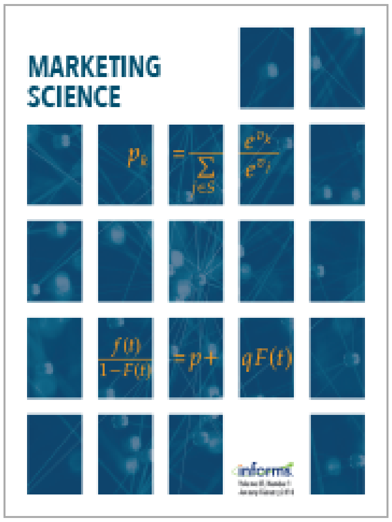

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When Harry Bet with Sally: An Empirical Analysis of Multiple Peer Effects in Casino Gambling Behavior

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In many consumption settings (e.g., restaurants), individuals consume products either alone or with their peers (e.g., friends). In this study, we propose a general framework for modeling peer effects by including two new peer effects: the exogenous peer effect (exogenous factors that could change the peer's behavior) and the peer presence effect (when the peer is present but not consuming). We also include the well known endogenous peer effect. We develop an empirical model that allows us to identify all three effects simultaneously and apply the model to behavioral data from a casino setting. It is a simultaneous equation model with the structural parameters expressed as a function of the ratio of the reduced form parameters. This necessitates the use of the Minimum Expected Loss approach, allowing us to obtain consistent estimates at the individual level. Our data comprise detailed gambling activity for a panel of individuals at a single casino over a two-year period. Our results show that all three types of peer effects exist. These effects vary across individuals and exhibit considerable asymmetry within pairs of peers. We discuss how our results can help managers allocate resources more effectively and policy makers formulate regulatory guidelines with more complete information.

Keywords: peer effects; social networks; simultaneous equation models; hierarchical Bayesian methods; MELO estimator; casino gaming and gambling

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1. Introduction

In many consumption settings (e.g., restaurants, casinos, theme parks, etc.), individuals consume products either alone or with their peers (e.g., friends and/or family members). In such settings, it is likely that through social influence, a consumer's decision on what to purchase or how much to consume is influenced by the purchase or consumption decisions of her peers. There has been much research in marketing that documents the effect(s) of the peer's behavior on the focal consumer's behavior. Some recent examples include Hartmann (2010), Zhang (2010), and Yang et al. (2006). This is the well known and documented endogenous peer effect. The focus of this literature has been to provide methods to distinguish the true causal (endogenous) peer effect from other confounds such as endogenous group formation (homophily), correlated unobservables, and simultaneity (Manski 1993). However, a consumer could not only be affected by the peer's behavior but also by other events that influence the peer to change her behavior. Specifically, suppose the peer gets a demand shock that leads to an increase in her consumption behavior. While the endogenous peer effect will capture the influence of this change in the peer's consumption on the focal consumer's behavior, it is also possible that the focal consumer's observing the peer getting the demand shock could directly affect her (the focal consumer's) behavior. An example of such a demand shock could be a marketing promotion. If the peer gets a promotion but the focal consumer does not, the focal consumer might judge the differential treatment to be unfair and react negatively (Darke and Dahl 2003, Feinberg et al. 2002). Another mechanism by which social influence could operate could be when the peer is physically present but does not engage in the behavior in question. In other words, the peer's presence could directly affect the focal consumer's consumption behavior as the lack of consumption by the peer may signal a subtle or transient change in preferences. In response to this, the focal consumer may modify her behavior. One possible mechanism leading to this could be self-monitoring, wherein the focal peer may moderate her consumption in response to the lack of consumption of her peer. The self-monitoring behavior could be heightened in settings where consumption is controversial as in the case of casino gambling.

In this paper, we conduct a detailed examination of joint consumption by allowing for multiple types of peer effects that could influence the focal consumer. Besides the endogenous peer effect, we allow for the two other effects described above. We label the first as the *exogenous peer effect* and the second as the *peer presence effect*.[1] We develop an empirical model that allows us to simultaneously identify all three effects and apply it to behavioral data from a casino setting. We use a simultaneous equation model. Our data comprise detailed gambling activity for a panel of individuals at a single casino over a two-year period. Our results show that all three types of peer effects exist. These effects vary across individuals and exhibit considerable asymmetry within pairs of peers. The results also indicate that accounting for these peer effects simultaneously and identifying them at an individual level could help marketing managers develop better guidelines for promotion policies. Finally, our results are likely to provide a more complete picture of gambling behavior (with and without peers) for policy makers and help them implement a more informed regulatory regime for the casino industry.

Recently there has been a surge of interest in documenting (endogenous) peer effects in the marketing literature using behavioral data at the individual level (see Hartmann et al. 2008 for an overview). As noted earlier, the focus of most of these papers is identification of the endogenous peer effect at the individual level. Our research builds on two of these papers in particular: Yang et al. (2006) and Hartmann (2010).[2] Yang et al. (2006) build a simultaneous equation model using a spatial autoregressive structure to capture the interdependence of preferences among spouses in the domain of TV watching. Using aggregate data at the monthly level, they find an asymmetry in the watching behavior between spouses, i.e., husbands seem to have a bigger impact on their wives' behavior. Using a structural approach, Hartmann (2010) examines the decisions of golfers to visit a golf course together versus alone. Using the game theoretic framework proposed in the literature for market entry models (Bresnahan and Reiss 1990), he estimates a discrete choice model with all possible combinations of visit outcomes for a pair of golfers included in the choice set. While both of these papers (and others) have documented various strategies to identify peer effects, to our knowledge they have focused only on the endogenous peer effect. In our work, we provide a general framework to capture all types of peer effects, i.e., those that are related to the behavior in question as well as those that operate independent of the peer's behavior. In addition, using a specific estimator (details in §2.3), we capture heterogeneity in all three effects by exploiting the panel structure of our data. We do this while accounting for the common identification issues previously detailed in the literature (Nair et al. 2010, Manski 1993).

Specifically, our empirical approach allows for the identification of all three peer effects described above while controlling for simultaneity, endogenous group formation (i.e., homophily), and the correlated unobservables confounds that make the identification of peer effects challenging. The approach is based on a simultaneous equation model. Each equation reflects a consumer's consumption behavior. Our estimation strategy, formulated in a Hierarchical Bayesian framework, allows us to obtain individual-level reduced form parameters. We then recover the structural parameters of the simultaneous equation system from these reduced form parameters. The technical challenge inherent in the estimation is that the structural parameters are functions of ratios of the reduced form parameters. To our knowledge, prior literature, especially in marketing, on peer effects had not directly addressed this challenge. We address it using the Minimum Expected Loss (MELO) estimator, which allows us to obtain consistent estimates at the individual level.

As noted earlier, our research setting is casino gambling. The main reason we choose this setting is that peers seemed to play a significant role in affecting consumption behavior in this industry. This is based on previous research that documents that one of the most important motivations to visit a casino and play games is social, i.e., being with others such as family and friends (Platz and Millar 2001, Lee et al. 2006). Anecdotal feedback from industry sources also suggests that frequent visitors to the casino visit more

[1] It is important to distinguish the peer presence effect from the mere presence effect documented in the consumer research literature (Argo et al. 2005). The mere presence effect is based on the effect of the presence of a stranger. In our case, the peer presence effect is based on the presence of the peer (who is known to the focal consumer) when the peer is not engaging in the behavior in question. The theory literature has identified the potential for socio-spatial peer spillovers in contexts such as video gaming (DeKort and Ijsselsteijn 2008). Other work in a lab (with imaginary peers) has documented that peer presence can change hypothetical impulse purchasing behavior (Luo 2005). However, to our knowledge, there are no studies that measure the effect of a *present but not consuming* peer in real settings.

[2] Some other relevant papers include Yang and Allenby (2003) and Manchanda et al. (2008). The first paper develops an autoregressive multivariate binomial model that allows the unobserved demand shocks of consumers that exhibit demographic and geographic proximity to be correlated. The second paper documents contagion between physically proximate physicians in the context of adoption of a new drug.

often with others than alone. The second reason we choose this setting is that the casino industry is a major industry in the United States with revenues greater than that of sports teams and clubs, amusement parks and arcades, and museums (US Census Bureau data).[3] In terms of visits, more than a quarter of all Americans 21 and older visited a casino at least once in 2006 (AGA 2007). Despite its prominence, research on this industry seems quite limited. Most of the research on gambling uses data from a laboratory (e.g., Gilovich et al. 1985),[4] as opposed to a field setting. While some research focused on casino gambling based on field data is beginning to emerge (Croson and Sundali 2005, Narayanan and Manchanda 2012), to our knowledge peer effects have been ignored in these studies.[5] Overall, it seems that research on the behavior of the gambling population in the United States has generally been neglected and, as a consequence, demands more attention.

We apply our model to a rich panel data set of casino gamblers who visit a single casino over a two-year period and gamble on slot machines. The data contain information on the gambling activity and the marketing promotions provided to each gambler during her visit to the casino as well as demographics. We identify peer dyads using temporal and geographic proximity in plays at the casino. Our dependent variable is the total amount of money bet by a consumer on slot machines on a given day.

Our results indicate the existence of all three peer effects on the amount bet on a given day, i.e., the endogenous peer effect, the exogenous peer effect, and the peer presence effect. The endogenous peer effect is positive, i.e., an increase in the peer's bet leads to an increase in the focal consumer's bet. The exogenous peer effect is negative for promotions, suggesting that when the peer's bet is affected by a promotion, the focal consumer reduces the amount that she bets. Finally, the mere presence of the peer also leads the focal consumer to reduce the amount she bets, i.e., the peer presence effect is negative as well. Our individual-level approach allows us to quantify the variation in the size of this effect across individuals. More interestingly, we find that within pairs of peers, there is considerable asymmetry in these effects.

