Social Evaluation Dynamics in Global Platform Markets

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Abstract

Peer-to-peer platform markets have recently expanded on an unprecedented scale and changed the way many business activities are organized. Given their differences from traditional firm-based capitalist markets, this dissertation seeks to understand peer-to-peer market participants' behavioral patterns and assess the repercussions of platforms' efforts to engineer an efficient, transparent, and accessible market. Chapter 1 illustrates key differences between a peer-to-peer platform system and a traditional firm-based system, highlights opportunities to generate new economic sociological insights, and provides an overview of the three empirical studies included in this dissertation. Chapter 2, "Strategic Downward Selection: Evidence from a Peer-to-peer Platform Market", reveals unintended consequence of instituting a performance evaluation system. Chapter 3, "Seal of Approval? Trust Signals and Cultural Distance in Global Peer-to-peer Platform Markets" shows the presence of cultural bias in exchange partner selection and how this may influence the effects of various quality signals. Chapter 4, "Markers of Mission Commitment: Career, Gender, and the Evaluation of Social Entrepreneurs", shows the presence of social biases associated with career background and gender among crowd funders. Across these three empirical chapters, I leverage both quantitative and qualitative research methods to analyze proprietary data, archival data, and experiment data. As the studies in this dissertation illustrate, despite the efforts to engineer a highly-functioning market, how economic transactions on these platforms eventually unfold are subject to social processes.

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CHAPTER 1.

Introduction and Overview

The sweeping penetration of peer-to-peer platform markets for the circulation of goods (eBay), durable assets (Airbnb and Uber), time and skills (TaskRabbit, Upwork, time-sharing banks) has changed the way many business activities are organized. In peer-to-peer markets, two private individuals interact to buy/sell goods and services directly with each other, or produce goods and services together. While peer-to-peer transactions have a long history, modern capitalist systems have largely been firm-based as the transaction cost involved in a production process—including searching for partners, negotiating deals, guarding against opportunism—favors traditional corporations (Coase 1937; Williamson 1985). Information technologies such as search engines and online platforms, however, have greatly reduced such cost by enabling individuals to more effectively gather, share, and filter information about other transaction partners; in addition, a reliable online system of market intermediaries such as insurance and payment systems have increased individuals' ability to enforce business contracts (Cook, Snijders, et al. 2009; Davis 2016; Schor and Fitzmaurice 2015). Powered by these modern technologies, peer-to-peer platform markets have vastly expanded on an unprecedented scale.

A peer-to-peer platform system differs from a firm-based capitalist market in several ways. First, the production and transaction process by firms is highly centralized—decisions are made within hierarchical organizations with centralized operations (Powell 1990); by contrast, platform market transactions are rather discrete and decisions are made by individual providers. For example, in the traditional investing market, professional venture capitalists control critical resources for entrepreneurs, but on crowdfunding platforms, individual laymen investors evaluate entrepreneurs and make discrete funding decisions. This empowers individual laymen investors and makes resources available to entrepreneurs who might not attract professional investors' attention, democratizing the market (Sorenson et al. 2016). For another example, Airbnb hosts make discretionary decisions about whether they accommodate a guest or not, while in the traditional lodging market, professional hotels' accommodation procedures and policies are largely centralized and standardized. Given the discrete nature of the decision-making process, platform participants' selection of exchange partners may exhibit different patterns from those in a firm-based offline system, or they may replicate or even exacerbate some patterns such as biases against certain groups that are prevalent offline.

Furthermore, a peer-to-peer platform system and a firm-based system provide different types of information to market participants. Table 1 below summarizes varying degrees of information in different exchange scenarios. In a firm-based system, external audiences (i.e, market participants who did not participate in a focal transaction) have social information on firms and on their exchange partners, such as their status, reputation, and network positions. Direct information about the exchange per se between firms and their partners—for example, which party performs better and contributes more—is oftentimes not disclosed to outsiders. In a traditional large-scale market, external audiences have thicker information on relationships (who exchanged with whom) but less information on performance (how each party performed), unless they are tied to these exchange partners and information flows through social networks—this is likely to occur in a "small world" scenario (Hillmann and Aven 2011; Raub and Weesie 1990; Powell, 1990).

By contrast, in a peer-to-peer system, platform users as external audiences/decision-makers have relatively scarce social information on a participant and her exchange partners—many participants are anonymous or have only provided limited social information; furthermore, external audiences do not have rich information about exchange networks. For example, Uber passengers do not know Uber drivers' prior passengers, and employers on Upwork have limited knowledge about employees' prior employers. External audiences, however, have direct performance information because these platforms create public feedback systems that allow participants to evaluate their exchange partners; performance information thus becomes available to every platform user. A public feedback system is one of the hallmarks of a peer-to-peer platform market.

Table 1 Information Available to Decision-makers

		Relationship Information (High)	Relationship Information (Low)
Performance Information	(High)	"Small world"	Platform
	(Low)	Traditional large-scale market	

As a unique type of economic organization with features different from "small world" situations or traditional large-scale markets, peer-to-peer platforms promise efficiency, transparency, and accessibility. Specifically, information gathering, sharing, and filtering are highly organized by algorithms, which promises efficient information distribution and exchange partner matching. In addition, as discussed above, performance information is disclosed publicly to all market participants, which promises transparency and in turn promotes efficiency. Furthermore, platforms have low market entry barriers for individuals, which promises accessibility. For product/service providers, professional credentials for their goods, assets, or skills is not a must; for product/service receivers, the cost of entering into platform markets is also low—for example, entrepreneurs who might not attract professional investors' attention could start a fundraising campaign on crowdfunding platforms.

However, whether efforts to engineer highly-functioning markets can truly deliver is a question. For instance, many platform markets hinge on a performance evaluation system, either one-sided (e.g., Care.com and eBay) or two-sided (e.g., Airbnb, Uber, and Upwork), that allows participants to evaluate an exchange partner and choose their prospective exchange partner based on her prior evaluations. While instituting a performance evaluation system aims to reduce quality information asymmetry among market participants, it leaves room for gaming the system—platform participants may strategically select with whom they would exchange and thus by whom they would be evaluated. This decision-making process might be different from that in "small world" situations or traditional large-scale markets. In addition, despite an ample amount of quality information being disclosed on platforms, platform participants' selection of exchange partners might still be subject to social bias that is prevalent in the offline world.

The three empirical chapters in my dissertation each look at a platform-related phenomenon, seek to understand the repercussions of efforts to engineer an efficient, transparent, and assessible platform market, and aim to contribute to economic sociological theories. Specifically, my work reveals the unintended consequences of instituting a performance evaluation system (Chapter 2) and the presence of social biases in exchange partner selection despite these prospective partners potentially having identical performance information (Chapters 3 & 4). Across these three empirical chapters, I leverage both quantitative and qualitative research methods to analyze proprietary data, archival data, and experiment data.

Specifically, Chapter 2, "Strategic Downward Selection: Evidence from a Peer-to-peer Platform Market", looks at how the presence of an evaluation system may affect market participants selection of exchange partners in a peer-to-peer lodging platform market. The dominant view in the partner selection literature holds that market participants seek exchange partners with *superior* or at least *similar* market standing because such partnerships beget access to instrumental resources such as information, materials, and visibility that can contribute to good market outcomes (Magee and Galinsky 2008; Merton 1968; Sauder, Lynn, and Podolny 2012; Thye 2000). Yet, in this chapter, I posit that the partner selection dynamics might be different in markets designed with partner evaluation systems, such as platform markets in which market participants are rated by their exchange partners after transactions. I argue that concerns regarding these post-hoc evaluations could influence whom one chooses to transact with at the outset. I theorize that market participants seek to reduce their anxiety about evaluations made by transaction partners by selecting partners with *inferior* market standing—who they presume are more likely to be satisfied with their offerings and will thus be more likely to provide positive evaluations.

I test this idea in a peer-to-peer lodging platform where every user lists a home and everyone can see and compare each other's home. Would a host be more inclined to accommodate a guest with nicer homes, similar homes, or homes not as nice as hers? Insights from the literature suggest that prospective partners with superior market standing would be more sought after; one might assume that hosts would choose guests with nicer or at least similar homes. Analyses of both quantitative and qualitative data including over 1 million user transactions and interviews with 45 platform users and 6 company executives reveal that, instead of hosts selecting guests with nicer or equivalent homes, hosts, driven by evaluation anxiety, are more likely to accept guests whose homes are more inferior to their own. This in-depth study of a peer-to-peer platform market provides a novel theoretical account to explain why, in some exchanges, transaction partners with inferior market standings are more sought after. It contributes to theories of exchange partner selection, social evaluation, and commensuration, and has implications for the design of new markets or ventures that rely on evaluation systems.

Chapters 3 and 4 investigate whether platform participants' selection of exchange partners is biased such that social factors such as national origins, professional backgrounds, and gender may distort their decision-making processes net of performance information. Specifically, Chapter 3 examines whether cultural distance between online participants could affect the occurrence of peer-to-peer transactions, while Chapter 4 focuses on whether professional identity and gender identity of social entrepreneurs could bias individuals' investment decisions on crowdfunding platforms.

By examining social biases associated with cultural distance in platform markets, Chapter 3, "Seal of Approval? Trust Signals and Cultural Distance in Global Peer-to-peer Platform Markets", revisits a lingering conceptual puzzle— the literature holds contradictory perspectives on whether quality signals narrow or widen the gap between socially advantaged and disadvantaged market participants. I offer a new perspective to this puzzle by comparing two types of quality signal: *process-based* signals tied to a record of prior transactions such as reputation, and, *institutional-based* signals tied to organizational institutions such as third-party accreditation (Schofer and Meyer 2005; Williamson 1981; Zucker 1986). Peer-to-peer markets have instituted various quality signals such as partner evaluations (which I categorize as process-based signals) and platform verifications (which I categorize as institutional-based signals), allowing me to contrast and compare different quality signals. Using a proprietary dataset of a global peer-to-peer lodging platform, my analysis reveals that prospective guests who are more culturally distant from hosts are in a disadvantaged position: their lodging requests are less likely to be approved by hosts. (This is somewhat ironic given platforms like this are often marketed as allowing users to experience cultural differences). My findings reveal the importance of distinguishing the two types of quality signals. First, I find that process-based quality signals (user ratings) are weaker for culturally distant guests, and thus *widen* the gap in host acceptance of culturally proximate versus culturally distant guests. Second, I find that institutional-based quality signals (platform verification) are stronger for culturally distant guests, indicating that they help *narrow* the gap. These findings suggest unexplored contingencies to theories of evaluations and social bias, and contribute to the literature on culture and trust in the global online economy

Chapter 4, "Markers of Mission Commitment: Career, Gender, and the Evaluation of Social Entrepreneurs", examines social biases in crowdfunding platforms with a novel focus on social enterprise start-ups, and specifically on whether a social entrepreneur's professional identity and gender identity could bias crowdfunders' funding decisions. The entrepreneurship literature has documented extensively how crowdfunders and professional investors select for-profit entrepreneurs (e.g., Baum and Silverman 2004; Burton et al., 2002; Colombo and Grilli 2005; Hsu 2007), but the hybridity of social entrepreneurs might incur unique dynamics. This chapter includes one field study of 451 social entrepreneurs' fundraising campaigns in crowdfunding platforms, one lab-based experimental study imitating crowdfunding campaigns, and one lab-based experimental study imitating professional venture capital investments. The first two studies reveal that crowdfunders are biased towards social entrepreneurs with nonprofit work experience and female social entrepreneurs because these social cues help alleviate funders' concerns over mission drift —the pressures to sustainably generate commercial benefits suppress entrepreneurs' pursuit of social goals. Furthermore, the third study suggests that professional investors might make similar decisions with crowdfunders on platforms.

Overall, the three empirical chapters in this dissertation each seek to reveal a social economic phenomenon at the nexus of platforms and markets. Using a peer-to-peer lodging market as a case, Chapter 2 shows that post-hoc performance evaluation concerns may drive market participants' selection of inferior exchange partners at the outset, providing a counter case for a dominant view in off-line markets. Chapters 3 and 4 reveal that, even after taking into account performance variations, social biases exist in platform markets. Chapter 3 revisits a lingering conceptual puzzle—whether quality signals narrow or widen the gap between socially advantaged and disadvantaged market participants—and shows that process-based quality signals may widen the gap while institutional-based quality signals could narrow the gap. Chapter 4 suggests that biases and stereotypes held by crowdfunders advantage social entrepreneurs with nonprofit backgrounds and women, and this may apply to professional impact investors. Taken together, these chapters illustrate how platforms, as an explosively expanding venue for market exchanges, could breed new insights for economic sociological theories.

CHAPTER 2.

Strategic Downward Selection:

Evidence from a Peer-to-peer Platform Market

A counterparty's market standing is an important consideration when individuals and organizations select exchange partners. A long line of research has established that those with superior market standing, based on the value or expected value of their offerings, are more sought after because such partnerships beget access to instrumental resources such as information, materials, and visibility that can contribute to good market outcomes (Magee and Galinsky 2008; Merton 1968; Ridgeway et al. 1998; Sauder et al. 2012; Thye 2000). Furthermore, because there is no incentive to pursue inferior exchange partners, partnerships are often consummated with those with similar market standing (Burt 1978; Gulati and Gargiulo 1999; Podolny 1994; Roth 2004)

Yet, a growing body of scholarship has challenged these narratives and pursued an opposite question: why, in some exchanges, are counterparties' with inferior market standing more sought after despite having fewer resources and being less prominent? To date, the prevailing answer is that inferior counterparties can offer deference in collaborations (Cowen 2012; Gould 2003; Tiedens, Unzueta, and Young 2007; Trapido 2013). For example, in commercial voyage partnerships, the more professionally prominent parties have the final say in decisions over vessel purchase and staff hiring, so they seek partnerships with inferior counterparts instead of equally prominent ones to maintain stable collaborations (Trapido 2013). While the need for deference is an appealing rationale in these empirical contexts, this paper offers an alternative explanation for the downward selection of exchange partners when one's primary concern might not be the exchange per se, but the counterparty's post-hoc feedback. For example, platform markets such as Upwork and Airbnb are built on such feedback systems (Bolton, Greiner, and Ockenfels 2013; Cook et al. 2009; Dellarocas and Wood 2008; Diekmann et al. 2014) and for many organizations, such as educational institutions, performance ratings (e.g., instructor ratings) are material for employees (Rivera and Tilcsik 2019). In these contexts, when one's success depends significantly on the evaluations of exchange partners, one's most salient concern is their evaluation criteria and processes, as scholars in this tradition contend (Correll et al. 2017; Goffman 1967; Ridgeway and Correll 2006; Schelling 1960; Sharkey and Kovács 2018; Troyer and Younts 1997). Because the counterparties' post-transaction feedback is so consequential, it becomes an integral part of the decision-making process by which they are chosen and anxiety over evaluation outcomes could, in fact, trump other considerations.

Building on recent developments in the economic-sociological literature claiming that evaluative measures fuel "engines of anxiety" (Espeland and Sauder 2016), I develop a theory of strategic downward selection of exchange partners driven by evaluation anxiety. I posit that, in economic exchanges in which evaluations are critical but standards are ambiguous, market participants rely on heuristics to approximate others' expectations; specifically, they infer their prospective partners' evaluation standards from their *relative* market standing. Comparing themselves with their prospective partners, they anticipate that those with superior market standing are likely to have higher evaluation standards for a transaction—standards that can be difficult for them to meet. To reduce evaluation anxiety, they seek transaction partners with inferior market standing who are more likely to be satisfied with their offerings and provide positive evaluations. Because this tendency toward downward selection is driven by evaluation anxiety and relies on comparisons between transaction parties, I posit that it is likely to be stronger when evaluation anxiety intensifies and when social comparison is more cognitively convenient.

This theory brings to light market participants' responses to evaluation anxiety as a factor to explain why partners with inferior market standing may be more sought after in some markets. It applies to the many contexts in which evaluations are critical and preemptive selection is possible. I test it in one such setting: a peer-to-peer platform market for lodging. Because every user must list her own home on the site, homes serve as heuristics with which users can approximate others' expectations, a feature of this platform that enables me to capture key concepts in my theory. I analyzed over one million user transaction records to test my hypotheses and supplemented the quantitative analyses with interviews with 45 users and 6 executives of this platform company. There are several reasons one might assume that hosts would choose guests with nicer or at least similar homes. When a host looks for lodgings in the future, she will be more likely to be approved by her prior guests out of reciprocity (Coleman 1990; Kollock 1994); accommodating a guest with a nicer or equivalent home thus begets instrumental resources. Furthermore, owners of nicer homes are likely to be seen as more affluent and therefore better stewards of one's own property (Johnson-Spratt 1998; Yinger 1995).

Analyses of user transaction data and insights from interviews reveal, however, that a host is more likely to approve requests from prospective guests with inferior homes. This is more pronounced when the host has recently experienced a decrease in ratings, such that the host's evaluation anxiety is heightened, and when the host is familiar with the comparison group—for example, domestic as opposed to foreign guests—so that social comparison is easier. These findings corroborate market participants' downward selection strategy under evaluation anxiety and foreground an agentic perspective that actors proactively shape the interaction context for favorable evaluations. This expands our knowledge of market actors' responses to being evaluated, which is particularly relevant now that evaluations have become so prevalent and influential that they "take on a seemingly moral imperative" (Bromley and Powell 2012).

