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Consumer preferences for network liquidity and opponent quality in online poker

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ABSTRACT

Several online gambling platforms use marketplace business models where the operator facilitates wagers between players instead of directly banking games. There is a large theoretical literature on marketplace business models, but there is little empirical evidence that suggests how it may apply to gambler preferences or behavior. This study contributes to the understanding of consumers in gambling markets by testing multi-sided market theory in online poker. Using data collected from a diverse sample of online poker players ($n = 719$), this study empirically demonstrates how players value game availability and product quality. Our results show evidence of diminishing marginal returns to scale and benefits from product differentiation across a range of conditions found in the market. Consumers prefer that operators grow their networks when size is sufficiently small but would prefer more focus on the types of players added to games as the network grows. From a policy perspective, these findings provide support for using multi-sided market theory as a framework for taxation and licensure in gambling products.

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Network effects; online poker; externality; multi-sided markets; discrete choice experiment

Introduction

Online poker sites, like many digital marketplace businesses, rely on network effects to attract customers. These effects exist when the value that customers receive is a function of the number of other users also on the platform (Evans & Schmalensee, 2016; Katz & Shapiro, 1994; Rohlfs, 1974). Users typically create value for other consumers through two mechanisms: counterparty quality and network liquidity (Cennamo, 2019; Rochet & Tirole, 2006; Sriram et al., 2015). In online poker, quality tends to refer to the ability of a user to find games or wagers that match their interests, such as action-oriented opponents with similar game preferences, while liquidity refers to the speed and volume by which those matches can be filled. Larger networks can add value by providing players with more options in terms of game stakes, variants (e.g. No Limit Texas Hold'em vs Pot Limit Omaha), and opponent types (Fiedler & Wilcke, 2012).

Network effects can become externalities when users do not account for their effects on other marketplace participants (Rochet & Tirole, 2006). For example, a professional online poker player may add value to a poker site by being available for games with other

players throughout the day but may reduce value by increasing the difficulty for recreational players to win. In both cases, professional players will generally not consider their impacts on other players and the online poker operator may need to actively manage these negative or positive externalities to maximize the site's value. Effective intermediation of platform users has led online marketplace models to become some of the largest businesses in the world (Coolican & Barros, 2021).

In this study, we focus on the identification and measurement of network size and player quality value to better understand how these theoretical models may apply to online poker markets. Despite the perceived importance of network effects to many gambling products like daily fantasy sports, sports betting exchanges, pari-mutuel betting, and prediction markets, the application of network theory to policy decisions has largely not been observed (van Damme, 2007, 2008). Our study contributes to the literature as the first empirical study of multi-sided markets in any gambling industry and one of the few empirical studies of multi-sided markets more generally.

The absence of prior empirical studies may be related to measurement challenges in multi-sided markets. Estimating user trade-offs must overcome the econometric problems associated with simultaneously identifying the impact of participant characteristics and network size on consumer utility. Since preferences are interdependent and usage decisions are determined simultaneously, consistent estimation of liquidity effects requires that researchers account for unobserved factors that affect an individual's demand for a product and its number of users (Manski, 1993; Rysman, 2019). We overcome these econometric identification problems by using data from a discrete choice experiment administered to online poker players. Discrete choice experiments circumvent identification and reflection problems because they rely on the randomization of attribute characteristics to identify their effects on respondents' utility and the prices consumers are willing to pay for different product attributes (Hartmann et al., 2008).

Related literature

Multi-sided markets

An extensive theoretical literature examines multi-sided markets. This literature explores the effects of cross and same-side externalities on profit-maximizing prices, the role of competition and multi-homing on market outcomes and business strategies, as well as the conditions under which network effects lead to winner-take-all outcomes (Armstrong & Wright, 2007; Armstrong, 2006; Caillaud & Jullien, 2003; Parker & Van Alstyne, 2005; Rochet & Tirole, 2003, 2006; Rysman, 2009; Weyl, 2010). The seminal theoretical works by Rochet and Tirole (2003) focused on two-sided markets, and is self-described as merging literature on multiproduct pricing (Baumol et al., 1982) with literature on network effects (Katz & Shapiro, 1985; Rohlfs, 1974). Subsequent work generalized these ideas to multi-sided markets (Evans & Schmalensee, 2016), such as a three-sided social media platform with individual users, content producers, and advertisers all using the same network.

In general, network effects exist when the number of participants using network goods affects a user's utility. Indirect network effects arise when the demand for a network good depends on the availability of related goods. The effects are indirect because the demand for related goods depends on participants' usage of the network good. Network effects are

direct when users are directly affected by others' use of a product. Communication services, such as telecom networks, e-mail, and social networks, exhibit direct network effects because more subscribers increase the number of potential network interactions (Katz & Shapiro, 1985, 1994; Rohlfs, 1974; Schmalensee, 2011).

Schmalensee (2011) observes that many of today's internet-based services and applications do not require long-term customer commitments and have low switching costs. Consumers may also multi-home, consuming several differentiated but related services on different platforms. Others propose that differences in the abilities of users, their roles and interactions, and perceived trust also affect the value of networks (Afuah, 2013; Lee et al., 2006). While many internet-based services like social networks benefit from direct network effects, network effects are not the only factor important to platforms competing in markets with differentiated products (Cennamo, 2019; Schmalensee, 2011; Sriram et al., 2015).

Despite the importance of marketplace businesses, the growing theoretical literature is largely untested due to econometric difficulties associated with estimating direct network effects (Rysman, 2019). Some studies have found evidence of direct network effects in specific settings. Tucker (2008) and Ryan and Tucker (2012) provide evidence of direct network effects using data on employee adoption of video-messaging machines. This work shows that the magnitude of estimated direct network effects differs by employee type. Other studies examined the mobile phone market. Sobolewski and Czajkowski (2012) demonstrate the impact of direct network effects on market outcomes in the Polish wireless telephone market using data from a discrete-choice experiment. Kim and Kwon (2003) argue that increases in market share provide information about a network's quality. Björkegren (2019) demonstrates the importance of network effects on inframarginal users, presenting evidence that most of the benefits from universal-service requirements accrue to users not directly affected by the government programs that expand Rwanda's mobile phone network.

Other literature estimates the impact of indirect network effects in two-sided markets. For example, Rysman (2004) shows that internalizing network effects in the market for Yellow Pages increases surplus and that competition significantly improves market performance. Kaiser and Wright (2006) and Song (2021) find significant relationships between the demand for advertising and readership in the market for magazines; Cennamo and Santalo (2013) demonstrate the importance of product differentiation in the market for video games and Chu and Manchanda (2016) show that both product variety and the quality of users significantly affect the number of buyers and sellers on Alibaba Group's Taobao.com platform.

