The Effect of Social Interaction on Economic Transactions: An Embarrassment of Niches?

Avi Goldfarb, Ryan C. McDevitt, Sampsa Samila, and Brian Silverman*

May 2013

Abstract

We show that reducing social interaction increases the diversity of products purchased by consumers in two retail settings. First, we consider a field experiment conducted by Sweden's monopoly alcohol retailer and find that moving purchases from behind the counter to self-service disproportionately increases the sales of difficult-to-pronounce products. Second, we use individual-level panel data from a pizza delivery restaurant to show that online orders have more complexity, calories, and diversity, and measure the consequences for consumer and producer surplus. Combined, these results suggest that social frictions can substantially affect market outcomes.

JEL: D12, L81, L86
Keywords: social cues; consumer choice; retail; Internet economics; long tail

*Respectively at University of Toronto, University of Rochester, National University of Singapore, and University of Toronto. We thank Heski Bar Isaac, Liran Einav, and seminar participants at the Booth School of Business, City University of Hong Kong, Columbia GSB, Harvard Business School, McMaster University, NYU Stern, the Ross School of Business, Singapore Management University, the University of Texas, and the University of Toronto for helpful comments. We gratefully acknowledge financial support from SSHRC (grant #486971 and #493140).

1 Introduction

Many economic transactions are verbal and social, such as ordering drinks from a bartender, making appointments with a doctor, or buying products from a sales clerk. In this paper, we consider whether such social interactions influence consumers and, as a result, inhibit certain types of economic activity. Specifically, we show that consumers in two different retail settings purchase a wider variety of goods when transactions are less social, and that much of the change comes from the products most likely to be affected by social frictions. By showing that a transaction's social context and its potential for embarrassment can alter consumers' choices, our results suggest a way in which sociality affects preferences not yet considered in the literature (McFadden 2010, 2013).

In our first setting, we use data from a field experiment conducted by Sweden's government-run alcohol monopoly retailer, Systembolaget, in which stores changed formats from behind-the-counter to self-service. From seven pairs of matched towns, each with a single retail outlet, we show that the stores randomly converted to self-service sell a greater variety of products (as defined by a less-concentrated sales-distribution), with a significant fraction of this change coming from products with difficult-to-pronounce names. As shown in Section 2, the market share of products with difficult-to-pronounce names increases 6% in stores that switch to self-service. And because difficult-to-pronounce products are relatively less popular, an increase in their market share leads to a decline in the stores' overall concentration of sales.

In our second setting, we use individual-level panel data from a pizza delivery restaurant that introduced a Web-based ordering system to supplement its phone and counter service. Comparing sales from before and after the advent of online ordering, we document a considerable change in consumers' purchases. As shown in Section 3, the average item in an online order is 14% more complex and has 3% more calories; the different choices made by online consumers also reduce the store's sales concentration, as orders with more calories and complexity are more likely to include less-popular items. Importantly, we can exploit several institutional details to conclude that the non-social nature of online transactions drives these differences, which ultimately have a substantial effect on both consumer and producer surplus. From a structural demand model, we estimate that reducing social interaction through online ordering has increased consumer surplus by 5.4%, an estimate larger than that of Brynjolfsson et al. (2003) for the benefits of online booksellers' greater selection of products. Moreover, we estimate that producer surplus has increased 3.5% due to non-verbal online orders.

Combined, these findings suggest that interpersonal exchange affects both the type and the diversity of products purchased by consumers. In the case of alcohol sales, consumers may fear appearing unsophisticated if they mispronounce a name when ordering from a sales clerk; once a store introduces a self-service format and eliminates the need to pronounce a name, consumers may become more comfortable pursuing an otherwise mildly embarrassing or frustrating transaction. In the case of pizza orders, consumers may prefer to avoid social judgment of their food choices — an order with peculiar instructions or excessive calories may elicit negative judgment from others. When consumers remove a layer of social interaction by ordering through the website, their tendency to make complicated or high-calorie orders increases. Given these institutional details, both settings help us isolate the effect of potentially embarrassing social interactions on market outcomes while allowing us to rule out several alternative explanations for our results.

First, the products and prices remain fixed for each of our settings, reducing concerns that concurrent institutional changes cloud our results. Because greater product variety can result mechanically in a less-concentrated sales distribution, markets commonly associated with the long tail where retailers offer a wider selection of products, such as online books or videos, would not provide a suitable setting for our analysis (Brynjolfsson et al. 2003). Similarly, online retailers may differ from bricks-and-mortar stores beyond just the extent of social interaction. The panel nature of both settings — and the field experiment used in the alcohol setting — reduce the concern that these other factors confound our findings.

Second, the straightforward menus and webpage in our settings, as well as the nature of the products themselves, allow us to provide evidence that search and learning do not drive our results. For example, in the alcohol setting, the increase in sales comes from difficult-to-pronounce products in particular, rather than from the broader set of historically unpopular products. In the pizza setting, the website does not have sophisticated search tools that Brynjolfsson et al. (2011) argue will confound a comparison of bricks-and-mortar retailers with online stores that facilitate searching for customers. Relatedly, robustness checks that control for the amount of product information available to consumers yield consistent findings.

Third, similar settings have been considered extensively in the economics and management literatures to study sales distributions (Pozzi forthcoming, Brynjolfsson et al. 2003), search costs (De los Santos et al. 2012), and economic efficiency (Seim & Waldfogel 2012). Thus, our settings are firmly in the mainstream and complement previous studies by explicitly examining the impact of social frictions on market outcomes.

Fourth, while not from an experiment, the pizza data allow us to control for individual-level tendencies and selection into the online channel because the transaction history includes customers who purchased from the store both before and after online ordering became available, reducing concerns over selection bias. Combined with information on profit margins, the pizza data also permit us to estimate the changes in consumer and producer surplus attributable to online ordering.

Furthermore, the pizza data allow us to consider an important alternative explanation for our results: that consumers may wish to avoid misunderstandings while ordering. Although we cannot reject this explanation in the alcohol setting, in the pizza setting we show that customers who made more complex or error-ridden orders before online ordering was available are not more likely to make subsequent orders online. Moreover, instructions that are trivial to make on both channels but associated with more calories and complexity, such as ordering double toppings, appear more often in online orders.

For these reasons, we argue that concerns over mistakes in complicated orders do not primarily explain the markedly different choices consumers make online.

The notion that individuals avoid potentially uncomfortable social interactions has received considerable attention in sociology, psychology, medicine, and political science. The foundation for these ideas dates (at least) back to Goffman's claim that social interactions are performances in which individuals act to project a desired image of themselves, and embarrassment occurs when this projection is disrupted (Goffman 1956, 1959). Embarrassment is therefore a social phenomenon.[1]

In their review article on the psychology of embarrassment, Keltner & Buswell (1997) discuss how a fear of embarrassment harms individuals as they take self-destructive steps to avoid it. For instance, a fear of embarrassment leads patients to delay seeking medical help for chest pain (Meischke et al. 1995), as well as for more sensitive conditions such as urological and breast cancers (Chapple et al. 2004, Lerman et al. 1990, McDevitt & Roberts 2011). Others have shown that embarrassment can affect voting choices (Niemi 1976), alter food consumption (Lee & Goldman 1979, Polivy et al. 1986, Banaji & Prentice 1994, Roth et al. 2001, Allen-O'Donnell et al. 2011), and stifle contraceptive purchases (Dahl et al. 1998). Within this vein, removing even one layer of social interaction by using electronic questionnaires rather than in-person interviews at doctors offices significantly increases patients' willingness to report incidents of domestic abuse (Ahmad et al. 2009).

Recent research in economics has studied the importance of sociality and emotions on preference formation and behavior. While no work has addressed embarrassment directly, recent studies have shown that anger following a loss by the local football team leads to increased violence (Card & Dahl 2011), that emotions affect time preferences (Ifcher & Zarghamee 2011), and that guilt impacts family resource allocations and money transfers (Li et al. 2010). Other research has shown that social cues, even if un-

[1] This literature emphasizes that embarrassment differs from humiliation and shame. Humiliation relates to a change in an individual's sense of dignity (Lindner 2001), whereas shame relates to a person's core self-image and can be experienced in social isolation. In contrast, embarrassment can only be experienced in the presence of others (Klass 1990).

related to embarrassment, may also influence individuals' choices. For instance, Akerlof & Kranton (2000) and Akerlof & Kranton (2008) show that social identity affects how individuals behave; Ariely & Levav (2000) find that social norms change variety-seeking behavior; and Rabin (1993) and Fehr et al. (1993) document that perceptions of fairness influence actions both in theory and in practice. Similarly, DellaVigna et al. (2012) show that "social pressure costs" reduce donors' welfare in door-to-door fundraising and impact charitable giving.

Also directly related to our work, McFadden (2010) emphasizes that "*sociality*, the influence of direct interpersonal interaction on human behavior, must be taken into account in modeling choice behavior" (p. 4), particularly in regards to the role of social networks, altruism, and reciprocity. Our results and welfare estimates suggest an alternative role for sociality in preference formation, as we show that a transaction's social context and potential for embarrassment have a marked impact on consumers' choices.

Given the changes we document in consumers' choices and the prior work in social psychology referenced above that would predict such a result, we emphasize embarrassment as the predominant type of social friction in our settings. At the same time, we cannot isolate embarrassment from other plausible social frictions, such as impatience or frustration, due to the nature of our data. Even without pinning down the precise source of social discomfort, however, the broader implications of our work remain largely the same and nevertheless represent a novel contribution to the literature by demonstrating how the sociality of a transaction affects its outcome; this interpretation thus distinguishes our work from the models of social networks, altruism, and reciprocity emphasized in prior research.

Also closely related to our framework is the model of privacy in Daughety & Reinganum (2010), where they derive a demand for privacy within a model in which agents receive utility from other agents' perceptions of their type; when actions are public, "social pressure" influences individuals' choices. In some sense, our analysis examines the basic assumption of this model: whether social pressure does indeed affect choices.

Related to its implications for privacy, our paper contributes to the Internet economics literature by explicitly examining the effect of social interaction on market outcomes. The perceived anonymity of digital technology (perhaps best captured in a 1993 *New Yorker* cartoon showing a dog sitting at a computer saying, "On the Internet, nobody knows you're a dog") has been credited with an increase in the distribution of pornography (Edelman 2009), Pfizer's decision to sell Viagra online (Thomas 2013), and with the recent bestseller status of erotica novels such as *Fifty Shades of Grey* (Rosman 2012). To this point, Griffiths (2001) asserts that Internet pornography is popular because "it overcomes the embarrassment of going into shops to buy pornography over the shop counter," a phenomenon Coopersmith (2000) labels a "social transaction cost."

We explore the idea that social frictions may even affect settings with a comparatively mild potential for embarrassment. As such, our findings provide a new explanation for a commonly discussed Internet phenomenon — that niche products comprise a comparatively large share of total sales online, dubbed the "long tail" in Anderson (2004) — by showing that a reduction in social interaction leads to a less-concentrated sales distribution. The current literature emphasizes the roles of inventory capacity and search technologies (Brynjolfsson et al. 2003, Scott Morton 2006, Pozzi forthcoming), but does not discuss how the impersonal nature of online transactions could affect sales patterns. While a lengthy social psychology literature has studied how a lack of personal interaction affects online behavior (Gackenbach 2007), labeling it the "online disinhibition effect" (Suler 2004), no work (to our knowledge) has examined its implications for market outcomes. As the perception of anonymity is a distinguishing feature of many online transactions, our paper emphasizes a key aspect of Internet commerce not previously considered by the economics literature.

The purpose of our paper is therefore to formalize and measure the impact of social frictions on market outcomes across two common retail settings. We proceed by first detailing the results from a field experiment that moved alcohol purchases from behind the counter to self-service, providing evidence that difficult-to-pronounce products experienced a disproportionately large increase in sales. We then document a change in sales patterns at a pizza delivery restaurant after the introduction of online ordering, providing evidence of a rise in unusual orders; from this change, we also estimate the impact on consumer and producer surplus. We conclude by summarizing our results, discussing their limitations, and speculating about their broader implications.