Exchange Partner Selection and Evaluation Systems

One's market standing rests on the value or expected value of one's offerings (Berger, Cohen, and Zelditch 1972; Gould 2002; Lynn, Podolny, and Tao 2009; Ridgeway et al. 1998; Sauder et al. 2012). The dominant view in the literature is that individuals and organizations seek exchange partners with superior or similar market standing because they can provide more or comparable instrumental resources—such as materials, information, and visibility—than partners with lower standing. This finding has been made in empirical contexts including negotiations (Thye 2000), academic collaboration (Merton 1968; Zuckerman 1967), professional work relationships (Ibarra 1992), employee mobility (Burton, Sørensen, and Beckman 2002; Roberts, Khaire, and Rider 2011), new ventures' fundraising (Stuart, Hoang, and Hybels 1999), and investment banks' co-investing (Chung, Singh, and Lee 2000; Li and Berta 2002; Podolny 1994). Other researchers contend that there is also a need to coordinate and to avoid conflicts in economic exchanges (Gould 2003), suggesting that market participants seek inferior partners who are most likely to exhibit deference (Cowen 2012; Tiedens et al. 2007; Trapido 2013).

However, decision-making contexts vary widely in the extent to which the counterparty's evaluation of the focal actor matters, from those in which its importance is negligible to those in which it is decisive to the focal actor's success (Correll et al. 2017). The resource and deference perspectives were predominantly developed in contexts in which the influence of the counterparty's evaluation is small or moderate, either because it is not publicized—absent or kept private for small groups (Hillmann and Aven 2011; Raub and Weesie 1990)—or because it is not incorporated into important decisions (e.g., laymen's reactions might not be important for professionals). For example, in business partnerships such as VC investment, whether an entrepreneur is competent is private information, which spreads only to those with direct or indirect ties to that entrepreneur (Shane and Cable 2002). Similarly, a team member's actual performance is known only to those outsiders connected with other team members. In these scenarios, the counterparty's evaluations are not broadcast and may therefore have only limited influence. Counterparty evaluations can be more consequential, however, when quantified, systemized, and institutionalized. For example, in rapidly expanding platform markets such as Upwork, Airbnb, and TaskRabbit, evaluations provided by exchange partners are public, available to all potential partners, and can therefore influence one' survival (Cook et al. 2009). In other contexts, although evaluations are not publicized, they are incorporated into important decisions. For example, in many organizations such as educational institutions, counterparties' performance ratings (e.g., students' instructor ratings) are essential for organizational decisions such as promotion or termination (Rivera and Tilcsik 2019).

These evaluation systems can fuel anxiety (Espeland and Sauder 2016). While research in this tradition looks at third-party evaluations (Chatterji and Toffel 2010; Espeland and Sauder 2007; Sauder and Espeland 2009; Sharkey and Bromley 2014), in many of the contexts described above evaluations are provided by one's transaction partners and are at least as likely to stimulate anxiety, as negative evaluations can undermine future opportunities. Furthermore, in some contexts, evaluations are taken personally and thus can make one question one's self-perception (Cook and Hardin 2001; Kollock 1999) or threaten one's self-image, especially in peer-to-peer transactions that involve one's personal resources and services (Kuwabara 2015; Schor et al. 2016). In fact, the platform literature has extensively documented post-hoc strategies for gaining good ratings under evaluation anxiety, such as reciprocal rating (Bolton et al. 2013; Diekmann et al. 2014) and underreporting negative ratings for fear of retaliation (Dellarocas and Wood 2008; Fradkin, Grewal, and Holtz 2018; Zervas, Proserpio, and Byers 2015). Unfortunately, these studies focus exclusively on strategies following a consummated transaction. There is a dearth of research on the occurrence of a transaction from a partner selection perspective; that is, concerns regarding evaluations that will be made by one's exchange partners after transactions can also influence whom one chooses to transact with at the outset.

While evaluative measures are instituted only as a means (to ensure the quality of an exchange relationship), they can, under evaluation anxiety, become ends (Bromley and Powell 2012). I therefore propose that, in markets with evaluation systems, actors choosing exchange partners may prioritize whether their own output is likely to be satisfactory to those partners, such concerns may even trump other considerations, such as gaining instrumental resources. In fact, recent studies show that when counterparties' reactions are critical, people base their decisions not on their own preferences, but on others' assumed preferences (Correll et al. 2017; Ridgeway and Correll 2006). For example, (Smith and Gaughan 2016) study of the negative stock market reaction to the appointment of a female CEO finds it due to focal shareholders' anticipation of potential shareholders' negative reactions and not to any negative beliefs they themselves have about female leaders. Sharkey and Kovacs (2018) find that during the December holiday season, the sales gap between prizewinning books and other books increases because people have greater confidence that others will value prizewinning books as gifts rather than the giver's own favorites. Although these studies are not about exchange partner selection, they do suggest that when counterparties' reactions or evaluations matter, this concern could eclipse other considerations. Below, I elaborate on how evaluation concerns can influence exchange partner selection.

Strategic Downward Selection under Evaluation Anxiety

Despite the central role of evaluations in many decision-making situations, there can be significant ambiguity and uncertainty regarding the counterparty's expectations and evaluation standards. That is, "objective, non-social evaluation standards" (Festinger 1954) are unavailable and the two parties' standards might differ. For instance, in peer-to-peer ridesharing markets such as Uber, drivers and passengers might differ in what they consider a clean vehicle and a safe drive. Such ambiguity and uncertainty escalate market participants' evaluation anxiety.

To approximate their counterparties' expectations under ambiguity and uncertainty, people often rely on heuristics. The literature emphasizes that roles and stereotypes can serve as such heuristics (Correll et al. 2017; Ridgeway and Correll 2006; Sharkey and Kovács 2018; Smith and Gaughan 2016). For example, as aforementioned, (Smith and Gaughan 2016) study highlights that people rely on gender stereotypes to approximate others' reactions. I propose that in certain situations, people exercise social comparison and interactants' *relative* market standing can serve as convenient heuristics with which people approximate their expectations. Social comparison is critical for evaluation processes, especially when there are no "objective, non-social evaluation standards" (Festinger 1954: 118). By comparing themselves with others, market participants can (a) make sense of their own positions in the market and (b) surmise what their counterparties expect of them. Specifically, people anticipate that counterparties with superior (inferior) market standing are likely to have higher (lower) evaluation standards. Because interactants with higher market standing are believed to offer superior output (Berger et al. 1972; Lynn et al. 2009; Sauder et al. 2012), people presume that they might also have higher expectations and standards for the offerings of their partners. In fact, many studies find that people presume that productive colleagues have high expectations of their colleagues' productivity and that people will therefore work harder to meet these assumed expectations (Tziner and Eden 1985; Zuckerman 1967). Companies with inferior market standing also expend greater efforts to meet the demands and expectations of superior partners (Castellucci and Ertug 2010; Trapido 2013). Experimental evidence further shows that people are more concerned about being devalued or rejected by those with superior positions; in contrast, the superior party shown to be significantly less concerned about devaluation in a given social interaction (Chen, Brockner, and Greenberg 2003; Magee and Galinsky 2008; Ridgeway et al. 1998; Sidanius and Pratto 1999).

Interactions with counterparties with higher market standing can therefore increase one's anxiety over how one is perceived by them. Improving one's own output to meet their standards may be a solution (Castellucci and Ertug 2010; Tziner and Eden 1985; Zuckerman 1967), but when that is not readily achievable, one might choose to avoid such exchanges, even if that means forgoing the instrumental resources they might provide. Research suggests that individuals who feel threatened on a particular dimension are inclined to prevent others who surpass them on that dimension from entering into their comparative context (Garcia, Song, and Tesser 2010). For instance, (Duguid, Loyd, and Tolbert 2010) reveal that concerns over external appraisals drive women and racial minorities who are numeric minorities in high-prestige work groups to prevent demographically similar but superior performers from joining. While the concern in these studies is with third-party appraisals, this inclination to avoid superior counterparties and to shape a favorable comparison context is also likely present when one is concerned about the counterparties' own evaluations. Driven by evaluation anxiety, market participants might be more inclined to choose counterparties with lower market standing, assuming them to have lower expectations and to be more likely to be satisfied by the focal actor's offerings. The focal actor thus becomes the superior party in the transaction and devaluation is less of a concern for the superior party in a given social interaction (Chen et al. 2003; Magee and Galinsky 2008; Ridgeway et al. 1998; Sidanius and Pratto 1999). This is a strategic downward selection to shape the interaction context to the focal actor's advantage, which not only minimizes the risks of devaluation but also, more importantly, garners favorable evaluations and gains a competitive edge.

H1: In markets with partner evaluation systems, participants are inclined to seek exchange partners with inferior market standing.

When Evaluation Anxiety Is Heightened

Because this downward selection strategy is driven by evaluation anxiety, I posit that it will be more salient when evaluation anxiety is heightened. Evaluation anxiety is likely to be particularly salient when market participants experience a decrease in evaluations that could threaten their images and dampen their market success. A classic proposition in the literature holds that when performance is below aspirational levels, it can stimulate problemistic search and changes to existing strategies (Bromiley 1991; Cyert and March 1963; Singh 1986). This suggests that market participants may change—for example, mitigate or reverse—their downward selection strategies.

Yet, recent development in this theory shows that market actors' responses to a performance decline is not as straightforward as previously assumed. When performance is below aspirational levels, it can exacerbate resistance to change and increase reliance on more conventional and well-learned responses (Audia and Brion 2007; Greve 1998; Jordan and Audia

2012; March and Shapira 1992). I argue that evaluation decrease drives market actors to invest enhanced efforts in the downward selection strategy due to (a) narrowed attention and (b) uncertainty concerning alternative strategies.

Specifically, anxiety may narrow decision-makers' attention and simplify their decision-making process (Cowen 1952; Freeman and Audia 2006; Luchins 1942). In markets with partner evaluation systems, participants facing heightened evaluation anxiety are even more likely to prioritize whether their output is satisfactory to their counterparties over other considerations, such as gaining resources from superior counterparties. Furthermore, decision makers rely more on existing strategies when uncertainty concerning alternative strategies is high (Ocasio 1995; Sitkin and Pablo 1992). Uncertainty may invoke "downward" counterfactual thinking; that is, comparing the status quo to an imagined catastrophic outcome that could have occurred, which in turn puts one's current strategy in a more positive light (Jordan and Audia 2012). Thus, in marketplaces with uncertainty concerning the counterparty's expectations and standards, people rely more on their existing assumptions. Since people infer a counterparty's expectations from its relative market standing, they are even more likely to pursue partners with inferior standing who they believe might be easier to satisfy.

For these reasons, I hypothesize that heightened evaluation anxiety caused by an evaluation decrease drives market actors to further prioritize evaluation concerns and invest enhanced efforts in the downward selection strategy. Thus, the positive effect of having inferior market standing on prospective partners being selected by the focal decision maker will be stronger.

H2: In markets with partner evaluation systems, a decrease in evaluations enhances participants' tendency toward downward selection.

When Social Comparison Is Facilitated

Because the downward selection strategy presupposes comparisons between transaction parties' relative market standing, I argue that it is likely to be more pronounced when social comparison is facilitated. To carry out a comparison, people have to obtain judgement-relevant information about a target, including information for the assessment of (a) whether a target is a comparable referent and if so, (b) a target's relative standing on the judgmental dimension (Kulik and Ambrose 1992; Mussweiler 2003; Mussweiler and Strack 2001). Thus, familiarity with a target, meaning having more judgement-relevant information, can facilitate social comparison by making the process cognitively convenient.

Information on familiar targets is highly accessible in memory and cognitively easy to compute; familiar targets are thus more likely to be selected as referents (Herr, 1986; Wilson, Houston, Etling, and Brekke, 1996; Kulik and Ambrose, 1992). For instance, empirical evidence shows that employees are likely to compare their bonuses with those of colleagues who are in neighboring offices and are personal friends because these colleagues are more salient and observable (Obloj and Zenger 2017). Thus, the social comparison process is less likely when prospective exchange partners are unfamiliar and thus are not on the radar, which then weakens the tendency of strategic selection based on social comparison. In the platform market which is the site of this study, domestic hosts might be more likely to be prompted to compare themselves to domestic guests, and hosts with children to guests with children, because hosts may be more familiar with these groups regarding their housing requirements, making the comparison process easy to compute.

Furthermore, target familiarity is also associated with people's ability to capture these differences between themselves and their comparison target. Specifically, people can better capture nuanced differences among subjects they are familiar with than among unfamiliar ones (Elfenbein and Ambady 2003; Kulik and Ambrose 1992; Mussweiler 2003). For example, because hosts are likely more familiar with domestic socio-economic conditions than with foreign conditions, they might be able to capture the nuanced differences between their own and their prospective guests' homes. In contrast, for foreign guests, there may have to be a larger gap between hosts' and guests' homes for the hosts to capture the difference. Thus, differences in homes will have a greater effect for domestic guests than for foreign guests on having one's lodging request approved.

Taken together, these arguments suggest that familiarity with prospective exchange partners enables *and* enhances social comparison, increasing the positive effect of prospective partners' inferior market standing on their being selected by the focal decision maker. I therefore hypothesize:

H3: In markets with partner evaluation systems, familiarity about prospective exchange partners enhances participants' tendency toward downward selection.

DATA AND METHODS

The Setting: Peer-to-peer Platform Markets

Peer-to-peer platform markets provide an ideal testing ground for my theory. First, they allow selection: market participants can take preemptive actions and select their exchange partners. Second, they rely on evaluation systems (i.e., ratings) (Bolton et al. 2013; Cook et al. 2009; Dellarocas and Wood 2008; Diekmann et al. 2014; Fradkin et al. 2018; Zervas et al. 2015). Thus, they provide an ideal setting in which to examine how concerns over evaluation after a transaction influence participants' selection of exchange partners at the outset. Specifically, I examine my hypotheses in one peer-to-peer lodging platform that required anonymity as a condition of sharing its data. The dataset includes all listings, lodging requests, messages, and transactions (defined as consummated stays) between hosts and guests (defined collectively as users) from 2014 through 2017 as well as information on each user (but not the name or email address).

Certain characteristics of this platform allow me to capture key concepts in my theory. Every user must list her own home. The site then assigns each home a price per night in a platform-specific virtual currency, using a unique algorithm that considers the home's location, size, and facilities. For the purpose of this study, I refer to the currency as "coins" and the price per night as "coins-per-night." An 845-square-foot Manhattan apartment with two bedrooms is 218 coins-per-night; a similar apartment would list for about $200 on Airbnb. On this platform, the maximum home coins-per-night is 441 and the minimum is 40, with an average of 150. Each user is allocated an initial amount of coins upon listing her home; she can then earn coins by accommodating guests and use coins to pay hosts. The platform thus engineers a market hierarchy: nicer homes in better locations are of higher price and are perceived to be more valuable, giving their owners higher market standing. This feature enables market participants to compare each other's homes and allows me to directly measure the relative differences of their market standing.

Sample

To analyze user transaction data, I use a logistical regression model—with conditional fixed effects for hosts—to estimate the probability of a *request approval*; the individual request is the unit of analysis. The dataset I received included more than one million lodging requests, but I pare this down to construct my analysis sample as follows. First, I omit 7,730 users who had more than one home ID because it is difficult to gauge whether these users actually had two or more homes listed or whether they once removed a home from the platform but then re-listed it, which could generate different home IDs for the same home. These users are involved in 240,178 lodging requests. Second, I omit 23,897 users who list homes in foreign countries—for example, an American who lists a home in France—because it is difficult to gauge their primary country of residency. These users are involved in 63,232 requests. Of the remaining lodging requests, only 2 percent are for reciprocal lodging (meaning that the host will also stay at the guest's home) and 98 percent are for non-reciprocal lodging. For my analysis, I focus on non-reciprocal transactions. This results in 1,158,366 lodging requests.

The conditional logit models were estimated only for requests associated with hosts who exhibited some variation in acceptance. That is, the model drops hosts who declined all requests (725,181 observations) or approved all requests (382 observations), leaving 432,803 observations (Allison 2009; Mcfadden 1973) (for other empirical examples, see (Eisenhardt and Tabrizi 1995; Short and Toffel 2010; Xiao and Tsui 2007; Zenger and Marshall 2000).[1] The estimation sample thus consists of 432,803 lodging requests sent by 37,745 guests in 55 countries to 11,749 hosts in 52 countries. In this sample, each host receives 2 to 845 requests, with an average of 97 requests and a median of 60. The most common host countries and guest countries are France, Spain, and Italy;[2] the rest are elsewhere in Europe, the Americas, Australia, and Asia.

Dependent Variable and Independent Variables

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[1] In unreported robustness tests, I reestimate my specifications as linear probability models using ordinary least squares (OLS) with host fixed effects. Unlike the primary conditional logit models, OLS models yield estimates based on the entire sample of 1,158,366 requests because OLS does not drop hosts that lack variation in the dependent variable. These OLS models yielded the same inferences as the logistic conditional fixed-effects models.

