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Gift giving generates high revenues for retailers. It is also marked with significant welfare, or deadweight, loss in that givers tend to pay more than the receivers' valuation. Previous research has attributed this discrepancy to givers' inaccurate predictions of the receivers' preferences. This research demonstrates that reduced price sensitivity is another important source of the deadweight loss: givers use gift prices to signal the importance of their relationship with the receiver. In order to demonstrate this mechanism, the authors develop a new Bayesian gift-choice model that captures both preference predictions as well as the signaling value of price. The model is estimated on two choice-based conjoint studies for gift giving that allow for the manipulation of the giver's uncertainty about the receiver's preferences. Both studies show the strong signaling value of price, especially when givers are uncertain about receivers' preferences. Decomposition of the deadweight loss shows that the signaling value of price is an important source of welfare loss, especially in markets with heterogeneous prices. These findings have key implications for the gift industry.

Keywords: gift giving, choice models, deadweight loss, price sensitivity, preference predictions

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Modeling Gift Choice: The Effect of Uncertainty on Price Sensitivity

Gift giving is an important and long-standing tradition that generates high economic revenues to the retail market. In the United States, the overall annual spending on gifts reached $135 billion in 2014 (U.S. Bureau of Labor Statistics 2014) and increased by 6.4% between 2009 and 2014 (Unity Marketing 2015). At the same time, many consumers encounter financial problems as they overspend on gifts for family members, friends, and acquaintances. For example, after the 2015 Christmas season in the United Kingdom, one in ten people struggled financially as a result of overspending on gift giving (Money Advice Service 2016). Moreover, receivers tend to assign lower monetary value to gifts than givers paid, resulting in an estimated 10%–33% welfare, or deadweight, loss caused by gift giving (Waldfogel 1993). This deadweight loss has been attributed to the difficulty of predicting the preferences of the receiver, and research has made great strides in understanding how givers make such predictions (Baskin et al. 2014; Lerouge and Warlop 2006). However, in addition to inaccurate preference predictions, overspending on gifts could also be caused by lower price sensitivities during gift purchase. Surprisingly, this factor has not been investigated in previous research, and the relative impact of these two sources on the deadweight loss of gift giving is unknown.

Price plays a dual role in gift giving. On the one hand, as with regular purchases, price is a cost to the giver and has a negative effect on gift-choice utility. On the other hand, a giver may demonstrate the importance of the relationship by buying a more expensive gift. In this case, price may have a positive effect on choice utility because it signals the care of the giver toward the receiver. This positive signaling value of price may reduce the giver's price sensitivity, leading to a higher willingness to pay, even if the giver accurately predicts the receiver's preferences. Based on this, we argue that the deadweight loss of

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gift giving is driven not only by inaccurate predictions of preferences but also by a decrease in price sensitivity. Moreover, the importance of these two sources may depend on the giver's uncertainty about the receiver's preferences. If uncertainty increases, it becomes more difficult to predict receiver's preferences, and the giver may therefore decide to put more weight on the signaling value of price. Interestingly, retailers and salespeople often try to influence the giver's uncertainty about receiver's preferences. For instance, many online retailers such as Amazon and Walmart provide wish lists (Vanhamme and De Bont 2008) to reduce the giver's uncertainty about receiver's preferences. Similarly, product recommendations toward popular gifts may reduce the giver's uncertainty about receiver's preferences (Carare 2012). In contrast, recommendations toward alternative gifts that were not part of the giver's consideration set may increase the giver's uncertainty about receiver's preferences (Goodman et al. 2013).

The aim of this research is to determine the relative impact of preference prediction and the signaling value of price on the deadweight loss of gift giving, as well as how these effects are moderated by the giver's uncertainty about the receiver's preferences. To achieve this, we develop a new gift-choice model that incorporates preference prediction by taking into account both the giver's and the receiver's preferences. Moreover, the proposed choice model captures the signaling value of price while controlling for different levels of the giver's uncertainty about the receiver's preferences. To estimate the model, we propose a hierarchical Bayesian procedure that controls for (1) heterogeneity across individuals, (2) homophily in preferences between giver and receiver, and (3) different distributions of the error term between choosing for own consumption versus gift choices. The gift-choice model is estimated on data from a two-stage conjoint procedure that is specifically developed to capture the underlying processes of gift giving.

The gift-choice model is applied to two conjoint experiments for gift giving that were specifically designed for this research. An important feature of our experimental approach is that it enables us to manipulate the giver's uncertainty about the receiver's preferences by providing the giver feedback about the receiver's preferences, which enables us to test our hypotheses. The results across two different categories (headphones and computer mice) demonstrate that gift givers rely on their own preferences if they have limited information about receivers' preferences. More interesting, in both applications, we find strong evidence for the signaling value of price. This implies that gift givers are less price sensitive than receivers, especially if they are uncertain about the preferences of the receiver. As a consequence, we find that a significant part of the deadweight loss of gift giving can be attributed to the signaling value of price, especially when there are strong price differences between alternatives. These results have important managerial implications for pricing strategies in the gift giving industry, as well as policy implications to reduce the deadweight loss of gift giving.

The rest of the article is organized as follows. The next section introduces our conceptual model of gift choice. Based on this, "A Model for Gift Choice" develops the gift-choice model and details the Bayesian estimation method. "Study 1: Headphones Gift Choices" introduces the two-step conjoint experiment for gift giving and applies the model to a study in which givers choose headphones for their friends. "Study 2: Wireless Mouse Gift Choices" applies the model to a larger conjoint study in a different category and rules out alternative explanations. Subsequently, "Decomposition of Deadweight Loss" decomposes the deadweight loss of gift giving into two sources: inaccurate preference predictions and price signaling. Finally, we conclude with managerial and policy implications and present directions for future research.

A CONCEPTUAL MODEL OF GIFT CHOICE

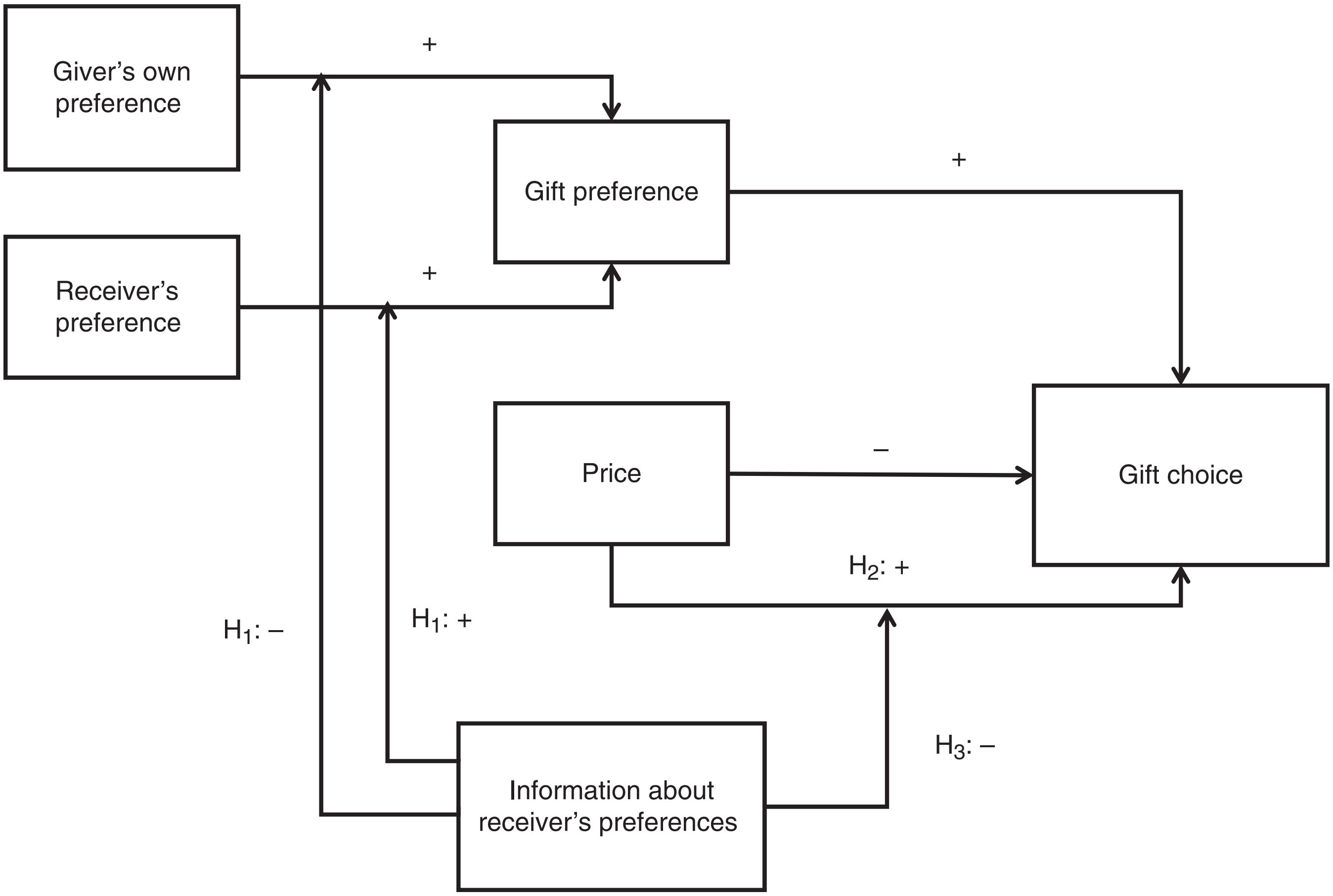
When consumers purchase gifts, we often observe different purchase patterns than we would observe if the receiver had chosen the gift (Baskin et al. 2014; Waldfogel 1993). The reasons for these differences are (1) the preferences of the gift giver may not match the preferences of the receiver and (2) price sensitivity of the gift giver may differ from that of the receiver. In these two components, gift preferences and price sensitivity correspond to the weights in the utility function of a choice model, respectively, for attributes and prices of gift alternatives. Therefore, to understand gift choice, it is important to understand the underlying processes of gift preference formation as well as the factors that influence price sensitivity. Figure 1 summarizes these underlying processes in a conceptual model of gift choice. This conceptual model indicates that gift preferences are determined by the giver's own preferences as well as the preferences of the receiver. In addition to giver's and receiver's preferences, the giver's information about the preferences of the receiver is another important factor that determines both gift preference and price sensitivity. Next, we detail for each of these factors how they determine gift choice.

Preference Prediction

Consumers may have both altruistic and instrumental motives when buying gifts for others (Barasz, Kim, and John 2016; Sherry 1983). Under an altruistic motive, the gift giver tries to please the receiver by buying a gift that satisfies the receiver. If the motive is instrumental, gift giving can be viewed as an economic or social exchange, in which the giver aims to achieve personal benefits through reciprocity. Interestingly, in both situations, the goal of the gift giver is to please the receiver, as the propensity for the receiver to reward the giver depends on the receiver's satisfaction and perceived value of the gift (Antón, Camarero, and Gil 2014). Therefore, independent of the motives of gift giving, it is important for the gift giver to accurately predict the receiver's preferences in order to maximize the satisfaction of the receiver. Not surprisingly, most research on gift giving has focused on understanding how givers predict receivers' preferences.

