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Reference:
Zijlstra Toon, Goos Peter, Verhetsel Ann.- A mixture-amount stated preference study on the mobility budget
Transportation research : part A : policy and practice - ISSN 0965-8564 - 126(2019), p. 230-246
Full text (Publisher's DOI): https://doi.org/10.1016/J.TRA.2019.06.009
To cite this reference: https://hdl.handle.net/10067/1605400151162165141

A Mixture-Amount Stated Preference Study on the Mobility Budget

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Declaration of interest: none

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Abstract
The mobility budget is considered a promising new tool in remuneration and transport policy in Belgium, especially due to its potential of shrinking the company car fleet and lowering car use. Because revealed preference data were scarce in the context of the mobility budget, we conducted a stated preference study to examine the potential outcomes of the introduction of the mobility budget. A challenge in our study is that it required the respondents to choose between mixtures of remunerations for different total budget amounts. In other words, the study was a mixture-amount stated preference study, which involved modeling challenges as well as experimental design challenges. In this paper, we therefore introduce advanced mixture-amount regression models in the choice modeling literature and present a generic method to set up mixture-amount stated preference studies to collect suitable data. Our case-study data comes from an online questionnaire administered to employees at 12 large companies in Belgium (n=817). For our choice data, a second-order polynomial mixture model in combination with a quadratic effect for the amount led to the most suitable utility function. Our results indicate that current company car users prefer additional days off, income or a car. The bicycle, pedelec and public transport options are disregarded by most employees. Based on our results, we call for a critical reflection on the current system of company cars and reimbursements in Belgium.

Keywords: *commuting, company car, mixture-amount experiment, mobility budget, optimal experimental design, panel mixed logit model*

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1. Introduction: a mixture of fringe benefits

In recent years, as in some other countries, the concept of the mobility budget (MB) gained popularity in Belgium. This concept is framed as an alternative to the company car with fuel card (CC); the primary target group consists of CC users. The key principle of the concept is that, instead of a CC, employees are provided with a virtual budget by their employer. The size of this budget is equal to the sum of the current fixed and variable costs of the CC. The employees can then use the MB to meet their work-related transport needs. Options available within 'the virtual shop' are mostly transport modes and services, although many proponents also stress the need to add non-transport options, to ensure that employees are tempted to opt for something other than a CC. Many of the options enable private use because a CC can be used privately as well in Belgium, if the employee agrees to pay a (relatively small) tax on this benefit-in-kind. For a company bicycle or a public transport (PT) card provided by the employer, no tax on the benefit-in-kind has to be paid. In the most popular interpretation of the MB concept (see Zijlstra & Vanoutrive, 2018), one is also able to save money, by selecting cheaper travel options. The remaining budget is then paid to the worker as an end-of-the-year bonus, with a favorable tax treatment. This can be an incentive to pick alternative transport options, in addition to or in exchange for the relatively expensive CC (Zijlstra & Vanoutrive, 2018).

The concept of the MB is strongly related to flexible benefit plans (Barringer & Milkovich, 1998; Benders, Delsen, & Smits, 2006; Hillebrink, Schippers, Doorne-Huiskes, & Peters, 2008), as both evolve around fringe benefits, use the idea of input equals output, and deviate from the traditional one-size-fits-all approach. In both concepts, a new form of remuneration is created for employees. However, the MB is dominated by transport related input and output, and there are some clear transport policy goals attached to it. To understand the dominance of transport related options, one must understand that Belgium has a particularly strong culture when it comes to transport cost compensations, as these are either remunerated by the employer or they are tax deductible (Mérenne-Schoumaker, Van der Haegen, & Van Hecke, 1999; Vanoutrive, 2010). The treatment of the CC in the Belgian tax system is particularly advantageous, as only about 40% of the benefit is taxed (De Borger & Wuyts, 2011; Harding, 2014).

The objective of the MB is that employees would prefer other modes of transport over a CC or would combine other models of transport with a cheaper (and smaller) car. When successful, the MB would lead to a reduction in the number of cars on the Belgian roads, the vehicle kilometers driven and fuel consumption, and it would lead to an increase in multimodal transport. More specifically, it is hoped that the congestion levels during rush hours would decrease (Zijlstra & Vanoutrive, 2018). The current congestion levels, especially near Brussels and Antwerp, are known to be problematic (e.g. OECD, 2013). A switch from CCs to other modes of transport is considered feasible for many employees, as many CC owners do not actually need a car for business purposes. As a matter of fact, the CC is used by employers as a bonus in the wage package, due to a favorable tax rate (De Borger & Wuyts, 2011; KPMG, 2012). Especially for employees with a high income, the CC is an attractive option, as Belgium has a progressive income tax. For these reasons, a relatively large number of employees possess a CC in Belgium: one out of ten passenger cars is a CC. These CCs account for 15% of the vehicle kilometers by passenger cars (Harding, 2014; Laine & Van Steenbergen, 2016; May, 2017). Laine and Van Steenbergen (2016) and Zijlstra (2016) estimate that access to a CC results, on average, in 5,800 to 6,800 additional vehicle kilometers for non-work-related trips on an annual basis, compared to the mileage of vehicles privately owned by a suitable control group. Simply because car, fuel and maintenance costs are paid by the employer.

The implementation of a multimodal MB by employers is not straightforward in Belgium, partly due to the complex tax and social security systems: transport modes (public transport, car, bicycle) and trips motives (business, commute, and private) are treated differently in the current regulations on reimbursements or fringe benefits (Vanoutrive, 2010). To overcome this barrier, the implementation of a new federal law (next to the existing legislation) was necessary (Zijlstra & Vanoutrive, 2018). The work we present in this paper was motivated by the transport related effects of the MB and the need for new legislation to make its introduction possible.

Due to the existing barriers for the implementation of the MB, revealed preference data are scarce and fragmented in Belgium (Zijlstra, 2016). Moreover, pilot tests performed by a small number of employers were generally motivated by an acute situation (for example, relocation of the headquarters or a shortage in parking capacity) and accompanied by the introduction of other corporate mobility policy measures, like the introduction of parking fees. As a result, the outcomes are biased. For these reasons, we used a stated preference technique (Hensher, Rose, & Green, 2005).

A key property of the MB is that it involves mixtures of alternative CCs or alternatives to the CC. For instance, some employees may prefer a combination of a pedelec with a public transport network card, while others may prefer a smaller car and a financial bonus at the end of the year. As a result, our stated preference study is concerned with preferences for mixtures. As the composition of the mixtures depends on the total available budget and as the preferences may depend on the total available budget, our study also takes into account the total amount of the mixtures. For this reason, conceptually, our regression model resembles mixture-amount models in medicine (where the recovery of a patient depends on the dose of a medical drug taken (= amount) and the mixture of ingredients that composes the drug), agriculture (where the yield of a crop depends on the dose of a fertilizer and the mixture of ingredients that composes the fertilizer), and marketing (where the sales of a product depend on the amount of advertising as well as the proportions of TV, radio, magazine and internet advertising) (Aleksandrovs, Goos, Dens, & Pelsmacker, 2015; Piepel & Cornell, 1985).

In this paper, we embed mixture-amount models in a panel mixed logit framework to describe preferences and preference heterogeneity for the MB. We believe that this type of modeling is relevant to transportation researchers, in situations where a mixture and an amount might drive preferences. A simple example of such a scenario is a travel route choice, where the choice sometimes is between (i) a journey consisting of two connecting train services and requiring a longer travel time, and (ii) a journey consisting of three connecting train services and requiring less travel time. In such cases, a traveler’s preference may depend on the total travel time (= amount) and the mixture of travel modes required.

In Section 2, we offer an introduction to mixture-amount modeling. We discuss fields where the mixture and mixture-amount choice experiments can be successfully applied and describe the state-of-art. Next, we introduce the MB case study in Section 3. In that section, we also explain how we designed and set up our mixture-amount stated preference study. In Section 4, we present the results of our study, discuss the goodness of fit of the various models we considered, and study the effects of the amount of the MB as well as its component's proportions. In Section 5, we summarize the key insights, discuss the policy implication of our MB stated preference study, and address a number of issues with respect to choice modeling with mixtures.

2. Mixture-amount modeling

The collection and the analysis of data concerning the MB has two key features. First, a total amount is involved. Second, the total amount is assigned to different components, which gives rise to a mixture of components. The total amount refers to the fixed individual budget each employee is entitled to, regardless of what components are selected within the MB. Certain employees will spend their entire budget on a company car, resulting in a proportion of 100% for the company car component and a proportion of 0% for all other components. Other employees may spend 50% of their individual budget on a company car, 25% on an electric bike and 25% on public transport. Yet other employees may abandon their company car and invest 50% of their individual budget on public transport and 50% on extra days off. This way, each employee selects a mixture of benefits, the proportions of which all sum to 100% or 1.

In this scenario, the employees' preferences may depend on the proportions of the various components of the MB mixture and on the total amount of the MB. For instance, an employee with a small budget may spend it completely on a small CC, while an employee with a large budget may spend half of the MB on a small CC and the other half on a public transport network card. Modeling these kinds of preferences requires a specific kind of regression model, known in the literature as a mixture-amount model. In this section, we discuss the key properties of mixture-amount models. We start by explaining what the most common mixture models are. Then, we extend these models with additional explanatory variables called process variables. Mixture-amount models are special cases of mixture models involving process variables. As mixture models and their extensions have been applied originally in the food industry, chemistry, agriculture and pharmaceutics, our initial examples are taken from these disciplines. In the final part of this section, we provide an overview of the still limited use of mixture models in transportation and other branches of social science.

2.1 Mixture models

The sum of all component proportions in a mixture always equals 100% or 1 (Cornell, 2011; Scheffé, 1958). This equality is known as the *mixture constraint*:

Eq. 1
$$\sum_{i=1}^{q} x_i = x_1 + x_2 + \cdots + x_q = 1$$

In this equation, x_i represents the proportion of component *i* (or attribute *i*), while *q* represents the number of components. Each component proportion x_i is potentially in the range [0, 1], though, in many practical applications, smaller intervals apply.

