DOES IT ALL FIT UNDER THE GOLDEN ARCHES?: DYNAMICS OF DISRUPTIVE HORIZONTAL PRODUCT DIFFERENTIATION WITH CONSUMER HETEROGENEITY AND NETWORK EFFECTS

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Abstract

This paper examines dynamics following introduction of nutritious food by a company well known for high-motivational and low-nutritious products. Employing a system dynamics model, we investigate how consumer dynamics affect uptake of the disruptive product. Our example is the burger chain McDonald's, which introduced salads, fruit and other healthier options in the early 2000s. Focusing on consumer choice, we analyze the process of newcomers trying McDonald's and either becoming "core" customers, or not. The paper distinguishes overall commercial success from that of the new product per se. We examine conditions that separate commercial success (by drawing in new types of customers, whether these are the profitable ones or whether they simply accompany more burger-eaters), neutrality (in which existing customers simply change over), or failure (by alienating existing customers so that they abandon the company). We focus on the role of heterogeneity in products and consumers, and on interactions with social exposure-mediated network effects. We consider in detail the large and inertial installed base of pre-existing burger eaters, and the degree to which its dominance is hard to unseat, drawing parallels with reactions to other disruptive and 'progressive' products in industries ranging from consumer products to electric vehicles to utilities.

Summary of results

When one looks at whether a new product launch will be successful, one needs to consider overall profitability, rather than just sales of the new product per se. In this paper we look at two factors that can affect this: first, the psychological 'distance' between the new product and the original product, and second, network effects. Considering 'distance,' the model shows that having a product that is very distant is in fact likely to offer some advantages over one that is close. This makes sense according to standard consumer choice theory--by satisfying an unmet need, a firm can draw in new customers and minimise cannibalization. It is important to consider distance here in particular because this is the most 'distant' product McDonald's has ever introduced. In the simplified world of the base case, the model suggests success.

However, we need to look at network effects because customers do not make their purchasing choices in a vacuum. Additionally, this may give us some insight into the perils of 'blurring' the initial brand. Indeed, we see that if more- and less-health-conscious customers are allowed to influence each other, this increases the important of the large pre-existing stock of burger eaters and makes it harder to unseat their dominance. Take-up of salads is retarded and overall sales reduced, although McDonald's does still come out ahead compared to not introducing salads at all. Interestingly, initial burger customers actually are retained a little bit longer than in the base case. The dominance of their initial stock seems to protect them from the potential alienating effect of a changed brand.

We postulate that such fine effects depend on the degree of homophily – that is, the relative extent to which customers experience network effects with regard to other customers who are more like them, rather than with regard to those less like them. Indeed, when we consider a network effect scenario in which each customer group (More Health Conscious (MHC) and Less Health Conscious (LHC)) looks exclusively or predominantly at what others in their group are buying, McDonald's has the best overall outcome in terms of total sales. Health campaigners might also be happy; McDonald's sells the most salads to MHCs in this scenario. However, LHCs are left out of the health gains.

Introduction

This paper examines the dynamics of when a company, well known for a particular type of product, introduces something new, which appears highly disruptive compared to its existing brand. The example we examine in this paper is taken from the well-known burger chain McDonald's, which introduced salads, fruit and other healthier options around 2002. The paper is 'set' in the years just before this launch, and uses this case as an example to consider all the scenarios that might occur, rather than the particular one, which did. While in one sense the paper sheds light in particular on how firms can profitably improve the mass accessibility of healthier foods, the larger goal is to determine what the key factors are which a company preparing to launch a 'disruptive innovation' should consider in order to affect the best overall change in corporate profitability.

While at first it may seem that success or failure is understood from the intrinsic efficacy of the disruptive product on its own, empirical evidence suggests that the study of success requires more careful scrutiny. Increased overall profit might be achieved in many different ways. The product in question could be a big hit, like those of the world's biggest carmaker, which began with Toyoda Automatic Loom Works' 1933 foray into automobile production. But success could also be achieved by the sheer novelty of the new item improving brand distinction and recognition. Consider Apple, which, having put itself on the map with the introduction of the graphical user interface in the 1980s, can now command substantial brand-based premiums for their entire line of laptops. More subtly, the new product could provide arriving customers with a 'feel-good' factor regardless of what they actually choose to order (witness the advertisement of optional higher-priced 'green' electricity by certain utility companies), or, in a related phenomenon, the new product could make the vendor's overall product variety more socially acceptable, thus attracting larger, more diverse groups of customers. McDonald's itself notes that its Canadian Lighter Choices menu, introduced around the same times salads were introduced to the U.S. market, seemed to appeal to moms, who ate them while bringing their kids for Happy Meals (*2002 McDonald's Corporation Summary Annual Report (henceforth referred to as the '2002 Report'))*.

However, just as success can be multifaceted, there are also many ways to fail. Most simply, the new product could sell poorly, and perhaps even turn off customers to the existing brand. For instance, Coca Cola's disastrous experience replacing traditional Coca Cola with New Coke in 1985 followed testing in focus groups in which 10 to 12 per cent of respondents reported feeling angry and alienated simply at the thought of replacement of the sacrosanct beverage. They stated they might cease drinking Coke altogether (Prendergast, 1994) While that case is clearly unique in that the original product was completely withdrawn, the example does show not only the potential for alienation, but also for strong responses tied to cultural solidarity. Once New Coke was launched, the company initially saw sales rise, all to face growing resistance in the American Southeast. Many former Coke drinkers who objected to the new formula were Southerners who 'viewed the company's decision to change the formula through the prism of the

Civil War', seeing Atlanta-based Coca Cola's choice to change formula as a second surrender to the North. Although vocal opponents were a small minority nationwide, peer pressure kept proponents of the change quiet in many areas, even stifling bottlers who were embarrassed to tout the new product.[1] In a striking example of the power of network effects to subvert a product introduction, even when resistance apparently stemmed from a fairly small percentage, Coke executives reintroduced Coke Classic just three months after it had been withdrawn.

This case also suggests that social exposure mediated the network effects that were in play: the ability of a seemingly small percentage of strong objectors on a nationwide scale (just 10 to 12 percent) to nonetheless spawn a strong regional revolt, lends evidence to the hypothesis that people are more affected by the buying behaviour of those more similar to them or with whom they have more social interaction. This can lead to striking (and easily underestimated) 'power' stemming from the opinions and actions of a few crucially-connected customers (or ex-customers). Furthermore, the ability of this strong regional revolt to lead to the national downfall of a new product introduced by one of America's leaders in the casual consumables sector, suggests that McDonald's would be wise not to underestimate this effect.

An example of more successful navigation of the challenges of updating and broadening a brand without turning off loyal customers comes from famous Maine-based L.L. Bean. While it has become more fashion-conscious over the years, particularly after reaching hard times in the mid-1990s, the company is careful to stick to its roots of high levels of customer service and to pitch its expansions as a wider implementation of outdoor pursuits throughout ones' activities, rather than to become a designer brand. For instance, a newly-launched skincare line included products chosen to protect skin during outdoor pursuits, while a co-branded car marketed by Bean was the Subaru Outback Limited Special L.L. Bean Edition. According to Bean's entry in *Gale Contemporary Fashion*, a scholarly compendium of entries on more than 450 fashion houses, designers, and the like, Bean is conscious that a decisive move into the 'designer' world would alienate its existing, loyal customer base. (*Gale Contemporary Fashion*) We see here a clear example of active management of 'product distance;' that is, the degree of difference (in a

[1] (Oliver, 1986, pp. 149-151, as cited in Wikipedia (http://en.wikipedia.org/wiki/New_coke, accessed 18 March 2011. Quotation from Wikipedia.).

consumer's mind) between two products or groups of products, in this case, between existing and new offerings

With McDonald's brand profile in mind, a sobering story is provided by another company which tried to take a 'value' brand into higher-end products. Bic, long synonymous in the public's eyes with disposable pens, single-use razors, and cheap lighters, acquired an existing watersports company in 1979 and re-introduced the products under the Bic name in the mid-1980s. Bic may insist on its website that an item in its surfboard line has 'gained a reputation [as a]… versatil[e], long-lasting and affordable surfboard'.[2] But the company's entry in Wikipedia, which by its collaborative nature is a unique window into collective impressions, leads off with the unfortunate statement that Bic is 'known for making disposable products including lighters, magnets, ballpoint pens, shaving razors and watersports products'.[3] And indeed, we have been told that indeed it took a while for Bic Surf to catch a swell, because initially nobody wanted what they perceived, from their prior image of the brand, would be a disposable surfboard.

When considered in tandem with the Bean's example, the Bic case makes clear the care required with product distance. While Bean's wanted to minimise the apparent distance between old and new products, Bic would have liked the new product to be more distinct in consumers' minds than it was. McDonald's may be caught in a dilemma here: like Bean's, they don't want to alienate existing customers, but like Bic, they want to attract new diners. Salad customers are probably both drawn by the idea of consistency, quick service and affordability promised by McDonald's (Ray Kroc's guiding mantra was 'quality, service, cleanliness and value'[4]), but are also desiring something with a bit more 'cachet' – i.e., a slightly different brand image- than a fast-food burger.

