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

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Abstract

We perform a simultaneous empirical study of demand and competition patterns in 40 product categories of the Israeli food sector. In each category we estimate a differentiated product demand model, and use the estimates to compute indicators that capture the category's potential of sustaining equilibria with prices that are above the competitive levels. These indicators are *threshold discount factors*: the smallest ones required for supporting such hypothetical equilibria, whether or not they are actually played in practice. We then investigate how those thresholds vary with within-category concentration levels, and also how they respond to cross-category interactions (multimarket contact). We also study the relationship between a category's concentration and its demand elasticity. 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 the intensity of competition across industries is a staple of the Industrial Organization literature. The Structure-Conduct-Performance tradition (SCP, Bain 1951) stipulated a cross-industry relationship between an industry's competitive conduct, often approximated by observed profit margins, and its structure: namely, its observed levels of concentration and barriers to entry. A large empirical literature examined this relationship by regressing measures of profitability on measures of concentration.

Several authors have pointed out the limitations of this empirical paradigm.[1] Those limitations span several dimensions: first, the measurement of markups has been notoriously challenging. Second, the interpretation of the markup concept has proved far from obvious. For example, increased markups may signal a decline in the intensity of competition, but could alternatively reflect the adoption of technologies that involve a shift from marginal to fixed costs. Third, the relationship between markups and concentration involves a simultaneity problem, casting doubt on the ability to draw causal inferences. Finally, the theoretical foundation for the exercise becomes challenging outside of a small family of very specific stylized models.

As a consequence of those concerns, attention has shifted to single-industry studies where conduct is considered to be unobserved, and an empirical model of demand and supply is used to infer it (the New Empirical Industrial Organization, NEIO, Bresnahan 1989). The single-industry focus is well-suited to capture institutional features of the industry in question, and has proved instrumental in addressing important policy questions in a variety of economic sectors.[2] Nonetheless, the intellectual endeavour of identifying patterns that hold *across industries*, the primary goal of the SCP paradigm, has remained somewhat under-served by this literature. 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.[3] The relationship between observed concentration levels and firms' competitive conduct therefore remains elusive.

In this paper we revisit the task of studying this relationship. 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 three questions: (1) what is the relationship between an industry's concentration and its competitive conditions? (2) does multimarket contact facilitate less competitive pricing equilibria? and (3) how is concentration related to the category's demand elasticity?

1. The concentration-competition relationship. While it may seem natural to expect higher

[1] See Schmalensee (1989), Berry, Gaynor and Scott-Morton (2019).
[2] See Pakes (2016) for a recent survey of some of these contributions.
[3] An example of such work is Martin (2012).

concentration to result in lower competition, this relationship is in fact complex, even if one were to ignore the endogeneity of concentration. Repeated games of firm interaction (Abreu 1986, 1988) typically have infinitely-many equilibria, spanning both highly competitive and least competitive possibilities. Absent a credible equilibrium selection mechanism, the "higher concentration yields lower competition" comparative static is, therefore, difficult to establish on theoretical grounds, motivating empirical work.

Our strategy avoids the thorny empirical task of identifying the actual competitive conduct of the studied industries. We therefore avoid both the testing particular models of conduct (as in Nevo 1998, 2001), and the estimation of continuous conduct parameters.[4] Instead, we connect with the repeated-game literature mentioned above and estimate a measure of the ease with which minimal-competition equilibria can be sustained — whether or not such equilbria are actually played in practice.

The measures we estimate are threshold discount factors: the minimal values that satisfy firms' Incentive Compatibility Constraints (ICCs) at low-competition equilibria. The lower are these thresholds, the bigger is the category's potential for sustaining such equilibria. For concreteness, we show how to estimate the threshold discount factors for the least-competitive equilibrium, but they could be estimated for a range of equilibria with differing degrees of competition.

Importantly, this exercise has a clear theoretical interpretation independently of whether the least competitive equilibrium is the one actually played. Even if firms actually engage in much more competitive behavior, the threshold index still captures the potential ease with which the industry could shift into the least competitive equilibrium. It is this index that we then correlate, across industries, with standard measures of industry concentration — the HHI, C1, C2, and C3 measures — to uncover the statistical relationship between concentration and the nature of competition.[5] In this we connect with some fundamental policy debates: for example, an established empirical relationship between our index and measures such as C2 and C3 would challenge the assertion in Bork (1978) that only mergers to monopoly raise competitive concerns.

Several important caveats apply. First, while we depart from the SCP tradition, simultaneity continues to be an issue. Unobserved characteristics that affect an industry's competitive potential will also affect entry and, as a consequence, the industry's concentration. We should also wish to obtain a better theoretical foundation for the measured relationship. Our exercise therefore provides descriptive evidence regarding this relationship, with the hope that this will help propel a deeper understanding of its underlying mechanisms. In light of recent debates regarding the rise of concentration in the U.S. and elsewhere, we view this descriptive evidence as useful, though we emphasize the need to tread carefully when interpreting it.

