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Consumer Preferences for Mass Customization

Benedict G. C. Dellaert and Stefan Stremersch

Mass customization lets customers "create" products that closely match their needs, but too much complexity in the product offering can diminish its value. This study examines how managers can design mass customization offerings to maximize consumer product utility and minimize perceived complexity.

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Report Summary

Mass customization—allowing consumers to create their own products online by specifying the product characteristics they desire—offers firms an exciting opportunity to build consumer satisfaction and loyalty by delivering products that closely match consumers' actual needs. But to be most effective, these mass-customization interfaces must tread a fine line: They must be simple to use so that consumers do not give up in frustration, yet complex enough to allow the consumer to specify exactly the product that will most satisfy them.

Using the example of mass customization of personal computers, Dellaert and Stremersch examine how four mass-customization configuration design parameters affect consumers' perceptions of a configuration's complexity and usefulness: extent of mass customization (how many variables can be specified by the consumer or how many choices are offered for each variable), level heterogeneity (how widely dispersed the range of choices is), individual pricing of modules (whether the consumer is informed of the price of individual product elements as well as the overall product price), and presence and nature of a default version (whether a default is offered at all, and, if it is offered, whether the default is at the high or low end in quality and price).

The authors find that these four factors do indeed affect consumer perceptions of mass-customization configuration utility and complexity, and they make the following recommendations. First, firms should offer consumers a wide range of choices, because this raises product utility without a significant rise in perceived complexity. Second, more of the options offered to consumers should be close to the most popular option than at the extremes. Third, prices should be shown only at the entire-product level and not for individual components. Fourth, default versions should be offered to minimize complexity, and they should be at the low end. Finally, expert consumers, who experience mass customization as less complex, are ideal targets for mass customization offerings. ∎

Introduction

Advances in engineering and information technology have allowed firms to be highly flexible and responsive in providing product variety through mass customization (e.g., Pine, Victor, and Boyton 1993).[1] Marketing researchers, however, are just beginning to explore the effectiveness of mass-customization strategies from a customer's perspective (Huffman and Kahn 1998; Wind and Rangaswamy 2001). Liechty, Ramaswamy, and Cohen (2001) modeled the product choices consumers make in a mass-customization configuration.

Our research focuses on consumer preferences for different mass-customization configurations. Mass-customization configurations refer to the outline or arrangement of the different product modules that can be mass customized. For instance, mass-customization configurations may differ in the number or levels of product modules that the consumer may customize or in the way total-product and module-level prices are presented to consumers. Little is known about how different mass-customization configurations differentially affect the utility a consumer derives from mass customization.

The theory we develop to explain consumer preferences for mass-customization configurations builds on choice task complexity theory (e.g., Bettman, Johnson, and Payne 1990; Johnson and Payne 1985), consumer choice theory (McFadden 1986), and loss aversion theory (Tversky and Kahneman 1991). Its central premise is that consumers' latent utility for using a certain mass-customization configuration ("mass-customization utility") is simultaneously affected by (1) the product utility that can be achieved by using the mass-customization configuration ("product utility") and (2) consumers' perception of the complexity of composing their product when using the mass-customization configuration ("complexity"). It also identifies mass-customization configuration factors that may differentially affect both product utility and complexity. To test the

developed theory, we use data from an experiment involving mass-customized PC purchases. The extended logit model (Ashok, Dillon, and Yuan 2002) that we specify simultaneously estimates (1) the measurement equations for the latent constructs: product utility, complexity, and mass-customization utility; (2) the effects of product utility and complexity on mass-customization utility; and (3) the effects of mass-customization configuration factors on product utility and complexity. It also allows for differences between consumers based on consumer expertise (e.g., Alba and Hutchinson 1987) and unobserved factors (through a random coefficient specification).

This paper contributes to the marketing literature in several ways. First, our focal question—why consumers prefer one mass-customization configuration over another—is novel and relevant. For instance, this question is relevant for companies such as Dell or HP in developing and adjusting their mass-customization configurations. Second, we develop a structural model that details which factors determine the utility a consumer derives from a mass-customization configuration. Third, we find empirical support for the developed theory through estimating a random coefficient specification of the extended logit model.

Research Hypotheses

In this section, we first theorize that two latent factors determine the utility a consumer derives from a mass-customization configuration, namely product utility and complexity (see Figure 1). Second, we discuss the effect of mass-customization configuration factors on product utility and complexity.

The effect of product utility and complexity on mass-customization utility

First, we expect that mass-customization configurations that allow consumers to select products of higher utility are evaluated more positively and therefore have higher mass-

Figure 1
Mass-Customization Utility Model*
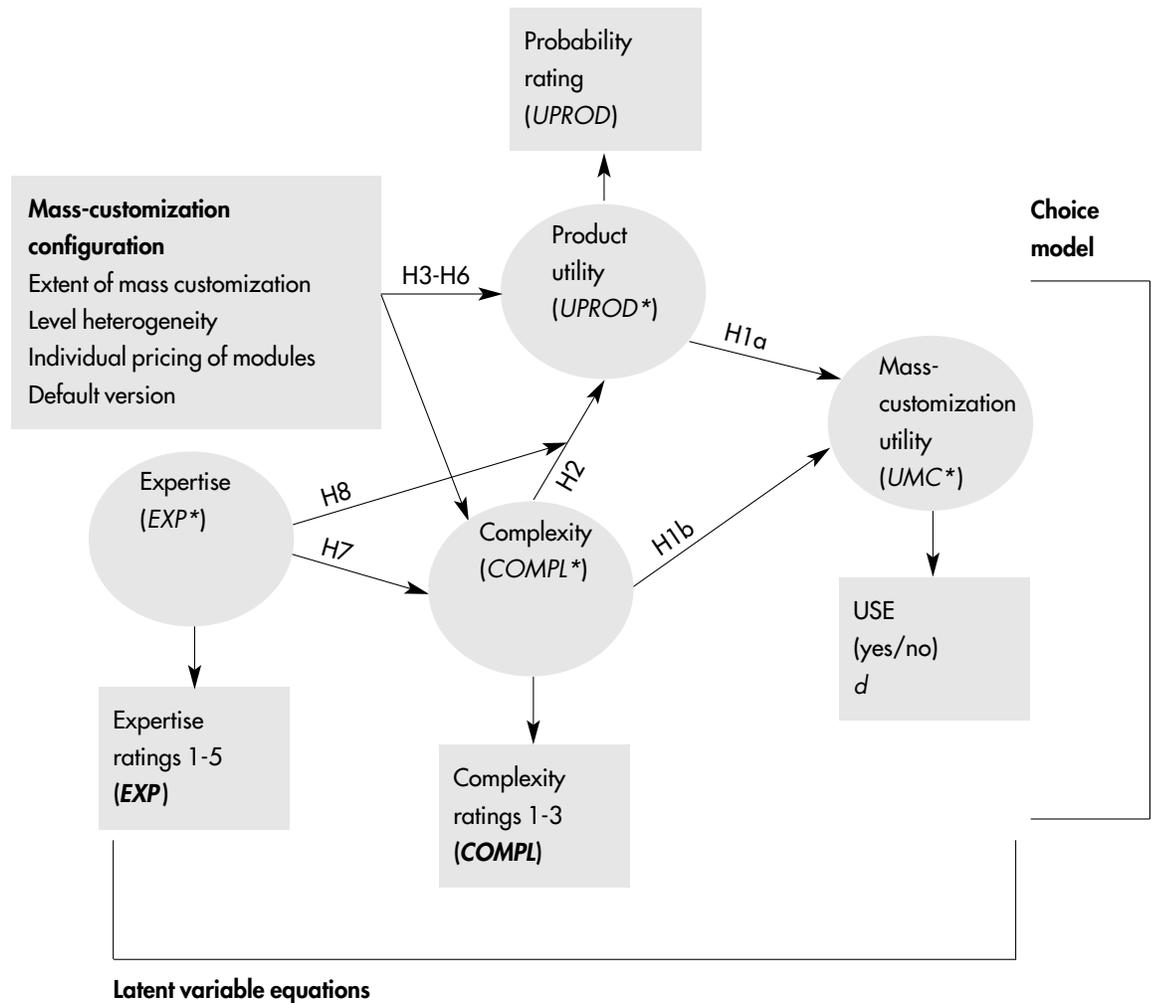
* Note: Rectangles represent the observed measures and the factors manipulated in the experimental study, and circles represent the underlying latent constructs. Arrows running from left to right represent hypothesized relationships, where an arrow between boxes represents a hypothesized main effect, and an arrow pointing at another arrow represents a hypothesized interaction effect. Vertical arrows represent measurement relationships.

customization utility. Second, we expect that more-complex mass-customization configurations are evaluated more negatively and therefore have lower mass-customization utility. The reason is that increased complexity requires greater consumer effort to generate the same mass-customized product (Johnson and Payne 1985) and that, all else equal, consumers prefer to minimize decision effort (Wright 1975).