To model data involving explanatory variables that are proportions of mixture components, Scheffé (1958) introduced a series of specific polynomial regression models (Eq. 2a – Eq 2d). The simplest Scheffé model in the table is a first-order model (Eq. 2a), while the most complex is the full cubic model (Eq. 2d). Equations 2a, 2b and 2c are also referred to as the linear, quadratic and special cubic Scheffé model. As in any regression model, the term ε is the random error term. The models of Scheffé are the ones predominantly used for data involving mixture components (Cornell, 2011; Goos & Jones, 2011; Smith, 2005). The Scheffé models have a few specific characteristics. For instance, due to the mixture constraint, no intercept is present. Otherwise, perfect collinearity would be present, and the model parameters would not be identified. Also, the second-order and third-order Scheffé models do not involve quadratic terms in addition to cross-product terms, since this would also result in perfect collinearity (Prescott, 2004; Ruseckaite, Goos, & Fok, 2017).

Eq. 2.a First-order

$$Y = \sum_{i=1}^{q} \beta_i \, x_i + \varepsilon$$

Eq. 2.b Second-order

$$Y = \sum_{i=1}^{q} \beta_i \, x_i + \sum_{i=1}^{q-1} \sum_{j=1+i}^{q} \beta_{ij} \, x_i x_j + \varepsilon$$

Eq. 2.c Third-order

$$Y = \sum_{i=1}^{q} \beta_i \, x_i + \sum_{i=1}^{q-1} \sum_{j=1+i}^{q} \beta_{ij} \, x_i x_j + \sum_{i=1}^{q-2} \sum_{j=i+1}^{q-1} \sum_{k=j+1}^{q} \beta_{ijk} x_i x_j x_k + \varepsilon$$

Eq. 2.d Full cubic

$$Y = \sum_{i=1}^{q} \beta_i \, x_i + \sum_{i=1}^{q-1} \sum_{j=1+i}^{q} \beta_{ij} \, x_i x_j + \sum_{i=1}^{q-1} \sum_{j=1+i}^{q} \delta_{ij} x_i x_j (x_i - x_j) + \sum_{i=1}^{q-2} \sum_{j=i+1}^{q-1} \sum_{k=j+1}^{q} \beta_{ijk} x_i x_j x_k + \varepsilon$$

The cross-product terms in the Scheffé models capture possible interactions between the components of the mixture. More specifically, these terms allow antagonistic or synergetic effect between components to be captured. Synergy is the interaction of multiple components to produce an effect (a utility or a preference) larger than the weighted sum of their individual effects (their marginal utilities). An antagonistic effect is the opposite of synergy. The most commonly used Scheffé models in the literature are the second-order and third-order models in Eq. 2b and 2c (Goos, Jones, & Syafitri, 2016).

In this article, we pay explicit attention to interaction effects. This distinguishes our work from most published stated preference studies which focus on the main effects of the attributes (often called part-worth values) and ignore interaction effects. With respect to transportation studies, synergetic and antagonistic interactions might be highly relevant. Within Mobility-as-a-Service packages some combinations of services can outperform others – in terms of utility - due to combinations of modes and services within a single package (Matyas & Kamargianni, 2017). Transport authorities are confronted with investment programs with constrained budgets, here some combinations of projects might also generate synergetic or antagonistic effects (Hensher, Ho, & Mulley, 2015). Antagonistic of synergetic effects might occur in intermodal trip chaining, for example, to cover the first mile to the train station a bicycle is often preferred over a bus (Rietveld, Bruinsma, & van Vuuren, 2001). With respect to the MB, this might result in a synergetic effect for a combination of a bicycle and a seasonal train card. Other relevant interaction effects within MB schemes might occur if one can combine additional days off with a bicycle (to be used during the extra free time) or with additional cash (to spend during the extra days off).

2.2 Mixtures with process variables or amounts

Often, preferences for mixtures of components are also impacted by so-called process variables. For instance, the preference for bread does not just depend on the proportions of the ingredients used to prepare the dough, but also on the baking time, the proofing time and the baking temperature. The effect of these process variables is additive or integral to the mixture effects. In the former case, the effect of the mixture component proportions does not depend on the levels of the process variables. In other words, the effect of the mixture component proportions is the same for each level of the process variables. In the bread baking example, this would imply that the best recipe for bread is independent of the baking time, proofing time or baking temperature. In a transportation context, an additive effect for a process variable would correspond to a scenario in which the preference for a mix of travel modes does not depend on whether the journey is for work reasons or for leisure. In the event there is a single process variable named a with an additive linear effect, we can modify the models from Table 1 as follows:

Eq. 3a $$Y = [mixture\ model\ (Eq.\ 2a\text{-}d)] + \gamma a$$

In the event the process variable has an additive quadratic effect, the mixture-process variable model can be modified as follows:

Eq. 3b $$Y = [mixture\ model\ (Eq.\ 2a\text{-}d)] + \gamma_1 a + \gamma_2 a^2$$

When it is unrealistic to assume that the effects of the mixture components do not depend on the levels of the process variables, cross-products are required between the mixture proportions, on the one hand, and the process variables, on the other hand. The most traditional models for a single process variable are obtained by crossing all terms of the mixture model (Eq. 2a-d) with the process variable. The models in which the process variable has a linear effect only and a linear effect as well as a quadratic one are as follows:

Eq. 4a $$Y = [mixture\ model] + a[mixture\ model]$$

Eq. 4b $$Y = [mixture\ model] + a[mixture\ model] + a^2[mixture\ model]$$

With integral effects, it is assumed that the levels of the process variables have an effect on the blending characteristics of the mixture components (Cornell, 2011; Prescott, 2004). Prescott (2004) points out that the additive effect assumption is ‘not practically realistic’ (p. 90) and recommends the use of integral-effect models. He also points out that the standard integral effect models ‘will contain far too many parameters in [their] unreduced form’, which may result in overfitting and necessitates large datasets. For this reason, Kowalski, Cornell & Vining (2000) proposed a series of *composite models* in which elements from integral and additive effects of process variables are combined. As Smith (2005, pp. 302–303) demonstrates, a second-order mixture model with three components and two process variables with quadratic effects typically results in a 36-term model. If a composite model is used instead, the number of terms drops to 21.

In some cases, the only process variable to take into account is the total amount of the mixture. This is relevant when the mixture under investigation is a fertilizer and the response is the yield of a crop, or when the mixture under investigation is a medical drug and the response is the survival time of the patients. In these kinds of studies, not only the composition of the fertilizer or drug has an impact on the response, but also the total amount (dose). Mixture models that do account for the total amount of the mixture are known as mixture-amount models (Piepel & Cornell, 1985; Smith, 2005). With respect to the MB, we expect an amount effect, as more options and combination come within reach with a larger budget to spend.

2.3 Preference modeling with mixtures

Mixture models, with or without process variables, can be combined with choice models to model preferences for mixtures of components. Raghavarao and Wiley (2009) provide a number of examples in which working with mixtures in a stated preference study might be appropriate, like in product or service development, and insurance. Their empirical case evolves around the design of tourism packages for a certain period. Holiday and travel time are scarce resources, as there are only 24 hours in one day. Hence, in the context of tourism packages, it might be interesting to look into the optimal balance or mixture of activities. Not only temporal or financial budgets are constrained: traffic engineers, architects and urban planners need to deal with spatial limitations in the allocation of functions. In short, there are many fields in which the use of mixtures and mixture-amount stated preference studies might be of added value. A key requirement is that the mixture components need to be transferable to a single dimension with similar units in the modeling process, like costs expressed in euro, surface area expressed in squares meters, or travel time expressed in minutes. In our stated preference study, concerning the MB, all components of the mixture to be chosen have a specific cost in euro, so that this requirement is fulfilled.

Despite the work of Raghavarao and Wiley (2009), mixtures are still uncommon in the field of choice modeling. We only found a few examples involving empirical data. The first application involves the choice of cocktails and is described by Courcoux & Séménou (1997). In that application, which is also studied by Goos & Hamidouche (2019), the focus is on the taste of cocktails consisting of three ingredients. The taste only depends on the ingredient proportions, and not on the total amount of cocktail. The only other applications with mixtures in a choice context come from one research group in the Netherlands. Dane, Timmermans & Wiley (2011) as well as Khademi & Timmermans (2012) consider the optimal allocation of travel time budgets. Yang, Timmermans & Borgers (2016) look into the optimal combination of energy consumption savings within a constrained budget. In none of these papers, a state-of-the-art efficient experimental design tailored to choice models is used, even though the sample sizes used were often relatively small (n = 304 in Khademi & Timmermans (2012); n = 317 in Yang, Timmermans & Borgers (2016)). And in most of these papers, we cannot find an examination of the various alternative models that exist for mixture-amount data.

The near absence of mixture and mixture-amount models in the context of choice is striking, since these types of models offer interesting features and certain products and services can be regarded as mixtures with or without process variables. In the next section, we explain how preferences for the MB can be modeled using a mixture-amount choice model. We also discuss how a sensible mixture-amount choice design can be constructed. While there exists a substantial body of literature on the optimal design of stated preference studies (e.g. Hensher et al., 2005; Huber & Zwerina, 1996; Kessels, Goos, & Vandebroek, 2006; Louviere, Hensher, & Swait, 2000; Rose & Bliemer, 2009), the optimal design of choice experiments involving mixtures with process variables or amounts is unknown research territory. The optimal design of choice experiments involving mixtures in the absence of process variables or amounts was discussed by Ruseckaite et al. (2017), who build on design construction algorithms for industrial mixture experiments such as those described in Piepel, Jones & Cooley (2005). Ruseckaite et al. (2017) are the first to present a proper optimal design approach for choice experiments with mixtures, as opposed to other authors who combine traditional mixture experimental designs with balanced incomplete block designs in an ad hoc fashion. While the focus in the present paper is on presenting a suitable model for the mixture-amount choice data resulting from our MB stated preference study, we also present a procedure to construct an efficient design for a stated choice experiment involving mixtures and amounts.

3. Case study of the mobility budget

In this section, we discuss the experimental design approach we used for the stated preference study we carried out in Belgium concerning the MB. We also provide details on the data collection strategy and the resulting data set.