[4] See, e.g., Bresnahan (1989), Corts (1999), Genesove and Mullin (2001), Miller and Weinberg (2017), Michel and Weiergraeber (2018).

[5] As familiar, C1, C2, and C3 measure the aggregate market share of largest, two largest, and three largest firms.

Second, while the lowest discount factor associated with the least-competitive equilibrium is meaningful even if that equilibrium is not the one actually played, its estimation does depend on the true Data Generating Process (DGP). A first step towards calculating the index is to recover the firm's marginal costs based on some assumed model of conduct and given estimates of the industry's demand system. We perform this exercise twice: once, assuming that the true DGP involves the most-competitive equilibrium, and a second time, assuming that the true DGP involves the least competitive equilibrium. Marginal costs are backed out and the threshold index is computed under both scenarios. We therefore obtain a range of measures while remaining silent with regard to the industry's actual competitive conduct.[6]

A third and final issue involves the interpretation of the threshold index at which the least-competitive equilibrium can be sustained. Satisfying the ICC is a necessary, but not a sufficient condition for that equilibrium to be played. This stems from the presence of infinitely-many equilibria. What, then, do we actually learn from a low value for this threshold index?

An alternative theoretical approach, that offers a unique equilibrium prediction in the relevant class of repeated games, is offered by Blonski et al. (2011). This work proposes an axiomatic approach that delivers a threshold discount factor, above which the non-competitive price equilibrium is *predicted to be selected*. We do not follow their approach and instead focus on the "traditional" threshold discount factor. As Blonski et al. discuss, this traditional threshold has been used extensively in comparative static analyses to identify conditions that are conducive to competitive vs. non-competitive behavior.[7] Of interest, these authors also cite experimental evidence of a positive relationship between the standard threshold and cooperation frequencies.[8]

Our approach is therefore well in line with the relevant theory literature, and focuses on taking it to data. 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.

2. Does multimarket contact result in "soft" competition? The economic theory of multimarket contact is well established. Articulated by Bernheim and Whinston (BW, 1990), this theory seeks to understand whether interaction among firms across multiple markets makes it easier to sustain prices above their competitive levels. This again requires that the ICCs hold for each firm. The question of interest is whether multimarket contact makes such ICCs less stringent, in the sense of allowing them to hold at lower discount factors.

[6] Alternatively we could estimate a conduct parameter, back out the marginal costs given this conduct parameter and then interpret the threshold index as that necessary to sustain the equilibrium actually played in the data, as identified by the conduct parameter. While this could be an interesting application of the ideas developed in this paper, we favor our approach as it avoids confounding our exercise with the question of whether we were able to credibly identify the conduct parameter in light of the familiar critique by Corts (1999).

[7] They cite Tirole 1988 (chapter 6.3.2.1), Bernheim and Whinston 1990, Narayana 1996, Ligon et al. 2002, Sanchirico 2004, Motta 2004 (chapter 4.2.5), Gilo et al. 2006, and Athey et al. 2007.

[8] Dal B'o 2005, in Blonski et al. (ibid.)

The analysis in BW90 reveals that such constraints need not necessarily be relaxed by multimarket contact. To understand why, note that for a particular equilibrium (with prices above competitive levels) to be sustained, no firm should find it profitable to deviate by undercutting its rivals' prices. Multimarket contact leads to an aggregation of both the benefits and the costs associated with such deviations. On the one hand, multimarket contact implies that the deviator can be punished across multiple markets. On the other hand, the deviation itself can be performed across multiple markets, increasing its associated short-term gain. As a consequence, we cannot determine the effect of multimarket contact on the ICCs in a general sense.

Assessing the role of multimarket contact in an applied setup therefore requires one to evaluate these conflicting effects, which magnitude depends on market-specific parameters. We view this as an invitation to perform empirical work: we take the theory of BW90 directly to data. We again appeal to the ability to compute components of the ICCs given estimated cost and demand structures. Our structural approach allows us to compute the threshold discount factor with and without the presence of multimarket contact. If multimarket contact reduces this threshold, we conclude that it has the potential of generating less competitive outcomes.

This approach stands in clear contrast to the extant empirical literature on multimarket contact. This literature uses observed variation in the degree of multimarket contact to estimate its (in-sample) treatment effect on realized measures of competition such as prices, markups, or structurally-estimated conduct parameters. Our approach, instead, evaluates the impact of multimarket contact on the potential of sustaining prices above their competitive levels. This allows us to conduct out-of-sample analyses. In particular, our approach offers an empirically tractable method for the ex-ante evaluation of mergers that increase firms' contact across industry borders. Previous papers, in contrast, study the effect of multimarket contact that has already materialized in the data.

We focus 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 the same two firms are the market leaders. Our estimated threshold discount factors for each of these categories, already obtained in the analysis of question (1) above, serve as the departure point. We then sum the IC constraints over these categories to reveal whether this allows low-competition equilibria to be supported at a lower discount factor.