In this paper we examine product diversification dynamics, focusing on the role of network effects, jointly with heterogeneous consumers in relation to the alternative and existing product. In what follow we describe, first, our motivating example, McDonald's Introduction of Salads, and develop from that initial hypotheses. Then we describe the method and scope of the model.

[2] ('7'9" Natural Surf 2,' http://www.bicsportsurfboards.com/products/acs,3,61/7-9-natural-surf-2,480.html, accessed 16 March 2011).
[3] Wikipedia entry for Société Bic, http://en.wikipedia.org/wiki/Soci%C3%A9t%C3%A9_Bic, accessed 16 March 2011).
[4] 'The Ray Kroc Story,' http://www.mcdonalds.com/us/en/our_story/our_history/the_ray_kroc_story.html, (accessed 16 March 2011).

Next, we provide an exposition of the model and analyze this. We do this by first focusing on the product distance, after which we also include network effects. This is work in progress, we end with a discussion on furthering our hypotheses and next steps.

McDonalds and the Introduction of Salads

At the turn of the millennium, McDonald's was in trouble. Years of fast expansion abroad had led to an overextended network and disappointing shareholder return. In McDonald's 2002 Summary Annual Report ('2002 Report'), then Chairman and CEO Jim Cantalupo acknowledges in his letter to shareholders (dated 21 March 2003) that 'McDonald's has lost momentum...and lost what it takes to make customers feel special' [ellipses in original]. He summarises his plan to make the company great again by noting that 'McDonald's is in transition from a company that emphasizes "adding restaurants to customers" to one that emphasizes "adding customers to restaurants."' He presents a determination to 'offer more products that provide the wholesome choices and variety people are seeking' as part of a 'plan to attract new customers and encourage existing customers to visit us more often.' (2002 Report, pp. 1-2)

For the U.S., 'premium salads,' including 'fresh Caesar, California Cobb and Bacon Ranch salads, topped with slices of warm, juicy grilled or crispy chicken breast meat,' are presented as permanent additions to keep the menu 'contemporary'. In Canada, the Lighter Choices menu, including salads as well as veggie burgers, Whole Wheat Chicken McGrill sandwiches, and yogurt parfaits are being introduced to give customers 'more choices' and to respond to 'changing eating habits' (2002 Report, p. 25-26).

McDonald's used to be known the world over for a hot, quick, consistent meal of burger, fries and Coke – 'billions and billions served!' However, the fast food market isn't what it was in the days Ray Kroc discovered the McDonald brothers' carry-to-car service in California surfland: for one thing, customers are beginning to worry about the health consequences of those burger meals – films such as *Super Size Me* certainly haven't helped – and other chains such as Subway are now offering meals that are almost as quick, almost as low-priced, and (at least as advertised) a good deal healthier. Government is pressuring for people to eat more healthily, and for restaurants to offer healthier options.

The potential gains of a diversified menu are clear: McDonald's could steal market share back from Subway. They could beat more conventional rivals such as Burger King to the punch in introducing a new product line. They could make McDonald's, for the first time, a socially acceptable option for those looking for a quick meal for a large and diverse group that includes some health-conscious people, some vegetarians, and some people still looking for a good old Happy Meal. More health-conscious eaters might be less price elastic, so that they could reap better margins from those sales (Renaghan, M., Pers. comm., 31 May 2010).[5] Introduction of a higher-margin product reduces the impact of any possible cannibalisation.[6] And McDonald's might be able to delay government intervention: the *Economist*, looking back from an (all-knowing) 2010 vantage point, notes that, ''[s]o far, fast-food firms have nimbly avoided government regulation. By providing healthy options, like salads and low-calorie sandwiches, they have at least given the impression of doing something about helping to fight obesity' (The changes facing fast food : good and hungry, *The Economist,* 17 June 2010).

But – there are risks as well. McDonald's is known for burgers and McNuggets. They aren't known for crisp greens, broiled chicken, and fancy dressings with unpronounceable exotic names. There is a risk that the diehard burger fans will begin to feel that their old standby has forsaken them**.** This is not an unknown concern; as explained above, other companies have had to tread very carefully in expansion and re-positioning of their lines to avoid alienation of existing customers.

Hypotheses: Product distance and social exposure-mediated network effects

In this paper we develop hypotheses on underlying explanations of the various patterns observed. Focusing on the point of customer decision and using a system dynamics model of the process of newcomers trying McDonald's and either becoming regular ('Core') customers, or not, this paper investigates what factors can make introduction of an innovative or disruptive product go

[5] Mark Renaghan is a principal of consultancy RMS, which has done detailed store-by-store pricing work for McDonalds.

[6] This stands in sharp strategic contrast to Burger King's recent decision to emphasise its value menu. Success of these offerings has unfortunately come at the expense of higher-profit items, with value options accounting for 20 per cent of all sales in June 2010, up from 12 per cent in October 2009 (The changes facing fast food : good and hungry, *The Economist,* 17 June 2010).

in totally different ways. The product could become a commercial success (drawing in new types of customers, whether these are the profitable ones or whether they simply accompany more burger-eaters), neutral (in which existing customers simply change over), or a failure (by alienating existing customers so that they abandon the company). The concept of the large and inertial 'installed base' of existing burger eaters which would exist at the point of salad introduction, perhaps exerting a dominance which would be hard to unseat, is considered in detail.

Of particular note, while this paper looks at what is in some ways a new product, in other ways, there is absolutely nothing new about salads – they've been around much longer than thin mincemeat patties between sandwich buns have. What is new is the way and the setting in which they are being sold (as a standardised, relatively processed product) and who is selling them (an established fast-food restaurant not previously known for particularly healthy options). The fact that most of what is new is just the positioning and business model for salads mean that substitution is likely to be an important effect. Whether in terms of cannibalisation of McDonald's original sales, or in terms of sales won from (or lost to) other quick-serve chains that have emphasised their health benefits for longer (for instance, Subway), substitution is a phenomenon particularly liable to social exposure-mediated network effects.

We center our analysis, first, on the distance between the conventional and alternative products, and, with that, on the effect of heterogeneity of potential customers. That is, we examine dynamics where the alternative product may attract a different customer base. We focus on social exposure mediated network effects as the central mechanism by which different customer types are being attracted and get habituated in the consumption of, predominantly, one or the other product.

Network effects have long been studied as demand-side drivers of adoption (see, for instance, Katz and Shapiro 1986; Arthur 1989;). Network effects can refer to network externalities, a term often used to represent the increased attractiveness of certain goods or services once more people are using that product. See, for example, Anderson, de Palma and Thisse, 1992, who illustrate the 'importance of positive externalities' (Anderson, DePalma and Thisse, 1992, p. 258) by noting that the French government gave initial free access to the Minitel interactive system in order to boost user base. As a subclass of network effects falls the effect of social influence. If everyone around you is using e-mail, you will be more likely to do so. This is not just because of the convenience, but because you may feel increasingly silly continuing to rely on postal mail or the telephone. Similarly, if everyone around you at McDonald's is ordering burgers, it becomes harder to choose a salad.

Not everybody has the same influence on others. People tend to be more influenced by people "like them", whether status or value (Lazarsfeld and Merton 1954). That is, under social influence, people are subject to forces of homophily. Furthermore, Christakis and Fowler applied a social network analysis approach to longitudinal data from the famous Framingham Heart Study cohort and reported in the New England Journal of Medicine that an adult's chances of becoming obese in a given time period increased if a friend, sibling or spouse became obese. They conclude that '[n]etwork phenomena appear to be relevant to the biologic and behavioural trait of obesity, and obesity appears to spread through social ties.' (Christakis and Fowler, 2007, p. 370). Following on from this, we hypothesise here – as we consider healthy and less-healthy food choices that may be tied to obesity - that people are more likely to be socially influenced by those whom they perceive as being more like them. So, if you are health-conscious and you see another health-conscious person order a burger, that is likely to have a greater effect on you than if you see a person who does not appear to be healthy-conscious choose a burger.

If we envision network effects as an example of social interactions layering themselves over the purely technical and practical concepts of network externalities, then what we might term 'relevance-selective' social influence – social exposure-mediated network effects - is the next logical step in uniting sociology with the 'harder' systems beneath. There is a good deal of literature available on basic network externalities (one example is Anderson, DePalma and Thisse, 1992, cited above) as well as on strategy in the face of network effects. For example, Katz and Shapiro (1985) are concerned with the compatibility between different products, and incentives to standardise, while Sun, Xie and Cao (2004) look at business model strategy for innovating firms in the face of the network effect. However, our key focus here is different: to capture the effect of homophily on consumer choice.

