Structure, Conduct, and Contact: Competition in Closely-Related Markets*

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Abstract

We perform a simultaneous empirical study of competitive conduct in 40 categories of the Israeli food sector. In each category we estimate a differentiated product demand model, and compute several indicators to assess the category's degree of competition. Specifically, we test particular modes of competitive conduct (competitive Nash-Bertrand pricing, collusion) and compute a threshold discount factor — the discount factor that would support a hypothetical collusive regime. We then investigate several pervasive questions in the Industrial Organization literature: (1) what is the relationship between an industry's concentration and its intensity of competition? (2) are industries characterized by inelastic consumer demand more or less prone to be concentrated? (3) how is concentration related to the stability of collusive regimes? And (4) what is the role of multimarket contact in determining the degree of competition? By combining these analyses we provide a multi-faceted picture of competition and concentration in closely related markets.

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1 Introduction

The study of industry conduct is a staple of Industrial Organization literature. The Structure-Conduct-Performance tradition (SCP, Bain 1951) stipulated a cross-industry study where conduct, reflected in observed profit margins, was regressed on measures of industry concentration and barriers to entry. Attention has shifted over time to single-industry studies where conduct is taken to be unobserved, and an empirical model of demand and supply is used to infer it (the New Empirical Industrial Organization, Bresnahan 1989). The single-industry focus results in an analysis that is tailored to the institutional features of the industry in question. This approach has proved instrumental in addressing important policy questions in a variety of economic sectors.[1] It is less helpful, however, in identifying patterns that hold *across industries*, the primary goal of the SCP paradigm. While it should be possible to learn about such patterns via a meta-analysis of multiple industry studies, there has not been much work in that direction.[2] As a consequence, the relationship between observed concentration levels and firms' competitive conduct remains elusive.

In this paper we revisit the task of studying the relationship between concentration and conduct across industries. Rather than studying 4-digit SIC industries, as in typical SCP studies, we focus on closely related industries: 40 categories of the Israeli food sector. We follow the NEIO paradigm by estimating a structural model of demand in each category, and then employ these estimates to address the following questions: (1) what is the relationship between an industry's concentration and the extent to which firms compete with each other? (2) are industries characterized by inelastic consumer demand more or less prone to be concentrated? (3) how is concentration related to the stability of collusive regimes? And (4) what is the role of multimarket contact in determining conduct across markets?

To address the first three questions, we compute several measures for each category and examine the statistical relationship between them. These measures include the following: the category's concentration measured by the HHI, C1, C2, and C3 indicators[3]; the category's demand elasticity; indicators for whether specific models of firm interaction — Nash-Bertrand pricing, and collusion among the leading firms — are rejected by the data; and finally, an indicator for the stability of collusive interaction, on which we elaborate below. We then correlate these measures over the 40 industries to address the research questions above.

To address question (1) above we examine the correlation between concentration and the extent to which particular conduct models are rejected by the data. We test specific supply models following Pakes (2016) and Miller and Weinberg (2017) by regressing the observed price

[1]See Pakes (2016) for a recent survey of some of these contributions.
[2]An example of such work is Martin (2012).
[3]Where, as familiar, C1, C2, and C3 measure the aggregate market share of largest, two largest, and three largest firms.

on an estimated markup term implied by the relevant model. We explore novel instruments for the endogenous markup term using information on the firm's activity in other categories, a strategy we discuss in detail below. We then examine whether HHI has a clear relationship with suggestive evidence for collusive behavior.[4] We further explore whether particular indicators such as C2 or C3 are strong predictors of non-competitive behavior. In this we connect with some fundamental debates in the literature on competition and antitrust, such as the assertion in Bork (1978) that only mergers to monopoly raise competitive concerns.

To address question (2) we explore the relationship between the category's elasticity of demand and its concentration levels. Interest in this question dates back at least to Modigliani (1958) who established that more elastic demand could be associated with lower barriers to entry.[5] The theoretical relationship between this elasticity and the degree of concentration is, however, ambiguous: Becker (1971, in Pagoulatos and Sorensen 1986) postulates that more elastic demand should be expected in the presence of *lower competition* since colluding firms would likely attempt to price along the elastic portion of the demand curve.[6] This ambiguity motivated Pagoulatos and Sorensen (1986) to perform an empirical study of this relationship in a cross-section of U.S. food and tobacco industries, where the aggregate demand elasticity in each category was estimated by regressing the log of total quantity on log prices. Their results validate the positive relationship motivated by Becker (ibid.). We revisit this exercise using demand estimation techniques that account for price endogeneity, product differentiation, and flexible substitution patterns within a category and towards the outside option.

To address question (3) we develop an empirical indicator of the stability of cooperative conduct, building on the theory literature concerning supergame models of collusion (Green and Porter, 1984, Rotemberg and Saloner, 1986, Abreu 1986, 1988). Consistent with this literature, our measure of cartel stability is the lowest discount factor given which a coordinated regime can be maintained. We estimate this indicator for each category in which collusive behavior was not rejected, allowing us to examine if more concentrated categories result in more stable collusive regimes. Treatment of categories where collusion is rejected by the data is explained below.

Supergame models of collusion prescribe optimal punishment schemes that, given firms' discount factors, enable them to attain the highest possible level of collusive prices. Our empirical analysis rests on the observation that the objects that appear in the Incentive Compatibility constraints associated with such equilibria are amenable to empirical estimation given standard estimates of an industry's demand system. Similar observations have been exploited in recent work, some of which being contemporaneous with ours (see Goto and Iizuka 2016, Igami and

[4] As will become clear below, failing to reject a model of collusion falls short of detecting actual collusion. Furthermore, it should be understood that our use of the term "collusion" is completely unrelated to the legal context where it implies that firms illegally communicate to fix prices. Rather, we refer to non-competitive prices that may be legally achieved (e.g., via tacit collusion).

[5] Modigliani bases this analysis on oligopoly theory developed in Sylos (1957) that relies on quite a few special assumptions.

[6] Yet another analysis with a different view is offered in Connor and Peterson (1992).

Sugaya 2017, Miller, Sheu and Weinberg 2018 and Fan and Sullivan 2018).

In categories where collusive behavior was not rejected by the data, we back out marginal cost estimates implied by collusion. We assume that firms in the category indeed act cooperatively, and that this regime is supported by a simple grim-trigger strategy: upon deviation, firms revert to a Nash-Bertrand pricing regime forever. While falling short of the sophistication embedded in the optimal punishment scheme, this simplification goes a long way towards an empirical implementation of the supergame framework, given that profits under a hypothetical reversion to Nash Bertrand pricing are very easily computed.[7] Estimating the one-shot profit gain obtained by deviating from the collusive arrangement is also straightforward. Fed into the firms' incentive compatibility constraints, these estimated quantities imply a lower bound on the discount factor that supports the hypothesized cooperative regime. The lower bounds captures the ease with which firms can sustain prices above competitive levels, and we correlate them with category-level concentration to address question (3).

We acknowledge the limitation that even if collusion has not been formally rejected by the data, we cannot determine whether or not it takes place. Our threshold indicator therefore has the following interpretation: to the extent that collusion takes place, how stable is it? This interpretation is consistent with the literature. Ross (1992) analyzes the question of whether product differentiation facilitates or hurts the ability to collude. In his theoretical analysis, collusion is assumed, and the threshold discount factor is computed under varying degrees of product differentiation. Our analysis can be thought of analogously as estimating this indicator empirically under varying degrees of concentration manifested across categories of the food sector. Our goal is to inform the debate regarding how concentration is related to the firms' ability to raise prices above competitive (i.e., Nash-Bertrand) levels. While our approach may be misspecified, we emphasize that our mission is to compare such indicators across categories, rather than to detect the existence or stability of collusive regimes in any particular category.

In categories where Nash-Bertrand pricing is *not rejected* by the data, we use similar procedures to compute the threshold discount factor that would sustain a hypothetical switch to a collusive regime. If firms are currently avoiding cooperative pricing, say, because of fear of regulatory response or other public scrutiny, this approach provides a measure of the extent to which the market could potentially become less competitive if such threats were weakened. We correlate this threshold discount factor with industry concentration (across the set of categories where competitive pricing was not rejected) to determine the relationship between concentration and the potential ease of switching to a collusive regime.

The procedure described above also allows us to compute the stability indicator for any degree of cooperative behavior, and we pursue this strategy, for fixed degrees of cooperation, in

[7] See, for example, Bernheim and Whinston (1990) for a demonstration of the complexity of analyzing optimal punishment in the presence of differentiated products — a fundamental aspect of the real-world markets we analyze in this paper.

industries where *both perfect collusion and Nash Bertrand pricing are rejected by the data.* Alternatively, we could estimate conduct parameters, following a long tradition in the literature with contributions including Bresnahan (1985, 1989) and more recent studies by Ciliberto and Williams (2014), Sullivan (2017) and Michel and Weiergraeber (2018). The interpretation of conduct parameters and their ability to identify the true industry conduct has been questioned by Corts (1999). Sullivan (2017) emphasizes the importance of cross-sectional variation across markets in identifying conduct parameters, which is absent from our data as we only observe a given category over time. For these reasons we focus on exercises that are conceptually and empirically sound. First, we test concrete static models of interaction (namely, perfect collusion and Nash Bertrand). While these tests have their own limitations (in particular, they may have low power under some conditions), they raise no conceptual difficulties. Second, we back out cartel stability measures from a repeated game which is also theoretically sound.

We finally address question (4) that concerns the potential role of multimarket contact. Here we explicitly build on results from Bernheim and Whinston (BW, 1990) who analyze whether firms that compete in multiple markets can leverage this contact to facilitate non-competitive behavior. BW's analysis shows that summing over the IC constraints across markets may, but need not, allow those to hold at a lower discount factor level. Whether or not multimarket contact can facilitate collusion is therefore an empirical question: the answer depends on market-specific parameters that enter these constraints.

