Rami Levi:After*Treatment -0.025 -0.048^{**} -0.006 Rami Levi:After*Treatment -0.009 -0.002 0.016 Rami Levi:After*Treatment -0.009 -0.002 0.016 Rami Levi:After*Treatment -0.009 -0.002 0.015 Store F.E. \checkmark \checkmark \checkmark \checkmark Date F.E. \checkmark \checkmark \checkmark \checkmark Linear Item Specific Time Trend \checkmark \checkmark \checkmark Control Group 0.006 0.015 0.0115 NItem F.E. \checkmark \checkmark \checkmark Linear Item Specific Time Trend \checkmark \checkmark \checkmark R ² \checkmark \checkmark \checkmark \checkmark Control Group 0.9037 0.962 0.911 NIseer the regression results for each of here of the new of	Shufersal: After*Treatment	-0.048^{**}	-0.053^{**}	-0.035^{*}
Victory: After*Treatment -0.062^{**} -0.044^{**} -0.052 Yeinot Bitan: After*Treatment -0.025 -0.048^{**} -0.056 (0.006) (0.016) (0.016) Rami Levi: After*Treatment -0.025 -0.048^{**} -0.006 (0.016) (0.016) (0.016) Rami Levi: After*Treatment -0.009 -0.002 (0.015) Barn F.E. $\langle \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ $		(0.008)	(0.006)	(0.015)
Yeinot Bitan: After*Treatment $(0.020) (0.007) (0.026)$ Yeinot Bitan: After*Treatment $(0.014) (0.006) (0.016)$ Rami Levi: After*Treatment $(0.014) (0.006) (0.015)$ Bani Levi: After*Treatment $(0.008) (0.006) (0.015)$ Bani Levi: After*Treatment $(0.008) (0.006) (0.015)$ Store F.E. $(0.008) (0.006) (0.006) (0.015)$ Store F.E. $\langle \langle \rangle \rangle \rangle \rangle \rangle$	Victory: After*Treatment	-0.062**	-0.044^{**}	-0.052
Yeinot Bitan: After*Treatment -0.025 -0.048^{**} -0.006 Rami Levi: After*Treatment -0.025 -0.048^{**} -0.006 Rami Levi: After*Treatment -0.009 -0.002 0.015 Rami Levi: After*Treatment 0.008 (0.016) (0.015) Store F.E. \checkmark \checkmark \checkmark \checkmark Date F.E. \checkmark \checkmark \checkmark \checkmark \checkmark Item F.E. \checkmark \checkmark \checkmark \checkmark \checkmark \checkmark Linear Item Specific Time Trend \checkmark \checkmark \checkmark \checkmark \checkmark Control Group 0.937 0.962 0.911 M ² N^2 0.962 0.911 N The unit of observation is item i in store j in date t The unit of observation is item i in store j in date t The Table presents the regression results of a version of Equation 2 in which the post-transparency indicator is interacted with each supermarket chain dummy. As shown in the table, the regression nesults, for each of the control groups, suggest that prices have significantly declined for the large, more upscale chains (i.e., Mega and Shufersal) and have not changed for the heavy discount chains (i.e. Rami Levy). These results suptor Hamin text.		(0.020)	(0.007)	(0.026)
Rami Levi: After*Treatment (0.014) (0.006) (0.016) Bami Levi: After*Treatment -0.009 -0.002 (0.015) Store F.E. (0.006) (0.015) (0.015) Store F.E. \checkmark \checkmark \checkmark Date F.E. \checkmark \checkmark \checkmark Item F.E. \checkmark \checkmark \checkmark Linear Item Specific Time Trend \checkmark \checkmark Control GroupOnlineICCSuper Pharm R^2 0.937 0.962 0.911 N186810 274669 57734 The unit of observation is item i in store j in date t \cdot Time period covered $7/2014$ - $6/2016$ $6/2016$ 57734 The unit of observation is item i in store j in date t \cdot The unit of observation is item i in store j in date t \cdot The unit of observation is item i in store j in date t \cdot The unit of observation is item i in store j in date t \cdot The unit of observation is item i in store j in date t \cdot The unit of observation is