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The Effects of Mandatory Disclosure of Supermarket Prices

Abstract

We study how mandatory online disclosure of supermarket prices affects prices and price dispersion in brick-and-mortar stores. Using data collected before and after a transparency regulation went into effect in the Israeli food retail market, multiple complementary control groups and relying on a differences-in-differences research design, we document a sharp decline in price dispersion and a 4% to 5% drop in prices following the transparency regulation. The price drop varied across stores and products; it was smaller among private-label products than among branded products, and it was smaller among stores and products that were likely to have been associated with more intense search patterns even before prices became transparent (e.g., products in heavy-discount chains; popular products; products that meet stringent kosher requirements). Finally, we show that prices declined as more consumers used price-comparison websites, and we highlight the role of media coverage in encouraging retailers to set lower prices.

JEL-codes: D830, L810, L660.

Keywords: price transparency, information, mandatory disclosure, retail food, supermarkets.

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1 Introduction

Numerous websites and online platforms currently provide information on prices, product availability and quality measures, and these have had a tremendous impact on retail markets, consumers and firms. As is often the case, the public sector has been quite slow to adapt to these technological changes and government agencies and legislators have only recently begun to embrace measures that take advantage of the Internet as a means to disclose and disseminate information. Such regulatory initiatives include requirements from public entities to publish information online about their practices,[1] and in other cases these regulations impose a mandate on firms to disclose real time prices. For instance, in various Latin American countries, such as Argentina, Uruguay and Mexico, governments require retailers to post online the prices of many of the products that they sell.[2] In other countries, such as Germany, Italy, Australia, South Korea and Chile, gasoline prices are now available online.

What are the effects of transparency regulations on price dispersion, and on retailers' tendency to price discriminate? Do these transparency regulations result in higher or lower prices? Do these effects differ across stores and products? While the motivation behind these transparency regulations is to foster competition and incentivize retailers to lower prices, the availability of price information can also be detrimental to competition, as firms can use this information to coordinate and subsequently increase prices. Clearly, if the pro-competitive impact of price transparency is stronger than its anti-competitive impact, then it is worthwhile for policy makers to advance policies that mandate price disclosure. But, if such initiatives actually help firms to tacitly collude, then such policies should be abandoned. Price transparency regulations are also related to a recent debate in the macroeconomic literature. Because online prices are more accessible than off-line prices, they offer an attractive solution for measuring inflation and price rigidity. However, since transactions conducted off-line still account for the majority of the economy, it is unclear to what extent online prices accurately represent off-line prices and, in particular, how transparency regulations affect price differences between online and brick-and-mortar stores. Surprisingly, though these issues are central to economics in general, and specifically to the fields of IO and macroeconomics, the empirical evidence on the impact of mandatory online disclosure of prices hardly exists.

[1] The aim of these transparency regulations is often to increase accountability and curtail spending. For instance, as of 2014, the DATA Act requires the U.S. federal government to transform its spending into open data (https://www.datacoalition.org/issues/data-act). Also in 2014, the Centers for Medicaid Services https://preview.overleaf.com/public/xhyjfsgnyqrf/images/532600898e25b4cef84205ec564cd6ed5c74eff4.jpegdisclosed payment information for the first time as part of its Open Payment program (https://www.cms.gov/Newsroom/MediaReleaseDatabase/Press-releases/2014-Press-releases-items/2014-09-30.html). In Europe, regulators have also recently sought to use information disclosure as a means of ensuring the competitiveness of the e-commerce environment. See, for instance, the Sector Inquiry published by the European Commission in May 2017.

[2] In 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 across different retailers. The website is called "Precios Claros" (https://www.preciosclaros.gob.ar) and it provides daily prices for about 20,000 products sold in 2,300 different physical locations in Argentina.

In this paper, we begin to fill this gap by studying the impact of a mandatory price disclosure regulation in the Israeli supermarket industry. The food retail industry is a meaningful domain in which to begin to unpack the economic effects of mandatory information disclosure, given that consumers spend about one-sixth of their disposable income on food, and that fluctuations in food prices have the potential to drive profound societal effects. In particular, food prices worldwide underwent a steep increase between 2005 and 2011, and this increase was associated with social unrest and even violence in both developed and developing countries.[3] In Israel, social protests in 2011 regarding, among other concerns, the high prices of food ultimately culminated in the legislation of the Food Act in March 2014. An important component of the Food Act was a clause requiring supermarket chains to post their prices online and to update their prices continuously. This requirement came into effect in May 2015, and since then Israeli supermarkets have been posting and continuously updating the prices of each and every item sold in their stores. Starting in August 2015, independent websites have begun to offer price comparison services, which are freely available to consumers. We take advantage of these changes to evaluate the effects of transparency on the prices that retailers set. We further examine how these effects vary across stores operating under different market conditions, and across products that can be characterized with different search patterns by consumers.

To reliably identify the impact of transparency on prices, it is necessary to overcome several challenges. The first is the need to access price data corresponding to the period after the change in transparency as well as to the period before, when such data may not be readily available. To address this challenge, we exploited the fact that the Food Act went into effect more than a year after it passed in the parliament. Over the course of the year before the regulation took effect, we hired a survey firm to collect data on prices of multiple items sold in 61 traditional stores. For the period after the regulation went into effect (the post-transparency period), we collected data from one of the price comparison platforms. A second challenge is the need to take into account additional factors, aside from transparency, that might affect pricing decisions (e.g., local competition, costs, seasonality and consumers' tastes). In particular, 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. Consider, for instance, Figure 1 which 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. The figure suggests that both prices and price dispersion dropped after May 2015, when the transparency regulation went into effect. Price dispersion

[3]For instance, Spain, Greece and Israel have witnessed social unrest that is often linked to the rise in food prices (Bellemare (2015)). Though price increases are partially explained by increased demand from emerging economies, drought conditions and changes in commodity markets, policy makers are looking for ways to improve the functioning of food markets and ensure that food prices do not soar. The OECD, for instance, published a lengthy report (OECD (2013)) describing the policies taken by each OECD country to improve the operations of the retail food market in that country.

declined soon after transparency became mandatory, whereas the decline in prices seems to have occurred several months later. Yet, it is impossible to tell from the figure whether these patterns are indeed attributable to the transparency regulation taking effect, or whether additional factors might have caused these patterns.

Our research design enables us to address such concerns. First, we use price data on many food items sold in multiple stores. In some specifications, we use weekly price data on more than 350 food items sold in nearly 600 stores. The price data were collected at multiple points in time both in the year that preceded the transparency regulation as well as in the following year. Our reliance on such a large set of items and stores mitigates concerns that the observed price changes are driven by unobserved local trends or changes that are relevant to specific types of products. Second, and perhaps more importantly, the identification of the effects of the transparency regulation come from comparing changes in prices among a group of "treatment" items, that is items that became transparent after the regulation, against price changes in four distinct control groups. The first control group consists of the same products included in the treatment group, but sold in the online channels of the various supermarket chains considered herein. These items constitute a useful control group because their prices were transparent before the transparency regulation became effective (and remained transparent thereafter). The second control group consists of products whose prices in specific stores, including the stores in which the market survey firm collected the prices of products included the treatment group, have been collected by the Israeli Consumer Council (ICC) since March 2013. The prices of these products, which do not overlap with the products in our treatment group, are often cited in the media and referred to in chains' ad campaigns as a reliable source of price data. Thus, effectively, the products in the ICC basket constitute another set of items whose prices were transparent before and after the transparency regulation came into effect. The third control group consists of products that also appear in the treatment group, but sold in Super-Pharm, the largest drugstore chain in Israel. Drugstores were exempt from the Food Act, and therefore Super-Pharm's prices are not likely to have been affected by the mandate for transparency. The final control group consists of a subset of the products in our treatment group, but sold in mom-and-pop grocery stores, which were also exempt from the transparency regulation. In the empirical specifications, we also include a rich set of fixed effects, such as store, item and date. Although each of the control groups might be subject to critique, the fact that we use several (complementary) control groups and obtain similar results, alleviate potential concerns and gives us confidence that our results indeed reflect the impact of transparency on prices. To further substantiate our claim that price transparency is driving our results, in the analysis we experiment with several alternative specifications and also check that the parallel trend assumption holds (see Section 5.5.2 and Figure 3 in the Online Appendix).

Our first analyses examine how price dispersion changed after the transparency regulation went into effect. We find that shortly after prices became transparent, the average number of distinct prices that a given item was sold for in brick-and-mortar supermarket stores decreased significantly. Before price became transparent, we observed 16 distinct prices per item, on average, across the 61 stores from which we collected data during that period. After prices became transparent, the average number of distinct prices across these stores fell to about 5, resulting in lower price dispersion overall, and nearly similar prices across stores affiliated with the same chain. Figure 2 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. This difference is consistent with our view that the prices of products in these two control groups, and especially the prices of products that are sold online were transparent already before the regulation. Quickly after the regulation went into effect, the differences between the treatment and the control groups diminished. We obtain similar findings when using more conventional measures of price dispersion, such as the coefficient of variation or the percentage price range.

Next, we turn to analyzing the impact of the transparency regulation on price levels. Our estimation 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 further examine how the effect on prices varied across different chains and across different local competitive environments. We find that prices primarily decreased among chains that are considered more expensive, whereas the impact of the regulation on heavy-discount chains was largely insignificant. We also find that prices have declined less in supermarkets that faced fiercer local competition. Arguably, consumers who purchase at heavy-discount chains or at stores that face fiercer competition have lower search costs, already before prices became transparent. Therefore, price transparency is likely to have less of an impact in these stores.

