CHAPTER

Marketing and public policy☆

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1 Introduction

Research in quantitative marketing has broadly focused on two areas, as the previous chapters in this Handbook demonstrate: understanding consumer demand and deriving the implications for firm strategy. A logical next step is to consider the interaction of consumer behavior and firm strategy with public policy. Historically, quantitative marketers have largely left public policy and social consideration to economists. However, with the inflow of researchers trained in economics into the field of marketing this has started to change.[1] In our view, the true impact marketing can have on policy debates has yet to be realized. Large parts of the policy space are directed at affecting the behavior of consumers and firms, yet policy work has not always relied as much as it could on the insights from marketing. The main thesis of this chapter is that research in quantitative marketing, and the marketing profession more generally, has important tools and insights that can be useful to public policy, and that there are potentially large gains from collaboration that are only starting to be realized.[2]

There are potentially many areas of public policy that we could discuss, including, for example, health (nutrition, smoking, pharmaceutical drugs, and medical treatment), antitrust, intellectual property and innovation, environmental, financial regulation, privacy, economic development, globalization, and more. We could not do justice to all these areas in one chapter, so we explicitly focused on only two areas: competition policy and nutrition policy. Furthermore, we generally do not attempt to provide a comprehensive literature review of all the academic work that has been written in these areas. Instead, we use these areas to demonstrate how the field of marketing can contribute to policy questions.

We focus on competition policy and nutrition policy for two main reasons. First, these are areas that are near and dear to our heart. Besides dealing with them in our research we have both spent time working on them in actual policy settings.[3] Second, we think these areas, and the contrast between them, demonstrate both how

[1] For some recent examples where researchers have extended the traditional areas of quantitative marketing to study public policy issues see Bollinger and Gillingham (2012), Bollinger (2015), and Bollinger and Karmarkar (2015), looking at environmental questions, Shapiro (2018a, 2018b), looking at pharmaceutical drugs, Lewis et al. (2014), Wang et al. (2016), and Tuchman (2017) looking at smoking behavior, and Wei et al. (2016) looking at credit markets.

[2] We are not the first to realize the potential of the field of marketing to contribute to public policy. For example, since 1982 the American Marketing Association has been publishing the Journal of Public Policy & Marketing. The focus of the journal has been mostly "managerial", and as far as we can tell very little overlap exists between authors that publish in that journal and authors of chapters in this Handbook.

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quantitative marketing can be helpful for policy and how there is room for improvement.

Competition policy is an area where economists have long had an impact. As Tim Muris, then Chairman of the U.S. Federal Trade Commission (FTC), noted in 2003: "Policy discourse no longer focuses on whether economics should guide antitrust policy. That debate was settled long ago. The pressing question today is how."[4] Historically, how economics has shaped competition policy has tracked rather closely, but with a 20 year or so lag, the academic field of Industrial Organization (IO). This, combined with the availability of rich data, suggests that modern empirical IO, which is closely intertwined with modern quantitative marketing, is bound to take a leading role in shaping the future of competition policy. As we discuss in more detail below, a key input in almost any analysis in competition policy involves consumer diversion: if prices were to go up or quality were to go down where would consumers substitute. This same question is key to understanding many marketing problems and therefore an area where marketers and applied economists have developed significant expertise.

In the area of nutrition policy a different picture emerges of the role that economists and marketers have played, despite the fact that many of the fundamental issues – such as understanding the role of consumer substitution and heterogeneity – are similar. For example, policy makers around the world are considering various forms of nutrition taxes; methods and insights from economics and quantitative marketing have a lot to offer in terms of understanding the impact of such policies. Suppose, for example, we want to quantify the effect of a tax on sugary drinks. We first need to know the incidence of the tax, i.e. how much of the tax would be passed on to consumers. Second, we need to know how consumers would respond to the higher price. Would they switch to alternative products? If so, which ones? Would they reduce overall consumption? Will the effect vary across consumers? If so, which consumers will be impacted the most? To answer these questions we need to understand consumer behavior and firms' strategies.

Quantitative marketing also has a lot to add in other policy areas. For example, if we want to understand the effects of restrictions on advertising unhealthy food we would need to understand how firms will respond to the restrictions and the implications this has for consumer behavior. Suppose advertising of unhealthy food is banned. Intuitively, we think this should lead to lower consumption of unhealthy food. However, in response to the ban firms might charge different prices. Indeed, if prices are reduced consumption of unhealthy food might actually increase. Once again, to answer these questions we need to understand firms' pricing and consumer behavior, both of which are the core of quantitative marketing.

The rest of this chapter proceeds as follows. In the next section we discuss the impact that academics and academic research can and does have on policy making.

[4] "Improving the Economic Foundations of Competition Policy," Remarks before George Mason University Law Review's Winter Antitrust Symposium, Washington, D.C., January 15, 2003. Available at https://www.ftc.gov/public-statements/2003/01/improving-economic-foundations-competition-policy.

In Section 3 we discuss antitrust and in Section 4 nutrition policy. A final section makes a few concluding remarks.

2 The impact of academic research on policy

As we noted in the Introduction, academic work in quantitative marketing has had more impact on policy in some areas than in others. Specifically, in the two areas we focus on in this chapter the impact of economists and marketers in antitrust policy has been larger than in nutrition policy. However, even in the competition policy setting, where academics have been influential, it is not necessarily marketers who have taken the lead. In this section we discuss why this is the case.

Up to this point we have not distinguished between research done by IO economists and quantitative marketers. Indeed, we referred to the fields as being intertwined and one could claim that there is little difference between IO economists and modern quantitative marketers. However, it was not so long ago that one would draw a line between IO and marketing, by saying that IO looked at public policy while marketing stopped at the interaction of firms and consumers. Some marketers defined their role this way. For example, a prominent marketing professor writing in Forbes claims that the difference between marketers and economists is "The marketer's desire is to understand the way the world *really* works – not how it *should* work [italics in the original] . . . "[5]

There are various ways to read this quote. One interpretation, which explains why economists are often more involved in policy, is that economists are more focused on how the world can and *should* change rather than merely describing how it *really* is. We suspect that many quantitative marketers, especially those trained as economists, would disagree with the above characterization. We surely disagree with it. Nonetheless, this does reflect the view that some in the marketing profession hold. If marketers want to have an impact on policy and be part of the public discourse they need to learn from economists and focus not just on describing the world but also on describing how it should be. By the same token, the knowledge that marketers have on how consumers (really) make choices and how firms (really) respond, as opposed to how theory tells us that they should act, is extremely valuable addition to policy debates. We strongly believe that there are true intellectual gains from trade.

We are not the first to point to the value marketers can bring to public policy. For example, Stewart (2015) directly addresses why marketers should study public policy, and what marketers can contribute to the understanding of public policy – because they have a lot to add to the debate in terms of methods and insights into how businesses and markets work, which is important for the formation of effective

[5] https://www.forbes.com/sites/wharton/2012/06/15/marketing-vs-economics-gymnastics-or-high-wire-act/.

and efficient policy. Indeed, a new generation of quantitative marketers are taking on this challenge and expanding the methods and ways of thinking of marketing into new directions (see footnote 1 for examples).

We now turn to the question of why has the impact of academic research been so different in antitrust and nutrition policy? In both these settings, understanding consumer behavior is very important. So the answer to the question of why the outcome is different does not lie, in our view, in the social return to the insight quantitative marketing might have.

A cynical view might be that the private monetary returns to consulting in the competition policy area are higher than the private return in nutrition policy. This might be true, and as economists, we would have to admit that economic agents likely respond to monetary incentives. However, this is unlikely to explain why the research that has been done is less influential. In our view, there are more fundamental reasons for the difference.

Empirical work in policy analysis can take on two complementary roles: ex-post and ex ante analysis. Ex-post analysis involves the evaluation of a policy after it has occurred. The goal is to measure the effect of the policy, possibly to learn ways to improve it, and maybe consider ways to generalize beyond the specific setting. Two key challenges are internal validity – how to infer the causal effect of the policy – and external validity – how to extrapolate beyond the specific setting to other environments (see Deaton, 2009, and Heckman and Urzua, 2010).

A different approach is one that involves ex ante policy analysis, where we ask what the likely effects of a policy are before the policy is implemented. When doing ex ante analysis the researcher needs to figure out not just what would happen in the absence of the policy, as in ex-post analysis, but also what would be the effect of the policy (which is observed in the case of ex-post analysis). To perform the analysis one needs to develop an economic model, estimate its primitive parameters using historical data, and use the estimates to compute counterfactuals.

Many economists, and for sure many non-economists, feel uncomfortable with this approach, since they believe it relies on many untested assumptions. Some have argued that a better way to perform ex-ante analysis is to rely on ex-post analysis of past events and adjust the outcomes as needed (see Angrist and Pischke, 2010, and the response by Nevo and Whinston, 2010). In our view this side steps the key question, which is how should the outcome be adjusted. In order to know how the outcomes should be adjusted we need a "model". This can be a purely statistical model or it can be an economic model, which is what the ex-post analysis does.

Economists do, and should, rely on both carefully done ex-post and ex-ante analysis. However, in our view, the tools and methods of economics and quantitative marketing have a clear comparative advantage is in the more structural, ex-ante, analysis. This is both a curse and a blessing. It means that where structural ex-ante analysis is accepted so will the work of quantitative marketing be accepted. However, where ex-post, program evaluation, type analysis is the prominent paradigm quantitative marketing might play a lesser role.

For a variety of reasons ex-ante structural analysis is more prevalent in the competition policy world. Consider the case of mergers. The basis of the analysis is prospective: a competition agency has to decide in advance if the merger is "likely to lessen competition."[6] By nature, this requires ex-ante policy analysis. One could argue that the inference should be based on the outcomes of past mergers, but not surprisingly it is rare to have outcomes of similar mergers available. Furthermore, given the adversarial process in which mergers are evaluated, even if outcomes of past mergers were observed one could imagine that the relevance of these outcomes would be an area of great controversy. The adversarial process might also lead to an "arms race" in economic analysis, with each side trying to get the advantage by bringing in the latest and greatest methods from academic research.

In the nutrition policy world the decision makers are usually politicians and public servants. The decision process could be laced with controversy, but it is less adversarial and therefore rarely leads to the same type of arms race as with competition policy.[7] Decision makers are content to rely on simple, intuitive, and easy to explain methods, which often leave out important insights in particularly about the way that markets work; these insights are central to the design of effective and efficient policy. In order to provide these insights economists have to work harder to explain the value of their analysis.[8]

There is an additional component that contributes to the difference. In many areas of public policy there is a sense of "us" and "them" and that business is the "enemy". Under this (misguided) view of the world, marketers whose day job involves teaching future executives how to sell products and maximize profits cannot contribute an unbiased view to the policy discourse. Indeed, the close connections marketers often have with firms – the same connections that often lead to incredible data sources – lead to concerns about impartiality. It is not uncommon to hear of research proposals that are not funded because of research collaboration with a firm.

3 Competition policy

In this section we discuss the role that economics and quantitative marketing do, and can, play in competition policy analysis. We start by discussing the policy framework in order to motivate how methods from quantitative marketing can be useful in

[6] The legal standard that controls mergers in the US is Section 7 of the Clayton Act that states that a merger should be deemed unlawful if "the effect of such acquisition may be substantially to lessen competition, or to tend to create a monopoly."

[7] While firms do sometimes resist policies such as taxes, advertising restrictions or labeling in court, these typically do not revolve around the functioning of markets or an economic analysis of the impacts of the policies.

[8] Interestingly, one area of policy closely related to nutrition policy is tobacco control. In this area, litigation and an adversarial process are prevalent and indeed economists have played a much more prominent role.

competition policy. Specifically, we focus on the key role that consumer demand and diversion play. Next, we discuss a few recent examples that demonstrate the use of the methods and how they can be influential in both litigation and regulatory settings. A key point is that it is unrealistic to expect policy to be based on state-of-the-art methods that have not been fully vetted and might require data and time that is not always available. Finally, we discuss directions moving forward.

In order to understand how economics and quantitative marketing can contribute to competition policy analysis we need to understand how competition policy is conducted. Take for example the case of a merger. If two firms want to merge they typically have to notify the government. Once they do, the competition agencies have a pre-determined period to evaluate the merger and decide whether they want to challenge it.[9] The exact legal standard for challenging a merger differs from country to country but generally involves a question as to whether the merger will lessen competition. The key questions are: (i) How does a competition agency determine whether a merger will lessen competition? (ii) How can it prove in court that indeed the merger does reduce competition? Broadly speaking there are two approaches to answering these questions. First is an approach based on market definition and concentration analysis, often referred to as "structural analysis" (not to be confused with structural modeling). Second is an approach based on economic modeling of the likely competitive effects. Economics can play a crucial role in both of these approaches as we detail below.

Similar type of questions arise in non-merger cases. The one exception is explicit collusion among firms, which is generally *per-se* illegal, and therefore does not depend on the competition agency demonstrating that the conduct had anti-competitive effects. The mere fact that firms colluded is illegal, and therefore little economic analysis is needed. Other forms of anticompetitive behavior, such as exclusionary conduct, predatory pricing, and agreements that restrain trade are generally evaluated under rule of reason, and therefore typically require significant economic analysis. Since these cases are somewhat more complicated and somewhat case specific we will not discuss them here.

3.1 Market definition and structural analysis

A starting point in many, if not all, competition matters is the definition of the relevant antitrust market. This is done for two main reasons. First, to frame the relevant area in which there will likely be competitive harm. One goal of market definition is to

[9] The exact process differs from country to country. In the US, for example, if the merger is above a certain threshold the parties generally need to notify both the DOJ and the FTC. The agencies will then have 30 days to decide if they want to further review the merger. If an agency wants further review it will issue a second request to get more detailed information from the parties. Usually the parties and the agency will negotiate the scope of the request and the time the agency has to review the transaction. By the end of the agreed upon period the agency needs to either clear the transaction, possibly subject to some divestitures, or challenge it in court.

understand in what market would there will be harm to the competitive process? Who are the competitors in the market? And how difficult would it be to enter this market? Second, in the case of a merger another goal of market definition is to conduct a structural analysis. Once the market is defined one can compute the Herfindahl-Hirschman Index (HHI), which is the sum of the squares of the market shares of all firms. Typically the index is multiplied by 10,000.[10] The higher the level of the HHI the more concentrated is the industry. For example, the FTC-DOJ joint Horizontal Merger Guidelines define a market as highly concentrated if the HHI is over 2,500. In addition to the level of the HHI one also computes the change in the HHI due to the merger.[11] The Guidelines talk about a merger that raises the HHI by over 200 points and generates a highly concentrated industry, i.e. generates a post-merger HHI of over 2,500, as one that "will be presumed to be likely to enhance market power".