While these studies provide some insight into indirect network effects in the presence of Manski's reflection problem, the marketplaces considered are not generally peer-to-peer platforms like poker, but instead have buyer-seller relationships. The nearest comparisons for online poker may be in the sharing economy (Knote & Blohm, 2016) and financial markets (Cantillon & Yin, 2011), where platform users will often be buyers and sellers on different occasions but there may also be a 'professionalization' with one group of users, similar to professional online poker players. Cullen and Farronato (2021) examine the TaskRabbit small job marketplace and find that network effects are constrained by geographic proximity requirements. They note that winner-take-all equilibriums may not emerge as marketplaces must compete on quality characteristics. Fradkin (2017) examines

Airbnb users and finds substantial value is created by the platform by more effectively facilitating matches between renters and hosts. In US equity markets, O'Hara and Ye (2011) find that fragmentation reduces asset spreads and improves speed of execution, particularly for small and illiquid securities.

Online poker

Online poker is a player-versus-player game that requires the simultaneous participation of multiple players. Players in online games compete against opponents seated at virtual tables that include as few as two and as many as ten participants. Games can consist of hundreds of virtual tables and thousands of players. Poker sites generate revenue by charging players a fee known as the 'rake.' The rake can be a time-based fee or a percentage surcharge on the total wagered, up to a maximum amount per hand. Player utility is increasing in the money won at the tables and the enjoyment received from playing the game.

Users' expected profit from playing poker depends on their ability, skill, and style relative to their opponents. Successful poker strategies require information on opponent characteristics and styles of play. The rate at which players 'Voluntarily Put Money in the Pot' (VPIP) is a characteristic used to define player types. VPIP reflects the percentage of hands where a player places a bet when not required to do so. It equals the percentage of hands where a player places a bet before the dealer reveals the hand's first three community cards but does not count forced bets known as blinds. The big blind equals the game's minimum unforced bet. The small blind typically equals one-half of the big blind (for more game rules, see pokernewsdotcom (Director), 2013).

Players who tend to remain in hands when the probability of winning a showdown (*i. e.*, a comparison of final hands) is relatively low are considered *Loose* players. By contrast, those who generally play only premium hands are considered *Tight* players. *Loose* play increases a game's action by increasing pot sizes and the likelihood that showdowns decide hands. Studies on the profitability of poker strategies find that *Loose* play generally correlates with losing play, especially in low-stake games (Johansson & Sönströd, 2009; Siler, 2010). VPIP therefore provides a useful proxy of product differentiation through user composition, as high VPIP sites will generally be seen as more favorable, both in terms of providing more entertainment to recreational players and more profitable situations for professional players.

H1: *The quality of users on the platform significantly affects the demand for online poker.*

Since opponent characteristics impact a player's expected profit and enjoyment, it is not uncommon for players to search for favorable opponents. Players search by playing multiple hands of poker simultaneously at different virtual tables – a practice known as multi-tabling. Multi-tabling enables players to gather information about more opponents, allowing them to identify and compete against participants with favorable characteristics. To the extent that more popular sites improve a game's liquidity and attract a wider variety of participant types, increases in site size facilitate players' search efforts. Many players engage in 'table selection,' where they search for tables that include players with attractive characteristics. We assume that players know the distribution of

participant characteristics but cannot observe an opponent's type without competing against them.

Players search by simultaneously playing multiple hands of poker at different virtual tables. Multi-tabling enables players to gather information about the strategies, characteristics, and skill sets of more opponents. Increased play also evens the effects of luck and statistical noise on player returns and reduces the variance of player earnings. Increases in site size create direct network effects by improving a game's liquidity, expanding player choice sets, and facilitating users' search for favorable opponents. While an increase in site size generates various benefits, it is unclear the extent to which more games affect a player's utility. Limitations on users' ability to play multiple poker hands simultaneously constrain the returns players receive from search and multi-tabling. Since multi-tabling allows players to search for favorable opponents, we expect that players who *Multi-Table* are willing to pay a premium for increases in network size and increases in a game's share of *Loose* players.

The benefits associated with increases in site size and improved liquidity depend partly on the extent to which search affects a player's expected returns. There is no return from search when players' opponents are identical. Search returns increase in the dispersion of participant characteristics and the size and number of bets (Stigler, 1961). A player's search intensity and the number of hands played simultaneously depend on a player's ability and the expected returns from search. Increased dispersion in player characteristics increases the expected returns from search because increased uncertainty increases the option value of search. Search models predict that this option value is higher for *Inexperienced* players because *Inexperienced* players are more uncertain about the quality of opponents than *Experienced* players (Kim et al., 2010; Weitzman, 1979).

H2: *Users that search the platform for better matches have a higher willingness to pay for network size and quality of users.*

Methods

Empirical framework

Player utility is increasing in the earnings and the enjoyment they receive from playing poker. The empirical analysis uses McFadden's (1974) random utility model to estimate the effects of game characteristics on the players' utility for online poker games. The analysis assumes that poker player $i = 1, 2, \dots, I$ obtains utility from poker game $j = 1, 2, \dots, J$. Consumer i 's actual utility, U_{ij}^* , equals the sum of mean utility, V_j , and an unobservable additive error term, ε_{ij} . The analysis assumes that mean utility varies over game and site characteristics. An individual consumer's deviation from this mean utility equals ε_{ij} .

Assume that players are either *Loose* or *Tight* players, where the number of *Loose* players in game j equals L_j and the number of *Tight* players equals T_j . The total number of players equals N_j , where $N_j = L_j + T_j$. We assume that players observe the total number of players participating in a game and know the distribution of player types. The effect of

an increase in the number of participants on a player's utility depends in part on participant characteristics. An increase in the number of *Loose* participants creates value because it creates more action and increases a player's expected profit. The increase in site size improves a game's liquidity and the returns from search. Identifying the effects of an increase in site size on mean utility requires that the empirical analysis controls for the composition of participant characteristics. Consumer i 's expected utility from poker-game alternative j equals:

$$V_{ij}(N_j, L_j, T_j, I_i, P_j, X_j, F_j) + \varepsilon_{ij} = \lambda(I_i - P_j) + X_j\beta + h(a_j(L_j, T_j); \delta) + v(N_j; \gamma) - F_{ij} + \varepsilon_{ij}, \quad (1)$$

where I_i equals player i 's income, P_j equals the price of game j , and λ equals the marginal utility of income. The vector X_j contains other game characteristics, and β contains the associated vector of coefficients. The function $h(a_j(L_j, T_j); \delta)$ captures the compositional effects of a game's participants' characteristics on mean utility. The function $a_j(L_j, T_j)$ measures the composition of a game's player characteristics and δ equals the vector of coefficients to be estimated. The function $v(N_j; \gamma)$ measures the effects of network size on mean utility; γ is the vector of the function's coefficients. Player i 's entry cost for game j equals F_{ij} . Because our discrete choice experiment does not ask respondents to distinguish between the effects of game characteristics on their expected earnings and enjoyment from playing the game we assume that the terms $X_j\beta$, $h(a_j(L_j, T_j); \delta)$, and $v(N_j; \gamma)$ capture both the pecuniary and non-pecuniary effects of game characteristics on a player's utility.