After establishing the decline in both price dispersion and price levels, we examine the timeline over which these changes took place. We show that the change in price dispersion occurred immediately after the regulation became effective, whereas the change in price levels materialized several months afterwards, at the beginning of 2016. In our next set of analyses, we delve deeper and attempt to characterize how price changes in the wake of the transparency regulation varied across different types of products. In this analysis, we analyze data only from August 2015 and onward (the post-transparency period). Our focus on this period, when price data were made accessible to the public, enables us to collect additional data for a large number of products (specifically, 355 products), and a much wider set of stores (589 stores). To facilitate the identification of the effect of transparency, we take advantage of our previous finding that changes in price levels did not surface until early 2016, and redefine the post-transparency period between January and July 2016, and the pre-transparency period between August and December 2015. This empirical analysis suggests that the prices of more expensive and less popular products fell more. We also find that the prices of branded products, that could be compared across retailers, decreased more than did the prices of "similar" private-label products. Finally, we show that the prices of goods that conform to the most stringent levels of Jewish dietary law ("Mehadrin kosher" items)— which certain groups of customers are likely to actively seek out on a regular basis — decreased less than the prices of "similar" regular kosher items.

Our findings regarding the decline in prices are consistent with standard search models: prices fall as search costs decline. Furthermore, the decline in prices is smaller among products and stores that can be characterized by a higher level of consumer search, already in the pre-transparency period (see Sorensen (2000) and Lach (2007) for related arguments). We also provide evidence on increased consumer search by showing that the reduction in prices is negatively associated with the extent to which customers used the price comparison websites. In particular, we observe an increase in usage of the three websites in the beginning of 2016, when prices have declined. In the Online Appendix, we present evidence that prices have fallen more in localities that more consumers accessed price comparison websites. We also highlight the role of the media in disciplining retailers' pricing decisions. We argue that media outlets act as intermediaries in disseminating available price information to the market. Moreover, beyond simply making customers aware of the prices on the market, media coverage of food retail prices might create positive incentives for supermarket chains and managers to keep prices low - e.g., by providing them with opportunities for favorable publicity. With regards to the drop in price dispersion and particularly in the number of unique prices per item, we claim that fairness concerns, exacerbated by the transparency regulation, contributed to chains' decisions to adopt a nearly uniform pricing policy.

The remainder of the paper is organized as follows. In the next section we review the relevant literature. In Section 3 we provide the necessary background on the regulation and the Israeli food retail sector. In Section 4 we describe the research design and the data, and in Section 5 we present the estimation results. We discuss our findings and the potential mechanisms driving them in Section 6. Section 7 concludes.

2 Related literature

Economic theory provides conflicting predictions regarding the consequences of mandatory disclosure of prices. On the one hand, standard search models show that as search costs decline, both price levels and price dispersion are expected to decrease (e.g., Salop and Stiglitz (1977); Stahl (1989); Stigler (1961)). Theoretical search models also emphasize that not all consumers need to actively search for cheap prices in order to influence them. In particular, price may decrease even when only a fraction of consumers are informed about prices. On the other hand, studies in industrial organization (e.g., Green and Porter (1984), Rotemberg and Saloner (1986), Campbell et al. (2005)) have shown that better access to price information can help retailers monitor their rivals' prices and adjust their own accordingly, thereby facilitating tacit collusion. In this case, we might expect transparency to lead prices to increase and price dispersion to fall.

Only few empirical studies have investigated the economic consequences of mandatory disclosure of prices or wages. Mas (2017) examine how various outcomes were affected by pay transparency regulations that required the wages of public officials to be disclosed online. Other papers that studied the effects of mandatory disclosure predominantly focused on the gasoline market and typically used price data only from the post-transparency period. Byrne and Roos (2017) document how tacit collusion was initiated and formed during the post-transparency period. Albek et al. (1997) used post-transparency data to show that the price of ready-mixed concrete in Denmark significantly increased after firms were required to disclose prices. Luco and Lemus (2017) also use post-transparency price data from the gasoline market to show that gasoline stations in Chile misreport prices in areas where consumers were more likely to search for low prices. Luco (2017) used gasoline prices collected before and after a mandatory disclosure regulation in Chile, and found that prices increased after the regulation. Our paper is different from these studies for several reasons. First, we focus on the food retail market, in which the consumer purchases a bundle of goods rather than one product. This difference may have implications on firms' ability to coordinate prices as opposed to the gasoline markets in which few products are sold. In Section 5.4, we exploit this difference to further examine why the prices of certain products fell more than the prices of other products. Second, our data and research design enable us to use both pre- and post-transparency price data to examine how the effect of the regulation depends on the pre-transparency market conditions. Finally, our qualitative results differ substantially from the results documented in previous studies.

In contrast to the dearth of evidence on the impact of mandatory price disclosure, few streams of the literature study the effects of voluntary price disclosure. First, early studies in the advertising literature have explored how shifts in advertising affects prices and other performance measures. For instance, Milyo and Waldfoegel (1999) investigated how removing a ban on advertising prices of alcohol products affected retailers‘ decisions which alcohol products to advertise and how these advertising decisions affected prices. Second, several studies have examined how online markets are formed, and how prices in these markets are determined (e.g., Brynjolfsson and Smith (2000), Ellison and Ellison (2009)). These studies tended to focus on industries in which actual transactions are conducted online, and to assume away selection issues with regard to the types of retailers who begin or expand their online operations. Another important related study is that of Brown and Goolsbee (2002), which shows how firms' decisions to post their prices online affect prices in traditional markets. The authors find that prices have fallen and that price dispersion initially increases and then decreases. Brown and Goolsbee's study focused on a single product and did not examine how local market conditions affect firms' pricing decisions, and which firms choose to post prices online. Finally, Grennan and Swanson (2016) study how price transparency between hospitals and their suppliers affects prices.

Our study is also related to the literature that studies the retail industry in general (Basker (2016), DellaVigna and Gentzkow (2017), Hitsch et al. (2017)) and the supermarket industry in particular (e.g., Matsa (2011), Pozzi (2013)). Finally, few studies focused on the Israeli supermarket industry. Hendel et al. (2017) studied Israeli consumers' boycott of cottage cheese in the summer of 2011. Eizenberg et al. (2017) studied the period 2005 to 2007 in the Israel supermarket industry and Heffetz et al. (2016) also study the impact of the Israeli Food Act. Finally, given the growing importance of e-commerce and the lower cost of collecting prices from online markets, macroeconomists have also been trying to understand to what extent online prices behave like prices set in traditional stores. For instance, Cavallo (2017) provides evidence that online and off-line prices exhibit similar patterns. Gorodnichenko et al. (Forthcoming) focuses on price rigidity and shows that price rigidity is prevalent online. Our results show that the differences between online and off-line prices substantially declined once prices became transparent.

3 Institutional background

The average household expenditure on food items in Israel accounts for 16% of disposable income. 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. These two chains operate in many localities throughout Israel, and each has several sub-formats. The other chains we consider operated fewer stores at the end of 2014: Rami Levy, a heavy-discount chain, operated 27 stores; Victory operated 28 stores and Yeinot Bitan operated 67 stores. We selected these supermarket chains because of their substantial collective market share, 73% in 2014, 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. In addition, sales of private label items are growing but still account for a relatively small fraction of total grocery sales in the Israeli food market.

The cumulative annual growth rate of food prices in Israel between September 2005 and June 2011 was 5%, compared with 2.1% for the period between January 2000 and September 2005, and compared with 3.2% across all OECD countries for the 2005-2011 period.[4] This steep rise in food 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 heavy-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, 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. 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. For instance, 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 wrong."[5] 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

[4] See the Kedmi Committee report, 2012, page 8 - http://economy.gov.il/publications/publications/documents/kedmireport2012.pdf.

[5] See 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)).

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."[6]

On May 20, 2015, the transparency clause went into effect, and retailers began uploading price data to dedicated websites (other parts of the Food Act became effective in January 2015). 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, at least three websites offered food price comparison services: MySupermarket.co.il, Pricez.co.il and Zapmarket.co.il. Figures 1 ans 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.

4 Methodology and data

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 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

[6] See http://www.themarker.com/opinion/1.2506245.

differences-in-differences research design, discussed in detail below, offer a unique opportunity to address these empirical challenges.

4.1 Data and descriptive statistics

We collected price data for a treatment group of products, as well as for four control groups of products. In additional analyses, we also supplemented these data with rich post-transparency data that correspond to a larger array of products and stores, in addition to data on local competition, and the usage of the price comparison websites. Below we provide more details on the data and its sources.

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 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. The chosen items do not include fruits and vegetables since the quality of these products is harder to measure and may vary across stores and retailers. 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. Figure 1 presents a time series of the total price of the treatment basket, averaged across individual stores for each of the five chains. 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 heavy-discount chain, is the cheapest.[7] The patterns observed in the figure might be driven by other factors besides price transparency. To take these factors into account, we collected data for four control groups of products.

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 are often determined locally and vary across stores (even within a single chain), prices of items sold online by a given chain are not dependent on

[7] In Sec 5.4 we restrict attention to the post-transparency time period, when we obtain the data from a price transparency platform. In this analysis, we can therefore use a much larger set of stores (580 stores) and items (355 items) including, for instance, private-label products.

the customer's location. 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. Figure 4 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. One potential reason for this difference is that online prices were transparent in the pre-regulation period, and this transparency led to fiercer competition in the online channel. More importantly, we also see that the price gap between online and traditional stores diminished after May 2015, when prices in traditional stores became transparent. Specifically, prices in the online channel increased, whereas the prices in traditional stores decreased.

Control group 2: ICC products. This control group comprises 48 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 firms 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 top-rated 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 ads mentioning the ICC price comparison initiative. 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.[8] Figure 5 shows a time series of basket prices, for the treatment group and for control group 2 (products whose prices were collected by the ICC). In this case, the products included in the control group are not included in the treatment group basket; accordingly, we normalized the total basket prices of the control and the treatment groups to 100 in April 2015 (the month before the regulation became effective). Similarly to what we observed for control group 1, Figure 5 suggests that, over the relevant time period, the aggregate price of the treatment basket dropped

[8]Further evidence that the ICC basket prices can serve as a reasonable transparent control group is that the prices of items in the ICC basket declined in 2013 when the ICC began collecting the prices of these items.

substantially more than did the aggregate basket price of the control group. Figure 6 presents a time series for a subset of seven items from the treatment group and for a subset of seven comparable items from the control group 2. In other words, it presents time series of two groups of products that can be considered substitutes for each other. For instance, we match a 200-gram jar of Nescafé Taster's Choice instant coffee, included in the ICC group 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. 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.[9] 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 8 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 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 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 present summary statistics for the number of products and observations in the treatment group and in the first three control groups.