3.1 Preparation of the mixture-amount stated preference study

Our stated choice study was based on the most popular version of the MB in Belgium in 2014. In that version, the target group consists of current CC owners. Within a fixed budget, the idea of the MB is that these CC owners are allowed to combine transport-related fringe benefits (including a car), additional income and some other benefits like a day off. In order to limit the complexity of the choice tasks for the respondents, we reduced a long list of options to a total of five well-known and potentially popular components. Our final selection of components (or ‘attributes’ in common stated preference vocabulary) and their absolute levels, expressed in euro, are presented in Table 1. For example, the bicycle component has three possible levels. If a respondent does not desire a bicycle (or pedelec), the cost is obviously zero. If the respondent does desire a bicycle, there are two options: an expensive bicycle costing 2,000 euro and a less expensive bicycle costing 1,000 euro.

While Table 1 presents the factor levels in absolute costs, we converted these costs into proportions in our choice models. This is in line with the Scheffé models and the mixture-process variable models introduced in the previous section. In the actual choice situations presented to the respondents, however, we presented the options in a realistic fashion, using descriptions such as ‘Standard bicycle’ for the 1,000-euro bicycle or ‘First class public transport network card’ for the 4,500-euro public transport option. The components and levels were introduced to the respondents with descriptive texts and pictures on screens prior to the experiment. The proportions of the five components are coded as x_1 to x_5 in the remainder of this paper (see also Table 1).

Table 1: MB components, coding and levels expressed in text and absolute costs

Component	Company car w. fuel card	Bicycle	Public transport	Days off	Bonus
Code	x_1	x_2	x_3	x_4	x_5
Label (displayed)	No	No	No	No	No
	Cat. I	Standard	2nd class network card	2 days extra	2000 euro
	Cat. II	Luxurious	1st class network card	4 days extra	4000 euro
	Cat. III			6 days extra	6000 euro
	Cat. IV				
Cost (not displayed)	€ 0	€ 0	€ 0	€ 0	€ 0
	€ 6,000	€ 1,000	€ 3,000	€ 500	€ 2,000
	€ 7,500	€ 2,000	€ 4,500	€ 1,000	€ 4,000
	€ 9,000			€ 1,500	€ 6,000
	€ 10,500				

Since employees with a CC receive different salaries, have different levels of fuel consumption and are entitled to different sizes of CCs, the individual MBs also have to differ in size. It is conceivable that employees with an expensive CC view this as a status symbol and will be reluctant to give up their CC or exchange it for a smaller one plus some other benefits. In contrast, it is possible that employees with a small CC are enthusiastic about the possibility of replacing their CC with other benefits. As a result, we expected the effects of the different components of the MB to differ with the overall size of the MB. Consequently, it was important to model the employees' preferences as a function of the component proportions as well as the total size of their MB, and to allow for interaction effects between these proportions and the MB size. In the remainder of the paper, we refer to the size of the MB as the total amount a. We express the total amount in thousands of euro (× 1,000). In the planning phase of our stated choice study, we found out that most MBs in practice will be in the range from 6,000 to 11,000 euro per year, given the gross costs of a fully operational lease car (including a fuel card) for the period of one year. Consequently, a belongs to the interval [0.6, 1.1]. In our study, we considered amount values a ranging from 0.6 to 1.1 in steps of 0.05, corresponding to 500 euro.

Using the MB components listed in Table 1, we can define 720 ways to spend a MB, because there is one component with five levels, there are two components with three levels and two more components with four levels, and 5×3×3×4×4=720. However, not all the 720 combinations are feasible. Certain combinations have a cost exceeding the upper limit of 11,000 euro, while other combinations have a cost that is lower than the lower limit of 6,000 euro. Because we wanted to use realistic amounts of MBs in our study, we did not use these kinds of combinations in our stated choice experiment. Instead, we only used the 151 combinations whose cost falls within the interval from 6,000 to 11,000 euro. The number of acceptable combinations of MB components increases with the size of the MB, i.e. with the total amount. So, a budget size of 11,000 euros allows for more combinations than a budget size of 6,000 euro. For instance, the number of acceptable combinations is 9 for a budget of size 6,000, as opposed to 20 for a budget size of 11,000.

3.2 Constructing the design for the stated choice experiment

In our choice experiment, we used choice situations involving two options, i.e., two combinations of MB components. Since, for any given employee, the total amount of the MB is fixed, any choice situation should involve two options with the same total cost. This limits the number of possible choice situations, because it means that not all pairs of the 151 acceptable MB component combinations are allowed. For instance, a combination with a cost of 6,000 euro cannot appear in a choice situation that also has a combination that costs 11,000 euro. It turned out that, using the 151 acceptable MB component combinations, we could form 1,023 acceptable choice situations, instead of 11,325 (=151×(151-1)/2). The constraint to have equal costs or amounts for both alternatives in a choice situation is inherent to the MB concept. In other applications involving mixtures and amounts, there may be no need for such a constraint and choice situations involving two alternatives with different amounts may make sense. An illustration of such a scenario can be found in Raghavarao and Wiley (2009).

After defining the 1,023 acceptable choice situations, the next challenge was to select the choice situations to be used in the actual choice experiment. To ensure that we selected choice situations with a high information content, we made the selection of the choice situations using the D-optimal design approach that has been advocated by various groups of authors (Bliemer, Rose, & Hess, 2008; Graßhoff, Großmann, Holling, & Schwabe, 2004; Kessels, Jones, Goos, & Vandebroek, 2011; Rose & Bliemer, 2009; Rose, Bliemer, Hensher, & Collins, 2008). For any given number of choice situations used in the choice experiment, a D-optimal design guarantees the most precise parameter estimates, in the sense that the determinant of the parameter estimates' variance-covariance matrix is minimized (Rose & Bliemer, 2009). To limit the computational burden when generating a D-optimal set of 96 choice situations, we adopted the utility-neutral design approach of Großmann et al. (2009; 2006). This allowed us to use the modified Fedorov point-exchange algorithm implemented in the OPTEX procedure for optimal experimental design in the SAS software (SAS Institute Inc., Cary, North Carolina).

When creating our experimental design, we started from the special cubic Scheffé model for the mixture effects and a linear integrated amount effect. More specifically, we based our experimental design on the following utility model involving 38 parameters:

Eq. 5
$$E(U) = \sum_{i=1}^{q-1} \beta_i\, x_i + \sum_{i=1}^{q-1} \sum_{j=1+i}^{q} \beta_{ij}\, x_i x_j + \sum_{i=1}^{q-2} \sum_{j=i+1}^{q-1} \sum_{k=j+1}^{q} \beta_{ijk} x_i x_j x_k + \sum_{i=1}^{q-1} \beta_i\, a x_i + \sum_{i=1}^{q-1} \sum_{j=1+i}^{q} \beta_{ij} a\, x_i x_j$$

where q equals 5. In this expression, $E(U)$ represents the systematic utility for an alternative. The assumed model in Eq. 5 involved many interaction terms to ensure that the experimental design we obtained would be capable of estimating possibly interesting interaction effects of the MB components precisely and of modeling the complex relationship between the respondents' preferences, on the one hand, and the MB component proportions and the total amount of the MB, on the other hand. Because any experimental design tailored to a complex model also allows estimation of any simpler model, our experimental design is suitable for estimating a broad variety of models.

Initially, we generated an experimental design involving 96 choice situations. We picked this number because it was our intention to let each respondent evaluate 12 choice situations and 96 is an integer multiple of 12, and because, according to Sándor & Wedel (2005), using different choice situations for different respondents enhances the quality of the experimental design. When studying the D-optimal set of 96 choice situations produced by the SAS procedure OPTEX, we observed that these included very few alternatives involving a CC: 53.6% of the alternatives contained no CC, and only 4.7% of the alternatives involved a CC without any other benefits. This was at odds with the fact that the targeted respondents currently only receive a CC. Due to this mismatch, we were concerned about a lack of choice situations involving the current default in the D-optimal choice situations and the possible drop-out of respondents this might entail (Fernandez & Rodrik, 1991; Kahneman, Knetsch, & Thaler, 1991; Samuelson & Zeckhauser, 1988).

A remedy for this problem would have been to include a 'status quo' option in each choice set. However, this could have led to a substantial loss of important information in the likely event that the respondents would massively pick the 'status quo' option. Instead, we added 32 choice situations involving a(n) (expensive) CC. These additional choice situations were randomly drawn from a subgroup of choice situations, with high proportions for the CC component. The additional choice situations implied an increase from 96 to 128 choice situations. An alternative approach with a 'forced choice' each time a respondents selected the 'status quo' option, seemed less attractive to us, as respondents might quickly learn that picking the status quo option was followed by a 'forced choice' and therefore take a shortcut in later choice situations, by no longer selecting the 'status quo' option to complete the entire questionnaire faster.

The total of 128 choice situations were divided over eight blocks of 16 choice sets each. Each block contained 12 choice situations from the original D-optimal design and four additional ones involving a(n) (expensive) CC. The full design was split into four blocks with relative low budgets or amounts (with values for a ranging from 0.6 to 0.9) and four blocks with relative high budgets or amounts (with values for a ranging from 0.9 to 1.1). Eventually, the respondents were randomly assigned to one of the four high-budget blocks or one of the four low-budget blocks, depending on their current CC. The full experimental design can be found in the appendix.

3.3 Data collection and descriptive statistics

We approached multiple employers in Belgium with a request to collaborate in the context of the MB project and to provide us with a sample of their employees with a CC. In return, employers were allowed to add questions at the end of the survey and were offered a company-level report on the results. In total, 12 companies participated. Most of these companies considered the implementation of the MB in the future. The questionnaire with the stated choice experiment was administered in two rounds in 2014. The overall response rate of 38.5% is excellent for an online non-panel questionnaire.

Our cleaned data set only contains target group members, i.e. CC users. Individuals with missing data for key questions, such as questions concerning the CC use, were removed from the dataset. In total, we received useful data from 817 individuals and a total of 13,072 choice situations. This should be sufficient for robust results (Rose & Bliemer, 2013). The basic socio-demographics of our final sample are shown in Table 2.