[2] In the estimation sample, 45 percent of the requests are sent to hosts in France and 56 percent are from guests from France; 20 percent to hosts in Spain and 20 percent from guests from Spain; 12 percent to hosts in Italy and 9 percent from guests from Italy

The dependent variable, *request approval*, is a dummy variable coded "1" when the host approved the lodging request from the guest and "0" otherwise. In the final sample, 31,277 requests—7.2 percent—were approved.[3]

To operationalize the concept in H1—exchange partners with inferior market standing—I create a continuous variable, *guest inferiority*, by subtracting the guest's home coins-per-night from the host's. Thus, a positive value indicates that the host's home is worth more than the guest's home and the guest has an inferior relative market standing. The maximum difference is 319 and the minimum is -344. In the analyses below, I facilitate the interpretation of coefficients by dividing the home's coins-per-night differences by 100, making the maximum *guest inferiority* 3.19 and the minimum -3.44. Thus:

Guest inferiority = (host's home coins-per-night – guest's home coins-per-night)/100

To operationalize the concept in H2—a decrease in evaluations—I create a dummy variable to measure whether the host's rating declined in her most recent transaction. *Host's rating decrease* is "1" when rating_{t-1} (i.e., for her most-recent transaction, t-1) is lower than rating_{t-2} (i.e., for her second-most-recent transaction, t-2), and "0" otherwise.[4] As a robustness test, I also measure this variable by comparing rating_{t-1}, rating_{t-2}, and rating_{t-3}, which yields largely identical results.

[3] Of the approved requests, fewer than 5 percent were cancelled by the guests or the hosts due to schedule changes. Results are robust to excluding these. Of the declined requests, 9 percent received no responses from the host, 84 percent received standard decline messages (the host can choose from several templates provided by the platform), and the rest received nonstandard decline messages customized by the host.

[4] Because a user can be a host in some transactions and a guest in others, she has three ratings: (a) rating as a host, which is the numeric average of ratings—on a scale of 0 to 5—from all her prior guests, (b) rating as a guest, which is the numeric average of ratings—on a scale of 0 to 5—from all her prior hosts, and (c) an overall rating received from all her prior hosts and guests. The three ratings are displayed on the user's profile page, with the overall rating at the top. In my analyses, I use the host's decrease in her overall rating because it is displayed first on the user profile page and she might be responsive to an overall rating decrease. Constructing this variable based on her rating as a host yields largely identical results.

Core to H3 is the availability of judgement-relevant background information and, in the context of my study, homes are the comparison target. Thus, to operationalize the concept in H3— familiarity with prospective exchange partners—I code two dummy variables. First, because hosts are likely to have more background information about domestic guests' homes, there is greater familiarity among same-country users, which facilitates social comparison among them. I code a dummy variable, *same-country guest*, as "1" when the prospective guest's residence is in the same country as the host's, and "0" otherwise. In the estimation sample, 44 percent of lodging requests are from guests in the same country as the host. Second, because people with(out) children might be familiar with each other's housing requirements, hosts with(out) children might be more likely to be prompted to compare themselves with guests with(out) children. I code a dummy variable, *same-child-status guest*, as "1" when both the host and the prospective guest (do not) have children. In the estimation sample, 54 percent of lodging requests are from guests with the same child-status.

Control Variables

I control for several characteristics of the lodging, the guest, and the host that might influence whether a host approves or declines a lodging request.

Lodging. Because interviews with users revealed that hosts vary in their preferences for the duration of a guest's stay, I control for *duration of requested stay* measured in days and *advance notice of request*, the number of days prior to the guest's desired starting date that a host received the request.[5]

[5] A robustness test including these two variables' squared terms yields largely identical results.

Guest. Because hosts might prefer guests with good evaluations, I control for *guest's rating*.[6] For users who have never participated in a transaction on the platform prior to the focal request, their rating is coded as "0." To distinguish these never-transactors from ever-transactors, I include *guest's total prior transactions* in all models.[7] In the estimated sample, 50 percent of lodging requests were sent by guests with no prior transactions. Users can apply to be verified by the platform as having a real offline identity by submitting official documents to the platform and will then have a checkmark on their profiles. I therefore control for a dummy variable *guest identity-verified*. Because hosts might want to repay prospective guests who had previously been their hosts for their past hospitality or might trust prior guests more, they are more likely to approve requests from former exchange partners. I therefore control for a dummy variable, *guest transacted with the host before.* Because a host might prefer guests with popular homes because these homes appeal to the host as well, I control for *guest's home popularity,* measured as the number of requests a guest received in the past month.[8] Because some hosts might prefer guests travelling with children while others might prefer guests without children, I create a dummy variable *guest with children*. Because hosts might differ in their preferences concerning guest age and gender, I control for *guest age, guest-host age difference, female guest requester* (a dummy), and *same-gender guest requester* (a dummy). Because hosts might differ in their

[6] See Footnote 4. In my models, *guest's rating* is the overall rating a guest has received from all her prior hosts and guests. An alternative measure using the guest's rating only as a guest yields largely identical results.

[7] A user's profile page lists the number of transactions as a guest and as a host, plus a total shown at the top. In my analyses, I use the guest's total. An alternative measure using the guest's number of transactions as a guest yields largely identical results. I also create a dummy variable—*guest has prior transactions*—to distinguish never-transactors from ever-transactors. Being highly correlated with guest's ratings, it is not included in the estimation models. In addition, *total prior transactions* correlates with a user's membership tenure—the number of months since registration—at 0.5. To avoid multicollinearity issues, the latter is not included in the estimation models.

[8] Results are robust to alternative measures such as the number of requests each guest received in the past three, six, nine, and twelve months.

preferences regarding a guest's country's level of economic development, I control for the per-capita GDP of the guest's country in the year of the request.

Host. Because the regression models include host fixed effects, I do not control for host characteristics that vary little or not at all over time, such as their age, gender, whether they have children, whether they are identify-verified, and their country's per-capita GDP. Because hosts might be more selective during the peak seasons, I control for *host's home popularity*, measured as the number of requests received by the host in the month prior to the focal request.[9] Because hosts might be less selective when they are low on coins, I control for *host's coin balance*, measured as the number of coins the host has. I control for *host's rating*[10] because it might influence a host's decision-making in two directions: highly rated hosts might be pickier about guest selection in order to defend their ratings records, while low-rated hosts might be more cautious in order to improve their rating records. For users who have never participated in a transaction on the platform prior to the focal request, their rating is coded as "0." To distinguish them, I include *host's total prior transactions* in all models.[11] In the estimated sample, 24 percent of lodging requests were received by hosts with no prior transactions.

Estimation and Results

I test my hypotheses using logistic regression with conditional fixed effects for hosts and report standard errors clustered by host country. In addition to the independent variables and

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[9] Results are robust to alternative measures calculated as the number of requests received in the past three, six, nine, and twelve months.

[10] See Footnote 4. In my models, a host's rating is her overall rating from all prior hosts and guests. An alternative measure using the host's rating only as a host yields largely identical results.

[11] A profile page lists the number of transactions as guests and as hosts and a total shown at the top. In my analyses, I use the host's total. An alternative measure using the host's number of transactions as host yields largely identical results. I also create a dummy variable—*host has prior transactions*—to distinguish never-transactors from ever-transactors. But since it is highly correlated with host's ratings, it is not included in the estimation models. Alternative measure using the guest's number of transactions as guest yields largely identical results.

control variables described above, I also include year fixed effects to capture the aggregate trends. Summary statistics are reported in Table 2, correlations in Tables 3A and 3B, and regression results in Table 4. To facilitate interpretation, I center the continuous variable *guest inferiority* (by subtracting its mean value) because it is included in interaction terms.

Table 2. Summary Statistics

	Sample in Columns (1), (3), and (4) of Table 4				Sample in Column (2) of Table 4			
Variable	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Request approval	0.07	0.26	0	1	0.08	0.26	0	1
Guest inferiority (unit: 100)	-0.10	0.77	-3.44	3.19	-0.09	0.77	-3.44	3.16
Guest inferiority (centered; unit: 100)	0	0.77	-3.34	3.29	0	0.77	-3.35	3.25
Host's rating	3.59	2.04	0	5	4.69	0.38	1.5	5
Host's rating decrease					0.20	0.40	0	1
Host's total prior transactions	3.85	4.44	0	18	7.11	4.67	2	18
Host's home popularity	10.31	10.46	1	52	11.63	10.91	1	52
Host's coin balance (unit: 100)	11.16	6.26	0.1	18.11	11.72	6.83	0.1	18.11
Guest's rating	2.25	2.37	1	5	2.38	2.37	1	5
Guest identity-verified	0.74	0.44	0	1	0.75	0.43	0	1
Guest's total prior transactions	2.38	4.12	0	21	2.59	4.31	0	21
Guest transacted with the host before	0.004	0.06	0	1	0.004	0.09	0	1
Guest's home popularity	3.74	5.17	0	29	3.70	5.17	0	29
Same-country guest	0.44	0.50	0	1	0.46	0.50	0	1
Guest with children	0.54	0.50	0	1	0.53	0.50	0	1
Same-child-status guest	0.53	0.50	0	1	0.53	0.50	0	1
Guest age	44	11	21	72	44	11	21	72
Guest-host age difference	12.03	9.36	0	53	12.24	9.52	0	53
Female guest requester	0.66	0.47	0	1	0.66	0.47	0	1
Same-gender guest requester	0.56	0.50	0	1	0.56	0.50	0	1
Guest country per-capita GDP	35.80	9.69	1.61	96.84	35.77	9.66	1.61	96.84
Advance notice of request	72	66	0	308	71	66	0	308
Duration of requested stay	8	8	1	61	7	7	1	61
	N=432,803				N=190,633			

Table 3A. Correlations

		1	2	3	4	5	6	7	8	9	10	11
1	Request approval	1										
2	Guest inferiority	0.019	1									
3	Host's rating	-0.083	-0.001	1								
4	Host's total prior transactions	-0.033	0.013	0.464	1							
5	Host's home popularity	-0.107	-0.051	0.102	0.159	1						
6	Host's coin balance	-0.012	0.010	0.088	0.095	0.084	1					
7	Guest's rating	0.041	-0.053	0.076	0.068	-0.052	0.044	1				
8	Guest identity-verified	0.041	-0.083	0.027	0.018	-0.028	0.030	0.281	1			
9	Guest's total prior transactions	0.047	-0.043	0.066	0.066	-0.040	0.041	0.590	0.230	1		
10	Guest transacted with the host before	0.138	0.003	0.037	0.047	-0.024	0.014	0.067	0.015	0.074	1	
11	Guest's home popularity	0.006	0.009	-0.004	-0.008	0.008	0.014	0.197	0.175	0.220	0.008	1
12	Same-country guest	0.059	0.042	0.030	0.009	-0.207	-0.035	0.084	0.023	0.057	0.027	-0.080
13	Guest with children	-0.015	-0.114	0.001	-0.011	-0.031	-0.002	0.040	0.102	0.022	-0.006	0.014
14	Same-child-status guest	0.000	0.004	0.000	-0.005	-0.006	-0.004	-0.006	-0.005	-0.005	0.003	-0.003
15	Guest age	0.054	-0.086	0.013	0.021	-0.008	0.018	0.122	0.171	0.157	0.022	0.058
16	Guest-host age difference	-0.003	0.029	0.003	0.021	0.011	0.048	-0.027	-0.042	-0.018	-0.002	-0.026
17	Female guest requester	0.001	0.040	0.005	0.003	0.004	0.001	0.024	-0.020	0.010	-0.001	-0.001
18	Same-gender guest requester	-0.001	0.001	-0.001	0.001	0.001	-0.015	0.008	-0.007	0.002	-0.003	-0.001
19	Guest country per-capita GDP	0.011	0.006	-0.006	-0.009	-0.021	-0.001	0.046	0.086	0.024	0.005	0.048
20	Advance notice of request	-0.034	-0.035	-0.008	-0.020	0.011	0.033	-0.024	0.049	-0.021	-0.016	0.013
21	Duration of requested stay	-0.089	-0.010	-0.048	-0.066	-0.012	-0.020	-0.132	-0.017	-0.092	-0.024	0.026

		12	13	14	15	16	17	18	19	20	21	22
12	Same-country guest	1										
13	Guest with children	0.036	1									
14	Same-child-status guest	0.005	0.031	1								
15	Guest age	0.004	0.044	-0.019	1							

Table 3A (Continued). Correlations

16	Guest-host age difference	0.012	-0.114	-0.036	-0.124	1					
17	Female guest requester	0.021	0.041	-0.001	-0.072	-0.003	1				
18	Same-gender guest requester	0.017	0.015	0.001	-0.025	-0.018	0.318	1			
19	Guest country per-capita GDP	0.097	0.113	0.010	-0.004	0.021	0.061	0.024	1		
20	Advance notice of request	-0.138	0.110	0.010	0.084	-0.037	-0.005	-0.010	0.034	1	
21	Duration of requested stay	-0.083	0.060	0.012	0.010	-0.010	-0.025	-0.012	0.030	0.295	1

Notes: N=432,803. Sample in Columns (1), (3), and (4) of Table 4.

Table 3B. Correlations

		1	2	3	4	5	6	7	8	9	10	11
1	Request approval	1										
2	Guest inferiority	0.028	1									
3	Host's rating	0.021	-0.014	1								
4	Host's rating decrease	-0.011	0.000	-0.284	1							
5	Host's total prior transactions	-0.024	0.011	-0.065	0.023	1						
6	Host's home popularity	-0.115	-0.077	0.001	-0.015	0.140	1					
7	Host's coin balance	-0.005	0.002	0.048	0.009	0.070	0.079	1				
8	Guest's rating	0.047	-0.055	0.024	0.006	0.043	-0.071	0.026	1			
9	Guest identity-verified	0.038	-0.085	0.031	0.001	0.005	-0.043	0.019	0.284	1		
10	Guest's total prior transactions	0.056	-0.052	0.015	0.010	0.047	-0.058	0.026	0.581	0.233	1	
11	Guest transacted with the host before	0.193	0.006	0.007	-0.007	0.023	-0.037	0.014	0.086	0.020	0.096	1
12	Guest's home popularity	-0.001	0.008	0.012	-0.005	-0.007	0.005	0.010	0.196	0.169	0.219	0.011
13	Same-country guest	0.061	0.040	0.030	-0.016	-0.024	-0.199	-0.052	0.087	0.022	0.064	0.034
14	Guest with children	-0.016	-0.113	0.011	-0.001	-0.017	-0.033	-0.010	0.038	0.096	0.024	-0.008
15	Same-child-status guest	0.001	0.003	0.005	0.007	-0.008	-0.011	-0.004	-0.002	-0.003	-0.004	0.004
16	Guest age	0.063	-0.085	0.007	-0.001	0.018	-0.008	0.020	0.122	0.171	0.161	0.030
17	Guest-host age difference	-0.003	0.032	-0.017	0.003	0.023	0.002	0.072	-0.031	-0.044	-0.023	-0.003
18	Female guest requester	0.003	0.038	0.009	-0.003	-0.002	0.006	0.000	0.025	-0.015	0.009	0.000
19	Same-gender guest requester	0.000	-0.002	-0.001	0.002	-0.002	-0.007	-0.019	0.008	-0.004	0.000	-0.004
20	Guest country per-capita GDP	0.014	0.010	0.014	-0.003	-0.012	-0.023	-0.001	0.055	0.084	0.032	0.007
21	Advance notice of request	-0.026	-0.033	0.003	0.003	-0.024	0.004	0.039	-0.031	0.051	-0.027	-0.017
22	Duration of requested stay	-0.086	-0.008	-0.014	-0.003	-0.060	-0.004	-0.010	-0.130	-0.009	-0.087	-0.028

		12	13	14	15	16	17	18	19	20	21	22
12	Guest's home popularity	1										
13	Same-country guest	-0.086	1									
14	Guest with children	0.013	0.037	1								
15	Same-child-status guest	-0.001	0.005	0.029	1							
16	Guest age	0.055	0.005	0.035	-0.019	1						
17	Guest-host age difference	-0.030	0.018	-0.114	-0.040	-0.148	1					
18	Female guest requester	0.003	0.026	0.048	-0.002	-0.063	-0.003	1				
19	Same-gender guest requester	0.000	0.021	0.019	-0.001	-0.021	-0.018	0.318	1			
20	Guest country per-capita GDP	0.048	0.110	0.109	0.010	0.003	0.022	0.064	0.024	1		
21	Advance notice of request	0.014	-0.150	0.107	0.009	0.085	-0.041	-0.006	-0.017	0.026	1	
22	Duration of requested stay	0.029	-0.091	0.063	0.009	0.013	-0.010	-0.024	-0.013	0.024	0.308	1

Notes: N=190,633. Sample in Column (2) of Table 4.