In order to predict the preferences of the receiver, previous research shows that gift givers use both their own preferences and inferred preferences of the receiver. As argued by Davis, Hoch, and Ragsdale (1986), a giver's own preferences may act as an anchor to infer a friend's preferences. Indeed, when choosing a gift for others, people often consider whether they themselves perceive the gift as interesting, surprising, and useful (Milkman and Berger 2014; Paolacci, Straeter, and De Hooge 2015). This "buy what I like" heuristic may be especially useful when givers have limited information about the receivers' preferences (Otnes, Lowrey, and Kim 1993). Through observations and interactions with the receiver, gift givers may adjust their own preferences (Barasz, Kim, and John 2016; Lerouge and Warlop 2006). Taking into account the preferences of the receiver increases the likelihood that the receiver likes the gift, improves the symbolic worth of the gift (Belk and Coon 1993),

Figure 1
CONCEPTUAL MODEL



Notes: The overall price sensitivity is the sum of both arrows from "Price" to "Gift choice," which is the effect of price on utility. The top arrow with the negative sign represents the negative effect of price on utility. The bottom arrow with the positive sign represents H_2, which states that in gift choice, price has an additional positive effect on utility.

and conveys a message that the giver cares about the receiver (Otnes, Lowrey, and Kim 1993).

In sum, when forming gift preferences, consumers take into account their own preferences as well as the preferences of the receiver. Hence, gift preferences can be expressed as a weighted average between givers' own and receivers' preferences. The relative weights of both factors depend on givers' information about receivers' preferences (Davis, Hoch, and Ragsdale 1986) and can be derived using Bayes' rule. If givers have no information about receivers' preferences, we expect that they will fully rely on their own preferences (Otnes, Lowrey, and Kim 1993). In Bayesian terms, when information is limited, gift givers use their own preferences as prior to predict receivers' preferences. As soon as givers obtain information about receivers' preferences, they update their predictions and corresponding gift preferences. Following Bayes' rule, when new information arrives, givers update their prior predictions by increasing the relative weight of receivers' preferences. The updated (posterior) predictions have reduced uncertainty and serve as the new and updated gift preferences. This leads to the following hypothesis:

H_1: Gift preferences are a weighted average between receivers' and givers' own preferences. Information about receivers' preferences increases the weight of receivers' preferences relative to the weight of givers' own preferences.

Price Sensitivity

Price is an important determinant of consumer choice that brings disutility to the consumer, resulting in negative price sensitivity. Interestingly, during gift choice, price may also have a positive effect on choice utility for two reasons. First, price or the effort that givers put into acquiring a gift may be a positive signal of the giver's care about the relationship with the receiver (Flynn and Adams 2009). Indeed, receivers often view price as a sign of commitment and willingness to invest in the relationship (Camerer 1988; Cheal 1987), and price is a factor that significantly influences the price of reciprocated gifts (Pieters and Robben 1998). Furthermore, social norms about relationships often force givers to buy more expensive gifts to avoid looking cheap (Austin and Huang 2012; Goodwin, Smith, and Spiggle 1990), which may trigger a prevention focus goal to avoid negative impressions (Ashworth, Darke, and Schaller 2005). Second, price may signal the popularity and quality of a product. Consumers often infer quality from price (Rao and Monroe 1989) and assume that expensive products possess higher quality (Erickson and Johansson 1985). Consequently, givers may use price as an important indicator of the receivers' preferences, especially when they are uncertain about receivers' preferences. Therefore, we argue that consumers are, on average, less price sensitive when buying gifts than when buying for themselves. This leads to the following hypothesis:

H_2: The gift giver is, on average, less price sensitive when purchasing a gift than when purchasing for self-use.

We expect that the reduction in price sensitivity is moderated by the giver's information about the receiver's preferences. If the giver uses price to signal the importance of the relationship, higher uncertainty about the receiver's preferences may stimulate the giver to rely more on the price signal (Camerer 1988). Similarly, if the giver uses price as a signal to infer the preferences of the receiver, we also expect that the giver puts more weight on this signal when s/he has less information about the receiver's preferences.

H_3: Information about receivers' preferences increases givers' price sensitivity.

The hypothesis that price sensitivity increases with information about the receiver's preferences is new and opposite to the findings of uncertainty in previous research on consumer choice for self. For instance, Erdem, Swait, and Louviere (2002) find that uncertainty about the quality and utility of alternatives results in higher price sensitivity. Consequently, firms often try to reduce uncertainty by advertising and building brand credibility (Erdem, Swait, and Louviere 2002; Kaul and Wittink 1995). Similarly, in the gift giving industry, companies often try to reduce uncertainty about the preferences of the receiver by offering gift cards (Austin and Huang 2012) and wish lists (Vanhamme and De Bont 2008). Except in situations in which firms communicate information about prices, such as price advertising (Kanetkar, Weinberg, and Weiss 1992), previous research argues that providing information reduces price sensitivity. In this research, we hypothesize another situation in which providing information about the receiver's preferences may increase price sensitivity.

In sum, in gift purchase, givers have a motive to please the receiver and demonstrate their care about the relationship. As illustrated in our conceptual model (Figure 1), this goal can be achieved through two routes. First, givers may try to purchase a gift that matches the preferences of the receiver. Second, givers may buy a more expensive gift, to signal their care about the relationship. When givers have limited information about receivers' preferences, it becomes more difficult to please the receiver by buying a gift that matches the receivers' preferences (i.e., route 1). Hence, in such situations, we expect that givers rely more on the signaling value of price and buy more expensive gifts to please the receiver (i.e., route 2).

A MODEL FOR GIFT CHOICE

Using the conceptual model (Figure 1), we introduce our gift-choice model. We first present a multinomial probit gift-choice model, after which we explain how we derive givers' preferences and price sensitivities. After that, we discuss how we control for heterogeneity, homophily in givers' and receivers' preferences, and differences in the error term distributions between gift choices and situations in which givers choose for themselves.

Gift Choices

Consider giver i choosing a gift for receiver j from a set of $k = \{1, \ldots, K\}$ choice alternatives. Following standard choice models, giver i's utility u_{ijk} of choosing alternative k as a gift for receiver j is determined as follows:

$$u_{ijk}^{Gift} = x_{ijk}^{Gift}\beta_{ij}^{Gift} + p_{ijk}^{Gift}\gamma_{ij}^{Gift} + \varepsilon_{ijk}^{Gift}. \tag{1}$$

In Equation 1, x_{ijk}^{Gift} is an M-dimensional vector of attribute levels of alternative k, and β_{ij}^{Gift} is the corresponding M-dimensional vector of giver i's preferences for each of the attributes when buying a gift for receiver j. The price of alternative k is captured by p_{ijk}^{Gift} and is coded as an (L − 1)-dimensional vector of dummy variables reflecting L different price levels, representing a partworth model for price (Krishnamurthi and Wittink 1991).[1] Giver i's price sensitivity when buying a gift for receiver j is captured by (L − 1)-dimensional vector γ_{ij}^{Gift}. Finally, ε_{ijk}^{Gift} is a random utility shock that is assumed to follow a normal distribution with mean 0 and variance $\sigma_{ij,Gift}^2$, leading to a multinomial probit model for gift choice. Given utilities u_{ijk}^{Gift} for each of the K alternatives, the giver chooses alternative k that maximizes utility, that is,

$$y_{ijk}^{Gift} = \begin{cases} 1 \text{ if } u_{ijk}^{Gift} = \max\left\{u_{ij1}^{Gift},\ u_{ij2}^{Gift},\ \ldots,\ u_{ijK}^{Gift}\right\} \\ 0 \text{ otherwise} \end{cases}. \tag{2}$$

In Equation 2, y_{ijk}^{Gift} equals 1 if giver i chooses gift k for receiver j and 0 otherwise.

As explained in the derivation of our conceptual model (Figure 1), we follow Bayes' rule (DeGroot 2005; Narayan, Rao, and Saunders 2011) to formally derive gift preferences β_{ij}^{Gift}. In our derivation, we assume that giver i observes information z_{ij} about the preferences β_j^{self} of receiver j. Information variable z_{ij} could represent marketing activities, such as wish lists and recommendations. Alternatively, as in our studies described below, it could capture experimental manipulations, such as feedback that giver i receives about receiver j's preferences. First, assume that if giver i has no information about receiver j's preferences (i.e., $z_{ij} = 0$), giver i's prior belief about receiver j's preferences β_j^{self} is assumed to follow a normal distribution with mean at the giver's own preference β_i^{self} and variance V_0 (Davis, Hoch, and Ragsdale 1986). When giver i receives information z_{ij} about receiver j's preferences, the giver updates his/her belief about the receiver's preferences in a Bayesian way. Assume that the giver observes information signal $S(z_{ij})$ about the receiver's preferences as a function of information z_{ij}. Following standard Bayesian assumptions, this information signal is unbiased and drawn from a normal distribution with mean β_j^{self} and variance $V_S(z_{ij})$, that is, $S(z_{ij}) = \beta_j^{self} + \varepsilon_S$, where $\varepsilon_S \sim N(0, V_S(z_{ij}))$. The variance $V_S(z_{ij})$ is assumed to be a decreasing function of z_{ij}, because more information about the receiver's preferences reduces the giver's uncertainty about the receiver's preferences. Following Bayes's rule, the giver's updated belief about the receiver's preferences follows a normal distribution with mean β_{ij}^{self} and variance $V_1(z_{ij})$, which are derived as follows:

[1]In our applications, we also tested models with linear specifications for price. Our findings were robust for this specification, and model fit statistics favored the partworth statistics.

$$\beta_{ij}^{gift} = \frac{V_S(z_{ij})}{V_0 + V_S(z_{ij})}\beta_i^{self} + \frac{V_0}{V_0 + V_S(z_{ij})}\left(\beta_j^{self} + \varepsilon_S\right), \text{with}$$
$$V_1(z_{ij}) = \frac{1}{\frac{1}{V_S(z_{ij})} + \frac{1}{V_0}}.$$

Using the above derivation and taking into account that the expected value of ε_S equals 0, β_{ij}^{gift} is a weighted average between the giver's own preferences β_i^{self} and the receiver's preferences β_j^{self}. Defining the weight of giver i's own preference as $\rho_{ij} = V_s(z_{ij})/[V_0 + V_S(z_{ij})]$, we obtain the following:

$$\beta_{ij}^{gift} = \rho_{ij}\beta_i^{self} + \left(1 - \rho_{ij}\right)\beta_j^{self}. \tag{3}$$

In Equation 3, $\rho_{ij} \in (0, 1)$ is the weight that the giver attaches to his/her own preferences, and $1 - \rho_{ij}$ is the weight of the receiver's preferences, when both choose for themselves. Finally, we assume that givers take into account uncertainty $V_1(z_{ij})$ by setting their gift preferences equal to the expected posterior mean β_{ij}^{gift} of the belief distribution, which minimizes the expected difference with the receivers' preferences. Following H_1, the relative weight ρ_{ij} of giver i's preferences depends on the information z_{ij} that giver i receives about receiver j's preferences, which we model as follows:

$$\rho_{ij} = \frac{\exp\left(\phi_0 + z_{ij}\phi_1\right)}{1 + \exp\left(\phi_0 + z_{ij}\phi_1\right)}. \tag{4}$$

The exponential function in Equation 4 assures that $\rho_{ij} \in (0, 1)$, and ϕ_0 and ϕ_1 are parameters. Following H_1, we expect that $\phi_1 > 0$, implying that givers put less weight on their own preferences if they observe more information about the receivers' preferences.