Our results are likely to be of interest to marketing managers trying to incorporate peer effects into marketing strategies. First, accounting for three peer effects allows a manager to obtain the complete picture with respect to pairwise interactions in consumption settings. Second, the asymmetry of the peer effect within a pair of peers can help managers identify the peer to focus on in terms of influencing joint behavior. Finally, our results suggest that leveraging peer effects to influence consumption needs should be done carefully as both the exogenous peer effect and the peer presence effect tend to work in the opposite direction of the endogenous peer effect. In fact, in our setting, we find that the endogenous peer effect resulting from a promotion given to the focal consumer and exogenous peer effect cancel each other out. The use of our estimates to implement counterfactuals indicates that changes in promotion policies, especially with respect to targeting the more influential peer for promotions, is likely to result in economically significant gains for managers.

In addition to managers, our results are likely to be of use to policy makers in that they provide more complete information on the gambling behavior of consumers in group and individual settings. In general, the results suggest that gambling with peers tends to moderate responsiveness to promotion and weaken patterns suggestive of addictive behavior. Finally, we discuss how our approach can be applied to other (social) settings.

The rest of the paper is organized as follows. We develop our model, discuss the identification of parameters, and provide details on the estimation procedure in §2. In §3, we provide details on the institutional setting, the data, and peer identification, and provide some preliminary evidence for peer effects in the data. We describe the model specification in §4 and the results in §5. We discuss the managerial and policy implications of our results in §6. Section 7 concludes with summary remarks and suggestions for future research.

2. Model

2.1. Model Development

We model the amount of money bet by customer A in peer dyad k at time t, q_{Akt}, as follows:

$$q_{Akt} = \theta'_{A1k} X_{Akt} + \theta'_{A2k} X_{Akt} I_{Bkt} + \theta_{A3k} q_{Bkt} I_{Bkt} + \theta'_{A4k} X^{s}_{Bkt} I_{Bkt} + \varepsilon_{Akt}. \tag{1}$$

Here X_{Akt} represents exogenous variables (including the fixed effect) that influence the consumption

[3] Part of the growth in the industry can be attributed to the increased presence of casinos in the United States in recent years. In the 1980s, casino gambling was legal only in Nevada and Atlantic City, New Jersey. Today, however, commerical casino gambling is legal in 23 states, generating total revenues of about $32 billion annually. If we include casinos operated on sovereign Native American land, the number of states that allow casino gambling increases to 28 (AGA 2013).

[4] While researchers can be quite versatile in terms of the questions that they address in lab settings, these settings have their own limitations. For example, participants are many times not required to risk anything of value and they receive an unlimited supply of (gambling) tokens (Kassinove and Schare 2001).

[5] The only exception that we found is Narayanan (2013), who uses gambling data in an application to illustrate the Bayesian estimation of discrete games.

(money bet) level of customer A in peer dyad k at time t. The parameter θ_{A2k} represents the peer presence effect that captures whether the peer's presence increases or decreases customer A's level of consumption. The variable q_{Bkt} represents the consumption level of consumer B in peer dyad k during time t. The binary variable I_{Bkt} indicates whether peer B visited with the focal agent ($I_{Bkt} = 1$) ($I_{Bkt} = 0$). The parameter θ_{A3k} represents the endogenous peer effect, i.e., the impact of the peer's level of consumption on customer A's consumption behavior. The parameter θ_{A4k} represents the exogenous peer effect, i.e., the effect on customer A's consumption when customer B's consumption is influenced by an exogenous demand shock. The variable X^s_{Bkt} (i.e., subset of X_{Bkt}) represents exogenous factors of customer B that also could affect customer A. Note that the peer's consumption and exogenous variables are multiplied by I_{Bkt} since they are observed by the focal agent only when the peer is present. Finally, ε_{Akt} is the demand shock. All upper case letters (e.g., X_{Akt}) except I_{Akt} and I_{Bkt} represent vectors.

Similarly, the amount of money bet by customer B in peer dyad k at time t can be represented as

$$q_{Bkt} = \theta'_{B1k} X_{Bkt} + \theta'_{B2k} X_{Bkt} I_{Akt} + \theta_{B3k} q_{Akt} I_{Akt} + \theta'_{B4k} X^s_{Akt} I_{Akt} + \varepsilon_{Bkt}. \quad (2)$$

We allow a free correlation structure between ε_{Akt} and ε_{Bkt} as follows:

$$[\varepsilon_{Akt}, \varepsilon_{Bkt}]' = MVN(0, \Sigma) = MVN\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{bmatrix} \sigma_A^2 & \rho\sigma_A\sigma_B I_{At} I_{Bt} \\ \rho\sigma_A\sigma_B I_{At} I_{Bt} & \sigma_B^2 \end{bmatrix}\right). \quad (3)$$

2.2. Identification

The identification of peer effects using behavioral data can be challenging due to multiple confounds. We therefore describe how we control for three major possible confounds. These are endogenous group formation, correlated unobservables, and simultaneity. Endogenous group formation occurs because consumers with similar tastes could have a tendency to form social groups. This correlation could be mistaken as casual effect of one's behavior on another (Manski 1993). Second, correlation in behavior within the peer group could also arise due to correlated unobservables (such as common demand shocks). Third, we need to control for simultaneity as with behavioral data it is hard to causally distinguish A's influence on B from the other way around (Manski 1993). Econometrically, these confounds are potential sources of correlation between ε_{Akt} and q_{Bkt} (and between ε_{Bkt} and q_{Akt}) that would result in a bias in θ_{A3k} and θ_{B3k} due to endogeneity (see Nair et al. 2010 for a detailed description of these confounds).

The correlation due to endogenous group formation can be controlled via the panel structure of our data and the model (Nair et al. 2010). The fixed effects included in X_{Akt} and X_{Bkt} will account for nontime varying factors that are idiosyncratic to peers A and B, respectively, in peer dyad k.[6]

These fixed effects, however, do not capture time varying factors (such as common demand shocks) and thus do not control for biases due to correlated unobservables and simultaneity. We resolve this problem by imposing an exclusion restriction condition. Specifically, we introduce variables Z_{Akt} and Z_{Bkt} such that Z_{Akt} only affects A's bet (q_{Akt}) but not the peer's bet (q_{Bkt}) and Z_{Bkt} only affects B's bet (q_{Bkt}) but not the peer's bet (q_{Akt}) as follows:

$$q_{Akt} = \theta'_{A1k} X_{Akt} + \theta'_{A2k} X_{Akt} I_{Bkt} + \theta_{A3k} q_{Bkt} I_{Bkt} + \theta'_{A4k} X^s_{Bkt} I_{Bkt} + \theta_{A5k} Z_{Akt} + \varepsilon_{Akt}, \quad (4)$$

$$q_{Bkt} = \theta'_{B1k} X_{Bkt} + \theta'_{B2k} X_{Bkt} I_{Akt} + \theta_{B3k} q_{Akt} I_{Akt} + \theta'_{B4k} X^s_{Akt} I_{Akt} + \theta_{B5k} Z_{Bkt} + \varepsilon_{Bkt}. \quad (5)$$

One concern about the peer presence effect could be that it is also endogenous, i.e., the peer strategically decides to accompany the peer but not play. While this situation seems unlikely, the excluded variable Z_{Akt} helps to provide an unbiased estimate of both the endogenous peer effect, θ_{A3k}, and the (potentially endogenous) peer presence effect, θ_{A2k1}. The intuition for this is the following: The peer presence effect is a limiting case of the endogenous peer effect. Specifically, the peer presence effect can be seen as the endogenous peer effect at the zero level of play of the peer. The total endogenous peer effect can be decomposed into an intercept and a slope, with the intercept representing the peer presence effect and the slope representing the endogenous peer effect (as reported in the paper). From the data point of view, the peer presence effect is identified by the observations for which the peer's bet (q_{Bkt}) is zero (or approaches zero in the limit) along with the observations wherein the focal peer plays alone. The endogenous peer effect is mainly identified from the observations with both peers present and betting amounts larger than zero.[7]

[6] These individual fixed effects also allow us to explore implications for targeting marketing policy at the individual level (via the provision of controls for cross-sectional heterogeneity).

[7] We thank an anonymous reviewer for alerting us to the possibility of such a scenario occurring and helping us to provide this clarification of the identification argument.

In addition, note that many studies have assumed that there are no exogenous peer effects ($\theta_{A4k} = \theta_{B4k} = 0$) and treated exogenous factors (X^s_{Akt} and X^s_{Bkt}) as excluded variables (Moffitt 2001). This, however, will also result in biased estimates of the structural parameters if the assumption of no exogenous peer effect is incorrect. In such a case the focal consumer's exogenous factors used as excluded variables will not be independent of the peer's behavior. For example, if consumer B gets a large demand shock (e.g., an exogenous promotion) and that is used as an excluded variable, it might bias endogenous peer effect θ_{B3k} because consumer A could have not only changed her behavior due to a change in consumer B's behavior but also due to observing consumer B's promotion.