Table 4. Regression Results of Conditional Logit Models

DV: Request approval	(1)	(2)	(3)	(4)
Guest inferiority[c]	0.1780**	0.1970**	0.1528**	0.1623**
	(0.0112)	(0.0194)	(0.0088)	(0.0140)
Guest inferiority[c] × Host's rating decrease		0.0613*		
		(0.0266)		
Guest inferiority[c] × Same-country guest			0.0474**	
			(0.0100)	
Guest inferiority[c] × Same–child-status guest				0.0296**
				(0.0088)
Host's rating	-0.1589**	0.0822	-0.1589**	-0.1589**
	(0.0050)	(0.1056)	(0.0049)	(0.0050)
Host's rating decrease		-0.0481		
		(0.0450)		
Host's total prior transactions	-0.0913**	-0.0998**	-0.0913**	-0.0913**
	(0.0033)	(0.0022)	(0.0033)	(0.0033)
Host's home popularity	-0.0135**	-0.0175**	-0.0135**	-0.0135**
	(0.0025)	(0.0030)	(0.0025)	(0.0025)
Host's coin balance	-0.0754**	-0.0665**	-0.0754**	-0.0754**
	(0.0029)	(0.0050)	(0.0029)	(0.0029)

Table 4 (Continued). Regression Results of Conditional Logit Models

Guest's rating	-0.0178**	-0.0198**	-0.0177**	-0.0178**
	(0.0048)	(0.0046)	(0.0047)	(0.0048)
Guest identity-verified	0.3396**	0.2722**	0.3398**	0.3396**
	(0.0413)	(0.0288)	(0.0414)	(0.0413)
Guest's total prior transactions	0.0124**	0.0117**	0.0125**	0.0124**
	(0.0016)	(0.0018)	(0.0016)	(0.0016)
Guest transacted with the host before	2.8846**	2.9732**	2.8846**	2.8843**
	(0.1033)	(0.0990)	(0.1032)	(0.1033)
Guest's home popularity	-0.0014	-0.0055	-0.0013	-0.0014
	(0.0028)	(0.0045)	(0.0028)	(0.0028)
Same-country guest	0.1159**	0.1299**	0.1135**	0.1159**
	(0.0116)	(0.0087)	(0.0115)	(0.0116)
Guest with children	-0.0713**	-0.0561**	-0.0710**	-0.0740**
	(0.0068)	(0.0127)	(0.0067)	(0.0070)
Same−child-status guest	0.0283**	0.0263+	0.0287**	0.0270**
	(0.0085)	(0.0145)	(0.0085)	(0.0085)
Guest age	0.0171**	0.0186**	0.0171**	0.0171**
	(0.0011)	(0.0009)	(0.0011)	(0.0011)
Guest-host age difference	-0.0063**	-0.0059**	-0.0063**	-0.0063**
	(0.0013)	(0.0010)	(0.0013)	(0.0013)
Female guest requester	0.0192*	0.0252*	0.0191*	0.0192*
	(0.0096)	(0.0113)	(0.0094)	(0.0096)
Same-gender guest requester	-0.0107	-0.0204	-0.0107	-0.0107
	(0.0215)	(0.0206)	(0.0215)	(0.0216)
Guest country per-capita GDP	0.0064**	0.0062**	0.0064**	0.0064**
	(0.0012)	(0.0014)	(0.0012)	(0.0012)
Advance notice of request	0.0006**	0.0007**	0.0006**	0.0006**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Duration of requested stay	-0.1080**	-0.1039**	-0.1080**	-0.1080**
	(0.0039)	(0.0044)	(0.0039)	(0.0039)
Observations	432,803	190,633	432,803	432,803

Notes: Conditional logit models with host and year fixed effects. Robust standard errors clustered by host country in parentheses. Model (2) excludes hosts with only one or no prior transactions.
** p<0.01, * p<0.05, + p<0.1 (two-tailed tests). ^{C} denotes centered.

Model (1) in Table 4 tests H1. The coefficient on *guest inferiority* is positive and statistically significant (β=0.1780, p<0.001), indicating that the more inferior the prospective guest's home is relative to the host's, the more likely the host is to approve her request, which supports H1 that market participants are inclined to seek exchange partners with inferior market standing. For a one-unit increase in guest inferiority (adding 100 coins, or 1.3 standard deviations calculated as 100/77) from the mean (0 coins), the odds of being approved increase by 19 percent (calculated as exp (0.1780) -1), which corresponds to a roughly 20 percent increase from the sample mean. As robustness tests, I reestimate my specifications as linear probability models using ordinary least squares (OLS) with host fixed effects and using the same estimation sample, yielding a nearly identical effect size (see Table 5, Column (1)).

Table 5. Regression Results of Linear Probability Models

DV: Request approval	(1)	(2)	(3)	(4)
Guest inferiority^c	0.0117**	0.0136**	0.0094**	0.0108**
	(0.0013)	(0.0018)	(0.0006)	(0.0015)
Guest inferiority^c × Host's rating decrease		0.0034*		
		(0.0016)		
Guest inferiority^c × Same-country guest			0.0054**	
			(0.0007)	
Guest inferiority^c × Same–child-status guest				0.0017**
				(0.0005)
Host's rating	-0.0117**	0.0038	-0.0117**	-0.0117**
	(0.0007)	(0.0060)	(0.0007)	(0.0007)
Host's rating decrease		-0.0030		
		(0.0032)		
Host's total prior transactions	-0.0072**	-0.0073**	-0.0072**	-0.0072**
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Host's home popularity	-0.0005**	-0.0007**	-0.0005**	-0.0005**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Host's coin balance	-0.0050**	-0.0045**	-0.0050**	-0.0050**
	(0.0001)	(0.0003)	(0.0001)	(0.0001)
Guest's rating	-0.0007+	-0.0011**	-0.0007+	-0.0007+
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Guest identity-verified	0.0173**	0.0137**	0.0172**	0.0173**
	(0.0020)	(0.0018)	(0.0020)	(0.0020)
Guest's total prior transactions	0.0011**	0.0011**	0.0011**	0.0011**
	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Guest transacted with the host before	0.5034**	0.5387**	0.5033**	0.5034**
	(0.0092)	(0.0101)	(0.0092)	(0.0092)
Guest's home popularity	-0.0002	-0.0004	-0.0002	-0.0002
	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Same-country guest	0.0099**	0.0100**	0.0098**	0.0099**
	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Guest with children	-0.0061**	-0.0058**	-0.0061**	-0.0063**
	(0.0007)	(0.0010)	(0.0006)	(0.0007)
Same–child-status guest	0.0015**	0.0018*	0.0016**	0.0015**
	(0.0005)	(0.0008)	(0.0005)	(0.0005)
Guest age	0.0010**	0.0011**	0.0010**	0.0010**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Guest-host age difference	-0.0004**	-0.0004**	-0.0004**	-0.0004**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Female guest requester	0.0012	0.0019*	0.0012+	0.0012
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Same-gender guest requester	-0.0005	-0.0011	-0.0005	-0.0005
	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Guest country per-capita GDP	0.0003**	0.0003**	0.0003**	0.0003**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Advance notice of request	-0.0000+	-0.0000	-0.0000+	-0.0000+
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Duration of requested stay	-0.0027**	-0.0027**	-0.0027**	-0.0027**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Observations	432,803	190,633	432,803	432,803

Notes: Linear probability models with host and year fixed effects. Robust standard errors clustered by host country in parentheses. Model (2) excludes hosts with only one or no prior transactions. ** p<0.01, * p<0.05, + p<0.1 (two-tailed tests). ^{C} denotes centered.

Model (2) in Table 4 tests H2 by adding the interaction term *guest inferiority × host's rating decrease.* This is undefined for request observations for which the host had fewer than two previous transactions; the model therefore drops them. The coefficient on this interaction term is positive and statistically significant (β=0.0613, $p<0.05$), indicating that the positive effect of guest inferiority will be enhanced when the host's rating has decreased, which supports H2 that a decrease in evaluation enhances a market participant's tendency toward downward selection. As a robustness test, I reestimate this specification as a linear probability model with host fixed effects, using the same estimation sample. The positive and statistically significant coefficient on the interaction term provides additional support for H2 (see Table 5, Column (2)), especially given concerns about drawing conclusions from interactions in logistic regression models (Ai and Norton 2003). Moreover, OLS results are helpful in interpreting the effect size: a one-unit increase in guest inferiority increases the probability of approval by 18.6 percent for hosts who do not have a rating decrease but 24.3 percent (a 31-percent difference) for those who do not.

Model (3) in Table 4 tests H3 by adding the interaction term *guest inferiority × same-country guest* to the baseline Model (1). The coefficient on this interaction term is positive and statistically significant ($\beta=0.0459$, $p<0.001$), indicating that the positive effect of guest inferiority will be enhanced when prospective guests are from the same country as the host, which supports H3 that familiarity with prospective exchange partners enhances market participants' tendency toward downward selection. Reestimating this specification as a linear probability model provides additional support for H3 (see Table 5, Column (3)). Based on OLS results, a one-unit increase in guest inferiority increases the probability of being approved by 12.9 percent for international guests but 21.4 percent (a 66-percent difference) for same-country guests.

Model (4) in Table 4 tests H3 by adding the interaction term *guest inferiority × same–child-status guest* to the baseline Model (1). The coefficient on this interaction term is positive and statistically significant ($\beta=0.0296$, $p<0.001$), indicating that the positive effect of guest inferiority will be enhanced when the host and the prospective guest both (do not) have children, which supports H3 that familiarity with prospective exchange partners enhances market participants' tendency toward downward selection. Reestimating this specification as a linear probability model provides additional support for H3 (see Table 5, Column (4)). Based on OLS results, a one-unit increase in guest inferiority increases the probability of being approved by 15 percent for guests with different–child-status but 18 percent (a 20-percent difference) for same–child-status guests.

Turning to control variables in Table 4, lodging requests sent by older, verified, more experienced guests and by prior transaction partners are more likely to be approved.[12] Guest with children are less likely to be approved. In addition, same-gender, same-country, and same–child-status guests are more likely to be approved. As hosts receive more applications and gain more transactions and a higher coin balance, they become pickier. The coefficients on host rating in Models (1) and (3), estimated on the full sample, and in Model (2), estimated on the ever-transactors sample (i.e., hosts with at least two prior transactions), have opposite directions. The negative coefficient on *host's rating* is driven by never-transactors or one-time-transactors, indicating that these hosts are pickier.

Additional Tests

I conduct four sets of additional tests to (a) examine if the results are robust to an alternative modeling approach—linear probability models, (b) rule out alternative mechanisms, and (c) explore whether guest inferiority, as speculated by hosts, indeed influences host's ratings.

First, as aforementioned, there are controversies over testing interaction effects based on the significance of the coefficient on interaction terms in nonlinear models (see (Ai and Norton

[12] The coefficient on guest rating is negatively significant. Guest rating and guest experience are highly correlated ($\rho = 0.5$). I reestimated my main model (Model (1) of Table 3), omitting guest rating and then, separately, omitting guest experience. This marginally reduced the magnitude of the significant positive coefficient on guest experience but led to the coefficient on guest rating becoming nearly 0 and nonsignificant. Thus, the coefficient on guest rating is likely driven by multicollinearity and should be interpreted with caution.

2003; Greene 2010). As robustness tests, I reestimated my specifications as linear probability models using OLS with host fixed effects based on the estimation sample in the primary conditional fixed logit models. These OLS models, reported in Table 5, yielded the same results as the conditional logit models.

Second, one could argue that inferior guests might be more persuasive in applying for lodgings to hosts with nicer homes and superior guests less persuasive with inferior hosts, which could result in the same findings. To test whether guest persuasiveness (a) varies by guest inferiority and (b) influences the outcome (request approval), I analyze the request messages received by hosts. I count the total number of words in the request messages under the assumption that more persuasive messages would be longer because guests might provide more information on their personal background, offer more specific travel plans, and express their interest in the host's place at greater length. Among these messages, the shortest have 23 words and the longest 150 words, with an average of 58. To test whether inferior (superior) guests send longer (shorter) requesting messages, I use an OLS model including host fixed effects and year fixed effects with standard errors clustered by host country. The coefficient on *guest inferiority* is not statistically significant, providing no evidence for the hypothesis that request-message length varies by guest inferiority (see Table 6). To test whether request-message length influences the outcome (request approval), I include this variable in the main analyses and find longer request messages associated with a higher likelihood of approval (see Table 7). Adding this variable does not, however, change previous findings for the hypothesized main relationships in Table 4.

Table 6. OLS Regression Results
(Predicting Length of Request Message)

DV: Initial message length	(1)	(2)
Guest inferiority	0.4682	0.6314
	(0.3501)	(0.3606)
Host's rating	-0.2004**	-0.0616
	(0.0418)	(0.4611)
Host's total prior transactions	-0.0565*	-0.0743**
	(0.0252)	(0.0267)
Host's home popularity	-0.0556**	-0.0383**
	(0.0110)	(0.0097)
Host's coin balance	0.0018	-0.0002
	(0.0104)	(0.0144)
Guest's rating	-0.9044**	-0.9132**
	(0.1146)	(0.1049)
Guest identity-verified	4.4939**	4.8799**
	(0.1866)	(0.1915)
Guest's total prior transactions	0.0989+	0.0904+
	(0.0579)	(0.0459)
Guest transacted with the host before	-10.1864**	-10.4464**
	(0.7808)	(0.7792)
Guest's home popularity	0.0830**	0.0682**
	(0.0164)	(0.0199)
Same-country guest	-3.0623**	-2.8099**
	(0.2868)	(0.1911)
Guest with children	1.6124**	1.4741**
	(0.5673)	(0.4748)
Same−child-status guest	-0.0076	-0.1079
	(0.0738)	(0.1111)
Guest age	-0.1089**	-0.1053**
	(0.0265)	(0.0334)
Guest-host age difference	0.0644**	0.0622**
	(0.0174)	(0.0213)
Female guest requester	-0.2363	0.2852
	(0.3254)	(0.2990)
Same-gender guest requester	0.1316*	0.1489
	(0.0653)	(0.1489)
Guest country per-capita GDP	0.0847**	0.0853**
	(0.0120)	(0.0133)
Advance notice of request	0.0105**	0.0100*
	(0.0029)	(0.0037)
Duration of requested stay	0.3595**	0.4039**
	(0.0316)	(0.0336)
Observations	432,803	190,633

Notes: OLS models with host and year fixed effects. Robust standard errors clustered by host country in parentheses. Model (2) excludes hosts with only one or no prior transactions.** p<0.01, * p<0.05, + p<0.1 (two-tailed tests). ^{C} denotes centered.

Table 7. Regression Results of Conditional Logit Models
(Controlling for Length of Request Message)

DV: Request approval	(1)	(2)	(3)	(4)
Guest inferiority^c	0.1769**	0.1965**	0.1522**	0.1614**
	(0.0119)	(0.0196)	(0.0089)	(0.0148)
Guest inferiority^c × Host's rating decrease		0.0608*		
		(0.0268)		
Guest inferiority^c × Same-country guest			0.0467**	
			(0.0100)	
Guest inferiority^c × Same−child-status guest				0.0294**
				(0.0090)
Host's rating	-0.1586**	0.0825	-0.1586**	-0.1586**
	(0.0049)	(0.1054)	(0.0048)	(0.0049)
Host's rating decrease		-0.0486		
		(0.0448)		
Host's total prior transactions	-0.0913**	-0.0997**	-0.0913**	-0.0913**
	(0.0033)	(0.0023)	(0.0033)	(0.0033)
Host's home popularity	-0.0133**	-0.0174**	-0.0133**	-0.0133**
	(0.0025)	(0.0031)	(0.0025)	(0.0025)
Host's coin balance	-0.0753**	-0.0664**	-0.0753**	-0.0753**

Table 7 (Continued). Regression Results of Conditional Logit Models

	(0.0029)	(0.0050)	(0.0029)	(0.0029)
Guest's rating	-0.0164**	-0.0190**	-0.0163**	-0.0164**
	(0.0054)	(0.0050)	(0.0053)	(0.0054)
Guest identity-verified	0.3325**	0.2681**	0.3327**	0.3325**
	(0.0403)	(0.0280)	(0.0404)	(0.0403)
Guest's total prior transactions	0.0123**	0.0116**	0.0123**	0.0123**
	(0.0016)	(0.0019)	(0.0016)	(0.0016)
Guest transacted with the host before	2.9016**	2.9829**	2.9016**	2.9013**
	(0.1079)	(0.1030)	(0.1079)	(0.1079)
Guest's home popularity	-0.0015	-0.0055	-0.0014	-0.0015
	(0.0028)	(0.0045)	(0.0027)	(0.0028)
Same-country guest	0.1207**	0.1322**	0.1183**	0.1207**
	(0.0117)	(0.0088)	(0.0116)	(0.0117)
Guest with children	-0.0740**	-0.0575**	-0.0737**	-0.0767**
	(0.0071)	(0.0125)	(0.0072)	(0.0074)
Same−child-status guest	0.0287**	0.0267+	0.0290**	0.0274**
	(0.0086)	(0.0147)	(0.0086)	(0.0086)
Guest age	0.0173**	0.0187**	0.0173**	0.0173**
	(0.0011)	(0.0009)	(0.0011)	(0.0011)
Guest-host age difference	-0.0064**	-0.0060**	-0.0064**	-0.0064**
	(0.0012)	(0.0010)	(0.0012)	(0.0012)
Female guest requester	0.0197*	0.0251*	0.0196*	0.0197*
	(0.0099)	(0.0114)	(0.0098)	(0.0099)
Same-gender guest requester	-0.0111	-0.0206	-0.0110	-0.0111
	(0.0216)	(0.0208)	(0.0216)	(0.0217)
Guest country per-capita GDP	0.0062**	0.0061**	0.0062**	0.0062**
	(0.0012)	(0.0014)	(0.0012)	(0.0012)
Advance notice of request	0.0005**	0.0007**	0.0005**	0.0005**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Duration of requested stay	-0.1087**	-0.1044**	-0.1088**	-0.1087**
	(0.0041)	(0.0046)	(0.0041)	(0.0041)
Request message length	0.0017*	0.0009	0.0016*	0.0017*
	(0.0007)	(0.0006)	(0.0007)	(0.0007)
Observations	432,803	190,633	432,803	432,803

Notes: Conditional logit models with host and year fixed effects. Robust standard errors clustered by host country in parentheses. Model (2) excludes hosts with only one or no prior transactions. ** p<0.01, * p<0.05, + p<0.1 (two-tailed tests). ^{C} denotes centered.