As illustrated in Figure 1, price plays a dual role in gift giving, and givers tend to be less price sensitive when buying gifts than when buying for themselves. Moreover, the positive signaling value of price depends on the information z_{ij} that giver i observes about receiver j's preferences. Based on this, we model giver i's price sensitivity γ_{ij}^{Gift} as follows:

$$\gamma_{ij}^{Gift} = \rho_{ij}\gamma_i^{Self} + \left(1 - \rho_{ij}\right)\gamma_j^{self} + \theta_0 + \theta_1 z_{ij}. \tag{5}$$

Similar to attribute preferences in Equation 3, we allow price sensitivity to be a weighted average of the giver's and the receiver's price sensitivity. As argued by Pieters and Robben (1998), people avoid buying expensive gifts for "cheap" friends. Moreover, gifts are often bought with an expectation of reciprocity (Sherry 1983), and price-sensitive receivers are less likely to return expensive gifts. We therefore expect that givers take into account the price sensitivity of the receiver. In addition to this weighted average, parameters θ_0 and θ_1 capture the signaling value of price, which may depend on z_{ij}. Following H_2 and H_3, respectively, we expect that $\theta_{01} > 0$ and $\theta_{11} < 0$ for higher price levels, and $\theta_{01} < 0$ and $\theta_{11} > 0$ for lower price levels.[2]

Giver's and Receiver's Preferences and Price Sensitivities

In order to be able to estimate the gift-choice model, it is important to infer the giver's and receiver's preferences β_i^{Self} and β_j^{Self} and price sensitivities γ_i^{Self} and γ_j^{Self} when they choose for themselves. We infer these parameters from the giver's and receiver's choices when buying for themselves. Similar to Equation 1, choice utilities in situations where a consumer $c \in \{i, j\}$ (either giver or receiver) is choosing for own consumption are determined as follows:

$$u_{ck}^{Self} = x_{ck}^{Self}\beta_c^{Self} + p_{ck}^{Self}\gamma_c^{Self} + \varepsilon_{ck}^{Self}, c \in \{i, j\}. \tag{6}$$

In Equation 6, u_{ck}^{Self} is the utility of alternative k to consumer c. Similar to x_{ijk}^{Gift} in Equation 1, x_{ck}^{Self} is an M-dimensional vector with the characteristics of alternative k, and β_c^{Self} are the corresponding preferences of consumer c when choosing for own consumption. The price p_{ck}^{Self} of alternative k for consumer c is captured by an (L − 1)-dimensional vector of dummy variables, and ε_{ck}^{Self} is a disturbance term. Similar to Equation 1, the disturbance term is assumed to follow a normal distribution with mean 0 and variance $\sigma_{c,Self}^2$. Using these utilities, the consumer chooses alternative k with the highest utility:

$$y_{ck}^{Self} = \begin{cases} 1 \text{ if } u_{ck}^{Self} = \max\left\{u_{c1}^{Self},\ u_{c2}^{Self}, ..., u_{cK}^{Self}\right\} \\ 0 \text{ otherwise} \end{cases}. \tag{7}$$

In Equation 7, y_{ck}^{Self} equals 1 if consumer c chooses alternative k and 0 otherwise.

Heterogeneity, Homophily, and Error Distributions

We assume that givers and receivers are heterogeneous in their attribute preferences and price sensitivities both when choosing for themselves and when choosing gifts. To incorporate heterogeneity, we assume that individual-level parameters of givers and receivers when they are choosing for themselves follow a multivariate normal distribution:

$$\begin{pmatrix} \beta_c^{Self} \\ \gamma_c^{Self} \end{pmatrix} = N\left[\begin{pmatrix} \mu_B \\ \mu_\gamma \end{pmatrix}, \sum\right]. \tag{8}$$

In Equation 8, μ_β is an M-dimensional vector with mean preferences of consumers when buying for themselves, and μ_γ captures the mean price sensitivities across consumers. Full $[(M + L - 1) \times (M + L - 1)]$ covariance matrix $\sum$ captures potential covariations between preferences and price sensitivity.

Similar to the consequences of endogenous group formation in social networks (Manski 2000), preferences and price sensitivities may be similar between givers and receivers. To control for potential homophily, we allow preferences between givers and receivers to be correlated:

$$\text{corr}\left(\beta_{im}^{Self}, \beta_{jm}^{Self}\right) = \tau_m, \forall m = 1, ..., M, \text{ and} \tag{9}$$

$$\text{corr}\left(\gamma_{il}^{Self}, \gamma_{jl}^{Self}\right) = \tau_{M+l}, \forall l = 1, ..., L - 1, \tag{10}$$

with (M + L − 1)-dimensional vector τ capturing the correlations between giver i's and receiver j's preferences and price sensitivities.

Finally, it is possible that standard deviations of utility shocks differ in situations when consumers are choosing for themselves ($\sigma_{c,Self}$) compared with when choosing a gift ($\sigma_{ij,Gift}$), which may be a function of information z_{ij}. Because the scale of utility in discrete choice models is not identified, preferences and price sensitivities are measured relative to the standard deviation of the error term (Salisbury and Feinberg 2010). Therefore, if there are differences in error term variances,

[2]In our empirical studies, we treat the lowest price level as baseline; thus, we expect $\theta_0 > 0$ and $\theta_1 < 0$ for all price levels.

it is not possible to directly compare and integrate preferences and price sensitivities across conditions. To control for potential differences in the error term variances, we follow Narayan, Rao, and Saunders (2011) and introduce parameter $\lambda_{ij} = \sigma_{ij,Gift}/\sigma_{i,Self}$, which captures the ratio of standard deviations of the disturbance terms in utilities for giver i when choosing a gift for receiver j ($\sigma_{ij,Gift}$) versus choosing for own consumption ($\sigma_{i,Self}$). We model heterogeneity in λ_{ij} across givers and receivers using a lognormal distribution in which the mean is allowed to depend on the information z_{ij} that giver i observes about receiver j's preferences:

$$\log(\lambda_{ij}) \sim N(\psi_0 + \psi_1 z_{ij}, \Delta^2). \quad (11)$$

In Equation 11, ψ_0 and ψ_1 are, respectively, an intercept and the effect of information z_{ij} on the mean of λ_{ij}, and Δ^2 captures the variance of the ratio across givers and receivers.

Identification

The parameters of the proposed model given by Equations 1–11 are identified under the following conditions. First, to be able to identify individual preferences ($\beta_i^{Self}, \beta_j^{Self}$) and price sensitivities ($\gamma_i^{Self}, \gamma_j^{Self}$) of givers and receivers, as well as their means μ_B and μ_γ and covariances Σ, repeated observations of consumers' choices for own consumption are required. In this case, the error term variance in the utility of buying for self $\sigma^2_{\varepsilon,Self}$ is assumed to be 1 for identification (McCulloch and Rossi 1994). Second, by assuming the gift purchase preferences to be a weighted average of the giver's and receiver's preferences, we keep the mean of the attribute preferences the same across gift purchase occasions and purchases for self. This consistency allows us to identify the ratio of the standard deviations of error terms in utilities of purchasing gifts and purchasing for self λ_{ij} (Train 2009). Third, given the identification of the distribution of the error term, the weight of the giver's preferences (ρ_{ij}) and the change in price sensitivity (θ_0) are identified if repeated gift choices are observed. Finally, observed variations in amount of information (z_{ij}) enable us to identify the effect of uncertainty on the weight of the giver's preferences (ϕ_1) as well as the effect on price sensitivity (θ_1) and the error term distribution (ψ_1) in Equation 11.

Estimation

We adopt a Bayesian method for estimating the parameters in our model and testing the hypotheses. We specify standard weakly informative priors for the parameters and derive their posterior conditional distributions (for details of the algorithm, see Web Appendix A). We use a Gibbs sampler to draw from these posterior conditional distributions iteratively with Metropolis–Hastings steps to draw the ϕ parameters, which determine the weight that givers attach to their own preferences, and λ_{ij}. To estimate correlations between givers' and receivers' preferences and price sensitivities τ, we follow Yang and Allenby (2003) and assume that friends' attribute preferences have a common, normally distributed element. In our estimations, we use the first 100,000 iterations as burn-in and then save every tenth draw of the following 50,000 iterations to get the posterior distribution of the parameters.

STUDY 1: HEADPHONES GIFT CHOICES

Obtaining observational data of consumer choices to estimate our gift-choice model and to test our conceptual framework (Figure 1) is challenging. First, observational data usually do not identify whether consumer purchases are for themselves or gifts. Second, in addition to distinguishing between regular purchases for own consumption and gifts, we also require information about the receiver's preferences, which may be hard to obtain. Third, a giver's uncertainty about the receiver's preferences is an important component of our theory of gift giving, which is generally not observed in panel data.

To address these challenges, we developed a new two-stage conjoint experiment for gift choices. This approach builds on recent developments in choice-based conjoint experiments that introduce multiple stages to infer social influence in consumer choice (Aribarg, Arora, and Kang 2010; Narayan, Rao, and Saunders 2011; Wang, Aribarg, and Atchadé 2013). In our conjoint experiment for gift choices, we invited pairs of individuals who knew each other before the experiment, such that a gift-giving scenario between them was realistic. The first stage of the experiment involves a regular choice-based conjoint task in which both individuals choose for themselves, which enables us to infer the preferences of givers and receivers. After this first stage, both individuals receive feedback about their friend's preferences, which enables us to exogenously manipulate the giver's uncertainty about the receiver's preferences. Subsequently, the second stage involves a choice-based conjoint task in which each individual needs to choose gifts for the other. The second stage reveals the gift preferences.

Study Design

We invited 99 pairs of friends (198 participants) from a large Southeast Asian university to participate in the experiments for monetary rewards. We selected headphones as the product because our participants are familiar with this category and headphones are considered an appropriate gift for friends. We defined four attributes: headphone style (three levels: in-ear, on-ear, over-ear), brand (two levels: Sony, Philips), microphone functionality (two levels: yes, no), and price (five levels: \$13, \$15.50, \$18, \$20.50, \$23). The meaning of each attribute and their levels were clearly stated. Participants were explicitly told that all other relevant attributes, such as weight, warranty, and wire length, were exactly the same for all models. At the start of the experiment, participants in a pair were seated separately in the computer lab so that they were not able to communicate with each other.