item i in store j in date t \cdot The Table presents the regression results of a version of Equation 2 in which the post-transparency indicator is interacted with each supermarket chain dummy. As shown in the table, the regression results, for each of the control groups, suggest that prices have significantly declined for the large, ince the super supparency indicator is indexed by stores* $p < 0.05$ $* p < 0.01$ * $p < 0.05$ $* p < 0.01$ The Table presents the regression results of a version of Equat	Yeinot Bitan: After*Treatment	-0.025	-0.048^{**}	-0.006
Rami Levi: After*Treatment-0.009-0.0020.021 (0.06) (0.06) (0.015) (0.015) Store F.E. \checkmark \checkmark \checkmark Date F.E. \checkmark \checkmark \checkmark Linear Item Specific Time Trend \checkmark \checkmark Control Group 0.037 0.962 0.911 R ² 0.937 0.962 0.911 NIsoson 0.937 0.962 0.911 NThe unit of observation is item i in store j in date t T \checkmark The unit of observation is item i in store j in date t T \bullet The unit of observation is item i in store j in date t T \bullet The unit of observation is item i in store j in date t T \bullet The unit of observation is item i in store j in date t \bullet \bullet The rube period covered $7/2014$ - $6/2016$ \bullet \bullet Errors are clustered by stores $*_{P} > 0.05$ \bullet * $P < 0.05$ **_{P} > 0.05 \bullet \bullet The unit of observation is interacted with each supermarket chain dummy. As shown in the table, the regression results of a version of Equation 2 in which the post-transparency indicator is interacted with each supermarket cha		(0.014)	(0.006)	(0.016)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Rami Levi: After*Treatment	-0.009	-0.002	0.021
Store F.E. \checkmark Date F.E. \checkmark		(0.008)	(0.006)	(0.015)
Date F.E. \checkmark Item F.E. \checkmark Item F.E. \checkmark Item F.E. \checkmark	Store F.E.	>	>	>
Item F.E. \checkmark Linear Item Specific Time Trend \checkmark	Date F.E.	>	>	>
Linear Item Specific Time Trend \checkmark	Item F.E.	>	>	>
Control GroupOnlineICCSuper Pharm R^2 0.9370.9620.911N18681027466957734The unit of observation is item i in store j in date t5773457734Time period covered 7/2014 - 6/2016Errors are clustered by stores $* p < 0.05$, $** p < 0.01$ * $p < 0.05$, $** p < 0.01$ resents the regression results of a version of Equation 2 in which the post-transparency indicator is interacted with each supermarket chain dummy. As shown in the table, the regression results, for each of the control groups, suggest that prices have significantly declined for the large, more upscale chains (i.e., Mega and Shufersal) and have not changed for the heavy discount chains (i.e. Rami Levy). These results support H3 in the main text.	Linear Item Specific Time Trend	>	>	>
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Control Group	Online	ICC	Super Pharm
N 186810 274669 57734 The unit of observation is item <i>i</i> in store <i>j</i> in date <i>t</i> Time period covered 7/2014 - 6/2016 Errors are clustered by stores * $p < 0.05$, ** $p < 0.01$ The Table presents the regression results of a version of Equation 2 in which the post-transparency indicator is interacted with each supermarket chain dummy. As shown in the table, the regression results, for each of the control groups, suggest that prices have significantly declined for the large, more upscale chains (i.e., Mega and Shufersal) and have not changed for the heavy discount chains (i.e. Rami Levy). These results support H3 in the main text.	R^2	0.937	0.962	0.911