We analyze the issue empirically by adapting the theory of BW to the empirical differentiated-product setup. We focus our analysis on categories of the Israeli food sector in which the same two firms play a leading role. In particular, we look at the Instant Coffee and Packaged Hummus Salad categories, where two specific firms (Strauss and Osem-Nestle) are the market leaders. Our estimated threshold discount factors for each of these categories, already obtained in the analysis of question (3), serve as the departure point. We sum the IC constraints over these markets to reveal whether, and to what extent, can a lower discount factor sustain collusion in both markets when firms take into account their cross market interaction. We propose using the estimated decline (if any) in the threshold discount factor as an empirical indicator for the extent to which multimarket contact can affect the competitive conduct.

In essence, we learn about how contact can potentially facilitate non-competitive outcomes, rather than testing for whether it actually does so. This approach could be used to evaluate theories of harm regarding mergers that do not increase the concentration level in any single market, but allow the same firms to interact in multiple markets.

Empirical strategy. To estimate demand we use data from Nielsen regarding about 40 categories of the Israeli food sector. In each category we observe monthly UPC-level revenue and quantity data for the period from January 2012 to July 2015, a total of 43 months. We treat these product categories as well-defined product markets. We note that some of these categories have been identified by the Israel Antitrust Authority as representing well-defined markets. This sector provides an interesting opportunity to study competition in concentrated markets as it features several prominent business groups that garner significant market shares within and across product categories.

We estimate a random coefficient logit (hereafter RCL) model following Berry, Levinsohn and Pakes BLP, 1995) in each of the 40 categories, allowing for rich substitution patterns via heterogeneous preferences towards the outside option, price, leading firms' brands, and additional category-specific characteristics. A flexible modeling of the substitution towards the outside option is particularly helpful in pinning down the category's elasticity of demand.

To identify the demand model and account for price endogeneity we use several sets of instruments. In addition to the traditional use of cost shifters, interacted with firm dummies, we rely on additional sets of variables that should shift markups and therefore the endogenous price. We generally lack continuous product characteristics and therefore use very simple versions of the competition shifters suggested by Berry and Haile (2014) or Gandhi and Houde (2016). We also depart from previous work by using the firm's revenue in *other categories* as a shifter of prices and markups. This allows us to leverage company-wide shifts in pricing strategy as exogenous supply shifters. We discuss and defend this approach in detail in section 3.

Given estimated demand parameters from each category, we turn to a test of particular models of competitive conduct. We regress price on marginal cost shifters and a markup term implied by the tested model of conduct, and test the hypothesis that the coefficient on the markup term is equal to 1. Since we have demand estimates in hand when doing this, we can instrument for the markup term not only using the instrumental variables listed above, but also with the estimated realizations of rivals' demand shocks.

Following a brief literature review, in section 2 we present the data and provide evidence regarding concentration across categories and the presence of major business groups in multiple categories. In section 3 we provide the structural demand specification and report preliminary estimation results from a simpler Nested logit specification in a particular category (to date we have obtained such estimates in 15 categories). Section 4 presents the single-market analysis that yields tests for models of industry conduct, and an estimated threshold discount factor in each category given the estimated demand system. In this preliminary draft we report results for a single category. Future versions would report these thresholds for all categories, enabling the study of the relationship between this indicator and measures of concentration. Section 5 presents the analysis of multimarket contact. The current draft does not yet have the empirical results for this analysis, but it provides a complete formal explanation of how it is performed. Section 6 concludes (TBC).

Relationship to the literature. The paper relates to a very large empirical literature devoted to the study of competitive conduct under the Structure-Conduct-Performance paradigm. The idea that estimating demand elasticities can help in these type of analyses is emphasized by Cowling and Waterson (1976) who have noted the familiar result that given Cournot competition with homogeneous products, the HHI measure of concentration is related not only to the Lerner Index, but also to the market demand elasticity. They therefore suggested that SCP studies may have suffered from an omitted variable bias where the omitted variable is the elasticity of demand. Their suggested empirical approach was to focus on a time-series analysis of a single industry and assume that the unknown market demand elasticity is time-invariant and can therefore be differenced out. Our approach, in contrast, estimates demand elasticities and, conceptually, plugs them into the structure-conduct analysis in a manner analogous to that envisioned by Cowling and Waterson.

We also study the relationship between the market demand elasticity and the industry's concentration, an issue which appears to be unsettled. Johnson and Helmberger (1967) derive a formal relationship between the two measures and advocate for the view that the market demand elasticity can be viewed as one of the features of an industry's structure, while also showing that previous contributions have been mixed with respect to this issue (specifically, Bain 1951 does not include this measure as an important characteristic of an industry's structure). Clark and Davies (1982) also contribute to this theoretical literature. Taken together with the literature surveyed above (Becker 1971, Modigliani 1958) there appear to be a diverse set of theories that generate conflicting predictions, motivating an empirical analysis.

As noted above, the idea of estimating cartel stability measures given an estimated structural model of demand has been recently pursued by several authors. Goto and Iizuka (2016) estimate such quantities in the medical services industry. Igami and Sugaya (2017) assess the stability of the vitamin cartels. The repeated game setup is also analyzed empirically in Miller, Sheu and Weinberg (2018) who estimate a price leadership model where a leader sets price to help the industry coordinate among the many potential collusive equilibria, and refer to ongoing work by Fan and Sullivan (2018). Our paper, which has developed independently of these contributions, shares some elements with these papers while focusing on different questions. We propose to construct threshold discount factors across multiple industries to study cross-sectional relationships between structure and conduct. In addition, our paper is the first (to the best of our knowledge) to propose the use of such estimated quantities to study multimarket contact across industries.

The strategic role of cross-market interactions has received considerable attention in the literature. As reviewed in Evans and Kessides (1994, EK), some early considerations of the issue include Edwards (1955, in Scherer, 1980), and Kahn (1961). Empirical work has generally found multimarket contact to have a significant impact on prices. EK exploit panel data to document the effect of changes over time in airlines' route overlaps, using fixed effects to control for time-invariant route characteristics. They contrast their approach with earlier work that has exploited cross-sectional variation only.[8] Ciliberto and Williams (2014) study multimarket contact in airline markets by explicitly estimating conduct parameters that are related to the extent of cross-market relationships.[9] Shim and Khwaga (2017) and Pus (2018) also study multimarket contact via a conduct parameter approach in the retail lumber and the freight industries, respectively. In contrast to these papers, we do not estimate conduct parameters and instead take the theory developed in BW90 to data to study the impact of cross-category interactions. To the best of our knowledge, this is the first paper to take this approach.

Finally, the issue of "conglomerate mergers" has received some attention in the industrial organization and antitrust literatures. Ashenfelter, Hosken and Weinberg (2014) provide some historical perspective on the issue, citing Bork's (1978) argument regarding there being "no threat to competition in any conglomerate merger." Of note, the concerns regarding such mergers have often focused on other issues than multimarket contact. Nonetheless, our work adds to a literature that considers potential theories of harm associated with mergers that increase the presence of firms across market boundaries.[10]

2 Data

We use product-level data from Nielsen. These data cover 40 product categories in the Israeli food sector. The data are monthly and cover the period from January 2012 to July 2015, a total of 43 months. Product categories are presented in Table 1.

In each category and month, we observe UPC-level information which includes the UPC's name, from which we occasionally derive important information regarding characteristics. We also observe the brand name and the manufacturer, as well as total sales in both monetary terms, and in units. We compute the (monthly average) price charged to consumers by dividing total sales revenue by quantity. In some categories, the data is broken down by segments defined by Nielsen (e.g., regular rice vs. whole grain rice). The data are also broken down by distribution channels that include: Hard Discount Supermarkets, Supermarkets and Superpharm (Superpharm being the name of a large pharmacy chain), minimarkets, convenience stores, and ultra-orthodox (pertaining to retail establishments targeting ultra-orthodox Israeli consumers).

[8] For example, Haggestad and Rhoades (1978), Whitehead (1978), Strickland (1984), Mester (1987), Feinberg and Sherman (1985), and Gelfand and Spiller (1987).

[9] See also Ciliberto, Watkins and Williams (2018).

[10] See Blonigen and Pierce (2016) for an example of a broad analysis of mergers across the U.S. manufacturing sector, which differentiates between mergers among firms that compete in the same 2-digit SIC code, and mergers among firms who compete in different industries.

Our analysis effectively considers the 40 categories as well-defined product markets for the purpose of studying competitive conduct. We find this approach to be not only practical, but also strongly justified by the institutional background. A primary advantage to using Nielsen's categorization is transparency: this approach can be easily implemented and avoids a costly process in which we were to define the markets independently following some method. Second, and importantly, analyses by the Israel Antitrust Authority (IAA) confirm some of the market definitions reflected in this categorization. For example, in 2005 the IAA found that Black Coffee should be viewed as a separate market from Instant Coffee for the purpose of antitrust analysis. Kovo and Eizenberg (2017) describe an analysis performed at the IAA where demand estimates were used to conclude that cheese categories (specifically, Cottage cheese, Yellow Cheese, and Soft cheese that appears in Table 1) are well-defined submarkets of the dairy market. The IAA's analysis also concluded that they should be analyzed separately from categories such as Yogurt or Butter.

Concentration measures and subsidiary structure. We next explore variation across categories in concentration levels. To properly measure concentration within categories, we need to take into account that some manufacturers are subsidiaries of other manufacturers. This is a qualitatively important phenomenon in the Israeli food sector that has seen a fare amount of consolidation over time. To this end, we have prepared, based on a large number of online sources, a large matrix which rows describe the important players in the Israeli food sector, while the columns indicate the subsidiaries they own in each product category. The matrix does not document every subsidiary relationship in this sector. Rather, it captures the ownership of brands and companies that are quantitatively important. While this may result in some omissions, we believe, based on our familiarity with the market, that we have not missed important information. The matrix is available in Appendix B (TBC). Taking subsidiaries into account, we report in Table 2 concentration measures for each category: the Herfindahl-Hirschman Index (HHI), and the C1, C2 and C3 measures.