Choice stage 1. In the first stage of the choice-based conjoint experiment, participants in a pair simultaneously and independently answered six choice questions containing four choice alternatives (K = 4). The choice questions and alternatives were generated using the SAS OPTEX procedure to guarantee estimation efficiency of the partworths (Wang, Aribarg, and Atchadé 2013). The six choice questions were preceded by a training question to familiarize the participants with the choice task. Figure 2, Panel A, provides a screenshot of an example choice question in our experiment.

Uncertainty manipulation. After both participants finished answering the six choice questions, they were both randomly assigned to the same one of three experimental conditions: (1) no information disclosure, (2) minimal information disclosure, and (3) full information disclosure. In the no-information condition, neither participant received any information about the

Figure 2
TYPICAL DISPLAYS IN STUDY 1

A: A Typical Choice Question in Stage 1

Which product of the following four do you prefer to purchase?

(The features are type, brand, microphone function, and price.[a])

In-ear style	In-ear style	On-ear style	Over-ear style
Philips	Sony	Philips	Sony
No microphone	Microphone	Microphone	No microphone
160 HKD	120 HKD	180 HKD	140 HKD

B: A Typical Answer Display in Manipulation of the Giver's Uncertainty About Receiver's Preferences

In situation 1, from the four models, your friend chose

Over-ear style
Philips
Microphone
160 HKD

rather than

On-ear style	In-ear style	In-ear style
Sony	Philips	Sony
No microphone	Microphone	No microphone
100 HKD	140 HKD	180 HKD

C: A Typical Gift Choice Question in Stage 2

Which product of the following four do you prefer to purchase as a gift to your friend?

(The features are type, brand, microphone function, and price.)

In-ear style	Over-ear style	On-ear style	In-ear style
Sony	Philips	Philips	Sony
No microphone	Microphone	No microphone	Microphone
100 HKD	120 HKD	140 HKD	160 HKD

[a]Prices were presented in Hong Kong dollars (HKD).

other participant's choices.[3] In contrast, in the minimum-information condition, both participants were provided with the answer to one choice question of the other participant, while in the full-information condition, participants were provided with the other participant's answers to all six choice questions. Figure 2, Panel B, shows a screenshot of the information disclosure of one specific choice question. Participants were allowed to process the information and click to the next page at their own pace.

Choice stage 2. After the information disclosure manipulation in stage 1, each pair of participants was asked to imagine that their friend's birthday was next month and that they decided to purchase headphones as a gift. Subsequently, both participants were again exposed to six randomly generated gift-choice questions, consisting of four alternatives that were different from the six questions in stage 1. Figure 2, Panel C, shows a screenshot of one of the six gift-choice questions.

After the participants finished the six gift-choice questions in stage 2, we asked them to rate the extent of their agreement with several statements about their motivation and objectives of gift purchases (for details of the statements, see Web Appendix B).[4] We also collected demographic information (age, gender, and nationality) and the strength of the relationship between participants in a pair. Finally, we included one open question for general comments regarding the experiment, after which participants were debriefed.

Incentives. To ensure that participants made reliable and realistic decisions, we took steps to confirm that the experiment was incentive-aligned (Yang, Toubia, and De Jong 2015). At the start of the experiment, participants were told that they would join a lottery upon completion of the experiment. Each winner of the lottery would receive $26 minus the price of one set of headphones. This set of headphones was randomly selected from one of the 12 headphone choices that the winning participant had made during the study (i.e., six each during the two choice stages). If a set of headphones was selected from stage 1, the winner would receive the selected headphone set in addition to $26 minus the price of these headphones. If a set of headphones was selected from stage 2, the winner's friend would receive the headphones, while the winner would receive $26 minus the price of the selected headphones. In total, we randomly selected four winners at the end of the experiment. For example, if the random lottery determined choice question 2 in choice stage 1 for participant 15, this participant would receive the set of headphones with specifications that s/he had chosen in choice question 2, in addition to $26 minus the price of his/her choice. If the random lottery determined a choice question in choice stage 2, participant 15's friend would receive the headphones, while participant 15 would receive $26 minus the price of the headphones.

Results

Descriptive statistics and model-free evidence. Table 1 reports descriptive statistics of our conjoint experiment for gift giving (see also Web Appendix B). First, our post hoc measures illustrate that participants across all conditions were highly motivated to please the receiver (M = 6.25 out of 7, Cronbach's alpha = .83). In line with our conceptual model, participants relied both on their own preferences (M = 4.07) and the receiver's preferences (M = 6.34). Moreover, following H_1, givers relied less on their own preferences in the full-information condition (M = 4.03) than in the no-information condition (M = 4.50).

Table 1 also indicates that givers spend more money on gift giving than on buying for themselves, which is in line with H_2.

[3]In the no-information condition, participants are allowed to have prior information about receivers' preferences. This implies that the estimated weight for givers' own preferences may be smaller than one in this condition (see also Figure 3).

[4]Controlling for givers' motivation to please the receiver did not change our results substantively (see Web Appendix C).

Table 1
DESCRIPTIVE STATISTICS FOR STUDY 1

Variables	*All*	*No Information*	*Minimum Information*	*Full Information*	*Group Difference* p-*Value*
Mean Price ($)					
Choice for gift	18.49	18.84	18.41	18.20	.07
Choice for self	17.48	17.80	17.27	17.34	.13
Gift − Self	1.01**	1.04**	1.14**	.86**	.75
Measures of Relationship Strength					
Friendship length (months)	28.46 (39.98)	28.09 (43.96)	23.59 (26.35)	33.58 (46.14)	.36
Communication frequency	3.32 (.75)	3.30 (.77)	3.23 (.75)	3.44 (.72)	.26
Measures of Gift-Giving Goals					
Please the receiver	6.25	6.26	6.19	6.29	.74
Self-signaling	5.23	5.32	5.20	5.16	.67
Trade	1.62	1.60	1.64	1.62	.98
Measures of Gift-Giving Routes					
Avoid cheap	4.42	4.72	4.55	3.98	.01
Giver's own preference	4.07	4.50	3.64	4.03	.01
Receiver's preference	6.34	6.26	6.33	6.42	.63
Correlations with "Please the Receiver"					
Avoid cheap	.12	.34**	.12	−.09	.01
Giver's own preference	.04	.12	−.05	.06	.34
Receiver's preference	.37**	−.02	.69**	.55**	<.01
Number of participants	198	68	64	66	

**Significantly different from 0 at $p < .05$.

Notes: Measures of relationship strength are means, with standard deviations in parentheses. Communication frequency measures the average scores from both online and offline communication, which are rated from 1 (less than 5 times last month) to 4 (more than 20 times last month). The measures for gift-giving goals and routes are on rating scales from 1 ("strongly disagree") to 7 ("strongly agree"). For trade, the rating scale is from 1 (less than 10%) to 7 (more than 90%). For more details about the statements, refer to Web Appendix B.

Moreover, in line with H_3, the average spending difference is smallest in the full-information condition (M = .86), although differences are not significant across conditions. Interestingly, the extent to which givers avoid being perceived as cheap (M = 4.42) is significantly moderated by our information disclosure manipulation. It is more important to avoid being perceived as cheap in the no-information condition (M = 4.72) than in the full-information condition (M = 3.98). This is consistent with H_3 and suggests that givers may indeed become more price sensitive when they receive more information about the receiver's preferences. To further illustrate this point, we computed the correlations between "avoid cheap" and "please the receiver." As reported in Table 1, this correlation is only significant in the no-information condition (r = .34). Interestingly, the correlation between "receiver's preferences" and "please the receiver" is only significant in the minimum-information and full-information conditions (r = .69 and .55, respectively). These results are in line with our conceptual model and suggest that givers aim to please receivers by matching the receiver's preferences (i.e., when they have information about the receiver's preferences) or signaling the value of the relationship and avoid looking cheap (i.e., when they have no information about receiver's preferences). Finally, Table 1 also rules out the alternative explanation that the giver takes into account the possibility that the receiver will exchange the gift (M = 1.62, which does not differ across conditions).

While these results provide initial support for our conceptual model, the remainder of this section aims to formally test our hypotheses using our gift-choice model. Before we do so, we compare several versions of our model to test its robustness for specific modeling assumptions.

Model comparisons. Our full model controls for (1) homogeneity in preferences of givers and receivers (Equation 9) and (2) different error scales for choices for self and gifts (Equation 11). To empirically test whether it is necessary to control for these two features, we estimated four different versions of our model. First, we estimated the full model. Subsequently, we tested (1) a model without homophily (i.e., $\tau = 0$), (2) a model with equal error scales ($\lambda = 1$), and (3) a model without homophily and error scales (i.e., $\tau = 0$ and $\lambda = 1$). To compare model fit, we computed log-marginal density (LMD) using Chib and Jeliazkov's (2001) approach.

Table 2 reports the four model fit statistics. First, we do not find evidence that preferences of givers and receivers are systematically correlated in our sample (LMD = −2,071 vs. −2,162 for a model without and with homophily, respectively). Second, model fit decreases if we assume equal error-term scales across gift giving and buying for self, compared with

Table 2
MODEL FIT FOR STUDY 1

Model Tests	*Partworth Model Log-Marginal Density*
Full model	−2,162
Test: No homophily ($\tau = 0$)	**−2,071**
Test: No error scale ($\lambda = 1$)	−2,177
Test: No homophily and error scale ($\tau = 0, \lambda = 1$)	−2,120

Note: "Full model" refers to the model specified in Equations 1–11. Boldface indicates the model that best describes the data, for which we report the estimation results.

Table 3

RESULTS FOR STUDY 1: ATTRIBUTE PREFERENCES FOR PURCHASES FOR SELF

Attributes	Preference (μ)[a]
Style: on-ear	−1.89 [−2.40, −1.48]
Style: over-ear	−1.45 [−1.94, −1.05]
Brand—Sony	.22 [.09, .37]
Microphone	1.44 [1.19, 1.75]
Price: $15.50[b]	−.28 [−.55, −.02]
Price: $18	−.43 [−.69, −.18]
Price: $20.50	−.41 [−.72, −.13]
Price: $23	−.87 [−1.21, −.55]

[a]95% posterior intervals are reported in brackets.
[b]The lowest price level ($10.50) is set as the baseline level.

both the full model (LMD = −2,177 vs. −2,162) and the model without homophily (LMD = −2,120 vs. −2,071). Based on these comparisons, for the remainder of this section, we selected the model without homophily that allows for different error-term scales between buying for self and gift giving, which has the highest fit.