The network effects formulation presented here is structurally based on a related, but different, formulation presented in Struben and Sterman (2008). In that paper, which deals with the challenges of achieving 'sustained adoption' of alternative fuel vehicles (AFVs), the authors use weightings to represent willingness to consider a different type of vehicle from the one a driver currently owns. The 'willingness to consider' factor 'captures the cognitive, emotional, and social processes through which drivers gain enough information about, understanding of, and emotional attachment to a platform for it to enter their consideration set'. This is exactly parallel to the network effect desired in the McDonald's model, except that the AFV model captures the relative distance between vehicle platforms based on their adoption patterns, while this paper primarily focuses on the relative distance between two sets of consumers. While in the AFV model network effect heterogeneity arose from different channels (e.g. non-drivers – drivers), here we allow for variable network effects between the different types of consumers. Further, and more importantly, the model developed here allows the distance between consumers, not just between products, to be adjusted and the effects considered.

Scope and Method

We examine the decision to launch salads and the design of the launch as deriving from the interactions within the system – running the gamut from salads being a way to drive sales of conventional products, to the spectre of traditional customers decamping if they perceive their restaurant changing too much. Through the standard method process (Hines 2001), we have developed a model and a number of 'thought' experiments.

Of course, salads present a number of practical, logistical challenges to McDonald's, as well as the consumer-reaction issues mentioned so far. There are significant supply-chain challenges involved in stocking fresh food in a restaurant that has heretofore gained significant advantage from ease of handling processed food. This advantage is a key part of McDonald's traditional business model: according to Mark Renaghan, the consultant at RMS who has offered pricing advice to McDonald's, handling processed food makes national distribution easy and safe, and therefore makes it easier to protect the McDonald's brand (Renaghan, Pers. comm., 31 May 2010).While recognising the significance of operational and supply chain challenges, especially for fresh food, this is not the focus here.

This model, rather, is about consumer choice, and about discrete consumer choice at that (McFadden 1978). Therefore, we rely extensively on multinomial logit models. While powerful, these can only offer an idealised representation of market shares. Consumers' choosing food is inherently a human activity, and furthermore a dynamic one – for many people, food is chosen when they walk into the Golden Arches, based on factors around them at that moment. We hypothesise, therefore, that taking network effects into account within consumer choice (Struben and Sterman 2008) makes a significant difference in what factors can lead to profitability or financial disaster after launch of a new product (or a product new for its setting).

We presume first and foremost that firms which launch new products are most interested in improving their overall profits. Granted, there could be entirely different reasons for launching new products – for instance, to stay a step ahead of government regulation, or to diversify customer base to try to mitigate risk[7]– but as far as profit is at all concerned, we think it is defensible to say that overall profit is – or at least will be over time - the measure which matters. After an overview of the stocks and flows within the model, this paper covers briefly the main components of the model, then turns in detail to network effects. After deriving the network effect itself, based on total consumption of burgers and salads, we derive the network-adjusted appeals and network-adjusted market shares, then close the network effects loop by explaining how this influences development of loyalties of customers to one food or the other. We then present our hypotheses in more detail and present the results of model runs testing them.

In this paper, we first consider the effect of (1) on its own, in a base model without network effects. We then expand the model to take network effects into account, and examine the impact of varying degrees of cross-group influence.

Model i: Core Customers and Product Distance

This section introduces the basics of how people and foods are handled within the model, and then provides an overview of the main paths within the model.

[7] With 20/20 hindsight, it has become clear that the decision to introduce salads may well have helped McDonald's weather the 2008-2010 recession. Burger King, which focused on young men (presumably, through a more traditional fast-food menu), suffered as this demographic was hardest hit financially. McDonald's, on the other hand, with a more diverse menu and more varied clientele, including many women and older people, fared better. (Burger King: Whopper to go, *The Economist*, v. 396 (4 September 2010), p. 72).

The basics

The model groups people into two *customer types:* Less-health conscious (LHC), and More-health conscious (MHC). In addition, while McDonald's offers a range of and less- and more-healthy items, we consider the food products within two archetypal groups, denoted *'foodchoices:'* BURGERS, which represents McDonald's classic menu of burgers, McNuggets, fries, etc.; and SALADS, which represents their newer, supposedly healthier products, such as salads, fresh fruit, yogurt parfaits, and the like.

A number of variables in the model are indexed over customer types and/or foodchoices. An array structure is used within Vensim to allow us to draw the model structure once, while actually representing a number of indexed stocks and flows with any one model feature. Customer type is always indexed using the letter *c*, while foodchoice is indexed with *f*.

The stocks and flows give the model its 'inertia,' making it difficult to move away from the starting dominance of burgers. Figure 1 shows just the stocks and flows in the model:

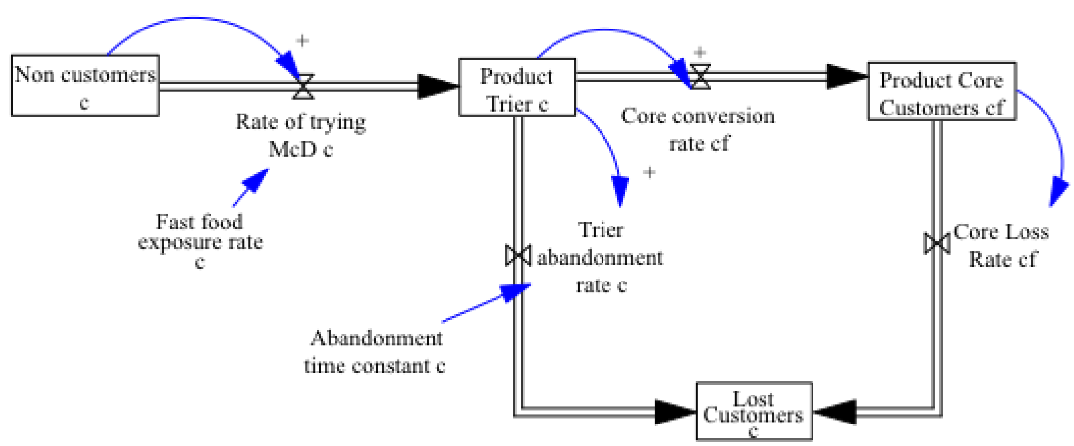

Figure 1: Stocks and flows in the model

McDonald's can gain from introducing healthy products as new Triers are attracted, some of whom become core customers (either using predominantly burgers or salads). However, McDonald's may lose core customers to competition as the product mix changes.To study the underlying dynamics, we focus on endogenous factors including habitual and peer pressure affecting dynamics of substitution of products (between healthy and less-healthy products) and firms (McDonald's vs. competitors). Index c refers to consumer type {More-health-conscious, Less-health conscious}; f refers to product type {healthier; less-healthy} (i.e., {salads, burgers}).

Non-customers are, first and foremost, people who meet two conditions: (1) they are not current *Product Triers* or *Core Customers;* and (2) they have either never tried McDonald's, or if they have and have then abandoned it, they have done so sufficiently long ago that they would consider trying it again if the right product were offered. In fact, since the model presented here leaves aside explicit theft of market share from a close competitor (focusing instead on implicit substitution via arrivals and departures of customers), we need to put a third condition on Non-customers as used here: they must be people who are not currently customers of *any* fast-food restaurant.

When non-customers decide to try McDonald's, they become *Product triers.* This occurs at the *Rate of trying. Product triers* are indexed over customer type *c,* but not over foodchoice BURG or SAL. The rationale is that people decide to try the restaurant without deciding necessarily what they are going to eat when they get there. *Triers* can eat either foodchoice depending only on the attractiveness, price, etc of the food and the interaction of those variables with their customer type.

Product Triers become *Core customers* at the *Core conversion rate* appropriate to their customer type, and at this point they also choose which foodchoice will be their core interest. Some *Product Triers* instead give up on McDonald's and become *Lost Customers* at the *Trier abandonment rate.*

Product Core Customers do not necessarily stay that way forever. Every month a certain fraction of them decide that McDonald's no longer meets their needs and they also become *Lost Customers.* This occurs at the *Core Loss Rate. Alternatively, core customers can convert to the other core product (Figure 2).*