2.3. Estimation

We begin with Equation (6) that is the reduced form of our model (Equations (4) and (5))

$$\begin{aligned} q_{Akt} &= \varphi_{A1k}[\theta'_{A\cdot k} Y_{Akt}] + \varphi_{A2k}[\theta'_{B\cdot k} Y_{Bkt}] + \eta_{Akt}, \\ q_{Bkt} &= \varphi_{B1k}[\theta'_{B\cdot k} Y_{Bkt}] + \varphi_{B2k}[\theta'_{A\cdot k} Y_{Akt}] + \eta_{Bkt}, \\ &[\eta_{Akt}, \eta_{Bkt}]' \sim MVN(0, \Omega), \end{aligned} \tag{6}$$

where $Y_{Akt} = [X_{Akt}, X_{Akt}I_{Bkt}, X^s_{Bkt}I_{Bkt}, Z_{Akt}]'$, $Y_{Bkt} = [X_{Bkt}, X_{Bkt}I_{Akt}, X^s_{Akt}I_{Akt}, Z_{Bkt}]'$, $\theta_{A\cdot k} = [\theta_{A1k}, \theta_{A2k}, \theta_{A4k}, \theta_{A5k}]'$, $\theta_{B\cdot k} = [\theta_{B1k}, \theta_{B2k}, \theta_{B4k}, \theta_{B5k}]'$, $\varphi_{A1k} = 1/(1-\theta_{A3k}\theta_{B3k})$, $\varphi_{A2k} = \theta_{A3k}/(1-\theta_{A3k}\theta_{B3k})$, $\varphi_{B1k} = 1/(1-\theta_{A3k}\theta_{B3k})$, $\varphi_{B2k} = \theta_{B3k}/(1-\theta_{A3k}\theta_{B3k})$, $\Omega = (I-W)^{-1}\Sigma((I-W)^{-1})'$, and

$$W = \begin{pmatrix} 0 & \theta_{A3k} \\ \theta_{B3k} & 0 \end{pmatrix}.$$

The structural parameters, θ_{A3k} and θ_{B3k}, can be expressed as functions of the reduced form parameters as in Equation (7) below.

$$\begin{aligned} \theta_{A3k} &= \varphi_{A2k}/\varphi_{B1k}, \\ \theta_{B3k} &= \varphi_{B2k}/\varphi_{A1k}. \end{aligned} \tag{7}$$

Conventional estimators such as Least Squares (LS) Estimator for θ_{A3k} and θ_{B3k} would be simply expressed as $\hat{\theta}^{LS}_{A3k} = \hat{\varphi}_{A2k}/\hat{\varphi}_{B1k}$ and $\hat{\theta}^{LS}_{B3k} = \hat{\varphi}_{B2k}/\hat{\varphi}_{A1k}$. Note, however, that these estimators are ratios of two normally distributed random variables. When the denominator has a significant amount of its density over zero (e.g., small absolute mean and large standard deviation), the ratio has Cauchy (i.e., distribution) like tails resulting in no finite moments.[8] Therefore, with conventional estimators we would be unable to obtain the (Bayesian) estimates of interest, especially the posterior means. To overcome this ratio estimation problem, we implement the MELO approach (Zellner 1978). This guarantees finite first and second moments. The MELO estimator is defined as follows:

$$\begin{aligned} &\hat{\theta}^{MELO}_{A3k} \\ &\quad = \frac{E(\varphi_{A2k})}{E(\varphi_{B1k})} \cdot \frac{1+\mathrm{cov}(\varphi_{A2k}, \varphi_{B1k})/(E(\varphi_{A2k})E(\varphi_{B1k}))}{1+\mathrm{var}(\varphi_{B1k})/E(\varphi_{B1k})^2} \\ &\quad = \frac{E(\varphi_{A2k})}{E(\varphi_{B1k})} \cdot F, \\ &\hat{\theta}^{MELO}_{B3k} \\ &\quad = \frac{E(\varphi_{B2k})}{E(\varphi_{A1k})} \cdot \frac{1+\mathrm{cov}(\varphi_{A1k}, \varphi_{B2k})/(E(\varphi_{A1k})E(\varphi_{B2k}))}{1+\mathrm{var}(\varphi_{A1k})/E(\varphi_{A1k})^2} \\ &\quad = \frac{E(\varphi_{B2k})}{E(\varphi_{A1k})} \cdot F, \end{aligned} \tag{8}$$

where $E(\cdot)$ denotes the posterior expectation, $\mathrm{var}(\cdot)$ denotes the posterior variance, $\mathrm{cov}(\cdot)$ denotes the posterior covariance, and F denotes the shrinkage factor. The MELO estimator is most effective for small sample sizes as F is not close to 1 for such cases (for details, see Diebold and Lamb 1997).[9]

Given the estimated parameters, $\hat{\theta}^{MELO}_{A3k}$ and $\hat{\theta}^{MELO}_{B3k}$, we then estimate the remaining parameters $\theta_{A\cdot k}$ and $\theta_{B\cdot k}$. Let us first consider $\theta_{A\cdot k}$. To account for the correlation structure between ε_{Akt} and ε_{Bkt}, we first derive the conditional distribution of $\varepsilon_{Akt} \mid \varepsilon_{Bkt}$ as follows:

$$\begin{aligned} q_{Akt} - \hat{\theta}_{A3k} q_{Bkt} I_{Bkt} &= \theta'_{A\cdot k} Y_{Akt} + \varepsilon_{Akt} \mid \varepsilon_{Bkt} \\ &= \theta'_{A\cdot k} Y_{Akt} + \frac{\rho\sigma_A}{\sigma_B}\varepsilon_{Bkt} + v_{A\mid B}, \end{aligned} \tag{9}$$

where $\mathrm{var}(v_{A|B}) \equiv \sigma^2_{A|B} = \sigma^2_A(1-\rho^2)$. We now perform a conventional regression analysis. Note that in our setting ε_{Akt} and ε_{Bkt} are assumed to be uncorrelated when a consumer visits alone. Therefore, for those observations, the joint estimation method described above does not apply. However, our estimation strategy (details provided in the appendix) allows us to augment the missing error term of the peer (Zeithammer and Lenk 2006). This allows us to follow the same joint estimation strategy for all observations.

We cast our model under a Hierarchical Bayesian framework and use Markov Chain Monte Carlo (MCMC) methods to obtain the parameter estimates (details are provided in the appendix).

[8] In contrast, when the denominator has a very small amount of its density over zero (e.g., large absolute mean and small standard deviation), the ratio can be approximated by a normal distribution (Hayya et al. 1975).

[9] We carried out extensive analyses to show that, for our setting, the MELO estimator was necessary to obtain meaningful results. Specifically, using both simulated and actual data, we found that the MELO estimator provided the most stable and accurate results relative to other estimators, including the LS. Details on these analyses are available from the authors on request.

3. Data

Our data were obtained from a gaming and gambling company operating a single casino property in the northwestern United States. The property is in a small town and the nearest casino is 160 miles away. Thus our casino can be considered a local monopoly. The casino uses a loyalty program to facilitate the building of relationships with its customers. Customers are encouraged to sign up for the loyalty card and to use the card whenever they engage in any activity at the casino. Typically, the customer swipes the card when she begins to gamble at a station. All gambling activity between the swiping of the card and exit from a station (e.g., a slot machine) is uniquely linked to that customer's account and is identified as a play.

Our data consist of a panel data set wherein the customer activity is recorded for a two-year period (July 2005 to June 2007). The data contain information about the games that are played, the amount that is bet, the amount that is won or lost, the start and end times (calendar time) of each play, and the identity of the slot machine (if the station is a slot machine). In addition to the activity information, the data also contain information on marketing policies of the casino. Based on feedback from the company, we learned that these policies take two forms at this property: comps and promotion. Comps refer to incentives or rewards that the casino gives to make customers play longer on a given trip. The nature of comps ranges from key chains to suites with all meals and beverages included. In our data, the comps are recorded in dollar equivalents. In general, comps are based on a tiered classification based on total dollars bet in the previous calendar year. Customers who bet more in a given year receive higher comps in the following year.[10] Promotions, on the other hand, are randomly given during a visit to create excitement and engagement among customers on that day. Promotion is recorded as a binary variable indicating whether a customer got a promotion on a given day. If a customer receives the promotion for that day, the customer's activity in terms of the amount of money bet is given double credit toward the comp tier classification for the next year.[11] Finally, the data also contain basic demographic information, such as age and gender, on each customer.

The total number of customers in the data is 44,732 accounting for 7,110,376 total plays. The average number of visits in a year to the casino for our panelists was 5.9. A survey of American gamblers by Harrah's/Caesar's in 2006 found that the average number of visits to a casino was 6.1.[12] The average time spent by a customer within a day was about 153 minutes. In terms of bet activity, the mean total amount bet and total money earned was \$975 (median \$425.20) and \$−185 (median \$−55.90), respectively, on a typical visit. A negative figure denotes a loss. Customers were given a promotion, on average, once every 25 visits to the casino. Our sample is evenly balanced in terms of gender (47% male and 50% female; gender data was missing for 3% of our sample). The mean age across panelists was 56 years with a standard deviation of 15.5 years.

We restrict our sample to slot machine players. Slot machine play accounts for 90% of play dollars in our data set. Consumer preferences in a casino are also overwhelmingly in favor of slot machines. Seventy-one percent of Americans prefer slot machines, while only 14% prefer table games (AGA 2007). Finally, slot machines represent games of chance (as opposed to table games which are considered games of skill) where outcomes (wins/losses) are determined purely randomly. This is an attractive feature that our modeling approach leverages for identification.

3.1. Peer Construction

We follow the approach in Hartmann (2010) for identifying peer groups. Specifically, in that paper, peers were identified based on temporal proximity in terms of beginning play on a golf course on at least two occasions. As in that paper, we assume that the (inferred) peer relationship is stable and does not evolve during the period of our data. This assumption seems reasonable as we do not have indications of any changes to the environment (new gamblers, new games, changes to the casino, etc.) and/or individuals over this time period. In settings where the institutional features and/or model-free evidence suggest that this relationship changes over time, the analyst will have to specify an evolution process for it. This

[10] Note that this could lead to an acceleration in amounts bet towards the end of the calendar year. However, when we regress the average daily amount bet in the last three months of the year on the average daily amount bet in the first nine months of the year, we find that the slope coefficient is 0.94. This suggests that there is no evidence of acceleration for the customers in our data.

[11] Executives at the casino told us that promotions were given randomly at the entrance every day. Because of this, customers do not have any prior expectation of receiving a promotion on a particular day. We verified that these promotions were indeed delivered randomly. Specifically, we carried out an analysis to see if more valuable customers were more likely to be given a promotion. The casino values customers based on the total amount bet in a calendar year. We therefore estimated a discrete choice model for the customers in our data with the dependent variable being whether a customer received a promotion in 2007 and the independent variable being the total amount bet in 2006. We found that the total amount bet in 2006 was not predictive of promotions received. This lends credence to the casino's assertion to us that promotions were delivered randomly.

[12] Survey results are available at http://www.caesars.com/images/PDFs/Profile_Survey_2006.pdf.