2 Systembolaget's Sales Format Experiment

2.1 Data and Setting

In our first setting, we examine a field experiment conducted in the early 1990s by Systembolaget, Sweden's government-run alcohol retail monopoly.[2] For Sweden's 1990 population of 8.5 million, Systembolaget operated approximately 400 stores across the country. Outside of these stores, Swedish law prohibits the sale of wine, distilled spirits, and strong beer (above 3.5% ABV). Systembolaget's directive stipulates that the organization's sole purpose is to minimize alcohol-related problems by selling alcohol in a responsible way. As such, it prohibits profit maximization from being an aim of the organization and dictates that no brands or suppliers be given preferential treatment.

Prior to 1989, all transactions at Systembolaget's stores occurred behind the counter, whereby customers approached the counter and ordered from a clerk who then retrieved items from a storeroom. In 1989, Systembolaget began to explore the impact of adopting a self-service format. To identify the likely effects of self-service and reduce the chances of simply cannibalizing sales across stores, Systembolaget chose 14 relatively isolated towns, each with a single Systembolaget store, to participate in a field experiment.[3] According to Skog (2000), Systembolaget used the 1984 to 1989 period to match towns into seven pairs "in such a way as to make the members of each pair as similar as possible

[2] Much of this description comes from Skog's (2000) assessment of the experiment's impact on alcohol consumption.

[3] Because the experiment was restricted to one-store towns, Stockholm and the other major cities in Sweden are not in the data.

in terms of population size, economic bases and sales of alcoholic beverages; the latter both in terms of volume per capita and pattern of variation over time." Systembolaget also chose pairs sufficiently far apart to prevent spillover effects and randomly selected the store converted to self-service within each pair. Table 1 lists the pairs of stores and their characteristics.

Table 1: Summary statistics for Systembolaget stores in the field experiment as of Jan. 1991.

Town	Treatment or Control	Date of Change	Town Population	Sales (Units)	Herfindahl	Revenue (Kr. mil.)
Filipstad	Treatment	June 1991	13296	58413	0.0296	234.7
Nybro	Control	None	20997	53542	0.0184	281.0
Koping	Treatment	July 1991	26345	97701	0.0215	418.0
Saffle	Control	None	17960	46807	0.0207	223.2
Vanersborg	Treatment	Nov. 1991	36734	99028	0.0144	449.0
Lidkoping	Control	None	36097	84143	0.0163	374.4
Motala	Treatment	May 1992	42223	92758	0.0155	441.3
Falun	Control	None	54364	123305	0.0094	614.2
Karlshamn	Treatment	Sept. 1993	31407	82538	0.0145	425.8
Lerum	Control	None	33548	88043	0.0167	345.5
Ludvika	Treatment	Sept. 1994	29144	78178	0.0237	371.6
Vetlanda	Control	None	28170	65646	0.0192	307.0
Mariestad	Treatment	Jan. 1995	24847	92972	0.0140	427.6
Varnamo	Control	None	31314	88514	0.0141	424.1

Several institutional details make Systembolaget's experimental design an appealing empirical setting for our analysis. First, prices and product offerings did not change in the converted stores relative to the control stores during the experiment — only the format of the stores changed. As a result, endogenous changes in prices and product offerings will not confound any observed changes in sales patterns. Second, Systembolaget is a monopoly seller of alcohol (above 3.5% ABV) within Sweden, and therefore competitors' responses to the format change are unlikely to be relevant outside of the weak beer and non-alcoholic drink segments. Third, according to the 2007 annual report, prices are based on a fixed (legislated) per-unit markup. Fourth and finally, Sweden prohibits advertising and promotions for alcohol above 2.25% ABV (though foreign magazines sold in Sweden may carry alcohol advertisements).

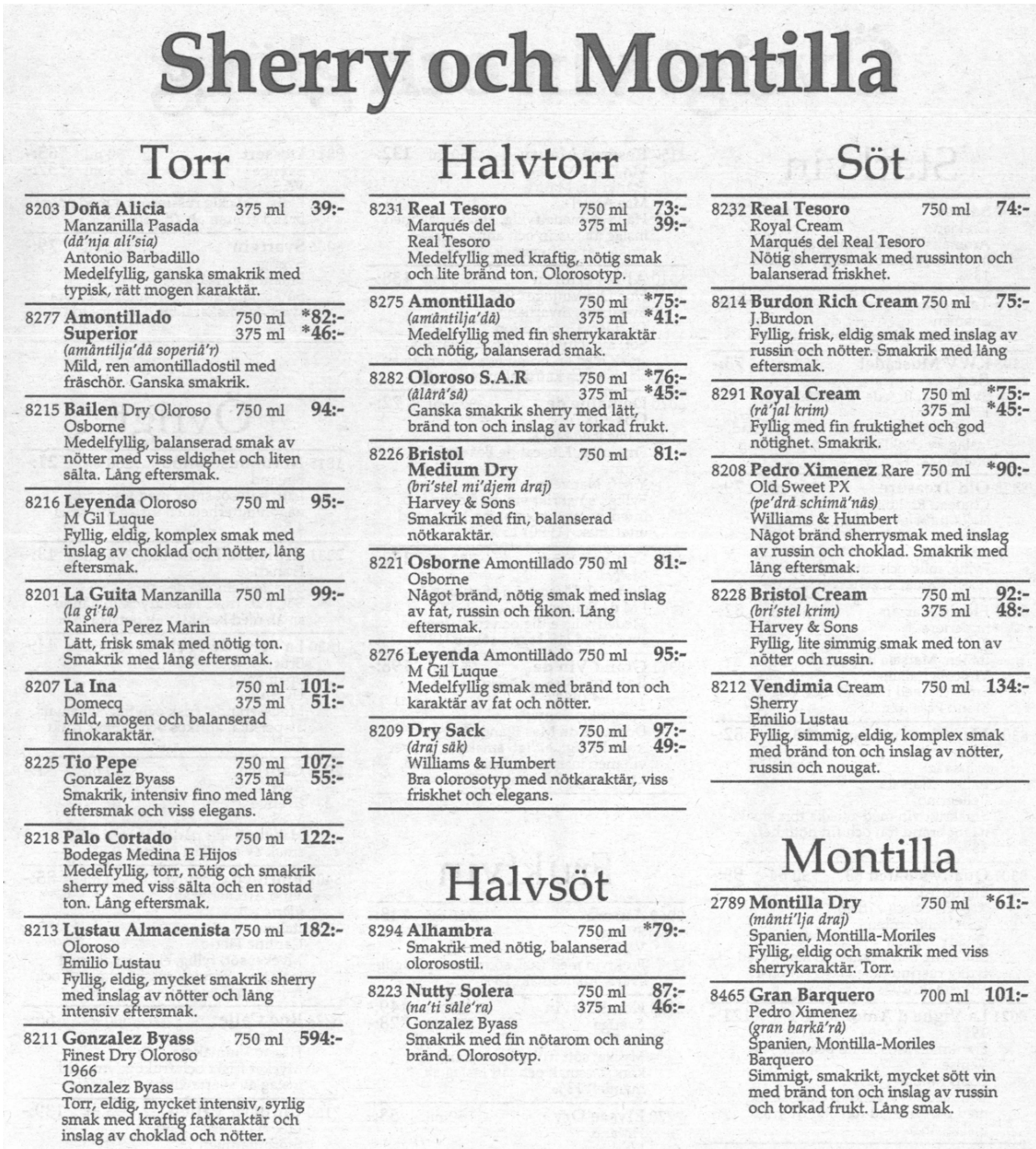
Systembolaget lists each item for sale at its stores in a menu. Every store provides the same menu (though they may stock different items), with Figure 1 showing a sample page from a 1996 menu. The menu lists product names (sorted by category and price) and prices, and is especially important at stores with behind-the-counter service because customers cannot simply pick up a bottle from the shelf before purchasing it. At behind-the-counter stores, shown in Figure 2, customers approach the counter and order verbally (with the option of pointing to an item on the menu); the staff then retreat to the back of the store to retrieve the items. At self-service stores, shown in Figure 3, customers make their selections from the shelves where items are arranged by category and price, with each item given shelf space roughly in line with its popularity (recall that Systembolaget is brand-neutral by its directive); customers then bring their selections to the cash register for purchase. Thus, the key changes in the experiment are that (i) customers may browse the aisles of products on display and (ii) customers need not ask a clerk for a product. For these reasons, if social frictions do impact consumers, then the format change should disproportionately affect difficult-to-pronounce products, rather than the broader set of products with historically lower sales for which browsing shelves may represent a type of learning or search process by consumers.

Our data contain monthly sales and prices for each product at the 14 stores in the experiment from January 1988 to December 1996, with products divided into seven categories: vodka, other spirits, wine, fortified wine, Swedish beer, imported beer, and non-alcoholic drinks.[4] Category-by-category results are shown in the appendix.

We examine the data at the store-category-month level. We first show how a store's format affects the variety and quantity of products purchased by consumers, with variety measured using a Herfindahl index of the sales concentration for each category in each store; this is the sum of the squared market shares of the products (stock-keeping units) in each store-category-month. Table 2 provides descriptive statistics.

We next show the differential sales patterns for difficult-to-pronounce products, which we classify using three distinct measures. First, we identify whether the menu provides a pronunciation guide for the product. As shown in Figure 1, several product listings are accompanied by a phonetic spelling of the product's name. We interpret the presence

[4]We also have data on product availability and popularity from January 1984 to December 1987.



Sherry och Montilla

Torr

8203 **Doña Alicia** 375 ml **39:-**
Manzanilla Pasada
(då'nja ali'sia)
Antonio Barbadillo
Medelfyllig, ganska smakrik med typisk, rätt mogen karaktär.

8277 **Amontillado Superior** 750 ml ***82:-** 375 ml ***46:-**
(amåntilja'då soperiå'r)
Mild, ren amontilladostil med fräschör. Ganska smakrik.

8215 **Bailen** Dry Oloroso 750 ml **94:-**
Osborne
Medelfyllig, balanserad smak av nötter med viss eldighet och liten sälta. Lång eftersmak.

8216 **Leyenda** Oloroso 750 ml **95:-**
M Gil Luque
Fyllig, eldig, komplex smak med inslag av choklad och nötter, lång eftersmak.

8201 **La Guita** Manzanilla 750 ml **99:-**
(la gi'ta)
Rainera Perez Marin
Lätt, frisk smak med nötig ton. Smakrik med lång eftersmak.

8207 **La Ina** 750 ml **101:-** 375 ml **51:-**
Domecq
Mild, mogen och balanserad finokaraktär.

8225 **Tio Pepe** 750 ml **107:-** 375 ml **55:-**
Gonzalez Byass
Smakrik, intensiv fino med lång eftersmak och viss elegans.

8218 **Palo Cortado** 750 ml **122:-**
Bodegas Medina E Hijos
Medelfyllig, torr, nötig och smakrik sherry med viss sälta och en rostad ton. Lång eftersmak.

8213 **Lustau Almacenista** 750 ml **182:-**
Oloroso
Emilio Lustau
Fyllig, eldig, mycket smakrik sherry med inslag av nötter och lång intensiv eftersmak.

8211 **Gonzalez Byass** 750 ml **594:-**
Finest Dry Oloroso
1966
Gonzalez Byass
Torr, eldig, mycket intensiv, syrlig smak med kraftig fatkaraktär och inslag av choklad och nötter.

Halvtorr

8231 **Real Tesoro** 750 ml **73:-** 375 ml **39:-**
Marqués del Real Tesoro
Medelfyllig med kraftig, nötig smak och lite bränd ton. Olorosotyp.