The unit of observation is item i in store j in date t Time period covered 7/2014 - 6/2016 Errors are clustered by stores * $p < 0.05$, ** $p < 0.01$ The Table presents the regression results of a version of Equation 2 in which the post-transparency indicator is interacted with each supermarket chain dummy. As shown in the table, the regression results, for each of the control groups, suggest that prices have significantly declined for the large, more upscale chains (i.e., Mega and Shufersal) and have not changed for the heavy discount chains (i.e. Rami Levy). These results support H3 in the main text.	Ν	186810	274669	57734
Time period covered 7/2014 - 6/2016 Errors are clustered by stores * p < 0.05, $** p < 0.01The Table presents the regression results of a version of Equation 2 in which the post-transparencyindicator is interacted with each supermarket chain dummy. As shown in the table, the regressionresults, for each of the control groups, suggest that prices have significantly declined for the large,more upscale chains (i.e., Mega and Shufesal) and have not changed for the heavy discount chains(i.e. Rami Levy). These results support H3 in the main text.$	The unit of observation is item i in store	j in date t		
Errors are clustered by stores * $p < 0.05$, ** $p < 0.01$ The Table presents the regression results of a version of Equation 2 in which the post-transparency indicator is interacted with each supermarket chain dummy. As shown in the table, the regression results, for each of the control groups, suggest that prices have significantly declined for the large, more upscale chains (i.e., Mega and Shufersal) and have not changed for the heavy discount chains (i.e. Rami Levy). These results support H3 in the main text.	Time period covered $7/2014 - 6/2016$			
* $p < 0.05$, ** $p < 0.01$ The Table presents the regression results of a version of Equation 2 in which the post-transparency indicator is interacted with each supermarket chain dummy. As shown in the table, the regression results, for each of the control groups, suggest that prices have significantly declined for the large, more upscale chains (i.e., Mega and Shufersal) and have not changed for the heavy discount chains (i.e. Rami Levy). These results support H3 in the main text.	Errors are clustered by stores			
The ratio presents are regression results of a version of requestion 2 m which the post-comparency indicator is interacted with each supermarket chain dumny. As shown in the table, the regression results, for each of the control groups, suggest that prices have significantly declined for the large, more upscale chains (i.e., Mega and Shufersal) and have not changed for the heavy discount chains (i.e. Rami Levy). These results support H3 in the main text.	* $p < 0.05$, ** $p < 0.01$ The Table means the measure the mean set of the m	of a monitor o	f Equation 9 in m	hich the next transmension
more upscale chains (i.e., Mega and Shufersal) and have not changed for the heavy discount chains (i.e. Rami Levy). These results support H3 in the main text.	indicator is interacted with each supern results, for each of the control groups, s	arket chain du uggest that pr	immy. As shown ices have significa	in the table, the regression atly declined for the large,
	more upscale chains (i.e., Mega and Shu (i.e. Rami Levy). These results support	fersal) and hav H3 in the mai	/e not changed foi n text.	the heavy discount chains