Table 2: Basic socio-demographic data of the respondents in the final data set

Aspect	Level	obs.	%
Gender	*Male*	505	62%
	Female	306	38%
Age group	*< 30 years*	42	5%
	30 – 39 years	313	38%
	40 – 49 years	329	40%
	50 – 59 years	121	15%
	≥ 60 years	9	1%
Children living at home	*Yes*	613	76%
	No	197	24%
Partner	*Yes*	695	86%
	No	115	14%

4. Analysis and results

4.1 Estimation procedure

As modeling data from mixture-amount stated preference studies is still largely uncharted territory, we explored the differences between the two most common estimation procedures for advanced mixed logit choice models: maximum simulated likelihood (MSL) and hierarchical Bayesian (HB) estimation (Allenby & Lenk, 1994; Rossi, Allenby, & McCulloch, 2005; Train, 2009). In our mixed logit choice models, we treated every model parameter as random, to allow for inter-employee differences in preference concerning any component of the MB.

Based on our comparison, we are inclined to recommend the use of HB procedures for the modeling for two reasons. First, for our data and all models we explored, the HB estimation procedure always provided estimates of the model parameters, while the MSL estimation approach did not converge on multiple occasions. More specifically, we encountered convergence problems with the MSL estimation procedure for higher-order models, because these models involve many parameters. Of course, before we can trust the HB estimation results, we need to confirm the stabilization of the Markov chains utilized in that estimation procedure. To this end, we used Geweke scores, Heidelbergers' stationary test and a visual inspection of the trace plots. Second, the use of popular Halton draws in the MSL estimation procedure becomes problematic for high-dimensional problems (Andersen, 2014; Bhat, 2003; cf. Yang et al., 2016). More specifically, large numbers of random draws are needed in MSL estimation. For instance, for our second-order quadratic effect mixed logit model, we had to use 50,000 draws to simulate the likelihood function (results not presented in this paper), and we had to rely on a high performance computer (a 168-node cluster with Intel IvyBridge (2680v2) processor) to obtain output from the MSL procedure within a reasonable amount of time (about 30 hours). In general, the results and the performance of HB estimation procedures seemed more robust and, moreover, this estimation procedure was feasible on an ordinary PC.

In the remainder of this paper, we discuss the results from models estimated by means of a HB procedure. In all cases, the model is a *mixed multinomial logit model* (MMNL) based on panel techniques and assuming a normal distribution for the random parameters. All models presented have been estimated using the package RSGHB in *R* for the HB procedure (Dumont, Keller, &

Carpenter, 2015; R core team, 2015), which builds on the generalized algorithms by Train (2006, 2009), derived from the work of Allenby and others (Allenby & Lenk, 1994; Allenby & Rossi, 2003; Sawtooth, 2009). For the statistical inference, we partly relied on the coda-package for the analysis of MCMC-chains in *R* (Plummer et al., 2015).

For all models we report below, we applied the same prior distributions and settings in the HB estimation procedure. More specifically, we performed 100,000 iterations, without thinning (thinning =1) and with a relatively long burn-in period. We only used the final 5% of the iterations for estimating the model parameters. We set the degrees of freedom for the prior covariance matrix of the random model parameters to 250. This large number for the degrees of freedom results in individual-level parameter estimates that do not deviate tremendously from the population-level, aggregate estimates (Sawtooth, 2009). This strategy was prompted by the fact that our primary interest is in the population-level estimates. We set the prior mean for each population-level parameter to zero, and used a normal prior distribution for each of the parameters. Finally, we set the prior variance for the population-level parameter estimates to 5,000.

4.2 Model comparison and selection

It is generally unclear which model is the most suitable one for any given data set. Also in our application involving mixtures and amounts, it is important to test various models, ranging from simple to complex, and to see which model fits the data best (Scheffé, 1958; Prescott, 2004). For linear regression models involving mixtures, Cornell (2011) recommends evaluating the gain in goodness-of-fit by studying the so-called F-scores. Since we need mixed logit models here, we cannot use F-scores. Instead, we evaluate the trade-off between model fit improvement and model complexity using BIC scores (Schwarz, 1978). This criterion penalizes the inclusion of additional parameters in models more severely than, for instance, Akaike's information criterion does (Akaike, 1974). For our problem, the number of parameters increases strongly with the model complexity (Table 3).

Table 3: Number of parameters (for mean and s.d.) in alternative mixed logit models

	Integrated amount-effect			**Composite**
Polynomial	*None*	*Linear*	*Quadratic*	**Models**
First-order	8	16	24	10
Second-order	28	56	84	40
Third-order	48	96	144	90
Full Cubic	68	136	204	-

The performance of most models is good. The initial or zero log-likelihood function value (L score), for a model without explanatory variables, was −9,026, while the highest L score found is −5,653. This implies a pseudo-ρ^2 value of 0.37. As shown in Fig. 1, there are substantial differences in BIC score for the models we fitted to our data. A general rule of thumb for BIC scores is that a 10-point decrease marks a highly significant improvement (Kass & Raftery, 1995). Figure 1 shows that the drops in BIC score are quite large for our data set (much larger than 10 units), when moving from an ordinary mixture model to a mixture-amount model. One model formulation involving a quadratic effect of the amount outperforms all other models tested. To some extent, this is surprising since we did not include quadratic amount effects in the model upon which the experimental design is based (Eq. 5). Nevertheless, the design, shown in the appendix, involves choice situations with many different amount levels. This allows the estimation and testing of higher-order amount effects.

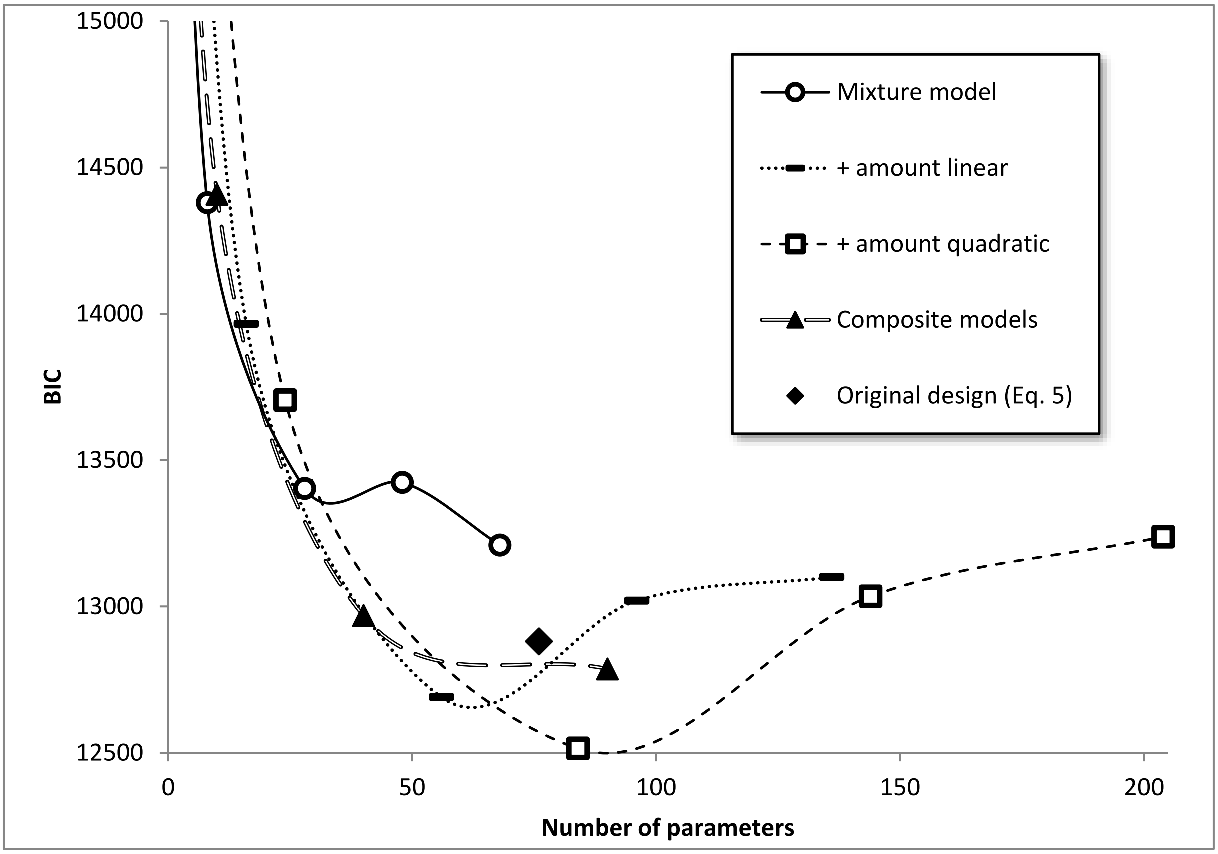

Fig. 1: BIC scores for the various fitted models

The best model in terms of BIC score for our data is *the second-degree Scheffé model with integrated quadratic amount effects*. The BIC score for this model, which involves 42 mean parameters and 42 standard deviations for these parameters, was 12,515. The form of this model is as follows:

Eq. 6

$$E(U) = \sum_{i=1}^{q-1} \beta_i x_i + \sum_{i=1}^{q-1} \sum_{j=1+i}^{q} \beta_{ij} x_i x_j + \sum_{i=1}^{q-1} \beta_i a x_i + \sum_{i=1}^{q-1} \sum_{j=1+i}^{q} \beta_{ij} a x_i x_j + \sum_{i=1}^{q-1} \beta_i a^2 x_i + \sum_{i=1}^{q-1} \sum_{j=1+i}^{q} \beta_{ij} a^2 x_i x_j$$

where q is again 5. The model in Eq. 5, on which the D-optimal design was based, involved 38 parameters for the means and has a BIC score of 12,882. While that model is among the best models we fitted to our data, in terms of BIC score, it is outperformed by several other models we fitted. The parsimonious composite models proposed by Kowalski et al. (2000), and adopted in nearly all publications on choice models of mixtures (Dane et al., 2011; Khademi & Timmermans, 2012; Raghavarao & Wiley, 2009; Yang et al., 2016) do not provide the best BIC score either. For example, the second-order composite model with quadratic amount effects involves 40 instead of 84 parameters (Table 3), but it results in a BIC score of 12,969, which is significantly higher than the best BIC value we obtained.