Given the mean utilities described by Equation (1), the probability that consumer i chooses alternative j equals:

$$\begin{aligned} \Pr_{ij} &= \left(U_{ij}^* > U_{ik}^*, \quad k \neq j \right) \\ &= (V_j + \varepsilon_{ij} > V_k + \varepsilon_{ik}, \quad k \neq j) \\ &= (\varepsilon_{ik} - \varepsilon_{ij} < V_j - V_k, \quad k \neq j) \end{aligned} \quad (2)$$

The analysis assumes that the random error term is distributed iid Type I extreme value and estimates mean utility using the logit probability formula (McFadden, 1974). The probability that a representative consumer selects alternative j equals:

$$\text{Prob}(y = 1) = \frac{\exp(V_{ij}(N_j, L_j, T_j, I_i, P_j, X_j, F_{ij}))}{\sum_k \exp(V_{ik}(N_k, L_j, T_j, I_i, P_k, X_k, F_{ik}))} \quad (3)$$

Any factor that increases the utility player i receives from game j increases the probability that consumer i selects game j . Maximizing the log-likelihood function derived from Equation (3) estimates the mean indirect utility function.

This study's hypotheses test propositions about the price players are willing to pay for changes to site size and other factors. Estimates of the representative user's compensating variation for the characteristics of a poker game's attributes are used to test these hypotheses. The compensating variation equals:

$$CV = -\frac{1}{\lambda} [V^1 - V^0], \quad (4)$$

Where V^0 is the indirect utility function from Equation (1), evaluated at base-level attributes, and V^1 equals indirect utility with altered attributes (Holmes & Boyle, 2003). The compensating variation produces a willingness-to-pay estimate that equals the change in income required to hold a consumer's utility constant when a product's characteristics change. The representative user's marginal utility of income equals λ . In our setting, a player's compensating differential is increasing in the player's expected earnings and recreational value.

Discrete choice experiment

A discrete choice experiment manipulates product characteristics and prices, creating series of hypothetical choices that obtain the optimal variation in the data needed to estimate the value of product characteristics (Allenby et al., 2014; Hensher et al., 2005). This study's experiment presents respondents with pairs of hypothetical internet poker games of No-Limit Texas Hold 'em that differ in attribute characteristics. The experimental design randomizes attribute characteristics, including the number and types of players participating in online poker games. The study's respondents face a forced-choice design where they are required to choose one of the two hypothetical poker games presented in each choice experiment. Allenby et al. (2014) suggest that forced-choice designs may elicit more information about product attributes than studies that include outside options.

The primary limitation of a discrete choice experiment is the requirement that responses to hypothetical scenarios reflect observed behavior. In general, data based on stated choices bias results when choice sets do not fully reflect reality, respondents have incomplete preferences, or respondents have a vested interest in the study's results (Quaife et al., 2018). We consulted active poker players with extensive online poker experience, individuals from the industry, and conducted two focus groups with online poker players to ensure the study's realism and the reasonableness of the experiment's attributes. The experts we consulted reviewed several versions of the survey and provided comments that we used to select the game attributes included in the discrete choice experiment and the variables used to measure these attributes.

All focus group members were at least 21 years of age and had experience playing online poker for money. Focus group members were selected from a pool of candidates who responded to flyers posted on the University of Nevada-Las Vegas (UNLV) campus. Selection was based on a first-come, first-served basis for the candidates who had active online-poker accounts. Each participant was awarded a \$50 cash stipend. Two focus groups were held on the UNLV campus before the survey was administered. The first focus group included six respondents. Respondents completed a hard copy of the survey and discussed various aspects of its design. The main objectives of the first focus group were to determine whether the survey included the correct characteristics, the attribute levels were realistic, and if respondents would make trade-offs when choosing between poker-site options. The focus group also explored whether respondents were able to hold all factors not included in the discrete choice experiment constant when taking the experiment.

The second focus group included three individuals from UNLV with experience in playing online poker. These respondents completed an online survey using Qualtrics. The second focus group assessed the look and feel of the survey and participants discussed survey design and whether they could make the required trade-offs between poker-game attributes and their characteristics. Poker experts consulted on this project noted that online poker players regularly make financial decisions based on hypothesized probabilistic trade-offs, suggesting that respondents have the background to understand and assess the trade-offs presented in the experiment. The UNLV Institutional Review Board approved the focus groups and the study.

Respondents accessed the survey online via Qualtrics. Survey respondents completed eight discrete choice experiments, where the characteristics of the attributes included differed depending on the respondent's preferred stake. Survey respondents indicate whether they preferred *Micro*, *Small*, or *High* stakes, where the game's minimum bet defines its stake. The minimum bet ranges from \$0.02 to \$0.50 for *Micro-Stake* players and ranges from \$0.50 to \$2.00 for *Small-Stake* players. The top minimum bet equals \$10 for games classified as *High-Stake* poker. The hypothetical poker games presented to respondents hold the minimum bet constant at the cutoff to define a player's preferred stake. Specifically, *Micro-Stake* respondents choose between hypothetical games with different levels of attribute characteristics, holding the minimum bet constant at \$0.50. The experiment's minimum bets, respectively, equal \$2 and \$10 for *Small-Stake* and *High-Stake* respondents.

The survey includes nine blocks of discrete choice experiments, each with eight different choice sets for each stake level. Qualtrics randomly assigns respondents to blocks of discrete choice experiments based on their preferred stake. Respondents received the following instructions: "(w)hile this is a hypothetical choice and not a real one, we ask you to consider your preferences and make choices just as if you were choosing a website to play No-Limit Texas Hold 'em," before taking the experiment. The survey asks respondents to hold all other game characteristics constant while making their choices and provides respondents with links to definitions of the attributes and characteristics included in the study.

The final choice set includes five different poker-site attributes. A fractional design ensures that the experiment questions are balanced and orthogonal (Aizaki, 2012). The number of levels included for each attribute ranges from two to six, creating 288 different combinations. The fractional design includes seventy-two of these combinations. Orthogonality precludes variables that equal the interaction of attributes included in the experiment in the empirical models estimated.

The experimental design includes six different levels for the network-size attribute. We used the industry monitor PokerScout.com to determine the number of players included in the network-size attribute. Specifically, we monitored games offered by state-regulated poker sites in Nevada in the year following the launch of the first state-regulated sites in the U.S. and games conducted on PokerStars, the world's largest online poker site. These data show that the Nevada-based site failed to create a single game at times, while the largest poker site had 10,077 active cash-game players competing across multiple game variants and stakes at the time of the observation. Fiedler's (2011) data on market shares imply that the largest pool of compatible users (*Micro-Stake*, No-Limit Texas Hold 'em players) on the global platform included 2,866 players (28.4% of total).

To capture the full range of site sizes available to players on different sites and in various jurisdictions, the range of size varies from 50 to 4,000 *Players* for respondents who prefer *Micro* and *Small-Stake* games. This range equals 25 to 2,000 *Players* for *High-Stake* respondents. The lower range for *High-Stake* respondents reflects the market conditions experienced by *High-Stake* players.