3. What is the relationship between a category's concentration and its elasticity of demand? In addition to the two main questions above, we also take the opportunity to examine yet another question that dates back at least to Modigliani (1958) who established that more elastic demand could be associated with lower barriers to entry.[9] In contrast, Becker (1971, in Pagoulatos and Sorensen 1986) postulates that more elastic demand should be expected in the presence of *lower*

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

concentration since firms with market power set prices along the elastic portion of the demand curve.[10] 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.

Demand estimation. To estimate demand we use data from Nielsen regarding 40 categories of the Israeli food sector. This sector is ideal for the study of our questions of interest as it features several prominent business groups that garner significant market shares within and across product categories.

In each category we observe monthly UPC-level revenue and quantity data for a total of 43 months. We estimate nested logit and random coefficient logit (hereafter NL and RCL, respectively) models following Berry (1994) and Berry, Levinsohn and Pakes (BLP, 1995) allowing for rich substitution patterns via heterogeneous preferences towards price and the leading firms' brands. To identify the demand model in each category we use several sets of instruments.

In addition to the traditional use of cost shifters, interacted with firm dummies and product characteristics, we rely on additional sets of variables that should shift markups and therefore the endogenous price. First, we use a count of competing UPCs with identical characteristics (see Berry and Haile 2014). Second, we use 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. Finally, we exploit a major regulatory change in the food industry (the Food Law, which took effect in January 2015 and placed substantial restrictions on the actions of leading suppliers), again interacted with firm dummies, as yet another source of exogenous variation.

Following a literature review, in section 2 we present the data and provide evidence regarding concentration within categories and firms' presence in multiple categories. In section 3 we provide the structural demand specification and report preliminary estimation results from a Nested logit specification in a particular category (to date we have obtained such estimates in 23 categories). Section 4 presents the single-market analysis that yields our threshold index measures in each category. In this draft we report results for a single category. Future versions would report these thresholds for all categories, enabling the study of the relationship between these indicators and measures of concentration. Section 5 presents the analysis of multimarket contact, including preliminary results for the Instant Coffee-Hummus case using Random Coefficient Logit estimates. Section 6 concludes (TBC).

Relationship to the literature. The paper relates to a very large empirical literature de-

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

voted 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 in 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 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 plugs them into a 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. They view the market demand elasticity as a feature of an industry's structure, while discussing previous contributions that have been mixed with respect to this issue (specifically, Bain 1951 did 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. This motivates our empirical analysis.

The idea of estimating the components of firms' IC constraints 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 1990s Vitamin cartels. Miller, Sheu and Weinberg (2018) estimate a price leadership model where a leader sets price to help the industry coordinate among the many potential 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 differing in the questions of interest, assumptions and the manner of execution.

The strategic role of multimarket contact 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.[11] Ciliberto and Williams (2014) study multimarket contact in airline markets by explicitly estimating conduct parameters that are related to the extent

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

of cross-market relationships.[12] 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 of BW90 to data. To the best of our knowledge, this is the first empirical study of multimarket contact 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.[13]

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 including 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 is a large pharmacy chain), minimarkets, convenience stores, and ultra-orthodox (retail establishments targeting ultra-orthodox consumers).

We consider 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, a casual examination of the categories in Table 1 confirms that most of them can easily be considered as well defined markets (e.g., Tuna vs. Rice vs. Breakfast cereals). Third, and importantly, in cases where one may

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

[13] 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 that compete in different industries.

worry that two categories should really be considered as a single market, these concerns have been ruled out by decisions and analysis by the Israel Antitrust Authority (IAA). For example, in 2003 the IAA ruled that Black Coffee is a well-defined product market (and, specifically, that it is a distinct market from Instant Coffee, another category in our data).[14] 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 appear 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 but rather those 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 is considerable, there also appears to be substantial variation in concentration across categories. This illustrates the usefulness of the Israeli food sector for the study of the questions posed in this paper.

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

[14]The decision (in Hebrew) can be found at the following link..

in the analysis of the relationship between conduct and structure, for example, it could have enabled us to use within-category variation to identify the effect of concentration on the nature of competition. Ultimately, however, our goal is not to identify a causal relationship but rather to uncover their statistical relationship. Some categories display a greater degree of HHI variation over time than others: for example, the Salt, Ketchup, Yellow cheese and Tea categories have standard deviations ranging between 0.083-0.10, while other categories display 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-Nestlé, 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. It is on this case that we shall focus our analysis of multimarket contact in Section 5.

3 An 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. This motivates deploying a relatively uniform and transparent estimation approach across categories.

We balance these considerations via an application of the standard Random Coefficient Logit (RCL) model (Berry, Levinsohn and Pakes, BLP 1995). Estimation is performed separately in each category using this model.[15] In specifying the model, we keep some elements uniform across categories, while tailoring other elements to the specific category examined.

[15] In this preliminary draft, we report below estimation results for a handful of categories only. Some results are based on the simpler Nested logit model, and other results based on the richer RCL model described here.

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 data. In practice, we aggregate UPCs into unique combinations of month, brand and observed characteristics, and allow the products j to correspond to these aggregated products. 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, and Kuskus. This was motivated by a news article in which an industry insider suggested that firms operating in these categories actually compete over carbohydrates consumed on a plate.[16] 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 are, however, able to employ a battery of instruments that can be classified into four sets.