Table 2 reveals that the degree of category concentration is significant. A simple average across categories reveals an HHI of 0.42, and a C1 measure of 0.57. The mean C2 and C3 values of 77 percent, and 86 percent, respectively, imply that the typical category is dominated by a handful of firms. Of note, several categories display C2 and C3 values of 100 percent (noting, however, that this is sometimes due to rounding, and the actual share is, in some of these cases, above 0.99 but below 1). This is particularly noteworthy in the dairy categories. While the overall degree of concentration appears to be considerable, there also appears to be substantial variation in the concentration measures across categories. These descriptive facts illustrate why the Israeli food sector is a suitable context for the questions posed in this study.

We next examine within category time-series variation in concentration, which appears to be limited. Computing the within-category standard deviation in HHI over time, and averaging over categories, yields a rather small number: 0.042. On the one hand, the stability of concentration within categories is reassuring in that it is consistent with these categories corresponding to well-defined markets. On the other hand, some degree of time series variation could be helpful in the analysis of the relationship between conduct and structure, for example, it would enable us to use category fixed effects when regressing our conduct measures on concentration measures. Ultimately, however, our goal is not to identify a causal relationship of concentration on conduct, but rather to uncover their statistical relationship. Furthermore, some categories display a greater degree of HHI variation over time than others: for example, the Salt, Ketchup, Yellow cheese and Tea categories have such standard deviations ranging between 0.083-0.10, while other categories display much lower variation.

Our descriptive analysis, so far, has focused on intra-category concentration. Cross-category relationships, however, are of primary interest in our study as they inform our subsequent analysis of multimarket contact. The Israeli food sector is characterized by the presence of important business groups that operate in many categories. Table 3 provides an outlook on this issue. The table reports, for each business group, the total number of categories (among the 40) in which it is present, and the total number of categories in which it holds a "substantial presence," which we define as commanding at least 10 percent volume share. The table confirms that the extent of cross-category presence is substantial. Groups such as Tnuva, Neto, Strauss-Elite, Osem-Nestle, Sugat and the Central Bottling Company Group are present in multiple categories and have a substantial presence in several of them.

Anticipating our analysis of Bernheim and Whinston's (BW, 1990) model of multimarket contact, it is instructive to explore the nature of multimarket contact present in the data. While Table 3 indicates that certain business groups are present in many categories, there are actually only a few cases where *the same set of firms are the leaders of multiple categories*. A notable example of such a case is the *Packaged Hummus Salad* and the *Instant Coffee* categories where the same two firms are the market leaders: Strauss-Elite and Osem-Nestle. It is on this case that we shall focus our analysis of multimarket contact in Section 5.

Yet another interesting example is the categories *Bread Crumbs* and *Kuskus*. In both categories, substantial presence is observed by the same two firms: Osem-Nestle and Sugat. In this case, however, the multimarket contact evolves dynamically over time. Figure 1 shows the evolution of volume shares in the Kuskus category. The main players in the category are Osem-Nestle, and a company called Kuskus Mazon that has a business relationship with Osem-Nestle.[11] Each of these companies has rather stable volume shares, ranging between 30 and 40 percent over the sample period. The interesting dynamics pertain to the identity of the third-largest producer. In

[11]Kuskus Mazon produces Kuskus for Osem-Nestle, see the following link.

the beginning of the sample, the Asif company has about 15-20 percent share. Over the course of the sample, its share declines, and Sugat replaces it as the third-largest player, with similar volume shares. What underlies this is an agreement signed in 2013, according to which Asif will produce various products for Sugat, and those would be sold under the Sugat brand name.[12]

In other words, Sugat, an important player in the Israeli food sector that is present in 9 categories according to Table 3, has expanded into the Kuskus category by taking over, to an almost exclusive extent, the volume share of Asif. This is an interesting example where the category's HHI does not change much over time — but a potentially important shift in players took place, with a more powerful player stepping into the shoes of the third-largest producer. Specifically, by the end of the sample period, Osem-Nestle and Sugat are prominent competitors in both the Kuskus and the Bread crumbs categories, whereas at the beginning of the sample period, this multimarket contact is not present.

In future versions of this paper, we shall implement our methodology from Section 5 to infer how threshold discount factors change when Sugat expands into the *Kuskus* category. The analysis will be performed twice: assuming that the firms internalize the multimarket contact, and assuming they do not. This will provide a measure of the effect of multimarket contact on competitive conduct in these categories. Combining with reduced form evidence on changes in pricing behavior as Sugat expands into the market, will shall attempt to provide a check of our conceptual framework.

3 Econometric Demand Model

In estimating the structure of consumer preferences in each category, we face a natural tradeoff. On the one hand, appropriately capturing consumer preferences requires a tailoring of the demand model to the specific institutional details of each category. On the other hand, we ultimately wish to make comparisons across a large number of categories, which motivates deploying a relatively uniform and easy-to-implement estimation approach across categories.

We attempt to balance these considerations by relying on the standard Random Coefficient Logit model (Berry, Levinsohn and Pakes, BLP 1995) to estimate the structure of demand. Estimation is performed separately in each category using this model.[13] In specifying the model, we keep some elements uniform across categories, while tailoring other elements to the specific category examined.

In each category we define markets $t = 1, ..., 43$ that correspond to the 43 observed sample months. Market t has products $j = 1, ..., J_t$ corresponding to UPCs observed in the Nielsen

[12] Ilanit Hayut, "Globes" (an Israeli business newspaper), August 2013 (link). The article mentions such an agreement without referring to Kuskus specifically, but actually to another product category.

[13] In this preliminary draft, we report below results based on the simpler Nested logit model, with future versions reporting results based on the richer model described here.

data.[14] The market size M_t is defined in each category based on its particular features. For example, when estimating demand for rice, we defined the market size as consisting of the observed total sales of Rice, Pasta, Kuskus. This was motivated by a news article in which an industry insider suggested that the correct market definition for these types of products should be carbohydrates consumed on a plate.[15] Elsewhere, we used a variety of sources to define the market size, consistent with standard practices in the literature.

In all categories we let the utility shifters contain brand dummies for brands with volume share in excess of 1 percent, and 42 year-month dummies that capture time effects as flexibly as possible across the 43 months in the data. We also control for context-dependent dummies for particular product characteristics, often based on information gleaned from the product's name or otherwise identified in the database. For example, in the Rice category we include a dummy variable for Whole Grain rice. These category-specific choices are described in the online appendix (TBC).

Our characteristics space is therefore discrete rather than continuous, which limits our ability to leverage the differentiation instruments proposed by Gandhi and Houde (2016) to address the endogeneity of the price term. We therefore include a battery of instruments that can be classified into three types.

The first set of instruments are obtained by interacting input prices and other cost shifters (e.g., Fuel, electricity, sugar, wheat, VAT tax, minimum wage) with dummy variables for leading brands. Data on the cost shifters were obtained from the IMF commodities index.[16] Since the input prices vary only by month, they cannot add identifying power by themselves, given the inclusion of monthly dummy variables as utility shifters. Interacting these cost shifters with brand effects allows for differential price response to cost variation across brands, e.g., some brands may pass on more of the cost changes to consumers than others. Both the Value Added Tax and the minimum wage were increased twice during the sample period, and our approach exploits the differential effects of these tax increases across brands.

The VAT is imposed on all items covered in this study.[17] The VAT rate at the beginning of the sample period, January 2012, was 16 percent. It was increased to 17 percent on September 1st, 2012, and was then increased again, to 18 percent, on June 2nd, 2013. It then stayed at that level until the end of our sample period, July 2015.[18] The minimum wage, an important indicator for the food industry, also experienced two substantial, discrete increases. In monthly terms, it was set at 4,100 NIS in the beginning of our sample period. It increased by 4.8 percent

[14] We opt to aggregate observations at a higher level in most cases. The preliminary results presented in this draft use the UPC level for the purposes of product definition.

[15] In an interview, Sugat's CEO has explained that "...we examined what actually competes with us, and understood that the competition is on the carbohydrates in the plate, and so we focused on that" (Ilanit Hayut, Globes, February 2016 (link)

[16] A link to these data is available here.

[17] Unprocessed fruits and vegetables are exempt, but they are not included in our categories, see link for additional information.

[18] Source: see the following link. The VAT decreased again to 17 percent on October 2015, i.e., after our sample period.

to 4,300 NIS on October 1st, 2012, and again, this time by 8.1 percent, to 4,650 NIS on April 1st, 2015.[19]

A second set of instruments follows Berry, Levinsohn and Pakes (1995): we count the number of products offered in the market (or within market segments) by the same producer, and by its competitors. These measures of "shelf space" are intuitively linked to firms' pricing decisions, with the precise combination of instruments varying by category.

While the first two sets of instruments are standard, our third and final instrument is, to the best of our knowledge, novel and leverages the cross-category aspect of our data. Consider a firm f that produces a product j in category c, and let p_j^c denote the price of that product. When estimating demand in category c, we use the total revenue of firm f in all categories *but category* c as an instrument for p_j^c. The rationale is that a firm's strategy could be correlated across categories: an overall decrease in a firm's overall sales in the food sector may prompt a change to its pricing strategy in category c which is unrelated to demand shocks that are specific to this category, and therefore may be viewed as exogenous. For example, numerous media reports have noted in recent years that firms have taken measures such as shrinking the package size while keeping the price fixed as a means of raising prices. One may envision a shift in strategy that prompts such changes in many categories, which does not stem from a response to a category-specific demand shock.

The identifying assumption that validates this third instrument is that firm-month effects can be excluded from the indirect utility that consumers derive in a particular category. In particular, a firm's total revenue in all categories (but the one in question) may well vary with time, and also depend on the firm's stable reputation or image. Our inclusion of time and brand fixed effects guarantees that those are controlled for and are not present in the demand error. If, on the other hand, the firm's reputation varies from month to month, this may affect both its total revenue (i.e., the instrument) and its utility shocks in the category in question. While the firm's overall reputation could vary over time, we find it unlikely that this would happen on a monthly basis. We include in the utility function an interaction of the leading brands' fixed effects with a time trend, to allow for the firm's overall image to change over time — but exclude monthly changes to the firm's effect.