H1a: The product utility that can be achieved by using a mass-customization configuration

has a positive effect on mass-customization utility.

H1b: The complexity of using a mass-customization configuration has a negative effect on mass-customization utility.

We also expect that complexity may directly affect product utility. As mass customization becomes more complex, it becomes more likely that consumers will resort to simplifying decision heuristics (e.g., Newell and Simon 1972).

The use of heuristics in turn makes it less likely that consumers will select the product with the highest possible product utility. The reason is that heuristics force consumers to take into account only a subset of all module tradeoffs, and therefore the product they compose may be suboptimal.

H2: The complexity of using a mass-customization configuration has a negative effect on the product utility that can be achieved by using a mass-customization configuration.

The effect of mass-customization configuration factors on product utility and complexity

We discern four factors on which mass-customization configurations may differ and that may have differential effects on product utility and complexity. The first factor is the extent of mass customization. A configuration low in extent of mass customization may offer fewer modules that can be mass customized (e.g., only memory and processor of a PC can be mass customized), or fewer levels among which to choose per mass-customizable module (e.g., for mass customization of the processor, only two processing speeds are available), than a configuration high in extent of mass customization.

The second factor is the heterogeneity in the levels available for a mass-customizable module. A configuration low in level heterogeneity may offer consumers only very similar module levels to choose from (e.g., a 17-inch or 18-inch screen), while a configuration high in level heterogeneity may offer consumers very different module levels (e.g., a 15-inch or 21-inch screen). The third factor is the individual pricing of modules within a mass-customization configuration. The price of individual modules may be shown along with the total product price (e.g., the price of the different processors as well as the computer's total price), or only the total product price may be shown. The fourth factor is the presence and level of a default. A mass-customization configuration may show a default version (e.g., preselected processor speed) or it may not, and a default

version may be high end (e.g., the highest processing speed is preselected) or low end (e.g., the lowest processing speed is preselected).

We identified these four mass-customization configuration factors for three main reasons. First, when we examined existing mass-customization configurations in the context of PC purchasing, we found that differences between mass-customization configurations were strongly pronounced on these four factors. Second, these four factors have a consistent theoretical background. They all affect complexity through the number of tradeoffs consumers make while composing their mass-customized product. They also all affect product utility through the extent to which consumers are able to select a product close to their ideal product (i.e., the product that has the most attractive combination of product components for that consumer).

Extent of Mass Customization. Increases in the extent of mass customization lead to a greater number of possible products that can be composed through the mass-customization configuration. On the one hand, such increases likely reduce the average distance between the mass-customized product a consumer may compose and his or her ideal product, thereby increasing product utility. On the other hand, consumers need to make tradeoffs among a greater number of possible product components, which increases the number of cognitive steps in the consumer decision-making process and thereby increases perceived complexity (Bettman, Johnson, and Payne 1990).

H3a: The extent to which products can be mass customized increases the product utility that can be achieved by using a mass-customization configuration.

H3b: The extent to which products can be mass customized increases the complexity of using a mass-customization configuration.

Level Heterogeneity. An important determinant of product utility may be whether con-

sumers can find their most preferred level, which is consistent with research on consumer perceptions of retail assortments (Broniarczyk, Hoyer, and McAlister 1998). Given a certain extent of mass customization, a mass-customization configuration that offers module levels that are relatively close to the mean (low level heterogeneity) allows a larger number of consumers to select their most preferred module levels than does a configuration with levels that are more dispersed (high level heterogeneity). Thus, we hypothesize that increasing level heterogeneity (for a given extent of mass customization) has a negative effect on product utility.

H4a: Increasing heterogeneity in module levels decreases the product utility that can be achieved by using a mass-customization configuration.

Note that this hypothesis assumes that consumer module-level preferences are heterogeneous and concentrated around the mean (for example, following a normal distribution [Allenby, Arora, and Ginter 1999]).

We also expect that greater level heterogeneity increases complexity, because decision complexity increases as the differences in the tradeoffs between different module levels increase. While Bettman, Johnson, and Payne (1990) highlighted the effect of the number of cognitive steps on consumer decision complexity, others have shown that larger variance in tradeoffs also increases choice complexity (Chatterjee and Heath 1996). As module levels become more heterogeneous, tradeoff variance increases, and hence we expect complexity to increase as well.

H4b: Increasing heterogeneity in module levels increases the complexity of using a mass-customization configuration.

Individual Pricing of Modules. Individual pricing of modules may affect product utility for several reasons. In particular, we expect that including individual pricing of modules makes price more salient to consumers since it more

clearly expresses the prices associated with each module, and consumers tend to focus on information that is explicitly displayed (e.g., Slovic 1972). Individual pricing may also lead to a more disaggregate perception of monetary losses and hence a higher perceived total price (e.g., Tversky and Kahneman 1991). Therefore we expect that individual pricing leads consumers to select less-expensive product components, thereby obtaining a lower-quality product when higher-quality product components have higher prices.

H5a: Individual pricing of modules decreases the product utility that is achieved when using a mass-customization configuration.

We also expect that individual pricing of modules increases complexity because of the greater cognitive effort involved in processing the separate price information. Presenting individual module prices along with the total price emphasizes more clearly the separate cost-benefit tradeoffs that consumers need to make for each module. Therefore, we expect that on average, consumers are likely to be more aware of the number of tradeoffs (i.e., cognitive steps) they need to make and that this in turn leads to a greater perceived effort in the decision and a higher perceived complexity (cf. Bettman, Johnson, and Payne 1990; Johnson and Payne 1985).

H5b: Individual pricing of modules increases the complexity of using a mass-customization configuration.

Default Version. A final mass-customization configuration factor that we address is the default version of the mass-customizable product that is offered, if any. Prior research suggests that across many different applications, consumers are more willing to switch "up" to higher-price, higher-quality products than to switch "down" to lower-price, lower-quality products (e.g., Simonson, Kramer, and Young 2003). A possible explanation for this effect is that there is an asymmetry in price and quality loss aversion that makes the quality loss rela-

tively harder to compensate in monetary terms than vice versa (Park, Jun, and MacInnis 2000; Tversky and Kahneman 1991). Based on these previous findings, we expect that consumers presented with a base default will select a product that is closer to their ideal product than will consumers presented with an advanced default, as the former will be more willing to switch up than the latter will be to switch down.

H6: Offering a base default version leads to a higher product utility when using a mass-customization configuration than offering an advanced default version.

We also expect that providing a default version will affect complexity. The reason is that a default version that is closer to a consumer's ideal product may allow the consumer to go through a smaller number of module-level comparisons than will a default that is further away from the consumer's ideal product. Thus a base default version or an advanced default version may be closer to a consumer's product preference, and complexity may be greater or smaller. We include a control variable in our model to allow for this effect.

The role of consumer expertise

Prior research has shown that consumer expertise plays a central role in consumer ability to deal with task complexity (e.g., Alba and Hutchinson 1987; Spence and Brucks 1997). Therefore we expect that consumers with high consumer expertise will experience less complexity when participating in mass customization than will consumers with low consumer expertise (cf. Huffman and Kahn 1998).

H7: Consumer expertise decreases the complexity of using a mass-customization configuration.