The first set of instruments involves 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.[17] 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 changes 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 and product types.

The VAT is imposed on all items covered in this study.[18] 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

[16] 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)

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

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

that level until the end of our sample period, July 2015.[19] 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 to 4,300 NIS on October 1st, 2012, and again, this time by 8.1 percent, to 4,650 NIS on April 1st, 2015.[20] A second set of instruments follows Berry, Levinsohn and Pakes (1995) and the identification results in Berry and Haile (2014): we count the number of products offered by competitors that share the same observed characteristics with the observation of interest.

While the first two sets of instruments are standard, our next two sets of instruments are perhaps more unique to our setup. These sets leverage shifts in supply-side strategies. Our third set of instruments exploits a discrete shift in regulation experienced by the Israeli food sector in January 2015, when the "Food Law" went into effect. This law placed substantial restrictions on the ability of "large suppliers," as defined in the law, to engage in Retail Price Maintenance (RPM) or to control the placement of products on retailers' shelves. We interact a post-January 2015 dummy variable with firm-specific effects, allowing the pricing strategies of firms to be differentially affected by the law.[21]

Our fourth and final set of instruments leverages shifts in company-wide pricing strategies that affect multiple categories. 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. As before, we allow such effects to be firm-specific using interaction terms. 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 unit 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 set of instruments 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

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

[20] Source: see the following link.

[21] The "Food Law" was a response to a major public protest in 2011 that prompted the government to seek remedies to the high cost of living, and, in particular, to the high prices in the food sector. Source: Shani Moses, Globes, May 2018 link.

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 there would be much variation in it on a monthly basis.

We briefly revisit the basic properties of the formal demand model here, referring the reader to the BLP (1995) paper for additional details. The indirect 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

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

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 brand dummies for the leading brands, and on price. The random coefficient specification overcomes the limitations of simpler models such as the Logit and delivers reasonable substitution patterns that would correctly inform our competitive analysis. 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. Identifying the portion of markups that can be explained by this differentiation is helpful in identifying, later, other sources of markups such as the category's potential of supporting low-competition equilibria.

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

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

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. The parameter σ^p captures taste heterogeneity with respect to price. We 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 $j \in J_t$,

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

where $P_v(\cdot)$ is the joint distribution of the taste shifters v_i. 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).[22]

Given the estimated demand parameters $\hat{\theta}^d$, one can compute demand elasticities following familiar procedures. Those, in turn, shall be helpful in analyzing the ICCs characterizing the repeated game framework. 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 addresses one of our research questions.

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 23 categories: Packaged Hummus Salad, Instant coffee, Rice, Pasta, Raw Tahini paste, Salt, Sugar, Sweet wines, Tuna, Flour, Kuskus, Ketchup, Oil, Tea, Black Soda, RTE Cereal, Corn Preserves, Carrot and peas preserves, Cottage Cheese, Frozen fish, Frozen vegetables, Tomato preserves, and Bread crumbs. We present Random Coefficient Logit results for the Packaged Hummus Salad and Instant Coffee categories in Section 5 when we analyze multimarket contact.

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 $j \in g$:

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

[22] The preliminary results reported in this draft use a Quasi-Newton optimizer (Matlab's *fminunc*) where tolerance is set to $e - 12$ and $e - 6$ for the inner and outer loops, respectively, and the number of simulated consumers is 3,000. The results appear robust to starting values, to an increase in the number of simulated consumers to 5,000 and 10,000, and to the alternative use of a Simulated Annealing optimization routine.

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 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:

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

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 valuation of these nutritional aspects 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.[23]

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 (A and B), the interaction of VAT with the A 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.

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

Brand dummies (A through I) 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. Compared to smaller brands, the willingness to pay for the included brands varies between 2.8 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 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): one of the brands 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 (2019), 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.[24] Nonetheless, future versions of this paper would allow for more flexible substitution patterns via the random coefficient model outlined above.

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

4 Single-market supply models

We next describe how to derive, given the demand estimates, our indicators of a category's potential of supporting low-competition equilibria. Subsection 4.1 explains how to compute two indicators of this potential. Preliminary empirical results (at this point, implementation in a single product category) are then provided in subsection 4.2.

4.1 Computing threshold discount factors

We next explain how to compute two indices that capture the stability of low-competition regimes in a given category given different assumptions on the actual conduct that has generated the data. To this end, we introduce the repeated game framework following 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 a and b, compete in some market (namely, a given category in a given month) m. Importantly, our framework does not restrict the number of firms in any way. Suppose that on the equilibrium path these firms garner supra-competitive profits: that is, the industry's conduct is not the competitive one. This may be the least competitive conduct where firms end up maximizing the category's total profits, but it may also be some conduct that lies between the most and least competitive modes.