The empirical analysis uses vectors of categorical variables to estimate the effects of size on utility. The variable N_n is a categorical variable that equals one when size equals n and zero otherwise. For *Micro* and *Small-Stake* games: $v(N_j; \gamma) = \sum_n \gamma_n^t N_n$, $n = \{50, 150, 500, 1,250, 2,000, \text{ and } 4,000\}$ and $t = \{m, s\}$. The term γ_n^t equals the vector of related coefficients. The study uses 50 *Players* (N_{50}) as the excluded category in the *Micro* and *Small-stake* regressions. Using categorical variables to measure the effects of size on utility imposes no restrictions on the functional form of the estimated effect of size on mean utility and estimated compensating variations. The *High-Stakes* regressions include the following set of categorical variables: $v(N_j; \gamma) = \sum_n \gamma_n^h N_n$, $n = \{25, 75, 225, 500, 1,000, \text{ and } 2000\}$. The analysis uses 25 players (N_{25}) as the excluded category in the *High-Stake* model.

The discrete choice experiment includes a set of categorical variables that measure a game's *Average VPIP*. The discrete choice experiment includes hypothetical poker games where the *Average VPIP* equals 37%, 28%, or 19% (Walker, 2014). The analysis labels these different *Average VPIPs* as *Loose*, *Neutral*, and *Tight* and creates corresponding categorical variables. The variable *Loose VPIP* equals one when a game's *Average VPIP* equals 37%, and zero otherwise. *Tight VPIP* equals one when a game's *Average VPIP* equals 19%, and zero otherwise. The analysis uses *Neutral VPIP* (28%) as its excluded category. The survey informs respondents that a game's *Average VPIP* applies to tables that include six players.

The experiment includes the variable *Cost*, where *Cost* equals the time-based rake per hour of play at a table. The study bases its *Cost* levels on data collected at rakeatpoker.com. The *Cost* levels used differ according to the respondent's preferred stake. The variable *cost* does not include any loyalty or reward bonuses. Since bonuses typically equal a share of a player's rake payments, bonus payments do not affect relative prices. The survey also includes *Regulation* and site *Security* characteristics. These variables address the importance of dependability and trust in the market for online poker. In the discrete choice experiment, a site is defined as *Regulated* when licensed by its State Gaming Commission, while an unregulated site does not have this approval.

A site has *Average Security* when it regularly passes security audits administered by private firms and adopts policies that guarantee that it does not use player balances for operational expenses. Sites have *Above-Average Security* when they have *Average Security* and use secure private third-party options for deposits and withdrawals. Sites with *Above-Average Security* also use additional security measures such as security keys. The analysis added the *Security* variables due to comments made by members of the first focus group, who noted that an increase in the number of a game's players signals a more secure environment. This comment led to the inclusion of explicit controls for game security. Table 1 provides definitions of the variables included in the discrete choice experiment.

Table 1. Discrete Choice Experiment Attributes and their Levels.

Attribute	Explanation	Levels			
		Micro	Small	Middle	High
<i>Stakes</i>	Size of the Big Blind at a short-handed table with six players playing No-Limit Texas Hold'em, the most popular variant of online poker (Fiedler, 2011).	< \$0.50	\$0.51–\$2.00	\$2.01–\$10.00	Above \$10
<i>Regulation</i>	The poker website is regulated by the government entity in the state where the respondent lives.	Yes/No	Yes/No	Yes/No	Yes/No
<i>Security</i>	The quality of the website's security features compared to the overall industry standard.	Average/ Above	Average/ Above	Average/ Above	Average/ Above
<i>Cost</i>	Per-Hour Rake for a short-handed table with 6 players playing No-Limit Texas Hold'em	\$1.50, \$2.50, \$3.50 or \$4.50.	\$5.00, \$8.25, \$11.50 or \$14.75.	\$9.00, \$15.00, \$21.00 or \$27.00.	\$10.00, \$17.00, \$23.00 or \$30.00.
<i>Players</i>	Number of players on a site playing No-Limit Texas Hold'em at Specified Stakes.	50, 150, 500, 1,250, 2,500, or 4,000 <i>Players.</i>	50, 150, 500, 1,250, 2,500, or 4,000 <i>Players.</i>	25, 75, 225, 500, 1,000 or 2,000 <i>Players.</i>	5, 25, 60, 150, 300 or 500 <i>Players.</i>
<i>Average VPIP</i>	<i>Voluntarily Put Money in the Pot</i> equals the percentages of hands that a player calls or raises before the first three community cards (flop) are dealt. Bets in the big and small Blinds are not included in the calculation of <i>VPIP</i> .	19%, 28% and 37%	19%, 28% and 37%	19%, 28% and 37%	19%, 28% and 37%

Respondents are asked to identify their preferred stake level. The levels of attributes for several characteristics in the experiment are based on a respondent's preferred stake level. The levels for *Players* are based on data on the peak number of players on regulated sites in the United States, as well as data on the number of players on unregulated international sites. These data were obtained from PokerScout.com, which is a website that tracks and reports data on the number of poker players on different sites. According to PokerBank.com, a player with a VPIP below 24% is considered a tight player, while players with VPIP above 32% are considered loose, which was validated in the focus groups.

The analysis uses the median experience category to define *Experienced* players in the empirical models. The variable *Experienced* equals one, and zero otherwise, for respondents with ten or more years of experience playing poker for money at any venue.

We posted links to the survey on several different poker-related forums. Members of the online poker community posted links to the survey on their social media accounts. Respondents must have played poker online for real money and be at least 21 years old to be eligible for the survey. Participation was voluntary, anonymous, and uncompensated.

Of the 1,481 people that started the survey, 937 started the discrete choice experiment, and 884 answered all experiment questions. The study includes only respondents from the United States who prefer *Micro*, *Small*, and *High-Stake* games. Respondents whose choices in the experiment did not provide any variation in the options selected were removed from the data because they do not provide information about the trade-offs players make when choosing sites. The final data set includes 5,033 decisions from 719 respondents. In addition to the discrete-choice experiment, the survey elicited information about respondent playing habits, experience playing poker, education, income, and other demographic information. Table 2 summarizes these data for the 719 players included in the study.

Table 2. Summary Statistics (Standard deviation in brackets).

Variable	All	Micro	Small	High
<i>Age Mean (Years)</i>	38.54 (12.18)	39.63 (13.18)	38.77 (11.60)	36.77 (11.66)
<i>Income Mean (000s)</i>	61.83 (33.89)	55.71 (35.67)	61.02 (31.87)	71.31 (32.94)
<i>Male (Proportion)</i>	0.87 (0.34)	0.86 (0.35)	0.86 (0.35)	0.90 (0.31)
<i>High School or Less (Proportion)</i>	0.11 (0.31)	0.13 (0.34)	0.12 (0.33)	0.04 (0.20)
<i>College or More (Proportion)</i>	0.54 (0.50)	0.55 (0.50)	0.53 (0.50)	0.54 (0.50)
<i>Pro Poker Player (Proportion)</i>	0.10 (0.30)	0.03 (0.17)	0.09 (0.28)	0.22 (0.41)
<i>Weekly Mean Hours Playing Poker</i>	17.51 (25.91)	13.17 (18.24)	17.22 (24.97)	23.51 (33.61)
<i>Money Motivation (Proportion)</i>	0.74 (0.44)	0.61 (0.49)	0.76 (0.43)	0.88 (0.33)
<i>Experience (Share of Sample) Less than One Year</i>	0.03 (0.17)	0.06 (0.24)	0.02 (0.13)	0.02 (0.13)
<i>Fewer than Five Years</i>	0.20 (0.40)	0.30 (0.46)	0.17 (0.37)	0.11 (0.32)
<i>Five or More Years</i>	0.80 (0.40)	0.70 (0.46)	0.83 (0.37)	0.89 (0.32)
<i>Ten or More Years</i>	0.41 (0.49)	0.34 (0.47)	0.42 (0.49)	0.49 (0.50)
<i>Multi-Table Frequency (Proportion)</i>				
<i>Always</i>	0.35 (0.48)	0.26 (0.44)	0.35 (0.48)	0.46 (0.50)
<i>Often</i>	0.24 (0.43)	0.27 (0.45)	0.25 (0.43)	0.19 (0.40)
<i>Sometimes</i>	0.24 (0.43)	0.26 (0.44)	0.23 (0.42)	0.24 (0.43)
<i>Observations</i>	719 100%	229 31.85%	309 42.98%	181 25.17%