8275 **Amontillado** 750 ml ***75:-** 375 ml ***41:-**
(amåntilja'då)
Medelfyllig med fin sherrykaraktär och nötig, balanserad smak.

8282 **Oloroso S.A.R** 750 ml ***76:-** 375 ml ***45:-**
(ålårå'så)
Ganska smakrik sherry med lätt, bränd ton och inslag av torkad frukt.

8226 **Bristol Medium Dry** 750 ml **81:-**
(bri'stel mi'djem draj)
Harvey & Sons
Smakrik med fin, balanserad nötkaraktär.

8221 **Osborne** Amontillado 750 ml **81:-**
Osborne
Något bränd, nötig smak med inslag av fat, russin och fikon. Lång eftersmak.

8276 **Leyenda** Amontillado 750 ml **95:-**
M Gil Luque
Medelfyllig smak med bränd ton och karaktär av fat och nötter.

8209 **Dry Sack** 750 ml **97:-** 375 ml **49:-**
(draj säk)
Williams & Humbert
Bra olorosotyp med nötkaraktär, viss friskhet och elegans.

Halvsöt

8294 **Alhambra** 750 ml ***79:-**
Smakrik med nötig, balanserad olorosostil.

8223 **Nutty Solera** 750 ml **87:-** 375 ml **46:-**
(na'ti såle'ra)
Gonzalez Byass
Smakrik med fin nötarom och aning bränd. Olorosotyp.

Söt

8232 **Real Tesoro** 750 ml **74:-**
Royal Cream
Marqués del Real Tesoro
Nötig sherrysmak med russinton och balanserad friskhet.

8214 **Burdon Rich Cream** 750 ml **75:-**
J.Burdon
Fyllig, frisk, eldig smak med inslag av russin och nötter. Smakrik med lång eftersmak.

8291 **Royal Cream** 750 ml ***75:-** 375 ml ***45:-**
(rå'jal krim)
Fyllig med fin fruktighet och god nötighet. Smakrik.

8208 **Pedro Ximenez** Rare 750 ml ***90:-**
Old Sweet PX
(pe'drå schimä'näs)
Williams & Humbert
Något bränd sherrysmak med inslag av russin och choklad. Smakrik med lång eftersmak.

8228 **Bristol Cream** 750 ml **92:-** 375 ml **48:-**
(bri'stel krim)
Harvey & Sons
Fyllig, lite simmig smak med ton av nötter och russin.

8212 **Vendimia** Cream 750 ml **134:-**
Sherry
Emilio Lustau
Fyllig, simmig, eldig, komplex smak med bränd ton och inslag av nötter, russin och nougat.

Montilla

2789 **Montilla Dry** 750 ml ***61:-**
(månti'lja draj)
Spanien, Montilla-Moriles
Fyllig, eldig och smakrik med viss sherrykaraktär. Torr.

8465 **Gran Barquero** 700 ml **101:-**
Pedro Ximenez
(gran barkä'rå)
Spanien, Montilla-Moriles
Barquero
Simmigt, smakrikt, mycket sött vin med bränd ton och inslag av russin och torkad frukt. Lång smak.

Figure 1: Sample page from Systembolaget's 1996 menu.

Figure 2: Picture of a typical behind-the-counter Systembolaget store.

Figure 3: Picture of a typical self-service Systembolaget store.

of these guides as indicating that a name is difficult to pronounce and use this as our primary measure. Notably, the inclusion of a pronunciation guide varies across products' countries of origin, with just 4% of Swedish products given guides compared to 78% of French products.[5] In our regressions, we will control for such regional variation. Second, we use the number of characters in the product's name. Third, we use the assessments of three native Swedish speakers hired to evaluate the difficulty of pronouncing each product listed in the January 1991 menu.[6]

2.2 Store Format and the Concentration of Sales

To estimate the impact of a store's format on the level and concentration of its sales, we use a straightforward difference-in-difference identification strategy. For store s, product

[5]In total, France represents 35% of difficult-to-pronounce products and we therefore show below that the results are not driven by a change in sales of French products overall.

[6]Details of this exercise appear in the appendix.

Table 2: Descriptive statistics for Systembolaget stores.

	Mean	Std. Dev.	Min.	Max.	N
Unit of Obs.: Store-Category-Month					
Herfindahl	0.0900	0.0778	0.0088	0.8059	10570
Units Sold	12439	15423	15	159917	10570
Liters Sold	6246	7092	3	63220	10570
Swedish Products	0.3819	0.3873	0	1	10570
French Products	0.0596	0.0739	0	0.4348	10570
Market Share Difficult-to-Pronounce					
Guide (by Units)	0.2162	0.2348	0	0.7737	10570
Guide (by Volume)	0.2347	0.2420	0	0.8193	10570
Over 30 Characters (by Units)	0.0099	0.0193	0	0.1255	10570
Over 30 Characters (by Volume)	0.0101	0.0194	0	0.1254	10570
Coder Rates Below Top (by Units)	0.4217	0.2872	0	1	10570
Coder Rates Below top (by Volume)	0.4626	0.3124	0	1	10570
Unit of Obs.: Product					
Pronunciation Guide	0.5428	0.4983	0	1	1658
Word Length	17.820	8.5537	3	70	1658
Mean Coder Score	8.3923	0.7953	5.33	9	1625
Coder 1 Score	8.1594	0.6612	6	9	1631
Coder 2 Score	8.7813	0.5341	4	9	1628
Coder 3 Score	7.9300	1.8721	1	9	1628
Vodka	0.0730	0.2602	0	1	1658
Other Spirits	0.2467	0.4312	0	1	1658
Wine	0.4608	0.4986	0	1	1658
Fortified Wine	0.0766	0.2660	0	1	1658
Swedish Beer	0.0844	0.2781	0	1	1658
Imported Beer	0.0308	0.1727	0	1	1658
Non-Alcoholic Drinks	0.0277	0.1642	0	1	1658
Unit of Obs.: Store-Product-Month					
Units Sold	129.35	485.17	-203^{a}	29836	1016428
Behind-the-Counter Format	0.2219	0.4156	0	1	1016428
Price (Krona)	90.011	80.467	3	2325	1016428

Only includes products in the 1991 guide (and therefore coded for pronunciation difficulty).
[a] Sales can be negative if returns for a product at a store in a month exceed sales. Negative sales represent less than one tenth of one percent of the observations. These observations will be dropped from most of the analysis because we use a measure of logged sales.

category c, and month t, our estimating equation is:

$$Outcomes_{sct} = \beta TreatmentGroups_{sc} * AfterTreatments_{sct} + \mu_{sc} + \tau_t + \varepsilon_{sct}, \quad (1)$$

where outcomes are either a Herfindahl index or sales volume in this subsection, and the fraction of sales within a store-category-month that are difficult to pronounce in the next subsection. Given this specification, we control for store-category fixed effects, μ_{sc}, and month fixed effects, τ_t; as such, all differences across stores at the category level and all systematic changes over time are controlled for in the regression. The coefficient β will therefore capture how sales in the treatment group of stores change after they convert to self-service compared to the control group of behind-the-counter stores over the same period.

Because our data come from a randomized field experiment, we have fewer concerns about endogeneity and omitted variables that typically arise in difference-in-differences studies — the differences between the treatment and control groups should be random. Nevertheless, we also verify that the change in sales is coincident with the format change. Because we observe each store multiple times and because the matched treatment-control pairs of stores might have correlated sales in each category, we cluster the standard errors by store-pair-category to reduce the potential for overstating statistical significance (Bertrand et al. 2004).[7]

Table 3 shows the results of the regressions described in Equation (1) for both the more-limited sample of products appearing in the 1991 guide that has a pronunciation key, as well as for the full sample of products across all guides. Columns (1) and (3) show that the sales concentration, as measured by a Herfindahl index, falls substantially after a store changes to self-service: the estimated marginal effect is 0.0154 relative to an average of 0.0900. Columns (2) and (4) show that sales, measured in units, increase by approximately 20%.

Figure 4 repeats the analysis in Column (1) at a finer level of detail. Rather than one discrete variable identifying when a store changes format, we substitute the *Self-Serve Stores After Change* variable with a sequence of dummy variables for the quarters before and after the format change. We find that, prior to the format change, stores in the

[7] Results are robust to clustering by store. We cluster by store-pair-category because of the potential for correlated sales of similar products across the similar treatment and control stores.

Table 3: Treated stores sell more volume and more variety after the change.

	Only Products in 1991 Guide		All Products	
	(1)	(2)	(3)	(4)
	Herfindahl	Log Sales in Units	Herfindahl	Log Sales in Units
Self-Serve Stores After Change	-0.0154***	0.1964***	-0.0158***	0.2283***
	(0.0041)	(0.0246)	(0.0037)	(0.0279)
N	10570	10570	10570	10570
Number of Groups	98	98	98	98
R^2	0.08	0.44	0.22	0.39

Regressions include category-store fixed effects (differenced out) and 107 monthly fixed effects.
Unit of observation is the store-category-month.
Robust standard errors clustered by store-pair-category in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%.

treatment group (i.e., those that change format) exhibit no trend towards a decreased sales concentration; the timing of the change in the estimated coefficient is coincident with the timing of the format change.

2.3 Store Format and Difficult-to-Pronounce Products

To assess how the format change affects the sales of difficult-to-pronounce products, we reestimate Equation (1) using the fraction of products sold in each store-category-month that are difficult to pronounce as the dependent variable, while adding controls for the Herfindahl index and the log of total quantity sold for that store-category-month. We use three different measures for difficult-to-pronounce products: (i) whether the menu provided by Systembolaget includes a phonetic pronunciation guide for the product, (ii) whether the product's name has over 30 characters, and (iii) whether any of the coders rated the product less than a "9" for ease-of-pronunciation.[8]

Table 4 presents the results from nine specifications that regress difficult-to-pronounce product sales on an indicator variable equal to one after a store converts to a self-service format, among other controls. As a baseline, Column (1) regresses the fraction of difficult-to-pronounce product sales on the treatment dummy. Column (2) adds con-

[8]Qualitative results are robust to various perturbations of the definitions of difficult-to-pronounce product, particularly using the hand-coded pronunciation measure. We show three representative examples here and, as discussed earlier, prefer using the pronunciation guide because the threshold is determined by a third party, independent of our study.

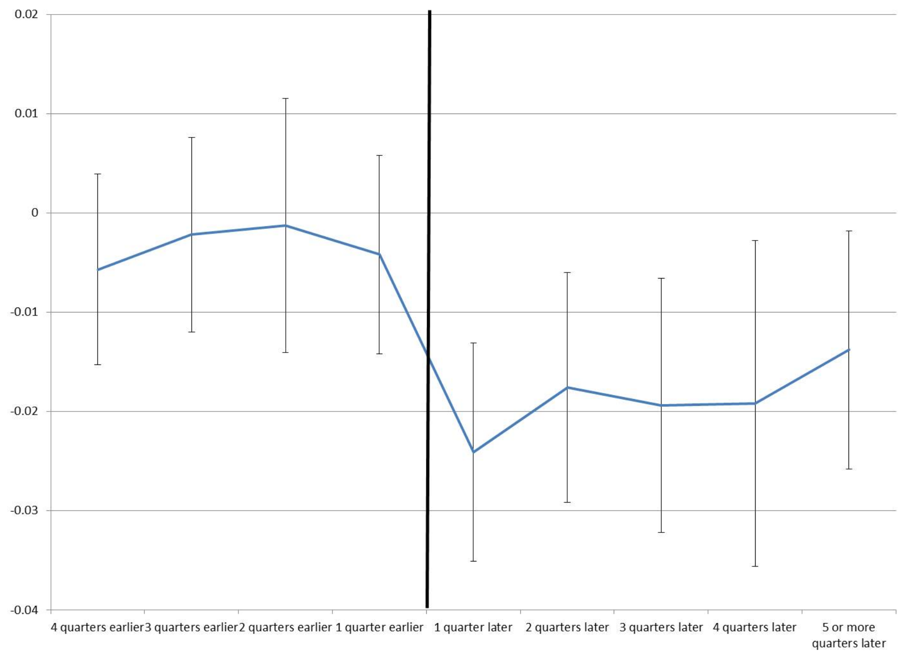


Figure 4: Coefficients of regression of Herfindahl on being in the treatment group over time
Specification resembles Column (1) of Table 3. Coefficients provided in the appendix.

trols for the Herfindahl index and the log of total quantity sold, while Column (3) controls for the percentage of sales that are of domestic (Swedish) products, as labeled in the menu; Column (4) weights the fraction of difficult-to-pronounce product sales by volume rather than units sold. The remaining columns show robustness to alternative definitions of difficult-to-pronounce names and to alternative sample restrictions. Collectively, all specifications demonstrate that the share of difficult-to-pronounce products rises substantially when stores switch formats from behind-the-counter to self-service. A back-of-the-envelope calculation based on Column (2) suggests that the share of difficult-to-pronounce products increases by 7%.