We briefly revisit the basic properties of the formal demand model here, referring the reader to the BLP (1995) paper for additional details. The utility function of consumer i from product j consumed in market t (understood to be a month $t \in \{1, 2, ..., 43\}$ in the category in question) is given by

$$u_{ijt} = x_{jt}\beta_i - \alpha_i p_{jt} + \xi_{jt} + \epsilon_{ijt}, \tag{1}$$

[19] Source: see the following link.

where x_{jt} is a vector of product characteristics, p_{jt} is the product's price, and ξ_{jt} captures the value of product characteristics that are unobserved to the econometrician, but are observed by consumers and firms. The parameters β_i capture the random utility weights placed by consumers on the observed product characteristics, while α_i represents the heterogeneous price sensitivity. The idiosyncratic term ϵ_{ijt} has the familiar Type-I Extreme Value distribution.

In each category we allow for normally-distributed random coefficients on the constant term, on the brand dummies for the leading brands, and occasionally on an additional characteristic that appears to be important in segmenting the market (such as the distinction between regular and whole-seed Tahini demonstrated below). In addition, we specify the distribution of the price sensitivity coefficient α_i as log-normal, effectively forcing it to have the correct (positive) sign.

The random coefficient specification aspires to overcome the limitations of simpler models such as the Logit and deliver reasonable substitution patterns that would correctly inform our competitive analysis. The random coefficient on the constant term allows for flexible substitution to the outside option, and thus helps us pin down the category's elasticity of demand which plays an important role in this study. The estimated distribution of random coefficients on leading brands' fixed effects reveals the degree to which consumer preferences generate market power for such brands: higher estimated standard deviations would suggest that substantial consumer groups can be viewed as strongly loyal to the relevant brand. Intuitively, identifying the portion of markups that can be explained by this product differentiation is helpful in identifying, later, other sources of markups such as the degree of cooperative pricing behavior.

Formally, applying the specification chosen for the random coefficients, the utility function can be re-written as

$$u_{ijt}(\zeta_{it}, x_j, p_{jt}, \xi_{jt}; \theta^d) = \underbrace{x_{jt}\beta + \xi_{jt}}_{\psi_{jt}} + \underbrace{[-\alpha_i \times p_{jt}] + \sum_{k=1}^{K} \sigma^k x_j^k v_i^k}_{\mu_{ijt}} + \epsilon_{ijt}, \tag{2}$$

where $\zeta_{it} \equiv (v_i, \{\epsilon_{ijt}\}_{j \in J_t})$ are the idiosyncratic utility shifters, with v_i being a vector of standard-normal variables (assumed IID across both consumers and product characteristics). As explained above we allow for random coefficients on a subset of characteristics, effectively setting some of the σ^k parameters to zero. We define $\alpha_i \equiv exp(\alpha + \sigma^p v_i^p)$ and separate the utility into a mean-utility component ψ_{jt}, and a household-specific term $\mu_{ijt} + \epsilon_{ijt}$. Defining $\theta_2 \equiv (\alpha, \sigma')'$ and conditioning on ψ_{jt}, the utility function can be expressed as $u_{ijt}(\zeta_{it}, x_j, p_{jt}, \psi_{jt}; \theta_2)$. The demand parameters are $\theta^d = (\beta', \alpha, \sigma')'$. We follow the standard normalization for the utility from the outside option: $u_{i0t} = \epsilon_{i0t}$.

Applying the market share equation (Berry 1994) we obtain the market share of product $j \in J_t$,

$$s_{jt}(x,p,\psi,v;\theta_2) = \int \frac{exp[\psi_{jt} + \mu_{ijt}(x_j, p_{jt}, v_i; \theta_2)]}{1 + \sum_{m \in J_t} exp[\psi_{mt} + \mu_{imt}(x_m, p_{mt}, v_i; \theta_2)]} dP_v(v_i) \tag{3}$$

Where $P_v(\cdot)$ is the joint distribution of the taste shifters v_i.[20]

We follow standard procedures to estimate the distribution of consumer preferences using GMM with the instruments discussed above and relay additional technical details to an online appendix (TBC).

Given the estimated demand parameters $\hat{\theta}^d$, one can compute demand elasticities following familiar procedures. Those, in turn, shall be helpful in analyzing supergame models of collusion, the task undertaken in the following sections. It is also straightforward to obtain an estimate for the category's elasticity of demand: evaluating (3) at the estimated parameter values and plugging $\tilde{p}_{jt} = 1.01 \cdot p_{jt}$ for the price of each inside good obtains the predicted market share for each inside product given a one percent increase in the price of *all inside goods*. Summing these shares over all inside goods, and comparing to the total share of these goods given the observed equilibrium, provides an estimate of the total percentage change to the category's sales given a one percent increase in the price of all products, namely, the category-level elasticity of demand. Analyzing the relationship of this measure with the category concentration and competitive conduct is one of the primary goals for this paper.

Preliminary estimation results. Complete details regarding the execution of these tasks in all categories shall be available in the online appendix (TBC). As a preliminary stage, we have estimated a simpler demand model — the Nested Logit following Berry (1994) — in 15 categories: Packaged Hummus Salad, Instant coffee, Rice, Pasta, Raw Tahini paste, Salt, Sugar, Sweet wines, Tuna, Flour, Kuskus, Ready-to-eat Cereals, Ketchup, Oil, and Tea.

The Nested logit model partitions the complete set of the category's products, $j = 0, ..., J$ (observed at the UPC level, with $j = 0$ representing the outside option) into $G + 1$ mutually exclusive nests, $g = 0, ..., G$. A random consumer i has the following indirect utility towards product $j \in g$:

$$u_{ij} = x_j\beta + \alpha p_j + \xi_j + \nu_{ig}(\sigma) + (1 - \sigma)\epsilon_{ij}, \tag{4}$$

where the idiosyncratic term $\nu_{ig}(\sigma) + (1 - \sigma)\epsilon_{ij}$ captures the deviation of consumer i's utility from its components that are common across consumers. It follows the unique distribution derived by Cardell (1997), and implies that the extent of within-nest correlation in consumer-level unobserved utility shifters increases in the parameter σ, where $\sigma \in [0, 1)$. This parameter, therefore, governs the degree of substitution, and hence the intensity of competition, within the nest. Intuitively, the model's parameters are estimated by matching observed market shares to

[20] The specification, notation and definitions for the demand model follow Eizenberg (2014) closely.

those that are predicted by this model. In particular, applying the familiar inversion strategy from Berry (1994), the parameters are estimable via the following linear regression:

$$ln(s_j/s_0) = x_j\beta + \alpha p_j + \sigma ln(s_{j/g}) + \xi_j \quad (5)$$

where two terms are endogenous, i.e., correlated with the error term ξ: the price, and the product's share as a fraction of its nest's share, $s_{j/g}$.

For concreteness, in this draft we provide here our estimates for one particular category, Raw Tahini paste. The natural nesting structure for this category suggests that whole seed Tahini should be treated as a separate segment than regular seed Tahini. Whole seed Tahini is made from whole sesame seeds, whereas other Tahini is made only from the inner part of the seed. The whole seed Tahini is richer in fiber, minerals and protein, and thus considered to be of a higher nutritional value. We may therefore expect stronger substitution to obtain among products of the same seed type. For example, consumers with strong awareness to nutritional value may only consider whole seed Tahini. The chosen nesting structure allows for such patterns.

Demand estimates are presented in Table 4. The size of the market was defined, in this case, in a very simple and practical form as 120 percent of the observed sales.[21]

Table 4 presents estimation results for the regular supermarket channel. The first two columns show the first-stage regressions, while the third column shows the results for the second stage estimation of the utility parameters. A total of four excluded instruments are used: the interaction of Fuel price with dummy variables for the two leading brands (Achva and Baracke), the interaction of VAT with the Achva brand, and the number of competing products within the nest. As expected, the number of competing products has a negative and significant effect on both endogenous variables: price, and the within-nest share. The other instruments also have significant effects, and exploit firm-specific responses to changes in the underlying cost structure.

The correlation parameter σ is estimated at 0.134. Recalling that it varies between 0 and 1, this is a rather low value suggesting that, while substitution within each nest is stronger than substitution across nests, this effect is not particularly strong. A negative time trend reflects an overall decline in the demand for raw Tahini relative to the outside option. In addition to the time trend, dummy variables for 42 of the 43 sample months are included, but are not reported for space considerations. Brand dummies are included for brands with volume share in excess of one percent.

The price effect is negative and significant, and the brand dummy effects are also precisely estimated. The most-right column reports willingness to pay for specific brands that are implied by the utility estimates (noting that Shufersal and Mega are private labels of large retail chains). Compared to smaller brands, the willingness to pay for the leading brands varies between 2.8

[21] Sensitivity checks for the role played by such restrictions will be performed in all categories.

NIS to 19 NIS per kilo. This measure can be put in perspective: raw Tahini is most often sold in 0.5 kilo containers, at a price that varies roughly between 15 and 20 NIS per container, i.e., the typical price is 30-40 NIS per kilo. The added willingness to pay for the popular brands is thus between 5-50 percent of the price normally paid. While no immediate strategy is available to evaluate the plausibility of these willingness to pay estimates, they do appear to be of a reasonable magnitude in a category where quality is believed to differ substantially across producers.

Estimation results for the HD (Hard Dicsount) channel are displayed in Table 5. There is slight variation in the set of brand dummies included as utility shifters (again, these are brands that hold at least 1 percent volume share): the brand "Hardoof" ("Jerusalem") is associated with a dummy variable in the regular supermarket channel (resp., HD channel) but not in the HD channel (resp., regular supermarket channel).

The estimates reveal very similar patterns to those obtained for the regular supermarket channel, with the correlation coefficient σ estimated at 0.190. The WTP measures are also very similar. One may expect the demand patterns to be different, as different customers shop at HD supermarkets and regular supermarkets. Nevertheless, it is not necessarily the case that the former customers should be more price-sensitive. This has to do with the geographic location of stores: as shown in Eizenberg, Lach and Yiftach (2018), HD supermarkets are often less accessible to non-affluent households than to higher-income households. One may cautiously interpret the similarity of the estimated demand patterns across the two segments as some indication of robustness.