Before we report the estimation results, we also tested several modeling assumptions for the selected model. First, in our model we assumed that the weights $\rho_{ij} \in [0, 1]$ were restricted between 0 and 1, such that gift preferences are a weighted average between givers' and receivers' preferences. Ignoring this restriction did not substantially improve model fit (LMD = −2,069 vs. −2,071), and none of the weights were significantly outside the [0, 1] range. Second, we assumed that the weights between giver i and receiver j's preferences did not vary across attributes m and m′ (i.e., $\rho_{ijm} = \rho_{ijm'}$). Relaxing this assumption did not improve model fit; in fact, it reduced it (LMD = 2,119 vs. −2,071). Third, a model that ignores price signaling also reduced model fit (LMD = −2,088 vs. −2,071). Fourth, a model in which givers do not take into account price sensitivity of the receiver (i.e., $\rho_{ij} = 1$ in Equation 5) also reduced model fit (LMD = −2,162 vs. −2,071). Finally, we estimated separate choice models for gift giving and choices for self. Although parameter estimates are not directly comparable across different models due to different error scales, the estimates are in line with price signaling (see Web Appendix D). In sum, these results support the assumptions of our gift-choice model, and we report the results next.

Estimation results. Tables 3 and 4 report the estimated posterior medians of the parameters. When participants were choosing headphones for themselves, they on average preferred the in-ear style over on-ear ($\mu_{On-ear} = -1.89$) and over-ear ($\mu_{Over-ear} = -1.45$), the Sony brand over Philips ($\mu_{Sony} = .22$), and headphones with a microphone over those without one ($\mu_{Microphone} = 1.44$). As expected, price coefficients for all price levels are negative compared with the lowest price of $10.50, which was set as baseline. We also found a significant difference in error term variances between choices for self and gift choices in the no-information condition ($\psi_{No-Info} = .43$) and the full-information condition ($\psi_{Full-Info} = -.54$).

Next, we tested our three hypotheses. We used dummy variables to code a giver's information about the receiver's preferences (z_{ij}). First, we found that the weight of the giver's preferences significantly decreased with information about the receiver's preferences, confirming H_1 (see also Figure 3). Second, Table 4 illustrates that participants are significantly less price sensitive when buying a gift for a friend ($\theta_{No-Info} > 0$ for all price levels), which supports H_2. Corroborating H_3, this effect is moderated by the giver's information about the receiver's preferences, as the signaling value of price is weaker under the minimum-information condition ($\theta_{Min-Info}$ is only significantly positive for two of the four price levels) and not significant for the full-information condition. These results are further illustrated in Figure 4, demonstrating that participants are less price sensitive when buying gifts in the no-information and minimum-information conditions. Moreover, price sensitivity for gifts in the full-information condition corresponds to the price sensitivity when participants choose headphones for themselves.

In sum, this study provides evidence for H_1–H_3 and our model specification. Moreover, to the best of our knowledge, it is the first study that demonstrates that consumers are less price sensitive during gift giving compared with buying for themselves, especially when they do not have full information about the receivers' preferences. As illustrated in our conceptual framework, there are two possible explanations for the moderating effect of givers' information about receivers' preferences: (1) price as a signal of relationship importance and (2) price as a quality signal. The goal of the second gift-choice conjoint experiment is to determine the driving mechanism. In addition, we will also test the generalizability of our findings by using a different product category and larger sample.

STUDY 2: WIRELESS MOUSE GIFT CHOICES

To determine the driving mechanism underlying the effect of the giver's uncertainty on price sensitivity, we extended the two-stage conjoint experiment of Study 1 by including two purchase conditions in the second stage of the conjoint experiment. The first condition is the same as in Study 1 and asks participants to choose gifts for their friends. In the added

Table 4

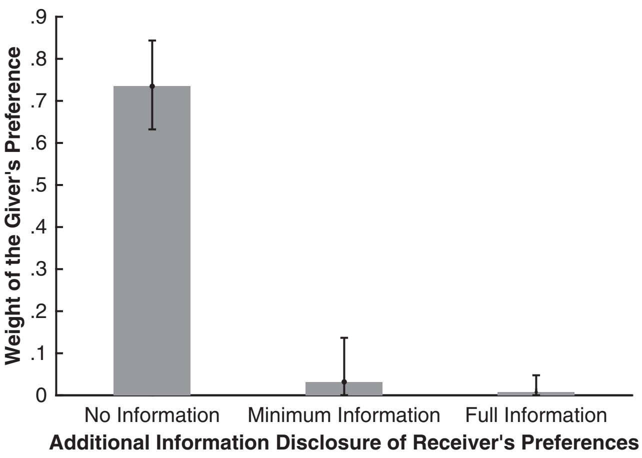
ESTIMATION RESULTS FOR STUDY 1: GIFT PURCHASE PREFERENCE FORMATION

Information Disclosure	Weight of Giver's Preference (ϕ)	Signaling Value of Price (θ): $15.50	$18	$20.50	$23	Error Scale (ψ)
No information	**−1.02** [.54, 1.68]	**.78** [.32, 1.33]	**.99** [.46, 1.60]	**1.38** [.82, 2.13]	**.94** [.39, 1.56]	**−.43** [.13, .77]
Minimum information	**−3.41** [−8.09, −1.84][a]	.19 [−.23, .64]	**.62** [.14, 1.12]	**.66** [.17, 1.21]	.36 [−.16, .91]	−.20 [−.08, .47]
Full information	**−4.88** [−9.83, −3.00]	.27 [−.07, .61]	.39 [−.02, .78]	.25 [−.13, .64]	.35 [−.09, .80]	**−.54** [−1.01, −.19]

[a]The 95% posterior intervals are wide due to the log transformation. The corresponding intervals of ρ are much smaller (see Figure 3).

Notes: Because we used dummy variables to capture the three manipulated information conditions, ϕ and ψ are 3 × 1 vectors and θ is a 3 × 4 matrix of parameter estimates, because L − 1 = 4. We report 95% posterior intervals in brackets. Boldface indicates parameter estimates whose 95% posterior interval does not contain 0.

Figure 3
WEIGHT OF THE GIVER'S PREFERENCE IN STUDY 1



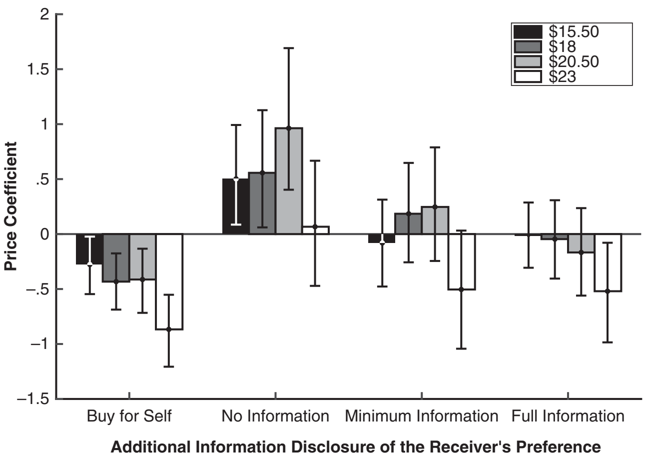
second condition, participants act as agents and need to choose a product for their friends, but not as gifts. Participants were randomly assigned to one of these two conditions.

If price is used to signal the importance of the relationship between giver and receiver, we should not find an effect of the agent's uncertainty about the receiver's preferences on price sensitivity. The reason is that agents spend the receiver's money to buy the product and thus are not able to use price to signal the importance of the relationship. If the second mechanism is driving the effect, similar to the gift-giving condition, we should find an effect of the agent's uncertainty about the receiver's preferences on price sensitivity. In this situation, the agent uses price to infer the preferences of the receiver, and this effect should be stronger if the agent is more uncertain.

Study Design

We invited 244 pairs of friends (488 participants) from a large Southeast Asian university to participate in the experiments for monetary rewards. In this study, we chose wireless mice as the

Figure 4
PRICE SENSITIVITIES IN STUDY 1



Note: The baseline price level is 13 USD.

Table 5
EXAMPLE OF REWARD IN STUDY 2

Choice Situations	*Reward of the Winner*	*Reward of the Winner's Friend*
Choice for self	Product and $8[a]	—
Choice as gift giver	$8	Gift
Choice as an agent	—	Product and $8

[a]$8 corresponds to the budget ($26) minus the price of the selected product ($18).

Notes: The selected product in this example has the following attributes: brand = Logitech, color = black, sensitivity = 100 dpi, battery life = 12 months, and price = $18.

focal product. We defined five product attributes: brand (two levels: Logitech, Microsoft), color (two levels: black, red), sensitivity (four levels: 500, 1,000, 1,500, 2,000 dpi), battery life (four levels: 6, 12, 18, 24 months), and price (four levels: $10.50, $13, $15.50, $18).

As in Study 1, we adopted the two-stage choice-based conjoint experiment. The first stage had eight choice questions, each containing three alternatives (K = 3). After both participants finished the first stage, they were both randomly assigned to the same one out of nine uncertainty levels, manipulated by revealing different numbers (0, 1, ..., 8) of their friends' answers from the first stage. In the second stage, both participants were randomly assigned to one of two choice conditions: (1) gift-purchase condition, or (2) agent-purchase condition. The gift-purchase condition is similar to stage 2 described in Study 1, consisting of eight choice questions with three options. In the agent-purchase condition, each participant was told to imagine that his/her friend wanted to buy a mouse but did not have time to go to the store and check available options. So each participant in this condition received $26 to purchase a mouse on behalf of his/her friend.

Similar to Study 1, the experiment was incentive-aligned using a monetary value of $26, and winners were randomly selected as in Study 1. In the agent-purchase condition, the winner's friend was rewarded with the chosen alternative as well as $26 minus the price of the product (for the rewards of participants in different choice situations, see Table 5). Finally, we also measured age, gender, and nationality, as well as the strength of the relationship[5] between participants in a pair.

To summarize, our second study consists of a two-stage conjoint experiment in which we manipulated the purchase condition (two levels: gift choice vs. agent choice) and the information level about receiver's preferences (number of answers revealed to the giver/agent; nine levels: 0, 1, ..., 8), resulting in a 2 × 9 experimental design. Each pair of friends was randomly assigned to one of the 18 conditions.

Results

Descriptive statistics and model-free evidence. Table 6 reports the average price of the chosen products across different conditions. Similar to Study 1, the price of the chosen gift is significantly higher than the price of choices for self (M = 13.63 vs. 13.23, $p < .01$). Moreover, we find that in the agent-purchase condition, prices of chosen alternatives did not differ from choices for self (M = 13.26 vs. 13.10, $p = .16$), while prices of agent choices were significantly lower than

[5]Relationship strength did not affect our estimates (see Web Appendix C).