To understand how increasing the market share of difficult-to-pronounce products leads to a less-concentrated sales distribution, note that difficult-to-pronounce products are comparatively less popular in general. Moreover, as shown in Table 5, most of the sales increase for difficult-to-pronounce products comes from the least popular among this group. To see this, consider Columns (1) and (2) that compare products in the top quartile of sales for the four years prior to our data with those not in the top quartile. In this comparison, only the difficult-to-pronounce products not in the top quartile experienced a meaningful increase in sales. Furthermore, Columns (3) and (4) compare products that were and were not in the top quartile of sales at a given store in a given month. Here, the magnitude of the coefficients shows that, once again, the relatively unpopular difficult-to-pronounce products experience the largest increase in sales. Thus, Table 5 suggests that the decrease in sales concentration is partially driven by the disproportionate increase in sales of difficult-to-pronounce products.

2.4 Alternative Explanations Unrelated to Social Frictions

The results presented above could be explained by factors other than social transaction costs. For example, the assignment of stores in the experiment may not have been independent of an increasing sales trend for difficult-to-pronounce products, which would then bias our results. To address this concern, we verify that the sales of difficult-to-

Table 4: Difficult-to-pronounce products have a disproportionately large sales increase.

		Guidance on Menu			Word Length Over 30	Any Coders Below Top	Guidance on Menu & Products Restricted to: French Names	Short Names	Short French Names
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	% Difficult-to-Pronounce	% Difficult-to-Pronounce	% Difficult-to-Pronounce	% Difficult-to-Pronounce	% Difficult-to-Pronounce	% Difficult-to-Pronounce	% Difficult-to-Pronounce	% Difficult-to-Pronounce	% Difficult-to-Pronounce
Self-Serve Stores After Change	0.0220***	0.0161**	0.0160*	0.0167***	0.0014*	0.0283**	0.0066**	0.0341***	0.0062**
	(0.0065)	(0.0081)	(0.0081)	(0.0062)	(0.0008)	(0.0119)	(0.0028)	(0.0096)	(0.0030)
Herfindahl		-0.8248***	-0.8235***	-0.5903***	-0.0060**	-1.1094***	-0.0568**	-0.3301***	-0.0933**
		(0.0514)	(0.0499)	(0.0590)	(0.0023)	(0.0981)	(0.0226)	(0.0870)	(0.0400)
Log Sales		-0.0345**	-0.0337**	-0.0292**	0.0023***	-0.1237***	-0.0012	-0.1138***	-0.0024
		(0.0137)	(0.0132)	(0.0136)	(0.0007)	(0.0155)	(0.0016)	(0.0214)	(0.0015)
Fraction Domestic			-0.0074						
			(0.0285)						
N	10570	10570	10570	10570	10570	10570	7564	10570	7549
Number of Groups	98	98	98	98	98	98	84	98	84
R^2	0.07	0.35	0.36	0.25	0.12	0.49	0.11	0.30	0.13

Dependent variable is percent sales that are difficult to pronounce. Percentage defined by units sold except in column (4).
Regressions include category-store fixed effects (differenced out) and 107 monthly fixed effects.
Uses all products observed in the 1991 data. Robust standard errors clustered by category-store pair in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5: Treated stores sell more relatively unpopular difficult-to-pronounce products after the change.

	Products from 1984-87		Products from All Years	
	Top Quartile	Not Top Quartile	Top Quartile	Not Top Quartile
	(1)	(2)	(3)	(4)
	% Difficult-to-Pronounce	% Difficult-to-Pronounce	% Difficult-to-Pronounce	% Difficult-to-Pronounce
Self-Serve Stores After Change	0.0047	0.0125**	0.0114*	0.0423**
	(0.0041)	(0.0058)	(0.0062)	(0.0193)
Herfindahl	-0.2852***	-0.2785***	-0.1506***	-0.2944***
	(0.0588)	(0.0819)	(0.0439)	(0.0859)
Log Sales	-0.0120**	0.0070	-0.0411***	0.0471**
	(0.0049)	(0.0103)	(0.0152)	(0.0190)
N	9052	10570	9534	10570
Number of Groups	84	98	98	98
R^2	0.24	0.19	0.14	0.07

Dependent variable is percent sales that are difficult to pronounce defined by guidance on the menu.
Regressions include category-store fixed effects (differenced out) and 107 monthly fixed effects.
Unit of observation is the store-category-month.
Robust standard errors clustered by category-store pair in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%.

pronounce products did not rise in the treatment stores relative to the control stores prior to the format change. In particular, Figure 5 shows the estimated coefficient of a regression of the fraction of sales that are difficult to pronounce on being in the treatment group, quarter by quarter. The results show a sharp increase in the share of difficult-to-pronounce products after the format change.

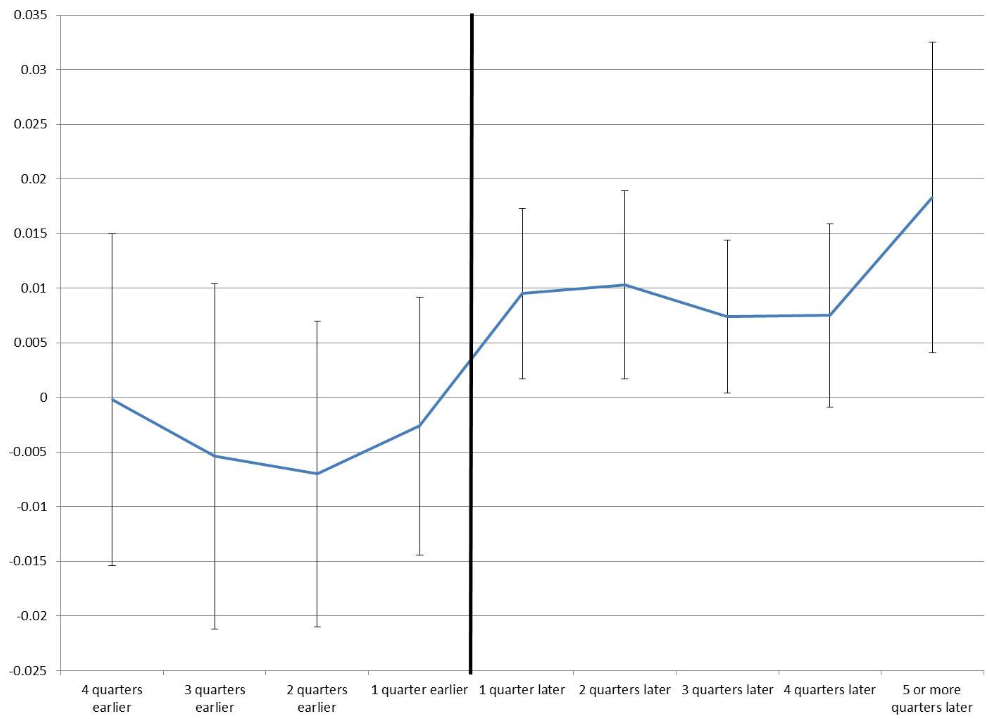


Figure 5: Coefficient of regression of fraction difficult-to-pronounce on being in treatment group over time. Specification resembles Column (1) of Table 4. Coefficients provided in App. Table 4.

More broadly, some other unobserved factor that is correlated with pronunciation difficulty may drive sales in the self-service format relative to behind-the-counter. For example, consumers may be unfamiliar with foreign products, and therefore a lack of familiarity, rather than any difficulty with pronouncing their names, causes the sales of difficult-to-pronounce products to increase as consumers become aware of obscure products while browsing the store's shelves. Although controlling for the Herfindahl index partly addresses this concern about the underlying popularity of products influencing sales, it does not address the interaction between familiarity and foreignness. To do so, we consider alternative specifications in columns (4), (7), (8), and (9) of Table 4. Column (4) shows that difficulty-of-pronunciation still has a significant effect when controlling for the proportion of domestic products sold (though this may understate the overall effect because domestic products are less likely to be difficult to pronounce). Furthermore, Column (7) shows robustness to a sample restricted to products from France, the country with the largest number of difficult-to-pronounce products.

A related concern is that the results might be explained by difficult-to-pronounce products being difficult to remember. While we cannot definitively rule out this possibility in the absence of an explicit memory test, our results are nevertheless robust to considering only products with shorter names, which may be easier to recall from memory (Baddeley et al. 1975). In particular, Column (8) shows robustness to restricting the sample to products with 20 or fewer characters and column (9) shows robustness to restricting the sample to French products with 20 or fewer characters.[9]

Another possible explanation is that consumers do not order difficult-to-pronounce products verbally because they do not want to be misunderstood by the sales clerk. While we cannot definitively reject this possibility, we still interpret it as a type of social transaction cost, albeit one unrelated to embarrassment. In other words, it is still the social nature of the interaction that influences behavior, whether out of frustration, impatience, or embarrassment.

Finally, we may overstate the magnitude of the effect if consumers who plan to buy difficult-to-pronounce items choose to go to the self-service stores specifically to avoid ordering from a sales clerk. We believe this is an unlikely explanation because Systembolaget is a monopoly retailer that deliberately selected geographically isolated stores to address this issue.

Overall, we interpret the results presented in this section as evidence that personal interactions have a meaningful impact on the sales of particular types of products: consumers are less likely to buy a product when they want to avoid a difficult pronunciation (or at least the need to point to it on a menu). We argue that this social transaction

[9] Furthermore, the sales of very large bottles (1.5L or greater) experience a disproportionately large increase at self-service stores, even after controlling for difficult-to-pronounce and French products. A social friction similar to the one inhibiting orders with excessive calories in the pizza section below may explain this result (i.e., consumers are reluctant to purchase excessive amounts of alcohol when ordering directly from a sales clerk), which is robust to alternative explanations such as search or recall.

cost is likely related to the potential for embarrassment, but we cannot rule out the possibility that it is explained by a consumer's desire to avoid misunderstandings and the frustration that comes with them. Furthermore, the store-level data make it difficult to estimate the effect of these social frictions on welfare given consumers' heterogeneous tastes. As such, we turn next to an alternative setting where we document a similar result, and also calculate its impact on welfare.

3 Online Ordering at a Pizza Delivery Restaurant

3.1 Data and Setting

To continue examining how social interaction affects consumers, this section uses data from a franchised pizza delivery restaurant operating in a mid-size metropolitan area.[10] The franchise is similar to prominent chains such as Domino's and Papa John's, but has a narrower regional presence. The store's menu is standard, offering pizza with traditional toppings, breadsticks, baked subs, wings, and salads. The store also sells beverages, but its distribution agreement prohibits the sharing of any beverage sales data and we therefore exclude beverages from our analysis.