The relative performance of the different kinds of models in Fig. 1 was not unique to the mixed logit setting, which assumes that every respondent has his/her own preference structure. We also compared the different models in a latent class model framework involving two classes and in a simple multinomial logit framework. In latent class models, the assumption is that there are different groups of respondents. Within each group, the respondents are assumed to have the same preference structure, but, across the groups, the respondents have different tastes. Also, in the latent class framework and in the multinomial logit framework, the model in Eq. 6 outperformed the alternatives in terms of BIC score. These models were, however, inferior to the mixed logit models we fitted and compared in Fig. 1.

The parameter estimates for the first- and second-order Scheffé mixture models with or without the linear and quadratic amount effects are shown in Table 4. The parameter estimates differ substantially from one model to the next in the table. This is due to the well-known phenomenon that dropping relevant terms causes bias in the remaining estimates. This phenomenon is quite pronounced for our data set, since multicollinearity is unavoidable when working with mixtures: when one proportion goes up, at least one other proportion must go down to ensure that the sum of all proportions equals one (Eq. 1). The occurrence of multicollinearity and the presence of many interaction terms also implies that interpreting individual regression parameters and performing individual significance tests makes little sense, and that it is better to take a prediction and optimization perspective.

Table 4: Mean estimates and time-series corrected s.e. for first- and second-order Scheffé models

	First-order Scheffé model						Second-order Scheffé model					
Amount effect	none		linear		quadratic		none		linear		quadratic	
Number of β's	4		8		12		14		28		42	
BIC score	14,380		13,966		13,705		13,403		12,690		12,515	
Term	est.	s.e.	est.	s.e.	est.	s.e.	est.	s.e.	est.	s.e.	est.	s.e.
β_1	-0.72	0.01	-8.33	0.21	-28.47	0.11	0.36	0.02	-11.46	0.10	-18.52	0.10
β_2	-2.91	0.02	-9.96	0.35	10.48	0.46	7.69	0.55	-9.62	0.34	-3.72	0.11
β_3	-4.22	0.01	-3.52	0.14	-8.47	0.22	-6.34	0.03	-11.98	0.32	-5.38	0.11
β_4	3.36	0.03	0.07	0.12	0.81	0.33	-16.31	0.06	-15.67	0.22	-4.47	0.23
β_{12}							-11.00	0.79	-15.91	0.64	-15.10	0.58
β_{13}							2.22	0.08	-0.23	0.74	-6.44	0.25
β_{14}							22.35	0.18	17.57	0.51	2.33	0.87
β_{15}							2.93	0.13	7.10	0.31	-4.10	0.11
β_{23}							-5.25	0.58	1.40	0.59	4.06	0.19
β_{24}							2.60	1.48	9.41	0.66	14.97	0.22
β_{25}							-12.57	0.79	-0.46	0.13	-0.23	0.37
β_{34}							36.25	0.11	35.38	0.36	14.86	0.09
β_{35}							6.96	0.09	7.67	0.10	6.09	0.16
β_{45}							28.70	0.31	7.08	0.97	-3.15	0.98
β_{1a}			8.30	0.22	58.23	0.21			14.14	0.13	31.16	0.12
β_{2a}			7.49	0.47	-47.54	0.49			13.45	0.08	-10.50	0.32
β_{3a}			-1.23	0.20	9.99	0.68			5.13	0.40	-8.37	0.45
β_{4a}			3.48	0.18	1.94	0.37			-1.62	0.10	-12.38	0.14
β_{12a}									12.56	0.22	7.83	0.80
β_{13a}									5.01	0.30	4.87	0.12
β_{14a}									8.21	0.18	13.23	0.17
β_{15a}									-1.98	0.47	18.67	0.21
β_{23a}									5.98	0.22	-1.67	0.29
β_{24a}									-2.93	0.73	-10.38	0.39
β_{25a}									-4.11	0.57	-2.79	1.11
β_{34a}									7.29	0.20	23.93	0.52
β_{35a}									4.30	0.31	2.52	0.68
β_{45a}									29.65	1.29	12.38	0.08
β_{1a2}					-29.62	0.13					-10.19	0.21
β_{2a2}					34.63	0.29					20.89	0.12
β_{3a2}					-6.41	0.47					6.22	0.44
β_{4a2}					1.32	0.48					5.28	0.50
β_{12a2}											0.36	0.50
β_{13a2}											6.07	0.13
β_{14a2}											3.70	0.24
β_{15a2}											-9.73	0.59
β_{23a2}											0.48	0.21
β_{24a2}											-3.35	0.16
β_{25a2}											-7.23	0.33
β_{34a2}											-5.34	0.21
β_{35a2}											2.42	0.16
β_{45a2}											23.40	0.09

Note: The columns labeled s.e. contain time-series corrected standard errors of the estimates, based on 5,000 iterations of the HB procedure and calculated with the coda package in "R" (Plummer et al., 2015). Amount effects: 'none' refers to models without the amount, 'linear' refers to models with integrated linear amount effects, and 'quadratic' refers to models with integrated quadratic amount effects.

4.3 Optimal mixtures: maximizing utility

Models for data from mixture experiments are generally used to identify optimal mixtures, and to investigate how the optimal mixtures vary with the amount. For instance, in agriculture, one may look for an optimal composition of a fertilizer in the event a low dose is used, and investigate whether that composition needs to be changed when a high dose is needed.

In order to optimize the MB composition in our application for various values of the amount variable a, we used the nonlinear constrained optimization function *fmincon* in *MatLab 2014a* (MathWorks, Natick, Massachusetts). First, we fixed the amount value to 8,807 euro, the estimated average budget size available to our respondents, and computed the optimal MB composition, using the estimates of the parameters from each of the fitted mixed multinomial logit models. Next, we also studied the effect of the amount on the optimal mixture. In our optimization, we did not impose any lower bound on the proportion of the various MB components. This implies that zero proportions are allowed in our optimal MB composition. A zero proportion in an optimal mixture should be interpreted as a component that the respondents dislike. A large proportion corresponds to a MB component that the respondents do like. We did use an upper bound, however, for each of the components during our optimization, to exclude impossible or extreme results. For example, the maximum spending we allowed on a bicycle was 3,000 euro. In general, the upper bound we use in this section for a given component is larger than that used in the initial experimental design (Table 1). More specifically, we allowed one extra level for each component of the MB. For example, the amounts that could be spend on a bicycle in the actual stated choice study were 1,000 and 2,000. Therefore, the new upper limit is 3,000 in absolute terms, or 0.341 (= 0.3/0.8807 = 34.1%) in relative terms.

The optimal mixtures obtained for the various models under investigation and for an amount value of 8,807 euro are listed in Table 5, along with the BIC scores of the various models and the ranks of the models in terms of BIC score. The results indicate that employees strongly prefer non-transport related fringe benefits: additional days off (x_4) and additional income (x_5). In the top-5 models in terms of BIC scores, the share of 'CC' (x_1) ranges from 32.4% to 40.8%, the share of 'days off' ranges from 13.3% to 19.6%, and the share of 'bonus' ranges from 45.3% to 49.1%. The optimal proportions for 'bicycle' (x_2) and 'PT' (public transport, x_3) are nearly always zero.

Table 5: Optimal mixtures for all models from Table 3 and the average MB size of 8,807 euro

Utility formula	BIC	Rank	*CC* (x_1)	*Bicycle* (x_2)	*PT* (x_3)	*Days off* (x_4)	*Bonus* (x_5)
first-order mixture	14.380	14	0.000	0.000	0.000	**0.227**	0.773
+ linear amount	13.966	13	0.000	0.000	0.000	**0.227**	0.773
+ quadratic amount	13.705	12	0.000	0.000	0.000	**0.227**	0.773
second-order	13.403	10	0.296	0.000	0.000	0.168	0.536
+ linear amount	12.690	2	0.384	0.000	0.000	0.163	0.453
+ quadratic amount	12.515	1	0.324	0.000	0.000	0.196	0.480
special cubic	13.424	11	0.000	0.000	0.000	0.213	0.787
+ linear amount	13.020	5	0.363	0.000	0.017	0.156	0.464
+ quadratic amount	13.035	6	0.229	0.000	0.000	**0.227**	0.544
full cubic	13.209	8	0.403	0.000	0.000	0.151	0.447
+ linear amount	13.100	7	0.249	0.000	0.000	0.116	0.635
+ quadratic amount	13.238	9	0.156	0.000	0.000	0.109	0.735
composite (1st order)	14.409	15	0.000	0.000	0.000	**0.227**	0.773
composite (2nd order)	12.969	4	0.408	0.000	0.000	0.133	0.459
composite (3rd order)	12.787	3	0.357	0.000	0.000	0.152	0.491

Note: Maximum values (upper bounds) in **bold**

Fig. 2 visualizes the impact of the amount on the preferences for the five MB components. More specifically, it shows the optimal proportions for the MB components for all budget sizes or amounts from 6,000 to 11,000 euro, calculated using the model from Eq. 6, which has the lowest BIC score. The figure clearly shows that the total amount is highly relevant for modeling the preferences. Across all amounts, the end-of-the-year bonus and days off components (whose proportions are denoted by x_5 and x_4, respectively) are popular parts of the MB mixtures. For people with a budget smaller than 6,500 euro, the optimal mix contains hardly anything other than these two components, but the days off component (x_4) is the only component whose proportion is actually maximized. Remarkably, the bicycle or pedelec (x_2) does not appear in any of the optimal mixtures. The preference for a CC (x_1) increases with the amount. The increase in the proportion of CCs in the optimal MB mixture is accompanied by a decrease in the proportion for the end-of-the-year bonus component. This is probably due to the phenomenon that more expensive cars, and thus status symbols, come within reach. It might also be related to income tax or to a lower relative utility for additional income in high-income groups, as these groups will generally be the ones who receive larger mobility budgets.