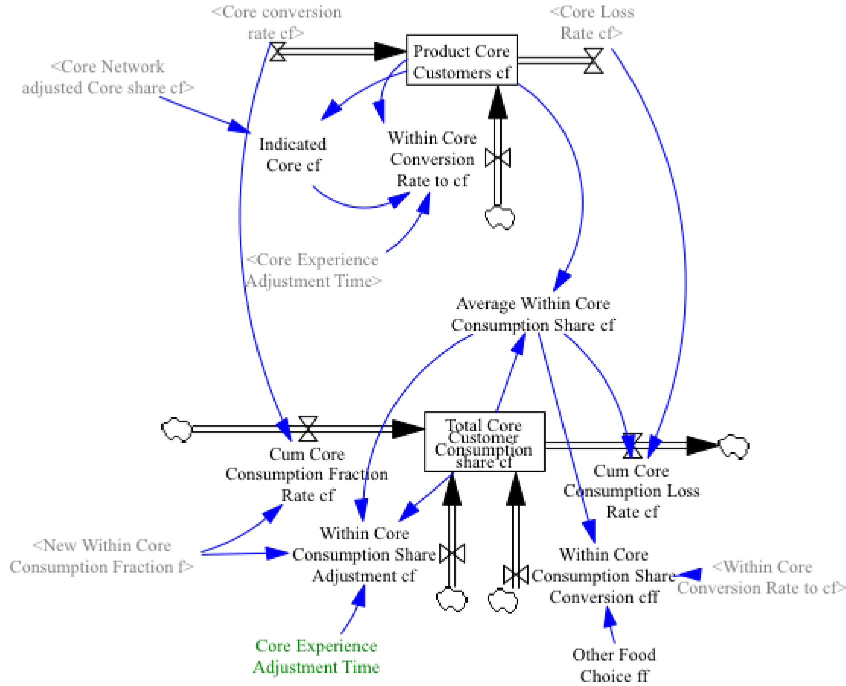

Figure 2. Core customer co-flows

Modelling discrete choice among restaurants and food options

We use a multinomial logit model based on the utilities of the options to represent the discrete choice among them. *'Pseudo-market share'* is so called because it does not represent McDonald's overall share of fast-food industry sales, but rather describes the fraction of non-fast-food customers, who are exposed to fast food, who choose to eat at McDonald's.[8] The pseudo-market share for each customer type is calculated by taking the ratio of the *anticipated appeal* of McDonald's by newcomers of that customer type, to the sum of the appeals anticipated from McDonald's as well as from all other fast-food and non-fast-food eating options. [9]

[8] Pseudo-market share is distinguished from unqualified market share (as the term is most commonly applied) in several respects: (a) it is restricted to the share of a small subset of total possible customers; (b) it represents share of people, not share of dollar or unit sales; and (c) it expresses McDonald's share with regard to all eating options, not just fast-food choices.

[9] Theoretical justification for this approach is provided by Cramer (2003); while he presents the multinomial logit formulation slightly differently, the form used in this paper can be derived from Cramer's formulation and his references to McFadden on use of the utility function within logit models.

Four McDonald’s *anticipated appeals* (one for each foodchoice, for each customer type) are calculated based on multi-attribute utilities (not shown in this schematic). The utilities include an importance-weighted contribution from the price and quality newcomers expect McDonald’s will provide, relative to other eating options, before they try it. Utilities are tempered by a ‘proximity’ factor, where we assume that burgers are fully proximate to LHCs and salads fully proximate to MHCs, while the ‘crossover’ foodchoices have their utility multiplied by a fractional factor, reducing the appeal.

‘Pseudo-market share’ determines what fraction of non-customers will, once exposed to fast food, become McDonald’s *Triers.*

Once customers are *Triers*, the model calculates the actual appeal, based on the real discovered values of the price and quality attributes. Nice surprises or regrettable disappointments with McDonald’s eating environment are also taken into account: the model scales the *discovered actual appeal* by the relative pleasantness of environment, compared to that which Triers were expecting. The frequency of *Triers’* visits to McDonald’s increases if this *consolidated discovered actual appeal* is higher than the *anticipated appeal*, and falls if it is worse. Additionally, for a given foodchoice *f*, the higher the *discovered actual appeal*, the higher the fraction of *Triers’* consumed units which are of that foodchoice (the *Foodchoice fractional market share,* which is simply the ratio of that foodchoice’s appeal to the appeal of both foodchoices).

Modelling consumption

Total consumption of each foodchoice by each customer type is the sum of consumption by *Triers* and consumption by customers who are already Core. For *Triers,* the model calculates an average personal consumption rate (for each customer type and each foodchoice) by multiplying a standard *Trier* visit frequency by an average number of food units ordered per visit. This is tempered, as explained above, by the relationship of the discovered appeal to that anticipated, as well by the relevant *Foodchoice fractional market share.* The result is then multiplied by the number of people currently in the *Product Trier* stock to yield the relevant *trier consumption* (food units/month).

To calculate consumption by *Core Customers,* recall that each stock of *Core Customers* also generates two consumption 'streams:' consumption of their Core food, and 'crossover' consumption, because even they occasionally choose the other kind of food (at a rate influenced by the same 'proximity' factor mentioned above). Thus, for instance, calculation of the consumption of salads by MHCs requires summing the core-foodchoice consumption by MHCs who are Core for salads, as well as the peripheral-foodchoice consumption of MHCs who are Core for burgers.

Conversion to a *Core Customer*

The real fundamental difference between *Triers* and *Core Customers* lies not in different visit frequencies and consumption rates, but rather in the fact that *Triers* are not assigned to a foodchoice, while *Core* customers are. In other words, while *Non-customers* make the choice to try McDonald's without specifying which product interests them most, the conversion to *Core* carries inherent within it a sort of pledge of primary allegiance to one foodchoice or the other. We postulate that in reality this decision is made as a single choice, not as a two-step process as is more the case for *Triers.*[10] People decide to go to McDonald's more regularly because they like a particular offering there, not just because they love the golden-arched shops. Therefore, the rate of conversion to the stock of *Core Customers* needs to incorporate a double-choice within one step (albeit represented by different terms): a decision to 'go Core,' and *for a particular foodchoice*.

For each customer type, the overall rate of conversion to *Core Customers* (for all foodchoices together) is given by an exponential function rising asymptotically towards the *Customer survival fraction*, with a time constant of *Trier conversion time constant*. This is scaled by multiplying it by the total number of *Product Triers* of that customer type. The share between those going to the BURGER core and those to the SALAD core is then determined by multiplying that overall conversion rate by the appropriate *Network-adjusted market shares*[11].

[10] While there is a crossover consumption rate for *Core Customers*, this is secondary to the Core allegiance. It is unlike *FFMS* which was the sole factor governing Triers' product choices.

[11] Note that since the conversion rate is dependent on the number of *Product triers* remaining, the stream of conversion to *Core* will dry up if no one new is coming to try the products (which is realistic).

The flows

Finally, three flows in the middle of the model, *Core conversion rate, Trier abandonment rate,* and *Core loss rate,* are shown. Looking first at dynamics surrounding *Triers*, note (see Figure 1) that there are two routes out from each *Trier* stock: *Triers* can convert to become *Core customers* of either burgers or salads, or they can abandon McDonald's entirely and go to the stock of *Lost Customers.* However, a certain percentage simply remain as *Triers,* continuing to go to McDonald's now and then, consuming at the *Trier* rate and choosing, on average, whichever product the *Foodchoice fractional market share* for *Triers* directs them to.

The shares of *Triers* in these three groups as the model approaches steady state are governed by several fractions. The fraction of those converting to *Core Customers* (of both foodchoices taken together) rises toward the *Customer survival fraction* (indexed over customer type *c*, endogenous, and explained in more detail below when we return to the *Core conversion rate*). The fraction of those remaining as *Triers* indefinitely is governed by the *Perennial trier fraction* (also indexed, but exogenous); the fraction of Triers remaining falls over time according to a time constant which is not defined explicitly in the model but which is clearly a function of the time constants for the two routes out of Trying. Finally, the fraction of those lost entirely to McDonald's simply approaches whatever the remainder is: the $Loss\ fraction_c$ is given by $(1 - Customer\ survival\ fraction_c - Perennial\ trier\ fraction_c)$. The model assumes that all three fractions are approached asymptotically according to a single-order process.[12]

The $Core\ conversion\ rate_c^f$ (hereafter abbreviated as CCR_c^f), which gives the rate of conversion of *Triers* of customer type *c* to *Core Customers* of foodchoice *f*, in units of *people/month,* is defined as

[12] This appears to be an goal-seeking formulation, where the fraction of Triers on each route 'seeks' the appropriate fraction – i.e., converges on it. The presentation here is somewhat different from the simple examples of goal-seeking behaviour shown in Chapter 8 of Sterman (2000) (see, for example, p. 277), in that we discuss the rates in terms of outflow from the stock of *Triers* rather than in terms of inflow into the *Product Core Customers* or Lost *Customers* stock, and the discrepancy between the current state and 'goal' state is not explicitly shown. However, the underlying concept is the same.

$$Core\ conversion\ rate_c^f = \frac{CSfrac_c}{TCTimeConst} * PT_c * \tilde{\sigma}_c^f \qquad [1]$$

where

- $CSfrac_c$ is the *Customer survival fraction* for customer type *c* (see explanation below)
- $TCTimeConst$ is the *Trier conversion time constant.* In the current version of the model, the details of how this constant is arrived at are not our main focus, so for simplicity we assume this to be an exogenous constant and one which is the same for all customer types and all foodchoices. (The section on 'Further avenues for exploration' towards the end of this paper lays out some ideas for how this constant could be represented in a more sophisticated manner, particularly with respect to differences between how good McDonald's is compared to what expectations were.)
- Finally, $\tilde{\sigma}_c^f$ is the *network-adjusted market share* for foodchoice *f* among converting customers of customer type *c*

The $CSfrac_c$ is not exogenous. Rather, logically it depends on how much *Triers* like McDonald's. To represent this, the model uses, as a first approximation, the product of the 'pseudo-market share' of McDonald's for customer type *c*, and *Trier visits relative to expected* for *c*:

$$CSfrac_c = \sigma_c^{McD} * TVrelE_c \qquad [2]$$

This makes sense since it represents scaling the fraction of people who try McDonald's, by the factor representing their relative pleasure or displeasure once they get there, and hence, their likeliness to continue to 'embed' McDonald's further into their lifestyle. Additionally, since by using *TVrelEc*, which incorporates *Relative pleasantness of environment*, rather than just the sum of the discovered actual appeals of the individual foodchoices, we take the effect of McDonald's environment into account.