A final note regarding the estimated demand model is that the nested logit demand model may seem, a-priori, to be ill-suited for the purpose of this study. Specifically, the segmentation of the market — a primary determinant of the results of any competitive analysis — is dictated by the econometrician, rather than being driven directly by data. Note, however, that this is not entirely correct. The data may easily reject the suggested specification by delivering correlation parameter estimates that exceed the $[0, 1)$ boundary, by delivering unreasonable coefficient signs, or implausible willingness-to-pay measures.[22] Nonetheless, future versions of this paper would allow for more flexible substitution patterns via the random coefficient model outlined above.

4 Single-market supply models

Having described the demand side of our framework, and the manner with which demand estimates deliver estimates of each category's elasticity of demand, we next proceed to explain how the demand estimates deliver two additional types of indicators at the category level: indicators for the rejection of specific models of competitive conduct based on statistical tests, and threshold

[22] For a related discussion in the context of market definitions, see Kovo and Eizenberg (2017).

discount factors. These tasks are taken, in turn, in the next two subsections.

4.1 Testing specific conduct models

We test models of competitive conduct following the spirit of analyses in Pakes (2016) and Miller and Weinberg (2017). Pakes (2016) summarizes the intuition underlying this approach as follows:

> "...the markup...can be calculated directly from the demand estimates (we do not need to estimate a pricing equation to get it). The twin facts that we can get an independent estimate of the markup and that the pricing theory implies that this markup has a coefficient of one in the pricing equation enables a test of the pricing model. In studies where reasonably precise estimates of the demand system are available without invoking the pricing equation, this test should give the researcher an idea of whether it is appropriate to use the Nash pricing equation as a model of behavior."

Indeed, in our application we recover demand estimates from demand-side moments alone, without resorting to restrictions from the supply side. In our application we wish to test for both Nash-Bertrand pricing, and for collusion, appealing to the "menu" approach advocated by Nevo (1998) as an alternative to estimating continuous conduct parameters. This motivates tests of non-nested models following Gasmi, Laffont and Vuong (1992). For the present moment, and for simplicity, we describe how to test each of these two models separately.

Considering collusion first, we note that the stacked first-order conditions for the problem in which all firms set prices to each of their products to maximize the category's profit are (Nevo 2001):

$$p - mc = \left(\mathcal{I} \odot \mathcal{S}\right)^{-1} s, \tag{6}$$

where $\mathcal{I}$ is a $J \times J$ matrix of ones, $\mathcal{S}$ is a matrix of demand derivatives evaluated at the observed prices given the estimated demand parameters (such that $\mathcal{S}_{jr} = \partial s_j / \partial p_r$ for all $1 \leq j, r \leq J$), $\odot$ denotes element-by-element multiplication, and s are observed market shares. Note that what we shall actually take to the data, in many cases, are models in which only the leading 2-3 manufacturers behave cooperatively, in which case the matrix of ones is replaced by an appropriate block-diagonal matrix.

Put differently, we obtain a J-vector of collusive markups, $CM = \left(\mathcal{I} \odot \mathcal{S}\right)^{-1} s$ that is easily calculated given observed market shares s and the estimated demand derivatives $\mathcal{S}$.

Denoting CM_j as the j^{th} element of the markup vector, and allowing marginal costs to depend linearly on observed and unobserved shifters, implies the following equation:

$$p_j = w_j \lambda + \kappa \cdot CM_j + \omega_j, \tag{7}$$

where w_j are observed cost shifters pertaining to product j, and ω_j is an unobserved cost shifter.

The parameter κ is the object of our interest: a coefficient that is different from the value 1 in a statistically significant fashion will imply a rejection of the collusive model. Instruments must be applied to the endogenous CM_j term. We follow the practice from the literature of using the same instruments that were applied in the demand estimation procedure. Appealing to section 3 above, we note that the second set of instruments (those that capture the number of own-firm and competing UPCs within particular cuts of the data) are shown in Berry and Haile (2014) to allow the nonparametric identification of supply models of the type considered here. Intuitively, such variables can shift and rotate the demand curve, the basic condition for identifying models of competitive conduct (Bresnahan 1989).

Important limitations of the above approach arise in our context. First, while our goal is to identify differences in the implied conduct across categories (i.e., whether collusion has been rejected, or not rejected), our approach may confound those with differences across categories in the accuracy with which we approximate the marginal cost function. The availability of credible instruments that shift the markup while holding marginal cost constant is therefore very important. Moreover, we shall attempt to estimate this relationship using multiple, flexible specifications for the marginal cost functions to determine whether the patterns we uncover are robust to this issue.

Second, our approach does not allow us to detect collusion. It only allows us to reject, or not to reject, the collusive hypothesis. Not rejecting the hypothesis, of course, does not imply that collusion takes place. Moreover, and related to the previous point, rejecting the hypothesis that κ is equal to 1 implies a rejection of the collusive hypothesis along with all the other assumptions embedded in our analysis, i.e., the assumed structure of the cost and demand functions.

This approach, therefore, does not allow us to credibly detect collusion in any particular category. But in a statistical sense, across categories, we may associate a higher probability of collusion taking place in categories where the hypothesis that $\kappa = 1$ is not rejected, than in those where it is rejected. So while we shy away of making any claims of collusive behavior in any particular category, we do believe that correlating an indicator for non-rejection with measures of concentration can inform research question (1) as outlined in the introduction.

Correlating an indicator for rejection of the Nash-Bertrand hypothesis with measures of concentration has a similar flavor, and we pursue both strategies. To test for Nash-Bertrand pricing we replace the matrix $\mathcal{I}$ with an appropriate block-diagonal ownership matrix Ω such that $\Omega_{jk} = 1$ if goods $(j, k) \in \{1, 2, ...J\}$ are produced by the same firm, and zero otherwise.

4.2 computing threshold discount factors

The next part of our analysis addresses research question (3) in the introduction section: how does the stability of cooperative regimes correlate with concentration? To address this question, and with estimates of the demand system in each category in hand, we next introduce the supergame model of collusion to each such category for the purpose of obtaining quantitative indicators of cartel stability in each. We begin by introducing the theoretical framework. The seminal papers in this literature were mentioned in the introduction. Here we follow notation from Bernheim and Whinston (BW, 1990) who build on the earlier work of (Abreu 1986, 1988).

Assume for simplicity that two firms, indexed by i and j, compete in some market m. Denote by $\pi_{im}(p_{im}, p_{jm})$ firm i's collusive per-period payoff on the equilibrium path. Namely, this is the profit firm i garners in the current period if both firms adhere to their collusive arrangement, in which firm i charges p_{im} and its competitor charges p_{jm}. Further, denote by $\pi_{im}(\hat{p}_{im}, p_{jm})$ the one-shot deviation payoff for firm i. That is: if the rival j adheres to the cooperative regime by charging p_{jm}, then this expression captures the maximal one-period payoff that firm i can obtain by deviating from that regime and charging $\hat{p}_{im}$, its most optimal deviation price, instead of its collusive price p_{im}.

The equilibrium strategies define a punishment for such deviations. Keeping the nature of the punishment general for now, denote by $\delta\underline{\nu}_{im}$ the discounted payoff that firm i should expect if it were to currently deviate from the collusive regime. The parameter δ is the firm's discount factor (as it may differ across the two firms, we may also denote it by δ_i), and $\underline{\nu}_{im}$ is the discounted stream of payoffs to firm i, under the punishment scheme, where the discounting is to the next period. Under these definitions, for firm i to follow the collusive strategy, the following condition must then apply:

$$\pi_{im}(\hat{p}_{im}, p_{jm}) + \delta\underline{\nu}_{im} \leq \frac{1}{1-\delta}\pi_{im}(p_{im}, p_{jm}) \tag{8}$$

Intuitively, this condition is easier to satisfy the more patient is the firm. Namely, it defines a threshold discount factor, such that if δ exceeds this threshold, firm i will abide by the cooperative regime:

$$\delta \geq \frac{\underline{\nu}_{im} - \hat{\pi}_{im} + \sqrt{(\hat{\pi}_{im} - \underline{\nu}_{im})^2 - 4\underline{\nu}_{im}(\pi_{im} - \hat{\pi}_{im})}}{2\underline{\nu}_{im}} \tag{9}$$

Ross (1992) proposes, in the context of a theoretical analysis, to use threshold discount factors as the one defined on the right-hand side of (9) to approximate cartel stability, noting that "though hardly a perfect measure it does have intuitive appeal, and has been used in this way in the past" (referring to Tirole 1988 and Shapiro 1989). In this paper we propose to estimate such thresholds empirically and to use them along the lines proposed by Ross in cross-category comparisons.

To that end, we next specify the steps required to estimate such thresholds empirically. Following on the discussion from the introduction, our approach begins with a "null hypothesis" that defines certain basic conditions regarding the Data Generating Process.

Assumption 1. *Let the Data Generating Process in market m have the following properties:*

1. *The data is generated by a Subgame Perfect Nash Equilibrium where, on the equilibrium path, firms obtain static collusive profits*

2. *Deviations are detected with certainty, before next-period play (Abreu 1988), and result in reversion to Nash-Bertrand pricing forever (grim-trigger strategies)*

3. *A firm expects a constant stream of its current collusive profits (current Nash Bertrand profits) if it cooperates (deviates).*[23]

4. *Fixed costs are low enough such that there is no exit (Porter 1983), independent of the actions. Marginal costs are constant in output.*

The merit of this "null hypothesis" is the following: we apply it to categories in which collusive conduct has not been rejected following the analysis in the previous subsection (and, some versions of it, for categories in which Nash-Bertrand pricing has been rejected). While non-rejection of collusion falls short of demonstrating that collusion takes place, we may still treat the collusive hypothesis as a basis for our analysis in such categories. We shall use this hypothesis to obtain a quantitative indicator that informs us about the ease of maintaining collusive arrangements in this category, to the extent that they hold. This indicator would then be correlated with measures of concentration across categories.