Table 1 Descriptive Statistics

	Population		Frequent visitor		Sample of dyads	
	$N = 44{,}732$		$N = 8{,}870$		$N = 1{,}626 \cdot 2$	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Number of days played during two years	11.84	31.95	48.44	58.79	70.01	73.18
Time spent per day	153.28	136.68	162.13	142.49	166.89	136.83
Money bet per day (dollar)	975.58	1,803.51	1,038.64	1,882.09	975.15	1,533.03
Money won per day (dollar)	790.10	2,108.04	844.99	2,271.71	821.76	1,317.88
Number of jackpots per day	0.01	0.14	0.01	0.16	0.01	0.13
Number of promotions per day	0.04	0.19	0.04	0.19	0.04	0.19

leads to a more complex modeling approach with novel identification challenges.

In our case, we conduct a similar analysis for frequent visitors to the casino (i.e., those that visit the casino at least five times a year), a total of 8,870 customers, to identify peers. For these customers, we identified how many times each customer visited the casino with another customer. We defined visiting together as starting the first game on a visit within five minutes of each other within the same geographic area (defined as a bank of machines in the casino). This resulted in a matrix of size 8,870 by 8,870, with the (i, j)th element of this matrix representing the number of visits that customer i made with customer j during the entire two year period. From this matrix, we identified the column with the highest element for each row, resulting in a matrix of size 8,870 by 1. This identified a customer who visited the casino most frequently with the focal customer as the most probable peer for her relative to all customers in our data.[13] To rule out peer group construction based on chance, we required that for each identified pair there were at least four occasions when they visited together.[14] This resulted in a total of 1,626 dyads. Table 1 provides descriptive statistics for our entire sample, our base sample of frequent visitors (visited more than five times a year), and the estimation sample consisting of the chosen dyads. In terms of activity at the casino, frequent gamblers accounted for 87% of the total amount bet across the time period of our data. Our chosen sample accounted for 47% of the total amount bet. However, in terms of activity, with the exception of a couple of measures, there is not much difference between all gamblers, frequent gamblers, and our estimation sample (see Table 1).

3.2. Evidence for Peer Effects in the Data

We now provide some basic evidence in the data for peer effects. In our estimation sample of 1,626 dyads, on average, each customer visited the casino alone 22 times and with a peer 48 times over the two year period. The mean amount bet when a customer visited with a peer was \$1,076 (with a standard deviation of \$1,653) while it was \$1,046 (with a standard deviation of \$1,862) when she visited alone. While the amount bet with a peer is higher on average, it is not statistically different. However, there could be significant heterogeneity across customers. Customers who primarily come alone could be different from customers who come primarily with the peer. To account for that, we run a simple ordinary least squares (OLS) model. In this model the dependent variable is the amount bet and the independent variable is a dummy denoting whether the customer visited alone or with the peer. To account for heterogeneity, we include individual fixed effects in the analysis. We find that a customer spends \$138 more when she visits with a peer relative to visiting alone. This difference is statistically significant (standard error 6.87, t-stat 19.69).

Note, however, that this study is designed to investigate various mechanisms that could have caused this difference in customer spending when a customer visits with a peer relative to visiting alone. We therefore try to find evidence of all three peer effects in the data without imposing any structure on it. To do so, we run an OLS model with the dependent variable as the amount bet. For the independent variables, the peer's bet was included to capture the endogenous peer effect. The peer's wins or losses on the previous visit, extra-large wins for the peers (jackpots)

[13] It is possible that the peer group contains more than two peers. Because we found that the number of such peer groups was very low, we dropped any customer that was part of such peer groups and restricted our analysis to customers that were in unique dyads.

[14] A potential issue with inferring rather than observing the dyads is that there could be individuals incorrectly classified as peers. This could lead to two types of classification problems. In the first type, our procedure could exclude true peers, while in the second type, we could classify a pair as peers when they are not. Note, however, that both of these errors will bias our results on the peer effects towards zero. In other words, both types of classification errors work against our finding any systematic peer effects. Hence, our results must be treated as conservative. Finally, we also test for the robustness of our results to number of visits by varying the common (overlap) visits to 2, 3, 5, or 6 (instead of 4). There is no material difference in our findings. These results, along with results from other robustness checks, are available in a Web appendix that accompanies this paper (available as supplemental material at http://dx.doi.org/10.1287/mksc.2014.0889).

from the previous visit, and marketing promotions given to the peer on the current visit were included to capture the exogenous peer effect. A dummy variable denotes whether the peer visit was included to capture the peer presence effect. The results suggest that there is a positive relationship between the focal customer's bet and that of the peer's (coefficient 0.43, standard error 0.002, *t*-stat 181.70). We also find that the peer's wins or losses on the previous visit has a positive effect (coefficient 0.09, standard error 0.007, *t*-stat 13.18), but that peer's jackpot from the previous visit has a negative effect (coefficient −140, standard error 21.04, *t*-stat −6.70) on the focal consumer's bet. Interestingly, there is a negative effect on the focal customer's betting when the peer gets a promotion (coefficient −165, standard error 15.24, *t*-stat −10.82).

Finally, peer presence also has a negative effect (coefficient −215, standard error 8.79, *t*-stat −24.56) on the focal consumer's bet. Note that the peer presence effect is identified from visits when the focal consumer visited together with the peer but the peer did not bet (or bet very small amounts). Patterns in the data also support the negative peer presence effect that we found in the OLS analysis. The data suggest that when peers bet a very small amount, less than \$10, the focal consumer typically bets an average of \$346 (with a standard deviation of \$932). This amount is much lower than the average amount bet when the focal consumer visited alone (\$1,046).

Taken together, the above suggests that there is enough variation in the data to identify all three peer effects. Obviously, the statistics/results presented above are only indicative. Specification of a full model is required to pin down the significance and magnitude of the peer effects.

4. Model Specification

Our dependent variable is $\ln(q_{Akt}+1)$, the log transformation of the total amount of money bet by a customer during a day of a visit (indexed by t).[15] We divide the factors that could influence a focal customer's betting behavior into own factors, peer factors, and environmental factors. For the own factors, we focus on four factors. These are: state-dependence, irrational beliefs, extra-large wins (i.e., jackpots), and marketing promotions.

$$X_{Akt} = \begin{pmatrix}1 & X^{(2)} & X^{(3)} & X^{(4)} & X^{(5)}\end{pmatrix}$$

with

$$X^{(2)} = \ln(q_{Akt-1}+1) \quad X^{(3)} = Earn_{Akt-1}$$
$$X^{(4)} = Jackpot\_self_{Akt-1} \quad X^{(5)} = Promo_{Akt}$$

Here q_{Akt-1} indicates the total bet by the consumer in the previous time period. This variable was included to account for state-dependence in the amount bet. Previous research has characterized positive state-dependence as evidence for addiction (Pollak 1970, Becker and Murphy 1988). Specifically, this research has defined addiction as the positive effect of past consumption on the marginal utility of current consumption with the reduced form test for addiction being a positive relationship between past and current consumption (Becker and Murphy 1988). More recent studies (Guryan and Kearney 2008, Narayanan and Manchanda 2012) have used this reduced form test and found evidence for addiction in gambling settings.

$Earn_{Akt-1}$ indicates the total money won or lost by the consumer in the previous visit. Previous literature has documented that wins and/or losses can affect future betting behavior in a variety of contexts. Often this is due to irrational beliefs, i.e., the "gambler's fallacy" and the "hot hand" myth, held by customers (Gilovich et al. 1985, Guryan and Kearney 2008). The gambler's fallacy is the belief that two consecutive independent outcomes are negatively correlated. Therefore, customers who hold this belief will bet less money if they won money in the previous visit and bet more money otherwise. The hot hand myth is the belief that two consecutive independent outcomes are positively correlated, i.e., it is the exact opposite of the gambler's fallacy. Thus, customers who hold this will bet more money if they earned money in the previous visit and bet less otherwise. Thus, the sign of the coefficient of this variable will provide information on whether customers in our sample hold such beliefs. A negative estimate suggests a belief in the gambler's fallacy while a positive estimate suggests a belief in the hot hand myth. Note that a zero estimate suggests that consumers do not hold either of these irrational beliefs.

$Jackpot\_self_{Akt-1}$ is a count variable indicating how many times the customer experienced winning a jackpot during the previous visit. A jackpot is a rare event and represents a larger than usual win[16] and therefore is accounted for separately as a count variable. Note that the dollar value of the jackpot win is represented by $Earn_{Akt-1}$. We expect that the number of jackpots won will influence a customer in a similar manner to dollar wins and losses (as above).

$Promo_{Akt}$ is a binary variable indicating whether the customer was given a marketing promotion during the visit. As described earlier, a promotion allows a customer to accrue activity points faster (typically at

[15] We carried out a log transformation of the dependent variable to be consistent with our assumption of a normally distributed error term. Also, as a few observations were zero, we added one to every observation.

[16] The dollar value of a jackpot win was about 18 times larger than a regular win. Customers won a jackpot, on average, once every 100 visits to the casino.

twice the normal rate). Our hypothesis is that this promotion will act as a typical marketing promotion, i.e., induce customers to bet higher amounts of money.

We next focus on peer factors that could affect the focal customer's betting behavior. The first is the log transformation of the total bet by the peer during the visit plus one, $\ln(q_{Bkt}+1)$. This represents the direct impact of the peers behavior on the focal customer's behavior and is the endogenous peer effect. The peer presence effect is captured by the interaction of I_{Bkt} (i.e., the binary variable indicating the peer's visit) and the intercept term in X_{Akt}. The interaction between I_{Bkt} and the rest of the variables in X_{Akt} (excluding the intercept) captures the difference in the focal customer's response to own factors when she was with a peer compared to when she was alone. For the exogenous peer effect X^s_{Bkt}, we focus on three factors. These factors are the peer's wins or losses on the previous visit, extra-large wins for the peers (i.e., jackpots) from the previous visit, and marketing promotions given to the peer on the current visit. We do not have a clear prediction of the effect of the peer's wins or losses and jackpots on the behavior of the focal customer. Based on previous research (Darke and Dahl 2003, Feinberg et al. 2002), we expect that the effect of the promotion given to the peer will lead to a decrease in the focal customer's bet amount.