Furthermore, we expect that even if they perceive a certain mass-customization configuration to be complex, consumers with high expertise are relatively less likely to have to resort to the use of decision heuristics, and the heuristics they use will be more effective (cf. H2). For

example, Alba and Hutchinson (1987) argued that higher consumer expertise leads to a greater ability to analyze information and to select the information that is most important and task relevant. Therefore, we expect that the product utility that experts can achieve in mass customization is affected less strongly by complexity than that of nonexperts.[2]

H8: The negative effect of complexity on product utility in using a mass-customization configuration is weaker for consumers with high expertise than for consumers with low expertise.

Data

We tested our hypotheses through an experiment in which we manipulated mass-customization configurations for PCs. We asked consumers to mass customize PCs under different experimental conditions that mimicked real-world mass-customization configurations and to choose whether or not they would use the mass-customization configuration if it were to become available. Thus we could study consumers' choices whether or not to use a mass-customization configuration depending on the factors that we hypothesized in H3-H6 and manipulated in the experiment.

Respondents

Respondents in the experiment were real-life consumers who are members of an ongoing consumer panel of approximately 2,000 individuals at Tilburg University. Data were collected in 2001. The Web-based panel was used to collect a variety of data. Respondents participated in the experiment via their home Web connections. Panel participants were selected randomly from the total population of the Netherlands and are provided with Web access by the panel management if they didn't have access at the time of becoming a member of the panel. After eliminating respondents under 16 years of age, respondents with no experience or interest in PC purchasing, and respondents with missing values or invalid responses, 409

Table 1a

Mass-Customization Configuration Factors as Manipulated in the Experiment

Characteristic	Levels	Description
Extent of Mass Customization		
Number of mass-customizable modules	Low	4 (processor, monitor, memory, and hard drive)
	High	8 (processor, monitor, memory, hard drive, mouse, keyboard, video card, and speakers)
Number of levels per mass-customizable module*	Low	4 (for first four modules); 2 (for second four modules)
	High	8 (for first four modules); 4 (for second four modules)
		Module levels included (ranked from 1 to 15)
Level Heterogeneity*	Low	4, 5, 6, 7
		4, 5, 6, 7, 8, 9, 10, 11
		4, 5, 6, 7 and 2, 3
		4, 5, 6, 7, 8, 9, 10, 11 and 2, 3, 4, 5
	High	3, 5, 7, 9
		1, 3, 5, 7, 9, 11, 13, 15
		3, 5, 7, 9 and 1, 3
		1, 3, 5, 7, 9, 11, 13, 15 and 1, 3, 5, 7
Individual Pricing of Modules	Individual	Price is given per module level and at the product level
	Combined	Price is given only at the product level
Default Version		
Default present	Yes	
	No	
Base default versus advanced default	Base	Lowest quality level is given as default
	Advanced	Highest quality level is given as default

* The first four modules were always included in the mass-customization configuration; the second four modules were fixed in the "low" number of mass-customizable modules condition and could be mass customized in the "high" number of mass-customizable modules condition.

respondents remained. These respondents all had indicated that they either had an interest in purchasing a PC in the next two years or had done so in the past four years. Average age of respondents was 43.7 years old, 37.2% of respondents were female, and 52.6% held a bachelor's degree or higher. Thus the sample was somewhat biased toward older males with relatively higher levels of education. However, this may be typical for PC purchase decision makers in the population.

Procedures

We took several steps to ensure the experiment's credibility and validity. First we explored several offerings of online and real-world PC vendors to select the total range of modules and module levels to be used in the experiment. A few weeks before the actual data collection, we conducted a pretest with the panel to validate that the range of levels we had selected was realistic for respondents. At this stage, we also measured the panel members' self-reported level of expertise regarding PCs. These measures were later used in the estimation of the model.

Meanwhile, we developed an experimental website that approximated the experience a consumer would have when buying a mass-customized PC online (in particular the

Table 1b
PC Modules Used in Experiment

Level	Processor	Monitor	Memory	Hard Drive	Mouse	Keyboard	Video card	Speakers
1	Intel Celeron 533MHz	Philips 105/S 15"	32 MB SD-RAM	10.2 GB Maxtor Diamond-max, 5400 rpm	Microsoft muis	BTC	SIS 6326 4MB	Philips MMS110, 1.5 watt
2	Intel Celeron 600MHz	Philips 107/E 17"	64 MB SD-RAM	15.3 GB Maxtor Diamond-max, 5400 rpm	Logitech wheel muis	Cherry G83-6104	SIS 6326 8MB	Philips MMS140, 4 watt
3	Intel Pentium III 600MHz	Philips 107/B 17"	96 MB SD-RAM	15.3 GB Maxtor Diamond-max+, 7200 rpm	Logitech pilot muis	Microsoft Internet	Diamond Speedstar A200 8MB	Philips MMS230, 6 watt
4	AMD Athlon (K7) 650MHz	iiyama S704HT Vision Master 404 17"	128 MB SD-RAM	20.4 GB Maxtor Diamond-max, 5400 rpm	Microsoft IntelliMouse	Microsoft Internet ValuePack	Diamond Speedstar A90 16MB	Labtec LCS 2408 universal subwoofer, 6.5 watt
5	Intel Pentium III 650MHz	iiyama A702HT Vision Master Pro 410 17"	192 MB SD-RAM	20.4 GB Maxtor Diamond-max+, 7200 rpm	Logitech trackball marble wheel	Microsoft Natural Elite	MSI-8808 Riva TNT2 M64 32MB	Labtec LCS 2514 4-point surround incl. subwoofer, 6.5 watt
6	AMD Athlon (K7) 700MHz	Philips 107/P10 Brilliance 17"	128 MB RD-RAM	9.1 GB Quantum Atlas IV, 7200 rpm	Logitech cordless wheel mouse	Cherry G81-3000	Diamond Viper II Z200 32MB	Philips MMS320 incl. subwoofer, 10 watt
7	Intel Pentium III 700MHz	Philips 109/E 19"	256 MB SD-RAM	30.7 GB Maxtor Diamond-max, 5400 rpm	Microsoft Intelli-Mouse explorer	Logitech desktop cordless iTouch	Matrox G400 SGRAM Dual Head 32MB	Labtec EDGE 418 flat panel incl. subwoofer, 10 watt
8	Intel Pentium III 750MHz	iiyama A901HT Vision Master Pro 450 19"	128 MB RD-RAM with ECC	30.7 GB Maxtor Diamond-max+, 7200 rpm				
9	AMD Athlon (K7) 850MHz	Philips 109/B XSD	384 MB SD-RAM	40.9 GB Maxtor Diamond-max, 5400 rpm				
10	Intel Pentium III 800MHz	Philips 109/P10 Brilliance 19"	256 MB RD-RAM	40.9 GB Maxtor Diamond-max+, 7200 rpm				
11	AMD Athlon (K7) 900MHz	iiyama A201HT Vision-Master Pro 510 22"	512 MB SD-RAM	18.2 GB Quantum Atlas IV, 7200 rpm				
12	Intel Pentium III 850MHz	Philips 150B TFT-LCD 15.1"	256 MB RD-RAM with ECC	75 GB Maxtor Diamond-max, 5400 rpm				
13	AMD Athlon (K7) 1GHz	iiyama TXA3812JT 15.1" TFT-LCD	384 MB RD-RAM	75 GB Maxtor Diamond-max+, 7200 rpm				
14	Intel Pentium III 933 MHz	Philips 201/B 21"	384 MB RD-RAM with ECC	36.4 GB Quantum Atlas IV, 7200 rpm				
15	Intel Pentium III 1 GHz	Philips 150P Brilliance TFT-LCD 15.1"	512 MB RD-RAM	45 GB Quantum Atlas IV, 7200 rpm				

"Customize Your Dell System" website). Like the Dell website, the experimental interface allowed consumers to choose their most preferred level from different modules, and it included as one of the manipulations a base default version resembling the default offered by Dell. The experimental mass-customization interface was pretested offline with several consumers and discussed with PC experts and the consumer panel management, who were experienced with online data collection. Based on the pretest and discussions, some minor clarifications to the experiment were added, and a click-through "help" option was added that explained in general terms the function of the different modules and that was accessible at any stage of the experiment.