Why do we postulate that the data are, in fact, generated by a model in which firms are on the equilibrium path in which they are able to obtain the perfect collusive payoff in every period? The answer has two parts. First, the empirical implementation, explained below, requires us to begin by backing out marginal costs, and this can be achieved given some specified behavior for firms. Conditioning on collusive behavior is a natural starting point given non-rejection of collusive behavior (or rejection of Nash-Bertrand pricing).

Second, in principle the content of Assumption 1 can also be viewed as a true null hypothesis to be tested in the data. For example, if we find that the threshold discount factor required to sustain the collusive regime outlined by Assumption 1 is exceedingly high, we may interpret this

[23] Sullivan (2017) makes the correct observation that the degree of cooperative behavior is likely to vary over time as it responds to demand shocks. For simplicity, our approach ignores this and assumes that firms use current estimates as predictors for flow payoffs in all future periods. We could relax this assumption by considering the actual estimated variation over time in the collusive payoffs as well as in the Nash reversion punishment payoffs, and assuming that firms are able to predict future shocks. We argue, however, that our goal here is to obtain a simple statistic that can be compared across categories, and this makes us somewhat lenient in allowing misspecification in the estimation of this statistic.

as a rejection of this Assumption by the data. Namely, the data may be telling us, under these circumstances, that an abnormal degree of patience would be required for this arrangement to be sustained. One could then envision estimating the threshold discount factors under declining degrees of collusive profits (captured empirically by setting lower values for conduct parameters), and stopping this process once the required threshold discount factor no longer appears to be "exceedingly high." We could then interpret the conduct parameter at which we stopped to be our inference on conduct in the market. While appealing, this is not the approach that we take to data. Instead, we use the estimated threshold as an indicator of the likely ease with which collusion could be attained.

In categories where Nash-Bertrand pricing is *not rejected*, we shall take a different starting point, assuming that the data are generated by Nash competition in prices. We shall then perform a procedure, analogous to the one described below, that delivers the lowest discount factor that would allow firms to switch into perfect collusion, as an alternative measure of firms' ability to collude. One interpretation of such an analysis is that firms may be deterred from collusion by fear of regulatory response, or public response to price increases (say, via a boycott, see Hendel, Lach and Spiegel 2016). In this case, even though firms are deterred from colluding, the threshold discount factor that would have allowed them to conclude is still interesting: it measures the potential ease with which firms could collude in this market, if free from regulatory and public outcry concerns. These threshold values can also be meaningfully correlated with measures of concentration to address the very same research question (3) outlined in the introduction.

For concreteness, let us return to discuss categories in which competitive pricing has been rejected (or where cooperative conduct has not been rejected), and focus on using Assumption 1 as our point of departure. Given Assumption 1, the term $\delta\underline{\nu}_{im}$ in equation (8) changes to $\frac{\delta}{(1-\delta)}\nu_{im}^{nb}$, where ν_{im}^{nb} is firm i's static Nash Bertrand payoff. This simplifies the expression for the threshold discount factor, which now becomes:

$$\delta \geq \frac{\hat{\pi}_{im} - \pi_{im}}{\hat{\pi}_{im} - \nu_{im}^{nb}} \tag{10}$$

Evaluating the threshold discount factor now requires only the estimation of the quantities on the RHS of (10): namely, the collusive flow payoff, the one-shot deviation flow payoff, and the punishment flow payoff. We next explain how to estimate these values given the estimated demand system. The algorithm has five steps, to be described here in order.

Step 1. Here we back out the vector of marginal costs for all products in market m appealing to the firms' first order conditions under the static equilibrium played in each period on the equilibrium path. Specifically, following Berry, Levinsohn and Pakes (1995) and Nevo (2001), we obtain the marginal cost vector by using the stacked first order conditions:

$$mc^{collusion} = p - \left(\mathcal{I} \odot \mathcal{S}\right)^{-1} s \tag{11}$$

where $mc^{collusion}$ is the vector of marginal costs, for each of the J goods sold in market m, under Assumption 1 which states that the observed data is generated by a regime in which firms are actually able to sustain perfect (static) collusive payoffs in each period. Given this assumption, the markup vector is given by $\left(\mathcal{I} \odot \mathcal{S}\right)^{-1} s$, as defined above. We note again that in our empirical application we will often not consider collusion by all firms in the market. In markets where two large duopolists compete with a fringe of small competitors, it will be more appropriate to consider collusion among the two leading firms, with other firms competing a-la Nash by setting individually-maximizing prices given prices of rivals. This is easily obtained by allowing the ownership matrix to once again be block-diagonal, where the products of the duopolists are represented by a single block of ones.

Step 2. With marginal costs at hand, we next compute variable flow profits on the equilibrium path. For a firm i that participates in the collusive arrangement, these are given by:

$$\pi_{im} = (p_i - mc_i^{collusion})'(s_i \cdot M) \tag{12}$$

where the i subscript refers to the vector's portion that pertains to firm i's products.

Step 3. We next obtain firm i's one-shot deviation payoff. For this purpose, we first solve numerically for the prices that firm i should charge for its products to maximize its current flow payoff, given that its rivals remain on the equilibrium path (i.e., they continue to charge their collusive prices). Denote this price level by

$$\hat{p}_i = argmax_{p_i} \sum_{j \in \mathcal{J}_i} \left(p_j - mc_j^{collusion}) \cdot s_j(p_i, p_{-i}) \cdot M\right],$$

where $\mathcal{J}_i$ is the set of firm i's products, and p_{-i} is the vector of prices charged by all rivals assuming they remain on the equilibrium path. We then compute the resulting one shot deviation payoff to firm i by:

$$\hat{\pi}_{im} = (\hat{p}_i - mc_i^{collusion})'(s_i(\hat{p}_i, p_{-i}) \cdot M) \tag{13}$$

Step 4. Finally, we obtain the Nash-reversion payoff that firm i would obtain in any future period if it were to deviate from the collusive arrangement in the current period. This too involves two logical steps. First, we calculate the price vector p^{nb} that would obtain under the reversion to Nash-Bertrand pricing by numerically solving the stacked first order conditions associated with that game:

$$p^{nb} - mc^{collusion} - \Big(\Omega \odot \mathcal{S}(p^{nb})\Big)^{-1} s(p^{nb}) = 0$$

It is then easy to obtain the Nash reversion punishment flow payoff for firm i via:

$$\nu_{im}^{nb} = (p_i^{nb} - mc_i^{collusion})'(s_i \cdot M) \tag{14}$$

Step 5. Finally, we simply input the computed expressions ν_{im}^{nb}, π_{im}, and $\hat{\pi}_{im}$ into equation (10) to obtain the threshold discount factor that would sustain the hypothesized collusive regime under Assumption 1.

Again, we note that simple modifications to the procedure outlined above could yield the threshold discount factor under alternatives to Assumption 1. We have already explained how to obtain these factors assuming that the data is actually generated by Nash Bertrand pricing, and the interpretation of these thresholds under that setup. But we can also begin with any assumption regarding observed conduct by setting the zeros in the ownership matrix Ω to some conduct parameter τ that ranges between 0 and 1, allowing firms to partially collude.

Implementation in the *Raw Tahini* category. Our ultimate goal is to estimate threshold discount factors in all 40 categories. As this is an ongoing effort, in the current draft we illustrate by showing the results of this analysis in the *Raw Tahini* category using Assumption 1 as the starting point (noting that we have not actually tested for collusion and that this choice is therefore made for illustrative purposes only). For simplicity, we assumed here that on the equilibrium path, all firms participate in the collusive regime. In future versions we shall allow only the two leading manufacturers to do so, as explained in the description of the algorithm above.

We have already presented above the demand estimation results from this category. Employing these estimates, and focusing attention of the first sample month, January 2012, the following economic implications are obtained. The own-price elasticities range between (-7.9) and $-(2.25)$, with a median of (-4.38). The median collusive margins calculated by following step 1 of the algorithm above obtain a median value of 0.29. That is, the markup of price over marginal costs represents 29 percent of the price.

A switch to Nash Bertrand pricing via the grim-trigger punishment strategy reduces the median price by 5.4 percent, and the median margin is reduced to 0.25. The one-shot Nash Bertrand payoff is only 1.3 percent lower than the collusive payoff. In other words, the punishment does not appear to be severe. This could be explained by the fact that the relatively-elastic demand implies that even a monopolist would be constrained in raising prices above marginal costs, so that the ability to collude does not yield a substantial increase in margins. At the same time, the same intuition is consistent with the finding that the one-shot deviation payoff is only 2.5

percent higher than the flow payoff from remaining on the equilibrium path.

Finally, step 5 of the algorithm above suggests that a rather low discount factor, 0.65, would be sufficient to sustain collusion by one of the leading firms in this sector. Many papers in economics calibrate such values at 0.95 or 0.99. It may be tempting to interpret this finding as suggestive evidence that collusion in this market is easy to sustain.

This, however, is not our interpretation. We argue that the level of the threshold discount factor, in itself, is not strongly informative regarding the ease of collusion. First, here we assumed that the relevant frequency for the repeated game is monthly, but one could argue that other frequencies are more appropriate.[24] Second, our assumption that the observed data are generated by perfect collusion could be an important driver of the value obtained. For these reasons, we believe that the absolute values of such indicators in particular categories are far less informative than a comparison of such values across categories, as we plan to do. We therefore view these thresholds as quantitative indicators that capture some sense in which the data is informative regarding the ability to sustain noncompetitive prices.