At this point it might be unclear what any of this has to do with quantitative marketing. However, it ends up that it has everything to do with a key element of quantitative marketing, namely, consumer choice. There are several ways to define a relevant market including qualitative analysis that relies on market realities and normal course of business documents. However, whenever possible the agencies and courts tend to rely on the so-called hypothetical monopolist test (HMT). The HMT tests if a candidate market is too narrow by asking whether a (hypothetical) profit-maximizing monopolist over this market would impose a small but significant and non-transitory increase in price (SSNIP). If the answer is no then the market is too narrow, because even a monopolist over this market would face significant competition from outside the market that limits its ability to (significantly) raise prices. There are potentially many markets that would pass the test so the Guidelines state that typically the smallest market is preferred to avoid defining markets too broadly.

The key force limiting the hypothetical monopolist's ability to raise prices is consumer substitution. If consumers have close enough substitutes then the monopolist will not raise prices because doing so would imply losing too many consumers. The HMT lays the framework but requires the key input of consumer substitution, or diversion, which is where quantitative marketing comes in. In practice, the HMT test is usually implemented in two ways.

First, we ask whether the hypothetical monopolist would find it profitable to impose a SSNIP on at least one of the merging parties products. Note that this asks the question of whether a SSNIP is more profitable than the benchmark (in a case of a merger usually pre-merger prices) and not whether a SSNIP is the profit-maximizing price. To answer the question of whether a SSNIP is profitable we compute the "critical loss", namely what share of demand has to be lost to make the SSNIP unprofitable. We then compare this critical loss to actual estimates of diversion in response to a SSNIP. If the estimate of diversion is higher than the critical loss a SSNIP will not be

[10] In a monopoly market the index will equal 10,000, while in a market with n equally sized firms the index will equal 10,000/n.

[11] It is easy to show that this change is equal to 2 times the product of the shares of the merging parties.

profitable. We do not need an exact estimate of diversion, or loss, due to the SSNIP just to know if it is higher than the critical loss.

Katz and Shapiro (2003) show that the critical loss is equal to

$$\frac{X}{X+M} \tag{3.1}$$

where X is the percent price increase and M percent gross margin (equal to $(P - MC)/P$), where P is price and MC is marginal cost. The inputs required to this computation are margins and demand substitution, both of which are key inputs into pricing decisions that we regularly teach in pricing classes. Indeed, the idea behind critical loss analysis is very similar to break even analysis typically taught in these pricing classes (for example, see Nagle et al., 2011). Finally, the estimates of the diversion are usually either recovered from normal course of business documents or estimated from data using the methods discussed earlier in this volume.

A slightly different way to conduct the HMT test is to compute the monopolist's profit-maximizing price. This is done by simulating a merger to monopoly using merger simulation methods (Werden and Froeb, 1994; Nevo, 2000). The basic idea is to recover demand elasticities, either from normal course of business documents or using data to estimate them. These elasticities are then fed into a supply model and used to recover pre-merger margins and simulate the likely effects of the merger. The supply model can be very rich and include many of the models discussed earlier in this volume, but a typical model to use is the Nash Bertrand pricing model for differentiated products. The difference between the pre-merger and post-merger simulated price directly answers the question of whether a profit-maximizing monopolist would impose a SSNIP.

3.2 Economic analysis of competitive effects

Most challenges that competition agencies make to mergers will involve the structural analysis described in the previous subsection. However, many economists are critical of it and would rather see a more economic based analysis (Kaplow, 2010; Ginsburg and Wright, 2015). This economics based analysis can take many forms that differ in the degree of econometric sophistication. In a data rich environment, which is more and more the case, econometric analysis of some form usually plays a role. Broadly speaking there are three types of econometric analysis that are used.

The first type of empirical analysis often conducted is a regression of price (or other outcomes) on concentration. Often this will be a cross sectional regression correlating concentration with price across different geographic or product markets. Occasionally, the regression will look at changes over time and sometimes use a panel. The correlation between market concentration and price is used to predict the effect of a merger on price by using the change in concentration caused by the merger. This type of analysis was motivated by Structure-Conduct-Performance type regressions originally proposed by Bain (1956) and applied by hundreds of academic papers (Schmalensee, 1989). Interestingly, a typical grad level class in IO will start

by explaining why these regressions are no longer used in academic work (see, for example, the discussion in Salinger, 1990).

A second approach that in some ways builds on the first, but tries to deal with some of the concerns, looks at a regression of price on market structure, but uses discrete events. A prime example is a merger retrospective where data before and after the merger is compared to a control market in a "diff-in-diff" analysis (see, for example, Weinberg et al., 2013). This can obviously only be done prospectively and therefore relies on having similar enough past mergers to evaluate. In many cases such events are not available

The third approach, and the one most closely related to the themes of this chapter, is merger simulation. Broadly speaking, merger simulation involves writing down an economic model of the industry and using it to simulate the likely outcome of the merger. The inputs for the model typically include demand, cost, and a model of how firms interact. Parameters of the model can either be estimated, if data are available, or recovered from internal documents of the merging firms.

To demonstrate the effect of a merger consider a merger in a differentiated products industry, where demand for each product j is given by $Q_j(p_1, \ldots p_J)$. For simplicity, assume single product firms that maximize static profits. The optimal price balances higher margins and lower volume and is given by the first order condition of the profit optimization problem,

$$p_j^* = mc_j - \frac{Q_j}{\partial Q_j / \partial p_j}, \tag{3.2}$$

where the last term is evaluated at the equilibrium prices of all firms.

How does the merger change this? Suppose firms 1 and 2 merge, then firm 1's optimal price takes account that some of the previously lost sales now go to its newly owned product 2. The first order condition becomes

$$p_1^* = mc_1 - \frac{Q_1}{\partial Q_1 / \partial p_1} - (p_2^* - mc_2)\frac{\partial Q_2 / \partial p_1}{\partial Q_1 / \partial p_1}. \tag{3.3}$$

The main difference from before is the addition of the last term. This term is the margin of product 2 times the diversion ratio from product 1 to product 2. The diversion ratio measures what fraction of the demand that product 1 loses, as its price increases, goes to product 2. The product of these two terms generates what is often called an "upward pricing pressure". The larger the margin and the larger the diversion, the larger this pressure will be. In the above, we left the marginal cost unchanged, but the merger might also generate efficiencies and reduce the marginal cost, which will reduce the optimal price.

There are several ways to use this sort of analysis to compute the likely effect of a merger. One approach is to compute the magnitude of the upward pricing pressure (Farrell and Shapiro, 2010). The idea is to use normal course of business financial and marketing documents to compute the margins and diversion, and use these to directly compute the upward pricing pressure. Once we have the inputs the computation is trivial, and the hope is that the inputs are known to managers of the firms.

One common complaint about this computation is that it is not clear what this upward pricing pressure index means. One way to think about this computation is that it is like a change in the cost of the firm. Post-merger firm 1 has an opportunity cost for each unit it sells. The opportunity is a lost margin on product 2. How this cost translates into a price increase depends on the curvature of the demand curve, which determines the degree of pass through. In order to compute a price effect one needs to determine the curvature of the demand curve (for a more detailed discussion on pass-through see Section 4.2). Advocates of this method propose leaving everything in the "cost space" by computing both the change in the pricing pressure and the change in marginal cost in the same metric.

Another, often missed, issue with this approach is that in principle both the margin and the diversion are a function of equilibrium prices. Even if we knew exactly what they were pre-merger we might do a bad job of predicting the post-merger effect. To see this, consider an extreme example. Consider a merger to monopoly in a nearly homogeneous good industry with two firms. Assuming Bertrand competition pre-merger the margins should be very low, because the products are nearly homogeneous. This implies a very low upward pricing pressure. However, if the two firms merge the price effect would potentially be very high. The reason is that in equilibrium the margin of firm 2 would significantly increase. If we know what the margin would be post-merger then we could compute the correct pricing pressure, but of course the whole point of the exercise is to compute what the margin will be post merger. This example is obviously extreme but it does provide a cautionary tale.

An alternative way to use the above information is to use the first order conditions from all the products to compute the post-merger equilibrium (Berry and Pakes, 1993; Hausman et al., 1993; Werden and Froeb, 1994; Nevo, 2000). Formally, the prices post-merger solve the following set of first-order conditions

$$p^* = mc + \Omega^{-1}(p^*)Q(p^*), \tag{3.4}$$

where p^* is the vector of equilibrium prices, and $\Omega(p^*)$ is a matrix with $\Omega_{jr}(p) = -\partial Q_j(p)/\partial p_r$ if j and r are produced by the same firm and zero otherwise. These prices can be compared to the pre-merger prices. Note that the computation can easily account for marginal cost reductions.

To modern quantitative marketers this approach should seem quite natural, as it fits very well with many of the topics and methods discussed in the previous chapters. Merger simulation offers a coherent approach that allows the decision maker to conduct sensitivity analysis as well as account for various effects such as cost reductions, product re-positioning, and entry.

On the other hand, merger simulation models are often perceived as being "too complicated" and dominated by the "simple" regression models described above that are viewed as more intuitive, or by the upward pricing pressure methods described earlier. These claims are not well founded. Consider the upward pricing pressure models. Conditional on having the inputs, merger simulation does really not require more assumptions. Margin and diversion information (and the pricing equation) can

be used to recover costs as well as own- and cross-price elasticities. Merger simulation does require knowing the shape of the demand curve, which one does not need in order to compute the upward pricing pressure, but which is needed in order to interpret this measure in a meaningful economic way.

Merger simulation is often equated with demand estimation. But this need not be the case. Of course if data are available then the tools of modern quantitative marketing can be brought to bear. Because merger simulation can only be as good as the model (and inputs) that it is based on, quantitative marketers can have a big impact. As demonstrated in earlier chapters, quantitative marketing has developed models for flexibly estimating heterogeneity, cross-price effects, and demand curves more generally. Many of these methods are not ready for policy work quite yet, but as we demonstrate in the next subsection demand estimation and merger simulation can be very useful and powerful if used correctly.

3.3 A few recent examples

In this subsection, we discuss a few recent examples where empirical quantitative models were used successfully in merger investigations and litigation. We first discuss the Aetna-Humana proposed merger that was successfully challenged by the DOJ. In this litigation the DOJ's economic expert, Aviv Nevo, heavily relied on quantitative methods, specifically a Nested Logit model of demand and merger simulation methods. The methods used in this case followed the academic literature quite closely. The analysis used in this case did not necessarily push the academic frontier forward. Instead, the analysis used in the case provides a good example of how methods and results from the quantitative literature can be used successfully in court.[12]

Next, we discuss the merger of AT&T and DirecTV, where a merger simulation model, constructed by Steve Berry and Phil Haile, was offered by the merging parties and relied upon by the U.S. Federal Communications Commission (FCC) in its order approving the merger. The model used here was in many ways not strictly "off-the-shelf" and in some ways advances the state of knowledge, which at least in part was feasible because it was used in the context of a regulatory investigation and not litigation. The analysis is also a good example of how data collection methods can be applied productively. The analysis was quite successful and helped the parties get the merger approved.

Finally, we conclude with a discussion of bargaining models in merger analysis. These models are an example where recent advances in academic work have had a great impact on competition policy in industries as varied as health care and video markets.

[12] As one reviewer of this chapter noted, it seems surprising that we use as an example a case where the methods used did not push the frontier of research. That this is a surprise shows the dis-connect between research and practice: just because a paper was published in an academic journal, even a leading one, does not make it ready for policy work, especially in the context of litigation. The mere fact that the court accepted the analysis, and dove into the technical details, is considered a significant advancement in practice.

3.3.1 The Aetna-Humana proposed merger

Aetna and Humana are health insurance companies that provide a wide range of insurance products. In 2015, they announced their intention to merge and in July 2016, the Department of Justice and several state attorneys general filed a complaint seeking to enjoin the merger. In January 2017, after a three week trial, the court decided to block the merger, at which point the parties abandoned the transaction. The DOJ's main concern was a loss of competition in the Medicare Advantage insurance market (for a more complete discussion of the case see Bayot et al., 2018).

Medicare is a program administered by the federal government through the Centers for Medicare and Medicaid Services ("CMS") to provide health insurance to eligible seniors aged 65 or older. The program partially covers the costs of hospital care, outpatient care, medical supplies, and preventive services. Enrollees pay deductibles, coinsurance, copayments, and a monthly premium for the outpatient services. Enrollees can seek care from any provider that accepts Medicare rates, which is the vast majority of all medical providers in the United States. Enrollees can offset the out-of-pocket costs by purchasing a Medigap plan and/or Medicare Part D coverage from a private insurer at additional premiums. Together these different combinations of Medicare with or without supplements are referred to as "Original Medicare options".

Alternatively, seniors can enroll in a Medicare Advantage insurance plan, which is administered by private insurers and use a network of providers. Unlike Original Medicare, Medicare Advantage insurers require or encourage their enrollees to use in-network providers. In exchange for the network restrictions, Medicare Advantage plans provide seniors with potentially lower cost and higher benefits.

In 2016, Humana was the largest insurer in individual Medicare Advantage plans, with a nationwide market share of 21.2%. Aetna was the fourth-largest Medicare Advantage insurer nationally, with a 6% nationwide market share. Within the 364 counties that the DOJ focused on Aetna and Human jointly had 59% market share and 100% market share within 70 of these counties. On the other hand, nationally at least half of the potential enrollees choose Original Medicare, and in some (mostly rural) counties as much as ninety percent choose this option.

Therefore, the key question became to what degree would competition from Original Medicare constraint any anti-competitive effects that might arise from the merger. The court's decision to adjoin the merger relied, at least in part, on the results of demand estimation and merger simulation.[13]

The demand estimation presented in court was of a Nested Logit model of plan choice, where all the Medicare Advantage plans were in one nest, $g = 1$, and Original Medicare options were in the outside good in another nest, $g = 0$. The utility of enrollee i from plan j in market m is given by

$$u_{ijm} = x_{jm}\beta - \alpha p_{jm} + \xi_{jm} + \zeta_{ig} + (1-\sigma)\epsilon_{ijm} \tag{3.5}$$

[13] The decision, along with other material from the trial, is available at https://www.justice.gov/atr/case/us-and-plaintiff-states-v-aetna-inc-and-humana-inc.

where x_{jm} is a vector of characteristics, such as a plan quality and additional benefits offered, p_{jm} is a measure of price of the plan, and ξ_{jm} is an unobservable demand shock. A key parameter was the nesting parameter, σ, which determines the degree of substitution between Medicare Advantage and Original Medicare.

The parameters were estimated using instrumental variables following the specification in Berry (1994). The instrumental variables used were attributes of competitors' plans. Both sides estimated very similar models. The main difference was in the exact variables used as IVs. As a result the exact estimate of the nesting parameter (and the price elasticity) varied somewhat.