Then, the data for the experiment were collected. In the experiment, an introduction page explained the respondent's task and the various components of the PC that could be mass customized. This was followed by a practice task that all respondents had to complete. Next, each respondent had to mass customize a PC in eight different experimental conditions, presented on different Web pages. These eight conditions differed on the four mass-customization factors (summarized in tables 1a and 1b). A pulldown menu showed all levels within each mass-customizable PC module. To make sure that respondents were confronted with the different aspects of the mass-customization configuration in each of the eight conditions, we asked respondents to mass customize a PC in all the scenarios they faced. This task situation resembles that of a consumer using a website to find out what PC they could configure and how much it would cost. If a default was present, respondents could choose the default if they wished. They could do this immediately, as well as after trying different mass-customization configurations. They could not, however, revert to a standard default option after trying other options; in this case, they had to compose the default version themselves. Prices were shown for all alternatives composed by the respondent and for the default. After

respondents had selected their preferred PC, we measured respondents' product utility, complexity, and mass-customization utility.

Independent variables

In the experimental conditions, we manipulated four factors based on H3-H6: extent of mass customization (number of modules and number of levels per module), level heterogeneity, individual pricing of modules, and type and availability of a default version (see Table 1a). The levels were chosen to represent realistic options at the time. We manipulated all factors at two levels except for default version, which had three levels: A default could either be present or absent, and when present it could have two levels, an advanced level or a base level. We also included a predefined part in the experiment that served as a baseline evaluation in the model.

Consumer expertise was measured using five aspects of consumer expertise about PCs (knowledgeable, competent, expert, trained, experienced) on a seven-point scale (for example, the measure for knowledge ranged from "not at all knowledgeable" to "very knowledgeable"). We adapted these measures of consumer expertise from Netemeyer and Bearden (1992), and the coefficient alpha showed very high reliability (.97).

Design

A fractional factorial design prescribed the variations over experimental conditions. The design was a 32-profile fraction of a $4*2^5$ full factorial representing all mass-customization options at two levels each, with the exception of the default variable, which varied on four levels (two out of the four levels represented "no default," and the other two represented "base default" and "advanced default" respectively). We divided the total of 32 profiles systematically into four versions of eight profiles using an additional free four-level factor that was also available in the 32-profile fraction. Each level of this factor represented one version of the survey. This procedure ensured that there was no confounding between versions and the other vari-

Mass-Customization Choice Model: Drivers of Mass-Customization Utility

	Parameter	*t*-Value
Effects on Mass-Customization Utility		
Intercept (α^{MC})	−4.320	−22.674*
Product utility (β^{MC}_{PROD})	6.095	14.646*
Random coefficient s.d.	8.597	18.759*
Complexity (β^{MC}_{COMPL})	−.430	−7.696*
Random coefficient s.d.	.210	21.017*
N = 409 (total number of observations is 2,427)		

* Significant at the 95% confidence level

ables in the design, but it did not allow estimation of separate parameters for each version in the analysis. The profiles in each of the four versions were randomized, and one practice task was added. We randomly assigned each respondent to one of the four versions of eight profiles.

Dependent variables

Our central variable of interest was the respondent's choice to use or not to use a certain mass-customization configuration. Therefore, we asked respondents to indicate whether they would use the mass-customization configuration they had just used if it were actually available. In the model, this choice is explained on the basis of the underlying latent utility that the respondent attaches to using the mass-customization configuration, as is common in consumer choice modeling (e.g., Ashok, Dillon, and Yuan 2002; McFadden 1986). As an indicator for product utility, we asked respondents to express the likelihood that they would purchase the product they selected if it were actually available. This approach is common in previous research in conjoint analysis (e.g., Huber et al. 1993). The response was given on a scale that ranged from 0% to 100%. To measure complexity, we used three ratings of the complexity of the configurations used to compose the PC—"complicated," "difficult," and "effortful"—measured on a seven-point measurement scale. For example, the measure for "complicated" ranged from "not at all complicated" to

"very complicated." The coefficient alpha on this measure showed a high reliability of .91. Confirmatory factor analysis showed that our measures of expertise, product utility, and complexity fitted well with three distinct factors.

Model

We first explain the model structure and specification, after which we discuss estimation.

Model structure and specification

We develop a model that captures how mass-customization configuration and consumer expertise affect product utility and complexity and how these latter two constructs in turn affect mass-customization utility (see Figure 1 for a graphical summary and tables 2a and 2b for notation). An intuitive starting point for understanding the proposed model structure is the mass-customization choice model. By itself, this model is a traditional binary logit model of the consumer choice for the mass-customization process. This choice is a function of the (latent) utility that the consumer obtains when choosing to use the mass-customization process. Next, in the model are a number of structural equations that relate the different latent variables and the experimental variables. To connect the observed measures to the underlying latent variables, the model structure also includes a set of measurement equations. Thus our model specification integrates measures of consumer expertise, perceptual measures of complexity, and product preference, all as explanatory variables in a discrete choice model for the mass-customization configuration.

To model the effect of these different types of behavioral components on consumer choice, we draw on a framework initially proposed by McFadden (1986) and later extended and implemented by Ben-Akiva et al. (1999) and Ashok, Dillon, and Yuan (2002). This framework incorporates psychometric data in a consumer choice modeling context, which allows

Table 2b
Mass-Customization Choice Model: Latent and Experimental Variables

	Effect on Product Utility		Effect on Complexity	
	Parameter	*t*-Value	Parameter	*t*-Value
Latent Variables				
Variable level intercept (α^{PROD} and α^{COMPL})	.388	64.217*	−.449	−19.362*
Random coefficient s.d.	.200	63.933*	1.436	45.580*
Complexity (β_{COMPL}^{PROD})	−.019	−9.667*	N/A	N/A
Random coefficient s.d.	.041	21.017*	N/A	N/A
Complexity * consumer expertise ($\beta_{EXPCOMPL}^{PROD}$)	.011	5.664*	N/A	N/A
Consumer expertise (β_{COMPL}^{PROD} and β_{EXP}^{COMPL})	.040	12.062*	−.743	−42.752*
Random coefficient s.d.	.088	32.154*	.044	4.450*
Mass-Customization Configuration$^£$				
Number of modules	.016	4.767*	.011	.843
Random coefficient s.d.	.009	2.277*	.029	1.974*
Number of levels	.007	1.507	−.018	−1.246
Random coefficient s.d.	.008	1.620	.007	.460
Level heterogeneity	−.012	−3.451*	.011	.762
Random coefficient s.d.	.002	.349	.038	2.103*
Individual pricing of modules	−.009	−2.057*	.048	3.565*
Random coefficient s.d.	.002	.328	.048	3.434*
Default version provided	−.012	−2.659*	.004	.265
Random coefficient s.d.	.004	.746	.004	.217
Base versus advanced default version	.025	4.463*	−.014	−.695
Random coefficient s.d.	.002	.390	.012	.536
Utility of predefined part	−.004	−1.101	.011	.835
Random coefficient s.d.	.002	.333	.013	.727

N = 409 (total number of observations is 2,427)

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* Significant at the 95% confidence level
$^£$ The main effects of all mass-customization configuration factors on complexity and product utility are captured by the vectors β_{CONF}^{PROD} and β_{CONF}^{COMPL}. For expositional clarity, the control variables for the interactions of mass-customization configuration with consumer expertise and for progress in the experiment are not reported in the table.

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for simultaneous estimation across the different data types. We estimate an integrated multiequation model consisting of a discrete choice model and a number of latent variable models. The approach results in estimates of the latent variables that provide the best fit with the information provided by both the observed choices and the indicators of the latent variables (i.e., complexity measures, a product-utility measure, and consumer-expertise measures).

Thus, the model structure has three main sets of equations:

1. The choice model for mass-customization config-uration. In this choice model, the individual's mass-customization utility is a latent variable that drives the choice of whether to use a certain mass-customization configuration.