5 Multimarket supply analysis: summing over the IC constraints

We now appeal to Bernheim and Whinston (BW, 1990) to investigate the effect of multimarket conduct on the ability to sustain collusion. Consider, again, two firms, indexed by i and j, that now compete in two markets: $k = 1, 2$. In each market k, we can once again define the condition that would induce firm i to participate in the collusive regime, exactly as in equation (8):

$$\pi_{ik}(\hat{p}_{ik}, p_{jk}) + \delta \underline{\nu}_{ik} \leq \frac{1}{1-\delta} \pi_{ik}(p_{ik}, p_{jk})$$

As BW show, the effect of multimarket contact is that such Incentive Compatibility constraints can now be summed over the two markets in which the firms compete, i.e,

$$\sum_{k=1}^{2} \left[\pi_{ik}(\hat{p}_{ik}, p_{jk}) + \delta \underline{\nu}_{ik} \right] \leq \sum_{k=1}^{2} \left[\pi_{ik}(p_{ik}, p_{jk}) \right] \tag{15}$$

An important insight from BW is that this does not necessarily facilitate collusion. Intuitively, multimarket contact allows punishments to be more severe: a deviator could now be punished in both markets for a digression performed in a single market. Nonetheless, the deviator in this case would likely also deviate in both markets. As a consequence, both the deviation payoff, and the punishment payoffs, may be higher relative to a baseline situation where firms do not internalize the multimarket contact issue.

[24] Such possibilities are explored in Miller, Sheu and Weinberg (2018).

As BW demonstrate, given the two conflicting forces, multimarket contact will have no effect on the ability to sustain noncompetitive prices in a stylized model with identical firms, identical markets, and constant marginal costs. They refer to this as an "irrelevance result." Under these conditions, adding the incentive constraints up over multiple markets does not relax them. But these authors also show that when these conditions are violated, a wide range of possibilities may obtain, and, in particular, conditions that allow multimarket contact to facilitate tacit collusion can arise. This can happen, for example, if the number of competitors varies across markets, if firms have different costs, or if products are differentiated.

Whether or not multimarket contact can facilitate collusion is therefore an empirical question, and the answer depends on market specific parameters that characterize cost and demand structures. To operationalize this idea, let us once again begin with Assumption 1, and notice that, absent multimarket contact (that is: if the firms do not internalize it), collusion would be sustained on part of firm i if its discount factor satisfies the following condition:

$$\delta_i \geq max\{\frac{\hat{\pi}_{i1} - \pi_{i1}}{\hat{\pi}_{i1} - \nu^{nb}_{i1}}, \frac{\hat{\pi}_{i2} - \pi_{i2}}{\hat{\pi}_{i2} - \nu^{nb}_{i2}}\} \tag{16}$$

Whereas, if firms internalize the multimarket contact, firm i would adhere to collusion in both markets if:

$$\delta_i \geq \frac{(\hat{\pi}_{i1} + \hat{\pi}_{i2}) - (\pi_{i1} + \pi_{i2})}{(\hat{\pi}_{i1} + \hat{\pi}_{i2}) - (\nu^{nb}_{i1} + \nu^{nb}_{i2})} \tag{17}$$

Following the steps outlined in the previous section, we can estimate all quantities on the right hand sides of the two conditions. If the estimated RHS of condition (17) is lower than that of condition (16), we would conclude multimarket contact facilitates collusion. If it is higher, then it does not do so.

We therefore propose viewing the difference between the RHS of these two equations as a quantitative index of the extent to which multimarket contact facilitates collusion. This approach could be used to evaluate the contribution of existing situations of multimarket contact to non-competitive prices. Or, it could be used to evaluate the potential harm to competition from a merger in which multimarket contact is established. Consider a situation where firm i initially operates only in market $k = 1$, but now proposes to acquire a firm that operates in market $k = 2$. Standard antitrust analysis is not well established with respect to such mergers, as they do not increase the concentration level in either market $k = 1$ or market $k = 2$. Our approach could be used to measure the extent to which such a merger would, nonetheless, potentially shift these markets towards a less competitive regime.

In future versions we would present empirical estimates of the RHSs of these conditions in two leading cases. One case is the markets for *Packaged Hummus Salad* and *Instant Coffee*, where

Strauss-Elite and Osem-Nestle have substantial presence in both. The second case involves the categories *Bread Crumbs* and *Kuskus*. Here, multimarket contact is not present in the beginning of our sample period, but is gradually established towards its end. Analysing this case will have the added benefit of examining, in raw data, how multimarket contact affects firm behavior, and contrasting that information with the information garnered from our structural approach.

6 Estimation Results: conduct and contact across categories

TBC (see preliminary results for the Tahini category in the sections above).

7 Concluding remarks

TBC

References

[1] Abreu, D, 1986. "Extremal Equilibria of Oligopolistic Supergames," *Journal of Economic Theory*, 39: 191-225

[2] Abreu, D, 1986. "On the Theory of Infinitely Repeated Games with Discounting," *Econometrica*, 56: 383-96

[3] Ashenfelter, O., Hosken, D., and Weinberg, M., 2014. "Did Robert Bork understate the competitive impact of mergers? Evidence from consummated mergers," *The Journal of Law and Economics*, 57(S3), S67-S100

[4] Bain, J. (1951). "Relation of Profit Rate to Industry Concentration: American Manufacturing, 1936-1940," *The Quarterly Journal of Economics*, 65(3), 293-324

[5] Becker, G.S., 1971, "Economic theory" (Knopf, New York)

[6] Bernheim, B. D., and Whinston, M. D. (1990). "Multimarket contact and collusive behavior," *The RAND Journal of Economics*, 1-26.

[7] Berry, S.T. (1994): "Estimating Discrete-Choice Models of Product Differentiation," *RAND Journal of Economics*, 25(2): 242-262

[8] Berry, S., Levinsohn, J., and A. Pakes (1995): "Automobile Prices in Market Equilibrium," *Econometrica*, 63(4): 841-90

[9] Berry, S. T., and Haile, P. A., (2014). "Identification in differentiated products markets using market level data," *Econometrica*, 82(5), 1749-1797.

[10] Blonigen, B.A., and J.R. Pierce, 2016. "Evidence for the effects of mergers on market power and efficiency," No. w22750. National Bureau of Economic Research

[11] Bork, R.H., 1978. "The antitrust paradox," New York: Basic books.

[12] Bresnahan, T.F., 1989: "Empirical studies of industries with market power," Handbook of Industrial Organization, in: R. Schmalensee & R. Willig (ed.), Handbook of Industrial Organization, edition 1, volume 2, chapter 17, pages 1011-1057 Elsevier

[13] Ciliberto, F., and Williams, J. W., (2014). "Does multimarket contact facilitate tacit collusion? Inference on conduct parameters in the airline industry," *The RAND Journal of Economics*, 45(4), 764-791.

[14] Ciliberto, F., Watkins, E., and Williams, J. W., (2018). "Collusive pricing patterns in the US airline industry," *International Journal of Industrial Organization*

[15] Clarke, R., and Davies, S. W., (1982). "Market structure and price-cost margins," *Economica*, 49(195), 277-287

[16] Connor, J. M., and Peterson, E. B., (1992). "Market-structure determinants of national brand-private label price differences of manufactured food products," *The Journal of Industrial Economics*, 157-171.

[17] Corts, K., (1999). "Conduct Parameters and the Measurement of Market Power," *Journal of Econometrics*, 88(8): 227250.

[18] Cowling, K. and M. Waterson, 1976. "Price-cost margins and market structure," *Economica* 43: 267-274.

[19] Edwards, C. D., 1955. "Conglomerate bigness as a source of power," in *Business concentration and price policy* (pp. 331-359). Princeton University Press.

[20] Evans, W. N., and Kessides, I. N. 1994. "Living by the 'golden rule': Multimarket contact

in the US airline industry," *The Quarterly Journal of Economics*, 109(2), 341-366.

[21] Eizenberg, A. (2014). "Upstream innovation and product variety in the us home pc market," *Review of Economic Studies*, 81(3), 1003-1045.

[22] Eizenberg, A., S. Lach, and M. Yiftach, 2018. "Retail prices in a city," *mimeo*.

[23] Gandhi, A., and Houde, J. F., (2016). "Measuring substitution patterns in differentiated products industries," *mimeo*

[24] Gasmi, F., Laffont, J. J., and Vuong, Q., (1992). "Econometric Analysis of Collusive Behaviorin a Soft Drink Market," *Journal of Economics & Management Strategy*, 1(2), 277-311.

[25] Green, E., and Porter, R. 1984. "Noncooperative Collusion under Imperfect Price Information," *Econometrica*, 52: 87-100

[26] Goto, U., and Iizuka, T, (2016). "Cartel sustainability in retail markets: Evidence from a health service sector," *International Journal of Industrial Organization*, 49, 36-58.

[27] Johnson, A. C., and Helmberger, P. (1967). "Price elasticity of demand as an element of market structure," *The American Economic Review*, 57(5), 1218-1221

[28] Kahn, A. E., 1961. "The Chemical Industry," in W. Adams, ed., The Structure of American Industry, 3rd ed. (New York, NY: Macmillan).

[29] Kovo, A., and Eizenberg, A. (2017). "Inferring Market Definitions and Competition Groups From Empirically-Estimated Demand Systems: A Practitioner's Guide,", *mimeo*

[30] Martin, S., 2012. "Market structure and market performance," *Review of Industrial Organization* 40(2): 87-108

[31] Michel, C., and Weiergraeber, S., (2018). "Estimating Industry Conduct in Differentiated Products Markets: The Evolution of Pricing Behavior in the RTE Cereal Industry," *mimeo*

[32] Miller, N. H., and Weinberg, M. C. (2017). "Understanding the price effects of the MillerCoors joint venture," *Econometrica*, 85(6), 1763-1791

[33] Miller, N., Sheu, G., and Weinberg, M. (2018). "Oligopolistic Price Leadership: An Empirical Model of the US Beer Industry," *mimeo*

[34] Modigliani, F. (1958). "New developments on the oligopoly front," *Journal of Political*

economy, 66(3), 215-232.

[35] Nevo, A., 1998. “Identification of the Oligopoly Solution Concept in a Differentiated Products Industry,” *Economics Letters*, 59(3): 391-395

[36] Nevo, A., 2001. “Measuring Market Power in the Ready-to-Eat Cereal Industry,” *Econometrica*, 69(2): 307-342

[37] Rotemberg, J., and Saloner, G., 1986. “A Supergame-Theoretic Model of Price Wars during Booms,” *American Economic Review*, 76: 390-407

[38] Pagoulatos, E., and Sorensen, R. (1986). “What determines the elasticity of industry demand?” *International Journal of Industrial Organization*, 4(3), 237-250.