Table 6
DESCRIPTIVE STATISTICS FOR STUDY 2

Variables	*All*	*Limited Information*	*Medium Information*	*Full Information*
Gift Purchase Mean Price ($)				
Gift	13.63	13.73	13.43	13.63
Self	13.23	13.20	13.17	13.36
Gift − Self	.40**	.53**	.26	.26
Agent Purchase Mean Price ($)				
Agent	13.26	13.36	13.13	13.18
Self	13.10	13.26	12.88	13.02
Agent − Self	.16	.10	.25	.16
Measures of Relationship Strength				
Friendship length (months)	28.21 (28.16)	26.89 (21.80)	29.06 (34.10)	30.05 (32.81)
Communication frequency	2.99 (1.07)	3.08 (1.09)	2.93 (1.09)	2.85 (1.00)
Number of Participants				
Gift-purchase condition	246	124	62	60
Agent-purchase condition	242	122	60	60

**Significantly different from 0 at $p < .05$.

Notes: Measures of relationship strength are means, with standard deviations in parentheses. Limited, medium, and full information correspond to the experimental manipulation in which givers were provided with, respectively, 0–2, 3–5, and 6–8 choices of the receiver. Communication frequency measures the average score from both online and offline communication, which are rated from 1 (less than 5 times last month) to 4 (more than 20 times last month).

those of gift choices ($p = .04$). Finally, in line with H_3, price differences between gift and own choices were significant different in the limited-information conditions (0, 1, or 2 answers; $p < .01$) but not in the medium-information (3, 4, or 5 answers; $p = .21$) or full-information conditions (6, 7, or 8 answers; $p = .17$).

Model comparisons. To analyze the data, we modeled giver's/agent's information about receiver's preferences using a log-linear (mean-centered) function of the number of revealed choices (i.e., z_{ij} = log(number of feedback choices + 1)). Furthermore, we modeled agent choices like gift choices but allowed the weight of the agent's preferences and the signaling value of price to be different from those of gift giving. As in Study 1, we used LMD to test whether controlling for homophily and equal error-term scales improved model fit. Table 7 reports fit statistics for the four different modelspecifications. First, removing homophily from the model improved model fit (LMD = −5,653 vs. −5,778). Second, fit was not much affected if we assume equal error-term scales across gift giving, agent purchases, and buying for self (LMD = −5,787 vs. −5,778). Third, ignoring homophily and assuming equal error-term scales best described the data (LMD = −5,639). We therefore continue with the model without homophily and equal error-term scales.

As in Study 1, we tested several modeling assumptions. First, we allowed givers and agents to update their preferences for gift/agent choices at different rates (i.e., $\rho_{ij}^{Gift} \neq \rho_{ij}^{Agent}$). Restricting the weights to be equal slightly improved model fit (LMD = −5,638 vs. −5,639). Hence, in our follow-up model comparisons, we continued with the model that assumed equal weights for gift and agent purchases (i.e., $\rho_{ij}^{Gift} = \rho_{ij}^{Agent}$). Second, as in Study 1, we compared our model with a version in which the weights ρ_{ij} were unrestricted. Ignoring this restriction did not improve model fit (LMD = −5,655 vs. −5,638), and all weights were within the [0, 1] range across all conditions. Third, we relaxed the assumption of equal weights across different attributes m and m′ (i.e., $\rho_{ijm} = \rho_{ijm'}$). Similar to Study 1, relaxing this assumption decreased model fit (LMD = −5,667 vs. −5,638). Fourth, a model that ignored price signaling for gift giving reduced model fit (LMD = −5,647 vs. −5,638). Fifth, a model that ignores the price sensitivity of the receiver for gift giving (i.e., $\rho_{ij} = 1$ in Equation 5) reduced model fit (LMD = −5,731 vs. −5,638). Finally, parameter estimates of separate models for own choices, gift choices, and agent choices are in line with our price-signaling hypotheses (see Web Appendix D). Next, we report the parameter estimates of our gift-giving model.

Estimation results. Tables 8 and 9 report the estimated posterior medians of the parameters from our proposed model. When participants were choosing wireless mice for themselves, they preferred Microsoft ($\mu_{Microsoft} = .09$), black color ($\mu_{Red} = -.06$), higher sensitivity ($\mu_{Sensitivity} = .12$), and longer battery life ($\mu_{Battery} = .06$), and none of the 95% posterior distributions contained 0. As expected, the price coefficients are negative for all price levels compared with the baseline price, which is the lowest price level.

As in Study 1, we found evidence for H_1–H_3 in the gift-giving condition. First, we found that the weight of the giver's preference decreases significantly with additional information about the receiver's preference ($\phi_1 = -7.45$; none of the posterior draws were >0), confirming H_1. Figure 5 illustrates this result and shows that givers fully rely on their own preferences when they do not receive information about their friends' preferences. Moreover, givers learn quickly, and after observing only three choices of the receiver, they fully rely on the receiver's preferences. Second, the signaling value of price is significantly positive for each price level in the gift-purchase situation (θ_0^{Gift} = .17, .38, and .51, respectively, for the $13, $15.50, and $18 price levels), confirming H_2. We also find that the signaling value of price significantly decreases with more information about the receiver's preference for all price levels (θ_1^{Gift} = −.19, −.24, and −.38, respectively, for the $13, $15.50, and $18 price levels), confirming H_3. Figure 6, Panel A, illustrates the pattern of price sensitivity as a function of the giver's uncertainty and compares it with the situation in which participants are choosing for themselves.

Finally, to determine which underlying mechanism drives the effect of uncertainty on price sensitivity, we focused on the results of the agent's purchase decisions. First, the signaling

Table 7
MODEL FIT FOR STUDY 2

Model Tests	*Partworth Model Log-Marginal Density*
Full model	−5,778
Test: No homophily ($\tau = 0$)	−5,653
Test: No error scale ($\lambda = 1$)	−5,787
Test: No homophily and error scale ($\tau = 0, \lambda = 1$)	**−5,639**

Notes: "Full model" refers to the model specified in Equations 1–11. Boldface indicates the model that best describes the data, for which we report the estimation results.

Table 8
ATTRIBUTE PREFERENCES FOR PURCHASES FOR SELF IN STUDY 2

Attributes	*Preference* (μ)
Brand: Microsoft	−.09 [.03, .16]
Color: red	−.06 [−.13, −.00]
Sensitivity in dpi	−.12 [.11, .12]
Battery life in months	−.06 [.05, .06]
Price: $13	−.12 [−.21, −.03]
Price: $15.50	−.65 [−.76, −.54]
Price: $18	−1.46 [−1.62, −1.30]

Notes: We report 95% posterior intervals in brackets. The lowest price level ($10.50) is set as the baseline level.

value of price is not significant for two price levels ($15.50 and $18) and is even significantly negative for the second-lowest price level ($\theta_0^{\text{Agent}} = -.20$ for $13). Moreover, we do not find any significant effects of information on the signaling value of price in the agent-choice condition (95% posterior intervals contain 0). Both results contradict the findings in the gift-purchase condition and support the first mechanism, in which price signals the giver's care about the relationship. Interestingly, and in contrast to our hypotheses for gift giving, participants are slightly more price sensitive in the agent-purchase condition (see also Figure 6, Panel B). A possible explanation is that participants become more careful when using a friend's money, as people tend to be more risk-averse when buying on behalf of friends rather than strangers (Montinari and Rancan 2013).

DECOMPOSITION OF DEADWEIGHT LOSS

As argued by Waldfogel (1993), gift giving leads to a significant welfare loss because the giver values the gift significantly higher than the receiver.[6] While previous research has attributed this welfare loss to inaccurate preference predictions, in the two studies described here, we find evidence that givers were also significantly less price sensitive than receivers. Consequently, the total welfare loss of gift giving is due to inaccurate predictions of preferences as well as the signaling value of price that reduces price sensitivity. In this section, we derive the relative importance of these two sources on the deadweight loss for Study 2.[7]

Measuring Deadweight Loss

Measuring deadweight loss is challenging. Previous studies in economics have mainly used questionnaires to measure deadweight loss but have reached different conclusions using different questions and definitions (List and Shogren 1998; Principe and Eisenhauer 2009; Waldfogel 1993, 1996). For instance, Waldfogel (1996) asks recipients of gifts how much they think the giver paid and how much cash they would like to receive to exchange the gift, and to not take into account any sentimental value. Obviously, it is difficult for recipients to guess the actual price that givers paid, and questionnaires have limitations in uncovering accurate preferences and utilities of participants (List and Shogren 1998). In contrast, our experimental approach avoids the need to guess the actual price of the gift, and conjoint experiments are superior in measuring receivers' preferences and utilities, naturally excluding the sentimental value of gift. Hence, our estimation results are valuable input for accurately decomposing the deadweight loss of gift giving into its underlying sources: (1) inaccurate preference predictions and (2) price signaling.

Drawing on Waldfogel (1996), we define deadweight loss as the difference in the receiver's utility when the receiver chooses versus that obtained when the giver chooses, which excludes any sentimental value attached to the gift. Let $u_k(\beta_j, \gamma_j, \varepsilon_j)$ denote the utility that receiver j gains from an alternative k with attributes x_k and price p_k (see also Equation 6):

$$u_k\left(\beta_j, \gamma_j, \varepsilon_j\right) = x_k\beta_j + p_k\gamma_j + \varepsilon_{jk}. \tag{12}$$

If receiver j chose for him/herself, s/he would choose alternative k from choice set K that maximized utility, equal to

$$\max_{k\in K} u_k\left(\beta_j^{\text{Self}}, \gamma_j^{\text{Self}}, \varepsilon_j^{\text{Self}}\right). \tag{13}$$

Instead, if giver i chose for receiver j, s/he would choose alternative k from choice set K that maximized the gift-purchase utility, and the receiver would get utility

$$u_{\arg\max_{k\in K} u_k\left(\beta_{ij}^{\text{Gift}}, \gamma_{ij}^{\text{Gift}}, \varepsilon_{ij}^{\text{Gift}}\right)}\left(\beta_j^{\text{Self}}, \gamma_j^{\text{Self}}, \varepsilon_j^{\text{Self}}\right). \tag{14}$$

In Equation 14, $\arg\max_{k\in K} u_k(\beta_{ij}^{\text{Gift}}, \gamma_{ij}^{\text{Gift}}, \varepsilon_{ij}^{\text{Gift}})$ corresponds to alternative k that maximizes gift utility $u_k(\beta_{ij}^{\text{Gift}}, \gamma_{ij}^{\text{Gift}}, \varepsilon_{ij}^{\text{Gift}})$. Using these expressions, the total deadweight loss for giver i and receiver j is the difference between Equations 13 and 14, that is,

$$\max_{k\in K} u_k\left(\beta_j^{\text{Self}}, \gamma_j^{\text{Self}}, \varepsilon_j^{\text{Self}}\right) - u_{\arg\max_{k\in K} u_k\left(\beta_{ij}^{\text{Gift}}, \gamma_{ij}^{\text{Gift}}, \varepsilon_{ij}^{\text{Gift}}\right)}\left(\beta_j^{\text{Self}}, \gamma_j^{\text{Self}}, \varepsilon_j^{\text{Self}}\right). \tag{15}$$

In Equation 15, the total deadweight loss consists of three sources: (1) inaccurate preference predictions ($\beta_{ij}^{\text{Gift}} \neq \beta_j^{\text{Self}}$), (2)

[6]As argued by Waldfogel (1993), it is possible that gift giving results in welfare gains if the receiver is not perfectly informed about his/her own preferences. In our studies, we assume that receivers know their preferences, and hence we do not consider welfare gains. This assumption is reasonable in many gift-giving situations and follows previous research in consumer behavior that investigates the factors that influence preference (mis)predictions (e.g., Barasz, Kim, and John 2016; Baskin et al. 2014; Lerouge and Warlop 2006).