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Table 6: The Effect of Price Transparency on Advertising Expenditure

	% Media-Based Ads.	% Promotional Ads.
	(1)	(2)
Hard Discount * After	48.846***	5.928
	(9.429)	(10.272)
Month F.E.	\checkmark	\checkmark
Hard Discount F.E.	\checkmark	\checkmark
R^2	0.789	0.725
Ν	191	191

* p < 0.1, ** p < 0.05, *** p < 0.01The table contains a regression analysis examining the change in advertising expenditures by food retailers, before and after the transparency regulation. The unit of observation is week \times hard discount dummy. The observations that refer to non harddiscount chains are aggregated for all retailers and assume the value. The dependent variable in column 1 is the weekly share of ads expenditure spent on media-based ads (see for example Figures 5 and 6 in the online appendix). The dependent variable in column 2 is the weekly share of ads expenditure spent on promotional ads (see for example Figure 7 in the online appendix). The results show that spending by the hard-discount chains on media-based ads increased significantly after the transparency regulation, whereas spending on promotional ads have not changed.

	#	# Unique Prices	ses	Standa	$Standard \ Deviation/Avg.$	on/Avg.	$\operatorname{Percentage}$	Percentage Range (100 * $\frac{P_{max} - P_{min}}{P_{max}}$	$* \ \frac{P_{max} - P_{min}}{P_{max}}$
	(1)	(2)	(3)	(4)	(5)	(9)	(2)	(8)	(6)
After*Treatment	-10.941^{**} (0.625)	-8.278^{**} (0.831)	-8.082^{**} (0.828)	-0.151^{**} (0.023)	-0.053^{**} (0.013)	-0.049^{**} (0.013)	-37.600^{**} (3.027)	-12.824^{**} (2.584)	-11.712^{**} (2.503)
Week F.E.	>	>	>	>	>	>	>	>	>
Item F.E.	>	>	>	>	>	>	>	>	>
Lin. Item Time Trend	>	>	>	>	>	>	>	>	>
Control Group	Online	ICC 1	ICC 2	Online	ICC 1	ICC 2	Online	ICC 1	ICC 2
Dep. Var. Average Value	16.265	17.317	17.317	0.211	0.211	0.211	55.006	55.642	55.642
R^2	0.836	0.828	0.823	0.459	0.615	0.614	0.637	0.752	0.748
N	2657	2070	2068	2568	2042	2042	2657	2070	2068

Table 7: The Effect of Transparency on Price Dispersion, using Similar Sampling Frequencies

ICC 1 refers to taking a single random week within month in the ICC-after period, but this week is the same for all stores ICC 2 refers to taking a single random week within month in the ICC-after period, but this week may differ across stores

Time period covered 7/2014 - 6/2016

To account for the different sampling frequncies in the different data sources,

keep a single observation for each item-treatment-month tripplet.

For the treatment-after, and online before and after keep the last obs. per month

For the ICC after keep a single week chosen at random.

Errors are clustered by items

* p < 0.05, ** p < 0.01

	(1) log(Price)	$ \begin{array}{c} (1) & (2) \\ \log(\text{Price}) & \log(\text{Price}) \end{array} $	$\begin{array}{c} (3) \\ \log(\mathrm{Price}) & \mathrm{l} \end{array}$	(4) og(Price)	(5) log(Price) lc	(6) g(Price)	(7) log(Price) lo	(8) pg(Price	(9) log(Price)	(10) $\log(Price)$
After*Treatment	0.024 (0.013)	0.003 (0.018)	0.010 (0.021)	0.021 (0.023)	0.028 (0.035)	0.000 (0.008)	0.001 (0.007)	-0.005 (0.008)	-0.008 (0.016)	0.011 (0.007)
Placebo Date	15/9/14	15/10/14	15/12/14	15/2/15	15/3/15	15/9/14	15/10/14	15/12/14	15/2/15	15/3/15
Store F.E.	>	>	>	>	>	>	>	` >	>	>
Date F.E.	>	>	>	>	>	>	>	>	>	>
Item F.E.	>	>	>	>	>	>	>	>	>	>
Linear Item Spec. Trend	>	>	>	>	>	>	>	>	>	>
Control Group	Online	Online	Online	Online	Online	ICC	ICC	ICC	ICC	ICC
R^2	0.873	0.873	0.873	0.873	0.873	0.925	0.925	0.925	0.925	0.925
Ν	34417	34417	34417	34417	34417	42186	42186	42186	42186	42186

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Time period covered 7/2014 - 7/2015Five differet nplacebo dates are used

Errors are clustered by stores

* p < 0.05, ** p < 0.01The table contains placebo regressions using price data from time periods earlier than the implementation of the transparency regulation. It aims to address the concern that other (unobserved) events that occurred prior to the implementation of the reform are the driving forces of the results. Columns 1-5 uses the online control group and columns 6-10 uses the ICC control. For each control group, five specifications are estimated, each using a different date as the fictitious date for the implementation of the reform implementation. The non-significant point estimates of the $After \times Treatment$ variable demonstrate that it is unlikely that the results are driven by an (unobserved) event that occurred prior to the regulation.