Third, a related concern is that guest profile pictures and guest home pictures—conveying information on the guest's ethnicity, physical attractiveness, and social class—might make a difference. Unfortunately, I am not able to attain user pictures from this platform company. To rule out these possibilities, in unreported analyses, I reestimate the main effect using two alternative models that account for guest heterogeneity—a conditional logit model with guest fixed effects and a logit model with standard errors clustered both by guests and by hosts. Both of these models yield consistent results supporting the main hypothesis: the more inferior a guest's home is, the more likely she is to be accepted by the host. This is consistent with prior research using internal data from Airbnb that shows that profile pictures do not have a significant impact on hosts' decisions (Fradkin et al. 2015).

Fourth, a home's coins-per-night is calculated based on the home's location, size, and facilities, but one could argue that homes' coins-per-night differences might not accurately approximate user's expectations because of the location factor. A Manhattan studio could be worth more than a countryside house, yet not as nice or comfortable. To tease out the location factor, I use an alternative measurement for *guest inferiority*—home deposit rates—calculated by the platform based only on the home's size and facilities. Home deposit rates are also displayed to every user. Reestimations of my hypotheses using this alternative measurement yield similar results (see Table 8).

Table 8. Regression Results of Conditional Logit Models
(Measuring Guest Inferiority by Home Deposit Differences)

DV: Request approval	(1)	(2)	(3)	(4)
Guest inferiority[c]	0.0181**	0.0201**	0.0170**	0.0161**
	(0.0007)	(0.0012)	(0.0013)	(0.0013)
Guest inferiority[c] × Host's rating decrease		0.0056*		
		(0.0026)		
Guest inferiority[c] × Same-country guest			0.0020+	
			(0.0011)	
Guest inferiority[c] × Same–child-status guest				0.0037*
				(0.0014)
Host's rating	-0.1589**	0.0841	-0.1589**	-0.1589**
	(0.0050)	(0.1046)	(0.0050)	(0.0050)
Host's rating decrease		-0.0495		
		(0.0451)		
Host's total prior transactions	-0.0914**	-0.0999**	-0.0914**	-0.0914**
	(0.0033)	(0.0023)	(0.0033)	(0.0033)
Host's home popularity	-0.0135**	-0.0175**	-0.0135**	-0.0135**
	(0.0025)	(0.0030)	(0.0025)	(0.0025)
Host's coin balance	-0.0754**	-0.0665**	-0.0754**	-0.0754**
	(0.0029)	(0.0049)	(0.0029)	(0.0029)
Guest's rating	-0.0186**	-0.0206**	-0.0186**	-0.0186**
	(0.0048)	(0.0046)	(0.0048)	(0.0048)
Guest identity-verified	0.3360**	0.2664**	0.3359**	0.3360**
	(0.0414)	(0.0286)	(0.0414)	(0.0414)
Guest's total prior transactions	0.0116**	0.0106**	0.0116**	0.0116**
	(0.0015)	(0.0018)	(0.0015)	(0.0015)
Guest transacted with the host before	2.8801**	2.9666**	2.8802**	2.8796**
	(0.1043)	(0.0999)	(0.1044)	(0.1042)
Guest's home popularity	-0.0024	-0.0066	-0.0023	-0.0024
	(0.0028)	(0.0045)	(0.0028)	(0.0028)
Same-country guest	0.1220**	0.1369**	0.1203**	0.1221**
	(0.0130)	(0.0108)	(0.0131)	(0.0130)
Guest with children	-0.0603**	-0.0431**	-0.0602**	-0.0645**
	(0.0073)	(0.0135)	(0.0074)	(0.0075)
Same–child-status guest	0.0286**	0.0267+	0.0288**	0.0259**
	(0.0085)	(0.0147)	(0.0086)	(0.0087)
Guest age	0.0172**	0.0187**	0.0172**	0.0172**
	(0.0011)	(0.0009)	(0.0011)	(0.0011)
Guest-host age difference	-0.0063**	-0.0060**	-0.0063**	-0.0063**
	(0.0013)	(0.0010)	(0.0013)	(0.0013)
Female guest requester	0.0269**	0.0329**	0.0268**	0.0269**
	(0.0097)	(0.0115)	(0.0097)	(0.0097)
Same-gender guest requester	-0.0108	-0.0202	-0.0107	-0.0107
	(0.0214)	(0.0205)	(0.0213)	(0.0215)

Table 8 (Continued). Regression Results of Conditional Logit Models

Guest country per-capita GDP	0.0067**	0.0066**	0.0067**	0.0067**
	(0.0012)	(0.0014)	(0.0012)	(0.0012)
Advance notice of request	0.0006**	0.0008**	0.0006**	0.0006**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Duration of requested stay	-0.1079**	-0.1039**	-0.1079**	-0.1079**
	(0.0039)	(0.0044)	(0.0039)	(0.0039)
Observations	432,803	190,633	432,803	432,803

Notes: Conditional logit models with host and year fixed effects. Robust standard errors clustered by host country in parentheses. Model (2) excludes hosts with only one or no prior transactions. ** p<0.01, * p<0.05, + p<0.1 (two-tailed tests). ^{C} denotes centered.

Fifth, the main estimation models controlled for host's home popularity (i.e., the number of requests received by the host) and advance notice of stay to account for potential competing offers a host might receive for a given time period. Alternatively, as robustness tests, I examine a host's selection of guests who request exactly the same time window (i.e., same starting dates and ending dates). Among the 432,803 requests in the main sample in Table 3, 92.7% do not compete with others for exactly the same window. Among the remaining 31,737 requests that compete for give time windows, the conditional logit model drops hosts how declined all requests thus exhibited no variation in acceptance, leaving 2,115 observations with 984 acceptance. Estimations based on this sample yield consistent support for all hypotheses, as reported in Table 9.

Table 9. Conditional Logit Models with Host-Window Fixed Effects

DV: Request approval	(1)	(2)	(3)	(4)
Guest inferiority^{c}	0.1775*	0.2230**	0.1294*	0.1693*
	(0.0767)	(0.0828)	(0.0650)	(0.0819)
Guest inferiority^{c} × Host's rating decrease		0.0860*		
		(0.0434)		
Guest inferiority^{c} × Same-country guest			0.0489*	
			(0.0245)	
Guest inferiority^{c} × Same–child-status guest				0.0501+
				(0.0284)
Host's rating	-0.1645*	0.3509	-0.1635*	-0.1667*
	(0.0713)	(0.8926)	(0.0706)	(0.0721)
Host's rating decrease		-0.2032		
		(0.2605)		
Host's total prior transactions	-0.0358**	-0.0345**	-0.0354**	-0.0366**
	(0.0050)	(0.0070)	(0.0047)	(0.0038)
Host's home popularity	-0.0076	-0.0063	-0.0076	-0.0076
	(0.0153)	(0.0155)	(0.0153)	(0.0150)
Host's coin balance	-0.0404+	-0.0514*	-0.0401+	-0.0408+
	(0.0243)	(0.0213)	(0.0218)	(0.0244)
Guest's rating	-0.0413**	-0.0270	-0.0412**	-0.0404**
	(0.0145)	(0.0346)	(0.0142)	(0.0151)
Guest identity-verified	0.2632**	0.1359*	0.2630**	0.2606**
	(0.0833)	(0.0693)	(0.0828)	(0.0840)
Guest's total prior transactions	0.0051	0.0059	0.0051	0.0060
	(0.0055)	(0.0062)	(0.0054)	(0.0060)
Guest transacted with the host before	2.8323**	2.8068**	2.8355**	2.8259**

Table 9 (Continued). Conditional Logit Models with Host-Window Fixed Effects

	(0.4619)	(0.5836)	(0.4732)	(0.4621)
Guest's home popularity	-0.0044	0.0021	-0.0045	-0.0051
	(0.0063)	(0.0143)	(0.0062)	(0.0067)
Same-country guest	0.2065**	0.2046**	0.2089**	0.2015**
	(0.0750)	(0.0718)	(0.0812)	(0.0753)
Guest with children	-0.1054	-0.0197	-0.1069	-0.0835
	(0.0700)	(0.0793)	(0.0737)	(0.0773)
Same–child-status guest	0.0608	-0.0172	0.0601	0.0581
	(0.0636)	(0.0549)	(0.0643)	(0.0639)
Guest age	0.0154**	0.0178**	0.0154**	0.0153**
	(0.0031)	(0.0050)	(0.0030)	(0.0030)
Guest-host age difference	-0.0057	-0.0138*	-0.0056	-0.0056
	(0.0045)	(0.0063)	(0.0045)	(0.0045)
Female guest requester	0.1387+	-0.1856+	0.1385+	0.1344+
	(0.0803)	(0.1049)	(0.0797)	(0.0791)
Same-gender guest requester	-0.1738	-0.0364	-0.1726	-0.1758
	(0.1120)	(0.0630)	(0.1108)	(0.1162)
Guest country per-capita GDP	0.0024+	0.0054	0.0025+	0.0025+
	(0.0014)	(0.0053)	(0.0014)	(0.0013)
Advance notice of request	0.0143**	0.0199**	0.0143**	0.0143**
	(0.0023)	(0.0032)	(0.0023)	(0.0023)
Duration of requested stay	NA	NA	NA	NA
Observations	2,117	1,156	2,117	2,117

Notes: Conditional logit models with host-window and year fixed effects. Robust standard errors clustered by host country in parentheses. Model (2) excludes hosts with only one or no prior transactions. ** p<0.01, * p<0.05, + p<0.1 (two-tailed tests). ^{C} denotes centered

Sixth, one could argue that guest inferiority and request approval might exhibit an inverted-U-shaped relationship because hosts may avoid guests whose homes are far inferior thus are at the very lower end of the market hierarchy. In unreported analyses, I investigate this possibility by adding a squared term of guest inferiority to the baseline Model (1) in Table 4. While the coefficients on Guest inferiority (β=0.1657, p<0.001) and the square term Guest inferiority squared (β=-0.0274, p<0.001) are statistically significant, suggesting an inverted-U-shaped curve that peaks when Guest inferiority reaches 3.02, the BIC difference between this and the baseline model is 0.245, far below the minimum BIC difference of 6 for a meaningful model improvement (Jeffreys, 1961; Raftery, 1995).

Lastly, does guest inferiority really influence ratings? In the analyses, I show that hosts seek inferior guests whom they anticipate are easier to satisfy. Here, I explore whether guest-host relative market standing indeed influences hosts' ratings after the transactions. Both parties are allowed to review each other, so people may under-report negative ratings for fear of retaliatory negative ratings and research has found that people tend to report positive (negative) ratings after they receive positive (negative) ratings (Dellarocas and Wood 2008; Fradkin et al. 2018; Zervas et al. 2015). I therefore look at hosts' ratings made by guests who had not been rated by those hosts (Table 10) and, separately, hosts' ratings made by guests who had been rated by those hosts (Table 11). Results in both tables provide no evidence that guest inferiority is associated with hosts' overall ratings or with the subcategory ratings, communication and home description. But results in Table 11 do show a significantly positive relationship between guest inferiority and the *perceived cleanness and tidiness* of the host's home by guests who had been rated by the same host (see Model (4)). This indicates that guests with inferior homes may be more impressed by the cleanness and tidiness of the host's home.

Table 10. OLS Regression Results
(Predicting Host's Rating Before Guests Were Rated)

	Model (1)	Model (2)	Model (3)	Model (4)
DV	*Host's rating score*	*Subscore 1: Good communication*	*Subscore 2: Host home is as described*	*Subscore 3: Host home is clean and tidy*
Guest inferiority	-0.0116	-0.0261	-0.0125	0.0038
	(0.0189)	(0.0174)	(0.0243)	(0.0263)
Guest's rating for all prior transactions	0.0028	0.0032	-0.0005	0.0058
	(0.0047)	(0.0079)	(0.0042)	(0.0059)
Guest identity-verified	0.0076	0.0353	-0.0042	-0.0084
	(0.0262)	(0.0338)	(0.0323)	(0.0285)
Guest's total prior transactions	0.0033	0.0028	0.0029	0.0043
	(0.0023)	(0.0031)	(0.0024)	(0.0037)
Guest transacted with the host before	0.0468*	0.0189	0.0349**	0.0867+
	(0.0179)	(0.0237)	(0.0105)	(0.0432)
Guest's home popularity	-0.0001	-0.0004	0.0003	-0.0003
	(0.0046)	(0.0028)	(0.0058)	(0.0056)
Same-country guest	0.0296	0.0443*	0.0504	-0.0061
	(0.0183)	(0.0207)	(0.0301)	(0.0429)
Guest with children	-0.0082	-0.0143	0.0094	-0.0199
	(0.0165)	(0.0183)	(0.0239)	(0.0272)
Same–child-status guest	0.0091	0.0179	-0.0005	0.0098
	(0.0253)	(0.0230)	(0.0261)	(0.0325)
Guest age	-0.0034*	-0.0036*	-0.0038**	-0.0027
	(0.0014)	(0.0014)	(0.0013)	(0.0019)
Guest-host age difference	-0.0007	-0.0013	-0.0008	0.0001
	(0.0015)	(0.0010)	(0.0023)	(0.0018)
Female guest requester	-0.0032	0.0085	0.0063	-0.0244
	(0.0414)	(0.0359)	(0.0288)	(0.0629)
Same-gender guest requester	0.0235	0.0279	0.0235	0.0191
	(0.0412)	(0.0365)	(0.0520)	(0.0377)
Guest country per-capita GDP	-0.0004	-0.0001	-0.0009	-0.0000
	(0.0013)	(0.0022)	(0.0011)	(0.0021)
Advance notice of request	-0.0001	-0.0001	0.0002	-0.0003
	(0.0002)	(0.0001)	(0.0002)	(0.0003)
Duration of requested stay	-0.0041	-0.0031	-0.0023	-0.0068
	(0.0030)	(0.0023)	(0.0037)	(0.0047)
Host's total prior transactions	-0.0047	-0.0028	-0.0041	-0.0074
	(0.0039)	(0.0054)	(0.0042)	(0.0058)
Host's home popularity	-0.0030+	-0.0024	-0.0041+	-0.0025
	(0.0017)	(0.0021)	(0.0023)	(0.0019)

Table 10 (Continued). OLS Regression Results

Host's coin balance	-0.0006	-0.0027	-0.0004	0.0012
	(0.0031)	(0.0047)	(0.0036)	(0.0034)
Observations	8,133	8,133	8,133	8,133

Notes: OLS models with host and year fixed effects. Robust standard errors clustered by host country in parentheses. ** p<0.01, * p<0.05, + p<0.1 (two-tailed tests).

Table 11. OLS Regression Results
(Predicting Host's Rating After Guests Were Rated)

	Model (1)	Model (2)	Model (3)	Model (4)
DV	*Host's rating score*	*Subscore 1: Good communication*	*Subscore 2: Host home is as described*	*Subscore 3: Host home is clean and tidy*
Guest inferiority	0.0088	0.0045	0.0037	0.0180*
	(0.0070)	(0.0050)	(0.0092)	(0.0084)
Guest's rating for the focal transaction	0.4259**	0.4727**	0.3671**	0.4379**
	(0.0659)	(0.0795)	(0.0745)	(0.0504)
Guest's rating for all prior transactions	0.0016	0.0002	0.0018	0.0026*
	(0.0017)	(0.0017)	(0.0029)	(0.0013)
Guest identity-verified	-0.0110	-0.0150+	-0.0053	-0.0127
	(0.0107)	(0.0084)	(0.0119)	(0.0130)
Guest's total prior transactions	0.0026*	0.0026*	0.0019*	0.0033*
	(0.0011)	(0.0012)	(0.0009)	(0.0015)
Guest transacted with the host before	0.0252	0.0166	0.0235	0.0357
	(0.0235)	(0.0169)	(0.0277)	(0.0283)
Guest's home popularity	-0.0002	-0.0005	-0.0000	0.0001
	(0.0007)	(0.0008)	(0.0009)	(0.0009)
Same-country guest	-0.0019	0.0114	-0.0080	-0.0092
	(0.0102)	(0.0146)	(0.0135)	(0.0172)
Guest with children	0.0033	0.0093	0.0055	-0.0048
	(0.0050)	(0.0113)	(0.0065)	(0.0113)
Same–child-status guest	0.0139	0.0101	0.0174	0.0141
	(0.0093)	(0.0088)	(0.0119)	(0.0094)
Guest age	-0.0013**	-0.0011**	-0.0020**	-0.0009*
	(0.0003)	(0.0004)	(0.0003)	(0.0004)
Guest-host age difference	-0.0002	-0.0003	-0.0003	-0.0000
	(0.0006)	(0.0006)	(0.0009)	(0.0005)
Female guest requester	-0.0110+	-0.0075	-0.0151*	-0.0103
	(0.0056)	(0.0122)	(0.0057)	(0.0066)
Same-gender guest requester	-0.0077	-0.0093	-0.0057	-0.0083
	(0.0116)	(0.0093)	(0.0062)	(0.0222)
Guest country per-capita GDP	-0.0001	-0.0004	-0.0001	0.0001
	(0.0005)	(0.0006)	(0.0004)	(0.0005)
Advance notice of request	-0.0001*	-0.0000	-0.0001	-0.0001*
	(0.0000)	(0.0001)	(0.0001)	(0.0001)
Duration of requested stay	-0.0014	-0.0009	-0.0016	-0.0018
	(0.0022)	(0.0025)	(0.0016)	(0.0027)
Host's total prior transactions	0.0003	0.0000	-0.0006	0.0015
	(0.0010)	(0.0009)	(0.0015)	(0.0010)
Host's home popularity	0.0008	-0.0008	0.0007	0.0024
	(0.0009)	(0.0011)	(0.0004)	(0.0016)
Host's coin balance	0.0000	-0.0004	-0.0002	0.0006
	(0.0003)	(0.0006)	(0.0004)	(0.0006)
Observations	18,087	18,087	18,087	18,087

Notes: OLS models with host and year fixed effects. Robust standard errors clustered by host country in parentheses. ** p<0.01, * p<0.05, + p<0.1 (two-tailed tests).