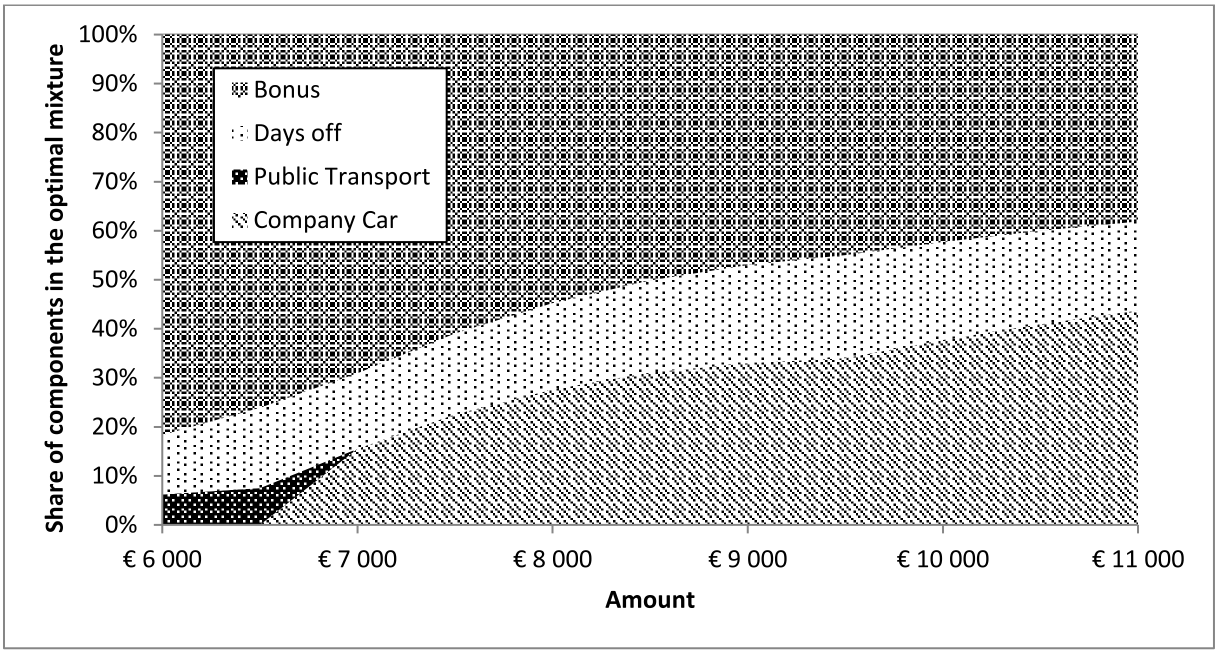

Fig. 2: Optimal proportions for the components of the MB as a function of the total amount available

Several remarks concerning the above analyses are in order. First, the utility formula used has an effect on the outcome in terms of the ideal proportions for x_1, x_4, and x_5, (i.e., the CC, 'days off' and 'bonus' components), while $x_2 = x_3 = 0$ for virtually each of the models when the amount is 7,000 euro or larger. Second, using a first-order Scheffé model results in an optimal mixture at the edge of the space of MB options we explored. A more nuanced image appears when interaction terms are included in the model and thus when a higher-order Scheffé model is utilized. Third, due to the popularity of both x_4 and x_5, the optimal MB option involves a very modest nonzero share for a CC for many of the models we tested, unless the budget is smaller than 6,500 euro. These modest nonzero proportions for CCs correspond to very cheap cars, which we considered as unrealistic options when setting up our study (Table 1). A simple explanation for this result is that it is based on the population-level mean estimates.

A more detailed analysis, using the individual level estimates, as obtained from the HB estimation of the model in Eq. 6, combined with estimated budget available to the individual, reveals that many respondents aim for (or cannot decide between) two components (Table 6). Popular options are, again, days off, bonus and the CC. These employees will probably allocate no budget to the remaining components. The upper bounds for the CC or bonus components are, however, rarely reached. In total, only 76 out of 817 participants dedicate a share of more than 90% of their budget to the CC. In only 23 cases, the maximum proportion for the bonus component is reached. Conversely, in 360 out of 817 cases, the maximum proportion for additional days off is reached. This confirms the popularity of less time for work or more time for family and leisure. Note that the average of all individually optimized mixtures in Table 6 differs from the optimal mixture derived from the population-level mean parameter estimates (for the model in Eq. 6).

Table 6: Optimization results for the first 10 individuals in our sample as well as the optimal mixture based on the population-level parameter estimates.

		Optimal situation					**Allocated budget** (= share * est. budget)				
ID	Est. budget	x_1	x_2	x_3	x_4	x_5	*CC* (x_1)	*Bicycle* (x_2)	*PT* (x_3)	*Days off* (x_4)	*Bonus* (x_5)
1	€ 7,352	18%	0%	0%	0%	82%	€ 1,322	€ 0	€ 0	€ 0	€ 6,031
2	€ 9,997	80%	0%	0%	20%	0%	€ 7,997	€ 0	€ 0	€ 2,000	€ 0
3	€ 9,396	0%	32%	48%	20%	0%	€ 0	€ 3,000	€ 4,500	€ 1,896	€ 0
4	€ 12,882	41%	23%	0%	0%	36%	€ 5,219	€ 3,000	€ 0	€ 0	€ 4,662
5	€ 8,068	69%	0%	6%	25%	0%	€ 5,575	€ 0	€ 493	€ 2,000	€ 0
6	€ 8,214	51%	0%	0%	0%	49%	€ 4,223	€ 0	€ 0	€ 0	€ 3,991
7	€ 9,269	41%	0%	0%	0%	59%	€ 3,806	€ 0	€ 0	€ 0	€ 5,463
8	€ 8,716	44%	0%	0%	0%	56%	€ 3,852	€ 0	€ 0	€ 0	€ 4,863
9	€ 9,082	78%	0%	0%	22%	0%	€ 7,082	€ 0	€ 0	€ 2,000	€ 0
10	€ 9,658	79%	0%	0%	21%	0%	€ 7,658	€ 0	€ 0	€ 2,000	€ 0
11	…	…	…	…	…	…	…	…	…	…	…
…											
817	…	…	…	…	…	…	…	…	…	…	…
AVG	€ 8,807	44%	6%	9%	13%	28%	€ 3,858	€ 561	€ 776	€ 1,113	€ 2,500

5. Conclusion

In this paper, we presented the set-up, design, implementation and data analysis of a mixture-amount stated preference study about the composition and combination of options within the mobility budget framework. The mobility budget is a new concept mainly aimed at reducing company car ownership and use. For a given individual and fixed budget (=amount), employees were allowed to make their own choices with respect to transport-related issues instead of getting a company car with fuel card. If they choose and travel wisely (i.e. if they do not opt for expensive company cars), these employees are able to save for an end-of-the-year bonus or obtain extra days off, for instance.

5.1 Policy implications

Our results demonstrate that current CC owners are hardly interested in a bicycle, pedelec or a network card for unlimited use of the PT network. Indeed, the MB seems to be a poor instrument to promote other modes of transport. Additional days off or a bonus are popular alternatives to the CC, as our results indicate. These options do have some potential to lower car ownership, to promote smaller (and lighter) vehicles and to reduce car use. However, it remains unclear how this additional time and money spend will be used by current CC users. Furthermore, when employees enjoy their days-off, other employees might be needed to carry out the work that needs to be done in their place. Some employees might cover more kilometers with their (less expensive) CC on a day-off than they would have on a regular day of work. In short, we do not expect that these options will necessarily result in a decrease of transport-related problems.

There are, of course, options to improve the relative position of the other transport modes, in comparison to the CC. This can be achieved by subsidies or tax-cuts for bicycles or public transport modes or by a less beneficial position for the CC. The latter is highly controversial, and was, in fact, the reason to promote the MB in the first place. The first option basically means an extension of the beneficial position of the CC to other modes. Meanwhile, one should be aware, that these options already receive subsidies and tax-cuts within the current legislative framework, especially for commutes.

One of the most obvious questions related to this paper would be: *should we implement the MB in Belgium?* In response, we would stress that *the* MB does not exist. In fact, multiple designs for the MB are possible, each with different highlights, key elements, and definitions. We only studied a popular interpretation of the concept via our experiment. The question regarding the need to implement the MB should therefore always be accompanied by a question regarding its design: what kind of MB should be implemented? This question, in turn, is directly related to the question of policy objectives and priorities. Moreover, the MB will always be nested within a larger framework of legislation and taxation (reimbursements, income tax, benefit-in-kind, etc.). Changes in any of these fields might have a direct or indirect effect on the success of the MB. Indeed, a seemingly technical-juridical issue is in fact political.

In general, we are relucted to promote the concept of the MB, as it does not directly deal with the issues associated to the CC. The beneficial treatment of the CC in current legislation and taxation was the reason to suggest the MB in the first place. The MB is not promoted instead of, but next to this beneficial position. Next, implementation of the MB is voluntary by employers, participation by employees is voluntary and within the MB these participants have the ‘freedom-of-choice’. Hence, it is a soft approach. The implementation of the MB requires serious investments by all parties involved, while the results from our stated choice study suggest that the modal shift potential of the MB will, most likely, be limited. In contrast, we would support a critical reflection and revision of the current system of the CC, which has its deficiencies. This revision does not, however, hinder the implementation of the MB, and might even boots its popularity.

If policy makers do feel the need to implement the MB or when the MB is already implemented, we would strongly suggest reconsidering the following design aspects: size of the budget, choice moments, and bonus option. In our experiment the size of the MB was equal to the current fixed and variable costs of the CC. The estimated budget available to the individuals ranged from 5,945 to 12,880 euros. For three reasons, we argue the size of the budget should not equal the current transport related costs. First, the current costs are also used to cover the costs for the excesses, like the annual 6,000 to 7,000 private kilometers (Section 1). If the current transport costs are transferred to a future budget, this budget will be sufficient to maintain current excesses. This first argument suggests that the budget should be lower. Second, establishing the current cost is not straightforward, especially not for new employees, as these costs might vary from time to time and there is no list readily available concerning what to include and exclude. A more robust approach is needed. Third, the use of current cost might be informative in the transition from one system to the next. Once the new system is in place, the current cost can no longer serve as guidance, as they do not exist anymore. The prices of fuel, cars, bicycles, public transport, and so on vary over time, not necessarily in same pace or direction. Especially when people decide to waive their CC a point of reference will be missing within just a few years.