Results

Table 3 contains the conditional logit model results and their associated compensating variations, or WTP estimates. It also includes incremental estimates for the effects of size on the estimated compensating variation. Estimates are grouped by stake, beginning with estimates for *Micro-Stake* games. Overall, the data fit the models well. McFadden's R^2 ranges from 0.274 in the *Micro-Stake* regression to 0.316 in the *High-stake* model.

The estimated coefficients on *Loose* and *Tight VPIP* receive their expected signs and are highly significant in all the specifications reported. These findings support the notion that users view *Loose* and *Tight* players as distinct user types. The coefficients on the categorical game-size variables are positive, significant, and increase in the number of a game's *Players* at a decreasing rate. The variable *Cost* receives a negative coefficient that is significant in the three models presented. The coefficients on the remaining variables receive their expected signs and are highly significant. Overall, these results support the notion that participant characteristics and size significantly impact a poker player's utility.

Compensating-variation calculations use the estimated *Cost* coefficients to measure a respondent's marginal utility of income. The results for *Loose VPIP* and *Tight VPIP* are

Table 3. Conditional Logit and WTP Estimates – by Stake+.

	Micro Stake			Small Stake			High Stake		
	Logit	WTP	Incremental WTP	Logit	WTP	Incremental WTP	Logit	WTP	Incremental WTP
Regulation	0.56*** (0.08)	0.89*** (0.12)		0.39*** (0.07)	2.01** (0.34)		0.60*** (0.09)	5.35*** (0.74)	
Security	0.53*** (0.08)	0.84*** (0.13)		0.57*** (0.07)	2.93** (0.37)		0.57*** (0.09)	5.05*** (0.77)	
Cost	-0.63*** (0.05)			-0.196*** (0.01)			-0.112*** (0.01)		
Tight	-0.43*** (0.10)	-0.68*** (0.15)		-0.63*** (0.08)	-3.24*** (0.43)		-0.68*** (0.12)	-6.09*** (0.97)	
Loose	0.34*** (0.10)	0.54*** (0.16)		0.21*** (0.08)	1.08*** (0.40)		0.34*** (0.10)	3.01*** (0.91)	
150 Players	0.69*** (0.15)	1.09*** (0.25)	1.09*** (0.25)	0.70*** (0.12)	3.58*** (0.63)	3.58*** (0.63)	0.76*** (0.18)	6.81*** (1.65)	6.81*** (1.65)
500 Players	1.04*** (0.19)	1.65*** (0.31)	0.56** (0.25)	1.13*** (0.16)	5.76*** (0.84)	2.18*** (0.64)	1.52*** (0.22)	13.58*** (2.28)	6.77*** (1.58)
1,250 Players	1.54*** (0.21)	2.44*** (0.35)	0.79*** (0.20)	1.59*** (0.19)	8.13*** (0.96)	2.37*** (0.59)	1.70*** (0.23)	15.18*** (2.37)	1.59 (1.30)
2,500 Players	1.73*** (0.19)	2.75*** (0.33)	0.31* (0.18)	1.61*** (0.17)	8.20*** (0.89)	0.08 (0.59)	2.14*** (0.24)	19.06*** (2.38)	3.88*** (1.28)
4,000 Players	1.91*** (0.17)	3.03*** (0.32)	0.28 (0.22)	1.83*** (0.15)	9.37*** (0.81)	1.17 (0.60)	2.32*** (0.25)	20.69*** (2.29)	1.63 (1.59)
Log Pseudolikelihood	-806.96			-1,098.8			-600.65		
Mcfadden's R ²	0.274			0.267			0.316		
Observations	3,206			4,326			2,534		
Respondents	229			309			181		

+Robust standard errors, clustered by respondent, in parentheses. Standard errors in WTP estimates were calculated using Delta method. ***p <0.01, **p <0.05, *p <0.1. Estimated Network Effects based on comparison to 50-player networks.

consistent with the proposition that players are willing to pay a premium for games with relatively *Loose* players. For instance, *Micro-Stake* players are willing to pay \$0.54 for an increase in *Average VPIP* from *Neutral* to *Loose*. The results are consistent with the proposition that participant characteristics significantly affect a game's value and support the notion that *Loose* and *Tight* players are distinct player types whose participation decisions differentially impact the amount players are WTP to play online poker.

The results suggest that the size of the network matters. For instance, the average *Micro-Stake* player is willing to pay \$1.09 per hour to increase the size from 50 to 150 *Players*, holding other factors constant. The effect of size on WTP estimates increase at a decreasing rate for *Micro-Stake* respondents, with incremental effects suggesting that network effects are exhausted at 2,500 *Players*.

Estimated incremental game-size effects for *High-Stake* respondents are less clear. The data do not reject the null hypothesis that the estimated compensating variation for a change in size from 225 to 500 *Players* equals zero. By contrast, the results indicate that increasing size from 500 to 1,000 *Players* significantly increases a *High-Stake* respondent's WTP estimate. The average *High-Stake* respondent is willing to pay \$3.88 to grow size from 500 to 1,000 *Players*. Overall, the data provide evidence that size matters and that the effects of size on WTP estimates increase at decreasing rates. The analysis also shows that the effects of size on player utility become less important in higher stake games. The finding that direct network effects become less extensive in higher-stake games is consistent with the proposition that search returns are lower in relatively high-stake games where the dispersion of participant characteristics is more compressed (Johansson & Sönströd, 2009; Siler, 2010). While the estimated effects of size on WTP estimates increase in stake, this is not the case when we normalize estimates by a game's minimum bet. The estimated effect of increasing size from 50 to 500 players equals 3.3 bets in *Micro-Stake* games and 2.88 bets in *Small-Stake* games. High-Stake players are willing to pay only 1.518 bets to increase size from 25 to 500 players.

The results presented in Table 4 compare the WTP estimates of *Single* and *Multi-Table* players. Since *Multi-Tabling* increases the likelihood that players compete against opponents with favorable characteristics, players who *Multi-Table* should be willing to pay a premium for relatively *Loose* games and games with more network players. *Multi-Table* players are willing to pay more than twice as much as *Single-Table* players for an increase in *Average VPIP* from *Tight* to *Neutral* in both *Micro-Stake* (\$0.97 versus \$0.34) and *Small-Stake* games (\$4.06 versus \$1.62). They are also willing to pay significantly more than *Single-Table* players (\$1.57 versus \$0.50) to increase the size of a *Micro-Stake* game from 50 to 150 *Players*.