It could be argued that the CSfrac should be higher, since at the point of conversion to *Core*, we are dealing not with the general set of *Non-customers* but rather with people who have already shown themselves to have some affinity for what McDonald's offers. However, a counterargument would hold that it is one thing to use to temper *Trier* consumption, and quite another to say that, for instance, discovering that McDonald's is better than expected is enough to increase by the same proportion a *Trier's* probability to convert to *Core*, rather than just to increase the frequency of his *Trier* visits.

Therefore, for this version of the model, Equation [2] is dimensionally consistent (all terms are dimensionless) and makes an adequate starting point.

Next, for each customer type c, the *Trier abandonment rate* is given by an exponential function rising asymptotically towards the *Loss fraction*, with a time constant of *Abandonment time constant*. This is multiplied by the total number of *Product triers* of that customer type:

$$Trier\ abandonment\ rate_c = \frac{Lfrac_c}{ATimeConst_c} * PT_c$$

[3]

where

- $Lfrac_c$ is the *Loss fraction* for customer type *c,* as described above, and
- $ATimeConst_c$ is the *Abandonment time constant* for customer type *c,* which is here exogenous
- PT_c is the number of *Product triers* of customer type c

Turning to the last flow in the model, the *Core loss rate* (indexed over customer type and over Core foodchoice) is modelled as a simple first-order process. The number of Core customers lost per month is given by multiplying the number of people currently in the relevant Core stock by an exogenous *Monthly core loss fraction* (which is also double-indexed).

Analysis of the Base Model - before network effects

We begin with the analysis with a base case with moderate product proximity (p=0.5) (Figure 3). The model begins in equilibrium. After 12 months (time=0) salads are introduced. The trier stock increases rapidly, due to a growth of health-conscious Triers. Most of the Triers become core salad eaters. In addition, Less- Health-Conscious consumers convert from burger eaters to salad eaters.

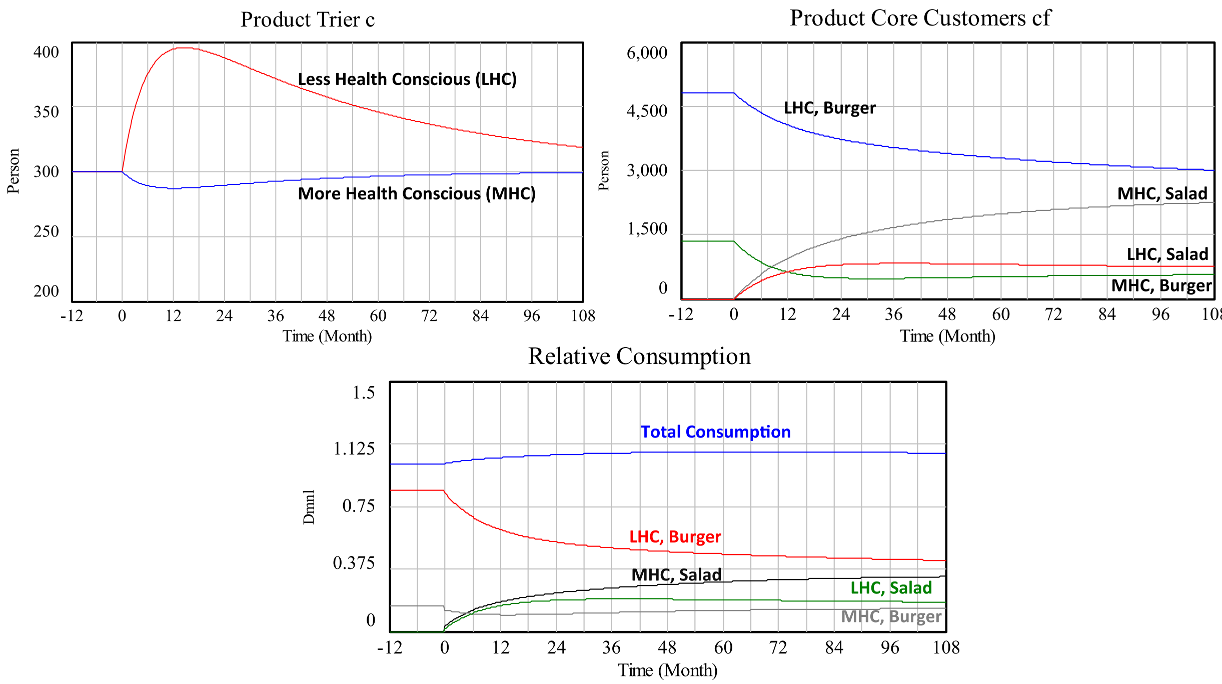

Figure 3. Base Run

We now look at the effect of product distance on consumption (Figure 4). Introducing a product with high proximity means that the products are full substitutes (Figure 4, left). The new product is hardly different from the old product, and sales converge so that each product receives about 50 per cent of the sales from each customer type. Low proximity between the product choices, on the other hand, means that consumers are less likely to switch. In this case, consumers are less likely to cannibalize sales of the other product, since each consumer category is mainly motivated by the product choice which is 'closer' to their customer type (Figure 4, right). In other words, when the food choices are further apart from each other, the distance between the customer types becomes more significant. The large stock of latent health conscious eaters results in a rapid growth of the salad eaters. While we observe a small overshoot of health conscious salad eaters, eventually the model equilibrates at the equal consumption level where both consumption groups are fully satisfied. Overall sales equilibrate well above initial sales.

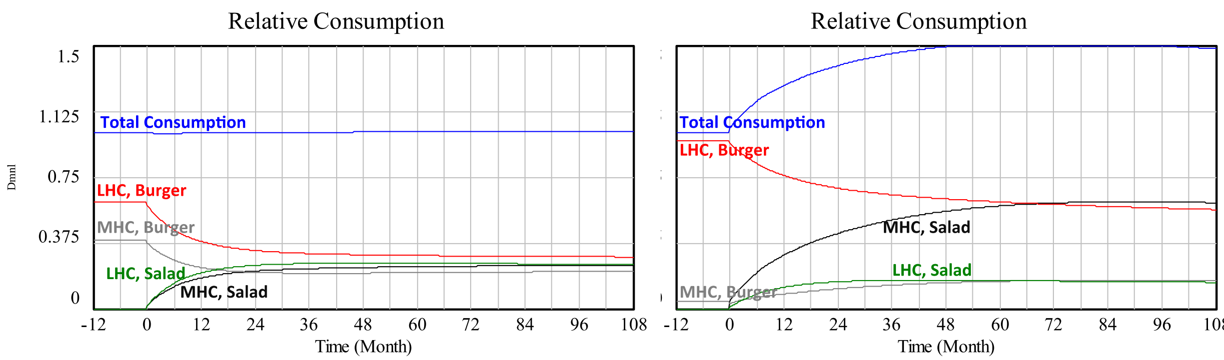

Figure 4. Relative consumption for high (left) and low (right) proximity.

These results are consistent with those from standard consumer choice theory. If additional products are being introduced that do not satisfy additional, unobserved, preferences, demand is not increased. Rather, each products receive an equal share of the market. In contrast, if we expand an heterogeneous choice set, preferences are increasingly satisfied across the population and sales increase. In more specific terms here, since salads have a lower proximity to burgers (in terms of perception, niche, market positioning, etc) than did, for instance, the Chicken McNugget, we can see that – at least before network effects are considered - McDonald's is likely to have a different experience when they introduce the 'healthy' menu than they may have had in past menu expansions.

Model Expansion: Network Effects

This section first introduces network effects, and then explains in detail how they have been applied to this model. We base our formulation on that applied for social exposure in Struben and Sterman 2008,   despite it being a somewhat different process (some adjustments are needed, as explained below). Additionally, a hidden benefit has come from the fact that the algebraic expressions used here are not simple to implement in Vensim: implementation has required thinking very carefully about the meanings of the terms in order to see them as composites of simpler building blocks. While conversion to a *Core customer* is the only part of the model which explicitly and directly taking into account network effects, the influence is felt more broadly because of the interacting nature of the feedback loops.

This a key difference with the simple model is that peer pressure network effects may lead consumers to eat products that are distant from them. At the same time, network effects may deter core customers. Here we modify the consumer choice equations to include network effects.

The Network effects loop

The Network effects loop is shown in Figure 5. *Trier consumption* (not shown in the figure) and consumption by Core customers feed into *Total monthly consumption.* From there, we have the *Network effects loop,* a reinforcing loop which shows the effects of social influence on choice of food: it acts on the customer-type- and foodchoice-specific Core conversion rate, encouraging more *Triers* who are in the process of converting to *Core customers*, to pick *that* foodchoice as their Core.