Additional data. 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'

[9] Starting in July 2017, drugstore chains also became subject to the transparency regulation. In Table 1 of the Online Appendix we present preliminary regression results demonstrating that prices at Super-Pharm declined soon after its prices became transparent.

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. Finally, we obtained data on the usage of the price comparison websites. In Section 6.2.1, we use these data to examine the relationship between the use of the price comparison websites and the observed price changes.

While the graphical illustration presented in figures 4, 5 and 6 is encouraging, the figures do not account for time and item specific changes that may have occurred over the relevant time period. In the regression analysis we take these factors into account. In the following section, we elaborate on our identification strategy, which enables us to determine whether these preliminary observations indeed reflect the effects of mandatory disclosure of prices.

4.2 Identification and research design

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 group 1 is not susceptible to this concern, as it contains the same items as the treatment group, purchased by the same chain. More generally, the use of the different control groups, and the fact that we obtain similar results using these alternative control groups, can provide confidence that our estimates are indeed driven by the transparency regulation rather than by other changes in the market.

4.2.1 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. Since the dispersion of prices might also depend on the number of observations per product-date, we include this measure in the specification. In each regression, we compare the treatment group to a single control group. Formally, we estimate the following equation:

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

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. Num_obs is the number of times that a price of a certain product was recorded in a given period, and that was used to compute the price dispersion measure. 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.

4.2.2 Price levels

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

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

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 time period fixed 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 change 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. 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.

4.2.3 Additional specifications

We subsequently introduce several modifications into Eq. 2 to delve deeper into the nature of the price changes that took place. First, we examine whether the change in prices varies across the five supermarket chains. To do so, we interact the $After * Treatment$ variable in Eq. 2 with an indicator for each of the five supermarket chains. 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.

We further carry out an analysis that examines whether 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 5.3). 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 post-transparency 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 5.4.

5 Results

5.1 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 table indicates that transparency 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.

5.2 Price levels

Table 3 presents the regression results of Equation 2, which reflects the 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.[10][11]

[10] 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 6). We obtain nearly identical 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).

[11] We also note that the regression results assume 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.

Table 4 presents the point estimates obtained for a modification of Equation 2 that simultaneously estimates the transparency effect for each of the supermarket chains. The regression results illustrate that the reduction in prices attributed to the transparency regulation took place mostly among the more expensive chains: Mega, Shufersal and also Victory (see the ranking of the total basket price, shown in figure 1). For the chains that set relatively cheaper prices, Yeinot Bitan and Rami Levi, we do not find strong evidence that prices decreased after the transparency regulation went into effect. 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 post-transparency changes in prices were greater in stores that faced weaker competition. Overall, these findings could suggest that the effect of transparency on prices was smaller in stores that, already before prices became transparent, catered to customers with relatively low-search costs.

5.3 How quickly do prices adjust?

Upon observing the effects of the transparency regulation on price dispersion and on price levels (Tables 2 and 3), it is natural to examine the pace at which these effects took place and their relative order. To this end, we conducted an analysis estimating the monthly effect of price transparency for each month included in our sample. We estimated the month-specific effects using modified versions of Equations 1 and 2. Figure 7 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. These observations suggest that supermarket chains responded to the mandatory disclosure of prices in two phases: First, they reduced the number of distinct prices for each item while maintaining the average price unaffected. Later, they decreased the levels of prices that they charged. The decrease in prices in the beginning of 2016 is consistent with the increase in usage of the price comparison websites at the beginning of 2016 (in Section 6.2.1 we present evidence on this trend).

5.4 Differences across products

Above we showed that the negative effect of transparency on prices materialized only several months after the transparency regulation became effective, i.e., at the beginning of 2016. We now 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. As noted above, we obtain these weekly data from a price comparison website beginning in August 2015, and in these analyses the comparisons are made between the prices of products sold in traditional stores and the price of the same products sold online by the same chain.

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 6, suggests that our initial sample of treatment products is largely representative of the products sold in supermarkets.

Next, we use a regression framework 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 8, we find a strong negative relationship between the price level and the corresponding decline in price. 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`.[12] 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 6. 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.

We now turn to evaluate whether price changes differed between private-label products 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

[12] 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.

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 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 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 were likely to have been characterized by a high degree of search before the transparency regulation decreased less compared with the prices of less-searched-for products.

5.5 Research design validation

5.5.1 Grocery stores as an additional 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. For example, the source of data for the treatment group in the pre-transparency period was a market survey firm, whereas after the regulation the treatment group data came from a price comparison website. 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 alleviate this concern, we obtained data collected by the Israeli Central Bureau of Statistics ("CBS") for the same time period as our main analysis. These data correspond to the prices of eight 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. Overall, the CBS data include nearly 9,500 observations from 110 supermarkets and 73 grocery stores. 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 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). More specifically, we estimated Equations 1 and 2 using the price data on the eight items collected by the CBS. 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 s 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 5.5.4, it seem unlikely that the owners of these small, independent stores would have responded strategically to the transparency regulation by changing their prices.

5.5.2 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 3 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 are able to reject it when using the ICC control group.

5.5.3 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 5 of the Online Appendix. These results mitigate the concern that another event that occurred prior to the implementation of the regulation explains our findings.

5.5.4 Strategic response by Super-Pharm

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. This could mean that our results regarding price levels are driven by a post-transparency increase in prices in the control group rather than by a post-transparency decrease in prices in the treatment group but rather by higher prices in the control group. This concern is applicable to our analyses with control group 3 (products sold in Super-Pharm) because Super-Pharm may have strategically responded to the transparency regulation. In particular, if following the transparency regulation, Super-Pharm decided to target price-insensitive consumers by raising its 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 6 of the Online Appendix, provide no evidence for such a relationship. Second, as mentioned in Section 5.5.1, 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.

6 Potential channels leading to the observed effects

In this section we discuss potential channels that we believe contributed to the findings that we document. We begin with the effect on price dispersion, and then discuss the channels which are more relevant to the effect on price levels.

6.1 The effect on price dispersion

We think that in our setting fairness concerns probably best explain the the observed effect on price dispersion and the stark decline in the number of unique prices that each chain sets for a given product. That is, retailers reduced the number of unique prices they set for a given product because they were concerned from a public outcry if consumers could observe large price differences across same-chain stores.[13] 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. Media reports often reported that prices of similar products sold by different stores affiliated with the same chain tend to be different, and that prices in affluent areas are often cheaper than prices in rural and poor areas (due to different local competition conditions). Retail chains tried to defend these differences, often promising to reduce these price differences.[14] Moreover, before the transparency regulation came into effect, a legislative attempt to require food retailers to set uniform prices across all their stores nearly passed in the Israeli parliament.[15] Second, the fact that the change in price dispersion and in the number of unique prices have taken place shortly after the regulation came into effect also suggests that this change was 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 a chain sets in its online channel were nationally uniform, regardless of the level of local competition that the chain faces, also suggests that chains recognized the reputational costs associated with charging different "transparent" prices in different markets.

6.2 The effect on the price level

6.2.1 Usage of price comparison websites

It seems natural to attribute the influence of transparency on prices to the fact that transparency offers consumers greater access to price information, which they subsequently exploit. To examine this channel, we obtained from Similarweb, a digital market intelligence company, data on the total

[13] In a recent paper, DellaVigna and Gentzkow (2017) discuss fairness and fixed costs of managerial decisions as potential explanations for retailers' decision to set uniform pricing in U.S retail chains.

[14] E.g., https://www.themarker.com/advertising/1.1613349.

[15] http://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.

number of pages viewed on each of the three websites that were offering price comparison services during the data collection period (`MySupermarket.co.il`, `Pricez.co.il` and `ZapMarket.co.il`). These data, at the monthly level, cover the time period from June 2014 to November 2016. Overall, the number of visitors to these websites increased over the relevant time period.[16] Thus, the total monthly number of pages viewed on `Pricez.co.il`, the only website whose core business relies on comparison of prices across the traditional stores, increased from about 100k before the regulation to above 300k in September and October 2016. Moreover, the average number of pages viewed per visitor increased from about 2 pages per visit before the regulation to 8 pages per visit towards the end of the period.

We estimated a treatment intensity version of Equation 2, replacing the transparency indicator in the original specification with a measure reflecting the number of price-comparison-website pages-viewed in a given month (we use two alternative measures of page views: either the total number of pages viewed across all three websites combined, or the number or pages viewed on `Pricez.co.il`).[17] We performed the analysis using each of the three control groups. The regression results, presented in Table 8, support our conjecture that increases in access to price information led to lower prices in traditional stores. The regression estimates are qualitatively similar across the three control groups and for the two intensity measures. If we focus on the results corresponding only to the page views on `Pricez.co.il`, the estimates suggest that a monthly increase of 100k pages viewed is likely to result in a price decrease in traditional stores that is 2.6% greater than that of online channels. In addition, the fact that we observe an increase in the usage of the different platforms in early 2016 is consistent with our observation that prices began to decline around that point in time (Section 5.3). To graphically illustrate the relationship between the change in price levels and the use of the price comparison websites, Figure 9 plots the total number of viewed pages in each month and the estimated monthly effect on prices. The Figure shows that starting in early 2016, the total number of viewed pages is negatively correlated with the decrease in prices.[18]

While the latter analysis supports the argument that better access to price information leads to price reductions, we are quite hesitant to conclude that this is the only channel through which the transparency regulation affected prices. This is because the overall number of visitors to the three websites seem rather low. Instead, we propose that the Israeli media, by using the price

[16]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.

[17]Given that the main business of MySupermarket is to facilitate online shopping, we are unable to disentangle customers who visit that website to shop online (e.g., at Shufersal Online) from visitors who want to obtain price information in traditional stores. ZapMarket, the third website, began operating only in November 2015.

[18]In the Online Appendix, we report additional analyses which is based on usage data from the price comparison websites. First, Table 7 shows regression results that exploit cross-sectional variation across cities in the usage of Pricez. We find a negative relationship between the per-capita number of Pricez' users in a given city and the transparency effect on prices in that city. Second, Table 8 in the Online Appendix shows regression results that suggest a negative relationship between the change in prices after the transparency regulation went into effect and the total time spent in each month on the mobile apps of Pricez.

comparison websites, was also contributing to the reduction in prices. We discuss this channel in the next subsection.