2. A set of structural equations. These structural equations define the relationships among the

Table 2c
Estimates of Measurement Equations*

	Parameter	*t*-Value	Standard Deviation	*t*-Value
Product Utility				
Scale 1	Fixed to 1		.175	103.856
Complexity				
Scale 1	Fixed to 1		1.050	74.162
Scale 2	1.041	27.422	.995	85.581
Scale 3	.696	31.808	1.501	95.936
Consumer Expertise				
Scale 1	Fixed to 1		.973	16.843
Scale 2	1.458	23.565	.735	19.447
Scale 3	1.447	24.747	.731	18.872
Scale 4	1.426	21.541	.819	23.009
Scale 5	1.392	19.202	.869	21.740

* All *t*-values are significant at the .95 confidence level. One of the parameters in each measurement equation was fixed to a value of 1 in the estimation for model identification purposes. $N = 409$.

latent variables in the model. A first structural equation defines the relationship between mass-customization utility on the one hand and product utility and complexity on the other hand. A second structural equation explains product utility from two other latent variables (i.e., consumer expertise and complexity) and the mass-customization factors. A third structural equation explains complexity from consumer expertise and the mass-customization factors.

3. A set of latent-variable measurement equations. These measurement equations allow for identification of the latent variables. Note that in these measurement equations, the latent variable "drives" the observed measures, similar to the way utility drives the consumer choice in the traditional choice models.

In developing the formal model structure, we start with the choice model part. First, we express UMC^*_{ci}, the utility of mass-customization configuration c to consumer i, as a function of product utility ($UPROD^*_{ci}$), complexity

($COMPL^*_{ci}$), and ε_{MCci}, an individual and mass-customization configuration specific error term that captures unexplained variation in consumers' choices due to measurement error and unobserved explanatory variables. To allow for differences between consumers, we model the parameters (β) in the model as random coefficients with their own error terms (v). We allow for different variances for the error terms in the equation and assume that they are independent and normally distributed.[3] Note that in our estimation this utility function drives the probability of a consumer choosing to use a given mass-customization configuration when we assume that the error terms ε_{MCci} are independently and identically Gumbel distributed to obtain the well-known binary logit specification.

$$UMC^*_{ci} = \alpha^{MC} + (\beta^{MC}_{PROD} + v^{MC}_{PRODi})UPROD^*_{ci}$$
$$+ (\beta^{MC}_{COMPL} + v^{MC}_{COMPLi})COMPL^*_{ci} + \varepsilon_{MCci} \quad (1)$$

Next, we express both product utility and complexity as a function of consumer expertise (EXP^*_i) and a vector of mass-customization configuration factors $\mathbf{CONF}_c$. In the product-utility model, we add to this specification the effect of complexity and allow for an interaction with consumer expertise. To control for further remaining heterogeneity, we also include: (1) a variable that represents progress through the experiment to capture possible differences in product utility and complexity that may arise, for example, due to boredom, fatigue, or learning in the experiment when individuals respond to multiple experimental scenarios ($PROGRESS$); (2) random coefficient parameters for the effects of the latent factors, mass-customization configuration, and progress; and (3) significant interactions of expertise with experimental variables (i.e., extent of mass customization).

$$UPROD^*_{ci} = \alpha^{PROD} + (\beta^{PROD}_{COMPL}$$
$$+ \beta^{PROD}_{EXPCOMPL}EXP^*_i + v^{PROD}_{COMPLi})COMPL^*_{ci}$$
$$+ (\beta^{PROD}_{EXP} + v^{PROD}_{EXPi})EXP^*_i + (\boldsymbol{\beta}^{PROD}_{CONF}$$
$$+ \boldsymbol{\beta}^{PROD}_{EXPCONF}EXP^*_i + \boldsymbol{v}^{PROD}_{CONFi})\mathbf{CONF}_c$$
$$+ \gamma^{PROD}PROGRESS + \varepsilon_{PRODci} \quad (2)$$

$$COMPL^*_{ci} = \alpha^{COMPL} + (\beta^{COMPL}_{EXP} + \nu^{COMPL}_{EXPi})EXP^*_i$$
$$+ (\boldsymbol{\beta}^{\mathbf{COMPL}}_{\mathbf{CONF}} + \boldsymbol{\beta}^{\mathbf{COMPL}}_{\mathbf{EXPCONF}} \, EXP^*_i$$
$$+ \boldsymbol{\nu}^{\mathbf{COMPL}}_{\mathbf{CONFi}})\mathbf{CONF}_c + \gamma^{COMPL} PROGRESS$$
$$+ \varepsilon_{COMPLci} \tag{3}$$

Finally, we define three measurement equations to estimate parameters (λ) that relate the observed measures of product utility, complexity, and consumer expertise to their underlying latent constructs. We allow for different error variances (η) for the different measures of each construct and assume independent normal distributions for each equation conditional on the latent constructs.

$$UPROD_{ci} = \lambda_{PROD} UPROD^*_{ci} + \eta_{PRODci} \tag{4a}$$

$$\mathbf{COMPL}_{ci} = \boldsymbol{\lambda}_{\mathbf{COMPL}} COMPL^*_{ci} + \boldsymbol{\eta}_{\mathbf{COMPL}ci} \tag{4b}$$

$$\mathbf{EXP}_i = \boldsymbol{\lambda}_{\mathbf{EXP}} EXP^*_i + \boldsymbol{\eta}_{\mathbf{EXP}i}c) \tag{4c}$$

Estimation

Appendix A describes the likelihood function we define for the model. We estimate the model using a smooth simulated maximum likelihood procedure (e.g., Train 2003). At the basis of this approach is the recognition that, conditional on both the values of the latent constructs and the individual-specific errors, our model is a traditional logit model. We can then express the unconditional likelihood as the expected value of the conditional contribution of each observation with the expectation taken over the joint density of the individual-specific error components and the distribution of the latent constructs. This is a multidimensional integral for which no analytical solution can be given. The simulated maximum likelihood procedure approximates the integral for each individual by a mean of simulated conditional likelihoods. Note that in our application we have several observations for each individual and that the individual random components in the random coefficients remain constant for the simulations

for all observations from the same individual. The individual-level probabilities are then multiplied to obtain the total simulated maximum likelihood for all individuals. In our estimations, we based this simulated mean per individual for each of the random coefficients and the three latent constructs on 100 Halton draws. Halton sequences are designed to give an even coverage over the domain of the mixing distribution and therefore have better simulation properties than random draws (for example, Train [2003] reports results in which the simulation error in the estimation of a mixed logit model was lower with 100 Halton draws than with 1,000 random draws). We then transform these draws with different variance parameters to allow for estimation of differences in variance between random variables.

In this procedure, instead of the true likelihood, the simulated likelihood is maximized. It can be shown that this procedure is asymptotically equivalent to regular maximum likelihood procedures, provided that the number of independent draws is large enough (e.g., Hajivassiliou and Ruud 1994). The latter result implies that standard ways of obtaining maximum likelihood estimates and standard errors can be used.

To test our estimation procedure, we examined its ability to capture correctly a set of prespecified parameter values in the model structure that we proposed. To do so, we generated synthetic data for the different measures and outcomes based on a known set of parameter values identical to the estimates from our application and using the same number of observations as in the application. In running our tests, we examined the estimation procedure's sensitivity to the number of draws in the simulation procedures. We compared the results of using 30, 50, 100, and 200 Halton draws.

The results of these tests indicated that the estimation procedure was able to reproduce the original values at 100 and 200 Halton draws but did not do as well at 30 or 50 draws. Performance of the estimation procedure for 100 and 200

Table 3
Hypothesized Effects and Results

Hypothesis	Hypothesized Effect	Result
H1a: Product utility on mass-customization utility	+	Supported
H1b: Complexity on mass-customization utility	–	Supported
H2: Complexity on product utility	–	Supported
H3a: The extent to which products can be mass customized on product utility	+	Supported
H3b: The extent to which products can be mass customized on complexity	+	Rejected
H4a: Heterogeneity in module levels on product utility	–	Supported
H4b: Heterogeneity in module levels on complexity	+	Rejected
H5a: Individual pricing of modules on product utility	–	Supported
H5b: Individual pricing of modules on complexity	+	Supported
H6: Offering a base default versus an advanced default version on product utility	+	Supported
H7: Consumer expertise on complexity	–	Supported
H8: Consumer expertise on the negative effect of complexity on product utility	+	Supported

draws was very similar. We observed that the model estimates of the standard deviations of the random coefficients were most sensitive and could only be recovered well if starting values were used that were close to the original values. This sensitivity did not decrease when moving from 100 to 200 draws, but it largely disappeared when we ran an additional test with twice the number of observations and 100 Halton draws. On this basis, we conclude that the estimation procedure worked well but that the random coefficient standard deviation parameters in our application may need to be interpreted with some caution.