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		101	
	(1)	(2)	(3)
	$\log(\text{price})$	$\log(\text{price})$	$\log(price)$
04/15	0.011	0.014	0.013
	(0.010)	(0.017)	(0.013)
10/15	-0.036^{**}	-0.028	-0.038^{**}
	(0.010)	(0.016)	(0.014)
04/16	-0.049^{**}	-0.041^{*}	-0.048^{**}
	(0.011)	(0.016)	(0.016)
04/15 * Close Competitor Indicator		-0.005	
		(0.020)	
10/15 * Close Competitor Indicator		-0.014	
		(0.020)	
04/16 * Close Competitor Indicator		-0.012	
		(020.0)	
10/15 * Distance (meter)			-0.000
			(0.000)
04/15 * Distance (meter)			0.000
			(0.000)
10/16 * Distance (meter)			-0.000
			(0.000)
Store F.E.	>	>	>
Date F.E.	>	>	>
Item F.E.	>	>	>
R^2	0.887	0.887	0.887
Ν	2386	2386	2386
The unit of observation is item i in Super Pharm store j in month t	ıarm store j i	n month t	
Data were collected in four months: $10/14$, $04/15$, $10/15$ and $04/16$	14/15, 10/15 a	nd 04/16	
Errors are clustered by store			
The omitted month is $10/15$			
Close competitor indicator $= 1$ if the closest supermerket is located less	supermerket	is located less	
than 204 meter. which is the median distance	Ű		

than 204 meter, which is the median distance

* p < 0.05, ** p < 0.01

The table examines the extent to which Super-Pharm pricing is affected by the proximity to competing supermarkets. The analysis is based on price data from Super-Pharm's stores before and after the transparency regulation took effect in May 2015. For each drugstore, we measure the distance to the closest supermarket. The regression presented in column 1 abstracts from strategic response, while the regressions presented in columns 2 and 3 allow the month F.E. to depend on the distance from the closest supermarket. In column 2 the distinction is between stores that are below or above the median distance from the closest supermarket. In column 3 the effect of the distance on the month F.E. is assumed to be linear in the distance. The table demonstrates that while prices decreased over time, this price reduction is not correlated with the distance from the closest supermarket.

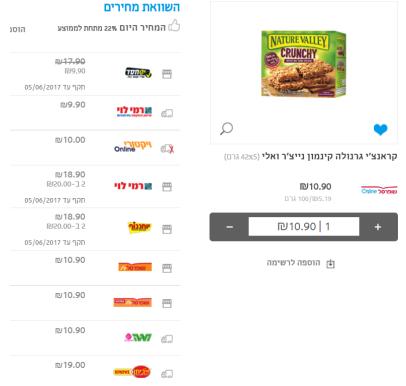


Figure 1: Single Item Price Comparison

The left side of the figure includes a list of retailers, sorted by price, that sell the item whose photo is shown on the right side of the figure. The small icon located to the right of the retailer name indicates whether the quoted price refers to a physical store of that retailer (indicated by a stand) or to an online store (indicated by a truck).

הסל שי	שלך ב :	: עלות הסל	מס מוצרים :	כתובת :
ภาวเม 🕄	Unline Condine	₪589.74	42 מוצרים	
<u> </u>	מרמי לוי 🚥	₪500.15	2 חסרים	בחירת סניף
æ	אושר עד	₪506.20	1 חסרים	בחירת סניף
Ē	יותננוף	₪528.54	8 חסרים	בחירת סניף
6	ויקטורי Online	₪532.35		ן החליפו חנות [
Æ	ייוק הטקמג באיטרנט סייוק אטקמג באיטרנט	回540.59	1 חסרים	ן† החליפו חנות
	ויקטורג	₪541.70		בחירת סניף
		₪571.34	4 חסרים	בחירת סניף

Figure 2: Price Comparison from a Price Comparison Platform

The Figure shows a comparison of the price of a basket of items taken from mysupermarket.co.il, a price comparison platform. The baskets are sorted by price. The first column refers to the name of the retailer. The second refers to the basket price and the third indicates the number of items that are unavailable in the corresponding retailer. The small icon located to the right of the retailer name in the first column indicates whether the quoted basket price refers to a physical store of that retailer (indicated by a stand) or to an online store (indicated by a truck).