6.2.2 The media

The Israeli media, especially since the massive social protests in the summer of 2011, has been actively involved in supporting pro-market agendas, criticizing attempts to gain market power and denouncing price increases. Both traditional and online news outlets report regularly on consumer issues, typically taking a pro-consumer point of view. The media coverage of consumer-related topics also involves price comparisons. Before the transparency regulation, reporters had to physically visit the stores and wander through the aisles to find the price of each product. Since the regulation, however, the costs of collecting and comparing prices have dropped significantly, providing the media with rich opportunities to report on price differences across stores or regions. 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.[19] On January 12, 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.[20] In this case, too, the reporter used the Pricez mobile app to compare prices across supermarket chains.

The media also devote substantial attention to the price comparison applications themselves: 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. This competition received national coverage.[21] The national media have also compared the user interfaces of food price comparison websites, their accuracy and their graphical design.[22]. 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, a leading national business newspaper, compared price differences at the merged firm before versus after the merger relative to price differences at another supermarket chain that did not take part in the merger. TheMarker used price data from one of the price comparison platforms and repeated this exercise a few weeks after the merger and then

[19] See `http://www.globes.co.il/news/article.aspx?did=1001108062` and `http://www.yediot.co.il/articles/0,7340,L-4858377,00.html` for additional examples.

[20] `www.mako.co.il/news-channel2/Channel-2-Newscast-q1_2016/Article-996f23598873251004.htm`.

[21] See `http://www.globes.co.il/news/article.aspx?did=1001056276` and `http://www.globes.co.il/news/article.aspx?did=1001074618`.

[22] See `http://www.themarker.com/consumer/1.2824847`.

again a few months after the merger.[23] 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.[24]

We believe that the media's extensive coverage of consumer issues has two potential effects on supermarket prices. First, thanks to the this coverage, the number of consumers who are exposed to price comparison services is significantly higher than the actual number of consumers who visit price comparison websites. Second, and at least as important, many food retailers value the positive press coverage that accompanies low prices. For instance, in 2012, Rami Levy, who owns and manages the heavy-discount chain Rami Levy, was chosen by TheMarker as the most influential figure in Israel in that year. Three years later, in 2015, Rami Levy was awarded the Israel Prize, Israel's most prestigious honor for Israelis who have made a difference to society. It seems likely that the media's praise and support contributed towards the widespread recognition of Rami Levy's achievements. In sum, this role of the media in disseminating information about retailers' pricing practices provides retailers with an incentive to set low prices and to be regarded as offering consumers good value for the money, regardless of whether consumers actually respond to those low prices directly.

7 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.[25] 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. How will, nevertheless, the rapid growth of the online market affect the traditional retail food market? 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

[23] See http://www.themarker.com/advertising/1.3006498 and http://www.themarker.com/advertising/1.3116830.

[24] See https://goo.gl/YsVT9a

[25] See https://goo.gl/R8pyTJ

functioning of markets. On the other hand, firms can use such information to better coordinate their actions in a manner that will harm consumers.

In this paper, we investigate the impact of a transparency regulation on the price distribution of food products sold in traditional stores. Somewhat surprisingly, while the impact of mandatory disclosure of price information is at the core of IO, to our knowledge, very few studies have examined this issue empirically, and those that have are somewhat limited in scope: they focus on markets in which firms sell one product and do not examine how the effect of transparency varies with pre-regulation market conditions or across products. 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, soon after the regulation went into effect, brick-and-mortar supermarket stores reduced the number of distinct prices that they set for each item offered. This finding suggests that supermarket chains, acknowledging that prices had become transparent, changed their pricing strategies. Second, we show that, several months later, price levels decreased. The decrease was particularly pronounced in stores whose customers probably face lower search costs: either stores affiliated with more pricey chains or stores that faced weaker competition in their local markets. Our findings regarding price levels suggest that as price information became available to consumers and to the media, the competitive role of information prevailed, and prices declined. Our estimates further 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 the average consumer saved about $27 per month and that chains lost about 46 million dollars in revenue each month. 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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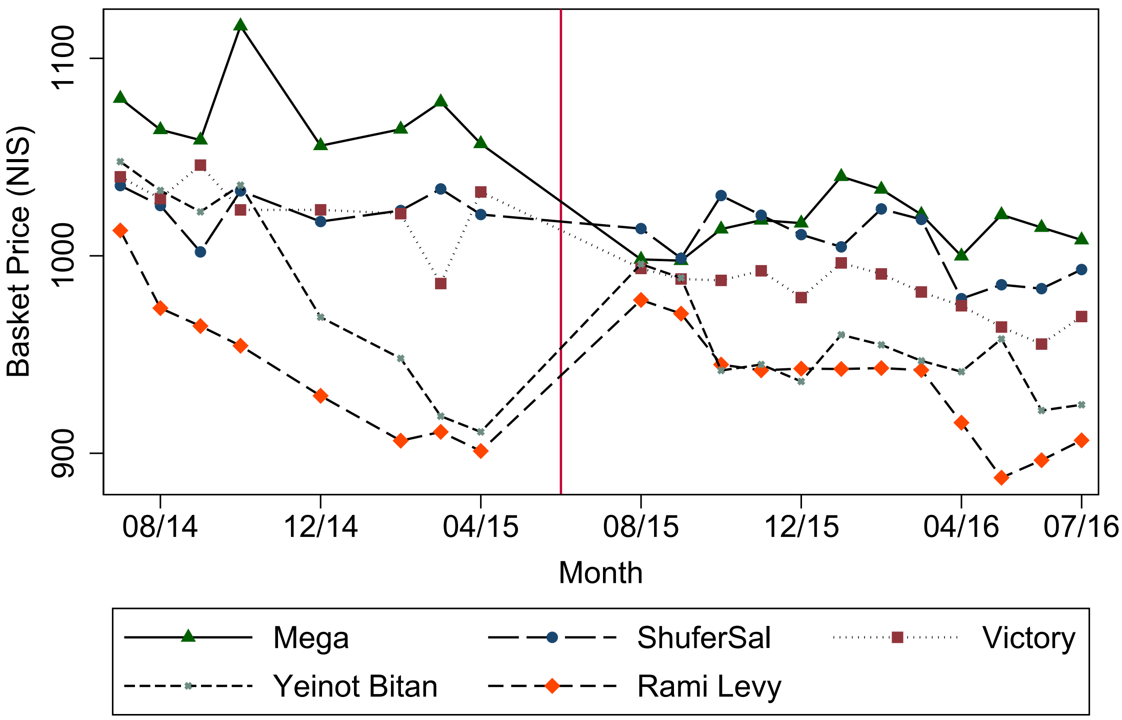
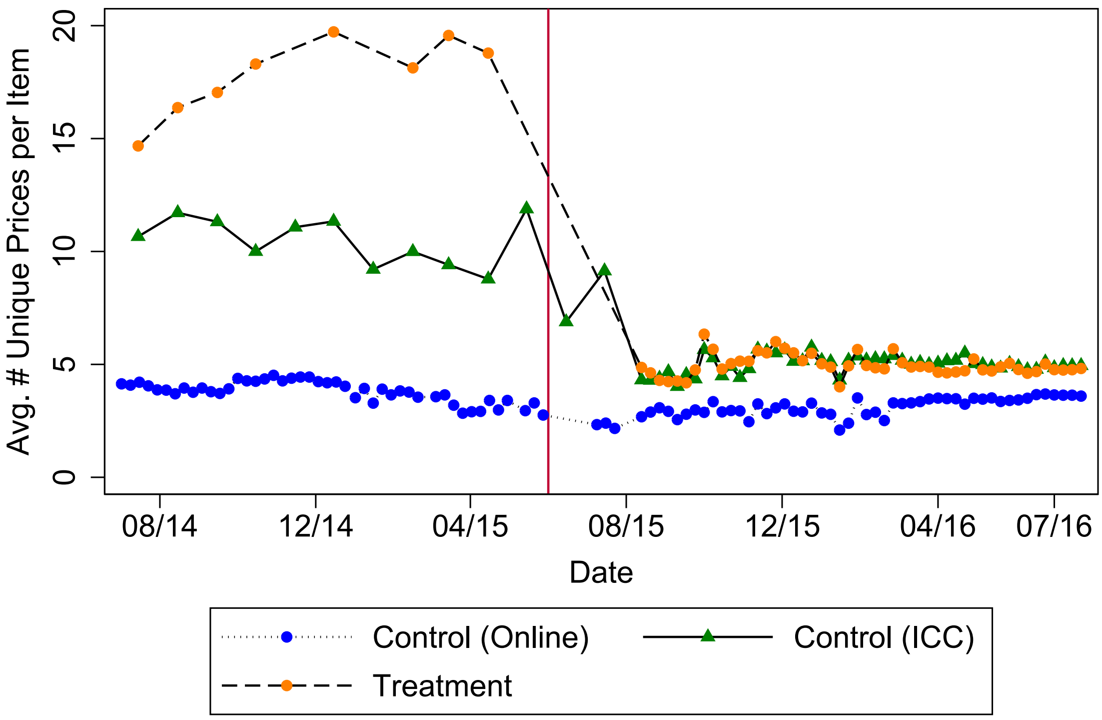
Figure 1: Retailer-Specific Basket Price