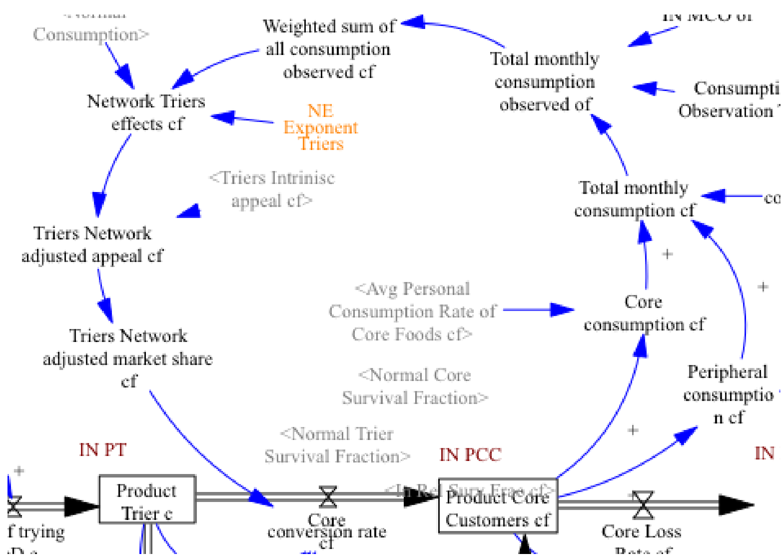

Figure 5. Network effects on triers. Similar dynamics act on core customers. Core customers can also defect if 'alienated' by the presence of too many consumers from their non-core products.

Note that network effects do not necessarily increase the overall conversion rate; rather, for a given foodchoice, if everything else is held constant, a stronger network effect *for that foodchoice* will increase the fraction of conversion which goes to that foodchoice.[13]

Of course, we do expect this network effect to increase absolute consumption of a given foodchoice: once there are more *Core customers* of a particular foodchoice, the consumption of that product rises. More Core customers mean more *Core consumption;* while it also means more *Peripheral consumption*, that effect is less, because the *Core consumption fraction* will usually mean that the large majority of consumption by *Core customers* is of their Core food.

We now explore the network effects in more detail.

Applying network effects to the McDonald's model

In comparison with Struben and Sterman 2008, we need to make some adjustments to the use of weightings within the calculation of network effects, since we are representing the perceived distance between two sets of consumers, rather than a product from a consumer. So, we need to use weightings to temper the effect of observed consumption by other consumers, rather than using them directly on the appeal of a product. Only after taking the ratio yielded by the quotient of the weighted sum of all observed consumption of the foodchoice in question, divided by the sum of the weighted sums of all of the available foodchoices, will we have the network effect in a form parallel to that of an appeal function. Then we will we be able to multiply that whole factor - the network effect - by the raw appeal in order to create our network-adjusted appeal. From that point, deriving network-adjusted market share is straightforward.

Calculating the network effect itself

We begin with the example of considering the network effect on the appeal of burgers to customers of the More Healthy Customer (MHC) type. They are influenced more heavily by burger consumption by other MHCs, although seeing LHCs eat burgers also makes them more likely to choose that option. The more people they see eating salads, the less likely they are to choose burgers, although again, consumption by their own customer type has a greater influence. The numerator of the network effect is given by summing, over all the customer types, the

[13] Because the network effects do not increase the overall conversion rate, there is not even the weak balancing loop which would arise if greater conversion pulled people out of the *Trier* stock and thus decreased *Trier consumption.*

products of the weighting representing perceived proximity of that customer type to MHCs, times the consumption of burgers by that customer type. For the denominator, where Struben and Sterman 2008 summed over all of the possible vehicle platform options, we need to have the weighted consumption of burgers plus the weighted consumption of the other option(s) – here, salads. Thus we have

We have

$$NE_{MHC,BURG}$$

$$= \frac{(W_{MHC,MHC} * CONS_{MHC}^{BURG} + W_{MHC,LHC} * CONS_{LHC}^{BURG})}{\left(W_{MHC,MHC} * CONS_{MHC}^{BURG} + W_{MHC,LHC} * CONS_{LHC}^{BURG}\right) + (W_{MHC,MHC} * CONS_{MHC}^{SAL} + W_{MHC,LHC} * CONS_{LHC}^{SAL})}$$

[4]

where

- $NE_{MHC,BURG}$ is the network effect on consumption of burgers by MHCs
- $W_{MHC,MHC}$ is the weighting representing relevance of consumption by MHCs as perceived by other MHCs
- $W_{MHC,LHC}$ is the weighting representing relevance of consumption by LHCs as perceived by MHCs
- $CONS_{MHC}^{BURG}$, $CONS_{LHC}^{BURG}$, $CONS_{MHC}^{SAL}$, and $CONS_{LHC}^{SAL}$ and are total consumption rates (units: *food units/month)* where the subscript is the customer type consuming and the superscript is the food consumed (i.e. $CONS_{group\ consuming}^{food\ consumed}$))

Generalising this to give the network effect on consumption of foodchoice *f* by customer type *c* gives us:

$$NE_{c,f} = \frac{\sum_o (W_{c,o} * CONS_o^f)}{\sum_f [\sum_o (W_{c,o} * CONS_o^f)]}$$

[5]

where *o* is the subscript for the customer type *being observed consuming*, and *c* is the subscript for the customer type that is *observing that consumption and being influenced.* (In the Vensim model, these are denoted CusTypObserved and CusTyp, respectively.) Therefore, $W_{c,o}$is the weighting representing the relevance of consumption by customers of customer type *o* as perceived by those of customer type c, and $CONS_o^f$ is the total consumption rate of food *f* by customer type *o*.

We assume in this model that people find the consumption habits of other customers of the same customer type to be entirely relevant (i.e., to have a weighting of 1) while they find the relevance of consumption of customers of the other type to be somewhat less. Therefore, we set $W_{c,o} = 1$ if *c*=*o*, and otherwise $W_{c,o} = \alpha_c$, where $0 < \alpha_c < 1$. Note that this is exactly parallel to the definition of R_c^f used earlier. While we used that to define the proximity of foodchoices to people of a particular customer type, we now use the same structure to define the relevance of customer types to each other.

In matrix terms, we have

$$W_{c,o} = \quad cus.type \begin{array}{c} \\ LHC \\ MHC \end{array} \begin{array}{c} cus.type\ observed \\ \begin{array}{cc} LHC & MHC \end{array} \\ \begin{bmatrix} 1 & \alpha_{LHC} \\ \alpha_{MHC} & 1 \end{bmatrix} \end{array}$$

[6]

Equation [5] is clearly in a form parallel to that of an appeal function, since it takes a calculation relating to the foodchoice in question, and divides it by the sum of the same calculations for all the possible foodchoices. So, we are now ready to multiply the network effect by the raw appeals to create our network-adjusted appeals, and then our network-adjusted market shares.

Creating network-adjusted appeals and market shares

Since we are dealing with people who have already tried McDonald's, it makes sense to use the discovered actual appeals, rather than the anticipated appeals, as the raw appeals for these calculations. Taking again as an example the case of the appeal of burgers to customers in the More Healthy Customer (MHC) type, we have network-adjusted appeal given simply by

$$\tilde{a}_{MHC}^{BURG} = NE_{MHC,BURG} * \dot{a}_{MHC}^{BURG}$$

[7]

(Recall that is the discovered actual appeal of foodchoice *f* to customer type *c*; we denote the network-adjusted appeal by putting a tilde mark above the *a*.)

Generalising this yields the *network adjusted appeal* of foodchoice *f* to customer type *c* as

$$\tilde{a}_c^f = NE_{c,f} * \dot{a}_c^f$$

[8]

Finally, we can calculate the *Network-adjusted market shares*. Like the 'pseudo-market share' used for calculating the *Rate of Trying*, this market share also has a very specific meaning: it is the share of *Triers* of customer type *c* who convert to *Core customers,* who choose to become Core for a particular foodchoice *f*. (*Triers* who do not convert to *Core customers* are already removed before this calculation.)

We have the *Network-adjusted market share* of foodchoice *f* for customer type *c* as

$$\tilde{\sigma}_c^f = \frac{\tilde{a}_c^f}{\sum_f \tilde{a}_c^f}$$

[9]

In parallel to the market shares calculated based on raw appeals, the network-adjusted market share of foodchoice *f* among customers of customer type *c* is given by the ratio of the network-adjusted appeal of foodchoice *f* for those customers, to the sum of the network-adjusted appeals of all of the foodchoices available (here, only two: burgers and salads).