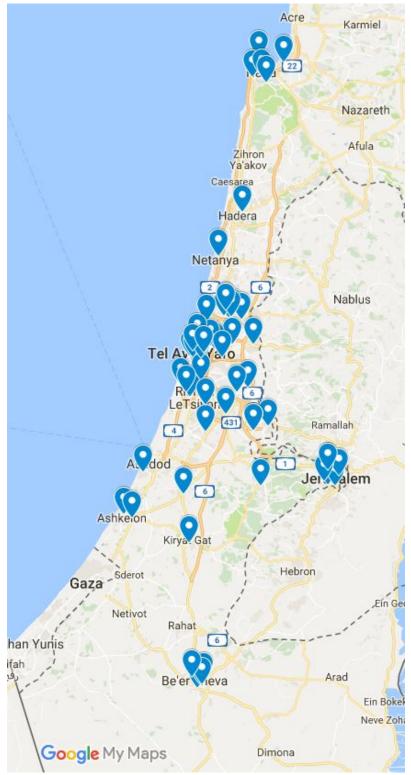
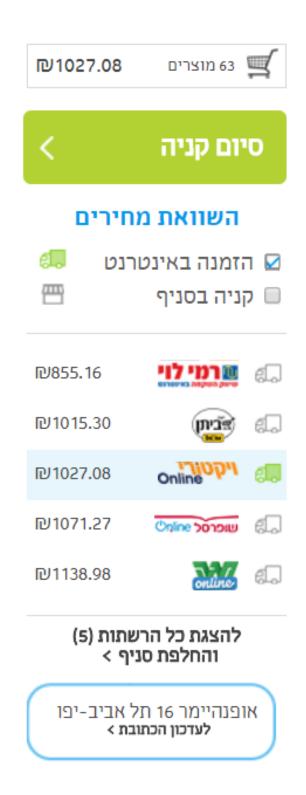


Figure 3: Map of Store Locations

The figure shows the locations of the 61 stores comprise the treatment group. These stores are located in 27 different cities.

Figure 4: Online shopping platform



The Figure shows a screen shot from MySupermarket.co.il webpage where consumers observe the respective price by each online retailer and can choose which online retailer they want to order from. Rami Levi, the heavy discount chain offers the cheapest price for this basket (855 shekels).

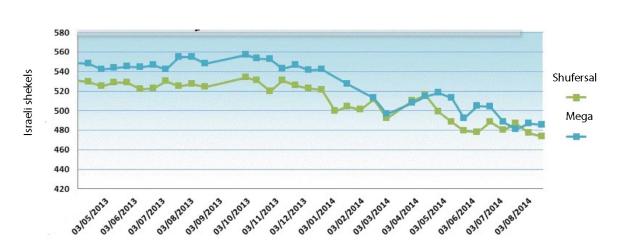


Figure 5: ICC basket prices

The figure shows the basket price of ICC products after the ICC began collecting prices in April 2013, nearly 2 years before the transparency regulation came into effect. The figure shows that prices of the ICC items have declined few months after the ICC began collecting these prices, providing suggestive evidence that transparency resulted in lower prices for these items.