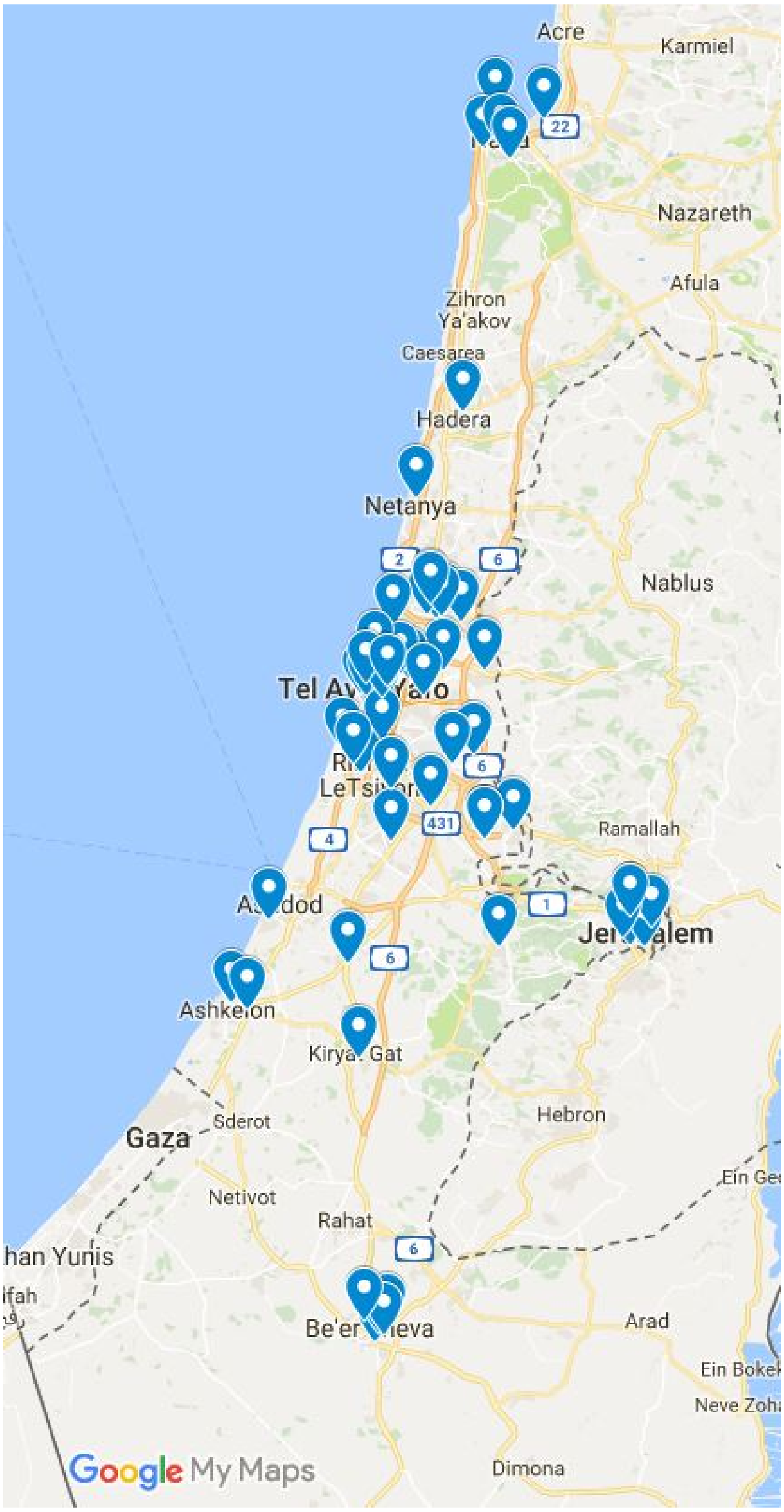
The figure shows a time series of the total basket price for each of the retailers. A basket consists of 58 items. Monthly basket price is the sum of items average price, where the average is taken over the retailers' stores. Missing price are imputed.

Figure 2: Number of Distinct Prices



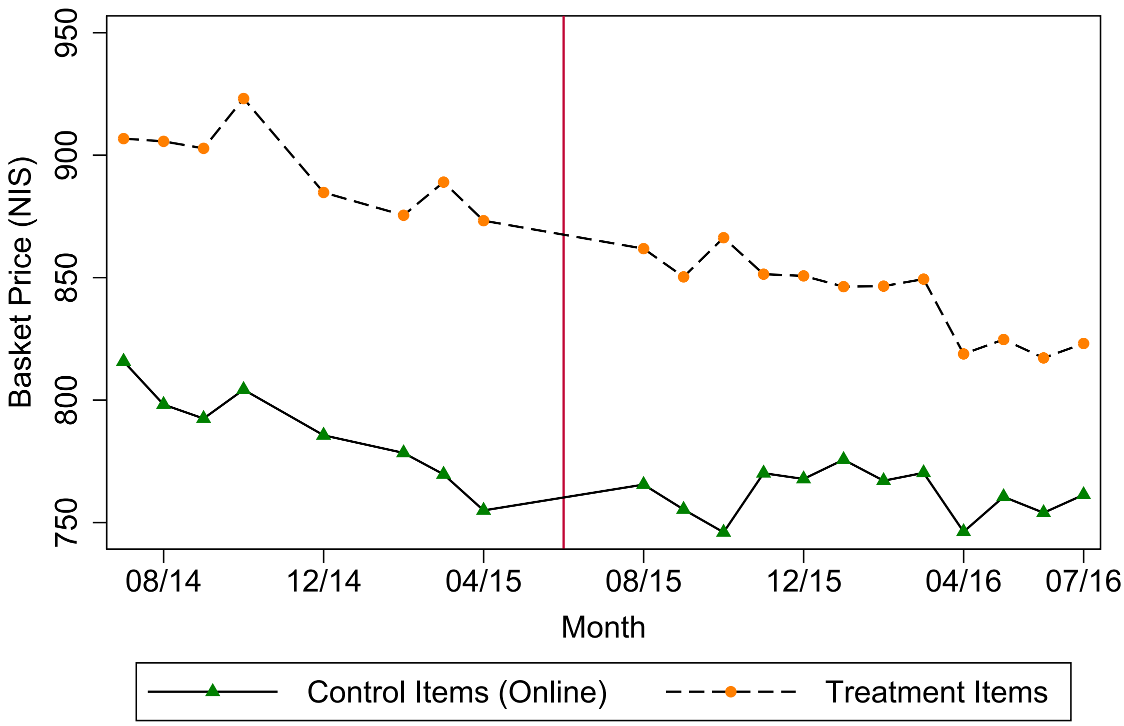
The figure shows a time series of the average number of distinct prices for the treatment group of items, the online control group and the ICC control group.

Figure 3: Map of Store Locations



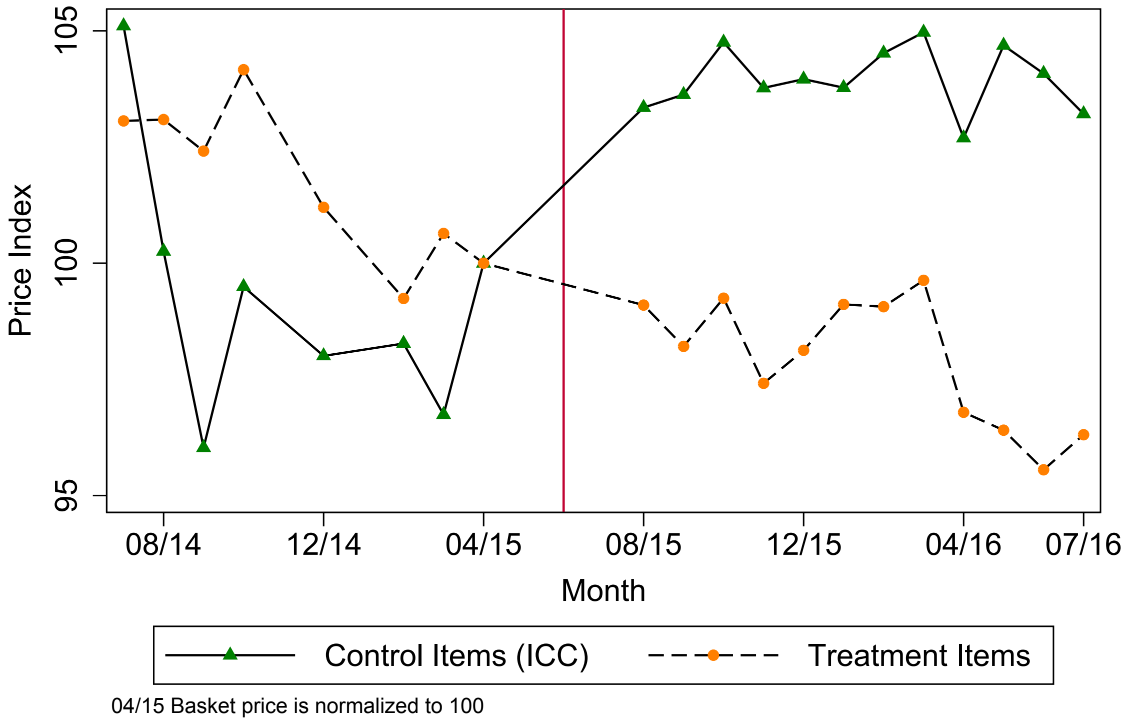
The figure shows the locations of the 61 stores comprise the treatment group. These stores are located in 27 different cities.