We saw within this section how *Trier consumption* and consumption by *Core Customers* are calculated, in order to yield *Total monthly consumption.* We have just explained how this consumption tempers the *discovered actual appeal* via network effects to yield the network-adjusted appeals and market shares. In the next section we close the *Network effects* loop by explaining how the network-adjusted market shares influence the rate of conversion of *Triers* to *Core Customers.*

Simulation results: Network effects

Figure 6 shows the role of Core Customer network effects on consumption by consumer and product category, with a proximity of 0.25. In the left-hand graph, network effects remain off and results as before, for the low-proximity case. In Figure 6 (right), we switch network effects on for both Triers and Core customers..

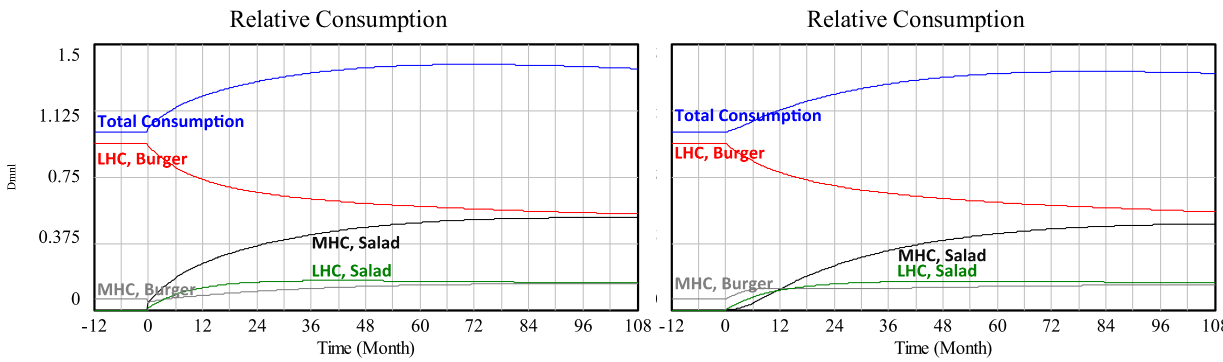

Figure 6. Network effects for moderately proximate products (proximity is 0.25, otherwise equal to Base run values). Network effects are switched on for triers and core customers on the right graph

When network effects are considered, we see that salad eaters tend to be selected out. Burgers dominate the scene and few people receive a signal to go to McDonalds for the salad. This difference holds in particular for health-conscious salad eaters, who reach steady state at about 47 per cent of total initial consumption levels, as opposed to almost 55 per cent without network effects. In addition, while total McDonald's consumption still rises, it rises less.

Homophily effects

The graphs below show the results for variation in the strength of network effects across consumer groups. The parameter α [0,1] captures the degree to which cross-consumer type social pressure is smaller than within-consumer type. We observe that reducing the impact of network effects across social groups increases sales (as well as total consumption, see NE, RCCI=0). In equilibrium, sales even increase beyond the case of zero network effects (and full information).

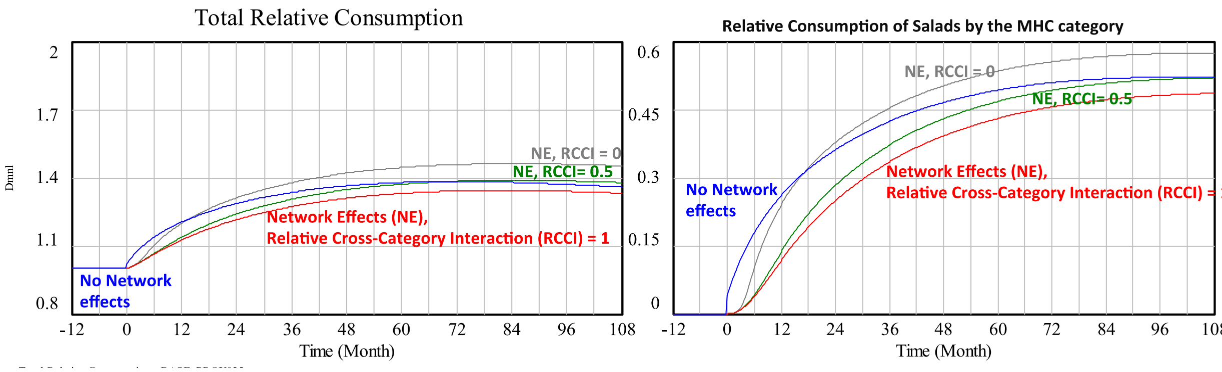

Figure 7: Consumption with varying relative cross-category interaction (RCCI)

Why do we get increased adoption for the asymmetric case? The new product (salads) gets the benefit of social exposure through peers, while existing burger customers (who were predominantly of the LHC customer type) are not 'frightened off' by this change. Hence, homophily helps by introducing the differentiated product to new customers.

Network Effects: Planned tests and sensitivity

We have performed sensitivity analysis on a range of parameters. The model allows assessing the parameters to which the model behaviour is most sensitive to. We performed initial analysis on the effect of social pressure on defection (not shown in graphs). We found that, absent other network effects, but allowing for defection, critically reduces McDonald's sales. However, including sufficiently strong network effects protects the dominant core product, and thus customer, making McDonald's and the core product robust against such consumer responses. In this case, salads become a small niche product. In future analysis we will be we will expand on this.

Only the factors which are very important are those on which it is worth spending significant time and money to collect more accurate data. A main question is whether the large 'installed base'of burger-eaters overwhelms the attempts of others foodchoices to 'muscle in' on its dominance. That said, we would like to know how sensitive this is to certain factors. Sterman et al (2007) reports on the underestimated difficulty of changing an inertial system in which anthropogenic has been building up over the past 160 years or so since industrialisation began .Similar, in the automotive industry major challenges in changing vehicle-propulsion types (from internal-combustion to electric) derive from its inertia; this is a system in which vehicles last perhaps a decade or more. Those are, respectively, systems with a really, really long time constant and merely a long time constant. Changing of eating habits may not involve time constants that are of equal length, however, social pressures and internal inertia (Dube 2010) make shifting markets a big challenge. Not only would we like to know if burgers overwhelm other foodchoices, but also whether varying the time constants affect this.

Tests of the sensitivity of the two parameters representing, respectively, the distance between the customer types and the distance between the two foodchoices, would be worthwhile because of the unfortunate difficulty in estimating them. Not only are these parameters very difficult to reason 'out of the blue,' but collecting empirical data on them would require a sophisticated and expensive market research study. Before devoting undue worry or money to this problem, we would like to know how important the two parameters really are. The model dynamics are mainly driven by competing positive feedback between food choices. Understanding in tipping points requires gaining a deeper understanding of at what densities networks have particular strength. That is, we may not assume linearity of these effects, and here with competing effects, understanding how and to what extend gains of the positive feedbacks shift seems critical. Representing these in more detail may reveal much stronger tipping points than has been done here.

Although the rate of becoming a product trier *(Rate of trying McD)* is not foodchoice-specific, trying does nonetheless occur at different rates for different customer types. Currently this is because of the different weightings of the attributes leading to the appeals. However, it would be interesting to include *product variety* and *rate of product innovation* as influencing factors, as those might affect LHC and MHC people differently. For example, a lot of quick innovation on McDonald's part to change the menu rapidly from burger-heavy to salad-heavy would be expected to result in more MHC people trying the restaurant. Later on in the model, therefore, we would expect to see more salads being consumed. Quicker innovation might also 'shock' more of the initial 'installed base' of burger eaters to abandon McDonald's. Struben and Sterman 2008 find that efforts to convert to alternative fuel vehicles need to be supported for a long time – self-sustainability won't come for several decades. This is primarily because of the length of time that people own cars, before having the opportunity to make a choice regarding a new one. While decisions to begin frequenting a new fast-food restaurant can be made much more quickly, it might still be interesting to see the effects of varying the time constants. We might represent more explicitly the effects of advertising and word of mouth, and we would be interested to know how long we needed to keep up the advertising, or how significant the fallout from a strategic mistake causing a brief spurt of bad word of mouth might be expected to be. When considering these questions, we would be interested in knowing how sensitive the model is to the time constant, so that we could decide how much money and effort it is worth to collect data on it.

One of the most intriguing suggestions made for possible outcomes to the introduction of salads is that it will, in fact, increase burger sales. It now feels socially acceptable to invite large groups (of colleagues, family, etc.) to McDonald's because there will be 'something for everyone.' In fact, though, few people actually choose the salads once there, and burger sales go up. It would be very interesting to construct an extension to the model which would allow us to test this dynamic. That would require, at a minimum, creation of a variable for 'variety of food offered' or 'social acceptability of inviting diverse parties to McDonald's.' We might also speculate that people within large parties are more influenced, in terms of foodchoice selected, by the people in their party, than even by others within their customer type of LHC or MHC. This would imply that a third customer type, 'same party,' should be created, and the parameters (for the network effects) adjusting accordingly.