The real difference, however, was in how these estimates were used. The expert for the government used the estimates to compute diversion and to perform a variety of HMTs, as described in the previous section. The test were both of the critical-loss variety and of a simulation of a merger to monopoly. The estimates were also used to simulate the likely effect of the merger. An important point in the trial was that as robustness test the estimates of the defendants' expert were used. The fact that results were qualitatively unchanged gave the analysis significantly more credibility.[14] Robustness is very important in academic settings but is significantly more important in a policy setting.

The merging parties' expert mainly used the nesting parameter to claim that Original Medicare should be included in the market because his estimate of the parameter was below 0.5. He also presented a regression that correlated the plan premium with concentration and found little correlation.

In some ways, this was set up as a battle between a simple and intuitive regression based on "real world" data and a complicated abstract model that is ungrounded in reality. Many would have predicted the former would win. Based on the outcome and reading the decision this was clearly not the case.

How is it that the "complicated" model won? In large part because the demand analysis was tied to the rest of the evidence. First, the approach was well grounded in market realities. The fundamental decision structure of the nested logit model was clearly supported in business documents. Second, the key result was supported by easy to understand simple patterns in raw data. Switching data on where consumers went once they left a Medicare Advantage plan clearly showed that at least eighty-five percent went to another Medicare Advantage plan. Third, results were consistent with the academic literature.[15] The model and estimates followed closely what was done in the academic literature studying this market. Finally, the results were extremely robust. The basic conclusions regarding market definition and competitive harm held

[14] A summary of the results presented in court are available at https://www.justice.gov/atr/us-and-plaintiff-states-v-aetna-and-humana.

[15] Several academic studies have used the Nested Logit model to study this market, and all estimated a nesting parameter in the same range as what was presented to the court. These studies include, Guglielmo (2016), Curto et al. (2015), Dunn (2010), Hall (2011), Dafny and Dranove (2008), Town and Liu (2003), and Atherly et al. (2004).

under a wide range of parameter values including those produced by the merging parties' expert.

The above principles help explain the court's decision and willingness to accept the choice modeling. But maybe more importantly, they give general guidance on how to convince policy decision makers to rely on the types of models used in quantitative marketing and economics. The models need to (i) be based on market realities; (ii) relate to simple statistics; and (iii) the conclusions need to be robust.

3.3.2 The AT&T-DirecTV merger

AT&T is a telecommunication company that offers many services including cellular phone service, landline phone, broadband and wireline TV service in many, but not all, states. DirecTV is a satellite video provider. In the spring of 2014 AT&T announced its intention to buy DirecTV. The merger was reviewed by the DOJ and the FCC. Because the FCC was involved there are public documents explaining the decision and redacted versions of submissions are available online.[16]

Broadly speaking the parties put forward two arguments why the merger would be pro-competitive. First, they claimed that post-merger AT&T would have increased incentives to invest. The argument made was mostly theoretical, and while the argument might be correct, it seemed to gain little traction with the FCC. The second argument was that the parties offer complementary products and therefore post-merger would have incentives to reduce prices. The parties backed up this claim with demand estimation and a merger simulation model. Judging by the FCC's order, which mostly accepted and slightly modified the merging parties' model, the empirical analysis was influential in getting the merger approved.

AT&T standalone video, offered mostly through its U-verse product, and DirecTV video are substitutes in areas where both are offered. It is well known, that absent cost savings a merger between substitutes will lead to higher prices. On the other hand, AT&T broadband service and DirecTV video may be complements, in which case the merger will lead to lower prices. Internet and video service might be complements because a provider offering both could offer a bundle discount, as most cable companies do, and install/service both together. The complementarity will not only lower the pricing of post-merger AT&T but also increase competition for bundles with the local cable provider. In theory it is unclear which effect dominates: the substitution or the complementarity.

In order to answer this question the merging parties offered a simulation model that was estimated using market level data and used to simulate the likely effect of the merger. A key modeling challenge is that standard discrete choice models have built in that all products are substitutes. In order to model complementarity the model allowed for discrete choices that included video alone, internet alone or both. Specifically, each consumer can choose between several options that were grouped into four nests: video only, broadband only, both video and broadband, and the "outside op-

[16] See https://docs.fcc.gov/public/attachments/FCC-15-94A1.pdf.

tion" of no video or broadband. The mean (conditional indirect) utility of product jk (where j indexes internet choice and k indexes video choice) in market m is given by

$$\delta_{jkm} = x_{jkm}\beta - \alpha p_{jkm} + \xi_{jkm}, \tag{3.6}$$

where x_{jkm} is a vector of characteristics, such as a product dummy, max speed offered, and DMA attributes interacted with product attributes, p_{jkm} is the price of the product, and ξ_{jkm} is an unobservable demand shock. Each of the products was placed in one of four groups, or nests. Let the market share, conditional on a choice set χ_m^l, be denoted by $\sigma_{jk}(\delta_m, \chi_m^l, \theta)$, where θ denotes the parameters to be estimated. The Nested Logit distributional assumptions imply that

$$\ln(\sigma_{jk}(\delta_m, \chi_m^l, \theta)) = \frac{\delta_{jm}}{1-\psi_g} - \psi_g \ln(D_{glm}) - \ln(1 + \sum_h D_{hlm}^{1-\psi_h}), \tag{3.7}$$

where the nesting parameter ψ_g measures the within-nest substitution in nest g. A simple specification, which is the one mostly relied upon, sets the parameter equal across groups. $\ln(D_{glm})$ is the "inclusive value" for group g and is given by

$$\ln(D_{glm}) = \ln \sum \frac{\delta_{jkm}}{e^{1-\psi_g}}, \tag{3.8}$$

where the summation is over the set of product that are in the nest and in the choice set, χ_m^l. One complication they needed to deal with is that the choice set varied within each DMA: not all consumers had access to the same choice set. The DMA level market shares are a weighted average of the conditional choice sets facing the different consumers

$$s_{jkm}(\delta_m, \theta) = \sum_l \sigma_{jk}(\delta_m, \chi_m^l, \theta) w_m^l \tag{3.9}$$

where the weight w_m^l is the fraction of DMA households facing choice set χ_m^l. The model was estimated using DMA level data. The model parameters were identified using instrumental variables including product characteristics, characteristics of other products in the choice set, DMA-level product availability, and other DMA attributes. Because the choice set varied within DMA the estimation could not follow the method suggested by Berry (1994) and instead was closer to the estimation in Berry et al. (1995).

One of the novelties of the analysis was the creation of different data sets and estimating using GMM based on marginal information (shares for video provider or broadband provider, but not shares the level of the jk "product"). Among other things, the authors utilized a survey conducted by a marketing professor. Such a sur-

vey would have been impossible to fund in an academic setting, but was possible here.[17]

The demand estimates were then fed into a merger simulation, like the one discussed above, and used to compute the likely effects of the merger. Reading through the FCC decision it is clear that the simulation model played an important role in getting the merger approved. The FCC used the merging parties model, modified it somewhat and "kicked the tires" a bit to check how robust it was. This analysis allowed the FCC to state: "We find that the combined AT& T-DIRECTV will increase competition for bundles of video and broadband, which, in turn, will stimulate lower prices, not only for the Applicants' bundles, but also for competitors' bundled products – benefiting consumers and serving the public interest. We also expect that this improved business model will spur, in the long term, AT&T's investment in high-speed broadband networks, driving more competition and thus expanding consumer access and choice. This is, in other words, a bet on competition."[18]

In many ways, the analysis done in this case was more novel than in the Aetna-Humana merger discussed earlier. The model was not a standard Nested Logit model, in the sense that it allowed for complements. Because of within DMA variation in choice sets, the estimation was not the garden variety estimation of Nested Logit as in Berry (1994). Finally, the construction of market shares required a massive data collection effort that was only feasible with the financial backing of a company like AT&T. One could complain about several aspects of the model, such as lack of additional heterogeneity and the fact that options that included the same product got independent unobserved shocks. Indeed, if this model was used in litigation one could imagine these becoming real issues. However, in a regulatory setting the key issue was whether any of these concerns were significant enough to overturn the results. The above quote suggest that this was not the case and that the results gave the FCC comfort in approving the merger.

3.3.3 Mergers that increase bargaining leverage

So far the examples have been on cases where modern methods of demand estimation have been used to estimate consumer demand and in turn simulate the likely effect of a merger. The merger simulation models used in these cases were relatively simple and based on linear Nash-Bertrand pricing. This is a reasonable assumption in some industries but not in others. For example, in many industries prices are negotiated. Recent academic work has empirically estimated bargaining models in a variety of industries (Draganska et al., 2010; Crawford and Yurukoglu, 2012; and Grennan, 2013). This is a prime example where recent academic work in marketing and economics has changed competition policy in industries as varied as health care and broadcast television.

[17] See https://ecfsapi.fcc.gov/file/60001044292.pdf and https://ecfsapi.fcc.gov/file/60000973737.pdf for a more detailed discussion.

[18] https://apps.fcc.gov/edocs_public/attachmatch/FCC-15-94A1.pdf at paragraph 5 on p. 4.

What is the effect of a merger in industries where prices are negotiated? Horn and Wolinsky (1988), Chipty (1995), and Chipty and Synder (1999) study this question. The basic ideas are described in Nevo (2014) and we follow that exposition closely here.

Consider an industry characterized by bargaining between providers, who produce content or provide services, and distributors, who sell the products or services to final consumers as part of a bundle. For example, in health care, the providers are hospitals or physicians, and the distributors are the insurers. The consumers are patients, who choose an insurance plan, and use providers as medical needs arise. In video markets providers license content to cable companies or satellite distributors and the consumers are viewers who choose a provider and bundle, and watch content.

The loss of competition from mergers in this setting is similar to the more standard setup, discussed above. Each provider supplies a potential improvement in the quality of a distributor's bundle, or network. Providers compete to not be the one left out of any distributor's bundle. That competition will impact the prices negotiated between the providers and distributors.

The bargaining is assumed to follow Nash bargaining (Nash, 1950). The parties split the surplus between the benefits of reaching agreement and those of disagreeing. The outcome relies on two key factors: the division of these gains, which we will call the bargaining power, and the leverage that each party has. The bargaining power each party has can be motivated by requiring certain axioms to hold, as Nash did, or by looking at the relative patience of the parties (Rubinstein, 1982).

As Horn and Wolinsky (1988) show, the effect of a merger depends on the curvature of the distributor's value function: if the value function is convex then the merger will lead to higher fees and if concave to lower fees. This can be illustrated numerically. Let's assume that the parties have equal bargaining power and that the split is fixed at 50:50.[19] Suppose a distributor negotiates with two providers. The distributor nets \$120 if its bundle includes both providers, \$100 if its bundle includes either provider but not both, and nothing with neither provider in its bundle. The provider only gains fees it gets if in the bundle, and zero otherwise. The incremental gain from adding either provider to the bundle, relative to disagreeing, is \$20 when the other provider is already in the bundle. Hence, the gain from making a deal is \$20. Split equally with the provider results in a fee of \$10.

Now suppose the two providers merge and negotiate as a single unit. The gain from making a deal with the merged provider is \$120. Split equally this results in the two providers acting together getting a combined \$60, while acting separately they were only able to negotiate for \$10 each or a total of \$20 for both. The providers gained from joint negotiation. If we change the numbers slightly the result could

[19] The level of the split is not important for what follows, but the assumption that it will not change with the merger is potentially important. A merger in this setting will have an effect on the fees negotiated between providers and distributors if it changes the value of an agreement relative to the value of disagreement. This change can happen for different reasons, but the key is whether the value of an agreement post-merger is more or less than the sum of the pre-merger values.

change. For example, if each provider generated a value of $60 regardless, then negotiating jointly or separately the providers would gain the same: $30 each. On the other hand, if the value of having either provider in the bundle alone was only $20, and both $120, then negotiating separately the providers would get $50 each, so more than negotiating jointly (where they would get a combined $60). This might seem surprising, but it is just the counterpart of two complements merging in a price setting framework.

There are several reasons why the distributor's value function might be convex. For example, if consumers view the providers as substitutes then every provider adds value to the distributor, by making its plan more attractive, because some subscribers prefer each provider over all others. But the more providers already in a bundle, then the lower is the incremental value of an additional provider.

Horn and Wolinsky cast this Nash bargaining model inside a Nash equilibrium, where each bargaining pair negotiates taking the bargaining outcome of other pairs as given. This is a strong assumption but has led to tractable empirical models (Crawford and Yurukoglu, 2012).

In practice, this bargaining model has been taken to the data in a variety of ways. The first method, often called the willingness-to-pay (WTP) model, relates prices to measures of competition. The effect of the merger is estimated by computing how the merger changes the measure of competition. The second method is the equivalent of merger simulation but uses the bargaining model described above instead of a Cournot or Bertrand model in the simulation.

Capps et al. (2003) propose estimating the WTP model in two steps.[20] In the first step one uses historical data on provider choices to estimate a provider choice model. The model estimates the weight that consumers put on different attributes by choosing the parameters that best explain why consumers choose the providers they did, over those they did not. The estimates from the consumer choice model allow us to compute what consumers are willing to pay to add an option to various bundles. For example, suppose providers A and B are very close substitutes in the eyes of consumers, but very far substitutes from any other provider. In that case consumers will not be willing to pay much to add provider A to a network that already includes provider B, nor to pay much to add provider B to a network that includes A. Since neither A nor B add much incremental value to consumers, if the other is already in the network, they also do not add much value to the distributor trying to construct a network. Thus, on their own neither provider can obtain favorable rates and we would expect to see prices for providers A and B to be low.

The second step of the WTP analysis simply correlates the expected value, or WTP, to prices paid historically and uses this relationship to simulate the likely effect of the merger. This regression is loosely motivated by the bargaining model, which says that WTP should be related to prices, but does not fully impose the relationship implied by the model. It parallels the idea of using historical data to estimate the

[20] See Farrell et al. (2011) for details on how this approach is implemented in practice.

relationship between prices and concentration, as measured for example by HHI, and using it to predict the effect of a change in concentration. The main difference is in the measure of competition used, WTP instead of HHI.

The second approach to empirically applying this model to the analysis of mergers expands merger simulation to these types of situations (Gowrisankaran et al., 2015). The key insight is that the equilibrium price equation given above can be modified to

$$p^* = mc + [\Omega(p^*) + \Lambda(p^*))]^{-1} Q(p^*), \tag{3.10}$$

where $\Lambda(p^*)$ is a function of the relative bargaining power of the two sides and various other bargaining terms (for details see Gowrisankaran et al., 2015). Ho and Lee (2017) build on this approach to study monopsony power.