[7]The results for Study 1 are similar. In the no-information condition, price signaling contributes 10% (low price variation, high attribute variation) to 60% (high price variation, low attribute variation) of deadweight loss. In the full-information condition, deadweight loss is strongly reduced and almost entirely due to price signaling (over 97%).

Table 9
GIFT PURCHASE PREFERENCE FORMATION STUDY 2

Choice and Information Disclosure Conditions	*Weight of Giver's Preference* (ϕ)	*Signaling Value of Price* (θ)[a]		
		\$13	*\$15.50*	*\$18*
Gift giving	**−2.25** [−3.70, −1.19]	**.17** [.03, .31]	**.38** [.23, .54]	**.51** [.33, .69]
Buy for others		**−.20** [−.33, −.07]	−.07 [−.23, .08]	−.14 [−.32, .05]
Gift giving × Information	**−7.45** [−10.99, −4.75]	**−.19** [−.34, −.04]	**−.24** [−.42, −.06]	**−.38** [−.59, −.18]
Buy for others × Information		−.08 [−.23, .06]	−.11 [−.29, .06]	−.22 [−.43, .00]

[a]The lowest price level (\$10.50) is set as the baseline level.
Notes: We report 95% posterior intervals in brackets. Parameter estimates in the top half of the table correspond to ϕ_0 and θ_0; those in the bottom half correspond to ϕ_1 and θ_1. Boldface indicates parameter estimates whose 95% posterior interval does not contain 0.

price signaling ($\gamma_{ij}^{Gift} \neq \gamma_j^{Self}$), and (3) different error terms ($\varepsilon_{ij}^{Gift} \neq \varepsilon_j^{Self}$). Because our focus is on the decomposition of deadweight loss into inaccurate preference predictions and price signaling, we control for different error terms by subtracting this source from Equation 15:

$$(16)\quad \begin{aligned} DL_{ij}^{Gift} = {} & \max_{k\in K} u_k\left(\beta_j^{Self}, \gamma_j^{Self}, \varepsilon_j^{Self}\right) \\ & - u_{\arg\max_{k\in K} u_k\left(\beta_{ij}^{Gift}, \gamma_{ij}^{Gift}, \varepsilon_{ij}^{Gift}\right)}\left(\beta_j^{Self}, \gamma_j^{Self}, \varepsilon_j^{Self}\right) \\ & - \left[\max_{k\in K} u_k\left(\beta_j^{Self}, \gamma_j^{Self}, \varepsilon_j^{Self}\right)\right. \\ & \left. - u_{\arg\max_{k\in K} u_k\left(\beta_j^{Self}, \gamma_j^{Self}, \varepsilon_{ij}^{Gift}\right)}\left(\beta_j^{Self}, \gamma_j^{Self}, \varepsilon_j^{Self}\right)\right] \\ = {} & u_{\arg\max_{k\in K} u_k\left(\beta_j^{Self}, \gamma_j^{Self}, \varepsilon_{ij}^{Gift}\right)}\left(\beta_j^{Self}, \gamma_j^{Self}, \varepsilon_j^{Self}\right) \\ & - u_{\arg\max_{k\in K} u_k\left(\beta_{ij}^{Gift}, \gamma_{ij}^{Gift}, \varepsilon_{ij}^{Gift}\right)}\left(\beta_j^{Self}, \gamma_j^{Self}, \varepsilon_j^{Self}\right). \end{aligned}$$

In Equation 16, DL_{ij}^{Gift} corresponds to the deadweight loss of gift giving caused by inaccurate preference predictions and price signaling, after we control for different error terms between givers and receivers.

Decomposition of Deadweight Loss

The deadweight loss of gift giving (DL_{ij}^{Gift}) in Equation 16 can be decomposed into two sources: (1) inaccurate predictions of attribute preferences (DL_{ij}^{Pref}) and (2) the signaling value of price (DL_{ij}^{Price}), in addition to an interaction term (Ξ)[8]:

$$(17)\quad DL_{ij}^{Gift} = DL_{ij}^{Pref} + DL_{ij}^{Price} + \Xi, \text{ with}$$

$$(18)\quad \begin{aligned} DL_{ij}^{Pref} = {} & u_{\arg\max_{k\in K} u_k\left(\beta_j^{Self}, \gamma_j^{Self}, \varepsilon_{ij}^{Gift}\right)}\left(\beta_j^{Self}, \gamma_j^{Self}, \varepsilon_j^{Self}\right) \\ & - u_{\arg\max_{k\in K} u_k\left(\beta_{ij}^{Gift}, \gamma_j^{Self}, \varepsilon_{ij}^{Gift}\right)}\left(\beta_j^{Self}, \gamma_j^{Self}, \varepsilon_j^{Self}\right) \end{aligned}$$

$$(19)\quad \begin{aligned} DL_{ij}^{Price} = {} & u_{\arg\max_{k\in K} u_k\left(\beta_j^{Self}, \gamma_j^{Self}, \varepsilon_{ij}^{Gift}\right)}\left(\beta_j^{Self}, \gamma_j^{Self}, \varepsilon_j^{Self}\right) \\ & - u_{\arg\max_{k\in K} u_k\left(\beta_j^{Self}, \gamma_{ij}^{Gift}, \varepsilon_{ij}^{Gift}\right)}\left(\beta_j^{Self}, \gamma_j^{Self}, \varepsilon_j^{Self}\right). \end{aligned}$$

In Equation 18, DL_{ij}^{Pref} corresponds to the difference in receiver j's utility between gifts chosen using receiver j's preferences and those chosen using giver i's gift preferences for receiver j, while controlling for different error terms and assuming that the giver has the same price sensitivity as the receiver ($\gamma_{ij}^{Gift} = \gamma_j^{Self}$). The deadweight loss due to the signaling value of price is computed similarly, except that we assume that the giver can accurately predict preferences ($\beta_{ij}^{Gift} = \beta_j^{Self}$). Finally, there is an interaction effect between the preference prediction bias and the price-signaling value on the total deadweight loss, which equals Ξ.

Using the decomposition in Equation 17, we can compute the shares of deadweight loss due to inaccurate preference predictions (SDL_{ij}^{Pref}) and due to the signaling value of price (SDL_{ij}^{Pref}):

$$(20)\quad SDL_{ij}^{Pref} = \frac{DL_{ij}^{Pref}}{DL_{ij}^{Pref} + DL_{ij}^{Price}}$$

and

$$(21)\quad SDL_{ij}^{Price} = \frac{DL_{ij}^{Price}}{DL_{ij}^{Pref} + DL_{ij}^{Price}}.$$

Moreover, since the giver's preferences and price sensitivities depend on the giver's uncertainty about the receiver's preferences, we can determine the relative importance of uncertainty on the total deadweight loss.

To compute the relative contributions of inaccurate preference predictions and the price-signaling value to the deadweight loss in Equations 20 and 21, we simulated the parameters from the posterior draws obtained in the Bayesian estimation. Given the giver's uncertainty about the receiver's preferences, for each draw of parameters, we simulated attribute preferences and price sensitivities for 5,000 randomly generated pairs of friends. Finally, we used the average estimates of Equations 20 and 21 across the 5,000 randomly generated friends as the final estimate of the relative contributions to deadweight loss of inaccurate preference predictions and price signaling.

A challenge of computing the deadweight loss in Equations 20 and 21 is that it depends not only on givers' uncertainty about receivers' preferences but also on the available alternatives K in the market. Because we do not know K, we

[8]The interaction term $\Xi = [u_{\arg\max_{k\in K} u_k(\beta_{ij}^{Gift}, \gamma_j^{Self}, \varepsilon_{ij}^{Gift})}(\beta_j^{Self}, \gamma_j^{Self}, \varepsilon_j^{Self}) + u_{\arg\max_{k\in K} u_k(\beta_j^{Self}, \gamma_{ij}^{Gift}, \varepsilon_{ij}^{Gift})}(\beta_j^{Self}, \gamma_j^{Self}, \varepsilon_j^{Self})] - [u_{\arg\max_{k\in K} u_k(\beta_{ij}^{Gift}, \gamma_{ij}^{Gift}, \varepsilon_{ij}^{Gift})}(\beta_j^{Self}, \gamma_j^{Self}, \varepsilon_j^{Self}) + u_{\arg\max_{k\in K} u_k(\beta_j^{Self}, \gamma_j^{Self}, \varepsilon_{ij}^{Gift})}(\beta_j^{Self}, \gamma_j^{Self}, \varepsilon_j^{Self})]$ represents the difference between the sum of the receiver's utilities under inaccurate preference prediction and price signaling and the sum of the receiver's utilities under own and gift choice. In our empirical example, it accounts for less than 4% of the total deadweight loss. In our decomposition, for ease of interpretation, we assume that both sources of deadweight loss contribute proportionally to Ξ.

Figure 5
WEIGHT OF THE GIVER'S PREFERENCE IN STUDY 2

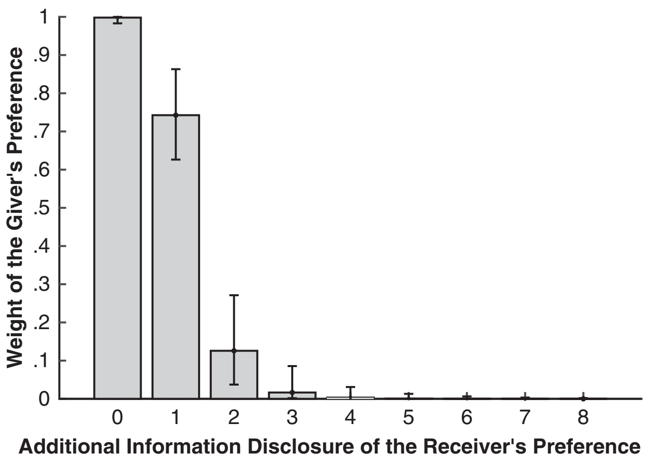
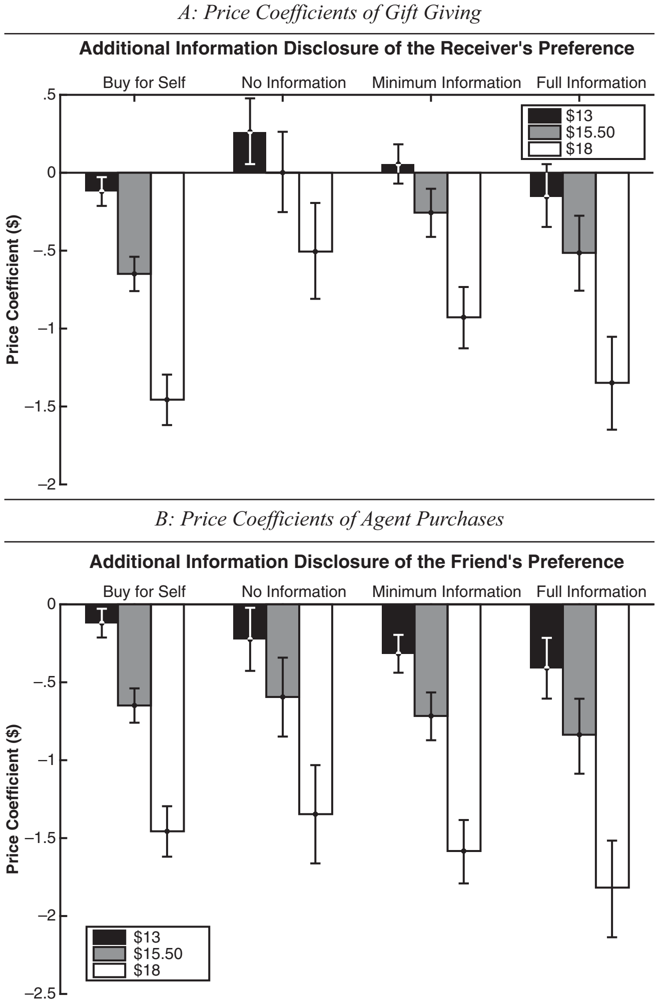