Figure 4: Basket Price in the Online Control and the Treatment Groups



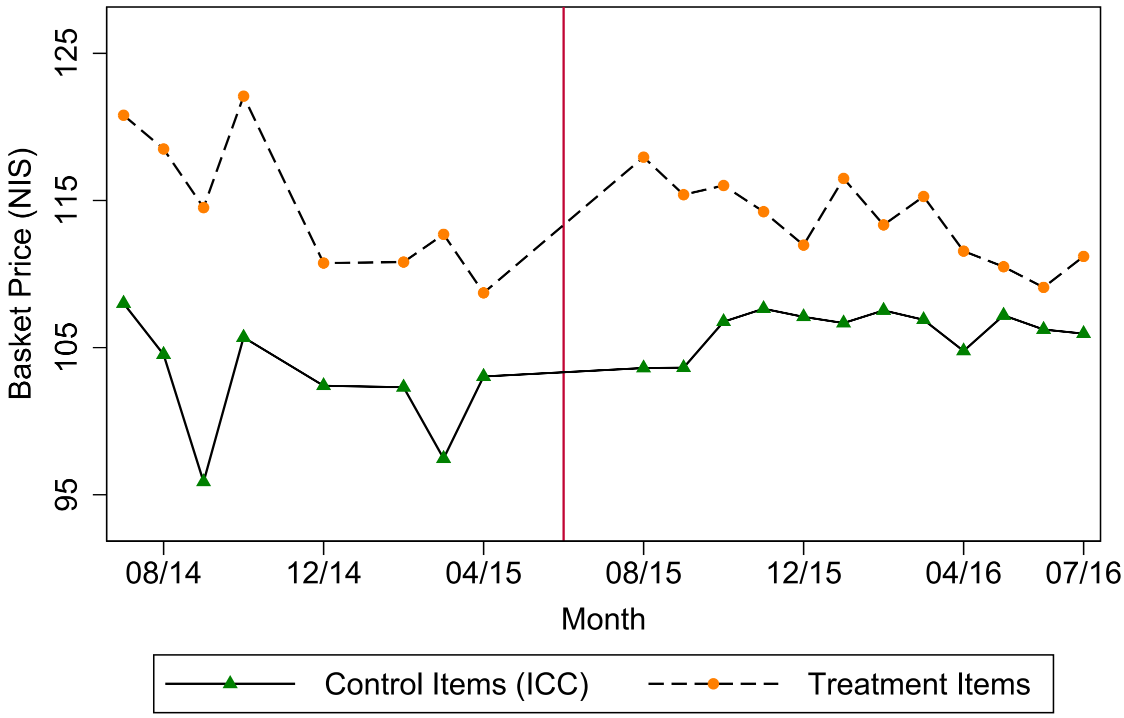
The figure shows a time series of the total basket price, divided into the online (control group) channel or traditional (treatment group) channel. In each channel, prices are averaged across stores and chains and missing prices are imputed. The figure shows that throughout the period the online basket 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.

Figure 5: Basket Price Index in the ICC Control and the Treatment Groups



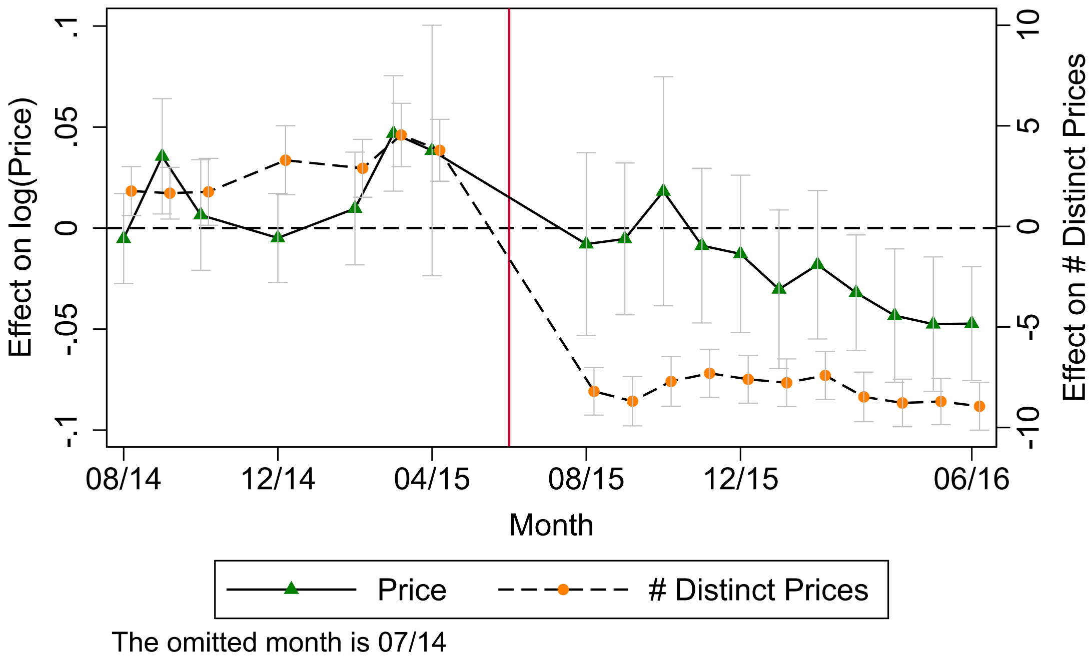
The figure shows a time series of the total basket price, divided into the ICC control basket and the treatment basket. In each group, prices are averaged across stores and missing prices are imputed. Since the two baskets contain different items, we normalize each basket price to 100 on April 2015, the last data point before price transparency became mandatory.

Figure 6: Comparable Basket Price



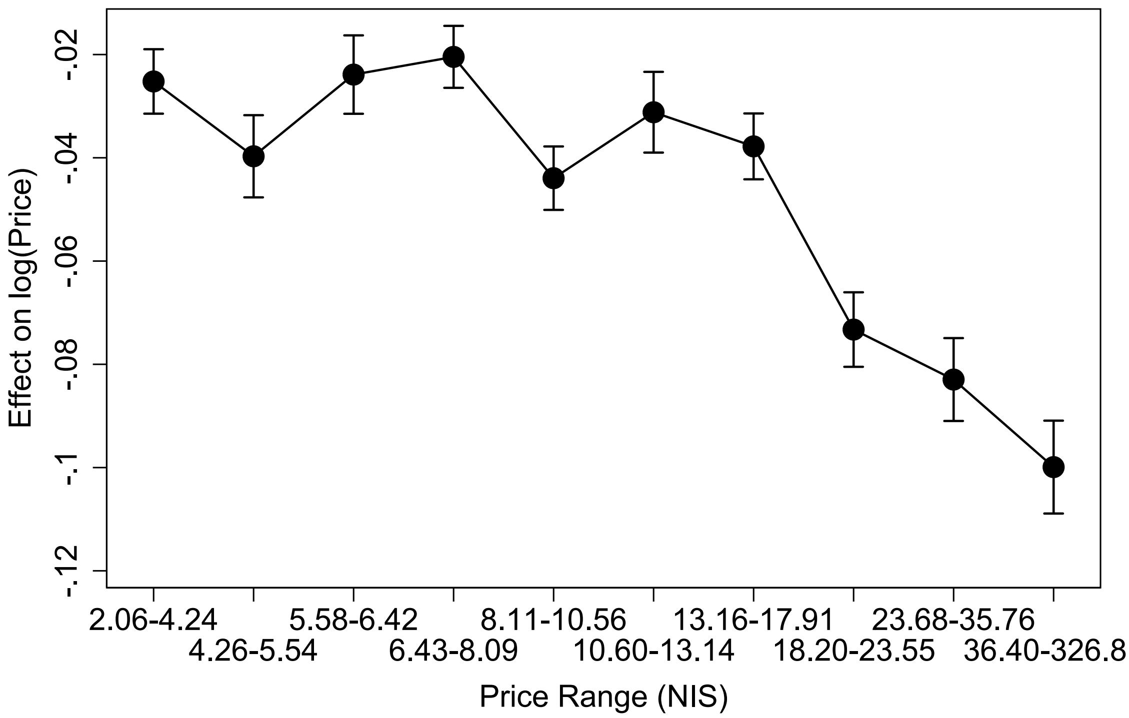
The figure shows a time series of the total basket price for two baskets. One basket consists of seven ICC control items (control group) and the other consists of seven comparable items from the treatment group. The figure demonstrates that the two baskets exhibited similar patterns before prices in the treatment group became transparent.

Figure 7: Monthly Effect on Price Level and Price Dispersion



The figure shows the monthly F.E. from two variants of Equations 1 and 2 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.

Figure 8: Post-transparency Analysis



The figure shows the relationship between the average price of a group of products and the 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 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.

Figure 9: Monthly Effect on Price Level and Price Comparison Website Page Views

The figure shows on the right vertical axis the monthly F.E. (and the corresponding 95% confidence interval) from a variant of Equation 2 in which the effect is estimated for each and every month before and after the regulation went into effect. This series is also presented in Figure 7. The right vertical axis shows the monthly page views from a price comparison website (Pricez.co.il).

Table 1: Descriptive Statistics

Data Source					
Supermarkets		# Stores	# Items	# Data Pulls	N
	Treatment group	61	69	58	159,214
	Online stores	5	69	99	30,865
	ICC	61	48	63	115,749
Drugstore		32	28	4	2,789

The table presents information on the number of stores, items and periods for which prices have been collected in the treatment and each of the control groups. For instance, the 115,749 prices of the 48 items in the ICC control group were collected in 61 stores at 63 different weeks.

Table 2: Mandatory Disclosure Effect on Price Dispersion

	# Unique Prices			Standard Deviation/Avg.			Percentage Range ($100 * \frac{P_{max}-P_{min}}{P_{max}}$)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
After*Treatment	-10.881**	-8.103**	-15.920**	-0.101**	-0.053**	-0.083**	-27.396**	-12.481**	-32.962**
	(0.549)	(0.812)	(1.700)	(0.011)	(0.012)	(0.024)	(1.679)	(2.436)	(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

The unit of observation in columns 1, 3, 4, 6, 7 & 9 is item i in date t in treatment/control group

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

* $p < 0.05$, ** $p < 0.01$

The 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 (drugstores, online and ICC). To get a sense of the magnitude of the change in price dispersion following the transparency regulation, we also report in the table the average value of the corresponding dependent variable. For all the measures of price dispersion and for each of the control groups, we find a significant reduction in price dispersion.

Table 3: Mandatory Disclosure Effect on Price

	(1) log(Price)	(2) log(Price)	(3) 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
N	186810	278228	58358

The unit of observation is item i in store j in time-period t

Time period covered 7/2014 - 6/2016

Errors are clustered by store

* $p < 0.05$, ** $p < 0.01$

The table presents the regression results of Equation 2. Each column corresponds to a different control group. The results indicate that prices have declined by 4% - 5% after the prices in traditional stores become transparent.