Within our experiment we did not include any information about the period associated with the choices made or the frequency of choice moments. Hence, people were unaware whether they selected options for one week, one year or a decennium. In practice, this information needs to be available to participant. Given the length of contracts with lease companies, some actors suggest a choice moment every five years. We believe that this is absurd, as there is too much uncertainty involved. Moreover, the current CC should not be the point of reference. In the

Flemish pilot project *Mobiliteitsbudget werkt!* many employees regretted their initial choices after merely a few weeks (Christiaens, De Witte, & Vanderbeuren, 2013). We favor a dual track approach. Fundamental choices such as a CC or a relocation bonus on the long-term track; and flexibility for relatively small expenses on a daily basis, like the use of bicycle sharing, car sharing, taxi, or public transport, for instance via an all-in-one mobility card or Mobility-as-a-Service app.

The option to save money within the MB for a bonus is a key characteristic of an efficient version of the concept to some actors involved, as it provides an incentive to 'choose wisely' (Zijlstra & Vanoutrive, 2018). Our choice experiment demonstrates that the Bonus-option is very popular. However, due to the use of the CC in wage-optimization, the two most relevant and interrelated questions here are: what ratio for car-to-cash is to be used and should this bonus be limited in size? The necessity of a limit in the budget that can be payed as additional wage is related the creation of a new loophole in the system; employers and employees might use the MB to increase net wages. Therefore, we suggest that the best and easiest way to avoid abuse is to subject the bonus to the same tax regime as ordinary wage and to create a more level playing field between CC and wage.

5.2 Scientific contribution

The stated preference study we conducted in the context of the mobility budget is of interest to choice modelers in transportation, because the mobility budget choice is essentially a *mixture-amount problem*: the respondents' preferences depend on a mixture of components and on the total amount available in their personal mobility budget. Similar dependencies have been modelled successfully for many years in agriculture, in the chemical industry and in the food industry using mixture-amount regression models (Cornell, 2011; Piepel & Cornell, 1985; Smith, 2005). We embedded traditional mixture-amount regression models in the usual choice models used in transportation studies, such as the multinomial logit model and the panel mixed logit model. We also adopted a D-optimal design approach to construct an informative set of choice situations. For the analysis of the data from a mixture-amount stated choice experiment, we obtained useful results in a limited amount of computing time by using hierarchical Bayesian estimation methods, as we did not encounter convergence problems with this estimation techniques and as it produced individual-level parameter estimates in addition to population-level parameter estimates.

The mixture-amount problem is certainly not unique to the mobility budget context. Many other potential applications exist in the field of transport and in other fields. Budgets, time and space are scarce, while there always exist multiple options to use a financial budget, a certain amount of time or a certain amount of space. Certain combinations of options may be more attractive than others, and the perceived utility of combinations of options is sometimes larger (smaller) than the sum of the perceived utilities of the individual components. In such scenarios, where synergetic (or antagonistic) interactions exist, combining choice models with mixture models, mixture-amount models, and mixture-process variable models may provide useful insights into the combinations that optimize the respondents' utility. Examples in the field of transport can relate to road design and the allocation of mode-specific space (bus, car or bicycle lanes), mode-specific and total time use in multimodal trips or packages in relation to Mobility as a Service. To conclude, we are convinced that mixture and mixture-amount modeling is an interesting new approach within the field of choice modeling.

The models for preference studies involving mixtures involve many parameters, especially if multiple process variables are included or complex interactions occur. This also implies that many choice situations are needed and that the choice task becomes quite burdensome for the respondents, unless blocking is used. For complex models involving many interaction terms, providing sensible prior information concerning the model parameters (i.e., specifying prior means as well as a prior variance-covariance matrix) is challenging. In this paper, we therefore used a utility-neutral design approach, in which we assumed that all model parameters were zero and that there was no uncertainty concerning these values. This reduced the computational burden tremendously and allowed us to come up with a suitable experimental design in a limited time period. A better, but computationally substantially more demanding approach would have been to allow for uncertainty concerning some or all of the values of the model parameters and use a Bayesian approach with zero prior means and nonzero prior variances. A yet better approach would be to perform a small pilot study to estimate the most important model parameters and quantify the uncertainty concerning these parameters, as recommended by Huber and Zwerina (1996). It would be an interesting topic for future research to investigate the added value of these computationally more intensive approaches to designing stated preference studies with mixtures and an amount.

Acknowledgements
The authors would like to thank all companies and respondents who participated in our study. The computational resources and services used in this work were provided by the HPC core facility CalcUA of the University of Antwerp, funded by the Hercules Foundation and the Flemish Government (EWI). This project was financed by the Flemish government in the context of the Research Centre on Commodities and Passenger Flows. The authors are grateful for the feedback received from the reviewers of an earlier version of the paper.

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Appendix: Choice design

In Table A.1, we present the experimental design of our stated preference study. In the table, Blk is short for block. Only one block was presented to each respondent. Blocks 1 to 4 were presented to respondents with a relatively small MB. Blocks 5 to 8 were presented to respondents with a relatively large MB. The column labeled 'Xtra' flags the added questions to make sure that a enough options with a CC were presented to the respondents, who currently all have a CC. The symbol a denotes the amount (in 10,000 euro). The proportions x_1, x_2, x_3, x_4, and x_5 correspond to the components CC, bicycle, PT, days off and end-of-year bonus, respectively.

Table A.1: Experimental design

				Option A					Option B				
blk	Set	xtra	*a*	X1	X2	X3	X4	X5	X1	X2	X3	X4	X5
1	1	1	0.9	1.00	0.00	0.00	0.00	0.00	0.83	0.11	0.00	0.06	0.00
	2	0	0.65	0.00	0.15	0.00	0.23	0.62	0.92	0.00	0.00	0.08	0.00
	3	0	0.8	0.75	0.00	0.00	0.00	0.25	0.00	0.00	0.56	0.19	0.25
	4	0	0.85	0.00	0.24	0.53	0.00	0.24	0.71	0.00	0.00	0.06	0.24
	5	1	0.9	0.67	0.00	0.33	0.00	0.00	1.00	0.00	0.00	0.00	0.00
	6	0	0.6	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.50	0.17	0.33
	7	0	0.6	0.00	0.00	0.75	0.25	0.00	0.00	0.17	0.00	0.17	0.67
	8	0	0.8	0.75	0.00	0.00	0.00	0.25	0.75	0.25	0.00	0.00	0.00
	9	1	0.9	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.67
	10	0	0.8	0.00	0.25	0.56	0.19	0.00	0.75	0.25	0.00	0.00	0.00
	11	0	0.7	0.86	0.14	0.00	0.00	0.00	0.00	0.29	0.43	0.00	0.29
	12	0	0.6	0.00	0.00	0.00	0.00	1.00	0.00	0.33	0.00	0.00	0.67
	13	1	0.85	0.88	0.12	0.00	0.00	0.00	0.88	0.00	0.00	0.12	0.00
	14	0	0.75	0.00	0.00	0.00	0.20	0.80	0.00	0.27	0.00	0.20	0.53
	15	0	0.65	0.00	0.00	0.69	0.00	0.31	0.00	0.15	0.69	0.15	0.00
	16	0	0.6	0.00	0.17	0.00	0.17	0.67	0.00	0.33	0.50	0.17	0.00
2	1	1	0.9	0.67	0.00	0.33	0.00	0.00	1.00	0.00	0.00	0.00	0.00
	2	0	0.8	0.00	0.25	0.00	0.00	0.75	0.75	0.00	0.00	0.00	0.25
	3	0	0.7	0.00	0.00	0.43	0.00	0.57	0.00	0.29	0.00	0.14	0.57
	4	0	0.6	0.00	0.17	0.75	0.08	0.00	0.00	0.33	0.00	0.00	0.67
	5	1	0.9	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.67
	6	0	0.75	0.00	0.00	0.00	0.20	0.80	0.00	0.00	0.40	0.07	0.53
	7	0	0.85	0.00	0.24	0.35	0.18	0.24	0.71	0.12	0.00	0.18	0.00
	8	0	0.6	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.17	0.33
	9	1	0.9	1.00	0.00	0.00	0.00	0.00	0.83	0.11	0.00	0.06	0.00
	10	0	0.6	0.00	0.00	0.75	0.25	0.00	0.00	0.33	0.50	0.17	0.00
	11	0	0.65	0.00	0.00	0.00	0.08	0.92	0.00	0.31	0.46	0.23	0.00
	12	0	0.8	0.00	0.00	0.56	0.19	0.25	0.00	0.25	0.56	0.19	0.00
	13	1	0.85	0.71	0.24	0.00	0.06	0.00	0.88	0.12	0.00	0.00	0.00
	14	0	0.6	0.00	0.00	0.75	0.25	0.00	0.00	0.17	0.50	0.00	0.33
	15	0	0.65	0.00	0.00	0.46	0.23	0.31	0.00	0.31	0.00	0.08	0.62
	16	0	0.85	0.00	0.24	0.00	0.06	0.71	0.71	0.12	0.00	0.18	0.00
3	1	1	0.9	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.67