Finally, to control for unobserved environmental factors that could affect the behavior of all gamblers (e.g., a day with unexpectedly good weather that could change the demand patterns for the casino), we use the average amount bet per customer across all customers (excluding the peer group in question) who visited the casino in time period t. We label this variable $EnvCtrl_{(-Ak)(-Bk)t}$.

As noted earlier, we use an excluded variable to break the simultaneity confound. The excluded variable we use, $Jackpot\_stranger_{Akt}$, is a count variable indicating how many times the focal customer observed other customers (excluding the peer) experiencing a jackpot. The key to the exclusion restriction is that these jackpot wins are observed by the focal consumer but not her peer. We try to ensure this by including only jackpot wins experienced by other customers in physical proximity to the focal customer but at some distance from the peer. We divide the

Figure 1 Casino Floor Plan

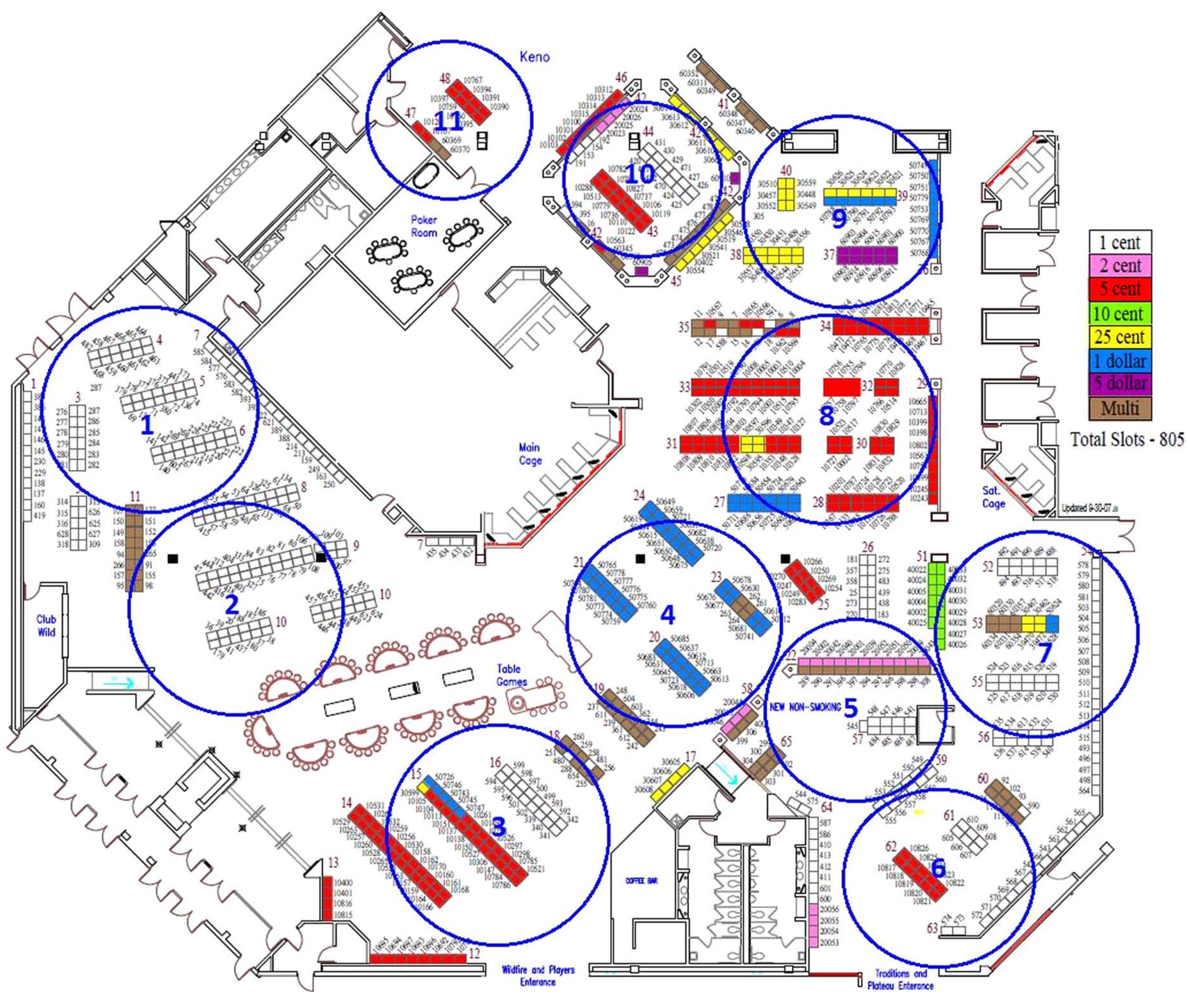


Table 2 Location Definition for the Excluded Variable

Focal consumer location	Peer location
1	All except 2
2	All except 1, 3
3	All except 2, 4
4	All except 3, 5, 8
5	All except 4, 6, 7, 8
6	All except 5, 7
7	All except 5, 6, 8
8	All except 4, 5, 7, 9
9	All except 8, 10
10	All except 9, 11
11	All except 10

casino floor into contiguous areas (below) and count a jackpot only if the peer was playing in any area that was not contiguous to the area that the focal customer was playing in (see Figure 1 and Table 2 for details). For example, if the focal customer was playing in Area 1 and experienced a stranger winning a jackpot in that area, the peer had to be playing in Area 3 or farther for the jackpot to be counted as part of the excluded variable. Based on this definition, the mean $Jackpot\_stranger_{Akt}$ for a focal consumer was 0.037.

To ensure that the $Jackpot\_stranger_{Akt}$ variable is a valid excluded variable, we ran a regression analysis as below. This is analogous to the first stage regression in the two stage LS estimation method. As can be seen from Table 3, the F statistic is high enough to reject the null hypothesis that the excluded variable is not valid.

The final specification is as follows:

$$
\begin{aligned}
&\ln(q_{Akt}+1)\\
&\quad=\theta_{A1k}(1 \quad \ln(q_{Akt-1}+1) \quad Earn_{Akt-1} \quad Jackpot\_self_{Akt-1} \quad Promo_{Akt})\\
&\qquad+\theta_{A2k}(1 \quad \ln(q_{Akt-1}+1) \quad Earn_{Akt-1} \quad Jackpot\_self_{Akt-1} \quad Promo_{Akt})I_{Bkt}\\
&\qquad+\theta_{A3k}\ln(q_{Bkt}+1)I_{Bkt}\\
&\qquad+\theta_{A4k}(Earn_{Bkt-1} \quad Jackpot\_self_{Bkt-1} \quad Promo_{Bkt})I_{Bkt}\\
&\qquad+\theta_{A5k}(Jackpot\_stranger_{Akt})\\
&\qquad+\theta_{A6k}\ln(EnvCtrl_{-(Ak)-(Bk)t})+\varepsilon_{Akt}.
\end{aligned}
\tag{10}
$$

5. Results

5.1. Parameter Estimates

We now discuss population-level parameter estimates in Table 4.[17] We first focus on the own parameters that affect the amount bet by the focal customer. The coefficient for $\ln(q_{At-1}+1)$ was positive (albeit small) at 0.18. It means that a 1% increase in the previous bet leads to a 0.18% increase in the current bet. This suggests evidence for positive state dependence (on average). This result is different from that in Narayanan and Manchanda (2012). However, it is difficult to pinpoint the reason for the difference in the result as the models differ in the level of aggregation and specification. The coefficient for $Earn_{At-1}$ was positive but not significantly different from zero. Customers, however, tended to bet more (21%) when they previously won a jackpot. Last, promotion had a positive effect on the focal consumer's bet with an increase of 75% on the days when the focal customer was given a promotion. This attests to the impact of the casino's marketing programs.

We now turn to the peer effects. The coefficient for the mean endogenous peer effect was 0.78 implying that the focal customer increases her bet by 0.78% when the peer increases her bet by 1%. In terms of the exogenous peer effect, we find that when the peer was given a promotion, the focal consumer reduced her bet by 23%. This confirms the findings from previous work (Darke and Dahl 2003, Feinberg et al. 2002). As this work has conjectured, this effect (rarely documented in field or behavioral settings) could arise due to feelings of envy and/or unfairness. In terms of the peer presence effect, the main effect (measured via the intercept) was negative, i.e., the presence of the peer when the peer was not betting reduced the amount bet by the focal customer. As noted earlier, one possible mechanism behind this effect could be self-monitoring, where the focal peer may moderate her consumption in response to the lack of consumption on the part of her peer. The presence of the peer also induced negative state dependence (though for a modest amount, a drop of 0.11% from 0.18% of state dependence when she was without a peer), leading to less addictive behavior. Finally, we find that the coefficient for $Promo_{At} \times I_{Bt}$ was negative (−0.24), suggesting that the focal consumer responds less to promotion in the presence of a peer. The result seems to indicate that the presence of a peer dampens the response to marketing promotion.

5.2. Heterogeneity and the Asymmetry in the Endogenous Peer Effect

Our individual-level approach allows us to quantify the variation in the size of peer effects across consumers. Specifically, use of the MELO approach enables us to estimate the all peer effects, including the endogenous peer effect, at the individual level. Figure 2 and Table 5 show the heterogeneity in the estimated endogenous peer effect across individuals. The size of the endogenous peer effect for a majority of the customers (83%) is between 0 and 1 implying that when the focal consumer increases her bet, the peer also increases her bet, but less than the amount increased by the focal customer. Of these customers, 48% had an endogenous peer effect coefficient that is significantly different from zero. Of the remaining

[17] We ran the sampler for 20,000 iterations and obtained the posterior mean and standard deviation for all parameters from the last 5,000 draws. Note also that we divided $Earn_{Akt-1}$ by 100 for computational tractability.