The last six columns in Table 4 present results that compare estimated WTP estimates for *Inexperienced* and *Experienced* respondents. *Inexperienced* respondents competing in *Micro-Stake* games are willing to pay significant premiums for bigger games and games with *Loose Average VPIP*. They are willing to pay over four times more than *Experienced* respondents (\$0.91 versus \$0.21) for an increase in *Average VPIP* from *Tight* to *Neutral*. They are also willing to pay \$1.41 more than *Experienced* respondents (\$1.53 versus \$0.13) to increase size from 50 to 150 players. The estimated difference in WTP across player types persists for games with 500, 1,250, and 2,500 *Players*, although the estimated gap narrows slightly. The estimated differences in WTP estimates between the *Inexperienced* and *Experienced* players narrow considerably and are not statistically

Table 4. WTP Estimates by Self-Reported Player Characteristic+.

Variables	Multi-Table and Single-Table Respondents						Inexperienced and Experienced Respondents					
	Micro Stake			Small Stake			Micro Stake			Small Stake		
	Multi	Single	Dif	Multi	Single	Diff	Inexp	Exp	Dif	Inexp	Exp	Dif
Regulation	0.95*** (0.17)	0.80*** (0.17)	0.15 (0.24)	1.95*** (0.38)	2.15*** (0.65)	-0.19 (0.75)	0.83*** (0.15)	0.96*** (0.21)	-0.13 (0.26)	1.52*** (0.48)	2.57*** (0.46)	-1.05 (0.66)
Security	0.76*** (0.19)	0.93*** (0.18)	-0.17 (0.26)	2.00*** (0.40)	4.73*** (0.73)	-2.74*** (0.83)	0.88*** (0.16)	0.77*** (0.21)	0.11 (0.26)	2.71*** (0.49)	3.03*** (0.54)	-0.32 (0.73)
Tight	-0.97*** (0.20)	-0.34 (0.21)	-0.63** (0.29)	-4.06*** (0.55)	-1.62*** (0.68)	-2.44*** (0.88)	-0.91*** (0.19)	-0.21 (0.22)	-0.70** (0.30)	-3.61*** (0.62)	-3.02*** (0.61)	0.59 (0.87)
Loose	0.51*** (0.21)	0.55** (0.24)	-0.04 (0.32)	1.29*** (0.47)	0.39 (0.70)	0.90 (0.84)	0.55*** (0.19)	0.46* (0.27)	0.09 (0.33)	1.11* (0.57)	1.10** (0.54)	0.02 (0.79)
150 Players	1.57*** (0.33)	0.50 (0.34)	1.07*** (0.47)	3.59*** (0.72)	2.84** (1.14)	0.75 (1.35)	1.53*** (0.31)	0.13 (0.35)	1.41*** (0.47)	3.43*** (0.86)	3.80*** (0.95)	-0.37 (1.28)
500 Players	2.06*** (0.43)	1.11*** (0.42)	0.95 (0.60)	5.65*** (0.99)	5.47*** (1.42)	0.18 (1.73)	2.01*** (0.38)	0.81 (0.49)	1.20* (0.62)	6.77*** (1.19)	4.47*** (1.18)	2.30 (1.68)
1,250 Players	2.81*** (0.50)	1.96*** (0.49)	0.86 (0.70)	8.17*** (1.19)	7.51*** (1.52)	0.66 (1.93)	2.80*** (0.44)	1.54*** (0.54)	1.26* (0.69)	8.64*** (1.39)	7.87*** (1.34)	0.77 (1.93)
2,500 Players	2.70*** (0.45)	2.73*** (0.47)	-0.03 (0.65)	7.91*** (1.09)	8.16*** (1.48)	-0.24 (1.84)	3.10*** (0.41)	2.00*** (0.48)	1.11* (0.63)	9.19*** (1.36)	7.28*** (1.12)	1.91 (1.76)
4,000 Players	2.91*** (0.45)	3.01*** (0.45)	-0.11 (0.64)	9.24*** (0.98)	9.22*** (1.37)	0.01 (1.68)	3.21*** (0.41)	2.64*** (0.48)	0.57 (0.63)	10.00*** (1.22)	8.97*** (1.06)	1.03 (1.62)
Log	-431.40	-361.27		-643.57	-423.29		-511.74	-277.28		-656.98	-421.68	
Pseudolikelihood												
Observations++	1,708	1,484		2,604	1,694		2,100	1,078		2,492	1,792	
Respondents++	122	106		186	121		150	77		178	128	

+Robust standard errors, clustered by respondent, in parentheses calculated using Delta method. ***p < 0.01, **p < 0.05, *p < 0.1. Estimated Network Effects based on comparison to 50-player networks. ++The total number of respondents is lower in these regressions because of missing data on players' Experience and Multi-Tabling behavior.

significant in *Small-Stake* games. Results from *Micro-Stake* games provide the most support for the proposition that search amplifies the effects of size and participant characteristics on WTP estimates.

Discussion

Overall, the empirical analysis produces three main results. First, game participants view *Loose* and *Tight* players as distinctly different user types and are willing to pay a premium for product differentiation through user composition. Second, the results show that an increase in size increases users' utility at a decreasing rate. While bigger networks confer benefits on game participants, the total impact of additional players on others' utility depends on the types of players added to the network. Finally, the data support the proposition that some increases in players' search returns and intensity amplify the effects of size and *Average VPIP* on respondents' WTP estimates.

The findings provide several takeaways. The first order effects are that poker players value both game availability and product quality. Prior gambling studies have shown that product availability impacts demand (Abbott, 2020; Philander et al., 2022), but this appears to be the first study to empirically demonstrate that product quality also impacts consumer demand. The diminishing marginal returns to scale and the product differentiation results suggest that consumers would prefer that operators grow their networks when size is sufficiently small but account for the types of players added to games as the network grows. Poker players appear to prefer sites with game availability but once the network reaches an adequate size, participants will prefer a site with more action-oriented players. These findings are consistent with rewards program used by market leader PokerStars, which rebates net losers more than net winners (MacAdam, n.d.).

The results provide insight into other marketplace-based business where users value high-quality matches and may explain why some markets with network effects can fragment into niche strategies rather than accrue to a single winner. It also explains other peer-to-peer markets where marketing platforms that appeal to niche groups of users have become a popular competitive strategy (Blackwell, 2016). The returns to better user composition and lower search costs may offset losses from a smaller pool of eligible matches.

From a regulatory and policy perspective, these findings provide support for using multi-sided market theory as a framework for taxation and licensure in several gambling products. In marketplace businesses like online poker, betting exchanges, and prediction markets, policymakers that wish to maximize public welfare should consider how licensing models will allow operators to reach requisite scale for liquidity effects but also encourage competition on product quality. A monopoly provider may produce a large network but the marginal value of those effects may be less than if there were multiple operators that needed to compete on quality. However, a more open licensing framework may excessively fragment liquidity in the short-run if the total addressable market is too small. Our online poker findings suggest that growth in network size is accretive until active *Micro-Stake* user counts reach 2,500 players, *Small-Stake* user counts reach 1,250 players, and *High-Stake* user counts reach 225 players. If markets appear well below these levels, policymakers should be more proactive in pursuing strategies that will grow network size, such as interjurisdictional player pooling compacts or smaller license quotas.