	2	0	0.6	0.00	0.17	0.75	0.08	0.00	1.00	0.00	0.00	0.00	0.00
	3	0	0.7	0.86	0.00	0.00	0.14	0.00	0.00	0.00	0.43	0.00	0.57
	4	0	0.6	0.00	0.00	0.00	0.00	1.00	0.00	0.17	0.75	0.08	0.00
	5	1	0.9	1.00	0.00	0.00	0.00	0.00	0.83	0.11	0.00	0.06	0.00
	6	0	0.6	0.00	0.17	0.50	0.00	0.33	0.00	0.33	0.00	0.00	0.67
	7	0	0.8	0.00	0.13	0.38	0.00	0.50	0.00	0.25	0.56	0.19	0.00
	8	0	0.65	0.00	0.00	0.46	0.23	0.31	0.00	0.00	0.69	0.00	0.31
	9	1	0.9	0.67	0.00	0.33	0.00	0.00	1.00	0.00	0.00	0.00	0.00
	10	0	0.6	1.00	0.00	0.00	0.00	0.00	0.00	0.33	0.50	0.17	0.00
	11	0	0.65	0.00	0.15	0.46	0.08	0.31	0.00	0.31	0.69	0.00	0.00
	12	0	0.75	0.80	0.00	0.00	0.20	0.00	1.00	0.00	0.00	0.00	0.00
	13	1	0.85	0.88	0.00	0.00	0.12	0.00	0.71	0.00	0.00	0.06	0.24
	14	0	0.7	0.86	0.00	0.00	0.14	0.00	0.86	0.14	0.00	0.00	0.00
	15	0	0.7	0.00	0.00	0.00	0.14	0.86	0.00	0.14	0.00	0.00	0.86
	16	0	0.6	0.00	0.00	0.50	0.17	0.33	0.00	0.17	0.50	0.00	0.33
4	1	1	0.9	1.00	0.00	0.00	0.00	0.00	0.83	0.11	0.00	0.06	0.00
	2	0	0.7	0.00	0.00	0.43	0.00	0.57	0.00	0.14	0.00	0.00	0.86
	3	0	0.85	0.00	0.24	0.00	0.06	0.71	0.00	0.24	0.35	0.18	0.24
	4	0	0.6	0.00	0.17	0.50	0.00	0.33	0.00	0.17	0.75	0.08	0.00
	5	1	0.9	0.67	0.00	0.33	0.00	0.00	1.00	0.00	0.00	0.00	0.00
	6	0	0.65	0.00	0.00	0.69	0.00	0.31	0.00	0.31	0.69	0.00	0.00
	7	0	0.6	1.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.00	0.67
	8	0	0.8	0.00	0.25	0.00	0.00	0.75	0.75	0.25	0.00	0.00	0.00
	9	1	0.9	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.67
	10	0	0.65	0.00	0.31	0.46	0.23	0.00	0.00	0.31	0.69	0.00	0.00
	11	0	0.6	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.75	0.25	0.00
	12	0	0.75	0.00	0.00	0.00	0.20	0.80	0.00	0.27	0.00	0.20	0.53
	13	1	0.85	0.88	0.00	0.00	0.12	0.00	0.71	0.12	0.00	0.18	0.00
	14	0	0.65	0.00	0.00	0.69	0.00	0.31	0.00	0.15	0.00	0.23	0.62
	15	0	0.85	0.00	0.12	0.00	0.18	0.71	0.71	0.24	0.00	0.06	0.00
	16	0	0.75	0.80	0.00	0.00	0.20	0.00	0.00	0.27	0.60	0.13	0.00
5	1	1	1.05	1.00	0.00	0.00	0.00	0.00	0.86	0.00	0.00	0.14	0.00
	2	0	1.05	0.00	0.19	0.43	0.00	0.38	0.57	0.10	0.29	0.05	0.00
	3	0	1	0.60	0.00	0.00	0.00	0.40	0.60	0.10	0.00	0.10	0.20
	4	0	1.05	0.00	0.19	0.29	0.14	0.38	0.86	0.00	0.00	0.14	0.00
	5	1	0.95	0.79	0.00	0.00	0.00	0.21	0.63	0.21	0.00	0.16	0.00
	6	0	1.1	0.82	0.18	0.00	0.00	0.00	0.55	0.09	0.27	0.09	0.00
	7	0	1.05	0.00	0.00	0.29	0.14	0.57	0.57	0.10	0.29	0.05	0.00
	8	0	0.95	0.00	0.21	0.00	0.16	0.63	0.00	0.21	0.47	0.11	0.21
	9	1	0.9	0.67	0.00	0.33	0.00	0.00	1.00	0.00	0.00	0.00	0.00
	10	0	1.05	1.00	0.00	0.00	0.00	0.00	0.57	0.00	0.29	0.14	0.00
	11	0	1.1	0.00	0.00	0.41	0.05	0.55	0.55	0.00	0.27	0.00	0.18
	12	0	1.1	0.55	0.09	0.00	0.00	0.36	0.68	0.18	0.00	0.14	0.00
	13	1	1.05	1.00	0.00	0.00	0.00	0.00	0.71	0.19	0.00	0.10	0.00
	14	0	1.05	0.57	0.00	0.29	0.14	0.00	0.00	0.19	0.29	0.14	0.38
	15	0	1.05	0.00	0.00	0.29	0.14	0.57	0.00	0.00	0.43	0.00	0.57

	16	0	1.05	0.00	0.00	0.43	0.00	0.57	0.00	0.19	0.29	0.14	0.38
6	1	1	1.05	1.00	0.00	0.00	0.00	0.00	0.57	0.00	0.29	0.14	0.00
	2	0	1.1	0.55	0.09	0.00	0.00	0.36	0.55	0.18	0.27	0.00	0.00
	3	0	1	0.00	0.10	0.45	0.05	0.40	0.60	0.20	0.00	0.00	0.20
	4	0	1.05	0.86	0.00	0.00	0.14	0.00	0.57	0.10	0.00	0.14	0.19
	5	1	0.95	0.79	0.21	0.00	0.00	0.00	0.79	0.00	0.00	0.00	0.21
	6	0	1.05	0.57	0.00	0.00	0.05	0.38	1.00	0.00	0.00	0.00	0.00
	7	0	1.1	0.00	0.09	0.41	0.14	0.36	0.55	0.00	0.00	0.09	0.36
	8	0	0.9	0.67	0.00	0.33	0.00	0.00	0.67	0.11	0.00	0.00	0.22
	9	1	0.9	1.00	0.00	0.00	0.00	0.00	0.83	0.11	0.00	0.06	0.00
	10	0	1.05	0.00	0.00	0.43	0.00	0.57	0.86	0.00	0.00	0.14	0.00
	11	0	1.1	0.55	0.00	0.27	0.00	0.18	0.82	0.00	0.00	0.00	0.18
	12	0	0.95	0.00	0.00	0.32	0.05	0.63	0.00	0.21	0.00	0.16	0.63
	13	1	1.05	1.00	0.00	0.00	0.00	0.00	0.57	0.00	0.00	0.05	0.38
	14	0	1.1	0.55	0.00	0.27	0.00	0.18	0.55	0.00	0.41	0.05	0.00
	15	0	1.1	0.55	0.18	0.27	0.00	0.00	0.95	0.00	0.00	0.05	0.00
	16	0	1.05	1.00	0.00	0.00	0.00	0.00	0.86	0.00	0.00	0.14	0.00
7	1	1	1.05	0.57	0.00	0.00	0.05	0.38	1.00	0.00	0.00	0.00	0.00
	2	0	0.9	0.67	0.00	0.33	0.00	0.00	0.67	0.22	0.00	0.11	0.00
	3	0	1.05	0.57	0.00	0.29	0.14	0.00	0.57	0.19	0.00	0.05	0.19
	4	0	1.1	0.55	0.18	0.00	0.09	0.18	0.55	0.18	0.27	0.00	0.00
	5	1	0.95	0.63	0.00	0.32	0.05	0.00	0.79	0.21	0.00	0.00	0.00
	6	0	1.1	0.68	0.00	0.27	0.05	0.00	0.68	0.18	0.00	0.14	0.00
	7	0	1.05	1.00	0.00	0.00	0.00	0.00	0.57	0.00	0.43	0.00	0.00
	8	0	0.9	0.00	0.11	0.50	0.17	0.22	0.67	0.00	0.33	0.00	0.00
	9	1	1.05	0.57	0.00	0.43	0.00	0.00	1.00	0.00	0.00	0.00	0.00
	10	0	1.05	0.00	0.19	0.43	0.00	0.38	0.71	0.00	0.29	0.00	0.00
	11	0	0.95	0.63	0.00	0.00	0.16	0.21	0.63	0.00	0.32	0.05	0.00
	12	0	1.1	0.55	0.09	0.00	0.00	0.36	0.68	0.00	0.27	0.05	0.00
	13	1	1.05	1.00	0.00	0.00	0.00	0.00	0.71	0.00	0.29	0.00	0.00
	14	0	1.1	0.00	0.18	0.27	0.00	0.55	0.82	0.18	0.00	0.00	0.00
	15	0	1.05	0.57	0.00	0.43	0.00	0.00	0.00	0.00	0.29	0.14	0.57
	16	0	1.1	0.00	0.00	0.41	0.05	0.55	0.00	0.18	0.27	0.00	0.55
8	1	1	1.05	1.00	0.00	0.00	0.00	0.00	0.57	0.00	0.43	0.00	0.00
	2	0	1.05	0.57	0.00	0.29	0.14	0.00	0.57	0.00	0.43	0.00	0.00
	3	0	1.1	0.55	0.00	0.27	0.00	0.18	0.55	0.18	0.27	0.00	0.00
	4	0	0.9	0.67	0.00	0.33	0.00	0.00	0.00	0.00	0.33	0.00	0.67
	5	1	0.95	0.00	0.21	0.47	0.11	0.21	0.79	0.00	0.00	0.00	0.21
	6	0	1	0.60	0.00	0.00	0.00	0.40	0.60	0.20	0.00	0.00	0.20
	7	0	1.1	0.55	0.00	0.27	0.00	0.18	0.82	0.18	0.00	0.00	0.00
	8	0	1.1	0.68	0.18	0.00	0.14	0.00	0.00	0.18	0.41	0.05	0.36
	9	1	0.9	0.00	0.00	0.33	0.00	0.67	1.00	0.00	0.00	0.00	0.00
	10	0	0.95	0.63	0.00	0.00	0.16	0.21	0.63	0.21	0.00	0.16	0.00
	11	0	0.95	0.00	0.21	0.00	0.16	0.63	0.63	0.00	0.00	0.16	0.21
	12	0	1.1	0.82	0.00	0.00	0.00	0.18	0.00	0.09	0.27	0.09	0.55
	13	1	1.05	1.00	0.00	0.00	0.00	0.00	0.86	0.10	0.00	0.05	0.00

14	0	1	0.00	0.00	0.45	0.15	0.40	0.00	0.10	0.30	0.00	0.60
15	0	1.1	0.00	0.18	0.27	0.00	0.55	0.55	0.00	0.00	0.09	0.36
16	0	1.1	0.82	0.18	0.00	0.00	0.00	0.68	0.00	0.00	0.14	0.18