The store's customers can place their orders over the phone, at the counter, or, since January 2009, through the franchise's website, shown in an anonymous format in Figure 6. By our own (admittedly casual) comparison of the store's website to larger national chains', it is less sophisticated and offers only basic functionality; it has no search capabilities, no consumer ratings, no recommendations, no online-specific promotions, and no saved order list. The store's rudimentary website is a virtue for identification because it closely resembles the layout of physical menus distributed to customers by the store, suggesting that consumers are unlikely to alter their behavior based on any particular feature of the website.

[10] Due to a confidentiality agreement required to access the data, many specific details related to both the franchise and store are omitted.

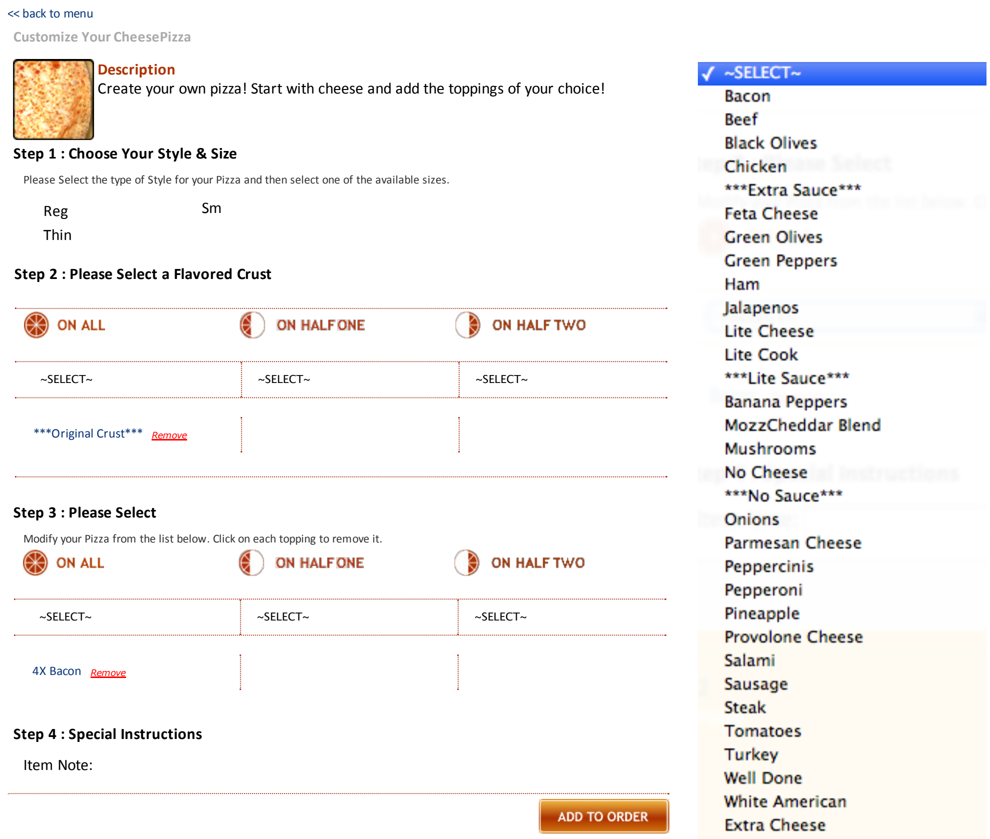


Figure 6: Screenshot of the store's website (stripped of identifying content), and the drop-down menu for toppings.

For phone and counter orders, an employee enters instructions through a touchscreen point-of-sales terminal which are then transmitted to a display in the food preparation area. For website orders, a customer clicks on a link for a particular base item and then configures it through a series of drop-down menus; the order then goes directly to the food preparation display. For all channels, customers may either pick up their orders at the store, or have them delivered for a fee plus an optional gratuity.

The dataset used for our analysis includes all food items from orders made between July 2007 and December 2011.[11] The store anonymized the data before releasing it and

[11] To preserve the confidentiality of sensitive competitive information, the store did not release data for orders over \$50 (typically large institutional orders) or for promotional orders under \$3.49, the price of the least-expensive food

assigned a unique identifier to all households through a third-party proprietary system. Because the store's identifier is at the household level, we use the terms household and customer interchangeably. Figure 7 provides a sample order made by a customer containing two base items placed over the phone for delivery.

The measure of complexity in this paper refers to the number of instructions a customer provides for each base item in his order. For example, we define a large pizza as having a complexity equal to 1, a large pepperoni pizza as equal to 2, a large pizza with half pepperoni and half sausage as equal to 3, and so on. Thus, the minimum complexity for any base item is 1, while the maximum in the data is 21. This store, like most pizza franchises, also offers "specialty" pizzas that have preconfigured toppings, such as a "veggie" pizza with seven toppings. We code specialty pizzas to have a complexity equal to 1 unless the customer provides instructions to add or remove toppings. Under this definition, the order in Figure 7 has a maximum base item complexity of 6 and a mean base item complexity of 4. The mean complexity comes from having two base items and a total of 8 instructions, which includes the base of 1 for each item.

The store also provided information for the number of calories in each item. As a benchmark, a large cheese pizza has 2080 calories, whereas a small garden salad with no dressing has 40 calories. In the data, the mean and maximum number of calories for the base items within an order are constructed in an equivalent manner to the measures for complexity. Using the example in Figure 7, the mean base item has 2521 calories and the maximum base item has 2779.

Finally, we measure popularity based on the number of times an item has been ordered at the store. For instance, a large pizza is the most popular item, having been ordered 95,846 times. For our order-level regressions, we use the proportion of items in an order among the store's top ten most popular to connect a consumer's choices to the store's sales distribution, which will then allow us to study the effect of social frictions on the long tail.

item.

Date:	03/12/2010	**Taken By:**	David Robison	**Customer:**
Order Number:	50	**Table:**		
Order Type:	Delivery			
Order Time:	05:17 PM			

1	Lg Create Your Own Pizza	9.99
	Butter Chz Crust	
1	Lg Create Your Own Pizza	9.99
	Pepperoni	1.49
	Sausage	1.49
	Green Peppers	1.49
	Mushrooms	1.49
	Butter Chz Crust	
	Subtotal	**25.94**
	Delivery Fee	**2.00**

Figure 7: Sample order from the store's sales terminal. Rows with a "1" in the leftmost column contain base items. The rows below a base item represent instructions to alter the base item above them (e.g., add a topping).

The dataset comprises 160,168 orders made by 56,283 unique customers, with summary statistics reported in Table 6. Of the store's orders, 6.7% have been placed online and notable differences exist between these and non-Web orders. Customers using the Web spend \$0.61 more, on average, though they order slightly fewer base items; this disparity stems from online customers ordering more toppings. The mean base item is 15.0% more complex and has 6.1% more calories in an online order, while the maximum base item is 16.9% more complex and has 7.2% more calories. In terms of popularity, the average online order contains 9 percentage points fewer top-ten items.

The average customer has made 2.8 orders since the store's opening, with a range from 1 to 88. Of all customers, 4,582 (8.1% of total) purchased from the store both before and after online ordering became available. Among this group, 700 (1.2% of total) made an order both during the pre-Web time period and through the website after the introduction of online ordering. These customers will be crucial for identifying the causal effects of Web use, as observing orders across both regimes makes it possible to difference out unobserved heterogeneity that might drive selection into the online channel.

The store frequently offers promotions, with the average customer using a coupon in

Table 6: Descriptive statistics for pizza data.

	Full Sample				Web Comparison		
Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Web Mean**	**Non-Web Mean**	**t-stat**
Web Order	0.067	0.25	0	1	0	1	
Order Price	14.702	6.829	3.49	49.99	15.46	14.85	9.04
Items in Order	2.036	1.156	1	17	1.99	2.02	3.27
Complexity – Mean Order Item	2.646	1.217	1	21	3.06	2.66	27.08
Complexity – Max Order Item	3.273	1.399	1	21	3.81	3.26	32.62
Calories – Mean Order Item	1694.613	607.077	110	6010.84	1798.84	1695.60	15.92
Calories – Max Order Item	2022.724	625.991	110	6010.84	2154.81	2009.20	21.74
Order Items in Top Ten	0.475	0.325	0	1	0.39	0.48	30.54
N		160168			10693	104804	

Summary statistics from the full dataset of orders, excluding beverages, appear on the left-hand side and from orders made in the post-Web period on the right-hand side. The unit of observation is an individual order. The variable "Web Order" is an indicator variable equal to one if the order was made through the website. The variable "Order Price" is the total price of the food items within an order before tax, delivery, and gratuity. The variable "Items in Order" is the total number of base items (pizzas, breadsticks, baked subs, wings, and salads) within an order. The variable "Complexity – Mean Order Item" is the average number of instructions provided per item within an order, with a base complexity of 1. The variable "Complexity – Max Order Item" is the maximum number of instructions provided for the items within an order, with a base complexity of 1. The variable "Order Items in Top Ten" is the proportion of items within an order that are among the store's top ten most ordered items.

54.3% of his orders. All promotions are available across all channels, and Web customers are slightly less likely to use a promotion. Because physical coupons come affixed to menus, any customer using a promotion can easily access the full list of the store's products, an institutional detail exploited as a robustness check below.

3.2 Online Orders and the Concentration of Sales

The store's online orders exhibit a significantly less concentrated sales distribution even though product selection, prices, and search capabilities remain fixed. To establish the significance of this result, we compare the sales distribution of the store's 69 items (i.e., the five base items, specialty pizzas, and toppings) across the Web and non-Web channels. Throughout, we consider distributions that do and do not distinguish items by size (e.g., whether a large pizza is considered distinct from a medium pizza). We drop any item purchased fewer than 500 times, a conservative restriction given the more dispersed nature of online sales.

As in our analysis of the alcohol setting, we use a Herfindahl index to provide a concise measure of the sales concentration: it is 0.0429 for the pre-Web period, 0.0403 for non-

Web sales in the post-Web period, and 0.0308 for Web sales. Using the percentage of total sales generated by the bottom 80% of products as an alternative measure of concentration, the share for pre-Web orders is 32.2%; the share for non-Web orders in the post-Web period is 32.3%; and the share for Web orders is 38.7%. Thus, the share of the bottom 80% of products is 6.4 percentage points greater for Web orders compared to non-Web orders during the same time period, which resembles the 4 percentage point difference documented by Brynjolfsson et al. (2011) for online and catalog clothing sales. Finally, the top ten products comprise 52.6% of sales pre-Web, 52.1% of non-Web sales in the post-Web period, and 45.4% of online sales.

To establish that the difference in sales concentrations across channels is statistically significant, we consider a regression similar to Equation (1) where the dependent variable is a Herfindahl index for the sales channel in a given month and "Web Orders" is an indicator variable equal to one for online sales. Table 7 presents the results from these regressions, and all specifications show that online sales are significantly less concentrated. For Columns (1) and (2), the sales distribution is approximately 26% less concentrated online, treating different sizes of the same item as distinct; adding a time trend does not affect the main parameters. For Column (3), the sales distribution is approximately 33% less concentrated online, treating different sizes of the same item as equivalent; adding a time trend in Column (4) moves the decline to 36%. Across all specifications, restricting the sample only to months in the post-Web period does not affect the qualitative results.

Consistent with the results found for alcohol sales in the previous section, these regressions establish that the store's online orders have a significantly less concentrated sales distribution. While other online markets also exhibit this pattern, the underlying cause of the shift is unlikely to be the same here as in previous studies — the selection of available products remains constant and search capabilities change little. As an alternative explanation, we next consider the role of social transactions costs.

Table 7: Online orders have a less concentrated sales distribution.