It remains an open question whether *Loose* sites are desirable because players prefer more volatility, higher expected returns, or both outcomes that result from high VPIP play. Future studies should consider using a structural approach that allows researchers to analyze the effects of pricing and exclusionary strategies on user behavior and equilibrium outcomes. Validation of these findings with other gambling products would provide an additional layer of insight into gambler preferences. Although we made significant efforts to reduce potential sources of bias, we were limited by interpretation of self-reported data based on hypothetical choices. Future studies could also consider validating our results through modeling player choice decisions using site and account data.

Conclusion

This paper applies insights from the literature on multi-sided markets to a peer-to-peer network with heterogeneous users. By estimating the effects of participant characteristics and network size on the utility of online poker players, we find evidence of direct network effects but also determine that the type of players added to games matters. The standard network effects theory suggests that regulators should not allow competition because network effects lead to natural monopolies. Our results show that this is not the case and that the composition of user types is just as important as total number of users. Poker players value the network liquidity that comes from larger sites but also value the quality of their opponents. We find that the value for these characteristics generally increases with stake size, but not when we normalize estimates by a game's minimum bet. Micro-Stake players are willing to pay \$0.56 per hour to increase network size from 150 to 500 players and \$0.54 per hour for *Loose* games. Small-Stake players are willing to pay \$2.18 per hour to increase size from 150 to 500 players and \$1.08 per hour for *Loose* games. High-Stake players are willing to pay \$6.77 per hour to increase size from 75 to 225 players and \$3.01 per hour for *Loose* games.

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Data availability statement

Due to the nature of this research, participants of this study did not agree for their data to be shared publicly, so supporting data is not available. The authors will collaborate with external researchers to replicate the findings.

References

- Abbott, M. W. (2020). The changing epidemiology of gambling disorder and gambling-related harm: Public health implications. *Public Health*, 184, 41–45. <https://doi.org/10.1016/j.puhe.2020.04.003>
- Afuah, A. (2013). Are network effects really all about size? The role of structure and conduct. *Strategic Management Journal*, 34(3), 257–273. <https://doi.org/10.1002/smj.2013>
- Aizaki, H. (2012). Basic functions for supporting an implementation of choice experiments in R. *Journal of Statistical Software, Code Snippets*, 50(2), 1–24. <https://doi.org/10.18637/jss.v050.c02>
- Allenby, G. M., Brazell, J. D., Howell, J. R., & Rossi, P. E. (2014). Economic valuation of product features. *Quantitative Marketing and Economics*, 12(4), 421–456. <https://doi.org/10.1007/s11129-014-9150-x>
- Armstrong, M. (2006). Competition in two-sided markets. *The Rand Journal of Economics*, 37(3), 668–691. <https://doi.org/10.1111/j.1756-2171.2006.tb00037.x>
- Armstrong, M., & Wright, J. (2007). Two-sided markets, competitive bottlenecks and exclusive contracts. *Economic Theory*, 32(2), 353–380. <https://doi.org/10.1007/s00199-006-0114-6>
- Baumol, W. J., Panzar, J. C., & Willig, R. D. (1982). *Contestable markets and the theory of industry structure*. Harcourt Brace Jovanovich.
- Björkegren, D. (2019). The adoption of network goods: evidence from the spread of mobile phones in Rwanda. *The Review of Economic Studies*, 86(3), 1033–1060. <https://doi.org/10.1093/restud/rdy024>
- Blackwell, D. (2016). 40 is the New 65? Older adults and niche targeting strategies in the online dating industry. *Social Sciences*, 5(4), 62. Article 4. <https://doi.org/10.3390/socsci5040062>
- Caillaud, B., & Jullien, B. (2003). Chicken & egg: competition among intermediation service providers. *The Rand Journal of Economics*, 34(2), 309. <https://doi.org/10.2307/1593720>
- Cantillon, E., & Yin, P. -L. (2011). Competition between exchanges: A research agenda. *International Journal of Industrial Organization*, 29(3), 329–336. <https://doi.org/10.1016/j.ijindorg.2010.12.001>
- Cennamo, C. (2019). Competing in digital markets: A platform-based perspective. *Academy of Management Perspectives*. <https://doi.org/10.5465/amp.2016.0048>

- Cennamo, C., & Santalo, J. (2013). Platform competition: Strategic trade-offs in platform markets. *Strategic Management Journal*, 34(11), 1331–1350. <https://doi.org/10.1002/smj.2066>
- Chu, J., & Manchanda, P. (2016). Quantifying cross and direct network effects in online consumer-to-consumer platforms. *Marketing Science*, 35(6), 870–893. <https://doi.org/10.1287/mksc.2016.0976>
- Coolican, D., & Barros, B. (2021). *The a16z Marketplace 100: 2021*. Andreessen Horowitz. <https://a16z.com/marketplace-100/>
- Cullen, Z., & Farronato, C. (2021). Outsourcing tasks online: matching supply and demand on peer-to-peer internet platforms. *Management Science*, 67(7), 3985–4003. <https://doi.org/10.1287/mnsc.2020.3730>
- Evans, D. S., & Schmalensee, R. (2016). *matchmakers: The new economics of multisided platforms*. Harvard Business School Press Books. <https://doi.org/10.1002/ejoc.201200111>
- Fiedler, I. (2011). The gambling habits of online poker players. *The Journal of Gambling Business and Economics*, 6(1), 1–24. <https://doi.org/10.5750/jgbe.v6i1.574>
- Fiedler, I., & Wilcke, A. C. (2012). Online poker in the European Union. *Gaming Law Review and Economics*, 16(1–2), 21–26.
- Fradkin, A. (2017). *Search, matching, and the role of digital marketplace design in enabling trade: evidence from Airbnb* (SSRN Scholarly Paper No. 2939084). <https://doi.org/10.2139/ssrn.2939084>
- Hartmann, W. R., 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 Letters*, 19(3), 287–304. <https://doi.org/10.1007/s11002-008-9048-z>
- Hensher, D. A., Rose, J. M., & Greene, W. H. (2005). Applied choice analysis: A primer. In *Applied choice analysis* (2nd ed.). Cambridge University Press. <https://doi.org/10.1007/9781316136232>
- Holmes, T. P., & Boyle, K. J. (2003). Stated preference methods for valuation of forest attributes. In E. O. Sills & K. L. Abt (Eds.), *Forests in a market economy* (pp. 321–340). Springer Netherlands. https://doi.org/10.1007/978-94-017-0219-5_18
- Johansson, U., & Sönströdm, C. (2009). Fish or Shark: Data mining online poker. In 5th International Conference on Data Mining-DMIN 09, Las Vegas, USA. CSREA.
- Kaiser, U., & Wright, J. (2006). Price structure in two-sided markets: Evidence from the magazine industry. *International Journal of Industrial Organization*, 24(1), 1–28. <https://doi.org/10.1016/j.ijindorg.2005.06.002>
- Katz, M. L., & Shapiro, C. (1985). Network externalities, competition, and compatibility. *The American Economic Review*, 75(3), 424–440.
- Katz, M. L., & Shapiro, C. (1994). Systems competition and network effects. *Journal of Economic Perspectives*, 8(2), 93–115. <https://doi.org/10.1257/jep.8.2.93>
- Kim, J. B., Albuquerque, P., & Bronnenberg, B. J. (2010). Online demand under limited consumer search. *Marketing Science*, 29(6), 1001–1023. <https://doi.org/10.1287/mksc.1100.0574>
- Kim, H. -S., & Kwon, N. (2003). The advantage of network size in acquiring new subscribers: A conditional logit analysis of the Korean mobile telephony market. *Information Economics and Policy*, 15(1), 17–33. [https://doi.org/10.1016/S0167-6245\(02\)00070-7](https://doi.org/10.1016/S0167-6245(02)00070-7)
- Knote, R., & Blohm, I. 2016. *Deconstructing the sharing economy: On the relevance for is research: Vol. Bd. 1*. In V. Nissen, D. Stelzer, S. Straßburger, & D. Fischer (Eds.). Universitätsverlag Ilmenau. <https://www.alexandria.unisg.ch/247801/>
- Lee, E., Lee, J., & Lee, J. (2006). Reconsideration of the winner-take-all hypothesis: complex networks and local bias. *Management Science*, 52(12), 1838–1848. <https://doi.org/10.1287/mnsc.1060.0571>
- MacAdam, T. (n.d.). *Stars Rewards Explained: Calculating PokerStars Chests Rakeback*. TopPokerValue. Retrieved August 8, 2022, from <https://toppokervalue.com/poker-articles/latest-poker-news/pokerstars-chests-rakeback>
- Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *The Review of Economic Studies*, 60(3), 531. <https://doi.org/10.2307/2298123>
- McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Ed.), *Frontiers in econometrics* (pp. 105–142). Academic Press. <https://doi.org/10.1108/eb028592>
- O'Hara, M., & Ye, M. (2011). Is market fragmentation harming market quality? *Journal of Financial Economics*, 100(3), 459–474. <https://doi.org/10.1016/j.jfineco.2011.02.006>