The bargaining model has influenced the FTC's approach to mergers between health care providers (Farrell et al., 2011). The principle and ideas have been accepted by courts and let the FTC and DOJ break a long streak of losing hospital merger cases.[21]

Bargaining models also played a key in the challenge of Comcast attempted acquisition of Time Warner Cable (Rogerson, 2018) as well as the attempt by the DOJ to block the acquisition of Time Warner by AT& T. In the latter case the District court did not accept the government's bargaining theory. Interestingly, a key empirical dispute involved a measure of diversion where two marketing professors – John Hauser for the DOJ and Peter E. Rossi for AT&T – were on either side.

3.4 Looking forward

As we noted earlier, while academics and academic research have been influential in the area of competition policy there is still a wide gap between the academic frontier and the models used for policy analysis. For example, both Aetna-Humana and the AT&T-DirecTV cases, discussed above, relied on the Nested Logit model and not a more general Random Coefficients model. Furthermore, the model used are generally static and do not include demand side dynamics (such as those in Hendel and Nevo, 2006, Hartmann, 2006, or Gowrisankaran and Rysman, 2012) or supply side dynamics (such as Jeziorski, 2014). These models have not been used in policy work because of their greater data requirement, the time it takes to get a working version, and because empirical estimates of these models are often not as robust as the simpler models. However, looking forward as the profession's understanding of these models increases, better computational methods are developed and more detailed data, such as consumer-level data, becomes available we could see the methods used in practice get closer to the frontier of research.

[21] See for example the decisions in FTC v. ProMedica Health Sys., Inc., 2011-1 Trade Cas. (CCH) 77,395 (N.D. Ohio Mar. 29, 2011) and FTC v. OSF Healthcare Sys., 852 F.Supp.2d 1069, 1084 (N.D. Ill. 2012).

4 Nutrition policy

Nutrition policy is a much newer area of activity, and one in which there is currently only a limited formal role for economics or quantitative marketing. The impact of economics on policy in this area to date has largely been to quantify the costs of public health interventions or provide cost benefit analysis. However, both ex post analysis, where we aim to measure the impact of an observed intervention, and ex ante analysis, where we aim to identify structural parameters that we can use to compute counterfactuals of situations that we have not observed, have important contributions to make to our understanding of the impact of policy interventions that aim to address problems associated with nutrition. As with antitrust analysis, key to understanding the effects of most policy interventions are empirical estimates of consumers demand behavior and understanding of how firms might strategically respond.

In this section we first discuss what are the general objectives of nutrition policy and why quantitative market research has a contribution to make. We focus on nutrition policy in developed countries, nutrition policy in developing countries is often of a different nature, and is a place where economists have played a more significant role. We then discuss three active policy areas – nutrient based taxes, restrictions on advertising, and front of package nutrition labeling.[22] We use these to illustrate some of the general points raised above, and some of the ways that quantitative research has and could make important contributions to our understanding of the effects of public policy.

4.1 Objectives of nutrition policy

What is nutrition policy and what is it trying to achieve?[23] There are many indicators that people are making poor food choices from a nutritional perspective. Obesity and the rise in diet-related disease is a major public policy issue; according to the World Health Organization (WHO) worldwide obesity has more than doubled since 1980, most of the world's population now live in countries where overweight and obesity kills more people than underweight. WHO estimates that 42 million children under the age of 5 were overweight or obese in 2013. Quality-adjusted life years lost due to obesity in U.S. adults more than doubled from 1993 to 2008 (Jia and Lubetkin, 2010). The concern arises not only over poor food choices, but also regarding other potentially poor lifestyle choices over smoking, levels of physical activity, and alcohol consumption.

[22] There are many other policies and research areas that we could discuss but have chosen not to; one example is work by Allcott et al. (2018a) and Handbury et al. (2015) who use household-level marketing data (from Nielsen) to analyze the roles of supply (i.e. availability and prices) and demand (i.e. consumer preferences) in the nutrition-income gap observed in the US. These analyses have been heavily cited in the popular press and will likely inform future policy over "food desert", i.e. whether restricted supply plays an important role in determining the nutritional quality of particularly poorer households shopping baskets.

[23] This section draws heavily on Griffith et al. (2017b).

There is widespread concern that excess sugar consumption in particular is contributing not only to growing rates of obesity, but also to other diet-related diseases, including diabetes, cancers, and heart disease, and that excess sugar consumption is particularly detrimental for children.[24] There is also evidence that poor nutrition, particularly early in life, leads to poor later life outcomes.[25]

This evidence has led to a deafening call for policy intervention[26] based on the idea that such behaviors create "externalities", costs that fall on others as a result of excess consumption, in the form of public health care costs, lost productivity, etc., and "internalities", where excess consumption imposes costs on the person themselves in future that they do not account for at the time of consumption.[27]

A report by McKinsey Global Institute (Dobbs et al., 2014) estimates that globally obesity has roughly the same economic impact as smoking or armed conflict. They document 74 different policies that have been implemented to target obesity, including policies focused on changing food choices, on promoting exercise, on improving the balance between food and exercise, and other policies such as surgery or medication. In this chapter, we focus on policies that target the food and drink industry, including taxes, restrictions to advertising, and regulation over labeling food and drink products, as these are areas in which we think that quantitative marketing clearly has a lot to contribute.

These policies are aimed at getting people to make better choices from a nutritional perspective over the foods they purchase and eat. There is not clear evidence about why people are making inappropriate choices (or indeed whether the choices are suboptimal from a welfare perspective). Maybe consumers are optimally trading off the benefits from consumption against the health costs. Or if not, is it because consumers are poorly informed about the nutritional composition of specific foods products? Do consumers not understand the implications of poor nutrition? Do consumers lack self-control (discount the future consequences of excess consumption at "too high" of a rate)? Do firms exploit these characteristics through advertising, obfuscation, and other means? There is a growing theoretical literature that suggests that all of these factors might be important.

Individuals may have imperfect information about what a healthy diet looks like, or about the future health costs of eating unhealthy foods. A number of papers show that there is a strong correlation between education and nutritional choices, which is loosely suggestive of information related issues (for example, Cutler and Lleras-Muney, 2010). Eating a healthy diet requires a balance of food types, and both what are the most nutritious foods and what are the consequences of a nutrient poor diet vary across individuals in complex ways related to genetics and lifestyle choices. It

[24] See, for example, WHO (2015), Azais-Braesco et al. (2017), Nielsen and Popkin (2004).
[25] See, for example, Belot and James (2011) and Glewwe et al. (2001).
[26] CDC (2016), WHO (1990), Dobbs et al. (2014).
[27] Gruber and Koszegi (2004), O'Donoghue and Rabin (2006), Haavio and Kotakorpi (2011), Allcott et al. (2014).

is likely that most people, and in particular children, do not fully understand the implications of poor decisions, and so might be easily influenced to make poor choices.

Consumers might not be consistent in the food choices that they make at different points in time, for example, preferring healthy foods when they are deciding the menu for future consumption but preferring unhealthy foods when choosing for immediate consumption. The marketing and economics literatures have incorporated some of the ideas from the psychology literature that capture this behavior. There are a large number of behavioral models of consumer choice; Della Vigna (2009) groups these into three broad categories: (i) models of non-standard preferences, for example, where the utility function is not time consistent; (ii) models of non-standard beliefs, for example, where consumers are incorrect in their predictions about the probability of future events; and (iii) models of non-standard decision-making, for example, where consumers use some simple rule of thumb rather than engage in maximizing behavior. An important feature of many of these models is that they result in consumers imposing costs on themselves in future that are not fully taken into account at the point of choice.

Models of time inconsistency[28] capture the idea that some individuals suffer from self-control problems, i.e. they value utility today more than utility tomorrow. This leads people to exhibit self-control problems; when asked today they would not want to eat a chocolate bar tomorrow, but when tomorrow arrives they decide to eat the chocolate bar. For example, Read and van Leeuwen (1998) ask participants in a study to make advance choices between healthy and unhealthy snacks to eat in a week's time and then again asked them to choose at the time of consumption. They found that participants were dynamically inconsistent: they chose far more unhealthy snacks for immediate choice than for advance choice. Milkman et al. (2010) also provide evidence of this type of behavior in a study of on-line grocery purchases that finds that as the delay between order completion and delivery increases grocery customers spend more on products like vegetables and less on products like ice cream. Sadoff et al. (2015) observe considerable dynamic inconsistency in food choice in a within grocery store experiment.

Other models that are relevant for understanding food purchases include those in which people incorrectly and systematically expect their future preferences to be the same or close to their present preferences (see Loewenstein et al., 2003). Gilbert et al. (2002) showed that a set of grocery shoppers who were randomly given a muffin prior to shopping (thereby satisfying their hunger) make fewer unplanned purchases than a control group who were not given a muffin. Read and van Leeuwen (1998) found evidence that making decisions while hungry leads to a higher likelihood of choosing an unhealthy option. They asked office workers to choose a healthy or an unhealthy snack to be delivered a week later (in the late afternoon). Workers were asked to make this decision either when they were likely to be hungry (in the late afternoon) or when they were satiated (after lunch). In the first group, 78 percent chose an unhealthy snack, compared to 42 percent in the second group.

[28] Strotz (1955), Laibson (1997), O'Donoghue and Rabin (2003, 2006).

The theoretical literature has been influential in policy, and given the level of concern and advocacy it is clear that this will continue to be an active area for policy. Well designed policy should be informed by an understanding of how markets work. Parts of the public health community argue that the private sector is to blame for the current state of affairs (in particular the tobacco, alcohol, and processed food industries), and that industry should therefore play no role in finding the solution (see, e.g., Moodie et al., 2013). It is in the interests of policy makers, firms, consumers, and all market participants that policies are efficient and effective. Policy made in the absence of an understanding of how markets work risk being ineffective and leading to unintended consequences.

The quantitative marketing (and economics) literatures potentially have a lot to contribute. In order to quantify the effect of specific nutrient taxes we need to have well identified demand models that will allow us to understand how consumers will respond to changes in prices. Will some consumers respond more than others? Are the consumers that respond the ones that the policy is seeking to target, i.e. those that have the highest internalities or externalities? We also need to understand the supply side of the market – how manufacturers and retailers will respond to the introduction of a tax – because this will determine the incidence of the tax. It will allow us to quantify by how much prices of each product will increase, and potentially whether firms will respond in other ways, for example, by withdrawing products from the market or introducing new products.

When conducting either ex post or ex ante analysis it is important to remember the reasons for policy interventions, and to ensure that these are appropriately reflected in the methods that we use to study the impact of the policy. For example, if the rationale for introducing regulations that require front of package labeling is that we believe that consumers do not have complete information about the nutritional content of the products that they are choosing between, then it probably does not make sense to study the impact of the policy in a model where we assume that consumers have complete information. The rationales for policy intervention in the area of nutrition are various, but are based largely on models of consumer decision making in the absence of complete information or where some consumers have some type of cognitive limitation, so fail to use all of the information that they have, e.g. they do not fully weight the potential future consequences of consumption, or they do not take the time to read the back of package label.

Modern methods for estimating demand allow us to study consumer behavior, and to understand how a particular policy intervention will change the incentives of consumers to purchase different products, in a robust way while remaining reasonably agnostic about the exact way that consumer behavior departs from the standard full information and fully rational model (subject to all the standard caveats about identification and external validity). However, to make statements about welfare generally requires that we are much more specific about the precise model of consumer behavior and about functional forms. Similarly, to make predictions about firm behavior we typically need to make additional assumptions about the nature of strategic interactions between firms.

4.2 Nutrient taxes

One popular policy instrument is taxation, which aims to increase prices and change relative prices of less nutritious products relative to more nutritious ones. Such corrective taxes have long been used to address excess consumption of alcohol, tobacco, and other "sin" goods that arises because consumers do not take account of externalities (see Pigou, 1920, and Diamond, 1973). They are popular because they also typically raise tax revenue. More recently they have been advocated as a way to correct internalities, where consumption today imposes costs on the individual themselves in the future that the individual does not take account of at the time that they make the consumption decision. Corrective taxes have the potential to improve welfare by correcting consumption that generates internalities. The optimal design of such taxes involves trading off the welfare gains of reducing externalities or internalities, with the welfare losses from a reduction in consumer surplus due to the tax.[29] A common criticism of excise style taxes is that they are regressive; the poor typically spend a higher share of their income on the taxed good, and so bear a disproportional share of the burden of the tax.[30] However, if the tax plays the role of correcting an internality, then the distributional analysis is more complicated; if low income consumers also save more from averted internalities this may overturn the regressivity of the traditional economic burden of taxation (Gruber and Koszegi, 2004). These redistributive concerns become more subtle when income transfers are considered.[31]

Nutrient taxes of various forms have been introduced in many countries with mixed success. Alcohol taxes exist in most countries. Taxes on soda or sugar-sweetened beverages have been introduced in a number of US localities.[32] Early ex-post analysis to measure the immediate effect of these policies suggest that the taxes in Mexico (Colchero et al., 2015) and Berkeley (Falbe et al., 2016) have led to reductions in consumption. Bollinger and Sexton (2017) find similar though more modest effects for the Berkeley tax reform, due to the very limited pass-through. Other policies have met with less success. For example, Denmark introduced a tax on foods that are high in saturated tax in 2011, but abolished the tax just over a year later over concerns that the tax was having little impact on consumption and was putting jobs at risk, as many of the products that were affected by the tax were produced in Denmark.

Key to the design of effective tax policy is an understanding of how manufacturers and retailers are likely to respond to a tax, in terms of pricing and potentially other strategic decisions (see e.g. Draganska et al., 2009), and how changes in prices (and other strategic variables) will affect consumption choices over food and drink products. A number of papers in the public health literature that have studied the impact

[29] See, for instance, Gruber and Koszegi (2004), O'Donoghue and Rabin (2006), Haavio and Kotakorpi (2011), Allcott et al. (2014), and Griffith et al. (2017b, 2017c).

[30] For instance, see Senator Sanders op-ed on the Philadelphia soda tax (Sanders, 2016).

[31] See e.g. Lockwood and Taubinsky (2017), Allcott et al. (2015), Allcott et al. (2018b, 2018c).

[32] Including Berkeley, Oakland, San Francisco, Boulder, Philadelphia, and others, in France in 2012, Mexico in 2013, and in the UK in 2016.

of sugar taxes have been influential in the policy debate and have relied on demand models that make restrictive functional form assumptions and where identification arguments are questionable.[33]

Modern methods in demand estimation and the availability of scanner data such as Nielsen Homescan and Kantar Worldpanel provide the opportunity to improve substantially on this work. Scanner data provides a rich resource that is only beginning to be exploited for public policy analysis. The advantages of these data over existing standard data resources that are used for the analysis of public policy include that they are typically longitudinal, they are at the transaction level, and they contain well measured prices and product characteristics. In particular, being able to study demand at the individual product level, instead of at the product category level (which is more typical in public policy work and in standard consumption panels) is important when studying policy interventions such as nutrient taxes. For example, to account for how people switch between the large numbers of disaggregate products in markets such as alcohol and many food markets, it is important because policies can affect products differently and products have different nutritional characteristics (see discussion in Griffith and O'Connell, 2009).