	Items Distinguished by Size		Items Not Distinguished by Size	
	(1)	(2)	(3)	(4)
	Herfindahl	Herfindahl	Herfindahl	Herfindahl
Web Orders	-0.0107***	-0.0107***	-0.0279***	-0.0292***
	(0.0006)	(0.0006)	(0.0008)	(0.0008)
Constant	0.0414***	0.0412***	0.0836***	0.0801***
	(0.0004)	(0.0009)	(0.0005)	(0.0011)
Month Trend	No	Yes	No	Yes
N	92	92	92	92
Number of months	56	56	56	56
R^2	0.7608	0.7611	0.9317	0.9458

Unit of observation is the channel-month.
Robust standard errors clustered by month in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%.

3.3 Online Orders and Items Affected by Social Frictions

As we did for alcohol sales in Section 2, we now consider whether the impersonal nature of online transactions can partly explain why online orders have a less-concentrated sales distribution. Specifically, we show that consumers who place orders through the store's website are more likely to make choices that might otherwise be inhibited by social frictions. Following an extensive literature in social psychology that has shown individuals alter their behavior when others observe them eating excessively or unconventionally, we examine two order attributes that consumers may wish to keep private: calories and complexity. For example, Polivy et al. (1986) show from an experiment that subjects eat less when they believe others will be aware of their consumption. At the extreme, studies of bulimia also find that binge eating occurs less often in the presence of others (Waters et al. 2001, Herman & Polivy 1996). Moreover, excessive complexity may cause embarrassment if customers fear appearing eccentric by ordering an unconventional combination of items, which relates to sociological and psychological theories of impression management (Goffman 1959, Banaji & Prentice 1994). To this point, Roth et al. (2001) provide experimental evidence that subjects adhere to norms for "appropriate" eating behavior around others. In keeping with these ideas, moving orders online, and thus removing a layer of social interaction, may lead consumers to purchase a different mix of items.

To test this theory, we consider a series of regressions that take the form

$$Y_{ij} = \alpha + \beta X_{ij} + \gamma Web_{ij} + \delta_i + \varepsilon_{ij}, \tag{2}$$

with $Y_{ij} \in \{\text{complexity, calories}\}$ for order j by customer i; X_{ij} includes order-specific characteristics such as the day of the week, the time of day, a customer's past order count, and a time trend; Web_{ij} is equal to one if the order was made online; and δ_i is a customer-level fixed effect.

Table 8 presents the results from 16 different linear regressions based on Equation (2) that use various dependent variables. For the regressions in Columns (1)–(12), we also restrict the sample to customers who have made at least 10 orders and have ordered during both the pre-Web and post-Web periods; this restriction rules out household-level selection into the sample based on the availability of Web ordering and therefore more cleanly identifies the causal effect. We cluster all standard errors by household.

Table 8: Regression results of order characteristics potentially influenced by social interaction among online orders.

	All Orders						Coupon Orders			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Complexity Mean Item	Complexity Max Item	Calories Mean Item	Calories Max Item	Complexity Half Topping	Complexity Double Topping	Complexity Mean Item	Complexity Max Item	Calories Mean Item	Calories Max Item
Web Order	0.386***	0.465***	51.52**	71.62***	0.107***	0.0328***	0.415***	0.462***	117.95***	148.25***
(0.0466)	(0.0515)	(21.24)	(23.296)	(0.0148)	(0.00812)	(0.0679)	(0.0689)	(28.61)	(34.52)	
N	48446	48446	48446	48446	48446	48446	25590	25590	25590	25590
Number of Groups	2030	2030	2030	2030	2030	2030	1993	1993	1993	1993
R^2	0.378	0.383	0.334	0.353	0.306	0.231	0.395	0.402	0.333	0.368

	One Item Orders		Small Pizza Orders		Six+ Item Orders	
	(11)	(12)	(13)	(14)	(15)	(16)
	Complexity Mean Item	Calories Mean Item	Complexity Mean Item	Calories Mean Item	Complexity Mean Item	Calories Mean Item
Web Order	0.463***	81.81**	0.514**	4.10	-0.008	-168.18
	(0.0827)	(40.27)	(0.2429)	(24.26)	(0.1345)	(105.58)
N	18437	18437	7556	7556	2708	2708
Number of Groups	1880	1880	4890	4890	1972	1972
R^2	0.500	0.456	0.871	0.839	0.902	0.951

Standard errors clustered by household in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Each column represents an OLS regression based on Equation (2). All regressions include controls for the day of the week and time of day an order was made, a customer's past order count, a monthly time trend, and customer fixed effects. Columns (1) - (12) are restricted to customers who have made (i) at least ten orders, (ii) at least one order during the pre-Web period, and (iii) at least one order during the post-Web period. Columns (7) - (10) are restricted further to those customers who used a coupon for their order. Columns (11) - (12) are restricted to those customers who ordered only one base item. Columns (13) - (14) are restricted to those customers who ordered only one small pizza. Columns (15) - (16) are restricted to those customers who ordered at least six base items.

The first two regressions show that consumers make more complicated orders online. Using the mean complexity of the order's base items as the dependent variable in Column (1), online orders are approximately 14.6% more complex than the sample mean. Similarly, in Column (2) where the maximum complexity of the order's base items is the dependent variable, online orders are 14.2% more complex.

A customer may also experience embarrassment if others observe him making an order with excessive calories (Allen-O'Donnell et al. 2011). To test this theory, Column (3) uses the mean calories of the order's base items as the dependent variable. Here, the mean base item within an online order has 3.0% more calories compared to the sample mean. Using the maximum calories as the dependent variable in Column (4), online orders have 3.5% higher calories.

Collectively, these regressions suggest that customers make choices with less potential for embarrassment when a transaction requires more social interaction. To conclude that these findings stem from a social friction rather than some other unobserved factor, we next show that several alternative theories unrelated to embarrassment do not fully explain the differences among online orders.

3.4 Alternative Explanations Unrelated to Social Frictions

While the findings discussed above are robust to customer-level fixed effects and conservative sample restrictions, we now present additional evidence to support our claim that the inhibiting effects of social frictions best explain our results.

Information About Available Items One potential explanation for the long tail of online orders is that customers without access to a menu may be more likely to order prominent items. That is, without information about the full menu of products, a customer may simply order a pepperoni pizza because he recalls that item more readily, not because social frictions inhibit ordering complicated items verbally. And because online customers necessarily have access to the full menu, this may lead to a long-tail sales distribution as they become more aware of less prominent items. Several pieces of supporting evidence suggest that this is not a primary explanation for our results.

First, this setting is a familiar one for most customers and the store's menu is typical; anyone who has ordered from another pizza delivery restaurant presumably could surmise most of the full menu. Moreover, the estimation sample contains only customers who purchased from the store before online ordering became available, which suggests that they have familiarity with the store's offerings from previous transactions. As such, customers having better information about available items is unlikely to generate the substantial changes we observe for online orders.

Second, consider the results from the regression of topping size on online ordering presented in Columns (5) and (6). Here, the dependent variable is equal to one if the order has a customized topping instruction of a half or double portion, respectively. In this case, any customer who knows that a topping is available is also likely to know the topping is available in different amounts. And because Web customers are more likely to alter the size of their toppings, especially for larger portions, it seems unlikely that information about product offerings is responsible for the greater complexity among online orders.

Third, consider Columns (7)–(10) which present results from a sample restricted to customers who used a coupon. Because coupons come affixed to menus for this store, any customer who uses one plausibly has access to the same information about products as those who order online. All results are robust to this more conservative sample restriction.

Fourth, previous studies have shown that consumers with better access to nutritional information may consume fewer calories (Bollinger et al. 2011). Because the store's website has more prominent information about nutrition, the results pertaining to the impact of online ordering on the number of calories per item are conservative along this dimension.

Finally, custumers do not exhibit behavior consistent with learning after ordering online. If a lack of information about product offerings leads consumers to order more-prominent items over the phone, then becoming aware of less-prominent items after using the website should result in customers altering their behavior for subsequent phone orders. Based on a comparison of Web and non-Web orders for customers following their first online purchase, no such change occurs: customers continue to purchase more popular items (as well as items with fewer instructions and calories) in their subsequent phone orders, suggesting that the website does not make them more aware of less-prominent items.[12]

Ease-of-Use and Order Accuracy Another potential explanation for the long tail of online orders is that complex orders are easier to make on a website; that is, the results may be driven entirely by an easy-to-use online interface. We contend that ease-of-use does not explain our results for three primary reasons. First, an ease-of-use explanation also would apply to the number of base items within an order, as the mechanics of the website that would facilitate customized topping instructions also would facilitate ordering more base items. Recall from Table 6, however, that the average online order actually contains slightly fewer base items. Second, the store's employees likely have greater facility with the ordering system than any customer could possibly have with the website; they are simply more adept at using the store's sales terminal than a customer is at navigating the website. This is especially true for complex orders that require multiple button clicks online but could be entered quickly on the store's touchscreen sales terminals. Third, recall from Table 8 that customers order double portions of toppings more often online. Although it is as trivial for a customer to say, for example, "double bacon" over the phone as it is for him to click through the online drop-down topping menu twice, double and triple bacon orders increase more than ten times as much as double and triple orders for vegetable toppings.

Related to the ease-of-use explanation, consumers may avoid making complex orders

[12] Summary statistics reported in Appendix Table 6.

over the phone to reduce the potential for misunderstandings. While in the alcohol setting we could not rule out a fear of miscommunication as an explanation for why the self-service format affected sales of difficult-to-pronounce items, three institutional details in the pizza setting suggest that social frictions, and not concerns over miscommunication, best explain customers' choices.[13]

First, as discussed above, customers order double portions of toppings more often online. Furthermore, the increase is not driven by vegetable toppings: double and triple bacon orders increase more than ten times as much as double and triple orders for vegetable toppings.

Second, for customers' concerns about order accuracy to confound our results, consumers would have to believe that employees make fewer mistakes fulfilling online orders. It may well be the case, for instance, that an employee taking an order over the phone in a loud restaurant might not understand a customer's instructions and mistakenly deliver the wrong items. For this point, we have a (somewhat noisy) measure of mistakes: "voided" items that occur when an order changes during a call, either because the employee makes a mistake or because the customer alters his order after the fact. To determine if such mistakes prompt customers to place future orders online, we compare customers who had voided items in their orders during the pre-Web period to those who did not. Customers with voided items in the pre-Web period are not more likely to eventually use the Web, suggesting that concerns over the accuracy of complicated orders due to previous bad experiences does not explain Web use.

Third, and relatedly, those who made the most complex orders during the pre-Web period are not more likely to switch to ordering online. These customers are unlikely to be embarrassed about making complicated orders — they have done so before — but they would benefit the most from switching to online ordering if it were easier to make complicated orders through the website or to ensure that the correct items are delivered.

[13]Regression results in this section are presented in the Appendix Table 8.

Group Size Another potential confound for our results is that we do not observe the size of the group making the order. Related to the ease-of-use explanation above, a complicated order for a large group may be easier to make online in the sense that each person can individually input his instructions on the website rather than having one person relay several complicated instructions for the entire group over the phone. To this point, first note that online orders have the same number of base items, on average, suggesting that large groups do not disproportionately use the website. Second, consider Columns (11)-(12) of Table 8 that restrict the estimation sample to those customers who ordered only one base item. These orders are presumably more likely to come from a single individual, and so will not be affected by any group dynamics. In this case, all results are robust. Similarly, Columns (13)-(14) restrict the sample to orders for a single small pizza (though without the other sample restrictions because only 62 Web orders were made for a single small pizza among this group) and the results for complexity remain robust while those for calories do not. Finally, Columns (15)-(16) consider orders for six or more base items — these orders are more likely to be made by a large group, and hence the social interaction among group members may overwhelm any disinhibition effect from the website. The results are consistent with this hypothesis, as online orders become statistically indistinguishable from phone orders.