Denote by $\pi_{am}(p_{am}, p_{bm})$ firm a's per-period payoff on the equilibrium path. Namely, this is the profit firm a garners in the current period if both firms adhere to the sustained equilibrium, where firm a charges p_{am} and its competitor charges p_{bm}. Further, denote by $\pi_{am}(\hat{p}_{am}, p_{bm})$ the one-shot deviation payoff for firm a. That is: if the rival b adheres to the equilibrium regime by charging p_{bm}, then this expression captures the maximal one-period payoff that firm a can obtain by deviating from that regime and charging $\hat{p}_{am}$, its optimal deviation price, instead of its equilibrium price p_{am}.

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

$$\pi_{am}(\hat{p}_{am}, p_{bm}) + \delta\underline{\nu}_{am} \leq \frac{1}{1-\delta}\pi_{am}(p_{am}, p_{bm}) \tag{6}$$

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 a's IC constraint shall be satisfied:

$$\delta \geq \frac{\underline{\nu}_{am} - \hat{\pi}_{am} + \sqrt{(\hat{\pi}_{am} - \underline{\nu}_{am})^2 - 4\underline{\nu}_{am}(\pi_{am} - \hat{\pi}_{am})}}{2\underline{\nu}_{am}} \tag{7}$$

We next specify the steps required to estimate such thresholds empirically. We first compute an index that asks the following question: assuming that the data were generated by the least-competitive conduct, how stable is that regime — i.e., what is the lowest discount factor that supports it in equilibrium? As will become clear below, the need to assume a particular conduct as the data generating process stems from the need to back out a vector of marginal costs for all products.

We therefore assume the following:

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 the static, least-competitive profits*

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

3. *A firm expects a constant stream of its current least-competitive profits (current most-competitive profits) if it adheres to the equilibrium (deviates).*[25]

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

Given Assumption 1, the term $\delta\underline{\nu}_{am}$ in equation (6) changes to $\frac{\delta}{(1-\delta)}\nu^{NB}_{am}$, where ν^{NB}_{am} is firm a's static Nash Bertrand payoff. This simplifies the expression for the threshold discount factor, which now becomes:

$$\delta \geq \frac{\hat{\pi}_{am} - \pi_{am}}{\hat{\pi}_{am} - \nu^{NB}_{am}} \tag{8}$$

[25] The degree of competition is likely to vary over time as it responds to demand shocks (Rotemberg and Saloner 1986, Sullivan 2017) . For simplicity, our approach ignores this and assumes that firms use current estimates as predictors for flow payoffs in all future periods. We also estimated the model allowing for the actual estimated variation over time in the most-competitive and least-competitive payoffs, 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.

Evaluating the threshold discount factor now requires only the estimation of the quantities on the RHS of (8): namely, the equilibrium 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. We use the stacked first order conditions:

$$mc = p - \left(\mathcal{I} \odot \mathcal{S}\right)^{-1} s \tag{9}$$

where mc 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 the least-competitive payoffs in each period. $\mathcal{I}$ 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. What we actually take to the data, however, is a model that assumes that only the leading firms price non-competitively. In this case, the matrix of ones is replaced by a block-diagonal matrix that indicates product ownership, allowing for joint ownership of the products of leading firms. Specifically, 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, considering the "participating" firms as a single firm.

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 non-competitive behavior, these are given by:

$$\pi_{am} = (p_a - mc_a)'(s_a \cdot M) \tag{10}$$

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

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

$$\hat{p}_a = argmax_{p_a} \sum_{j \in \mathcal{J}_a} \left(p_j - mc_j) \cdot s_j(p_a, p_{-a}) \cdot M \right],$$

where $\mathcal{J}_a$ is the set of firm a's products, and p_{-a} 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:

$$\hat{\pi}_{am} = (\hat{p}_a - mc_a)'(s_a(\hat{p}_a, p_{-a}) \cdot M) \tag{11}$$

Step 4. Finally, we obtain the Nash-reversion payoff that firm a would obtain in any future period if it were to deviate from the equilibrium 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:

$$p^{NB} - mc - \left(\Omega \odot \mathcal{S}(p^{NB})\right)^{-1} s(p^{NB}) = 0$$

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

$$\nu_{am}^{NB} = (p_a^{NB} - mc_a)'(s_a \cdot M) \tag{12}$$

Step 5. Finally, we simply input the computed expressions ν_{am}^{NB}, π_{am}, and $\hat{\pi}_{am}$ into equation (8) to obtain the threshold discount factor that would sustain the hypothesized regime under Assumption 1.

The procedure above delivers a threshold discount factor assuming that the Data Generating Process involves the least-competitive equilibrium. But as emphasized in the Introduction section, we actually wish to remain silent as to what the true DGP is. To that end, we also compute a second threshold index, this time assuming that the data were actually generated by the most-competitive behavior, i.e., by a Nash-Bertrand pricing rule.

To obtain this index, we perform a procedure, analogous to the one described above, that delivers the lowest discount factor that would allow firms to switch into the least-competitive equilibrium. One interpretation of such an analysis is that firms may be deterred from that least-competitive regime 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, the threshold discount factor that would have allowed them to switch to that equilibrium is still interesting: it measures the potential ease with which firms could obtain supra-competitive profits in this market, if regulatory or public pressures were eased.