Figure 6: An example of media-based advertising

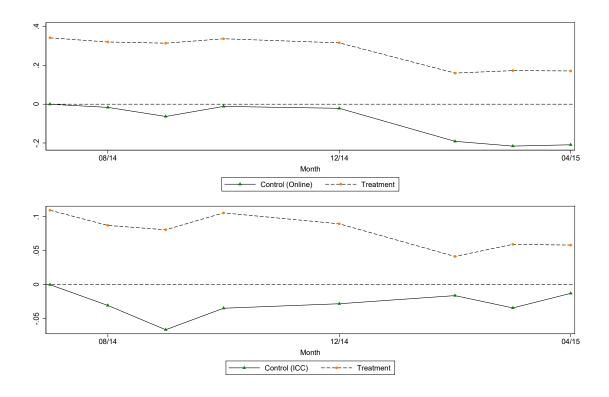
The Yeinot Bitan supermarket chain ad includes two references to comparisons of sales expenditures at supermarket chains which was conducted by a national radio station and a leading online news portal. In both examples, Yeinot Bitan offers the cheapest option.



Figure 7: An example of promotional/price advertising

The Victory supermarket chain ad includes several price promotions for products sold in its stores. Unlike the previous examples, there is no reference to a particular media source.

Figure 8: Validating the Parallel Time Trend Assumption - Monthly Effect on log(Price) by Group Association



Each figure presents the pre-regulation period group specific monthly effects estimated in regressions using log(price) as the dependent variable. Figures are distinguished by the control group used in each of them. The upper figure is based on the online control and the lower figure is based on the ICC control.

Figure 9: Translation of the transparency regulations

Regulations for Promotion of Competition in the Food Industry (Price Transparency)

1. In these regulations -

"Website" - a website of a large retailer;

"Barcode" - an identification number imprinted on or related to the product, used to identify the product of a large retailer;

"Total price" - as defined in section 29 of the Law.

2. A large retailer will publish to the public on its website, its chain of stores and, separately for each of its stores, the updated total price at the time of publication of each commodity sold in its stores in this manner:

(1) The website of the retail chain will be published on the website, as well as the file of commodities and prices and a collection of promotions for each of its stores separately (hereinafter - the files);

(2) file names must contain a fixed prefix consisting of network code, subnet code, and store number; In addition, each file name will include a time stamp (TIME STAMP) that includes the time and time of the file delivery;

(3) The chain of stores of the chain shall be in a uniform structure and shall include all and only the fields, as specified in the First Addition;

(4) The list of commodities and prices shall be in a uniform structure and shall include all and all the fields, as specified in the Second Addition;

(5) The promotion file shall be in a uniform structure and shall include fields as specified in the Third Addition.

(6) The promotional code shall be as specified in the Fourth Addition;

(7) The promotional data files will be in an XML format.

3. A large retailer will update the files on the website as follows:

(1) Every day on which a branch of a large retailer is opened, a large retailer shall publish the file of goods and prices and the complete list of promotions, no later than the opening hour of the store;

(2) no later than one hour from the date of update in the store's stores as stated in section 30 (a) of the Law, a large retailer will publish an update to the list of commodities and prices and the promotions, including all updates that occurred on that day. This update will include, inter alia, changes in the prices of commodities, including promotions, the addition of records for new commodities and the removal of records of goods whose sale has ceased;

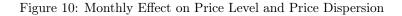
4. A large retailer will allow access to advertising on the website in this manner:

(1) The files may be downloaded in XML, Excel, Gzip and Deflate format as well as printing them;

(2) Every surfer will be able to retrieve any file on an ongoing basis; For this purpose, sufficient capacity of computer resources will be provided for recording, storing, and retrieving files;

(3) The availability of the website will be at least 99.5%.

5. A large retailer will keep the files, including their updating, for a period of three months from the date of their publication.





The figure shows the monthly F.E. from two variants of Equations ?? and ?? in which the effect is estimated for each and every month before and after the regulation went into effect. For each monthly estimate the 95% confidence interval is presented. The figure shows that the change in price dispersion occurred shortly after the regulation became effective, and that the change in price levels materialized later, at the beginning of 2016.