Selection Bias Consumers who order online may differ systematically from those who do not (Zentner et al. 2012). For instance, those more likely to use the Internet (e.g., teenagers) may also prefer to order complicated items for reasons unrelated to social frictions (e.g., teenagers have different preferences than adults). While we control for this confound directly by using individual-level fixed effects and conservative sample restrictions, we also provide further evidence that selection bias does not undermine our results in the appendix. Notably, customers who eventually order online make similar choices during the pre-Web period as those who never order online.

Discussion Given that the results on complexity and calories do not appear to be driven entirely by information, ease-of-use, order accuracy, or selection bias, we argue that the impersonal nature of Internet transactions is the most likely explanation for the different sales patterns across the online and offline channels. Next, we estimate the welfare effects that stem from such social transaction costs.

3.5 The Welfare Effects of Reducing Social Interaction

In contrast to the alcohol setting, the individual-level data from pizza orders allow us to estimate the welfare consequences of removing a layer of social interaction, both for consumers and the firm.

Consumer Surplus Because a number of customers switched to online ordering when given the choice, a straightforward revealed preference argument suggests that their welfare has increased. These potential welfare gains may derive from several sources. For one, some consumers may simply find ordering over the Internet more convenient. Moreover, the lack of social interaction may free consumers to configure their orders in a way that increases utility. On the other hand, some consumers may find ordering online more cumbersome, or even that complicated orders are easier to make in person. In light of such heterogeneity, this section outlines a random coefficients discrete choice model to quantify the gains in consumer surplus attributable to online ordering.

In the model, let consumer i choose among k discrete complexity options and m methods of ordering for each of his orders, o. In this case, k indexes the mean number of instructions for the base items within an order, rounded to the nearest integer such that $k \in \{1, \ldots, 6\}$, which captures 99% of orders. Furthermore, let $m \in \{Web, Non\text{-}Web\}$ represent the chosen method of ordering. The utility a customer derives from an order with a mean of k instructions through method m is then

$$U_{ikmo} = \beta_i^p Price_{ikmo} + \beta_i^c Complex_{ikmo} + \beta_i^w Web_{ikmo} + \beta_i^e Friction_{ikmo} + \varepsilon_{ikmo}, \quad (3)$$

where $Price_{ikmo}$ is the price associated with an order of mean complexity k; $Complex_{ikmo} \in \{0, \ldots, 6\}$ is the mean complexity of the order's base items associated with k ($Complex = 0$ is the outside option of no purchase), while β_i^c represents the utility consumer i derives from each unit of instruction; Web_{ikmo} is an indicator variable equal to one if the order was made online, while β_i^w represents the "cost" of ordering online — this estimated coefficient will be negative to rationalize why the majority of orders do not occur through the website; $Friction_{ikmo}$ is an indicator variable equal to one if the method of ordering m was not online and the mean complexity of the order's base items was $k \in \{4, 5, 6\}$ — β_i^e then represents the disutility of making a complex, potentially embarrassing or frustrating order in the presence of others;[14] and ε_{ikmo} is an unobserved error term that is identically and independently distributed extreme value and independent of $\{Price_{ikmo}, Complex_{ikmo}, Web_{ikmo}, Friction_{ikmo}\}$ and β_i. Finally, the outside option of not ordering has a utility normalized to zero. Estimation follows Train (2003).

The sample for estimation is restricted to the 2030 customers (i) who have made at least 10 orders, (ii) who ordered in both the pre- and post-Web period, and (iii) who have a mean base item complexity of six or less. The period spans 56 months and the counterfactual price is taken to be the average price across the sample period.

The results from a random coefficients logit appear in Column (3) of Table 9. The coefficients suggest that the mean "cost" of using the website has an implicit price of nearly \$8.90, with considerable heterogeneity around this mean. In addition, customers derive greater average utility from providing more instructions per item, holding price constant — about \$0.85 per instruction, on average. This preference varies considerably throughout the sample, however, as the standard deviation of the coefficient on complexity is more than twice as large as the mean effect. Finally, and most importantly, social interaction has a meaningful and heterogeneous effect on order choices: for orders that may be embarrassing or frustrating due to their complexity, social frictions have

[14] Approximately 20 percent of orders have a mean item complexity of 4 or higher.

an average implicit price of \$2.75, while those customers two standard deviations above the mean have a price equivalent to \$5.92. Characterizing social transaction costs based on excessive calories yields qualitatively similar results.

Table 9: Coefficient estimates of the structural demand model.

	(1)	(2)	(3)
Mean Price	-0.763***	-0.778***	-0.579***
	(0.00245)	(0.00194)	(0.0217)
Std. Dev. Price			0.390***
			(0.01118)
Mean Web	-3.019***	-3.007***	-5.154***
	(0.0226)	(0.0226)	(0.276)
Std. Dev. Web			3.187***
			(0.3286)
Mean Complex	0.377***	0.431***	0.491***
	(0.00734)	(0.00613)	(0.0701)
Std. Dev. Complex			1.083***
			(0.03829)
Mean Friction	-0.667***	-0.751***	-1.595***
	(0.0225)	(0.0187)	(0.164)
Std. Dev. Friction			2.592***
			(0.1062)
Constant	1.623***		
	(0.00446)		
Observations	3702720	3702720	3702720
LL	-384061.69	-376992.4	-208119.25

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Covariance	Price	Web	Complex	Friction
Price	0.1524			
Web	0.2464	10.16		
Complex	-0.4085	-1.0954	1.1728	
Friction	0.7318	3.1945	-2.3106	6.7167

This table presents the estimated coefficients from the discrete choice model in Equation (3). "Friction" is defined as highly complex requests ordered offline. Column (1) contains the results from a logit specification. Column (2) contains the results from a fixed-effects logit. Column (3) contains the results from a mixed logit.

A full covariance matrix also was estimated for the parameters in the random coefficient logit, as shown at the bottom of Table 9. Our measure of social frictions is positively related to price sensitivity and the cost of Web use, though negatively related to the utility of providing more instructions per item.

Importantly, the random coefficients model permits a calculation of a consumer's willingness to pay for certain order attributes. Following Train (1998), Train (2003), and Revelt & Train (1998), the change in consumer surplus for a given β is

$$C_{io} = \frac{ln \sum_k \sum_m exp(\beta x_{ikmo}) - ln \sum_k \sum_l exp(\beta x_{iklo})}{\beta^p}, \quad (4)$$

where l indexes a counterfactual choice setting without online ordering. The compensating variation for consumer i and order o is then

$$CV_{io} = \int C_{io}(\beta) f(\beta|\theta) d\beta, \quad (5)$$

where θ represents the true parameters.

The average compensating variation constitutes the average of CV_{io} taken over all orders by all consumers in the sample. Based on 1000 Monte Carlo simulations and 1% tail truncation, consumer surplus has increased 5.4% due to online ordering as consumers avoid social transaction costs while making more-complex orders. These gains resemble those of Brynjolfsson et al. (2003) who estimate that consumer welfare increased by up to 4.2% due to a larger selection of products available at online booksellers.[15] In this sense, freeing consumers to choose their most-preferred item configuration without the need for social interaction increases utility by an amount similar to having access to a greater selection of products over the Internet.

Producer Surplus Because an item's price is non-decreasing in its complexity, the store stands to gain by reducing social frictions through Web ordering. And the store does benefit, in that customers spend roughly $0.45 more when they order online, based on a regression with the same controls and restrictions as Equation (2). Notably, this increase in spending occurs on the intensive margin, so the store's per-item margin of

[15]Brynjolfsson et al. (2003) estimate a consumer welfare gain between $731 million to $1.03 billion in 2000 relative to overall book sales of $24.59 billion.

approximately 66% applies. That is, conditional on an order occurring, the store earns approximately \$0.29 in additional profits by allowing customers to order on the Web to the extent that other costs do not change (e.g., labor costs do not increase because orders have become more complex).

To account for the full effect of online ordering on the store's profits, note that customers using the Web would have made 0.416 orders per month, on average, but their spending increases by \$0.45. In addition, Web users increase their order frequency by 0.072 orders per month and spend, on average, \$15.46 per order. Thus, the store's average monthly gain from each Web customer is \$1.30, or 21.4%. As Web customers now constitute roughly 17% of the store's total sales, the store earns 3.6% more annually than it would in a counterfactual setting without online ordering. Note, however, that an absence of information about competitors restricts us to providing only a short-run approximation of the incremental profits the store earns each year from online orders.

These gains may seem underwhelming given the received wisdom that online platforms "disrupt" markets; however, online orders typically come from pre-existing customers — the store would reap a majority of these orders through traditional channels anyway, and thus a counterfactual estimate of the incremental benefits from online ordering must account for any cannibalized sales. In this sense, the findings here resemble the relatively modest counterfactual gains attributable to the Internet's diffusion documented elsewhere (Greenstein & McDevitt 2011).

Summary Overall, our calculations suggest that the frictions associated with social interaction have a substantial impact on welfare in this setting. For consumer surplus, the gain resembles prior estimates of the impact from online stores' larger selection of products. For producer surplus, the increase, while modest, nevertheless rationalizes the firm's decision to implement online ordering.

3.6 Social Transaction Costs and the Long Tail Phenomenon

As shown in Table 7, the store's online orders have a significantly less concentrated sales distribution than its phone and counter orders. Previous theories for why a long tail characterizes online sales — namely, greater product selection and better search capabilities — are unlikely to apply to pizza orders, however, as the menu remains constant and consumers search similarly across channels. Instead, the distinguishing feature of online pizza orders is that they require less social interaction. As such, we directly explore the impact of reducing social frictions by considering a series of regressions that use the fraction of items in an order that are among the top ten most popular products as the dependent variable and that include the same controls and restrictions as Equation (2); the results appear in Table 10.

Table 10: Regression results of orders influenced by social interaction and the long tail.

	(1) % Top Ten Items	(2) % Top Ten Items	(3) % Top Ten Items	(4) % Top Ten Items
Covariate →	Web Order	Extreme Complex	Extreme Calories	Extreme Comp./Cal.
	-0.0781***	-0.0684***	-0.0773***	-0.0802***
	(0.0103)	(0.0095)	(0.0129)	(0.0083)
Observations	48446	48446	48446	48446
R^2	0.408	0.407	0.407	0.408

Each column represents an OLS regression based on Equation (2). Dependent variable is the proportion of items within an order among the store's top ten most ordered items. Includes controls for the day of the week and time of day an order was made, a customer's past order count, a monthly time trend, and customer fixed effects. Sample restricted to customers who have made (i) at least ten orders, (ii) at least one order during the pre-Web period, and (iii) at least one order during the post-Web period. "Extreme" orders are defined to be approximately in the top 2% in terms of complexity or calories. Unit of observation is an order. Standard errors clustered by household in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Column (1) links online orders to the long tail. In this specification, those who order online have 7.8 percentage points fewer items among the top ten most popular, as would be expected given the results from Table 7. Columns (2)-(4) then directly show how social frictions impact the sales distribution: for all specifications, those customers who make extreme choices (defined as top 2%) in terms of complexity or calories also purchase fewer items among the store's most popular. As online orders are more likely to have an extreme number of calories or instructions, and these orders are more likely to be less concentrated, the long-tail effect thus prevails among the store's online orders.

4 Conclusions

We have documented that, in two different retail settings, social interactions have a substantial effect on the types of products purchased by consumers. First, using data from a field experiment in which stores changed formats from behind-the-counter to self-service, we showed that difficult-to-pronounce products experienced a disproportionately large increase in sales. Second, we showed that the addition of an online ordering channel increased the sales of high-calorie and complex items at a pizza delivery restaurant. Based on the covariates related to sociality incorporated into our choice model, consumer surplus increased by a proportion similar to that estimated by Brynjolfsson et al. (2003) for the greater selection of products available at online bookstores.