This second index therefore captures another aspect of the category's potential of supporting equilibria with low degrees of competition. And importantly, by deriving our thresholds under different assumptions regarding the true degree of competition that is present in the data, our analysis becomes free from dependence on any such particular assumption.

In practice, obtaining this index involves very simple modifications to the procedure above. In step 1, we back out marginal costs assuming that the data were generated by Nash equilibrium in prices. We then compute the hypothetical prices that would obtain if firms were to switch to the least-competitive regime by solving the appropriate FOCs. This delivers estimates of the flow profits from that hypothetical regime. It is then straightforward to obtain the firm's hypothetical deviation profits from this hypothetical regime, as well as the Nash-reversion punishment profits (obtained easily since the observed prices are now assumed to be Nash prices, and the marginal costs have been obtained).

To sum, we have described how to obtain indices of the category's potential of supporting low-competition equilibria that can be computed whether or not firms actually behave according to such equilibria. As discussed above, this is beneficial, and not only because identifying the true conduct is difficult.

4.2 Single-industry supply: preliminary results

Our ultimate goal is to estimate such 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 (i.e., assuming that the data were generated by the least-competitive equilibrium, and noting that this choice is made for illustrative purposes only). For simplicity, we assumed here that on the equilibrium path, all firms participate in the least-competitive 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 least-competitive 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 the most-competitive 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 most-competitive payoff is only 1.3 percent lower than the least-competitive 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. 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 the least-competitive equilibrium by firm A, one of the two 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 the least-competitive equilibrium is easy to sustain in this category.

This, however, is not our interpretation. We argue that the level of the threshold discount factor, in itself, is not strongly informative regarding the category's competitive potential. First, here we assumed that the relevant frequency for the repeated game is monthly, but one could argue that other frequencies are more appropriate.[26] Second, our assumption that the observed data are generated by the least-competitive equilibrium 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 view these thresholds as quantitative indicators that capture some sense of the category's ability to sustain supra-competitive profits.

To summarize, we have shown how to compute two indicators of a category's potential of sustaining supra-competitive profits given demand estimates. For illustrative purposes, we have computed one of those indices for one category, given simple nested logit estimates. Future versions would replace the nested logit with the random coefficient logit, obtain the two indices in each of the 40 categories, and then regress those on measures of concentration to learn about the relationship between an industry's concentration, on the one hand, and its competitive potential, on the other hand.

5 Multimarket supply analysis

We now appeal to Bernheim and Whinston (BW, 1990) to investigate the effect of multimarket conduct on the ability to sustain equilibria with prices above the competitive levels. Subsection 5.1 provides the assumptions and describes the procedure that carries out this analysis. Subsection 5.2 then provides preliminary (and incomplete) results of the analysis in the Instant Coffee and Packaged Hummus Salad categories.

5.1 Multimarket supply analysis: summing over the IC constraints

Consider, again, two firms, indexed by a and b, that now compete in two markets: $m = 1, 2$. As above, it is assumed that these firms also compete with additional firms in each of these markets. These additional firms are assumed to be Nash competitors, i.e., they set prices that individually best-respond to all other firms' prices. This assumption captures the notion that firms a and b are the market leaders whereas additional competitors are smaller. It is straightforward, however, to change this assumption in multiple ways, depending on the specifics of the markets considered

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

(e.g., it may be assumed that firms a and b *and all other firms in each market* m can participate in non-competitive equilibria).

In each market m, we can once again define the condition that would induce firm a to partake in the least-competitive equilibrium, exactly as in equation (6):

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

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,

$$\sum_{m=1}^{2}\left[\pi_{am}(\hat{p}_{am}, p_{bm}) + \delta \underline{\nu}_{am}\right] \leq \sum_{m=1}^{2}\left[\pi_{am}(p_{am}, p_{bm})\right] \tag{13}$$

An important insight from BW is that this does not necessarily relax the constraints. 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.

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 relax the constraints 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 enhance the potential of sustaining supra-competitive profits is therefore an empirical question, and the answer depends on market specific parameters that characterize the 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), firm a's IC constraints would be satisfied in both markets if its discount factor satisfies the following condition:

$$\delta_a \geq max\{\frac{\hat{\pi}_{a1} - \pi_{a1}}{\hat{\pi}_{a1} - \nu_{a1}^{NB}}, \frac{\hat{\pi}_{a2} - \pi_{a2}}{\hat{\pi}_{a2} - \nu_{a2}^{NB}}\} \tag{14}$$

Whereas, if firms internalize the multimarket contact, firm a's aggregate IC constraint would be satisfied if:

$$\delta_a \geq \frac{(\hat{\pi}_{a1} + \hat{\pi}_{a2}) - (\pi_{a1} + \pi_{a2})}{(\hat{\pi}_{a1} + \hat{\pi}_{a2}) - (\nu_{a1}^{NB} + \nu_{a2}^{NB})} \tag{15}$$

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 (15) is lower than that of condition (14), we would conclude that multimarket contact does indeed make it easier to sustain non-competitive equilibria.