- Parker, G. G., & Van Alstyne, M. W. (2005). Two-sided network effects: A theory of information product design. *Management science*, 51(10), 1494–1504. <https://doi.org/10.1287/mnsc.1050.0400>
- Philander, K. S., Tabri, N., Wood, R., & Wohl, M. (2022). Casino proximity, visit frequency, and gambling problems. *International Gambling Studies*, 0(0), 1–21. <https://doi.org/10.1080/14459795.2022.2035423>
- pokernewsdotcom (Director). (2013, August 20). *How to Play Texas Hold'em for Beginners*. <https://www.youtube.com/watch?v=b9HYxquQt-M>
- Quaife, M., Terris-Prestholt, F., DiTanna, G. L., & Vickerman, P. (2018). How well do discrete choice experiments predict health choices? A systematic review and meta-analysis of external validity. *The European Journal of Health Economics*, 19(8), 1053–1066. <https://doi.org/10.1007/s10198-018-0954-6>
- Rochet, J. -C., & Tirole, J. (2003). Platform competition in two sided markets. *The European Economic Journal*. <https://doi.org/10.1162/154247603322493212>
- Rochet, J. -C., & Tirole, J. (2006). Two-sided markets: A progress report. *The Rand Journal of Economics*, 37(3), 645–667. <https://doi.org/10.1111/j.1756-2171.2006.tb00036.x>
- Rohlf, J. (1974). A theory of interdependent demand for a communications service. *Bell Journal of Economics and Management Science*, 5(1), 16–37. <https://doi.org/10.2307/3003090>
- Ryan, S. P., & Tucker, C. (2012). Heterogeneity and the dynamics of technology adoption. *Quantitative Marketing and Economics*, 10(1), 63–109. <https://doi.org/10.1007/s11129-011-9109-0>
- Rysman, M. (2004). Competition between networks: A study of the market for yellow pages. *The Review of Economic Studies*, 71(2), 483–512. <https://doi.org/10.1111/0034-6527.00512>
- Rysman, M. (2009). The economics of two-sided markets. *Journal of Economic Perspectives*, 23(3), 125–143. <https://doi.org/10.1257/jep.23.3.125>
- Rysman, M. (2019). The reflection problem in network effect estimation. *Journal of Economics & Management Strategy*, 28(1), 153–158. <https://doi.org/10.1111/jems.12301>
- Schmalensee, R. (2011). *Jeffrey Rohlfs' 1974 model of facebook: An introduction* (SSRN Scholarly Paper No. 1802053). <https://doi.org/10.2139/ssrn.1802053>
- Siler, K. (2010). Social and psychological challenges of poker. *Journal of Gambling Studies*, 26(3), 401–420. <https://doi.org/10.1007/s10899-009-9168-2>
- Sobolewski, M., & Czajkowski, M. (2012). Network effects and preference heterogeneity in the case of mobile telecommunications markets. *Telecommunications Policy*, 36(3), 197–211. <https://doi.org/10.1016/j.telpol.2011.12.005>
- Song, M. (2021). Estimating platform market power in two-sided markets with an application to magazine advertising. *American Economic Journal: Microeconomics*, 13(2), 35–67. <https://doi.org/10.1257/mic.20160052>
- Sriram, S., Manchanda, P., Bravo, M. E., Chu, J., Ma, L., Song, M., Shriver, S., & Subramanian, U. (2015). Platforms: A multiplicity of research opportunities. *Marketing Letters*, 26(2), 141–152. <https://doi.org/10.1007/s11002-014-9314-1>
- Stigler, G. J. (1961). The economics of information. *The Journal of Political Economy*, 69(3), 213–225. <https://doi.org/10.1086/258464>
- Tucker, C. (2008). Identifying formal and informal influence in technology adoption with network externalities. *Management science*, 54(12), 2024–2038. <https://doi.org/10.1287/mnsc.1080.0897>
- van Damme, E. (2007). *Liberalising gambling markets: lessons from network industries?*. Tilburg University Research Portal. <https://research.tilburguniversity.edu/en/publications/liberalising-gambling-markets-lessons-from-network-industries/fingerprints/>
- van Damme, E. (2008). Closing remarks: How specific is the regulation of gambling? In T. Coryn, C. J. C. F. Fijnaut, & A. Littler (Eds.), *Economic aspects of gambling regulation: EU and US perspectives* (pp. 185–195). Brill | Nijhoff. <https://doi.org/10.1163/ej.9789004165595.i-208.56>
- Walker, G. (2014). *Poker VIP*. <https://www.thepokerbank.com/articles/software/vpip/>
- Weitzman, M. L. (1979). Optimal search for the best alternative. *Econometrica*, 47(3), 641. <https://doi.org/10.2307/1910412>
- Weyl, E. G. (2010). A price theory of multi-sided platforms. *The American Economic Review*, 100(4), 1642–1672. <https://doi.org/10.1257/aer.100.4.1642>