Together, these results suggest that personal interactions may inhibit certain kinds of economic activity, perhaps because customers wish to avoid the potential for embarrassment. While a prior literature in psychology, sociology, and medicine has documented that individuals behave differently in sexually-charged or health-related settings that involve personal interactions, our results suggest that the phenomenon is broader and applies even to relatively mild social frictions, such as mispronouncing the name of a product or making a complex pizza order. In addition to roles of social networks, reciprocity, and altruism discussed in McFadden (2010), our results suggest that the potential for embarrassment — in the sense described by Goffman (1959) — is another aspect of sociality that can influence preferences.

We hasten to note, however, that our empirical settings have certain limitations that limit the scope of our conclusions. First, we analyze just two settings. And though these settings are common, their applicability to other markets, particularly beyond retail, remains speculative. Second, while the lack of competition in our alcohol setting is an advantage in terms of cleanly linking the change in sales format to the change in sales patterns, our welfare analysis in the pizza setting is necessarily limited in that it does not take into account competitors' responses; thus, our estimate of the impact on welfare is necessarily a short-run approximation. Third, while we have attempted to eliminate other possible interpretations for our results, we have simply documented that contexts with different levels of social interaction yield different outcomes — we cannot definitively conclude that this change is due to a social friction such as embarrassment. Thus, a more cautious interpretation of our results is that they simply demonstrate the importance of a transaction's context on the transaction itself, while leaving unsettled which particular mechanism affects consumers. In our case, we emphasize the role of social frictions because other explanations, such as consumers' recall of products from memory, are unlikely to explain our results across both empirical settings.

Despite these limitations, documenting similar outcomes across two distinct empirical settings, each with their own strengths and weaknesses, highlights the extent to which social interactions can inluence consumers. As such, our results provide a new explanation for the prevalence of long-tail sales distributions in online markets: impersonal transactions lead consumers to purchase a different mix of products than they would in settings where social interactions might act as an impediment. Our results are also consistent with recent economic models of privacy, especially Daughety & Reinganum (2010), that frame privacy as an individual's desire for others to perceive her choices in a positive light. Consistent with Goffman (1959) and others, our results suggest that personal interactions are an important aspect in enhancing this desire. By adding this aspect of sociality into preference formation, our results help explain why online settings, which are devoid of personal interactions, lead consumers to alter their behavior and establish an important perceived benefit of online commerce not previously mentioned in the economics literature (Scott Morton 2006). Speculatively, as a larger share of transactions move online, the prevalence of what was previously embarrassing economic activity will continue to increase.

Overall, our results build on the recent work in economics that examines the effect of emotions and social cues on behavior (Card & Dahl 2011, Ifcher & Zarghamee 2011, Li et al. 2010, Akerlof & Kranton 2000, Rabin 1993, Daughety & Reinganum 2010, DellaVigna et al. 2012, McFadden 2013). Our results suggest that social interactions may inhibit economic activity, and including these social interactions in choice estimation demonstrates that they can lead to reductions in consumer surplus and overall welfare.

References

Ahmad, F., Hogg-Johnson, S., Stewart, D., Skinner, H., Glazier, R. & Levinson, W. (2009), 'Computer-assisted risk screening for intimate partner violence: A randomized controlled trial', *Annals of Internal Medicine* **151**(2), 93–102.

Akerlof, G. A. & Kranton, R. E. (2000), 'Economics and identity', *Quarterly Journal of Economics* **115**(3), 715–753.

Akerlof, G. A. & Kranton, R. E. (2008), 'Identity, supervision, and work groups', *American Economic Review Papers and Proceedings* **98**(2), 212–217.

Allen-O'Donnell, M., Cottingham, M., Nowak, T. & Snyder, K. (2011), 'Impact of group settings and gender on meals purchased by college students', *Journal of Applied Social Psychology* **41**(9), 2268–2283.

Anderson, C. (2004), 'The long tail', *Wired Magazine* **12**(10), 170–177.

Ariely, D. & Levav, J. (2000), 'Sequential choice in group settings: Taking the road less traveled and less enjoyed', *Journal of Consumer Research* **27**(3), 279–290.

Baddeley, A. D., Thomson, N. & Buchanan, M. (1975), 'Word length and the structure of short-term memory', *Journal of Verbal Learning and Verbal Behavior* **14**(6), 575–589.

Banaji, M. & Prentice, D. (1994), 'The self in social contexts', *Annual Review of Psychology* **45**(1), 297–332.

Bertrand, M., Duflo, E. & Mullainathan, S. (2004), 'How much should we trust differences-in-differences estimates?', *Quarterly Journal of Economics* **119**(1), 249–275.

Bollinger, B., Leslie, P. & Sorensen, A. (2011), 'Calorie posting in chain restaurants', *American Economic Journal: Economic Policy* **3**(1), 91–128.

Brynjolfsson, E., Hu, Y. J. & Smith, M. (2003), 'Consumer surplus in the digital economy: Estimating the value of increased product variety at online booksellers', *Management Science* **49**(11), 1580–1596.

Brynjolfsson, E., Hu, Y. & Simester, D. (2011), 'Goodbye pareto principle, hello long tail: The effect of search costs on the concentration of product sales', *Management Science* **57**(8), 1373–1386.

Card, D. & Dahl, G. B. (2011), 'Family violence and football: The effect of unexpected emotional cues on violent behavior', *Quarterly Journal of Economics* **126**, 103–143.

Chapple, A., Ziebland, S. & McPherson, A. (2004), 'Qualitative study of men's perceptions of why treatment delays occur in the uk for those with testicular cancer', *The British Journal of General Practice* **54**(498), 25.

Coopersmith, J. (2000), 'Pornography, videotape, and the internet', *IEEE Technology and Society Magazine* **19**(1), 27–34.

Dahl, D., Gorn, G. & Weinberg, C. (1998), 'The impact of embarrassment on condom purchase behavior', *Canadian Journal of Public Health* **89**(6), 368–370.

Daughety, A. & Reinganum, J. (2010), 'Public goods, social pressure, and the choice between privacy and publicity', *American Economic Journal: Microeconomics* **2**(2), 191–221.

De los Santos, B. I., Hortacsu, A. & Wildenbeest, M. (2012), 'Testing models of consumer search using data on web browsing and purchasing behavior', *American Economic Review* **Forthcoming**.

DellaVigna, S., List, J. A. & Malmendier, U. (2012), 'Testing for altruism and social pressure in charitable giving', *Quarterly Journal of Economics* **127**(1), 1–56.

Edelman, B. (2009), 'Red light states: Who buys online adult entertainment?', *Journal of Economic Perspectives* **23**(1), 209–220.

Fehr, E., Kirchsteiger, G. & Riedl, A. (1993), 'Does fairness prevent market clearing? an experimental investigation', *Quarterly Journal of Economics* **108**(2), 437–459.

Gackenbach, J. (2007), *Psychology and the Internet: Intrapersonal, Interpersonal, and Transpersonal Implications*, Academic Press.

Goffman, E. (1956), 'Embarrassment and social organization', *American Journal of Sociology* **62**(3), 264–271.

Goffman, E. (1959), *The Presentation of Self in Everyday Life*, Garden City, NY: Doubleday Anchor Books.

Greenstein, S. & McDevitt, R. (2011), 'The broadband bonus: Estimating broadband internet's economic value', *Telecommunications Policy* **35**(7), 617–632.

Griffiths, M. D. (2001), 'Sex on the internet: Observations and implications for internet sex addiction', *The Journal of Sex Research* **38**(4), 333–342.

Herman, C. & Polivy, J. (1996), 'What does abnormal eating tell us about normal eating?', *Food Choice, Acceptance, and Consumption* pp. 207–238.

Ifcher, J. & Zarghamee, H. (2011), 'Happiness and time preference: The effect of positive affect in a random-assignment experiment', *American Economic Review* **101**, 3109–3129.

Keltner, D. & Buswell, B. N. (1997), 'Embarrassment: Its distinct form and appeasement functions', *Psychological Bulletin* **122**, 250–270.

Klass, E. T. (1990), Guilt, shame, and embarrassment: Cognitive behavioral approaches, *in* H. Leitenberg, ed., 'Handbook of Social and Evaluation Anxiety', Plenham, New York, pp. 385–414.

Lee, A. & Goldman, M. (1979), 'Effect of staring on normal and overweight students', *The Journal of Social Psychology* **108**(2), 165–169.

Lerman, C., Rimer, B., Trock, B., Balshem, A. & Engstrom, P. (1990), 'Factors associated with repeat adherence to breast cancer screening', *Preventive Medicine* **19**(3), 279–290.

Li, H., Rosenzweig, M. & Zhang, J. (2010), 'Altruism, favoritism, and guilt in the allocation of family resources: Sophie's choice in Mao's mass send-down movement', *Journal of Political Economy* **118**(1), 1–38.

Lindner, E. G. (2001), 'Humiliation and the human condition: Mapping a minefield', *Human Rights Review* **2**(2), 46–63.

McDevitt, R. & Roberts, J. (2011), 'Market Structure and Gender Disparity in Health Care: Preferences, Competition, and Quality of Care'. Mimeo, University of Rochester.

McFadden, D. (2010), Sociality, rationality, and the ecology of choice, *in* S. Hess & A. Daly, eds, 'Choice Modelling: The State-of-the-Art and the State-of-Practice', Academic Press, pp. 3–18.

McFadden, D. L. (2013), 'The new science of pleasure', *NBER Working Paper 18687* .

Meischke, H., Eisenberg, M. S., Schaeffer, S. M., Damon, S. K., Larsen, M. P. & Henwood, D. K. (1995), 'Utilization of emergency medical services for symptoms of acute myocardial infarction', *Heart and Lung* **24**, 11–18.

Niemi, R. (1976), 'Costs of voting and nonvoting', *Public Choice* **27**, 115–119.

Polivy, J., Herman, C., Hackett, R. & Kuleshnyk, I. (1986), 'The effects of self-attention and public attention on eating in restrained and unrestrained subjects.', *Journal of personality and social psychology* **50**(6), 1253.

Pozzi, A. (forthcoming), 'Shopping cost and brand exploration in online grocery', *American Economic Journal: Microeconomics* .

Rabin, M. (1993), 'Incorporating fairness into game theory and economics', *American Economic Review Papers and Proceedings* **83**(5), 1281–1302.

Revelt, D. & Train, K. (1998), 'Mixed logit with repeated choices: Households' choices of appliance efficiency level', *Review of Economics and Statistics* **80**(4), 647–657.

Rosman, K. (2012), 'Books women read when no one can see the cover', *The Wall Street Journal* .

Roth, D., Herman, C., Polivy, J. & Pliner, P. (2001), 'Self-presentational conflict in social eating situations: A normative perspective', *Appetite* **36**(2), 165–171.

Scott Morton, F. (2006), 'Consumer benefit from use of the internet', *Innovation Policy and the Economy* **6**, 67–90.

Seim, K. & Waldfogel, J. (2012), 'Public Monopoly and Economic Efficiency: Evidence from the Pennsylvania Liquor Control Boards Entry Decisions', *American Economic Review* **forthcoming**.

Skog, O. (2000), 'An experimental study of a change from over-the-counter to self-service sales of alcoholic beverages in monopoly outlets', *Journal of Studies on Alcohol* **61**(1), 95–100.

Suler, J. (2004), 'The online disinhibition effect', *CyberPsychology & Behavior* **7**(3), 321–326.

Thomas, K. (2013), 'Facing black market, pfizer is looking online to sell viagra', *The New York Times* .

Train, K. (1998), 'Recreation demand models with taste differences over people', *Land economics* pp. 230–239.

Train, K. (2003), *Discrete Choice Methods with Simulation*, Cambridge University Press.

Waters, A., Hill, A. & Waller, G. (2001), 'Internal and external antecedents of binge eating episodes in a group of women with bulimia nervosa', *International Journal of Eating Disorders* **29**(1), 17–22.

Zentner, A., Smith, M. & Kaya, C. (2012), 'Bricks, clicks, blockbusters, and long tails: How video rental patterns change as consumers move online'. Mimeo, Carnegie Mellon.