Supplementary Qualitative Data and Findings

To illuminate the underlying mechanisms, I complemented the quantitative analyses with qualitative interviews. The purpose of these interviews was not to test hypotheses but, rather, to add some nuance to the analyses. I conducted one-on-one semi-structured interviews (40–90 minutes) with executives of the platform company and platform users. Interviews with executives helped me understand the design and operation of the platform, problems and complaints reported by users, and the company's responses. To solicit user interviewees, I worked with the Customer Service Department[13] to send out a system message to all users. Voluntary participants then emailed me to schedule a one-on-one interview via Skype/WhatsApp/FaceTime, with the understanding that their personal information would remain confidential (see Table 12 for the list of interviewees). During these interviews, participants were asked to describe (a) their motivation to join this community, (b) their reasons to select/decline a transaction partner, and (c) their most/least enjoyable transaction experiences. I recorded and transcribed these interviews with the participants' permission.

Table 12 List of Interviewees

Interviewees	Positions/Characteristics
6 executives of the platform company	▪ CEO & Co-founder ▪ Head of Public Relations ▪ Head of Technology ▪ Head of Data & Research ▪ Head of Customer Service ▪ Head of Client Service
45 platform users	a) 27 females. b) Ages range from 40 to 78 with an average of 59. c) Number of transactions conducted ranges from 0 to 55 with an average of 15. d) From Australia, Belgium, Canada, France, Italy, Japan, New Zealand, Spain, Switzerland, UK, and US.

My qualitative data offered numerous illustrations of the finding that concerns for evaluations prevail in this peer-to-peer lodging market. People develop a personal attachment to and pride in their homes and therefore have a strong desire for positive feedback on them. Asked to describe their favorite experiences, almost all hosts highlight guests who have appreciated and complimented their homes. As one host noted representatively:

> I read every comment… My guests appreciated my place and my service. I like to show people around my place, especially my garden… I clean the place for my guests [before

[13] All department names in the text and in tables are pseudonyms to protect confidentiality.

> they arrive]. Sometimes my guests left with an even cleaner place, and a bottle of wine for me! (User #26)

> I have paintings and other artworks in my place. It is a great house, and I put a lot of effort into it… You can tell that lots of people [on the platform] do not have nice places as mine. I like to invite people over. They will see what a great place it is. (User #9)

However, the market is rife with ambiguity concerning expectations; people have different standards for a roomy, clean, and comfortable home. When describing unpleasant experiences, interviewees frequently mentioned homes they visited that were not as nicely equipped or neatly arranged as they had expected or guests who were disappointed with the interviewee's own home:

> We only got a 4 [star] in "cleanliness." I do not know what they want from us. Of course we clean the home for our guests. But after all, it's a home, not a hotel. It cannot be perfect. (User #30)

> We went to Barcelona last summer... The place was fine. It was just too noisy for me... I read all reviews online before I booked it. Everyone said it was quiet. I didn't think so. (User #12)

When accommodating guests with better homes, hosts are concerned that the guests will be disappointed; in contrast, when accommodating guests with inferior homes, these concerns are less prominent. Many host interviewees described feeling nervous and embarrassed when they found their homes were far inferior to their guests' homes. In contrast, hosts believed that guests with inferior homes were more likely to be impressed by the host's home. As one host noted representatively:

> I wouldn't want to do it with [host] people who have much nicer homes. I'm not sure if my place can live up to their expectations. I had a family who came to my place before. My husband and I went to their place a few months later, and we were shocked. We felt quite embarrassed about ourselves. Their place is so much better. (User #5)

Hosts' evaluation concerns peak with low ratings. The head of the Customer Service Department reveals that over 90 percent of user complaints are about ratings and that resolving disputes over ratings is a significant part of their work:

> People take ratings very personally. It is difficult for them to accept a 3-star rating. They get annoyed. Some people call us multiple times to try to convince us it was not their fault and they deserved better ratings. (Senior Manager #2)

Many hosts who received unsatisfactory ratings attributed them to unmet expectations. When hosts face a rating decrease, they rely more than they otherwise would on their existing assumptions of guests' expectations, becoming even more likely to select guests with inferior market standing who they believe might be easier to satisfy. One host explained:

> I hosted one couple last summer. They did not give me 5 [stars]. I guess they expected more. My place is cozy but small. I locked the bedroom closet because I had my stuff in it. Maybe they wanted more space. Their place looks a lot bigger. (User #19)

Although primarily illustrative rather than conclusive, these qualitative data shed some light on how evaluation anxiety drive people to exercise strategic downward selection in this empirical context. People avoid guests with superior homes for fear of not getting good ratings and losing face. Instead, a host pursues guests with inferior homes, with the anticipation that the more inferior the guests' homes are in comparison to hers, the more likely they will be impressed by her homes, appreciate her offering, and provide her good ratings.

DISCUSSION

The key proposition of this study is that anxieties over evaluation influence one's selection of exchange partners. I offer an agentic perspective that market participants proactively exercise strategic downward selection of inferior transaction partners to achieve favorable feedback. When evaluations are critical but standards are ambiguous, market participants infer counterparties' expectations from relative market standing. Those with superior market standing are assumed to have expectations of a transaction that are higher and therefore harder to meet. Thus, driven by evaluation anxiety, market participants select inferior partners to garner positive evaluations. Data from a peer-to-peer lodging platform substantiate my theory: hosts are more likely to approve lodging requests from guests with inferior homes, the more so when hosts' evaluation anxiety intensifies because they recently had a decrease in rating and when hosts are more familiar with the comparison group.

Scope Condition

Before discussing this theory's broader implications, it is important to make explicit the scope condition that delimits its generalizability. First, an important premise is the absence of objective evaluation standards for a given transaction. Differences in evaluation-relevant dimensions therefore become heuristics with which market participants infer counterparties' evaluation standards. In contexts in which objective standards are available, this process might not be as pronounced. Second, this theory does not claim applicability to contexts in which ratings are not equally-weighted; that is, contexts in which evaluations made by partners with superior standing carry more weight. In such situations, actors might be more motivated to seek endorsement from those with higher market standing. But many peer-to-peer platform markets—such as Upwork, TaskRabbit, and Airbnb—and many other evaluation systems—such as entrepreneurs' ratings of venture capital firms (e.g., TheFunded.com) and instructor evaluations—do not incorporate raters' positions in their algorithmic calculations of ratings.

Contribution to the Literature on Evaluation and Exchange Partner Selection

The puzzle this paper aims to tackle is why, in some economic exchanges, actors with inferior market standing are more sought after despite having fewer instrumental resources and being less prominent. To date, the scholarship on exchange partner selection offers two main considerations: the need for instrumental resources (Merton 1968; Sauder et al. 2012; Stuart et al. 1999) and the need for coordination deference (e.g., Cowen 2012; Trapido 2013). It has rarely considered post-hoc evaluations by exchange partners, a material factor in some decision-making situations. When one's success depends heavily on an interactant's evaluation, one might give that outcome greater weight than other considerations. Recognizing the implications of counterparty evaluations on partner selection highlights an important yet under-explored contingency to the formation of partnerships in market exchanges.

Furthermore, a long line of evaluation research, emphasizing a structural view, focuses on *expectations for actors holding superior (inferior) positions*; they are expected to have higher (lower) performance and values (e.g., Berger et al. 1972; Lyness and Heilman 2006; Ridgeway and Correll 2006; Tsui and O'Reilly 1989; Umphress et al. 2007). The central tenet is that structural superiority can induce favoritism and skew ratings—a structural perspective that emphasizes how evaluations are determined by social position. This strand of research says little, however, about agency; that is, how people can choose with whom they interact and by whom they are evaluated. To illustrate agency in evaluation dynamics, I look at a different question: *anticipation of these actors' expectations*. Specifically, people anticipate that superior (inferior) actors have higher (lower) expectations and demands on their exchange partners. I propose an agentic view that people can strategically select transaction partners based on these anticipations in order to gain favorable evaluations, even though their access to information (i.e., about their counterparties' actual expectations) might be incomplete.

My focus on this agentic strategy based on social comparison of market standing also extends the symbolic interactionalism tradition that has long contended that anticipation of key interactants' beliefs influences one's decision making (Goffman 1959, 1967; Troyer and Younts 1997; Webster and Whitmeyer 1999). Recent developments in this tradition—emphasizing roles and stereotypes as heuristics in anticipating counterparties' preferences (Correll et al. 2017; Sharkey and Kovács 2018; Smith and Gaughan 2016)—have not yet highlighted the social comparison perspective. I propose that in some contexts, social comparison is also critical for anticipating interactants' beliefs. With the assumption that superior (inferior) partners have higher (lower) standards and expectations concerning a given transaction, the focal actor anticipates devaluation (appreciation) from those counterparties. This view also offers a novel extension to the social comparison literature, which has largely involved self-regarding contexts such as self-appraisal (e.g., Buunk and Gibbons 2007; Garcia et al. 2010). My research shows that in *other-regarding* contexts, in which one is concerned about how one is seen by key interactants, one may also actively shape the comparison context by avoiding superior interactants.

Lastly, this study contributes to our knowledge of market participants' reactions to evaluative measures by highlighting how those measures could distort the formation of partnerships in market exchanges. The literature has extensively documented how organizations change their status quo to meet external evaluation standards (Chatterji and Toffel 2010; Espeland and Sauder 2007; Sauder and Espeland 2009; Sharkey and Bromley 2014); selection is a different strategy. Admittedly, studies have already shown "rating shopping" in other empirical contexts; for example, securities issuers solicit ratings from multiple agencies and choose the most favorable (Bolton, Freixas, and Shapiro 2012; Sangiorgi and Spatt 2017) and drivers seek auto emission testing stations with more lax standards (Bennett et al. 2013). But in these contexts, ratings provided by professional monitors or expert evaluators are in fact the goods/services to be transacted. In my study, however, evaluations are provided by one's partners and are not intended to be the ends but rather the means to ensure the quality of economic exchanges.

Contribution to the Literature on Platform Markets

The platform literature having so far focused on post-hoc strategies that distort ratings after transactions are consummated, there is a dearth of research on the occurrence of a transaction. For instance, studies show that when both parties are allowed to review each other, participants under-report negative ratings for fear of retaliatory negative ratings (Dellarocas and Wood 2008; Fradkin et al. 2018; Zervas et al. 2015). There are also strong norms for reciprocity, such that participants are inclined to submit a positive (negative) rating after receiving positive (negative) feedback from the transaction partner (Bolton et al. 2013; Diekmann et al. 2014). These strategies distort ratings such that ratings on many platforms become overwhelmingly positive, giving rise to "rating inflation" (Hu, Zhang, and Pavlou 2009). Unlike those studies, mine looks at the occurrence of a transaction from a partner selection perspective because selection is a necessary prerequisite to the ratings. This study casts light on whether market participants have equal access to material opportunities in these platform markets and, if not, which participants are favored. My approach identifies dynamics of selection and reveals another potential explanation for rating inflation in peer-to-peer platform markets. Answers to these questions can inform platform designers.

Although this form of strategic selection does not apply to all peer-to-peer platform markets, it may exist in some other platforms on which comparison of relative standing in the market hierarchy is possible. For instance, Uber or Lyft drivers with cheap vehicles might avoid very rich neighborhoods for the fear that their vehicles' conditions will be unsatisfactory to those passengers. Schor et al.'s (2016) ethnographic study of the food swapping market, in which people trade homemade food, finds that despite the industry's hospitable language, some individuals cautiously gauge whether their homemade food is considered as "real food" or considered appropriate or desired by their upper-class counterparties and decide whether to swap with them based on these anticipations. Identifying these selection behaviors reveals how sharing-economy platforms can be at risk of not adhering to the sharing ethos. (Edelman, Luca, and Svirsky 2017) find that Black guests are less likely to be accepted by hosts on Airbnb, but their study cannot distinguish whether such selection is based on race or socioeconomic status. Findings from my theory could help disentangle these factors: if being Black is simply a signal for lower socioeconomic status, hosts might not avoid those guests who are likely to be satisfied with their listings.

Lastly, as evidence from this study and other work on peer-to-peer marketplaces suggests, evaluations in these contexts are different from evaluations in more conventional businesses contexts because numeric ratings are taken personally and have important implications for self-perception. This substantiates propositions by research on commensuration and market penetration that commensuration is necessary for the market, but it transforms qualities into quantities and difference into magnitude, which can jeopardize or discount some components of the self. Ratings of one's home are a quantification of one's personal and intimate space. The literature has identified a few mechanisms by which market actors refuse market penetration and commensuration, such as claiming certain objects to be incommensurable (Espeland and Stevens 1998; Raz 1986; Zelizer 1989, 1994) and creating a distinct narrative to insulate oneself from the broader practices (Anteby 2010). The downward selection behavior observed in my study is another strategy that market actors undertake to proactively defend their personal image in sharing-economy platforms on which individuals' personal resources—such as their skills, time, or homes—are evaluated and ranked.

CHAPTER 3.

Seal of Approval?

Trust Signals and Cultural Distance in Global Peer-to-peer Platform Markets

Social bias and associated distrust towards certain social groups exist widely in markets, putting some market participants in disadvantaged positions while advantaging others (Becker 1957; Berger et al. 1972; Foschi 2000; Tajfel 1978). To overcome these bias and distrust so that economic exchanges can cross social boundaries, various quality signals such as credentials and ratings are therefore instituted (Cook, Hardin, and Levi 2005; Woolthuis, Hillebrand, and Nooteboom 2005). Yet, quality signals may benefit different social groups unequally. An unresolved yet consequential question is: Do these quality signals narrow or widen the gap between socially advantaged and disadvantaged market participants? Addressing this question helps shed light on the theoretical debate over the social distortion of market information, and might also provide important insights for market designers and policy makers.

The literature holds contradictory perspectives on this question. Studies of discrimination and double standards show that the audience discounts information about socially disadvantaged groups, giving a further advantage to those already advantaged and thus widening the gap between advantaged and disadvantaged groups (Bertrand and Mullainathan 2004; Biernat and Kobrynowicz 1997; Foschi 2000; Foschi, Lai, and Sigerson 1994; Heilman 2001; Lahey 2008). But other research along the line of information economics contends that quality information may disproportionately benefit a disadvantaged group because it updates the audience's perception of that group to a greater positive extent, thus narrows the gap between advantaged and disadvantaged groups (Arcidiacono, Bayer, and Hizmo 2010; Lang and Manove 2011; Lendle et al. 2016; Neal and Johnson 1996).

In this study, drawing on sociological theories of the production of trust that highlight how various social systems act as different sources of trust (Zucker 1986), I offer a new perspective to this puzzle by comparing two types of quality signal: *process-based* signals (such as ratings or recommendations) tied to a record of prior exchanges and provided by prior exchange partners, and, *institutional-based* signals (such as credentials or accreditation) tied to organizational institutions (Schofer and Meyer 2005; Williamson 1981; Zucker 1986). I propose that process-based quality signals could widen the gap between socially advantaged and disadvantaged groups because this information is provided by transaction partners engaged in past exchanges, thus might be seen by the audience as reflecting these prior partners' idiosyncratic opinions – this information of the disadvantaged group might be discounted by the audience. In contrast, institutional-based quality signals are provided by organizational institutions and might be viewed by the audience as reflecting an institution's generic opinions and thus are less subject to social distortion; thus, quality information by institutions might disproportionally benefit the disadvantaged group because it updates the audience's perception of that group to a greater positive extent, narrowing the gap in their perceived quality relative to that of the advantaged group.

I test my propositions in the context of peer-to-peer platform markets. A few characteristics make these markets an ideal testing ground. Under the banner of the "sharing economy," these platform markets—such as Airbnb, Upwork, and TaskRabbit— enable participants to share their own personal resources—such as skills, time, vehicles, and real estate—with strangers. Social biases and associated distrust towards strangers prevail in these markets (Abrahao et al. 2017; Cui, Li, and Zhang 2016; Edelman et al. 2017). To facilitate peer-to-peer transactions across social boundaries, these platforms have instituted various systems such as ratings, credentials, and certifications to generate quality information that can signal the trustworthiness of market participants. This allows me to compare different types of quality signal and to examine whether these quality signals are devalued or appreciated when they cross those boundaries. In particular, I compare *rating*, a type of process-based quality signal, with *platform verification*, a type of institutional-based quality signal that platforms create to assure that a participant has a truthful offline identity.

While there are various dimensions of bias and distrust among socially heterogeneous market participants , my particular focus is cultural distance—the extent to which one country's norms, customers, and values differ from another's—among market participants, because (a) trust relies on shared background knowledge and common understanding of the rules and expectations of the transaction, which are often uncodified but encrypted in cultural systems (Zucker 1986), and (b) cultural heterogeneity is a fundamental fact of the global markets that many peer-to-peer platforms aim to create (Appadurai 1990, 1996; Scholte 2005). Studies of trust and culture, unfortunately, have focused mainly on either comparisons of societal culture (Buchan, Croson, and Dawes 2002; Yamagishi and Yamagishi 1994) or offline businesses in organization settings (e.g., Chua, Morris, and Mor 2012; Jang 2017; Kogut and Singh 1988).