Results

Tables 2a, 2b, and 2c present the estimation results for our model. Although we estimated all model parameters simultaneously, we present separate tables for expositional clarity. Table 3 summarizes our results in terms of the hypotheses, and Table 4 provides summary statistics of the experiment. On average across all scales, respondents rated themselves with 3.9 out of 7 (s.d. 1.7) on our five different expertise scales (which ranged from 1 to 7 with increasing expertise). The average perceived mass-custom-

ization complexity was 2.9 out of 6 (s.d. 1.9) across the three perceived complexity scales (which ranged from 0 to 6 with increasing complexity). The average reported product utility as measured by the likelihood of buying the PC was 32.3%. The average number of responses per scenario was 75.7, and across all experimental scenarios respondents chose to use the mass-customization configuration in 25.8% of the cases. The number of yes responses per scenario ranged between 12 (out of 80) for the least attractive scenario and 29 (out of 85) for the most attractive one.

We now summarize the results for our hypotheses.
- As expected, product utility has a strong and positive effect on mass-customization utility, while complexity has a negative effect (H1a and H1b).
- We also find support for our hypothesis that higher complexity in mass customization affects mass-customization utility not only directly, but also indirectly, through its negative effect on product utility (H2).
- We find support for the hypothesis that the higher the extent of mass customization (i.e., the higher the number of mass-customizable modules and the number of levels per

Table 4
Summary Statistics of the Experiment

		s.d.
Average expertise rating (1-7 scale)	3.9	1.7
Average complexity rating (0-6 scale)	2.9	1.9
Average product utility (likelihood of buying 0%-100%)	32.3	
Average number of responses per configuration scenario	75.7	
Average percentage of use for configurations	25.8	

module), the higher consumers' product utility (H3a). Somewhat surprisingly, we find that extent of mass customization does not have a significant effect on consumers' complexity (H3b). Neither increasing the number of mass-customizable modules nor increasing the number of levels per module increases consumers' complexity.

■ We also observe that, as hypothesized (H4a), the more heterogeneous the different levels for a mass-customizable module are, the lower product utility is. We do not find an effect on complexity (H4b).

■ We find support for the hypothesis (H5a) that individual pricing of modules negatively affects product utility. Furthermore, we find that individual pricing increases complexity (H5b).

■ In line with what was hypothesized (H6), we find that providing a "base" default version (low-end PC) leads to a higher product utility than providing an "advanced" default version (high-end PC).

■ As to consumer expertise, we find support for the hypothesized negative effect of consumer expertise on complexity (H7).

■ Finally, we observe that the effect of complexity on product utility is less negative for expert consumers than for novice consumers, which is also as hypothesized (H8).

Note that we capture consumer heterogeneity in the model in several ways. First, we introduce the effect of consumer expertise in different parts of the model. We find significant effects,

as hypothesized. A second way we capture heterogeneity in the model is by estimating random coefficients for the parameters in the model that define product utility and complexity. Here, we find significant heterogeneity on all parameters for the latent variables in the model (i.e., the effect of complexity on product utility and the effect of expertise). We find only one mass-customization parameter with significant heterogeneity for product utility and three for complexity. Apparently in the context of our experiment the impact of mass-customization configuration on product utility and complexity differs relatively little between consumers. Third, we also allow for heterogeneity in the measurement equations for product utility, complexity, and consumer expertise by estimating different standard deviations for all measurement scales that we used. These standard deviations all are significant and are reported in Table 2c. Fourth, we allow for unexplained heterogeneity in the core structure of our model by estimating different random error variations in the product utility and complexity models. These effects are also significant. Finally, we also controlled for respondents' progress through the experiment. We found that as respondents progressed, both product utility and complexity decreased, the former possibly due to boredom or fatigue, the latter more likely due to learning.

Further Analyses

We conducted further analyses to assess the robustness of our findings. More in particular, we estimated alternative model specifications and considered additional default options.

Alternative model specifications
We compared the proposed model to two nested model specifications (a model without random coefficients and a model in which the effect of consumer expertise was not included) and two non-nested specifications (a model that did not include complexity and a model in which neither complexity nor product utility were included). We found that, in all specifica-

tions, parameter estimates were identical in sign and had effects similar to those in the proposed model. A log-likelihood ratio test revealed that the proposed model outperformed both nested alternatives ($p < .01$), and a comparison of CAIC scores showed that it also outperformed the two non-nested alternatives.

We also investigated whether an alternative explanation for the observed effect of complexity on product utility could be a moderating effect of complexity on the relationship between product utility and mass-customization utility. We estimated a model including both effects and found our earlier results to be robust to the additional moderating effect. The moderating effect itself was also significant. A more detailed investigation of this effect suggested that consumers are more willing to accept the complexity of a mass-customization configuration if the configuration allows them to achieve a higher product utility. This finding may perhaps be explained by a residual-desire effect as proposed by Heath et al. (2000), who suggested that when consumers trade off product quality loss and price, they are more concerned about forgone product quality than forgone monetary costs. A similar effect could occur in the trade-off of product utility and effort, and consumers could be more willing to trade off effort for product utility than vice versa, making them less sensitive to complexity when product utility is high.

The role of the default in mass-customization participation utility

One important restriction of our experimental design was that in order to have control over the type of default version that respondents faced, we provided them with only one default version. This default option was either a base version or an advanced version. In the real world, however, firms often provide consumers with a number of defaults, for example by allowing consumers to first select a PC product type that is roughly in line with their preferences and then specify their most preferred configuration within this product line (cf. Dell online). This business

practice may be helpful to consumers if they can select a default version that is close to their preferences and compose their PC starting from this default version.

This default structure may affect complexity and product utility. We expect that consumers who are presented with a default version that is close to their preferred PC configuration have a lower complexity, because they have to go through fewer cognitive steps to configure their most preferred product. Consumers' product utility may also be affected by the type of default version they see because they need to "upgrade" less from a PC that is already closer to their most preferred option. We expect that most consumers' preferred configurations are somewhere between a base version and an advanced version. Since in our main study we observed that product utility is highest when consumers upgrade from a base default version and lowest when they downgrade from an advanced default version, we expect that their product utility is at an intermediate level if they are faced with a default version that is close to their most preferred PC.

Presenting consumers with multiple defaults also introduces a number of additional cognitive steps, thus increasing perceived complexity (Bettman, Johnson, and Payne 1990). A consumer facing multiple defaults first has to compare different PC types and choose one, and if they don't wish to decide on a PC type, they are forced to switch back and forth between PC configurations across the different types. Such comparisons require more effort than simply choosing a PC configuration within only one type that includes all possible modules and levels. Thus, we expect comparisons across PC types to increase complexity.

To explore these possible effects of introducing an intermediate default version and multiple defaults, we conducted a second follow-up experiment. Participants in this experiment were students at the first author's university who participated in return for a cash payment (in the

Table 5
Results Second Experiment: The Role of the Default Version[º]

Scenarios	Product Utility	Complexity	N
Base default version	***.317***	.039	61
Intermediate default version	.141	***−.281***	46
Advanced default version	−.126[§]	.176[§]	37
Three default versions offered as intermediate step	−.312[§]	.269[§]	41
No default version offered	−.214[§]	−.179	39

[º] Table reports factor scores, best scoring default version in bold italics: Lower complexity and greater product utility are more attractive.
[§] Significantly worse than best scoring default version ($p < .05$), based on MANOVA results

randomly assigned across versions. After choosing a PC configuration, respondents were asked about their complexity, the utility of the product they had selected, and mass-customization utility.