Table 4: Mandatory Disclosure Retailer-Specific Effect on Price

	(1) log(Price)	(2) log(Price)	(3) log(Price)
Mega: After*Treatment	-0.084**	-0.047**	-0.060**
	(0.008)	(0.005)	(0.014)
Shufersal: After*Treatment	-0.048**	-0.053**	-0.035*
	(0.008)	(0.006)	(0.015)
Victory: After*Treatment	-0.062**	-0.044**	-0.052
	(0.020)	(0.007)	(0.026)
Yeinot Bitan: After*Treatment	-0.025	-0.048**	-0.006
	(0.014)	(0.006)	(0.016)
Rami Levy: After*Treatment	-0.009	-0.002	0.021
	(0.008)	(0.006)	(0.015)
Store F.E.	✓	✓	✓
Date F.E.	✓	✓	✓
Item F.E.	✓	✓	✓
Linear Item Specific Time Trend	✓	✓	✓
Control Group	Online	ICC	Super Pharm
R^2	0.937	0.962	0.911
N	186810	274669	57734

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

Time period covered 7/2014 - 6/2016

Errors are clustered by store

* $p < 0.05$, ** $p < 0.01$

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 only slightly changed for the heavy discount chains (i.e. Rami Levy).

Table 5: Mandatory Disclosure Effect on Price by Degree of Competition

	(1) log(Price)	(2) log(Price)
After*Treatment - Low Comp.	-0.059**	
	(0.006)	
After*Treatment - High Comp.:	-0.044**	
	(0.006)	
After*Treatment		-0.039**
		(0.007)
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
R^2	0.962	0.962
N	259557	259557

Concentration ranges form 0 to 1, with 0 being perfect competition and 1 being monopoly

The $10^{th}, 50^{th}$ and 90^{th} percentiles of concentration are 0.13, 0.32 and 0.45, respectively

The unit of observation is item i in store j in time-period t

Time period covered 7/2014 - 6/2016

Errors are clustered by store

* $p < 0.05$, ** $p < 0.01$

In 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 supermarket 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. Because 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.

Table 6: Mandatory Disclosure Effect on Price using Post Data - Heterogenous Analysis

	Baseline Spec.	Popularity	Private Label	Mehadrin Kosher
	(1)	(2)	(3)	(4)
After*Treatment	-0.032**			
	(0.009)			
After*Treatment (property turned off)		-0.046**	-0.030**	-0.050**
		(0.009)	(0.010)	(0.007)
After*Treatment (property turned on)		-0.003	-0.010	0.014
		(0.009)	(0.010)	(0.010)
Store F.E.	✓	✓	✓	✓
Date F.E.	✓	✓	✓	✓
Item F.E.	✓	✓	✓	✓
Linear Item Specific Time Trend	✓	✓	✓	✓
R^2	0.983	0.983	0.978	0.982
N	4981472	4981472	1005062	415708

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

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.

Table 7: Mandatory Disclosure Effect on Price and price Dispersion using CBS Data

	(1) # Unique Price	(2) Standard Deviation/Avg.	(3) Percentage Range $(100 * \frac{P_{max}-P_{min}}{P_{max}})$	(4) log(Price)
After*Treatment	-1.465**	-0.042**	-9.407**	-0.022**
	(0.288)	(0.004)	(0.726)	(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	
R^2	0.832	0.905	0.778	0.975
N	400	400	400	9472

The unit of observation in columns 1-3 is item i in month t

The unit of observation in column 4 is item i in store j in month t

Time 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 price data obtained from the Israeli Central Bureau of Statistics as a control group. 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.

Table 8: Mandatory Disclosure Effect on log(Price) using Web Site Page Views as Intensity Measure

	(1) log(Price)	(2) log(Price)	(3) log(Price)	(4) log(Price)	(5) log(Price)	(6) log(Price)
After*Treat Intensity	-0.026**	-0.002**	-0.015**	-0.002**	-0.023**	-0.001*
	(0.003)	(0.000)	(0.002)	(0.000)	(0.006)	(0.001)
Store F.E.	✓	✓	✓	✓	✓	✓
Week F.E.	✓	✓	✓	✓	✓	✓
Item F.E.	✓	✓	✓	✓	✓	✓
Lin. Item Time Trend	✓	✓	✓	✓	✓	✓
Traffic Source	Pricez	All	Pricez	All	Pricez	All
Control Group	Online	Online	ICC	ICC	Super Pharm	Super Pharm
R^2	0.937	0.937	0.961	0.961	0.909	0.909
N	186810	186810	278228	278228	58358	58358

The unit of observation is item i in store j in time period t

Time period covered 7/2014 - 6/2016

Monthly treatment intensity is based on 100,000 page views

Errors are clustered by store

* $p < 0.05$, ** $p < 0.01$

The table presents the regression results of a version of Equation 2 in which the post-transparency indicator is replaced with the monthly number of page views from price comparison websites as an indicator for the intensity of the price transparency regulation. Page view figures are obtained from SimilarWeb. In odd columns, usage is based on data from Pricez.co.il. In even columns usage is based on the combined number of page views from MySupermarket.co.il, Pricez.co.il and ZapMarket.co.il.

Online Appendix to "The Effects of Mandatory Disclosure of Supermarket Prices"

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January 3, 2018

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

- Table 1 - the effect of price transparency in Super-Pharm stores, where disclosure was mandated on July 1, 2017. This change made the prices of all items sold in drug stores transparent, except the prices of non-prescription drugs. These items serve as a control group
- Table 2 - a chain-specific effect of transparency on price dispersion
- Table 3 - the effect of transparency on price, including a fourth column which focuses on 10 pairs of matched items, that is an ICC control item and a "similar" item from the treatment group
- Table 4 - using (log) special price instead of the (log) list price as the dependent variable. Special price also include prices that are calculated based on quantity discounts.
- Table 5 - placebo test using pre-transparency data only and focusing on five fictitious dates for the beginning date of the transparency implementation
- Table 6 - examine 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
- Table 7 - the relationship between the city-specific transparency effect on price and the penetration of price comparison website to that city
- Table 8 - the relationship between the transparency effect on price and the intensity of usage in a price comparison app

- Figures 1 - 2 present photos taken from `Mysupermarket.co.il`, a price comparison website. Figure 1 demonstrates a price comparison of a single item – Nature Valley bar 6-pack – sold by different retailers. Figure 2 shows a price comparison of a basket of 42 items.
- Figure 3 - presents the pre-regulation monthly F.E. for log(price) as the outcome variables using both online and ICC control groups

Table 1: Effect on Price and Price Dispersion in Super Pharm using Non-Prescription Drugs as Control

	(1) # Unique Price	(2) Standard Deviation/Avg.	(3) Percentage Range $(100 * \frac{P_{max}-P_{min}}{P_{max}})$	(4) log(Price)
After*Treatment	-2.861*	-0.030	-12.880	-0.069**
	(1.226)	(0.048)	(8.845)	(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
N	157	157	157	7867

The unit of observation in column 1 is item i in store j in month t

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 main results from a supplementary analysis that exploits a recent regulation (effective starting on July 1, 2017) which also 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 also 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 level decrease.

Table 2: Mandatory Disclosure Retailer-Specific Effect on # Unique Prices

	(1) # Unique Prices	(2) # Unique Prices	(3) # 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
N	37685	25978	6120

The unit of observation in columns 1 and 2 is item i in date t in chain c in treatment/control group

The unit of observation in column 3 is item i in date t in chain c

Time period covered 7/2014 - 6/2016

Errors are clustered by items

* $p < 0.05$, ** $p < 0.01$

The table presents regression results of Equation 1. 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 the dependent variable is based on.

Table 3: Mandatory Disclosure Effect on Price

	(1) log(Price)	(2) log(Price)	(3) log(Price)	(4) log(Price)
After*Treatment	-0.051**	-0.052**	-0.040**	-0.084**
	(0.008)	(0.005)	(0.014)	(0.007)
Store F.E.	✓	✓	✓	✓
Date F.E.	✓	✓	✓	✓
Item F.E.	✓	✓	✓	✓
Linear Item Specific Time Trend	✓	✓	✓	✓
Control Group	Online	ICC	Super Pharm	ICC Restricted
R^2	0.937	0.961	0.909	0.982
N	186810	278228	58358	58177

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 extends Table 3 from the manuscript by including a fourth column. This column is a variant of column 3 (ICC control group) which is based on a set of 20 items from the control and the treatment groups that are "similar" to each - 10 items from each group. For example, a 200-gram jar of Nescafée 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). The table reveals an even stronger effect when using this limited set of matched items compared to using the wider set of items composing the original ICC and treatment groups.

Table 4: Transparency Homogenous Effect on Special Price - DID Analysis

	(1) log(Special Price)	(2) log(Special Price)	(3) log(Special Price)
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

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 replicates Table 3 in the manuscript but uses the (log) special price rather than the (log) list price as the dependent variable. Special price refer sto various price 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.

Table 5: Placebo Test for Mandatory Disclosure Effect on Price

	(1) log(Price)	(2) log(Price)	(3) log(Price)	(4) log(Price)	(5) log(Price)	(6) log(Price)	(7) log(Price)	(8) log(Price)	(9) log(Price)	(10) log(Price)
After*Treatment	0.024	0.003	0.010	0.021	0.028	0.000	0.001	-0.005	-0.008	0.011
	(0.013)	(0.018)	(0.021)	(0.023)	(0.035)	(0.008)	(0.007)	(0.008)	(0.016)	(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
N	34417	34417	34417	34417	34417	42186	42186	42186	42186	42186

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

Time period covered 7/2014 - 7/2015

Five differetn placebo dates are used

Errors are clustered by stores

* $p < 0.05$, ** $p < 0.01$

The 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.

Table 6: Strategic Response of Super Pharm by the Distance to the Closest Competitor

	(1) log(price)	(2) log(price)	(3) 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	
		(0.020)	
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
N	2386	2386	2386

The unit of observation is item i in Super Pharm store j in month t

Data were collected in four months: 10/14, 04/15, 10/15 and 04/16

Errors are clustered by store

The omitted month is 10/15

Close competitor indicator = 1 if the closest supermerket is located less 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.