I hypothesize that cultural distance discourages trust among market participants such that those who are culturally proximate to the audience are at advantaged positions in peer-to-peer markets. Furthermore, ratings could widen the gap between culturally proximate and distant participants, while platform verification might narrow this gap. I test these hypotheses using a proprietary dataset from a global peer-to-peer lodging platform. My analyses of over one million lodging requests exchanged among these users reveal that hosts are less likely to approve requests from culturally distant guests, despite the fact that this global travel platform is marketed to people desiring cross-cultural experiences. While ratings have a positive effect on request approval, this effect *weakens* as the cultural distances between a host and a guest increase, further widening the gap in host acceptance of culturally proximate versus culturally distant guests. Furthermore, the effect of rating also *weakens* as the cultural distances between a host and a guest's prior host(s) increase. In contrast, while platform verification has a positive effect on request approval, this effect *enhances* as the cultural distance between a host and a guest increases, thus narrowing the gap in host acceptance of culturally proximate versus culturally distant guests.

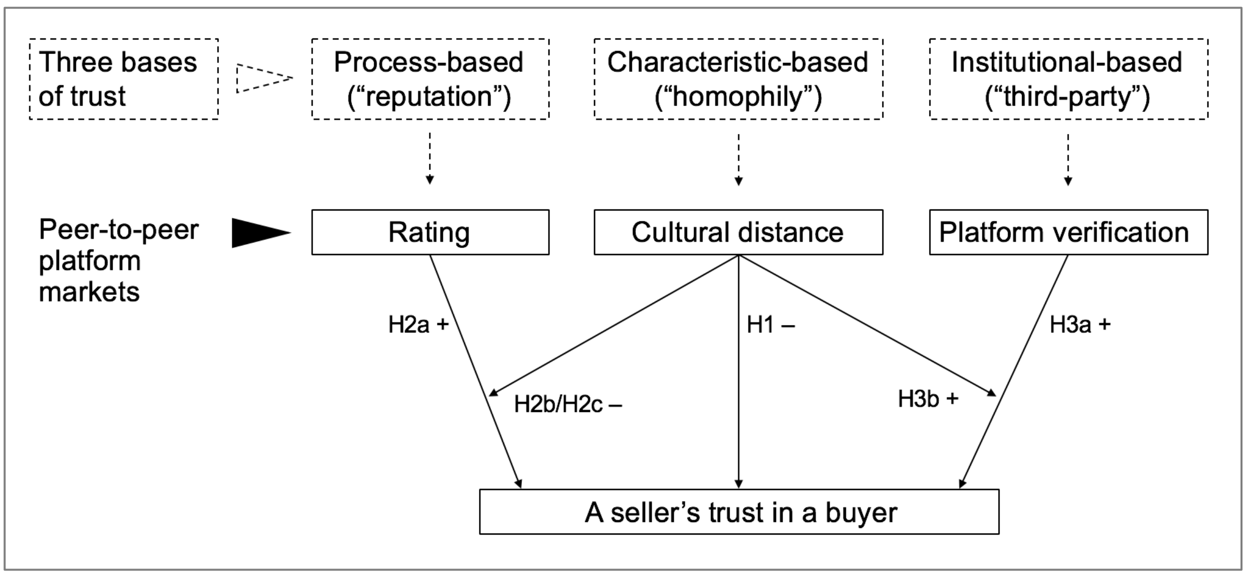
This study contributes to theories of evaluations and social bias, and the literature on culture and trust. First, building on Zucker's early work (1986) of the social production of trust, this study casts light on the debate over the social distortion of market signals by showing that different sources of quality signal might be subject to this interference differently. It is important to distinguish them. This also suggests that disadvantaged groups may leverage proof sources to mitigate their adversities in the market. Second, my investigation of cultural differences and trust in global markets provides important empirical evidence for the significance of shared cultural systems underlying the trust literature (Buchan et al. 2002; Chua et al. 2012; Jang 2017; Yamagishi and Yamagishi 1994), even in a market which many people join, ironically, in the hope of enjoying cross-cultural experiences. Lastly, this study also highlights the under-emphasized role of platforms themselves as institutional devices to generate trust between strangers and therefore has implications for engineering platform markets.

Bias and (Dis)Trust In Global Platform Markets

Trust figures prominently in market exchange relationships; it promotes cooperation, smooths transactions, and discourages malfeasance. The sociology of markets literature identifies three distinct bases/sources of trust in economic relationships: characteristic-based, process-based, and institutional-based (Zucker 1986). The theoretical underpinnings of these three bases of trust is that trust can be transferred from a trusted "proof source" to another actor with whom the trustor has little or no direct experience. *Characteristic-based trust* is tied to the similarity of actors' ascribed social characteristics such as ethnicity, kinship, and national origin (Dinesen and Sønderskov 2015; Mendes et al. 2002; Olsson 2005) and, in general, the greater the number of social similarities, the more interactants trust each other (Zucker 1986). *Process-based trust* is tied to a record of prior transactions which can be indicative of future behavior (Kollock 1994, 1999; Shapiro 1982; Wilson 1985); reputation is an example of such a record. Market participants, such as firms and individuals, often invest in building positive reputations to gain trust from prospective partners. *Institutional-based trust* is tied to organizational institutions and/or intermediary mechanisms, such as insurance and third-party accreditations (Schofer and Meyer 2005; Shapiro 1987; Williamson 1981; Zucker 1986). Market participants often rely on these organizations—which do not directly participate in economic transactions but rather facilitate and enable them—to ensure the quality of transactions partners (Cook et al. 2005; Woolthuis et al. 2005)

However, "Not all social systems generate the same amounts of trust" (Zucker 1986: 54). Below, I categorize and examine three factors that engender these three types of trust in global peer-to-peer platform markets that may benefit various participants differently. (Note that in a market transaction, an actor can be a seller or a buyer. The theories discussed below and my study focus on *a seller's trust in a buyer* – that is, whether she is a trustworthy buyer with whom to consummate the transaction without causing the seller any harm.) First, I illustrate how a type of social characteristics, national culture distance, can make some buyers be perceived as more trustworthy and therefore at advantageous positions in platform markets. I categorize the cultural-distance–driven (dis)trust as a type of characteristic-based (dis)trust. Second, I then explain how process-based quality signals and institutional-based quality signals that engender trust may benefit the advantaged and the disadvantaged groups differently. Specifically, I look at ratings as process-based signals and platform verification as institutional-based signals. I propose that the effect of rating *weakens* as the cultural distances increase, further widening the gap in culturally proximate versus culturally distant participants; in contrast, the effect of platform verification *enhances* as the cultural distance increases, thus narrowing the gap. Figure 1 below illustrates my theoretical framework.

Figure 1. Cultural Bias and Quality Signals in Global Platform Markets



Cultural Distance and Distrust in Global Markets

Cultural heterogeneity is one of the fundamental features for global markets (Appadurai 1990, 1996; Morley and Robins 2004; Scholte 2005). Researchers have been using "cultural distance," "cultural difference," or "cultural dissimilarity" to describe the degree to which one country’s norms and values differ from another’s (Bonikowski 2010; Kogut and Singh 1988; Salk and Shenkar 2001; Tihanyi, Griffith, and Russell 2005).

Cultural heterogeneity creates formidable challenges for global markets because differences in culture can impede trust. People perceive self-dissimilar alters as strangers or outgroup members and exposure to an outgroup predicates the activation of negative stereotypes, conflicts, and distrust. Favoritism toward one’s own group members is also referred to as ingroup bias or ingroup favoritism (Tajfel 1981). Greater cultural distance magnifies ingroup-versus-outgroup differences and invokes distrust. Furthermore, culture acts as a system for creating, sending, and processing information (Hall and Hall 1990) and information is the basis for trust (Mortensen and Neeley 2012). People thus perceive culturally similar others as more likely to share background knowledge. Cultural differences, however, impedes transactions through lack of “know-how” and background information such as what routines and repertoires are appropriate (Branzei, Vertinsky, and Camp 2007; Chua et al. 2012; Jang 2017; Jiang et al. 2011). Because of these, national cultural differences have been shown to influence international trades (Guiso, Sapienza, and Zingales 2009), market entry models (Kogut and Singh 1988), acquisition performance (Morosini et al. 1998), and global team collaborations(e.g., Chua, Roth, and Lemoine 2015; Jang 2017).

These challenges caused by cultural heterogeneity influence today’s peer-to-peer platform markets that have expanded on a global scale. In these marketplaces, great risks are entailed in transactions with strangers due to great uncertainty about both the provider and the buyer. Platform market participants are largely anonymous and thus can hardly be held accountable for (Nissenbaum 2004), and cultural distances further accentuate the distrust against anonymous out-group members. Furthermore, in these platform markets, rules and norms in a transaction can be difficult to communicate among strangers with cultural differences – behaviors that are acceptable in one cultural system might not be acceptable in another cultural system. For example, on online marketplace for lodging, culturally distant guests may have different beliefs and manners and thus may cause unexpected damages and conflicts; thus, hosts might be reluctant to accept requests from culturally remote regions. On platforms for freelancing, service providers might be less inclined to work for culturally distant employers as they might have different expectations on the transaction including time and quality of the work. Because of these cultural hurdles, market actors (buyers) who are culturally distant to the decisionmakers/audience (sellers) are at disadvantaged positions and therefore achieve subpar market outcomes.

H1: The audience (sellers) are less likely to select focal actors (buyers) who are culturally distant.

The Divergent Effects of Cultural Distance on Quality Signals

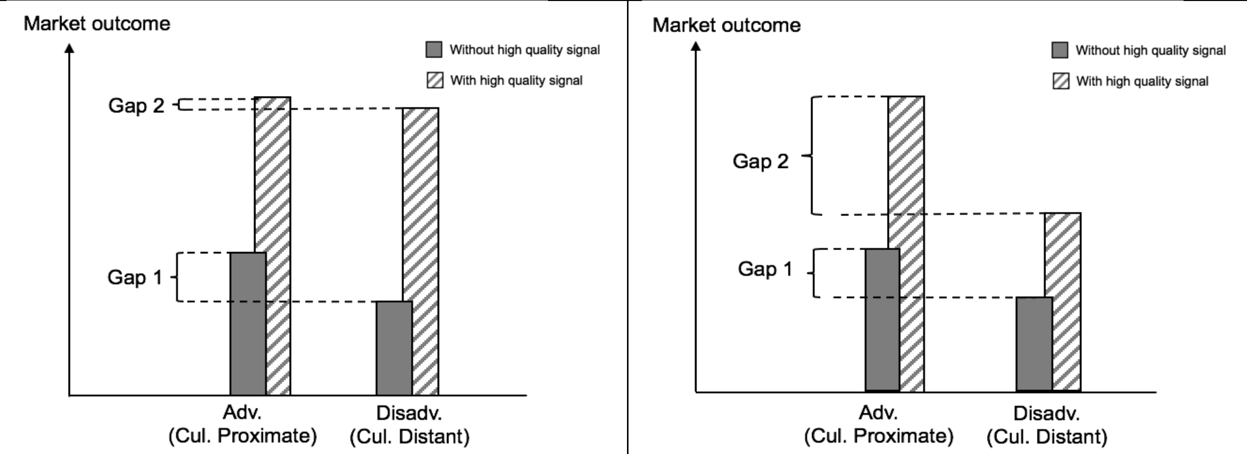
To facilitate economic exchanges, peer-to-peer platforms have instituted various systems to produce quality signals. These signals can help the audience (the seller) judge whether a focal actor (the buyer) is a trustworthy partner with whom to consummate the transaction without causing the audience/seller any harm. *Ratings* engender process-based trust, which is based on information provided by prior transaction partners (Bolton et al. 2013; Cui et al. 2016; Dellarocas 2003; Kollock 1999; Luca and Zervas 2016). When such ratings are available, the audience can infer the rated person's trustworthiness.

While process-based signals such as ratings have been extensively studied, quality signals created by platforms have received much less attention such as identity *verification*; that is, by examining a user's official documents to verify that she has a truthful offline identity. This is important because platform verification alleviates the anonymity issue and signals their commitment and accountability to the transaction. A flexible, transient online identity is less trustworthy (Nissenbaum 2004), and identity verification is a simple but powerful tool that increases confidence. It is difficult to hold an anonymous individual accountable (Kollock 1998), and identity-verified individuals are perceived as more committed to an online community and are willing to be held accountable for their behaviors. This quality signal is more than a minimum level of identification—platform users must overcome the tendency to protect their official documents and must trust the platform to be responsible for their privacy.

Thus, the premise of rating and platform verification in peer-to-peer markets is that they signal an individual's trustworthiness. However, their positive effects might vary with the cultural distance between market participants, and thus could, at the margin, harm or benefit culturally distant groups.

On one side, quality information may disproportionately benefit disadvantaged individuals because it has a higher influence on the audience's perception of them (Arcidiacono et al. 2010; Lang and Manove 2011; Lendle et al. 2016; Neal and Johnson 1996). In this context, culturally distant groups are at a disadvantage. Culture is a source of background information, including common beliefs and norms that can be critical for inferring a prospective partner's quality. Cultural distance enlarges the information gap between market participants, significantly disadvantaging culturally distant participants (Branzei et al. 2007; Chua et al. 2012; Jang 2017; Jiang et al. 2011; Rockstuhl and Ng 2008). Rating and platform verification are alternative sources of quality information to fill that information gap. As cultural distance between the audience (sellers) and focal actors (buyers) increases, the difference in perceived trustworthiness between focal actors with high-quality signals and those without them will increase. For culturally proximate individuals, however, the audience already has ample background knowledge. Thus, quality information leads to a smaller positive update in the audience's beliefs about them. Scenario A in Figure 2 below illustrates this relationship.

Figure 2. The Divergent Effects of Cultural Distances on Quality-signal Effects



Scenario A: Cultural distances enhance the quality-signal effect, narrowing the gap between the advantaged and disadvantaged.

Scenario B: Cultural distances mitigate the quality-signal effect, widening the gap between the advantaged and disadvantaged.

On the opposite side, the homophily literature suggests that people impose double standards on others with different attributes; in particular, they apply stricter standards to those they dislike and more lenient standards to those they like (Foschi 2000). Studies find that among groups subject to the negativity of double standards, such as minorities and outgroup members, the audience discounts quality information about these actors and imposes a higher bar that requires more evidence of quality, such as a better track record (Biernat and Kobrynowicz 1997, Foschi et al. 1994). For instance, Bertrand and Mullainathan's (2004) study of labor market discrimination finds that Whites with higher-quality resumes receive nearly 30 percent more callbacks than Whites with lower-quality resumes, but that resume quality has a smaller effect for African Americans. Therefore, quality information benefits individuals with an initial disadvantage to a smaller degree than it benefits advantaged individuals, because the audience (sellers) discounts information about the former and imposes a higher bar on them, increasing the advantage of those who already have it. In my study, as people exhibit favoritism and trust towards culturally similar others, they are likely to discount information about and impose stricter standards on culturally distant others. Thus, as the cultural distance between the audience (sellers) and focal actors (buyers) increases, the difference between focal actors (buyers) with high-quality signals and those without decreases. Scenario B in Figure 2 depicts this relationship.

I propose that these two contradictory processes may be due to the nature of the different "proof sources" of these quality signals and how they are perceived by the audience. Process-based quality signals, such as ratings and recommendations, are provided by prior exchange partners. And, process-based mechanisms require market exchanges with individual participants, and are highly specific to the market actors engaged in the transaction and reflect their idiosyncratic opinions (Zucker 1986). Therefore, they might be more subject to the ingroup-versus-outgroup bias and be viewed by the audience as less relevant to the current matter; both result in quality information being discounted.

Specifically, in the context of platform markets, ratings are provided by prior transaction partners (prior sellers) and reflect the quality of their specific transactions with the focal actor (buyers). As cultural distance between the audience (sellers) and the focal actor increases, the audience are more inclined to view the focal actor as outgroup members, invoking their distrust of the focal actor's subjective quality signals. For example, on Airbnb, a culturally-distant guest is endorsed by prior hosts and can "keep the house clean", but the focal host might trust these subjective individual endorsements less. Furthermore, the relevance of ratings might be questioned because the audience is inclined to view them as idiosyncratic opinions offered by the focal actor' specific prior transaction partners, with little to say about whether she can be trusted in the current transaction. As in the example of Airbnb, a culturally-distance guest may have different understandings and norms of keeping the house “clean” from the focal host; this guest’s behaviors might be accepted by prior hosts but might not by the focal host.

Taking this further, because process-based quality signals are provided by prior partners, and the audience and the focal actor’s prior transaction partners might not share similar understandings regarding the rules and norms of a transaction, the cultural distance between the audience and these prior partners also matters. Ratings provided by culturally distant prior partners might not seem informative to the current transaction, because the audience and these prior partners might have different understanding and different evaluation standards. As in the example of Airbnb, if a guest’s ratings are provided by prior hosts who are culturally distant to the focal host, the focal host might perceive these ratings as highly idiosyncratic and less relevant to the current transaction.

For these reasons, the function of quality signals such as ratings in filling the information gap caused by cultural distance is compromised. I therefore hypothesize:

H2a: The audience (sellers) are more likely to select focal actors (buyers) with process-based quality signals.

H2b: The effect of process-based quality signals is weaker as the cultural distance between the audience (sellers) and the focal actor (buyers) increases.