Before collecting data online, we first pretested the experiment offline with a number of respondents and discussed its structure with the manager of the panel and a number of knowledgeable PC users. For the full study, 224 respondents participated within the six-week response period we had set, in response to an e-mail to participants in an online student panel and course participants (approximately 900 individuals in total). An exploratory factor analysis of the responses showed that they loaded clearly on three different factors. We then ran a second factor analysis on the responses for each of the constructs separately, obtaining factor scores for each of the three constructs. To test for differences among the five versions, we conducted a MANOVA comparing the mean scores for each of the factors across the versions. The results are summarized in Table 5.

We find that, as expected, offering an intermediate-level default version leads to the lowest level of complexity. This level is significantly lower ($p < .05$) than the level of complexity if an advanced default version is offered or if three default versions are offered. Thus, complexity significantly decreases only if a default is offered that matches consumer preferences, but offering non-matching defaults or even multiple defaults—including one that matches consumer preferences—does not decrease complexity. This is an interesting further refinement of our findings in the main study, in which we observed that offering either a base or an advanced default did not decrease complexity.

The results of the second experiment support our findings with regard to the effect of a base default versus advanced default on product utility. Respondents reported the highest product-utility level when presented with a base

pretest) and a lottery to win a CD or DVD voucher (in the actual experiment). To set up this experiment, we copied the three default PC versions available at the Dell website at the time, duplicating all modules and levels as they were available. In setting up this experiment, we first explored with a sample of 52 students which of the three default versions was most popular. We found that the intermediate default version was most attractive, with the base default version as a good second. Only very few respondents preferred the advanced default.

Next we designed an online computer experiment that had five default versions. Versions 1, 2, and 3 had only one default, which was a base, intermediate, and advanced default respectively. In version 4, all these three default versions (base, intermediate, and advanced) were first shown and briefly described on a separate screen (again mimicking the Dell website), after which respondents could mass customize their PC within the PC type they preferred. Version 5 had no default, and all modules with all levels were shown directly to respondents.

In line with our main study, respondents were first shown an introductory screen explaining the task and then were asked to construct their most preferred PC. Respondents were only shown one mass-customization scenario that represented one of the five versions and were

default. This product utility was significantly higher (at $p < .05$) from that reported when an advanced default version was offered, or if no default or three default versions were offered. Product utility was at an intermediate level if the (most popular) intermediate default version was offered.

Finally, we ran a regression analysis of product utility and complexity on mass-customization utility (Adj. R-sq. of .124). This analysis showed that, as in the main study, product utility had a significant positive effect on mass-customization utility ($p < .001$), while complexity had a significant negative effect ($p < .001$).

Discussion

We can summarize the results of the study as follows. We find that mass-customization configuration affects the product utility consumers can achieve in mass customization, as well as their perception of mass-customization complexity. In turn, product utility and complexity affect the utility consumers derive from using a certain mass-customization configuration. More specifically, product utility has a positive effect and complexity has a negative effect on mass-customization configuration utility. The effect of complexity is direct as well as indirect, because complexity also lowers product utility.

Managerial implications
In terms of extent of mass customization, we find that when consumers were presented with the rather large range of modules and module levels we manipulated in this study, they did not perceive significant increases in complexity, while they were indeed able to achieve higher product utility. This is good news for those who wish to provide many options to consumers. We also found that the negative effects of complexity on mass-customization utility are lower for expert consumers, making them a potentially attractive target segment for mass-customization.

Within the context of our experiment, we found that firms can benefit from introducing extensive mass customization using a carefully designed mass-customization configuration. Three features deserve more attention. First, our results imply that firms increasing the number of module levels should offer consumers more additional options in the most popular range of a module and fewer additional options at the extremes. Second, pricing should be presented only at the total-product level rather than at the module and product level. We find that this approach reduces complexity and increases product utility. Third, firms should offer a default version that consumers can use as a starting point for mass customization, as doing so minimizes the complexity to consumers. The best default version to start out with is a base default version, because this type of default version allows the consumer to most closely approach his or her ideal product. The reason is that consumers presented with an advanced default may buy a product that is more advanced than they actually need.

We also find that simplifying a mass-customization process increases not only the probability of choosing this process but also the product utility achieved in the process. This suggests that easy-to-use mass-customization processes can also be a tool in achieving greater product appreciation and possibly higher customer loyalty in the long term. For managers, this may be a particularly interesting area of future investigation.

Limitations and future research
Some limitations of our study are worth noting. Consumers in our experiment made hypothetical mass-customization decisions and reported on their intended use of a mass-customization configuration in only one product context. Though we used real consumers in our study and took great care in developing realistic experimental conditions, consumers' decisions in the real world and for other product categories may differ. Moreover, we found evidence of learning as consumers progressed through

the experiment. It would be worthwhile to test our model in other contexts to see if these observed effects are generalizable.

Nevertheless, we hope that our research can be a starting point for further research in marketing on mass customization. We outline some promising areas for future research that also reveal further limitations of our study. Since our research focuses on consumers' utility for different mass-customization configurations, we do not address the question of how consumers choose between buying a mass-customized product and buying a standardized product available in the market. It would be quite relevant to study how consumers' choices to mass customize or not can be modeled.

There also are several aspects in our model that warrant more detailed future research, especially at the level of consumer information processing. For example, complexity may have more the character of an individual trait than a task-specific effect, which could explain why the extent of mass customization has little impact on complexity. Another complexity question that remains open for further investigation is whether the causal relationship between product utility and complexity could actually be the reverse of what we have assumed. It is possible that when consumers don't obtain the product they want, they report that a mass-customization configuration is complex. In our analysis, in contrast, we have assumed that complexity reduces product utility.

Variations in consumers' decision strategies regarding different aspects of mass-customization configurations would also constitute an interesting area for further research. For example, different consumers may process individual prices and default suggestions differently. Furthermore, it would be interesting to investigate whether consumers enjoy mass customizing a product. For instance, Dabholkar and Bagozzi (2002) have found that consumers enjoy self-service technology. It would be interesting to see whether such enjoyment also translates into consumers' utility for mass-customization configurations.

Finally, we believe it would be worthwhile to establish an evaluation criterion that is external to the mass-customization configuration and that could be used to study whether consumers buy "better" or "worse" products when they mass customize than when they choose among standardized products. A possible candidate for such a criterion could be consumers' product satisfaction measured after a certain period of use. Thus we hope the present study stimulates more marketing research into the vastly understudied phenomenon of mass customization. ∎

Acknowledgements

Appendix A

To write out the likelihood function for the total model, we first define the likelihood of an individual's mass-customization participation choice model without considering the latent variables (Ben-Akiva et al. 1999). For notational simplicity, we omit the individual subscript i. Note that we estimate the random coefficients in the model by a simulated maximum likelihood procedure based on this likelihood function.

$$P(d \mid UPROD_c, \textbf{COMPL}_c, \textbf{EXP}_c, \textbf{EXT}_c, \textbf{DES}_c, T; \alpha^{MC}, \beta_{PROD}^{MC}, \beta_{COMPL}^{MC}, \sigma_{\varepsilon MC}) \quad (A1)$$

In Equation A1, d represents a dummy variable that takes on the value of 1 if the consumer chooses to participate in

the mass-customization process and 0 otherwise. $\mathbf{EXT}_c$ and $\mathbf{DES}_c$ are the extent of mass customization and the other three mass-customization configuration factors respectively. T is the progress variable for the experiment.