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 non-competitive behavior. This approach could be used to evaluate the contribution of existing situations of multimarket contact to noncompetitive 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 a initially operates only in market $m = 1$, but now proposes to acquire a firm that operates in market $m = 2$. Standard antitrust analysis is not well established with respect to such mergers, as they do not increase the concentration level in either market $m = 1$ or market $m = 2$. 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.

Finally, note that just like before, we can use either Assumption 1 (namely, assume that the data were generated by the least competitive behavior) or the alternative assumption (that the data were generated by the most competitive behavior) as the starting point for this analysis. We can thus learn whether multimarket contact relaxes the Incentive Compatibility constraints of either actual, or hypothetical non-competitive regimes, freeing ourselves from the need to determine the actual conduct followed by firms in these markets.

5.2 Multimarket supply analysis: preliminary results

We pursue empirical estimates of the RHS of these conditions in two leading cases. One case involves the *Packaged Hummus Salad* and *Instant Coffee* categories, where the same two firms — denoted here as A and B — are the clear category leaders. The second case would involve a hypothetical merger that would create multimarket contact across two categories without increasing the concentration in either of them. This second case is being analyzed and will be presented in detail in future drafts of this paper. In this draft we only present results for the Hummus-Coffee case. These results are based on estimates of Random Coefficient Logit models of demand in both categories. We consider the results as preliminary as we explore and improve various aspects of the technical execution.

We proceed by describing the results in two stages. First, we present the demand modeling and estimation results for each of the two categories. Second, we employ the methodology developed above to make inference on the potential role of multimarket contact across these two categories. This second part is also left incomplete in this draft as we still explore several aspects of the analysis.

Demand estimates: Packaged Hummus Salad. Led by small producers until the early 1990s, the Packaged Hummus Salad category has been led in the past couple of decades by two producers, again denoted here as A and B. In 2017, for example, the market shares for these firms were 45.1 percent and 37.7 percent, respectively, with the third largest brand commanding 9.3 percent share.[27]

In addition to our standard inclusion of brand dummies and 42 month dummies, we also include in the utility function dummy variables for product characteristics. Examples of such characteristics are "spicy," pine nuts, masabacha (a middle eastern condiment), and tahini (relating to the presence of extra tahini in the product). The presence of such items in the product was determined by mining the text of the product name at the UPC level. An online appendix (TBC) will provide the full details on the assignment of these product characteristics. We also included interactions of some characteristics with the time trend, and of the leading three brands with the "spicy" characteristic.

We aggregate the UPCs up to unique combinations of brand, month and the characteristics, yielding a total of 2,031 observations over the 43 sample months. The market size was determined by considering the potential consumption of all prepared (chilled) salads. We used a number of sources to determine: the typical annual consumption of Hummus per person, the share of Hummus consumption out of total consumption of chilled salads, and the population size (complete details forthcoming in future versions).

Random coefficients were allowed on price, and on the A and B brand dummies. Instrumental variables for the endogenous price include: the number of competing products with identical characteristics, interactions of the world chickpea price (a cost shifter) with the pine nut, tahini and "other condiments" characteristics, interactions of the VAT rate (yet another cost shifter) with dummy variables for the leading producers and for the "masabacha," "spicy" and "cress" characteristics. Finally, we also include interactions of our "post Food law" (i.e., post January 2015) dummy variable with dummy variables for the leading manufacturers. In total, this yielded 13 excluded instruments, creating over-identifying restrictions (noting that we have only three random coefficients, and that characteristics with non-random coefficients instrument for themselves).

Estimation results are reported in Table 6. Generally speaking, coefficients on product characteristics and on brand dummy variables are precisely estimated, and so are the mean and standard deviation of price sensitivity, α and σ^p.

[27] Source: "Ahcla's market share surpasses that of Tzabar for the first time in 14 years," April 2017, Calcalist (an Israeli media outlet).

Demand estimates: Instant Coffee. The same two firms, A and B, that lead the Hummus category, are also the clear leaders of the Instant Coffee category. To model demand in this category, we again define product characteristics based on the presence of particular traits as evident in the product name (examples being "decaff,", "frozen," and "dry") that are included in the utility function along with brand and month dummies. We again aggregate the UPCs up to unique combinations of brand, month and the characteristics, yielding a total of 1,479 observations. The outside option was defined as the consumption of Black Coffee and Tea, easily computed from our data.

Random coefficients were again allowed on price and on the leading brand dummies. Instrumental variables for the endogenous price include: the number of competing products with identical characteristics, the firms' revenue in other categories, an interaction of fuel price with brand B's dummy variable, raw coffee price interacted with characteristics (non-decaff, "frozen" and "premium"), the firm's number of offered UPCs, interactions of the VAT rate with dummy variables for characteristics, and interactions of the "post Food law" with dummy variables for the leading manufacturers. In total, this again yielded 13 excluded instruments. Preliminary estimation results are reported in Table 7.

Multimarket contact. Given these demand estimates we have computed the threshold discount factors for firm A with an without the internalization of multimarket contact. We still do not report these results in this draft since we still explore some technical aspects of these calculations.