Table 3 **Validity Check on the Excluded Variable**

	On only excluded variable				First stage regression			
Variables	Parameter	S.E.	*t*-stat	*p* value	Parameter	S.E.	*t*-stat	*p* value
$\ln(q_{At-1}+1)$					0.09	0.01	29.32	<0.0001
$Earn_{At-1}$					0.17	0.01	2.44	<0.0146
$Jackpot\_self_{At-1}$					0.27	0.02	12.90	<0.0001
$Jackpot\_stranger_{At}$	0.32	0.01	26.01	<0.0001	0.39	0.01	34.64	<0.0001
$Promo_{At}$					0.32	0.01	20.67	<0.0001
$\ln(EnvCtrl_{-(A)-(B)t})$					0.08	0.01	5.39	<0.0001
I_{Bt}					−2.23	0.02	−96.87	<0.0001
$\ln(q_{Bt}+1)$					0.43	0.01	121.27	<0.0001
$Earn_{Bt-1}$					0.05	0.01	7.47	<0.0001
$Jackpot\_self_{Bt-1}$					0.13	0.02	5.70	<0.0001
$Promo_{Bt}$					−0.19	0.02	−11.16	<0.0001
F		61.66				84.70		
R^2		0.56				0.63		

Note. Note that individual fixed effects are not reported.

Table 4 **Parameter Estimates**

Variable description	Variables	Mean	S.D.	2.5%	Median	97.5%
Own factors	*Intercept*	3.98	0.18	3.62	3.98	4.34
	$\ln(q_{At-1}+1)$	0.17	0.01	0.15	0.18	0.20
	$Earn_{At-1}$	0.02	0.04	−0.05	0.02	0.11
	$Jackpot\_self_{At-1}$	0.19	0.09	0.00	0.19	0.39
	$Promo_{At}$	0.56	0.06	0.44	0.56	0.68
Endogenous peer effect	$\ln(q_{Bt}+1)$	0.78	0.01	0.76	0.78	0.80
Exogenous peer effect	$Earn_{Bt-1}$	0.01	0.02	−0.03	0.01	0.06
	$Jackpot\_self_{Bt-1}$	−0.06	0.05	−0.18	−0.06	0.03
	$Promo_{Bt}$	−0.24	0.07	−0.39	−0.24	−0.11
Peer presence effect	*Intercept*	−3.64	0.10	−3.83	−3.64	−3.44
	$\ln(q_{At-1}+1)\times I_{Bt}$	−0.11	0.01	−0.14	−0.11	−0.08
	$Earn_{At-1}\times I_{Bt}$	0.03	0.04	−0.06	0.03	0.12
	$Jackpot\_self_{At-1}\times I_{Bt}$	−0.04	0.12	−0.30	−0.04	0.19
	$Promo_{At}\times I_{Bt}$	−0.24	0.07	−0.39	−0.24	−0.11
Excluded variable	$Jackpot\_stranger_{At}$	0.33	0.02	0.30	0.33	0.37
Environmental factor	$EnvCtrl_{-(A)-(B)t}$	0.07	0.02	0.02	0.07	0.12

17% of customers, a majority (15%) of peers increase their bet more than the amount increased by the focal customer; for 94% of these customers the coefficient is

Figure 2 **(Color online) Heterogeneity in Endogenous Peer Effect**

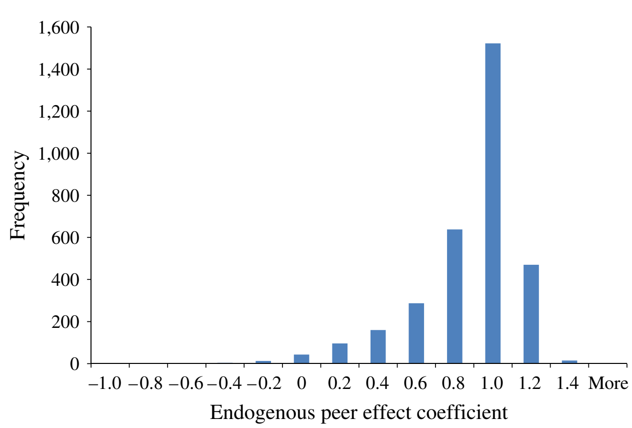


Table 5 **Distribution of Endogenous Peer Effect**

1st quantile	Median	Mean	3rd quantile
0.68	0.86	0.79	0.96

significantly different from zero. Finally, the endogenous peer effect was negative for the remaining 2% of the peers, i.e., they move in the opposite direction of the focal customer. However, the estimated peer effect for all of these customers is not significantly different from zero.

The correlation patterns between the individual coefficients also provide interesting insights. For example, we find a high and negative correlation coefficient (−0.87) between individual-level intercepts and the endogenous peer effect coefficients. This suggests that customers who tend to bet more on average are less susceptible to being influenced by peer

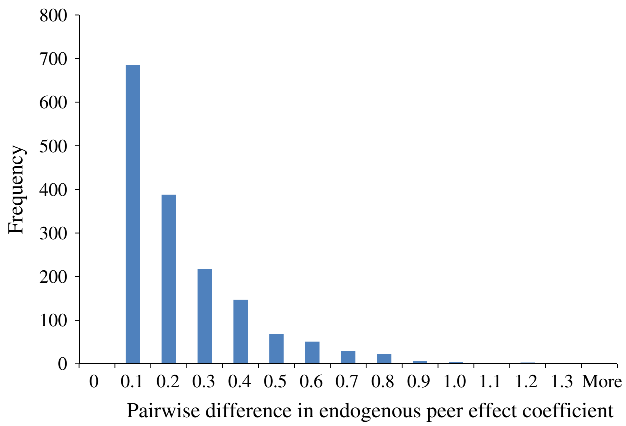


Figure 3 (Color online) Asymmetry in Endogenous Peer Effect

Table 6 Distribution of Asymmetry of Endogenous Peer Effect

1st quantile	Median	Mean	3rd quantile
0.06	0.13	0.20	0.26

behavior. We also find that customers who show high state dependence (i.e., more addictive behavior) are also less susceptible to the peer's behavior; the correlation coefficient is -0.62.

Next we examine the asymmetry of the endogenous peer effect within a peer group. We compute the asymmetry as the absolute difference in the endogenous peer effects between the two individuals in each peer group. Figure 3 and Table 6 document the distribution of this difference across the 1,626 dyads in our estimation data set. The figure shows that there is considerable asymmetry in this effect across groups. The difference between the endogenous peer effects is 0.2 (i.e., absolute difference in elasticity of endogenous peer effect is 0.2%) on average. The asymmetry of the peer effect in a pair of peers can help managers identify the peer to focus on in terms of influencing joint behavior.

6. Managerial and Policy Implications

We next investigate the implications of our results for managers. First, we compute the total response to a promotion delivered to a customer by quantifying the trade-off between the endogenous and exogenous peer effects. Second, we demonstrate the impact on bet behavior arising from the peer presence effect. Finally, we conduct two counterfactuals to show how managers could benefit from better resource allocation.

6.1. Trade-off Between the Endogenous and Exogenous Peer Effects

We use the estimates of the endogenous and exogenous peer effects to compute the overall spillover effect induced by a promotion given to an individual customer. Assume that a promotion was given to customer A. All else being equal, the estimates suggest that the promotion increases the amount bet by customer A by 36% ($= \exp(0.56-0.24)$). This results in a 27% ($= \exp(0.78\cdot(0.56-0.24))$) increase in the amount bet by customer B via the endogenous peer effect. However, via the exogenous peer effect, the promotion leads to a simultaneous decrease of 23% ($= \exp(-0.25)$) in the amount bet by customer B. The net spillover effect on customer B is, therefore, approximately *zero* ($= 1.27\cdot 0.77$). This suggests that managers cannot take a positive spillover for granted when they deliver a promotion to customers.

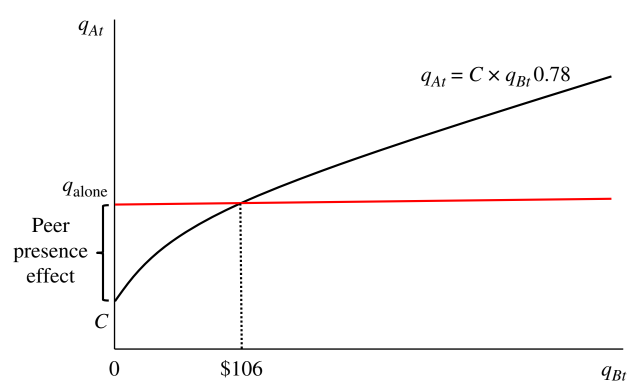
6.2. Implication of Negative Peer Presence Effect

As noted earlier, we find that peer presence has a negative effect on the focal customer's behavior. This implies that, all else being equal, if a peer is present but not consuming, the focal customer lowers her betting to a level even below that when she visits alone. To illustrate the magnitude of this effect, we plot the relationship between the amount bet by customers A and B in Figure 4. From the plot, it can be seen that the negative impact of the peer presence effect can be balanced out at a spend level of \$106 by the peer. The casino therefore needs to think about mechanisms that can incentivize play to at least this level.

6.3. Implications for Resource Allocation

The above analysis suggests that to have the most effective allocation of resources, managers need to eliminate factors that lead to a negative exogenous peer effect. In addition, resource allocation can be optimized by leveraging the asymmetry in the endogenous peer effects. We document the impact of both of these strategies via counterfactual analyses. For the first analysis, we fix all of the variables except the $Promo_{At}$ and $Promo_{Bt}$ at the average value for each customer. We then calculate the total amount bet by customers using the estimated parameters. Here we restrict our observations to when at

Figure 4 (Color online) Negative Peer Presence Effect



least one person in a group receives a promotion. By adding the amount bet over these observations per group, we obtain the total baseline amount across all groups under the current promotion strategy. We model a scenario wherein the casino can eliminate the negative exogenous peer effect by setting the parameter for this effect to zero. Our results show that the elimination of the negative exogenous peer effect results in an increase of 22% (with a standard deviation of 7%) relative to the baseline (assuming that elimination of the exogenous peer effect is costfree to the firm). Thus, the recommendation to the firm is to develop a mechanism to deliver a promotion to customer A in a manner that it is not observed by customer B, e.g., via email or smartphone. Of course, this will not preclude situations wherein customer A informs customer B of the promotion. Yet it may be worthwhile for the casino to develop and test such mechanisms.