Then the latent variables are added. The likelihood function is then the integral of the choice model over the distribution of the latent constructs, given the observed variables and taking into account for each latent construct the other latent constructs.

$$P(d \mid UPROD_c, \mathbf{COMPL}_c, \mathbf{EXP}, \mathbf{EXT}_c, \mathbf{DES}_c, T; \alpha^{MC},$$
$$\beta^{MC}_{PROD}, \beta^{MC}_{COMPL}, \alpha^{PROD}, \beta^{PROD}_{COMPL}, \beta^{PROD}_{EXPCOMPL}, \beta^{PROD}_{EXP},$$
$$\boldsymbol{\beta}^{PROD}_{EXT}, \boldsymbol{\beta}^{PROD}_{EXPEXT}, \boldsymbol{\beta}^{PROD}_{DES}, \beta^{PROD}_T, \alpha^{COMPL}, \beta^{COMPL}_{EXP},$$
$$\boldsymbol{\beta}^{COMPL}_{EXT}, \boldsymbol{\beta}^{COMPL}_{EXPEXT}, \boldsymbol{\beta}^{COMPL}_{DES}, \beta^{COMPL}_T, \sigma_{\varepsilon MC}, \sigma_{\varepsilon PROD},$$
$$\sigma_{\varepsilon COMPL})$$
$$=$$
$$P(d \mid UPROD_c, UPROD^*_c, \mathbf{COMPL}_c, COMPL^*_c, \int_{UPROD}$$
$$* \int_{COMPL} * \int_{EXP} * \mathbf{EXP}, EXP^*, \mathbf{EXT}_c, \mathbf{DES}_c, T; \alpha^{MC},$$
$$\beta^{MC}_{PROD}, \beta^{MC}_{COMPL}, \sigma_{\varepsilon MC}) f1(UPROD^* \mid \mathbf{COMPL}_c, \mathbf{EXP},$$
$$\mathbf{EXT}_c, \mathbf{DES}_c, T; \alpha^{PROD}, \beta^{PROD}, \beta^{PROD}_{COMPL}, \beta^{PROD}_{EXPCOMPL},$$
$$\beta^{PROD}_{EXP}, \boldsymbol{\beta}^{PROD}_{EXT}, \boldsymbol{\beta}^{PROD}_{EXPEXT}, \boldsymbol{\beta}^{PROD}_{DES}, \beta^{PROD}_T, \sigma_{\varepsilon PROD})$$
$$f2(COMPL^* \mid \mathbf{EXP}, \mathbf{EXT}_c, \mathbf{DES}_c, T; \alpha^{COMPL}, \beta^{COMPL}_{EXP},$$
$$\boldsymbol{\beta}^{COMPL}_{EXT}, \boldsymbol{\beta}^{COMPL}_{EXPEXT}, \boldsymbol{\beta}^{COMPL}_{DES}, \beta^{COMPL}_T, \sigma_{\varepsilon COMPL})$$
$$f3(EXP^*) dUPROD^* \, dCOMPL^* \, dEXP^* \qquad (A2)$$

Note that the conditional distributions of the latent constructs are expressed as $f1$ for $UPROD^*$, $f2$ for $COMPL^*$, and $f3$ for EXP^*. $f1$ and $f2$ are defined by equations 4 and 5, and $f3$ is the standard normal distribution.

Next, the measurement equations are integrated. The conditional distributions of the indicators given the values of the latent variables are expressed in equations 6, 7, and 8 and are included as $g1$, $g2$, and $g3$ respectively. Then the joint probability of the observable variables d, $UPROD_c$, $\mathbf{COMPL}_c$, and $\mathbf{EXP}$ is expressed as:

$$P(d, UPROD_c, \mathbf{COMPL}_c, \mathbf{EXP} \mid UPROD_c, \mathbf{COMPL}_c,$$
$$\mathbf{EXP}, \mathbf{EXT}_c, \mathbf{DES}_c, T; \alpha^{MC}, \beta^{MC}_{PROD}, \beta^{MC}_{COMPL}, \alpha^{PROD},$$
$$\beta^{PROD}_{COMPL}, \beta^{PROD}_{EXPCOMPL}, \beta^{PROD}_{EXP}, \boldsymbol{\beta}^{PROD}_{EXT}, \boldsymbol{\beta}^{PROD}_{EXPEXT}, \boldsymbol{\beta}^{PROD}_{DES},$$
$$\beta^{PROD}_T, \alpha^{COMPL}, \beta^{COMPL}_{EXP}, \boldsymbol{\beta}^{COMPL}_{EXT}, \boldsymbol{\beta}^{COMPL}_{EXPEXT}, \boldsymbol{\beta}^{COMPL}_{DES},$$

$$\beta^{COMPL}_T, \lambda_{PROD}, \boldsymbol{\lambda}_{COMPL}, \boldsymbol{\lambda}_{EXP}, \sigma_{\varepsilon MC}, \sigma_{\varepsilon PROD}, \sigma_{\varepsilon COMPL},$$
$$\sigma_{\eta PROD}, \boldsymbol{\Sigma}_{\eta COMPL}, \boldsymbol{\Sigma}_{\eta EXP})$$
$$=$$
$$P(d \mid UPROD_c, UPROD^*_c, \mathbf{COMPL}_c, COMPL^*_c, \int_{UPROD} *$$
$$\int_{COMPL} * \int_{EXP} * \mathbf{EXP}, EXP^*, \mathbf{EXT}_c, \mathbf{DES}_c, T; \beta^{MC}_{PROD},$$
$$\beta^{MC}_{COMPL}, \sigma_{\varepsilon MC}) g1(UPROD \mid UPROD^*; \lambda_{PROD}, \sigma_{\eta PROD})$$
$$g2(\mathbf{COMPL} \mid COMPL^*; \boldsymbol{\lambda}_{COMPL}, \boldsymbol{\Sigma}_{\eta COMPL})$$
$$g3(\mathbf{EXP} \mid EXP^*; \boldsymbol{\lambda}_{EXP}, \boldsymbol{\Sigma}_{\eta EXP}) f1(UPROD^* \mid \mathbf{COMPL}_c,$$
$$\mathbf{EXP}, \mathbf{EXT}_c, \mathbf{DES}_c, T; \alpha^{PROD}, \beta^{PROD}_{COMPL}, \beta^{PROD}_{EXPCOMPL}, \beta^{PROD}_{EXP},$$
$$\boldsymbol{\beta}^{PROD}_{EXT}, \boldsymbol{\beta}^{PROD}_{EXPEXT}, \boldsymbol{\beta}^{PROD}_{DES}, \beta^{PROD}_T, \sigma_{\varepsilon PROD})$$
$$f2(COMPL^* \mid \mathbf{EXP}, \mathbf{EXT}_c, \mathbf{DES}_c, T; \alpha^{COMPL}, \beta^{COMPL}_{EXP},$$
$$\boldsymbol{\beta}^{COMPL}_{EXT}, \boldsymbol{\beta}^{COMPL}_{EXPEXT}, \boldsymbol{\beta}^{COMPL}_{DES}, \beta^{COMPL}_T, \sigma_{\varepsilon COMPL})$$
$$f3(EXP^*) dUPROD^* \, dCOMPL^* \, dEXP^* \qquad (A3)$$

The total likelihood is then the product of the probabilities over all individuals and over all observations within individuals.

Estimation of the proposed model is done by means of a simulated maximum likelihood procedure that approximates the joint density of the distribution of the latent constructs and the individual-specific error components in the model. Simulated maximum likelihood procedures operate in the same way as maximum likelihood procedures but use simulated probabilities instead of the exact probabilities. The simulated probabilities in our estimation procedure are based on draws from random components for each individual for the three latent constructs and for each random coefficient. In our application, we have several observations for each individual, and therefore the individual random component for each individual remains constant for all observations from the same individual within each round of simulation. The draws are based on a Halton sequence to give an even coverage over the distributions.

We then transform these draws with different parameters to estimate the differences in variance, both across the latent constructs and across the random coefficients. The draws and the parameters jointly provide the value of the simulated likelihood, which is then maximized in its parameters instead of the true likelihood. It has been shown that this procedure is asymptotically equivalent to regular maximum likelihood procedures (e.g., Train 2003).

Notes

1. In this study, we define mass customization as customization in which an individual consumer's product preferences are met by choosing among predefined levels for each of a set of product modules. Product modules in this context are divisible components that jointly with other components make up a total product. The modules and levels that are included in the mass-customization process are predefined by the firm, and we analyze the case in which consumers "mass customize" the product by selecting their most preferred level for each product module. For example, PC vendors such as Dell allow customers to mass customize their PCs by choosing a level for each of the different PC modules, such as type of processor, memory size, monitor, etc.

2. In our analysis, we also control for the direct effect of consumer expertise on product utility.

3. Equations 2 and 3 follow the same structure and notation. We tested the assumption of independent errors in our application, and it could not be rejected.

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