There are also disadvantages of these data for studying nutrition. Most importantly, the data record purchases and not consumption, although they can be overstated, because while the ultimate aim of policy is to reduce consumption, policies such as taxes (as well as advertising restrictions and labeling) aim to change purchase behavior in the first instance. In addition, while individual transaction level data has advantages, it does not solve the fundamental identification problem, which is a key ingredient in identifying the shape of demand. One important identification issue is being able to isolate the impact of changes in prices on consumer demand from other potentially confounding factors – shocks to demand are likely to be correlated with prices.[34]

Another issue on which there is less empirical evidence is how to measure internalities – the difference between the consequences that people account for when making food choice and those that they do not account for. To set optimal nutrition taxes we would need these precisely, though if we know that they are positive, and have information on how they vary across the population, we might be confident that a particular tax is welfare improving, even if not necessarily optimal.[35]

4.2.1 The effects of taxes

What do we know about the effects of taxes on price and ultimately on consumer choices and welfare? There are some recent contributions using modern IO methods

[33] See, for example, Briggs et al. (2013), Brennan et al. (2014), Purshouse et al. (2010), Brownell et al. (2009).

[34] Berry (1994), Nevo (2011), Berry and Haile (2010).

[35] Several papers discuss the bias that might arise due to mis measuring internalities in the context of setting taxes, including, Mullainathan et al. (2012), Bernheim and Rangel (2009), and Handel and Schwartzstein (2018), and Allcott et al. (2015) in the context of setting taxes.

to carry out ex ante analysis of the impact of nutrient taxes using scanner data. For example, Wang (2015) studies the impact of a soda tax and shows the importance of accounting for the dynamics in demand that arise through stockpiling. Patel (2012) and Dubois et al. (2017) show the importance of allowing for rich consumer heterogeneity in preferences and responsiveness. Dubois et al. (2017) conduct an ex ante analysis of the introduction of soda taxes in the UK, and the results suggest that a soda tax would be effective at targeting young people who consume a lot of soda, but would not be so effect at targeting older consumers who drink large amounts of soda, because they are not very sensitive to price changes. Understanding better who responds to taxes, how they respond, how firms respond, and how all this varies in different contexts are important ingredients for better policy making. Other work has shown that it can be important to consider not just a single food category, but to consider possible interactions across food groups, for example, if taxing sugar in soda led consumers to substitute to sugar in other forms (Dubois et al., 2014; Harding and Lovenheim, 2017).

These ex ante studies are useful because we can consider the likely impact of policies that have not yet been introduced, we can study whether they target the right part of the population, and we can study the welfare implications of policy reforms. However, policy makers often find the assumptions that are required unpalatable, and in order for work in this vein to have a policy influence it is important to be able to articulate well the restrictiveness, or not, of the structural assumption. See the discussion in Section 3.3.1 regarding the Aetna-Humana merger and the importance of ensuring that a model is based on market realities, relates to simple statistics, and the conclusions need to be robust in order to be convincing to policy decision makers.

In some cases we can combine the advantages of ex post reduced form strategies, in particular that they are more transparent and so more palatable to the lay person and often rely on more easily explained and more credible identification strategies, with the ability of structural models to make statements about counterfactual situations and about welfare. The "sufficient statistics" approach, has been widely applied in public economics.[36] The basic idea is this, in order to answer some important policy relevant questions we do not need a full structural model, all we need to know is a sufficient statistic. If we can derive a formula for the welfare consequences of policies that are functions of objects (such as elasticities) that we can estimate from ex post analysis, then these might be sufficient for us to say whether welfare will be increased or decreased if we undertook some counterfactual reform, under some assumptions. For example, under the assumptions of the Mirrlees (1971) model we can make inference about the optimal progressive income tax schedule from labor supply elasticities (Saez, 2001). This can be a powerful result and empirical work can make two important contributions. First, ex post studies can provide robust evidence on the sufficient statistics of interest. Second, ex ante studies can help us to understand whether the assumptions required to implement the sufficient statistics approach are

[36] See Chetty (2009), Saez (2001), Gruber and Saez (2002), Jacobsen et al. (2016).

valid. To our knowledge these insights and methods have not been widely applied to inform the setting of taxes on alcohol, soda, and other nutrient related taxes.

4.2.2 Estimating pass-though

We can use standard demand methods in order to undertake ex ante analysis of the likely impact of a nutrient tax – we can estimate demand, assume supply behavior, specify the first-order conditions, invert these to recover marginal cost, and then do counterfactual analysis with and without the taxes (or at different tax rates).

When undertaking ex ante analysis the functional form assumption on demand can be particularly important. The effects of a tax on prices will depend on the shape of the market level demand curve, and on the supply-side and how much of the tax firms choose to pass-through to consumers by raising prices. It will also depend on whether firms respond in other ways, such as entering or exiting the market, reformulating products or changing other strategies, which we will not discuss here.

One general point that a number of papers have highlighted is that, in addition to the usual endogeneity concerns, the curvature of market demand is a crucial determinant of pass-through of cost shocks and taxes to consumer prices.[37] For example, in the case of a single product monopolist with constant marginal costs, pass-through of a cost shock will be incomplete if and only if the monopolist faces a demand curve that is log-concave. Let the demand curve be $q(p)$ and constant marginal cost be c; optimization implies $q + p(dq/dp) = c(dq/dp)$. Differentiating with respect to cost and substituting yields pass-through as

$$\frac{dp}{dc} = \frac{1}{2 - q\frac{d^2q/dp^2}{(dq/dp)^2}} = \frac{1}{1 - \left(\frac{d^2\ln(q)}{dp^2}\right)\left(\frac{q}{(dq/dp)}\right)^2}. \tag{4.1}$$

This expression shows that pass-through will be incomplete ($dp/dc < 1$) if and only if demand is log-concave ($d^2\ln(q)/dp^2 < 0$); if we restrict market demand to be log-concave then this rules out pass-through of more than 100% by assumption. More generally, assuming a particular degree of concavity or convexity of log demand will place strong restrictions on the possible range of pass-through even when it does not exactly imply under or over-shifting. In the mixed logit demand model the functional form of indirect utility and the heterogeneity that is allowed will be an important determinant of the curvature of the log of market demand, and therefore on pass-through.

Griffith et al. (2017a) discuss this and show its empirical relevance in the context of studying the impact of a fat tax on demand[38]; this discussion draws heavily on that paper. Consider a consumer with income y. The consumer makes a discrete choice from $j \in \{0, 1, \ldots, J\}$. Denote price p_j. Each product has an associated vector of observable product characteristics $\mathbf{x_j}$ and an unobservable characteristic ε_j. There is

[37] Bulow and Pfleider (1983), Seade (1985), Anderson (2001), Weyl and Fabinger (2013).

[38] Khan et al. (2015) also conduct an *ex ante* study of the likely impact of a fat tax.

a vector of parameters θ, some of which may be random coefficients. Assume that the consumer's indirect utility (conditional on purchasing j and spending $y - p_j$ on the outside good) is given by:

$$U(y - p_j, \mathbf{x_j}) + \varepsilon_j. \tag{4.2}$$

We assume that $U(y - p_j, \mathbf{x_j}) + \varepsilon_j$ satisfies the properties of an indirect utility function (it is non-increasing in prices, non-decreasing in grocery budget, homogeneous of degree zero in all prices and grocery budget, quasi-convex in prices, and continuous in prices and grocery budget); consumer theory does not impose further restrictions on how $y - p_j$ enters conditional utility. We assume that ε_j is independent and identically distributed across alternatives and drawn from a type I extreme value distribution, so the probability that the consumer selects option j is given by:

$$P_j = \frac{\exp(U(y - p_j, \mathbf{x_j}))}{\sum_{k \in \{0,\ldots,J\}} \exp(U(y - p_k, \mathbf{x_k}))}. \tag{4.3}$$

If we assume that utility is linear in $y - p_j$:

$$U(y - p_j, \mathbf{x_j}) = \alpha(y - p_j) + g(\mathbf{x_j}), \tag{4.4}$$

which means that the marginal utility of income (y) is constant and importantly, when comparisons are made across options y differences out of the model so that by assumption an increase in a consumer's income does not impact on demand for the inside products $j > 0$. To capture the fact that consumers with different incomes are observed to make systematically different choices it is common to include y in the model as a "preference shifter" (see, inter alia, Nevo, 2001; Berry et al., 2004; Villas Boas, 2007; and many other papers). For example, the parameter α can be allowed to vary linearly across consumers with y:

$$\alpha = \alpha_0 + \alpha_1 y + \nu, \tag{4.5}$$

where ν is a random coefficient. This "preference shifter" model allows researchers to capture, in a reduced form way, the empirical fact that spending patterns vary cross-sectionally with income. However, it rules out income effects at the individual level and is ad hoc in that consumer theory does not provide a theoretical explanation for why preferences should shift with y.

Papers that allow $y - p_j$ to enter non-linearly include Berry et al. (1995), Goldberg (1995), and Petrin (2002). These papers consider demand for large budget share product categories (automobiles and mini-vans) and specify:

$$U(y - p_j, \mathbf{x_j}) = \alpha \ln(y - p_j) + g(\mathbf{x_j}), \tag{4.6}$$

the marginal utility of income is given by $\frac{\alpha}{y - p_j}$ and is therefore inversely proportion to $y - p_j$. This specification implies that households with higher income are less price sensitive.

Consider the demand curve for a product in the market. Let each consumer be indexed by income and a vector of parameters, (y, θ). Normalizing the size of the market to one, the market demand curve for option j is:

$$q_j(\mathbf{p}) = \int P_j(y,\theta) g(y,\theta) dy d\theta, \tag{4.7}$$

where $P_j(y,\theta)$ is the individual purchase probability given in Eq. (4.3) and $g(y,\theta)$ is the joint density over the elements of (y,θ).

The second derivative of the log of market demand with respect to price is given by:

$$\begin{aligned}\frac{\partial^2 \ln q_j}{\partial p_j^2} = &\int \frac{P_j(y,\theta)}{q_j} \frac{\partial^2 \ln P_j(y,\theta)}{\partial p_j^2} g(y,\theta) dy d\theta \\ &+ \left[\int \frac{P_j(y,\theta)}{q_j} \left(\frac{\partial \ln P_j(y,\theta)}{\partial p_j} \right)^2 g(y,\theta) dy d\theta \right. \\ &\left. - \left(\int \frac{P_j(y,\theta)}{q_j} \frac{\partial \ln P_j(y,\theta)}{\partial p_j} g(y,\theta) dy d\theta \right)^2 \right].\end{aligned} \tag{4.8}$$

The curvature of this depends on: (i) the weighted average of the second derivatives of log individual demand, which is negative if individual level demand is log-concave, and (ii) the weighted variance of the slope of log individual level demand, which is non-negative and is positive when there is heterogeneity in individual demands. Log demand will be concave if individual demand is log-concave and if the cross-sectional variance of the slope of log demand is not too big. It will be convex if individual log demand is convex or if the variance term is large enough in magnitude.

If we assume that utility is linear in $y - p_j$, i.e. Eq. (4.4), then $\frac{\partial^2 \ln q_j}{\partial p_j^2}$ collapses to the second derivative of the log of individual level demand:

$$\frac{\partial^2 \ln q_j}{\partial p_j^2} = \frac{\partial^2 \ln P_j}{\partial p_j^2} = -\alpha^2 P_j (1 - P_j) < 0,$$

and curvature is then fully determined by the marginal utility of income parameter, α, and the market share. Both individual and market demand are restricted to be log-concave.

If we allow for heterogeneity in α then individual demand is still restricted to be log-concave, but the market demand curve could be log-convex or log-concave in some regions and log-convex in others, depending on the weighting of consumers.

If we allow $y - p_j$ to enter utility in a flexible nonlinear way then this allows flexibility in both individual level and market demand. In particular, individual level demand will not be constrained to be log-concave. The second derivative of the log

of consumer demand for option j with respect to its own price is given by:

$$\frac{\partial^2 \ln P_j}{\partial p_j^2} = (1 - P_j)\left[\frac{\partial^2 U(y - p_j, \mathbf{x_j})}{\partial (y - p_j)^2} - \left(\frac{\partial U(y - p_j, \mathbf{x_j})}{\partial (y - p_j)}\right)^2 P_j\right]. \tag{4.9}$$

The degree of log-concavity (or convexity) is determined by the shape of the function U, and therefore the flexibility of the curvature of individual demand depends on the flexibility of the function U. Therefore the specification is crucial to study pass-through.

There is a highly related literature in marketing that has analyzed the rate at which promotions are passed through by retailers to the final consumer.[39]

4.3 Restrictions to advertising

Another popular policy is restrictions to advertising. The aim of policies that restrict the advertising of specific foods is to lower consumption, as is the case with widespread restrictions to advertising of alcohol and tobacco products. This is in contrast to regulation of advertising in some other markets where the aim is consumer protection or information provision (for example, the advertising of pharmaceuticals). The World Health Organization (WHO, 2010) has advocated restrictions on advertising of some foods, and recommended that the "overall policy objective [of an advertising ban] should be to reduce both the exposure of children to, and the power of, marketing of foods high in saturated fats, trans-fatty acids, free sugars, or salt." The medical literature has called for restrictions on advertising on the basis of claims that advertising is especially effective among children (Gortmaker et al., 2011; National Academies, 2006; and Cairns et al., 2009). Many countries ban advertising of junk foods to children, with the exception of the US, which to date relies on voluntary restraints. For example, the UK bans advertising of foods that are high in fat, salt or sugar (HFSS) during children's programming (TV shows for which the primary audience is under 16), and is extending this to digital and other platforms.

What impact does a ban on advertising have on consumption, and who will it effect? How are junk foods defined and can firms game the system? These are important questions for the effective design of policy, and efficient and effective regulation is generally preferable to firms and consumers when compared to inefficient and ineffective regulation. Designing effective policy relies on understanding not only whether a policy works, but why it works and who it works on. Both ex post and ex ante analysis have a key role to play here.