6 Concluding remarks

TBC

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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	Legumes*

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
Legumes	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
A× VAT	53.09***	-112.2**		
	(12.48)	(50.47)		
A× Fuel	-0.00446*	0.0330***		
	(0.00270)	(0.0109)		
B× Fuel	-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)	
α			-0.151***	
			(0.0244)	
A	-5.606**	11.20	2.217***	14.7
	(2.423)	(9.805)	(0.227)	
B	3.726***	-8.698***	2.864***	19.0
	(0.409)	(1.656)	(0.182)	
C	2.205***	0.774**	2.222***	14.7
	(0.0929)	(0.376)	(0.153)	
D	0.951***	13.09***	2.825***	18.7
	(0.130)	(0.525)	(0.339)	
E	2.267***	1.047*	2.140***	14.2
	(0.148)	(0.597)	(0.179)	
F	2.135***	-0.913*	1.725***	11.4
	(0.125)	(0.507)	(0.182)	
G	1.799***	5.294***	2.433***	16.1
	(0.107)	(0.434)	(0.171)	
H	0.663***	-1.216**	0.422***	2.8
	(0.129)	(0.521)	(0.136)	
I	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. The capitalized A through I represent brand dummies. A× VAT captures the interaction of the A brand with the VAT cost shifter. 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: price	1st stage: within-nest share	2nd stage	WTP
A× VAT	44.97***	-48.97		
	(12.33)	(46.04)		
A× Fuel	0.000921	0.0156		
	(0.00266)	(0.00992)		
B× Fuel	-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)	
α			-0.113***	
			(0.0213)	
A	-5.576**	-0.649	1.338***	11.84
	(2.394)	(8.936)	(0.295)	
B	3.483***	-11.25***	2.244***	19.86
	(0.453)	(1.692)	(0.193)	
C	0.371***	-4.559***	-0.179	-1.50
	(0.109)	(0.406)	(0.141)	
D	2.222***	0.699**	1.972***	17.45
	(0.0952)	(0.355)	(0.151)	
E	1.519***	0.466	1.280***	11.33
	(0.119)	(0.444)	(0.128)	
F	1.137***	3.508***	1.323***	11.71
	(0.153)	(0.571)	(0.116)	
G	0.494***	1.821***	0.661***	5.85
	(0.102)	(0.381)	(0.0784)	
H	0.663***	-2.821***	0.235*	2.08
	(0.128)	(0.479)	(0.140)	
I	1.381***	-1.944***	0.976***	8.64
	(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. The capitalized A through I represent brand dummies. A× VAT captures the interaction of the A brand with the VAT cost shifter. Standard errors in parentheses. ***, ** and * stand for significance levels of 1, 5 and 10 percent, respectively.

Table 6: Demand estimates: Packaged Hummus Salad

Characteristics w/o random coefficients			**Characteristics with random coefficients**				
	β	SE		β	SE	σ	SE
Constant	-2.626	1.157	A	6.002	0.894	0.024	11.998
spicy	-1.201	0.179	B	5.769	0.595	0.109	7.512
cress	-1.018	0.156					
pine nut	-0.288	0.232	**Price sensitivity**				
tahini	-0.974	0.139					
masabacha	-0.286	0.195		α	SE	σ_p	SE
other condiments	-1.241	0.151					
spicy_trend	0.943	0.470		-3.082	0.836	0.926	0.379
Tahini_trend	1.597	0.421					
C	2.728	0.139					
D	1.722	0.159					
E	2.806	0.142					
F	0.617	0.114					
H	6.434	1.375					
I	1.754	0.303					
A_spicy	0.875	0.157					
B_spicy	0.747	0.187					
C_spicy	1.203	0.183					
Observations	2,031						

Notes: Utility parameter estimates. See text for description of product characteristics. The letters A-I represent brand dummy variables, where the A and B brands also have estimated random coefficients. The A, B and C brands were interacted with the "spicy" dummy variable. The spicy and Tahini characteristics were interacted with the time trend. Dummy variables for 42 months were included but not reported. Source: authors' estimates implied by the data and model assumptions.

Table 7: Demand estimates, Instant Coffee

Characteristics w/o random coefficients			**Price sensitivity**			
	β	SE	α	SE	σ_p	SE
Constant	-3.004	1.523	-4.001	1.715	1.153	1.021
decaff	1.464	0.477				
delicate	-0.199	0.120				
dry	1.405	0.459				
grained	-0.541	0.248				
golden	1.002	0.307				
country	-0.357	0.353				
A	3.871	0.312				
B1	6.029	0.399				
B2	5.342	0.354				
B3	4.611	1.435				
C	5.007	0.263				
D	-0.288	0.412				
E	5.503	0.633				
Observations	1,479					

Notes: Utility parameter estimates. See text for description of product characteristics. The letters A-E represent brand dummy variables, where A and B are the two leading manufacturers, and producer B sells three brands denoted B1-B3. Dummy variables for 42 months were included but not reported. Source: authors' estimates implied by the data and model assumptions.