[39] Pakes, A., 2016. “Empirical Tools and Competition Analysis: Past Progress and Current Problems,” *International Journal of Industrial Organization*, 53: 241-266

[40] Porter, R. (1983). “A Study of Cartel Stability: The Joint Executive Committee, 1880-1886,” *The Bell Journal of Economics*, 14(2), 301-314.

[41] Pus, D., (2018). “Tacit Collusion with Complementary Goods when Firms Meet in Multiple Markets: The Case of the U.S. Freight Railroad Industry,” *mimeo*

[42] Ross, T. W. (1992). “Cartel stability and product differentiation,” *International Journal of Industrial Organization*, 10(1), 1-13

[43] Shapiro, C., 1989. “Theories of oligopoly behavior,” in *Handbook of industrial organization* (North-Holland, New York) ch. 6, 329-414

[44] Shim, B., and Khwaja, A. (2017). “The Collusive Effect of Multimarket Contact on Prices: Evidence from Retail Lumber Markets,” In *2017 Meeting Papers* (No. 593), Society for Economic Dynamics

[45] Sullivan, C. (2017). “Three Essays on Product Collusion,” University of Michigan Doctoral dissertation

[46] Sylos Labini, P., 1957. “Oligopoly and Technical Progress,” *Milan: Giuffre*

[47] Tirole, J. (1988). “The theory of industrial organization,” *MIT press*

A Tables and Figures

Table 1: Product categories

Rice	Sugar
Eggs	Packaged Hummus salad
Yellow Cheese	Bread crumbs
Soft Cheese	Cottage cheese
Frozen Fish	Kuskus
RTE Cereal	Ketchup
Fresh milk	Flour
UHT milk	Carrot & Peas preserves
Butter	Tomato preserves
Tuna	Corn preserves
Raw Tahini	Oil
Sweet wines	Sour Cream
Frozen vegetables	Sweet cream
Pasta	Tea
Bread and buns	Baby formula
Leben & Eshel**	Black coffee
Salt	Instant coffee
Yogurt and dairy pudding	Packaged olives and cucumbers*
Black soda drinks	Frozen Chicken and Turkey*
Soy drinks	Fabaceae*

Notes: the table presents the 40 categories included in this study. These correspond to Nielsen's Base Categories. The last three, indicated by *, are defined as Super Categories.
** Leben & Eshel is a category of dairy products akin to Yogurt.

Table 2: Category level concentration measures

Category	HHI	C1	C2	C3	Category	HHI	C1	C2	C3
Fabaceae	0.35	0.53	0.75	0.85	Yogurt & dairy pudding	0.47	0.62	0.90	0.99
Frozen chicken and turkey	0.25	0.41	0.61	0.74	Leben & Eshel	0.77	0.87	0.96	1.00
Packaged olives & cucumbers	0.22	0.36	0.61	0.72	Bread & buns	0.32	0.46	0.73	0.89
Tea	0.52	0.66	0.96	0.98	Frozen vegetables	0.39	0.60	0.69	0.76
Pasta	0.34	0.57	0.66	0.73	Sweet wines	0.22	0.41	0.55	0.65
Black soda	0.67	0.81	0.92	0.99	UHT milk	0.56	0.67	1.00	1.00
Baby formula	0.46	0.57	0.95	0.99	Fresh milk	0.55	0.71	0.89	1.00
Sweet cream	0.61	0.77	0.86	0.93	Frozen fish	0.32	0.52	0.65	0.75
Sour cream	0.68	0.81	0.97	1.00	Soft cheese	0.44	0.58	0.89	1.00
Oil	0.25	0.41	0.64	0.74	Eggs	0.21	0.36	0.52	0.65
Corn preserves	0.24	0.38	0.65	0.78	Yellow cheese	0.80	0.88	0.98	0.99
Tomato preserves	0.29	0.44	0.70	0.85	Tuna	0.32	0.49	0.71	0.85
Carrot & Peas preserves	0.33	0.46	0.79	0.88	Tahini	0.23	0.35	0.62	0.78
Flour	0.11	0.20	0.37	0.50	Salt	0.53	0.67	0.87	0.98
Kuskus	0.30	0.38	0.72	0.89	RTE cereal	0.45	0.64	0.84	0.89
Cottage cheese	0.55	0.71	0.87	1.00	Ketchup	0.50	0.67	0.92	0.94
Packaged Hummus salad	0.34	0.43	0.80	0.89	Butter	0.66	0.80	0.91	0.97
Sugar	0.50	0.68	0.86	0.93	Rice	0.47	0.68	0.74	0.79
Soy drinks	0.40	0.58	0.77	0.90	Black Coffee	0.63	0.79	0.86	0.88
Breadcrumbs	0.18	0.35	0.50	0.62	Instant Coffee	0.38	0.48	0.85	0.96
Mean	0.42	0.57	0.77	0.86					

Notes: concentration measures are reported for each category, averaged over the 43 sample months. The measures take into account subsidiary structures and are computed over all distribution channels taken together. Source: authors' calculation using Nielsen data and multiple online sources, see text.

Table 3: Business groups and cross-category presence

Business group	Categories with presence	Categories with substantial presence
Tnuva	28	14
Strauss/Elite	14	8
Neto	12	2
Taaman	11	0
Osem/Nestle	10	9
The Central Bottling Company Group	10	4
Willi Food	10	1
Sugat	9	6
Maya	9	1
Shcestowitch	8	1
Unilever	6	2
Zanlakol	5	3
Diplomat	4	2

Notes: the table lists business groups that are present in multiple categories in the food sector. Substantial presence in a category is defined as having a volume share in excess of 10 percent. Source: Authors' calculation using Nielsen data and multiple online sources, see text.

Table 4: Demand estimates: Raw Tahini (regular Supermarkets)

Variable	1st stage: price	1st stage: within-nest share	2nd stage	WTP
achvaVAT	53.09***	-112.2**		
	(12.48)	(50.47)		
achvaFuel	-0.00446*	0.0330***		
	(0.00270)	(0.0109)		
barackeXFuel	-0.00553**	0.0622***		
	(0.00228)	(0.00923)		
# Competing products in nest	-0.0458***	-0.0732***		
	(0.00275)	(0.0111)		
σ			0.134**	
			(0.0570)	
Price per kilo			-0.151***	
			(0.0244)	
achva	-5.606**	11.20	2.217***	14.7
	(2.423)	(9.805)	(0.227)	
baracke	3.726***	-8.698***	2.864***	19.0
	(0.409)	(1.656)	(0.182)	
hanasich	2.205***	0.774**	2.222***	14.7
	(0.0929)	(0.376)	(0.153)	
hardoof	0.951***	13.09***	2.825***	18.7
	(0.130)	(0.525)	(0.339)	
zahav	2.267***	1.047*	2.140***	14.2
	(0.148)	(0.597)	(0.179)	
al_arz	2.135***	-0.913*	1.725***	11.4
	(0.125)	(0.507)	(0.182)	
mega	1.799***	5.294***	2.433***	16.1
	(0.107)	(0.434)	(0.171)	
saadi	0.663***	-1.216**	0.422***	2.8
	(0.129)	(0.521)	(0.136)	
shufersal	1.581***	1.195***	1.640***	10.9
	(0.102)	(0.413)	(0.136)	
Time trend	-0.0166***	0.102***	0.0126**	
	(0.00590)	(0.0239)	(0.00574)	
Constant	-4.738***	26.33***	-4.979***	
	(0.206)	(0.833)	(0.828)	
Observations	2,245	2,245	2,245	
R-squared			0.498	
F			36.37	

Notes: Utility parameter estimates in the Raw Tahini category (regular supermarket channel). Monthly dummy variables (in addition to the reported time trend) are included but not reported. Standard errors in parentheses. ***, ** and * stand for significance levels of 1, 5 and 10 percent, respectively.

Table 5: Demand estimates: Raw Tahini (HD Supermarkets)

Variable	1st stage: within-nest share	1st stage: price	2nd stage	WTP
achvaVAT	44.97***	-48.97		
	(12.33) (46.04)			
achvaFuel	0.000921	0.0156		
	(0.00266)	(0.00992)		
barackehFuel	-0.00459*	0.0637***		
	(0.00253)	(0.00945)		
# Competing products in nest	-0.0448***	-0.129***		
	(0.00235)	(0.00877)		
σ			0.190***	
			(0.0665)	
Price per kilo			-0.113***	
			(0.0213)	
achva	-5.576**	-0.649	1.338***	11.8
	(2.394)	(8.936)	(0.295)	
baracke	3.483***	-11.25***	2.244***	19.9
	(0.453)	(1.692)	(0.193)	
hamotag	0.371***	-4.559***	-0.179	-1.5
	(0.109)	(0.406)	(0.141)	
hanasich	2.222***	0.699**	1.972***	17.5
	(0.0952)	(0.355)	(0.151)	
al_arz	1.519***	0.466	1.280***	11.3
	(0.119)	(0.444)	(0.128)	
jerusalem	1.137***	3.508***	1.323***	11.7
	(0.153)	(0.571)	(0.116)	
mega	0.494***	1.821***	0.661***	5.8
	(0.102)	(0.381)	(0.0784)	
saadi	0.663***	-2.821***	0.235*	2.1
	(0.128)	(0.479)	(0.140)	
shufersal	1.381***	-1.944***	0.976***	8.6
	(0.0929)	(0.347)	(0.144)	
Time trend	-0.0160***	0.125***	0.00891*	
	(0.00564)	(0.0210)	(0.00498)	
Constant	-3.988***	28.14***	-5.083***	
	(0.190)	(0.710)	(0.854)	
Observations	2,373	2,373	2,373	
R-squared			0.685	
F			58.83	

Notes: Utility parameter estimates in the Raw Tahini category (HD channel). Monthly dummy variables (in addition to the reported time trend) are included but not reported. Standard errors in parentheses. ***, ** and * stand for significance levels of 1, 5 and 10 percent, respectively.

Figure 1: Market share evolution in the Kuskus category. Source: Authors' calculation using Nielsen data