In the second counterfactual, as noted earlier, we focus on leveraging the asymmetry in the endogenous peer effects in a pair. We followed a similar strategy for constructing the baseline as above, but restrict ourselves to those occasions when only one of the two peers receives a promotion. If the peer who received the promotion had a smaller effect on the other peer, we reversed the promotion (i.e., the peer with the bigger peer effect received the promotion). As a result, we reversed the recipient of the promotion on 47% of the occasions (when only one peer received a promotion). We then used our estimates to compute the change in the total amount bet. We found that the amount bet increased by 6% on average (with a standard deviation of 2%) across groups relative to the baseline condition. As before, we assumed that the reallocation of promotion was costfree to the firm.

Both counterfactual analyses suggest that there is considerable upside to developing better promotional mechanisms and targeting the more influential peer in a peer group.

Our approach is also likely to prove useful for managers in other industries and settings. One such setting is that of online social networks where peer effects and behavior are under a lot of scrutiny. Managers in these settings are actively seeking to leverage participation in these networks, as well as the power of social influence to influence consumption (Manchanda et al. 2015). In general, previous research has documented that participants in these communities obtain both social and informational benefits (Mathwick et al. 2008). While managers have focused on the endogenous peer effect, there is a strong possibility that both the peer presence and the exogenous peer effect will play a role. In networks where participants share a lot of information, the delivery of a marketing stimulus to a focal consumer but not to her peers is likely to trigger the exogenous peer effect. Previous research on these networks has also documented that a majority of members do not participate (in network activity) at all (they are classified as *lurkers*) but can have social influence by their very presence (Schlosser 2005). This behavior maps to the peer presence effect wherein the focal consumer is aware that her peers are present but not participating, leading to the possibility of behavioral change for the focal consumer.

6.4. Implications for Policy Makers

Our results could also be beneficial for policy makers and regulators in that they provide information on gambling behavior as a group versus an individual activity. While the positive endogenous peer effect suggests that peer influence leads to increased consumption of gambling, our results also suggest that facets of gambling behavior are moderated by the presence of peers. For example, we find that the presence of a peer lowers the extent of addictive behavior as the coefficient of $[\ln(q_{Akt-1}+1) \times I_{Bkt}]$ is negative (see §4 for details on how the previous literature has inferred the presence of addiction). There is some criticism of the casino industry in that it uses promotional activities to encourage gambling (Narayanan and Manchanda 2012). While we do find a positive main effect of promotion on gambling activity, the effect is moderated in the presence of a peer. Specifically, the negative coefficient of $[Promo_{Akt} \times I_{Bkt}]$ suggests that consumers are less responsive to promotions in the presence of a peer. Finally, the peer presence effect also dampens the play behavior of the focal consumer. Thus these findings document previously unknown moderating effects of peers on gambling behavior. Based on this, our recommendation to policy makers would be to consider the totality of peer effects in formulating policies to regulate the industry and provide consumers incentives to change their gambling behavior.

7. Conclusion

Our paper adds to the small but growing body of research that investigates individual-level peer effects in marketing settings. Our main contribution is to provide a general framework for measuring these effects via the inclusion of peer effects based on the behavior in question as well as peer effects that operate independent of that behavior. Specifically, our approach allows us to verify the existence of and measure the endogenous peer effect, the exogenous peer effect, and the peer presence effect. We choose casino gambling as our setting as both the academic literature and the industry suggest that peer effects play a large role in affecting consumer behavior. Yet, to our knowledge, there appear to be no estimates of such effects. The casino industry also represents a large and significant industry, with broad participation by American adults. Yet, study by economists and marketers of these consumers appears to have been limited. Our results, for our specific setting, suggest that the endogenous peer effect is positive but the other two effects are negative.

For managers, our approach is likely to be of interest whenever and wherever there is a desire to leverage peer effects in marketing strategies. First, accounting for three peer effects allows a manager to obtain the complete picture with respect to pairwise interactions in consumption settings. Second, the asymmetry of the peer effect in a pair of peers can help managers identify the focal peer in terms of influencing joint behavior. Our results suggest that leveraging peer effects to influence consumption should be done carefully as the exogenous peer effect and the peer presence peer effect tend to work in the opposite direction of the endogenous peer effect. The use of our estimates to conduct counterfactuals indicate that there is likely to be a high upside for managers, especially when they target the more influential peer for promotions. For policy makers, our analysis and results suggest that regulation of the industry should consider the totality of gambling behavior, i.e., both as a group and as an individual activity.

Our research suffers from some limitations. Our data comes from one industry and one casino property in particular. Our analysis and conclusions also apply to the heavy half of all casino customers. Our peer groups are inferred via data patterns rather than based on external information about the relationship. We do not observe peer groups larger than two in our data (based on our peer construction strategy) and therefore our model only accounts for dyadic relationships. Our setting also suggests that the peer relationship is stable over the duration of our data but this may not be true in other settings. We hope that future research can help address these limitations.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mksc.2014.0889.

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Appendix The Hierarchical Model and the Markov Chain Monte Carlo Algorithm

In this section we specify the hierarchy for the individual-level parameters and the MCMC algorithm. We assume that individual-level parameters follow normal distributions as follows: $[\varphi_{A1k}, \varphi_{A2k}, \varphi_{B1k}, \varphi_{B2k}]' \sim N(\bar{\varphi}, \pi)$, $\theta_{A\cdot k} \sim N(\bar{\theta}_{\cdot}, \psi)$, and $\theta_{B\cdot k} \sim N(\bar{\theta}_{\cdot}, \psi)$, where k refers to peer dyads. The prior distributions for the population-level, ($\bar{\varphi}$, π, $\bar{\theta}_{\cdot}$, ψ, Σ, Ω), parameters are as follows: $\bar{\varphi} \mid \pi \sim N(\varphi_0, \pi P^{-1})$, $\pi \sim$ Inverse Wishart (μ_π, S_π), $\bar{\theta}_{\cdot} \mid \psi \sim N(\theta_0, \psi Q^{-1})$, $\psi \sim$ Inverse Wishart (μ_ψ, S_ψ), $\Sigma \sim$ Inverse Wishart (μ_Σ, S_Σ), and $\Omega \sim$ Inverse Wishart (μ_Ω, S_Ω), where $\theta_0 = [0, 0, 0, \ldots, 0]'$, $\varphi_0 = [0, 0, 0, 0]'$, $P = 0.01$, $Q = 0.01$, $\mu_\pi = N_r + 3$, $S_\pi = \mu_\pi I_\pi$, $\mu_\psi = N_s - 1 + 3$, $S_\psi = \mu_\psi I_\psi$, $\mu_\Sigma = N_s + 3$, $S_\Sigma = \mu_\Sigma I_\Sigma$, $\mu_\Omega = N_r + 3$, and $S_\Omega = \mu_\Omega I_\Omega$. N_r is the number of reduced form parameters. N_s is the number of structural parameters.

The MCMC algorithm to generate posterior distribution for the individual-level parameters are as follows:

- Generating θ_{A3k} and θ_{B3k} (Endogenous Peer Effect Parameters for peer dyad k)

We first generate reduced form parameters

$$[\varphi_{A1k} \quad \varphi_{A2k} \quad \varphi_{B1k} \quad \varphi_{B2k}]' \sim MVN(U_k, S_k),$$

where

$$S_k = \left[\sum_{t=1}^{T_k} D'_{kt}\Omega^{-1}D_{kt} + \pi^{-1}\right]^{-1} \quad \text{and}$$

$$U_k = S_k\left[\sum_{t=1}^{T_k} D'_{kt}\Omega^{-1}q_{kt} + \pi^{-1}\bar{\varphi}\right].$$

Here

$$D_{kt} = \begin{bmatrix} \theta'_{A\cdot k}Y_{Akt}, & \theta'_{B\cdot k}Y_{Bkt}, & 0, & 0 \\ 0, & 0, & \theta'_{B\cdot k}Y_{Bkt}, & \theta'_{A\cdot k}Y_{Akt} \end{bmatrix},$$

$$q_{kt} = [q_{Akt} \quad q_{Bkt}]',$$

and T_k is the number of joint visits for peer dyad k.

We recover θ_{A3k} and θ_{B3k} from

$$\theta_{A3k} = \frac{E(\varphi_{A2k})}{E(\varphi_{B1k})} \cdot \frac{1 + \text{cov}(\varphi_{A2k}, \varphi_{B1k})/(E(\varphi_{A2k})E(\varphi_{B1k}))}{1 + \text{var}(\varphi_{B1k})/E(\varphi_{B1k})^2},$$

$$\theta_{B3k} = \frac{E(\varphi_{B2k})}{E(\varphi_{A1k})} \cdot \frac{1 + \text{cov}(\varphi_{A1k}, \varphi_{B2k})/(E(\varphi_{A1k})E(\varphi_{B2k}))}{1 + \text{var}(\varphi_{A1k})/E(\varphi_{A1k})^2}.$$

- Generating Ω

$$\Omega \sim \text{Inverse Wishart } \left(\sum_{k=1}^{N}\sum_{t=1}^{T_k}(q_{kt} - \hat{q_{kt}})(q_{kt} - \hat{q_{kt}})' + S_\Omega, NT + \mu_\Omega\right),$$

where $T = \sum_{k=1}^{N} T_k$ and N is the total number of dyads.