4.3.1 The mechanisms by which advertising might affect demand

Advertising can affect consumer choice behavior in a number of ways. Bagwell (2007) surveys the large literature on the mechanism through which advertising af-

[39] See, for instance, Tyagi (1999); Sudhir (2001); Moorthy (2005); Besanko et al. (2005).

fects consumer choice, and conveniently distinguishes between the persuasive, characteristic, and informative advertising traditions. It is possible to model the effects of restrictions to advertising on choice while remaining reasonably agnostic about the mechanisms through which advertising works, though see discussion below about important functional form considerations. However, in order to make welfare statements we typically have to take a stance on which of these mechanisms is dominant. For example, the welfare consequences of restricting advertising differ considerable if we take the view that advertising is a characteristic that consumers value compared to if advertising distorts consumers' decision making. If it is viewed as a product characteristic that consumers intrinsically value, as in Becker and Murphy (1993), then banning it will necessarily make consumers worse off; if it is persuasive (as in Dixit and Norman, 1978) then banning it will necessarily make consumers better off.

The early literature on advertising focused on its persuasive nature,[40] where the purpose of advertising is to change consumer tastes. The behavioral economics and neuro-economics literatures have focused on the mechanisms by which advertising affects consumer decision making. Gabaix and Laibson (2006) consider models in which firms might try to shroud negative attributes of their products, while McClure et al. (2004) and Bernheim and Rangel (2004, 2005) consider the ways that advertising might affect the mental processes that consumers use when taking decisions (for example, causing a shift from the use of deliberative systems to the affective systems that respond more to emotional cues). Rao and Wang (2017) and Jin and Leslie (2003) highlight firms' misleading or selective advertising respectively, the impact these can have on consumers, and why the role of the regulator is particularly important in such settings. Rao and Wang (2017) also examine consumer heterogeneity in detail using scanner data (a point relevant to this Handbook) and find that exposure of firms' deceptive activities primarily affects newcomers rather than existing consumers.

Becker and Murphy (1993) and Stigler and Becker (1977) consider advertising much as any other product characteristic as something that consumers may like or dislike, and advertising might act as a complement to other goods or characteristics that enter the utility function.

Advertising can also provide information to consumers – about the quality or characteristics of a product (Stigler, 1961 and Nelson, 1995), product price (Milyo and Waldfogel, 1999), or about the existence and availability of products (Goeree, 2008; Ackerberg, 2001, 2003). Firms may also have incentives to limit the informative content of adverts even when consumers are imperfectly informed (Anderson and Renault, 2006 and Spiegler, 2006), or provide false advertising (Rao and Wang, 2017).

4.3.2 Empirically estimating the impact of advertising

In order to quantify the effects of restrictions on advertising of particular (unhealthy) food we need to have a well identified model of consumer demand in which adver-

[40] Marshall (1921), Braithwaite (1928), Robinson (1933), Kaldor (1950), and Dixit and Norman (1978).

tising enters in a suitably flexible way. We also need to understand how firms will respond to the restrictions, for example, do they charge different prices, reformulate products, or change their behavior in other ways?

Advertising of a brand might increase purchases of that brand by drawing new customers into the category, or it might largely act to shift purchases from a rival brand. These have different implications for consumption, and the effectiveness of restrictions to advertising will depend crucially on which of these effects dominate.

Identifying the causal impact of advertising on demand can be challenging (see, for example, Lewis and Rao, 2015). Standard approaches to estimating demand in differentiated product markets impose that cross-price elasticities are positive, i.e. they do not allow products to be complements (recent exceptions include Thomassen et al. (2017) and work in the AT&T-DirecTV example discussed in Section 3.3.2). In many situations, for example, when we are modeling choice between a small number of branded products (think Coke and Pepsi) this seems like a reasonable assumption. However, sign restrictions on cross-advertising elasticities are not theoretically founded (advertising might tilt the demand curve or change the marginal rate of substitution between product characteristics, see e.g. Johnson and Myatt, 2006). Brand advertising may be predatory, in which case its effect is to steal market share of rival products, or it might be cooperative, so that an increase in the advertising of one product increases demand for other products, and there is a large literature showing empirical support for these effects across many product categories. For example, Rojas and Peterson (2008) find that advertising increases aggregate demand for beer; while other papers show that regulating or banning advertising has led to more concentration (Eckard, 1991, for cigarettes; Sass and Saurman, 1995, for beer; Motta, 2007, surveys numerous other studies) and in the case of partial ban in the cigarette industry, more advertising (Qi, 2013). Shapiro (2018c) finds that television advertising of prescription antidepressants exhibits significant positive spillovers on rivals' demand. Dhar and Baylis (2011) find that a ban on fast-food advertising in Quebec led to substantial reductions in fast-food consumption.

In order to allow for the possibility that advertising could be predatory, cooperative or some combination it is important to flexibly including both own brand and competitor advertising in the consumer's decision utility. Dubois et al. (2018) provide a discussion of this point and empirical estimates for a specific market; our discussion here borrows heavily from them.

Consider a model in which consumers i choose between products $j = 1, \ldots, J$. Choice occasions are indexed t. Consumer i's exposure to the advertising of product j is denoted a_{ijt}. Denote the consumer's payoff:

$$v_{ijt} = \left[\lambda_i a_{ijt} + \alpha_{2i} a_{ijt} p_{jt} + \rho_i \left(\sum\nolimits_{l \neq j} a_{ilt}\right)\right] + \alpha_{1i} p_{jt} + \psi_{1i} \mathbf{x}_j + \epsilon_{ijt} \qquad (4.10)$$

where p_{jt} is product price, $\mathbf{x}_j$ are other observed product characteristics, and ϵ_{ijt} is an i.i.d. shock drawn from a type I extreme value distribution.

The terms in square brackets captures the impact of advertising on the payoff function and incorporates enough flexibility to allow for the possibility that advertis-

ing is predatory (stealing market share from competitors) or cooperative (increasing market share of competitors); that advertising leads to market expansion or contraction; and that advertising may tilt the demand curve or change the marginal rate of substitution between product characteristics.

Own advertising enters directly in levels; the coefficient λ_i captures the extent to which differential time series exposure to own advertising affects the valuation or weight the consumer places on the unobserved brand effect. Own advertising also potentially interacts with price, the coefficient α_{2i} allows the marginal effect of price on the payoff function to shift with own advertising (as in Erdem et al., 2008). The coefficient ρ_i captures the extent to which time variation in competitor advertising affects the valuation or weight the consumer places on the unobserved brand effect.

Denote the payoff to the outside option:

$$\bar{v}_{i0t} = v_{i0t} + \epsilon_{i0t}.$$

The probability that consumer i buys product j at time t is:

$$s_{ij}(a_{it}, \mathbf{p_t}) = \frac{\exp\left(v_{ijt}\right)}{1 + \exp(v_{i0t}) + \sum_{j'=1}^{J} \exp\left(v_{ij't}\right)}. \tag{4.11}$$

What is the effects of advertising on consumer level demands? The marginal impact of a change in advertising of one product on the individual level choice probabilities is given by:

$$\begin{aligned}
\frac{\partial s_{ijt}}{\partial a_{ijt}} &= s_{ijt}\left[\lambda_i + \alpha_{2i} p_{jt} - \rho_i (1 - s_{i0t})\right] \\
\frac{\partial s_{ij't}}{\partial a_{ijt}} &= s_{ij't}\left[\rho_i s_{i0t}\right] \quad \text{for } j' \neq (0, j) \\
\frac{\partial s_{i0t}}{\partial a_{ijt}} &= -s_{i0t}\left[\rho_i (1 - s_{i0t})\right].
\end{aligned}$$

If advertising of one product did not directly enter the payoff of other products (imposing $\rho_i = 0$), then we require $\left(\lambda_i + \alpha_{2i} p_{jt}\right) > 0$ for advertising to have a positive own effect (so $\partial s_{ijt}/\partial a_{ib(j)t} > 0$). In this case advertising would necessarily be predatory, stealing market share from competitor products ($\partial s_{ij't}/\partial a_{ib(j)t} < 0$) and it would necessarily lead to market expansion ($\partial s_{i0t}/\partial a_{ib(j)t} < 0$). By including competitor advertising in the payoff function we allow for the possibility that, regardless of the sign of own demand advertising effects, advertising may be predatory or cooperative and it may lead to market expansion or contraction (i.e. we do not constrain the signs of $\partial s_{ij't}/\partial a_{ib(j)t}$ or $\partial s_{i0t}/\partial a_{ib(j)t}$).

Allowing advertising to interact with the consumer's responsiveness to price and the nutrient characteristic allows advertising to have a direct effect on consumer level

price elasticities. The consumer level price elasticities are, for any $j \neq (0)$:

$$\frac{\partial \ln s_{ijt}}{\partial \ln p_{jt}} = \left(\alpha_{1i} + \alpha_{2i}\mathfrak{a}_{ijt}\right)(1 - s_{ijt})\,p_{jt}$$
$$\frac{\partial \ln s_{ij't}}{\partial \ln p_{jt}} = -\left(\alpha_{1i} + \alpha_{2i}\mathfrak{a}_{ijt}\right)s_{ijt}\,p_{jt} \quad \text{for } j' \neq j.$$

This allows advertising to impact consumer level price elasticities in a flexible way, through its impact on choice probabilities and through its impact on the marginal effect on the payoff function of price, captured by α_{2i}.

Incorporating advertising into a demand model also raises additional identification challenges. Firms target advertising to specific consumers at specific times, and these might be correlated with the unobserved demand shocks. The increased access to big data on consumer behavior and on advertising is useful, but it is not a silver bullet, we still need to be careful about where the exogenous variation in exposure to advertising is coming from that allows us to identify the ceteris paribus effects of advertising.

One approach to identification uses field experiments, as in Anderson and Simester (2013) and Sahni (2016). Sahni (2016) for example shows that adverts placed on a restaurant search website were found to increase sales of non-advertised restaurants. These provide very useful small scale studies with clear identification, however we do need to worry about external validity. Another approach is to use an IV strategy, as in Hartmann and Klapper (2017), Sinkinson and Starc (2017), and Dubois et al. (2018).

In addition there are dynamic considerations. Advertising affects consumers choices today, but also potentially in the future, introducing the possibility that when firms choose their advertising strategies they play a dynamic game. Solving such a game entails specifying precisely the details of firms' dynamic problem and of the equilibrium concept that prevails in the market (Dube et al., 2005). This considerably complicates studying supply side responses.

A number of papers have shown that if advertising is primarily rivalrous, then firms are likely to advertise beyond the joint profit-maximizing level, largely canceling each other out in their efforts.[41] In contrast, if advertising is primarily expansionary, then there is less advertising than the joint profit-maximizing level, which raises the possibility that restrictions on advertising are welfare improving and that (some) firms might gain as well.

One effect that advertising has on consumer demand is to lower consumers' sensitivity to price. Banning advertising therefore leads to tougher price competition. Dubois et al. (2018) show that banning advertising on potato chips would lead to the (quantity weighted) average price in the market falling by 4%. This is important for understanding the impacts of the policy. While standard economic measures of wel-

[41] von der Fehr and Stevik (1998), Bloch and Manceau (1999), Netter (1982), and Buxton et al. (1984).

fare improve, consumer surplus rises because prices are lower, and profits do not fall by enough to compensate that, in fact quantity is likely to increase slightly.

Understanding how manufacturers and retailers are likely to respond to restrictions to advertising is key and a difficult task. One policy design issue in restricting advertising of junk foods is the definition of what is a junk food. The importance of this is illustrated in McDonald's adverts in Christmas 2017. The UK restrictions do not allow McDonalds to advertise their standard products during Children's TV programs because of their nutritional characteristics. To circumvent this McDonald's released an advert that featured carrots sticks (for the reindeer) see https://www.youtube.com/watch?v=XZ2PenyNRjE. Other ways in which firms can circumvent the regulations is by advertising similarly branded products or through product reformulation.

4.4 Labeling

There is a lot of legislation around front of package labeling and there have been many reforms in the US, UK, and other countries (see reviews in Cowburn and Stockley, 2005 and Heike and Taylor, 2013). In general the aim of nutritional labels is to provide information to consumers and to make the nutritional content more salient. Other policies, such as taxation, can also increase the salience of characteristics (see for example, Chetty et al., 2009).

When considering whether labeling is effective we need to consider what the policy is aiming to achieve. The impact of labeling on choices and demand will depend on what information consumers had in the absence of labeling, and how their expectations were formed prior to labeling. If consumers have a systematic misunderstanding of the composition of specific food products, or if increased salience is the key effect of labeling, then introducing labels should shift demand. However, if consumers have on average correct perceptions about the ingredients in food, and there is just noise around that, then we would expect labeling to have different effects, for example, compressing the estimated distribution of preferences for the characteristic that is labeled.

However, if the problem is that consumers have cognitive constraints in their ability to process information, or if they lack self-control, then labeling might be less effective. One interesting question is whether labels have direct effects in terms of inducing guilt or other utility-relevant emotions. Most of the literature focuses on the impact of introducing labels on quantity demanded, but these quantity effects are of course not welfare effects. Several papers make this point with respect to graphic cigarette warning labels.[42] Marketers might be able to contribute substantively to this literature by providing insights here on the psychology of how labels work and how to measure the potential welfare implications.

[42] For example, Cutler et al. (2015), Jin et al. (2015), Glaeser (2006), and Allcott and Kessler (2017) make related points about measuring the welfare effects of information provision and other nudges.

Empirical work has found that the introduction of more prominent nutrition labeling does lead to changes in consumption choices, for example, Bollinger et al. (2011) find that the introduction of mandatory calorie posting in Starbucks led to an average 6% reduction in calories purchased; Kiesel and Villas-Boas (2013) show that labeling effects consumer choice in an experimental setting in supermarkets, but that the impact depends on the exact design of the label and the information conveyed. However, other literature has shown that in some circumstances requirements for nutrition labeling can have unintended and perverse effects, for example, reducing the nutritional quality of products (Moorman et al., 2012). In response to this Ratchford (2012) emphasizes the need for theoretical and empirical research on the supply-side reactions to various policy measures and disclosure laws; Pappalardo (2012) highlights the role of marketing in policy design.

4.5 Looking forward

To date the influence of quantitative IO and quantitative marketing research on nutrition policy has been limited. There is large potential for future research to provide valuable input into the formulation of efficient and effective policy. This is in the interest of researchers, industry, and policy makers.

5 Concluding comments

In this chapter we discuss two areas of policy – competition policy and nutrition policy – and how quantitative marketing can impact and has impacted these areas. Despite having similar potential for impact from quantitative marketing, the actual impact has been quite different. In competition policy economists have been using the models and methods of quant marketing and IO to influence actual policy. The effect, at least up to now, has been smaller in nutrition policy. However, in both areas there is scope for great impact from recent research.

Our focus has been on how researchers can impact policy, but there is also an effect in the other direction. Marketers need to pay more attention to the policy debates for at least two reasons. First, a proper discussion of firm and consumer interaction, which is at the heart of marketing, cannot be complete without accounting for the regulatory, legal, and policy environment. Second, having a greater involvement with policy will help marketers shape their research in relevant and interesting directions. In order to have an impact the discussion with policy makers has to be a two way exchange.