Table 7: City-Specific Transparency Effect on Price and Price Comparison Website Penentration

	(1) Δ Price	(2) Δ Price	(3) Δ Price
% Penetration	0.0032**	-0.0045*	-0.0045*
	(0.0011)	(0.0018)	(0.0018)
Socio-Demog. Class		0.0019**	0.0025**
		(0.0004)	(0.0005)
% Higher Educ			-0.0001
			(0.0001)
N	65	65	65

The unit of observation is city c

Time period covered 8/2015 - 7/2016

Columns are estimated using variance weighted least squares with the standard error of the city-specific effect on price used as the (conditional) standard deviation of the effect on price

* $p < 0.05$, ** $p < 0.01$

The table contains city-level analysis which correlates the price treatment effect attributed to the transparency regulation with usage data from Pricez.co.il (a primary price comparison website) and other socio-demographic variables. To get a wider coverage of cities, the regression that estimates the city-level price effect is based on the post-transparency price data set, which is described in section 5.4 in the main text. In the analysis, we first estimate the city-level treatment effect on price which ranges from (-7.8) to (-3.6)%. We then examine the relationship between the city-level price effect with Pricez.co.il penetration data. The penetration data are the percent of households in a city that used the website (between 0.04% to 2.16%). The socio-demographic class of a city, which takes integers in 1-10, is assigned by the Israeli CBS. The table shows that once the socio-demographic class in taken into account, there is a negative relationship between the usage of the price comparison website in a given city and the estimated change in prices in that city.

Table 8: Mandatory Disclosure Effect on log(Price) using App Usage as Intensity Measure

	(1) log(Price)	(2) log(Price)	(3) log(Price)
After*Treatment Inten.	-0.012**	-0.014**	-0.049**
	(0.002)	(0.001)	(0.011)
Sore F.E.	✓	✓	✓
Week F.E.	✓	✓	✓
Item F.E.	✓	✓	✓
Lin. Item Time Trend	✓	✓	✓
Control Group	Online	ICC	Super Pharm
R^2	0.936	0.961	0.909
N	186810	278228	58358

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

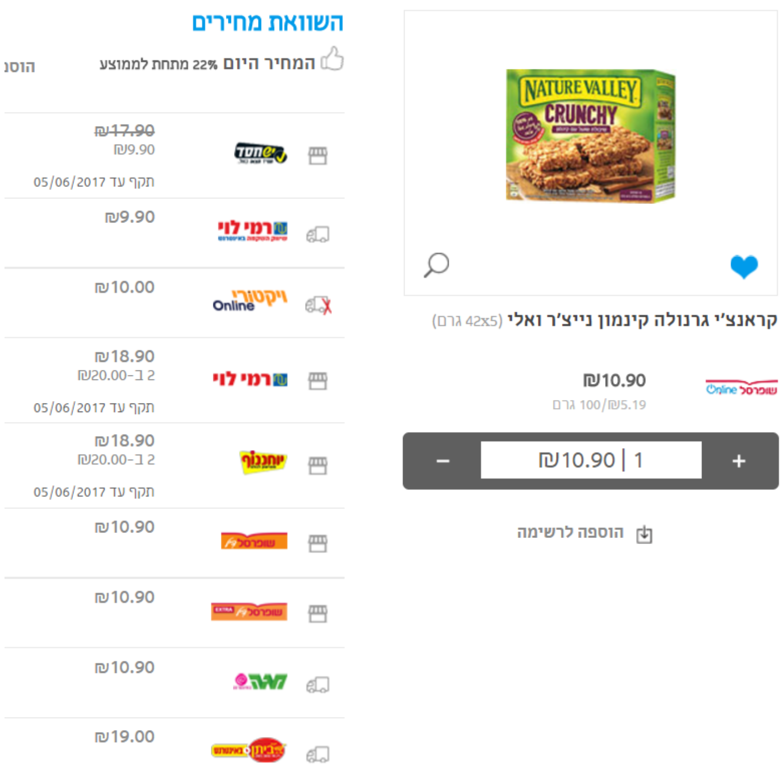
Time period covered 7/2014 - 6/2016

Errors are clustered by stores

* $p < 0.05$, ** $p < 0.01$

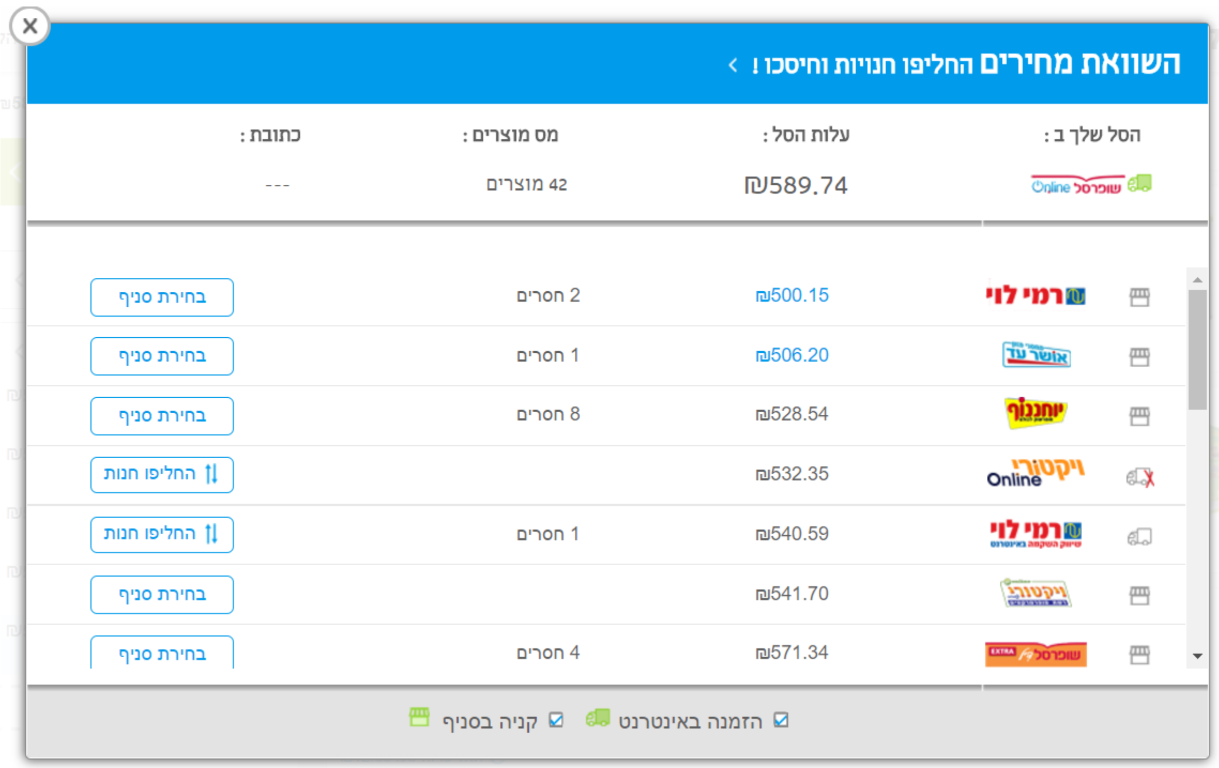
The table presents the regression results of a treatment intensity variants of Equation 2. Treatment intensity is based on usage data of the price comparison app Pricez (https://play.google.com/store/apps/details?id=il.co.PriceZ.android&hl=en). For each month we derive the share of time the app was used out of the total time it could have been theoretically used among all users. The treatment intensity measure we use in the regressions is a standardized version of the share of time mentioned above. Thus, the coefficients in the table are the effect on price of a one standard deviation increase in the app usage.

Figure 1: Single Item Price Comparison



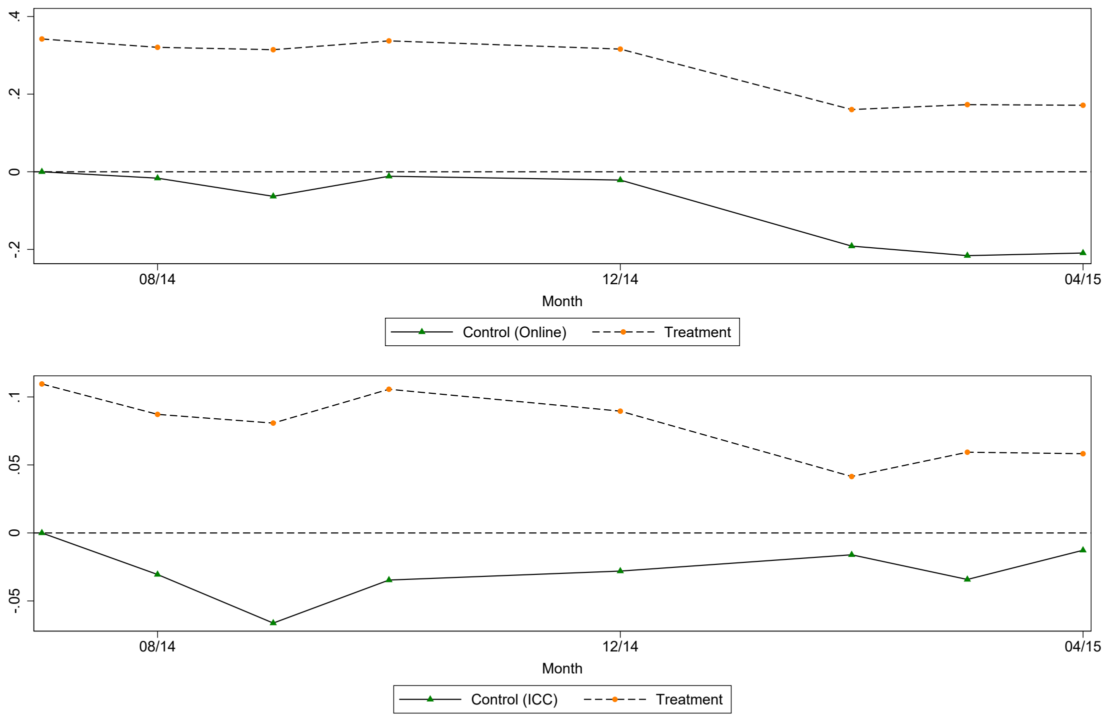
The left side of the figure includes a list of retailers, sorted by price, that sell the item whose photo is shown on the right side of the figure. The small icon located to the right of the retailer name indicates whether the quoted price refers to a physical store of that retailer (indicated by a stand)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

Figure 2: Basket of Items Price Comparison



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: 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.