- Generating $\bar{\theta}_3$ and ω (Endogenous Peer Effect Parameter for the population-level and its standard deviation)

$$\bar{\theta}_3 = (2N)^{-1}\sum_{k=1}^{N}\sum_{i}^{A,B}\theta_{i3k} \text{ and}$$
$$\omega = (2N-1)^{-1}\cdot\sum_{k=1}^{N}\sum_{i}^{A,B}(\theta_{i3k}-\bar{\theta}_3)^2.$$

- Generating $\bar{\varphi}$

$$\bar{\varphi} \sim MVN(L, K),$$

where

$$K = ((\pi^{-1}/N)^{-1} + 0.01I)^{-1} \text{ and}$$
$$L = K\left(\pi^{-1}\sum_{k=1}^{N}\varphi_k + 0.01I \times \varphi_0\right).$$

- Generating π

$$\pi \sim \text{Inverse Wishart}\left(\sum_{k=1}^{N}(\varphi_k-\bar{\varphi})(\varphi_k-\bar{\varphi})' + S_\pi, 2N+\mu_\pi\right).$$

- Generating $\theta_{i\cdot k}$

$$\theta_{i\cdot k} \sim MVN(M_{ik}, N_{ik}),$$

where

$$N_{ik} = \left[\sum_{t=1}^{T_{ik}} Y^{*\prime}_{ikt}Y^*_{ikt} + \psi^{-1}\right]^{-1},$$
$$M_{ik} = N_{ik}\left[\sum_{t=1}^{T_{ik}} Y^{*\prime}_{ikt}(I-W_k)q_{ikt} + \psi^{-1}\bar{\theta}_{\cdot}\right],$$
$$Y^*_{ikt} = Y_{ikt}/\sqrt{\sigma_i^2(1-\rho^2)},$$
$$q^*_{ikt} = (q_{ikt} - \theta_{i3}q_{jkt}I_{jkt} - ((\rho\sigma_i)/\sigma_j)\varepsilon_{jkt})/\sqrt{\sigma_i^2(1-\rho^2)},$$
$$W_k = \begin{pmatrix} 0 & \theta_{Ak3} \\ \theta_{Bk3} & 0 \end{pmatrix}, \quad \text{and}$$
$$\varepsilon_{jkt} = q_{jkt} - \theta_{j3}q_{ikt}I_{ikt} - \theta'_{j\cdot k}Y_{jkt}.$$

Here
$i = A, B$, $j = B, A$, and T_{ik} is the number of observations for i in peer dyad k.

- Generating $\bar{\theta}_{\cdot}$

$$\bar{\theta}_{\cdot} \sim MVN(H, V),$$

where

$$V = ((\psi^{-1}/(2N))^{-1} + 0.01I)^{-1} \text{ and}$$
$$H = V\left(\psi^{-1}\sum_{k=1}^{N}\sum_{i}^{A,B}\theta_{i\cdot k} + 0.01I\times\psi_0\right).$$

- Generating ψ

$$\psi \sim \text{Inverse Wishart}\left(\sum_{k=1}^{N}\sum_{i}^{A,B}(\theta_{i\cdot k}-\bar{\theta}_{\cdot})'(\theta_{i\cdot k}-\bar{\theta}_{\cdot}) + S_\psi, 2N+\mu_\psi\right).$$

- Generating Σ

In our model, the covariance term ($\rho_{AB}\sigma_A\sigma_B$) is defined across joint consumption occasions while the variance terms (σ_A^2, σ_B^2) are defined across all consumption occasions. This results in a different observation number to estimate the covariance term and the variance term. One consequence of this unbalanced observation number (or absent dimensions) is that the standard Bayesian analysis of the multidimensional covariance structure becomes difficult (i.e., the full conditional distribution for Σ is no longer inverted Wishart distribution). To overcome this difficulty, we implement the Zeithammer and Lenk (2006) method. The basic idea is to augment (Tanner and Wong 1987) the residuals for the absent dimensions.

First, we draw absent residual as follows. R^p_{jkt} is residual for the observation when customer j visited.

$$(R^a_{ikt} \mid R^p_{jkt}, \Sigma, \theta_j) \sim N(F_{ikt}, G_{ikt}),$$

where

$$F_{ikt} = (\rho\sigma_i\sigma_j)/\sigma_j^2 \times R^p_{jkt},$$
$$G_{ikt} = \sigma_i^2 - (\rho\sigma_i\sigma_j)/\sigma_j^2 \times (\rho\sigma_i\sigma_j),$$
$$R^p_{jkt} = q_{jkt} - \theta'_{j\cdot k}Y_{jkt},$$
$$i = A, B, j = B, A.$$

Together with the present residuals, the augmentation produces full-dimensional residual vectors (i.e., $R'_{ik} = [R^a_{ik1}, R^p_{ik2}, R^p_{ik3}, R^a_{ik4}. \ldots .R^p_{Akt-1}, R^p_{Akt}]$) that can be used as pseudo-observations in the conditional posterior draw of Σ as if there were no absent dimensions as follows.

$$\Sigma \sim \text{IW}(\sum_{k=1}^{N} R^k R^{k'} + S_\Sigma, 2N+\mu_\Sigma),$$

where $R^k = [R_{Ak}, R_{Bk}]$.

References

AGA (2007) The 2007 state of the states: The American Gaming Association survey of casino entertainment. Accessed December 31, 2014, http://www.americangaming.org/industry-resources/research/state-states.

AGA (2013) States with slots. Accessed December 31, 2014, http://www.americangaming.org/fact-sheets/states-slots.

Argo JL, Dahl DW, Manchanda RV (2005) The influence of a mere social presence in a retail context. *J. Consumer Res.* 32(2):207–212.

Becker GS, Murphy KM (1988) A theory of rational addiction. *J. Political Econom.* 96(4):675–700.

Bresnahan T, Reiss P (1990) Entry in monopoly markets. *Rev. Econom. Stud.* 57(4):531–553.

Croson R, Sundali J (2005) The gambler's fallacy and the hot hand: Empirical data from casinos. *J. Risk Uncertainty* 30(3):195–209.

Darke P, Dahl D (2003) Fairness and discounts: The subjective value of a bargain. *J. Consumer Psych.* 13(3):328–338.

DeKort YAW, Ijsselsteijn WA (2008) People, places, and play: Player experience in a socio-spatial context. *ACM Comput. Entertainment* 6(2), Article 18.

Diebold F, Lamb R (1997) Why are estimates of agricultural supply response so variable? *J. Econometrics* 76(1–2):357–373.

Feinberg F, Krishna A, Zhang ZJ (2002) Do we care what others get? A behaviorist approach to targeted promotions. *J. Marketing Res.* 39(3):277–291.

Gilovich T, Vallone R, Tversky A (1985) The hot hand in basketball: On the misperception of random sequences. *Cognitive Psych.* 17(3):295–314.

Guryan J, Kearney MS (2008) Gambling at lucky stores: Empirical evidence from state lottery sales. *Amer. Econom. Rev.* 98(1):458–473.

Hartmann WR (2010) Demand estimation with social interactions and the implications for targeted marketing. *Marketing Sci.* 29(4):585–601.

Hartmann WR, Manchanda P, Nair H, Bothner M, Dodds P, Godes D, Hosanagar K, Tucker C (2008) Modeling social interactions: Identification, empirical methods and policy implications. *Marketing Lett.* 19(3):287–304.

Hayya J, Armstrong D, Gressis N (1975) A note on the ratio of two normally distributed variables. *Management Sci.* 21(11): 1338–1341.

Kassinove JI, Schare M (2001) Effects of the "near miss" and the "big win" on persistence at slot machine gambling. *Psych. Addictive Behav.* 15(2):155–158.

Lee CK, Lee YK, Bernhard BJ, Yoon YS (2006) Segmenting casino gamblers by motivation: A cluster analysis of Korean gamblers. *Tourism Management* 27(5):856–866.

Luo X (2005) How does shopping with others influence impulsive purchasing? *J. Consumer Psych.* 15(4):288–294.

Manchanda P, Packard G, Pattabhiramaiah A (2015) Social dollars: The economic impact of customer participation in a firm-sponsored online customer community. *Marketing Sci.* ePub ahead of print February 4, http://dx.doi.org/10.1287/mksc.2014.0890.

Manchanda P, Xie Y, Youn N (2008) The role of targeted communication and contagion in new product adoption. *Marketing Sci.* 27(6):950–961.

Manski CF (1993) Identification of endogenous social effects: The reflection problem. *Rev. Econom. Stud.* 60(3):531–542.

Mathwick C, Wiertz C, Ruyter KD (2008) Social capital production in a virtual p3 community. *J. Consumer Res.* 34(6):832–849.

Moffitt R (2001) Policy interventions, low-level equilibria and social interactions. Durlauf S, Young P, eds. *Social Dynamics* (MIT Press, Cambridge, MA).

Nair H, Manchanda P, Bhatia T (2010) Asymmetric social interactions in physician prescription behavior: the role of opinion leaders. *J. Marketing Res.* 47(5):883–895.

Narayanan S (2013) Bayesian estimation of discrete games of complete information. *Quant. Marketing Econom.* 11(1):39–81.

Narayanan S, Manchanda P (2012) An empirical analysis of individual level casino gambling behavior. *Quant. Marketing Econom.* 10(1):27–62.

Platz L, Millar M (2001) Gambling in the context of other recreational activity: A quantitative comparison of causal and pathological student gamblers. *J. Leisure Res.* 33(4):383–395.

Pollak RA (1970) Habit formation and dynamic demand functions. *J. Political Econom.* 78(4):745–763.

Schlosser AE (2005) Posting versus lurking: Communicating in a multiple audience context. *J. Consumer Res.* 32(2):260–265.

Tanner T, Wong W (1987) The calculation of posterior distributions by data augmentation. *J. Amer. Statist. Assoc.* 82(398): 528–540.

Yang S, Allenby GM (2003) Modeling interdependent consumer preferences. *J. Marketing Res.* 40(3):282–294.

Yang S, Narayan V, Aasel H (2006) Estimating the interdependence of television program viewership between spouses: A bayesian simultaneous equation model. *Marketing Sci.* 25(4):336–349.

Zeithammer R, Lenk P (2006) Bayesian analysis of multivariate normal models when dimensions are absent. *Quant. Marketing Econom.* 4(1):241–265.

Zellner A (1978) Estimator of functions of population means and regression coefficients including structural coefficients: A minimum expected loss approach. *J. Econometrics* 8(2):127–158.

Zhang J (2010) The sound of silence: Observational learning in the U.S. kidney market. *Marketing Sci.* 29(2):315–335.