Figure 6
PRICE COEFFICIENTS IN STUDY 2



Notes: Baseline price level is $10.50. No, Minimum, and Full information correspond to the conditions in which, respectively, zero, two, and eight answers were revealed to the buyer.

computed Equations 20 and 21 for all possible markets in our second study consisting of three alternatives.[9] Hence, in total, we estimated the deadweight loss decomposition for over 2.7 million markets and nine uncertainty levels, resulting in almost 25 million decompositions. Interestingly, this enables us to investigate the relative importance of inaccurate preference predictions and price signaling as a function of givers' uncertainty about receivers' preferences, as well as market conditions. For our specific analysis, there are two important market conditions that affect the deadweight loss: (1) relative variation in attributes across alternatives and (2) relative variation in prices across alternatives.

Results

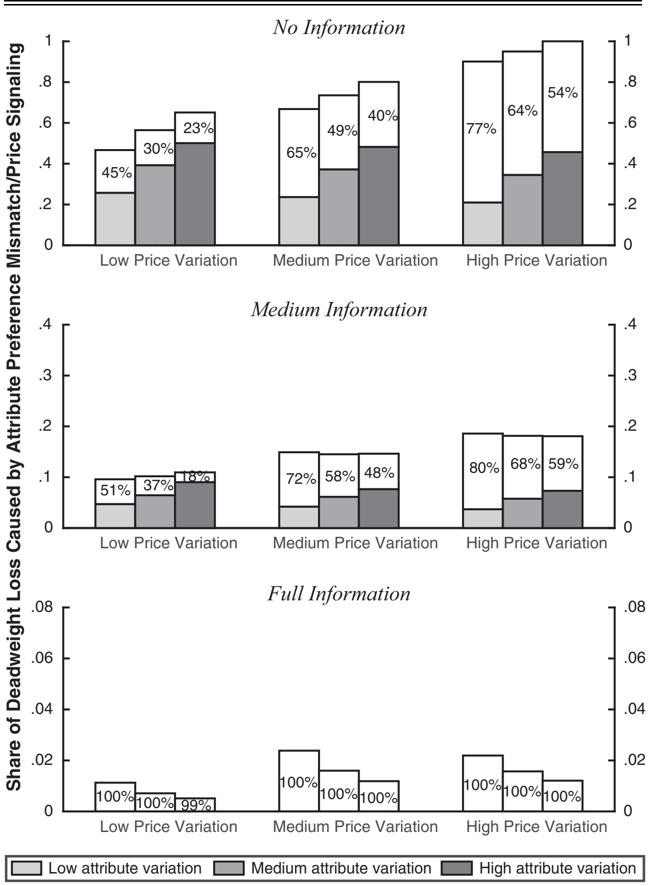
Figure 7 illustrates the decomposition of the average deadweight loss of gift giving across 27 different scenarios (3 information levels × 3 attribute variation levels × 3 price variation levels). First, the three information levels—no, medium, and full information—correspond to our experimental manipulation in which we disclosed, respectively, 0, 1–4, and 5–8 choices of the receiver to the giver. Second, the three attribute variation levels are low, medium, and high and correspond to situations in which the variance of the sum of attributes across alternatives is, respectively, smaller than 2, between 2 and 4, and larger than 4. Finally, the three price variation levels (low, medium, and high) correspond to situations in which the variance of prices across alternatives is smaller than 1, between 1 and 2, and larger than 2, respectively. For each scenario in Figure 7, the total deadweight loss of gift giving equals the entire bar, with the highest deadweight loss (situation: no information, high attribute, and price variation) normalized to 1. Finally, the white (shaded) area corresponds to the percentage of deadweight loss due to price signaling (inaccurate preference predictions).

As illustrated in Figure 7, both total deadweight loss and its decomposition into price signaling and inaccurate preference predictions strongly depend on the giver's uncertainty about the receiver's preferences, as well as market conditions. First, as expected, the total deadweight loss increases with givers' uncertainty about receivers' preferences. However, it also increases when variation in prices increases. In such situations, givers have a better opportunity to signal the value of the relationship by buying more expensive gifts. In contrast, the total deadweight loss does not vary strongly as a function of attribute variation. Second, the decomposition of deadweight loss into inaccurate preference predictions and price signaling demonstrates that both components play a significant role. On average, in a market with medium price and attribute variation, about 49% of deadweight loss is due to price signaling. However, when givers receive more information about the receivers' preferences, the relative importance of price signaling increases. Moreover, the relative effect of price signaling is much stronger in markets with large variations in price and relatively small variations in product attributes. In those markets, preference predictions play a much smaller role because products are relatively similar. Moreover, the opportunity to use price signaling is much stronger in these cases because there are

[9]Our results were similar for simulated markets consisting of K = 2 alternatives.

Figure 7

DEADWEIGHT LOSS DECOMPOSITION OF STUDY 2



Notes: Shaded (white) areas correspond to deadweight loss that can be attributed to inaccurate preference predictions (price signaling). Low, medium, and high variations in attributes correspond to markets in which variances of the sum of attributes levels across alternatives are, respectively, smaller than 2, between 2 and 4, and larger than 4. Low, medium, and high variations in prices correspond to markets in which variances of price levels across alternatives are, respectively, smaller than 1, between 1 and 2, and larger than 2. The total deadweight losses are normalized, with the highest deadweight loss (no information, high attribute variation, and high price variation) set to 1.

large variations in prices. Interestingly, markets with small differences among alternatives, but large price differences, are relatively common in the gift industry. Examples are jewelry, wines, and perfumes. Our results suggest that the deadweight loss in such markets is relatively high and that about 77% is caused by price signaling. This is in contrast to other markets, such as books and music, in which products are more differentiated and prices are relatively similar, in which case inaccurate predictions of preferences contribute to about 77% of deadweight loss.

DISCUSSION

In this article, we decompose the deadweight loss of gift giving into two sources: (1) inaccurate predictions of attribute preferences and (2) the signaling value of price. Our results show that although both sources play an important role in the deadweight loss, the signaling value of price may account for more deadweight loss than inaccurate preference predictions, especially in markets with large price variations. Moreover, we demonstrate that this effect is strongly moderated by the giver's uncertainty about the receiver's preferences, as well as market conditions. To derive the relative importance of preference predictions and price signaling on the deadweight loss of gift giving, we develop a gift-choice model estimated on a newly developed two-stage conjoint experiment for gift giving.

Our results have important implications for managers. First, the significant difference in purchasing behavior between consumers purchasing for themselves and those purchasing gifts calls for information collection on purchase purpose. Online retailers such as Amazon already obtain such information, as givers often send gifts directly to receivers who are also customers of Amazon. Similarly, online retailers such as Taobao are building social media platforms that allow shoppers to interact and buy gifts for each other. Hence, in these situations it is possible to apply our modeling approach because these companies are able to infer both givers' and receivers' preferences. Such information, in combination with our modeling approach, could assist online retailers and social media platforms in providing gift recommendations as well as studying the effect of wish lists and other marketing tools to influence givers' uncertainty about receivers' preferences. Second, our results on the effect of uncertainty on price sensitivity cast doubt on the effectiveness of wish lists and product recommendations, especially in markets with relatively large price differences. A wish list provides the giver information about the preferences of the receiver, which increases the giver's price sensitivity.

Future research could extend our findings in several directions. First, we restricted our study of gift choice to two specific product categories (headphones and computer mice) because this facilitated the use of conjoint experiments. We speculate that in practice, the price-signaling effect on deadweight loss may be even stronger, because consumers need to choose from more alternatives across multiple categories, increasing their uncertainty. Therefore, it will be important for future research to test the relative importance of preference mismatch and price signaling on deadweight loss using field data. Second, our results mainly focus on the short-term effects of uncertainty on price sensitivity and deadweight loss. One caveat is that from the point of view of long-term profit, it may be better for sellers to reduce uncertainty by providing a wish list. Reducing uncertainty may increase purchase likelihoods and loyalty, factors that we do not investigate in this research. Third, we assume that givers aim to match receivers' preferences when purchasing gifts, which may not be true in certain scenarios. For example, parents may purchase educational toys for their children, or givers may want to expose receivers to a novel experience when receivers are not perfectly informed about their own preferences (Waldfogel 1993). It would be interesting to investigate the role of price signaling in such situations and whether and when this leads to a welfare loss or gain. Fourth, we focus on monetary payments as costs of the giver. Alternatively, givers may signal their care about the relationship through investing more time and effort on acquiring gifts, for instance, by offering handmade gifts. Fifth, we do not consider signaling through attributes other than price. For instance, givers may signal the value of the relationship by buying certain prestigious brands, such as Godiva or Tiffany. Sixth, it would be interesting to investigate whether our results are moderated by cultural differences. Finally, future research could extend our model. For instance, our model ignores the sentimental value of the gift to the receiver and does not account for individual heterogeneity in givers' weights of receivers' preferences and price sensitivities. Moreover, instead of using givers' own preferences as a prior for gift preferences, it would be interesting to allow for alternative priors, such as average preferences in the population.

Our research sheds light on the causes of the deadweight loss of gift giving. For policy makers, it is important to test potential solutions to this problem. For example, do ads that encourage givers to imagine themselves buying a gift as if they were the receiver reduce deadweight loss? Our results of Study 2 for agent purchases suggest that givers may become more price sensitive in such situations. Should policy makers encourage gift givers to pay in cash? Prelec and Simester (2001) demonstrate that paying in cash is associated with higher psychological pain than paying with credit cards, which may increase price sensitivity of gift givers. Alternatively, will giving money instead of actual gifts reduce the deadweight loss? Waldfogel (2002) finds that people are reluctant to give money as gifts. Gift cards may reduce this stigma, but they may reduce the value for receivers because they impose restrictions. It is worth studying how the giver's uncertainty about the receiver's preferences influences the choice of a gift card and the amount givers would like to spend on different gift cards. We hope that this research inspires researchers to further explore this important area.

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