On the other hand, the homophily findings suggest that McDonald's might do well to attempt to separate the two customer groups, in order to reduce cross-group network effects. For instance, they could market each product type through specialised channels with more specific audiences, in order to reduce awareness of customers of the 'other' product and customer type. While the model suggests that this approach might lead to higher total unit sales, there is also a good argument to be made that the 'inclusive' feel of the restaurant mentioned in the previous paragraph is, in fact, a more important brand characteristic to cultivate for the long term – to say nothing of the fact that 'hiding' salads reduces their power to fend off government intervention in fast food. In a webcast announcing the company's recent decision (described by the Wall Street Journal as a 'pre-emptive strike against the food police') to replace half of the portion of fries in Happy Meals with sliced apples, McDonald's USA President Jan Fields said, 'From a business standpoint, [making meals healthier] is something we need to do to protect that business. Clearly, this is the way people are moving – we have a health-conscious society. We're in business for the long term, and we have to evolve' (Jargon, J., 'Under pressure, McDonald's adds apples to kids meals,' *The Wall Street Journal*, 27 July 2011, p. B1).

Conclusion

In this paper we examined dynamics related to when firms seek to introduce new products in order to move away from their existing brand recognition, or, alternatively, to broaden their brand. For McDonald's, will existing burger devotees find the presence of those green beds of lettuce so shocking that they do not consider them? Will they find them exciting and attractive? Perhaps salad availability will attract an entirely new clientele to the golden arches. Will this scare away the old-timers? Alternatively, salads will be, taken as an individual product line, a flop, but their presence will draw bigger and more diverse crowds to McDonald's, leading to a commercially (though not health-wise) compensative rise in burger sales. Such questions are critical, first, for companies, under pressure by public scrutiny and yet uncertain markets that seek to transfer to their product line towards higher nutritious categories. Beyond the companies, addressing such questions is important for public health Policy. For example, this may help explain why health-campaigners' push for more convenient availability of healthier food seems "fruitless". If businesses offering fast food cannot improve profits from introducing such options, they are not going to do so. Our research, partially discussed in this paper, addresses many of these questions.

The analyses, while preliminary, point to interesting findings. We developed hypotheses on drivers of diverse scenarios involving dynamics of alternative and dominant product sales and customers. We used the role of product distance and network effects as major explanations. Indeed these factors explain multiple reference modes we discussed. Finally, referring to the loop structure of the model and the ensuing dynamics, we identify the key factors which lead to relative loop strength and therefore to one scenario or another. While our results demonstrated that the final equilibrium depends on the adoption mediating parameters (in particular, network effect strength, product distance), we believe that subsequent work can help explain more of the dynamics we examined. The first factor we have begun focusing is on customer retention. The inflow of alternative customer base (families) as well as consumption practices (salads), may deter existing customers. On the other hand, upon limited take-off, healthy food triers may be deterred; in addition, we plan including endogenous product portfolio dynamics. Finally, regarding strategies, we plan to focus on rollout strategies targeted to socio-economically differentiated areas.

This paper focused on the well-studied concept of ‘disruptive’ innovations, whether that be a new product, or a familiar one appearing in an unusual setting. However, this work takes an angle that seems relevant for other industries under pressure to shift to alternative practices either because of unsustainable markets or threat of government intervention.

For instance, similar challenges (and opportunities) exist for alternative energy transitions. Water-wheels and windmills powered industry long before electric utilities were on the scene, just as salads existed long before McDonald’s. Now, however, the electric utility industry is increasingly bringing ‘green’ tariffs online, offering customers the choice to pay a little more per kilowatt-hour in exchange for the power distributor’s promise to buy a compensatory amount of power from a sustainable generator. How can the firm, if at all, transition to a more socially acceptable entity? Our point is not that fast food and power are identical, but rather that the type of model we put forward here could be employed to help executives in such industries explore how a marketing strategy could be integrated with product diversification and consumer targeting.

The analysis shows how the existing stock of customers is on the one hand the vehicle to transition, while on the other hand providing inertia and resistance. This is studied in other industries (e.g. Struben and Sterman 2008), but perhaps surprising, seems also critical for a fast-turnover retail product. For vehicles, the product turnover time is on the order of a decade, and while the time constants related to changing food preferences may be shorter, decision-makers may underestimate how the stock of burger eaters slows the rate at which salad eaters become an important factor. The research also demonstrates how product replacement may be either through core customer conversion or through core customer change. Because of this link to the customer base, as well as the potential knowledge that consumers have with the “locally” disruptive product, social-exposure-mediated network effects are critical in shaping the pathway of both the customer and product base.

While network effects have been studied in many contexts, we believe that the coupling of consumer heterogeneity, as mapped to the products available and network effects is a novel contribution. We incorporated two factors, each built in the same fashion, accounting for the difference between the perceived relevance of the 'similar' and the 'alternative', with the distant between them being a parameter. The *Foodtype 'proximity'* represents the limited relevance of the 'further' *foodchoice* to a customer of a given customer type, while the *Network effects weighting* represents the limited influence of *people* of the other customer type, which leads to the *Foodtype 'proximity,'*. This then affected the network effects weighting, are both given a value of one (full relevance) for the 'close' case and a lower, variable value, between 0 and 1, for the 'distant' alternative.

Finally, in developing our model, we demonstrated the agility of the time-tested model logit-model (McFadden 1973). Our model demonstrates how this structure can be replicated and transformed for different decision-points. For example, we used three types of "appeals" (anticipated appeal, trier discovered actual appeal, and network adjusted appeal) are derived, using on the same logit model formulation. In addition, several parameters are 'recycled' to good use at totally different points within the model. The first two types of appeal share the same beta values which are used to weight the attributes upon which they are built. And Foodtype 'proximity' [a measure of how relevant a particular foodchoice is to someone of a particular customer type] is used not only for both of these two types of appeals for Non-customers and Triers, but also to temper the Core consumption fraction for Core customers. In addition, the same equation structure is used for diverse calculations within the model, such as the Rate of trying and Trier consumption.

References

2002 McDonald's Corporation Summary Annual Report, Oak Brook, Illinois: McDonald's Corporation, 2003. Available at http://www.aboutmcdonalds.com/mcd/investors/publications/annual_report_archives/2002_annual_report.html (accessed 8 June 2011) ('2002 Report').

'7'9" Natural Surf 2,' http://www.bicsportsurfboards.com/products/acs,3,61/7-9-natural-surf-2,480.html, accessed 16 March 2011.

Anderson, S. P., de Palma, A., and Thisse, J. (1992), *Discrete choice theory of product differentiation,* Cambridge, MA: The MIT Press.

Burger King: Whopper to go, *The Economist,* v. 396 (4 September 2010), p. 72.

Cramer, J.S., *Logit models from economics and other fields,* Cambridge, UK: Cambridge University Press, 2003.

Christakis, N. A. and Fowler, J. H. (2007), 'The spread of obesity in a large social network over 32 years,' *New England Journal of Medicine* 357, pp. 370-379.

Dube 2010 tba

Hines 2001 tba

Jargon, J., 'Under pressure, McDonald's adds apples to kids meals,' *The Wall Street Journal*, 27 July 2011, p. B1.

Katz, M. L. and Shapiro, C. (1985), 'Network externalities, competition and compatibility,' *American Economic Review* 75(3), pp. 424-440.

Lazarsfeld and Merton 1954. tba

L.L. Bean's entries in *Gale Directory of Company Histories* and *Gale Contemporary Fashion*, both available at http://www.answers.com/topic/l-l-bean-inc (accessed 16 March 2011).

McFadden 1973, 8 tba

Oliver, T. (1986), *The Real Coke, The Real Story*, Penguin, p. 149-151, as cited in Wikipedia (http://en.wikipedia.org/wiki/New_coke, accessed 18 March 2011.

Prendergast, M (1994), *For God, Country and Coca-Cola: The Definitive History of the Great American Soft Drink and the Company that Makes It*, New York: Basic Books, p. 355, as cited in Wikipedia (http://en.wikipedia.org/wiki/New_coke, accessed 18 March 2011).

Renaghan, M., Pers. comm., 31 May 2010.

Sterman, J. D. (2000), *Business dynamics: systems thinking and modelling for a complex world,* Boston: Irwin McGraw-Hill.

Sterman, J. D. and Sweeney, L. B. (2007), 'Understanding public complacency about climate change: adults' mental models of climate change violate conservation of matter,' *Climatic Change* 80, pp. 213-238.

Struben, J. R. (2006) *Essays on transition challenges for alternative propulsion vehicles and transportation systems*, Ph.D. thesis, MIT. Used simply as a reference list for more sources on network effects.

Struben, J. and Sterman, J. D., et al (2008), 'Transition challenges for alternative fuel vehicle and transportation systems,' *Environment and Planning B: Planning and Design* 35(6), pp. 1070-1097.

Sun, B., Xie, J. and Cao, H. H. (2004), 'Product strategy for innovators in markets with network effects,' *Marketing Science* 23(2), pp. 243-254.

The changes facing fast food : good and hungry, *The Economist*, 17 June 2010.

'The Ray Kroc Story,' http://www.mcdonalds.com/us/en/our_story/our_history/the_ray_kroc_story.html, (accessed 16 March 2011).

Wikipedia entry for Société Bic, http://en.wikipedia.org/wiki/Soci%C3%A9t%C3%A9_Bic, accessed 16 March 2011.