References

Ackerberg, D., 2001. Empirically distinguishing informative and prestige effects of advertising. The Rand Journal of Economics 32 (2), 316–333.

Ackerberg, D., 2003. Advertising, learning, and consumer choice in experience good markets: an empirical examination. International Economic Review 44 (3), 1007–1040.
Allcott, H., Diamond, R., Dubé, J-P., 2018a. The Geography of Poverty and Nutrition: Food Deserts and Food Choices Across the United States. Stanford Business School Working Paper No. 3631.
Allcott, H., Kessler, J.B., 2017. The Welfare Effects of Nudges: A Case Study of Energy Use Social Comparisons. NBER Working Paper 21671.
Allcott, H., Knittel, C., Taubinsky, D., 2015. Tagging and targeting of energy efficiency subsidies. The American Economic Review 105 (5), 187–191.
Allcott, H., Lockwood, B., Taubinsky, D., 2018b. Regressive sin taxes, with an application to the optimal soda tax. The Quarterly Journal of Economics. https://doi.org/10.1093/qje/qjz017.
Allcott, H., Lockwood, B.B., Taubinsky, D., 2018c. Should We Tax Soda? An Overview of Theory and Evidence. NBER Working Paper 225842. Forthcoming in Journal of Economic Perspectives.
Allcott, H., Mullainathan, S., Taubinsky, D., 2014. Energy policy with externalities and internalities. Journal of Public Economics 112, 72–88.
Anderson, S., 2001. Tax incidence in differentiated product oligopoly. Journal of Public Economics 81 (2), 173–192.
Anderson, S., Renault, R., 2006. Advertising content. The American Economic Review 96 (1), 93–113.
Anderson, E.T., Simester, D., 2013. Advertising in a competitive market: the role of product standards, customer learning, and switching costs. Journal of Marketing Research 50 (4), 489–504.
Angrist, J., Pischke, J.S., 2010. The credibility revolution in empirical economics: how better research design is taking the con out of econometrics. The Journal of Economic Perspectives 24 (2), 3–30.
Atherly, A., Dowd, B.E., Feldman, R., 2004. The effect of benefits, premiums, and health risk on health plan choice in the Medicare program. Health Services Research 39 (4), 847–864.
Azais-Braesco, Sluik, Maillot, Kok, Moreno, 2017. A review of total and added sugar intakes and dietary sources in Europe. Nutrition Journal 16. https://doi.org/10.1186/s12937-016-0225-2.
Bagwell, K., 2007. The economic analysis of advertising. In: Armstrong, M., Porter, R. (Eds.), Handbook of Industrial Organization, vol. 3. Elsevier, pp. 1701–1844.
Bain, J., 1956. Barriers to New Competition: Their Character and Consequences in Manufacturing Industries. Harvard University Press, Cambridge, MA.
Bayot, D., Hatzitaskos, K., Howells, B., Nevo, A., 2018. The Aetna-Humana proposed merger. In: Kwoka Jr., John E., White, Lawrence J. (Eds.), The Antitrust Revolution, 7th edition. Oxford University Press.
Becker, G.S., Murphy, K.M., 1993. A simple theory of advertising as a good or ban. The Quarterly Journal of Economics 108 (4), 941–964.
Belot, M., James, J., 2011. Healthy school meals and educational outcomes. Journal of Health Economics 30 (3), 489–504.
Bernheim, D., Rangel, A., 2004. Addiction and cue-triggered decision processes. The American Economic Review 94 (5), 1558–1590.
Bernheim, D., Rangel, A., 2005. Behavioral Public Economics: Welfare and Policy Analysis with Non-Standard Decision-Makers. National Bureau of Economic Research Working Paper 11518.
Bernheim, D., Rangel, A., 2009. Beyond revealed preference: choice theoretic foundations for behavioral welfare economics. The Quarterly Journal of Economics 124 (1), 51–104.
Berry, S., 1994. Estimating discrete-choice models of product differentiation. The Rand Journal of Economics 25 (2), 242–262.
Berry, S., Haile, P., 2010. Nonparametric Identification of Multinomial Choice Demand Models with Heterogenous Consumers. Cowles Foundation DP 1718.
Berry, S., Levinsohn, J., Pakes, A., 1995. Automobile prices in market equilibrium. Econometrica 63 (4), 841–890.
Berry, S., Levinsohn, J., Pakes, A., 2004. Differentiated products demand systems from a combination of micro and macro data: the new car market. Journal of Political Economy 112 (1), 68–105.
Berry, S., Pakes, A., 1993. Some applications and limitations of recent advances in empirical industrial organization: merger analysis. The American Economic Review 83 (2), 247–252.
Besanko, D., Gupta, S., Dube, J.P., 2005. Own-brand and cross-brand retail pass-through. Marketing Science 24 (1).

Bloch, F., Manceau, D., 1999. Persuasive advertising in Hotelling's model of product differentiation. International Journal of Industrial Organization 17, 557–574.
Bollinger, B., 2015. Green technology adoption: an empirical study of the Southern California garment cleaning industry. Quantitative Marketing and Economics 13 (4), 319–358.
Bollinger, B., Gillingham, K., 2012. Peer effects in the diffusion of solar photovoltaic panels. Marketing Science 31 (6), 900–912.
Bollinger, B., Karmarkar, U., 2015. BYOB: how bringing your own shopping bags leads to pampering yourself and the environment. Journal of Marketing 79 (4), 1–15.
Bollinger, B., Leslie, P., Sorensen, A., 2011. Calorie posting in chain restaurants. American Economic Journal: Economic Policy 3, 91–128.
Bollinger, B., Sexton, S., 2017. Local excise taxes, sticky prices, and spillovers: evidence from Berkeley's soda tax. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3087966.
Braithwaite, D., 1928. The economic effects of advertisement. The Economic Journal 38, 16–37.
Brennan, A., et al., 2014. Potential benefits of minimum unit pricing for alcohol versus a ban on below cost selling in England 2014: modeling study. British Medical Journal 349.
Briggs, A., et al., 2013. Overall and income specific effect on prevalence of overweight and obesity of 20% sugar sweetened drink tax in UK: econometric and comparative risk assessment modelling study. British Medical Journal 347.
Brownell, K., et al., 2009. The public health and economic benefits of taxing sugar-sweetened beverages. The New England Journal of Medicine 361 (16), 1599–1605.
Bulow, J., Pfleider, P., 1983. A note on the effect of cost changes on prices. Journal of Political Economy 91 (1), 182–185.
Buxton, A., et al., 1984. Concentration and advertising in consumer and producer markets. Journal of Industrial Economics, 451–464.
Cairns, G., Angus, K., Hastings, G., 2009. The Extent, Nature and Effects of Food Promotion to Children: A Review of the Evidence to December 2008. Technical Paper for World Health Organization.
Capps, C., Dranove, D., Satterthwaite, M., 2003. Competition and market power in option demand markets. The Rand Journal of Economics 34 (3), 737–763.
CDC, 2016. Cut back on sugary drinks. Centers for Disease Control and Prevention. http://www.cdc.gov/nutrition/data-statistics/sugar-sweetened-beverages-intake.html.
Chetty, R., 2009. Sufficient Statistics for Welfare Analysis: A Bridge Between Structural and Reduced-Form Methods. NBER WP 14399.
Chetty, R., Looney, A., Kroft, K., 2009. Salience and taxation: theory and evidence. The American Economic Review 99 (4), 1145–1177.
Chipty, T., 1995. Horizontal integration for bargaining power: evidence from the cable television industry. Journal of Economics & Management Strategy 4 (2), 375–397.
Chipty, T., Synder, C., 1999. The role of firm size in bilateral bargaining: a study of the cable television industry. Review of Economics and Statistics 81 (2), 326–340.
Colchero, M., Popkin, B., Rivera, J., Ng, S., 2015. Beverage purchases from stores in Mexico under the excise tax on sugar sweetened beverages: observational study. British Medical Journal 352, h6704.
Cowburn, G., Stockley, L., 2005. Consumer understanding and use of nutrition labelling: a systematic review. Public Health and Nutrition 8 (1), 21–28.
Crawford, G., Yurukoglu, A., 2012. The welfare effects of bundling in multichannel television markets. The American Economic Review 102 (2), 643–685.
Curto, V., Einav, L., Levin, J., Bhattacharya, J., 2015. Can Health Insurance Competition Work? Evidence from Medicare Advantage. National Bureau of Economic Research Working Paper 20818.
Cutler, D., Jessup, A., Kenkel, D., Starr, M., 2015. Valuing regulations affecting addictive or habitual goods. Journal of Benefit-Cost Analysis 6 (2), 247–280.
Cutler, D., Lleras-Muney, A., 2010. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2824018/.
Dafny, L., Dranove, D., 2008. Do report cards tell consumers anything they don't already know? The case of Medicare HMOs. The Rand Journal of Economics 39 (3), 790–821.
Deaton, Angus S., 2009. Instruments of Development: Randomization in the Tropics, and the Search for the Elusive Keys to Economic Development. National Bureau of Economic Research Working Paper 14690.

Della Vigna, S., 2009. Psychology and economics: evidence from the field. Journal of Economic Literature 47 (2), 315–372.
Dhar, T., Baylis, K., 2011. Fast-food consumption and the ban on advertising targeting children: the Quebec experience. Journal of Marketing Research 48, 799–813.
Diamond, P., 1973. Consumption externalities and corrective imperfect pricing. The Bell Journal of Economics 4 (2), 526–538.
Dixit, A., Norman, V., 1978. Advertising and welfare. Bell Journal of Economics 9 (1), 1–17.
Dobbs, R., et al., 2014. Overcoming Obesity: An Initial Economic Analysis. McKinsey Global Institute Report.
Draganska, M., Klapper, D., Villas-Boas, S., 2010. A larger slice or a larger pie? An empirical investigation of bargaining power in the distribution channel. Marketing Science 29 (1), 57–74.
Draganska, M., Mazzeo, M., Seim, K., 2009. Beyond plain vanilla: modeling joint product assortment and pricing decisions. Quantitative Marketing and Economics 7 (2), 105–146.
Dube, J-P., Hitsch, G., Manchanda, P., 2005. An empirical model of advertising dynamics. Quantitative Marketing and Economics 3, 107–144.
Dubois, P., Griffith, R., Nevo, A., 2014. Do prices and attributes explain international differences in food purchases? The American Economic Review 104 (3), 832–867.
Dubois, P., Griffith, R., O'Connell, M., 2017. How Well Targeted Are Soda Taxes? CEPR Discussion Paper 12484.
Dubois, P., Griffith, R., O'Connell, M., 2018. The effects of banning advertising in junk food markets. The Review of Economic Studies 1 (1), 396–436.
Dunn, A., 2010. The value of coverage in the Medicare advantage insurance market. Journal of Health Economics 29 (6), 839–855.
Eckard, E., 1991. Competition and the cigarette TV advertising ban. Economic Inquiry 29 (1). https://doi.org/10.1111/j.1465-7295.1991.tb01258.x.
Erdem, T., Keane, M., Sun, B., 2008. The impact of advertising on consumer price sensitivity in experience goods markets. Quantitative Marketing and Economics 6 (2), 139–176.
Falbe, J., Thompson, H., Becker, C., Rojas, N., McCulloch, C., Madsen, K., 2016. Impact of the Berkeley excise tax on sugar-sweetened beverage consumption. American Journal of Public Health 105 (11), 2194–2201.
Farrell, J., Balan, D.J., Brand, K., Wendling, B.W., 2011. Economics at the FTC: hospital mergers, authorized generic drugs, and consumer credit markets. Review of Industrial Organization 39 (4), 271–296.
Farrell, J., Shapiro, C., 2010. Antitrust evaluation of horizontal mergers: an economic alternative to market definition. The B.E. Journal of Theoretical Economics, Policies and Perspectives 10 (1).
Gabaix, X., Laibson, D., 2006. Shrouded attributes, consumer myopia, and information suppression in competitive markets. The Quarterly Journal of Economics 121 (2), 505–540.
Gilbert, D., Gill, M., Wilson, T., 2002. The future is now: temporal correction in affective forecasting. Organizational Behavior and Human Decision Processes 88 (1), 430–444.
Ginsburg, D., Wright, J., 2015. Philadelphia National Bank: bad economics, bad law, good riddance. Antitrust Law Journal 80 (2).
Glaeser, E., 2006. Paternalism and psychology. Regulation 29 (2), 32–38.
Glewwe, P., Jacoby, H., King, E., 2001. Early childhood nutrition and academic achievement: a longitudinal analysis. Journal of Public Economics 81 (3), 345–368.
Goeree, M., 2008. Limited information and advertising in the U.S. personal computer industry. Econometrica 76 (5), 1017–1074.
Goldberg, P., 1995. Product differentiation and oligopoly in international markets: the case of the U.S. automobile industry. Econometrica 63 (4), 891–951.
Gortmaker, S., et al., 2011. Changing the future of obesity: science, policy and action. The Lancet 378, 838–847.
Gowrisankaran, G., Nevo, A., Town, R., 2015. Mergers when prices are negotiated: evidence from the hospital industry. The American Economic Review 105 (1), 172–203.
Gowrisankaran, G., Rysman, M., 2012. Dynamics of consumer demand for new durable goods. Journal of Political Economy 120 (6), 1173–1219.

Grennan, M., 2013. Price discrimination and bargaining: empirical evidence from medical devices. The American Economic Review 103 (1), 145–177.
Griffith, R., Nesheim, L., O'Connell, M., 2017a. Income effects and the welfare consequences of tax in differentiated product oligopoly. Quantitative Economics. https://doi.org/10.3982/QE583.
Griffith, R., O'Connell, M., 2009. The use of scanner data for research into nutrition. Fiscal Studies 30 (3–4), 339–365.
Griffith, R., O'Connell, M., Smith, K., 2017b. Corrective taxation and internalities from food consumption. CESifo Economic Studies. https://doi.org/10.1093/cesifo/ifx018.
Griffith, R., O'Connell, M., Smith, K., 2017c. Design of Optimal Corrective Taxes in the Alcohol Market. CEPR Discussion Paper 11820.
Gruber, J., Koszegi, B., 2004. Tax incidence when individuals are time-inconsistent: the case of cigarette excise taxes. Journal of Public Economics 88, 1959–1987.
Gruber, J., Saez, E., 2002. The elasticity of taxable income: evidence and implications. Journal of Public Economics 84 (1), 1–32.
Guglielmo, A., 2016. Competition and Costs in Medicare Advantage. University of Wisconsin. http://www.eief.it/files/2015/12/guglielmo-rev.pdf.
Haavio, M., Kotakorpi, K., 2011. The political economy of sin taxes. European Economic Review 55 (4), 575–594.
Hall, A.E., 2011. Measuring the return on government spending on the Medicare managed care program. The B.E. Journal of Economic Analysis & Policy 11 (2).
Handbury, J., Rahkovsky, I., Schnell, M., 2015. Is the Focus on Food Deserts Fruitless? Retail Access and Food Purchases Across the Socioeconomic Spectrum. NBER Working Paper 21126.
Handel, B., Schwartzstein, J., 2018. Frictions or mental gaps: what's behind the information we (don't) use and when do we care? The Journal of Economic Perspectives 32 (1), 155–178.
Harding, M., Lovenheim, M., 2017. The effect of prices on nutrition: comparing the impact of product- and nutrient-specific taxes. Journal of Health Economics, 53–71.
Hartmann, W., 2006. Intertemporal effects of consumption and their implications for demand elasticity estimates. Quantitative Marketing and Economics 4 (4), 325–349.
Hartmann, W., Klapper, D., 2017. Super bowl ads. Marketing Science. https://doi.org/10.1287/mksc.2017.1055.
Hausman, J., Leonard, G., Zona, D., 1993. Competitive analysis with differentiated products. Annales d'Économie et de Statistique 34.
Heckman, James J., Urzua, Sergio, 2010. Comparing IV with structural models: what simple IV can and cannot identify. Journal of Econometrics 156 (1), 27–37.
Heike, S., Taylor, C., 2013. A critical review of the literature on nutritional labeling. The Journal of Consumer Affairs 46 (1), 120–156.
Hendel, I., Nevo, A., 2006. Measuring the implications of sales and consumer inventory behavior. Econometrica 74 (6), 1637–1673.
Ho, K., Lee, R., 2017. Insurer competition in health care markets. Econometrica 85 (2), 379–417.
Horn, H., Wolinsky, A., 1988. Bilateral monopolies and incentives for merger. The Rand Journal of Economics 19 (3), 408–419.
Jacobsen, M.R., Knittel, C.R., Sallee, J.M., van Benthem, A.A., 2016. Sufficient Statistics for Imperfect Externality-Correcting Policies. NBER Working Paper 22063.
Jeziorski, P., 2014. Estimation of cost synergies from mergers: application to U.S. radio. The Rand Journal of Economics 45 (4), 816–846.
Jia, H., Lubetkin, E., 2010. Obesity-related quality-adjusted life years lost in the US from 1993 to 2008. American Journal of Preventative Medicine 39 (3). https://doi.org/10.1016/j.amepre.2010.03.026.
Jin, L., Kenkel, D., Liu, F., Wang, H., 2015. Retrospective and Prospective Benefit-Cost Analysis of US Anti-Smoking Policies. NBER Working Paper 20998.
Jin, G., Leslie, P., 2003. The effect of information on product quality: evidence from restaurant hygiene grade cards. The Quarterly Journal of Economics 118 (2), 409–451.
Johnson, J., Myatt, D., 2006. On the simple economics of advertising, marketing, and product design. The American Economic Review 96, 756–784.

Kaldor, N., 1950. The economic aspects of advertising. The Review of Economic Studies 18, 1–27.
Kaplow, L., 2010. Why (ever) define markets? Harvard Law Review 124 (2).
Katz, M., Shapiro, C., 2003. Critical loss: let's tell the whole story. Antitrust (Spring), 49–56.
Khan, R., Misra, K., Singh, V., 2015. Will a fat tax work? Marketing Science 35 (1), 10–26.
Kiesel, K., Villas-Boas, S.B., 2013. Can information costs affect consumer choice? Nutritional labels in a supermarket experiment. International Journal of Industrial Organization 31, 153–163.
Laibson, D., 1997. Golden eggs and hyperbolic discounting. The Quarterly Journal of Economics 112 (2), 443–477.
Lewis, R.A., Rao, J.M., 2015. The unfavorable economics of measuring the returns to advertising. The Quarterly Journal of Economics 140, 1941–1973.
Lewis, M., Wang, Yanwen, Berg, Carla J., 2014. Tobacco control environment in the United States and individual consumer characteristics in relation to continued smoking: differential responses among menthol smokers? Preventive Medicine 65, 47–61.
Lockwood, B.B., Taubinsky, D., 2017. Regressive Sin Taxes. National Bureau of Economic Research Working Paper 23085.
Loewenstein, G., O'Donoghue, T., Rabin, M., 2003. Projection bias in predicting future utility. The Quarterly Journal of Economics 118 (4), 1209–1248.
Marshall, A., 1921. Industry and Trade: A Study of Industrial Technique and Business Organization and of Their Influences on the Conditions of Various Classes and Nations. MacMillan and Co., London.
McClure, S., Laibson, D., Loewenstein, G., Cohen, J., 2004. Separate neural systems value immediate and delayed monetary rewards. Science 306 (5695), 503–507.
Milkman, K., Rogers, T., Bazerman, M., 2010. I'll have the ice cream soon and the vegetables later: a study of online grocery purchases and order lead time. Marketing Letters 21 (1), 17–35.
Milyo, J., Waldfogel, J., 1999. The effect of price advertising on prices: evidence in the wake of 44 Liquormart. The American Economic Review 89 (5), 1081–1096.
Mirrlees, James A., 1971. An exploration in the theory of optimum income taxation. The Review of Economic Studies 38 (2), 175–208.
Moodie, R., et al., 2013. Profits and pandemics: prevention of harmful effects of tobacco, alcohol, and ultra-processed food and drink industries. The Lancet 381 (9867), 670–679.
Moorman, C., Ferraro, R., Huber, J., 2012. Unintended nutrition consequences: firm responses to the nutrition labeling and education act. Marketing Science 31 (5).
Moorthy, Sridhar, 2005. A general theory of pass-through in channels with category management and retail competition. Marketing Science 24 (1), 110–122.
Motta, M., 2007. Advertising Bans. UPF Technical Report 205.
Mullainathan, S., Schwartzstein, J., Congdon, W., 2012. A reduced-form approach to behavioral public finance. Annual Review of Economics 4 (1), 511–540.
Nagle, T., Hogan, J., Zale, J., 2011. The Strategy and Tactics of Pricing. Pearson, NY.
Nash Jr., J.F., 1950. The bargaining problem. Econometrica 18 (2), 155–162.
National Academies, 2006. Committee on Food Marketing and the Diets of Children and Youth Report on Food Marketing to Children and Youth: Threat or Opportunity? Technical Report. National Academies Press, Washington, DC.
Nelson, P., 1995. Information and consumer behavior. Journal of Political Economy 78, 311–329.
Netter, J., 1982. Excessive advertising: an empirical analysis. Journal of Industrial Economics, 361–373.
Nevo, A., 2000. Mergers with differentiated products: the case of the ready-to-eat cereal industry. The Rand Journal of Economics 31 (3), 395–421.
Nevo, A., 2001. Measuring market power in the ready-to-eat cereal industry. Econometrica 69 (2), 307–342.
Nevo, A., 2011. Empirical models of consumer behavior. Annual Review of Economics 3, 51–75.
Nevo, A., 2014. Mergers that increase bargaining leverage. Available at https://www.justice.gov/atr/file/517781/download.
Nevo, A., Whinston, M., 2010. Taking the dogma out of econometrics: structural modeling and credible inference. The Journal of Economic Perspectives (Spring), 69–82.

Nielsen, S., Popkin, B., 2004. Changes in beverage intake between 1977 and 2001. American Journal of Preventive Medicine 27 (3).
O'Donoghue, T., Rabin, M., 2003. Studying optimal paternalism, illustrated by a model of sin taxes. The American Economic Review 93 (2), 186–191.
O'Donoghue, T., Rabin, M., 2006. Optimal sin taxes. Journal of Public Economics 90, 1825–1849.
Pappalardo, J.K., 2012. Are unintended effects of marketing regulations unexpected. Marketing Science 31 (5), 739–744.
Patel, K., 2012. Obesity and the heterogeneous response to taxes. In: Essays in IO (Chapter 1). 2012 NWU PhD dissertation.
Petrin, A., 2002. Quantifying the benefits of new products: the case of the Minivan. Journal of Political Economy 110 (4), 705–729.
Pigou, A., 1920. The Economics of Welfare. McMillan and Co., London.
Purshouse, R., et al., 2010. Estimated effect of alcohol pricing policies on health and health economic outcomes in England: an epidemiological model. The Lancet 375 (9723), 1355–1364.
Qi, S., 2013. The impact of advertising regulation on industry: the cigarette advetising ban of 1971. The Rand Journal of Economics 44 (2), 215–248.
Rao, A., Wang, E., 2017. Demand for 'healthy' products: false claims in advertising. Journal of Marketing Research 54 (6), 968–989.
Ratchford, B.T., 2012. Suggestions for further research on firm responses to NLEA and other disclosure laws. Marketing Science 31 (5), 744–747.
Read, D., Van Leeuwen, B., 1998. Predicting hunger: the effects of appetite and delay on choice. Organizational Behavior and Human Decision Processes 76 (2), 189–205.
Robinson, J., 1933. Economics of Imperfect Competition. MacMillan and Co., London.
Rogerson, W., 2018. Economic theories of harm raised by the proposed Comcast/TWC transaction. In: Kwoka Jr., John E., White, Lawrence J. (Eds.), The Antitrust Revolution, 7th edition. Oxford University Press.
Rojas, C., Peterson, E., 2008. Demand for differentiated products: price and advertising evidence from the U.S. beer market. International Journal of Industrial Organization 26, 288–307.
Rubinstein, A., 1982. Perfect equilibrium in a bargaining model. Econometrica 50 (1), 97–109.
Sadoff, S., Samek, A., Sprenger, C., 2015. Dynamic inconsistency in food choice: experimental evidence from a food desert. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2572821.
Saez, E., 2001. Using elasticities to derive optimal income tax rates. The Review of Economic Studies 68 (1), 205–229.
Sahni, N.S., 2016. Advertising spillovers: evidence from online field experiments and implications for returns on advertising. Journal of Marketing Research 53 (4), 459–478.
Salinger, M., 1990. The concentration-margins relationship reconsidered. Brookings Papers on Economic Activity 21 (1990), 287–335.
Sanders, B., 2016. Bernie Sanders op-ed: a soda tax would hurt Philly's low-income families. Philadelphia, 24 April 2016. https://www.phillymag.com/citified/2016/04/24/bernie-sanders-soda-tax-op-ed/.
Sass, T., Saurman, D., 1995. Advertising restrictions and concentration: the case of malt beverages. Review of Economics and Statistics 77, 66–81.
Schmalensee, R., 1989. Inter-industry studies of structure and performance. In: Handbook of Industrial Organization, vol. 2, pp. 951–1009.
Seade, J., 1985. Profitable Cost Increases and the Shifting of Taxation: Equilibrium Responses of Markets in Oligopoly. Warwick Economic Research Papers No. 260.
Shapiro, B., 2018a. Informational shocks, off-label prescribing and the effects of physician detailing. Management Science 64 (12), 5461–5959.
Shapiro, B., 2018b. Advertising in health insurance markets. Marketing Science. https://doi.org/10.1287/mksc.2018.1086.
Shapiro, B., 2018c. Positive spillovers and free riding in advertising of prescription pharmaceuticals: the case of antidepressants. Journal of Political Economy 126 (1), 381–437.
Sinkinson, M., Starc, A., 2017. Ask Your Doctor? Direct-to-Consumer Advertising of Pharmaceuticals. National Bureau of Economic Research WP 21045.

Spiegler, R., 2006. Competition over agents with bounded rationality. Theoretical Economics I, 207–231.
Stewart, David, 2015. Why marketers should study public policy. Journal of Public Policy and Marketing 34 (1), 1–3.
Stigler, G., 1961. The economics of information. Journal of Political Economy 69, 213–225.
Stigler, G., Becker, G., 1977. De gustibus non est disputandum. The American Economic Review 67, 76–90.
Strotz, R., 1955. Myopia and inconsistency in dynamic utility maximization. The Review of Economic Studies 23 (3).
Sudhir, K., 2001. Structural analysis of manufacturer pricing in the presence of a strategic retailer. Marketing Science 20 (3).
Thomassen, O., Smith, h., Seiler, S., Schiraldi, P., 2017. Multi-category competition and market power: a model of supermarket pricing. The American Economic Review 107 (8), 2308–2351.
Town, R., Liu, S., 2003. The welfare impact of Medicare HMOs. The Rand Journal of Economics, 719–736.
Tuchman, A., 2017. Advertising and demand for addictive goods: the effects of e-cigarette advertising. https://papers.ssrn.com/abstract=3182730.
Tyagi, R.K., 1999. A characterization of retailer response to manufacturer trade deals. Journal of Marketing Research 36.
Villas Boas, S., 2007. Vertical relationships between manufacturers and retailers: inference with limited data. The Review of Economic Studies 74 (2), 625–652.
von der Fehr, N-H., Stevik, K., 1998. Persuasive advertising and product differentiation. Southern Economic Journal 65 (1), 113–126.
Wang, E., 2015. The impact of soda taxes on consumer welfare: implications of storability and taste heterogeneity. RAND 46 (2), 409–441.
Wang, Yanwen, Lewis, Michael, Singh, Vishal, 2016. The unintended consequences of counter-marketing strategies: how particular anti-smoking measures may shift consumers to more dangerous cigarettes. Marketing Science 35 (1), 55–72.
Wei, Yanhao, Yildirim, Pinar, Van den Bulte, Christophe, Dellarocas, Chrysanthos, 2016. Credit scoring with social network data. Marketing Science 35 (2), 234–258.
Weinberg, Matthew, Ashenfelter, Orley, Hosken, Daniel, 2013. The price effects of a large merger of manufacturers: a case study of Maytag/Whirlpool. American Economic Journal: Economic Policy 5.
Werden, Gregory, Froeb, Luke, 1994. The effects of mergers in differentiated products industries: logit demand and merger policy. Journal of Law, Economics, and Organization 10, 407–426.
Weyl, Fabinger, 2013. Pass-through as an economic tool: principles of incidence under imperfect competition. Journal of Political Economy 121 (3), 528–583.
WHO, 1990. Diet, nutrition and the prevention of chronic disease. http://apps.who.int/iris/bitstream/handle/10665/42665/WHO_TRS_916.pdf;jsessionid=BCD67FE6CB27BA80013ACE6BD0843451?sequence=1.
WHO, 2010. Set of recommendations on the marketing of foods and non-alcoholic. https://www.who.int/dietphysicalactivity/publications/recsmarketing/en/.
WHO, 2015. Sugars intake for adults and children. https://www.who.int/nutrition/publications/guidelines/sugars_intake/en/.