H2c: The effect of process-based quality signals is weaker as the cultural distance between the audience (sellers) and the focal actor’s prior partners (prior sellers) increases.

Compared to process-based quality signals provided by peer users, platform verification represents a different “proof source” that might be less subject to the subject to the ingroup-versus-outgroup bias and might be viewed by the audience as generalize beyond specific raters or transactions. A platform examines a user's official documents to verify a truthful sustained offline identity; thus, the platform itself is the rater. This system relies on the platform's wide acceptance as a broker for transactions (Davis 2016; Schor and Fitzmaurice 2015), making it an institutional device that can create quality signals. The platform can act impartially like third-party accreditation organizations and largely exempt itself from the social bias entailed in social (dis)similarities. Thus, the platform as a rater is less vulnerable to the ingroup-versus-outgroup bias of peer-user raters. This is consistent with the theoretical rationale for the rise of institutional certifiers and endorsers in the offline world in response to the growing number of transactions across social boundaries. Due to the acknowledgement of the platform's credibility and legitimacy across platform users, the credibility of this quality signal is less likely to be compromised.

Furthermore, as argued, identifiability ameliorates the anonymity and accountability tension at the heart of cooperation and social dilemma issues (Dawes, McTavish, and Shaklee 1977; Kollock 1998; Macy and Skvoretz 1998; Orbell and Dawes 1981). Market participants willing to be held accountable are more committed to the community than those who remain anonymous. This goes beyond any specific transactions and signals the focal actor's quality at a general level. As the cultural distance between market participants increase, the issues of anonymity and accountability remain critical. Thus, quality signals that can address them remain relevant and will be unlikely to be compromised; the audience will view platform verification as a legitimate and informative quality signal.

Thus, because of the perceived objectivity and relevance by the audience, institutional-based quality signals work differently: as cultural distance between market actors increases, so does the information gap between them; quality signals endorsed by institutional devices such as the platform can decrease this gap. Those with such quality signals will gain more advantage than those without. I therefore hypothesize:

H3a: The audience (sellers) are more likely to select focal actors (buyers) with institutional-based quality signals.

H3b: The effect of institutional-based quality signals is stronger as the cultural distance between the audience (sellers) and focal actors (buyers) increases.

DATA AND METHODS

Setting and Sample

I examine my hypotheses in one peer-to-peer lodging platform that required anonymity as a condition of sharing its data. This platform covers over 180 countries and is one of the major peer-to-peer lodging networks in the world. The dataset includes all listings, lodging requests, messages, and transactions (defined as consummated stays) from 2014 through 2017 between hosts and guests (defined collectively as "users"), and information on each user (but not the name or email address). Different from Airbnb, every user on this platform must a home. The site then assigns each home a price per night in a platform-specific virtual currency, using a unique algorithm that considers the home's location, size, and facilities. For the purpose of this study, I refer to the currency as "coins" and the price per night as "coins-per-night." An 845-square-foot Manhattan apartment with two bedrooms is 218 coins-per-night; a similar apartment would list for about $200 on Airbnb. On this platform, the maximum home coins-per-night is 441 and the minimum is 40, with an average of 150. During the study period, close to 80% of the listed homes are people's primary homes. Each user is allocated an initial amount of coins upon listing her home to start travelling; she can then earn coins by accommodating guests and use coins to pay hosts. Users can do simultaneous lodgings (meaning that the host will also stay at the guest's home) or non-simultaneous lodgings (meaning that the host will not stay at the guest's home). During the study period, only 2 percent are for simultaneous lodgings and 98 percent are for non-simultaneous lodgings. For my primary analysis, I focus on non-simultaneous transactions.

I analyze user transaction data to estimate the factors that increase the likelihood that a host approved a lodging request. I use a logistical regression model with conditional fixed effects for hosts to estimate the probability of a request approval; an individual request is the unit of analysis. The dataset I received included more than one million lodging requests, but I pare this down to construct my analysis sample as follows. First, because I focus on the cultural distance between guest country and host country, the selection of countries is determined by the availability of country-level data on culture characteristics from the data sources described below. This omits 185,763 observations for which such data are not available. Second, I omit 23,897 users who list homes in foreign countries—for example, an American who lists a home in France—because it is difficult to gauge their primary country of residency which is needed to measure cultural distance. These users are involved in 63,232 requests. Third, I omit 891,068 lodging requests sent by guests without any prior transactions and thus had no opportunity to acquire a rating. Lastly, I exclude simultaneous transactions among the remaining lodging requests. These restrictions result in an analysis sample of 393,041 requests.

The conditional fixed effects logit models were estimated only for requests associated with hosts who exhibited some variation in acceptance. That is, the model drops hosts who either declined all requests (265,730 observations)[14] or approved all requests (122 observations), and

[14] A significant number of hosts declined all requests. One of the reasons revealed by the company is that each user is allocated an initial amount of coins upon listing her home and users can thus have several stays for free using the endowed coins—this may allow free-riding such that some users do not intend to accommodate anyone at the outset.

generates estimates based on hosts who have variation in their decisions (127,189 observations) (Allison 2009; Mcfadden 1973) (for other empirical examples, see (Eisenhardt and Tabrizi 1995; Short and Toffel 2010; Xiao and Tsui 2007; Zenger and Marshall 2000). These 127,189 lodging requests in the estimation sample were issued by 11,069 guests in 52 countries to 6,612 hosts in 48 countries. In this sample, each host receives 101 requests on average, with a median of 65, a range of 2 to 932, and a standard deviation of 108. There are 745 guest-country and host-country pairs, among which 27 are domestic. Forty-nine percent of requests are from domestic guests and 51 percent are international.

Dependent Variable and Independent Variables

The dependent variable, *request approval*, is a dummy variable with "1" indicating that the host approved a lodging request and "0" indicating that she did not. In the final sample, 13,044 requests—approximately 10 percent —were approved.

Cross-cultural studies have developed at least three measurements for cultural distance: Kogut and Singh's (1998) index, based on Hofstede's (1980) dimensions of national culture; an index based on Schwartz's (1994, 1999) dimensions of national culture; and Inglehart and Baker's approach (2000), based on items from the World Value Survey. Hofstede derived his dimensions from data obtained between 1967 and 1973 and Schwartz derived his in the late 1980s. Since then, major cultural changes have occurred worldwide (Bonikowski 2010), introducing the risk that these approaches are outdated. I thus follow Inglehart and Baker's approach, which can be kept updated with the most recent surveys. Note that the three measurements correlate at $p>0.7$ (Inglehart and Baker's correlates with Schwartz's at 0.87 and with Kogut and Singh's at 0.74.). As robustness tests, I run the models using Schwartz's and Kogut and Singh's indexes respectively, yielding largely similar results.

On this platform, every user's primary country of residency is public information—a host can see which country a guest and her prior host(s) reside. I compute the *guest-host cultural distance* between a host's country and a guest's country using combined 2010–2013 data from the World Values Survey (WVS) and combined 2008–2010 data from the Europe Values Survey (EVS). Following Inglehart and Baker (2000), I use factor analysis to reduce 10 indicators from WVS to two latent dimensions of cultural differentiation specified by Inglehart and Baker, who argued that they capture the continuum between four poles of national values: traditional versus secular-rational and survival versus self-expression. The factor analysis is based on mean national scores measuring respondents' agreement with the statements shown in Table 13. These indicators were averaged for each country, then subjected to a factor analysis with varimax rotation. With the exception of the trust variable, the 10 indicators load onto the two dimensions observed by Inglehart and Baker. The results of the factor analysis were used to predict values on those two dimensions for each country, visualized on a scatterplot in Figure 3.

The dyadic independent variable, *guest-host cultural distance*, consists of the vector/Euclidean distance between all pairs of countries on this map generated from this data (e.g., Berry, Guillén, and Zhou 2010; Bonikowski 2010). CD_{ij} is the cultural distance between country i and country j, TS_i is country i's score on the traditional/secular-rational dimension, TS_j is country j's score on this dimension, SS_i is country i's score on the survival/self-expressive dimension, and SS_j is country j's score on this dimension. Thus:

$$CD_{ij} = \sqrt{\left(TS_i - TS_j\right)^2 + \left(SS_i - SS_j\right)^2}.$$

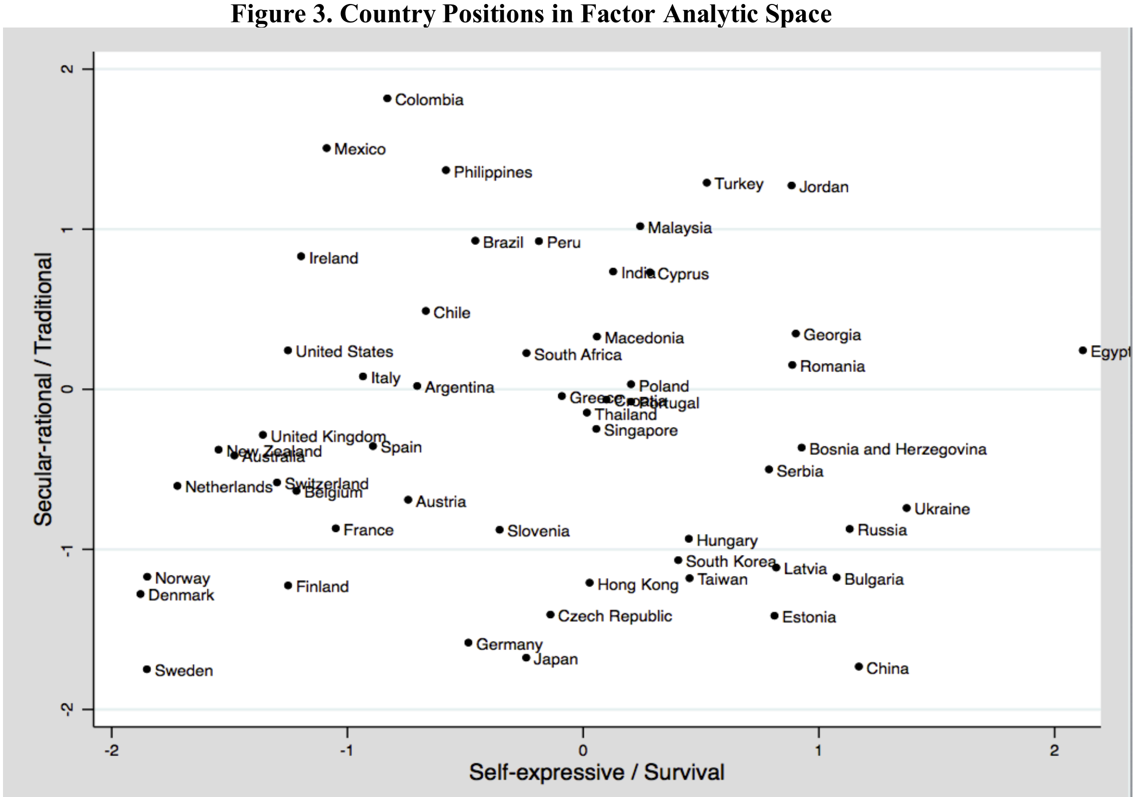
Table 13. World/Europe Values Survey Items and Factor Analysis Results

Dimension and items	Factor loadings		Uniqueness
	Axis A	*Axis B*	
Axis A: Traditional vs. secular-rational			
• God is very important in my life.	0.804	-	0.181
• It is more important for a child to learn obedience and religious faith than independence and determination.	0.753	-	0.364

Table 13 (Continued). World/Europe Values Survey Items and Factor Analysis Results

• Abortion is never justifiable.	0.693	-	0.218
• I'm proud to be [nationality].	0.704	-	0.487
• Greater respect for authority would be a good thing.	0.585	-	0.653
Axis B: Survival vs. self-expressive			
• I give priority to economic and physical security over self-expression and quality of life.	-	0.719	0.453
• Taking all things together, I am not very happy.	-	0.660	0.508
• I have not signed and would not sign a petition.	-	0.743	0.316
• Homosexuality is never justifiable.	-	0.835	0.159
• You have to be very careful about trusting people.	0.609	0.431	0.444

Figure 3. Country Positions in Factor Analytic Space



To verify that this approach is valid, I examine sample scores for key countries and find them to have face validity. For instance, the cultural distances, based on these dimensions, between France and China (2.4), India (2.0), the United States (1.1), Italy (0.9), the United Kingdom (0.6), Spain (0.5), and Belgium (0.3) are in an order that one would expect.

The cultural distance between the audience (host) and the focal actor's prior transaction partner(s)—that is, the guest's prior host(s)—is computed as the average cultural distance between the host and each prior host of this guest. For example, for a guest who had two prior hosts—one in France and one in the UK—and is now applying to a host in the US, *prior-host–host cultural distance* is 0.9 because the cultural distance between the US and France is 1.3 and that between the US and the UK is 0.5. Because *guest-host cultural distance* and *prior-host–host cultural distance* are skewed (skewness>1, kurtosis>4), I winsorize them at the 95th percentile. Using the raw unwinsorized values yields the same results.

Guest rating is the numeric average of prior ratings a guest received on a scale of 0 to 5, which is displayed on her profile page. *Guest verification* is a dummy variable, with "1" indicating identity verified guests and "0" unverified guests. Users can apply to be endorsed by the platform by paying a fee ($30) and submitting two documents: a photo identity card (such as a passport or driver's license) and a proof of address (such as a lease agreement or electricity bill). The platform's operating team manually checks and approves applications. A verified guest has a checkmark on her profiles.

Control Variables

I control for other factors related to the guest-host country dyad and control for several characteristics about the guest, the host, and the lodging opportunity that might influence whether a host approves or declines a lodging request. All variables are measured at the time of the request.

At the guest-host country level, because social interaction may increase with geographical propinquity, I control for *guest-host geographical distance* between a host's country and a guest's country (unit: 1000km), using the latitudes and longitudes of their most populous cities. A robustness test using the geodetic distance between their capitals yields identical results. In addition, *guest-host governance-quality distance* has been considered a significant component of institutional differences across countries (Antràs and Chor 2013;

Locke, Qin, and Brause 2007). As widely done in prior research, I measure the quality of governance using "Worldwide Governance Indicators" collected by the World Bank for 2014–2017. I measure *guest-host governance-quality distance* as the difference in this score between the host's country and the guest's country; thus, a positive value indicates that the host's country has a more developed governance system. Lastly, I control for *guest-host economic-development distance*, calculated by the difference in per-capita GDP between the host's and guest's countries. Other researchers also add some macro structural factors—such as official-language differences, colonial relationships, and political ties (e.g., international organizations)—as components of psychic distance (e.g., Brewer 2007; Evans and Mavondo 2002). Language and colonial ties both correlate with cultural distance at -0.83 and political ties correlate with geographic distance at -0.81, so these are not included in my models.

Regarding guests, because hosts might want to repay previous transaction partners for their past hospitality or might trust prior guests more, they might be more likely to approve requests from those partners. Thus, I control for a dummy variable *guest prior transaction with the host*. Because hosts might prefer guests with popular homes because these homes can also be appealing to them, I control for *guest home popularity*, measured as the number of requests a guest received in the past month. Results are robust to alternative measures calculated as the number of requests each guest received in the past three, six, nine, and twelve months. I also control for *guest's total previous transactions*. Because some hosts might prefer guests travelling with children and others might prefer guests without children, I control for a dummy variable *guest with children,* with "1" indicating a guest traveling with children and "0" otherwise. Because hosts might differ in their preferences concerning guest age and gender, I control for guest age and female guest requester (a dummy)

Regarding hosts, because hosts might be more selective during peak seasons, I control for *host home popularity*, measured as the number of requests received by the focal host in the past month. Results are robust to alternative measures calculated as the number of requests received in the past three, six, nine, and twelve months. Because hosts might be less selective when they are low on coins, I control for *host's coin balance*, measured as the number of coins the focal host has. Lastly, I control for *host's total prior transactions* and *host's rating* in all models. Because I include host fixed effects in the estimation models, I do not control for characteristics of the host—such as age, children, and gender—that do not vary much.

Regarding lodging, in this platform market, all users must have listings and all are able to see each other's listing price per night in coins. I calculate the *Host-guest home price difference* between a host and a guest by subtracting the guest's home coins-per-night from the host's home coins-per-night. Thus, a positive value indicates that the host's home is worth more than the guest's home. In the analyses below, I facilitate interpretation of coefficients by dividing the home price difference by 100. Because interviews with users reveal that hosts vary in their preferences for the duration of a guest's stay, I control for *duration of requested stay* measured in days and *advance notice of request*, the number of days prior to the guest's desired starting date that a host received the request.

Estimation

I test my hypotheses using logit models with conditional fixed effects for hosts and year fixed effects. I cluster standard errors by host country. Summary statistics are reported in Table 14, correlations in Tables 15, and regression results in Table 16A. Given some concerns about drawing conclusions from interactions in logistic regression models (Ai and Norton 2003), I re-estimate this specification as linear probability model with host fixed effects using the same estimation sample, reporting results in Table 16B. To facilitate interpretation, I standardize the continuous variables *guest-host cultural distance*, *guest rating*, and *prior-host–host cultural distance* because in some models they are involved in the interaction terms. I computed variance inflation factors (VIFs) to ensure the intercorrelations between variables did not bias my results. The VIFs range from 1.01 to 2.35, and the mean VIF is 1.26, all below the rule-of-thumb cutoff of 10 (Greene 2003). Therefore, the analysis is unlikely to suffer from multicollinearity.

Table 14. Summary Statistics

	Mean	SD	Min	Max
Request approval	0.10	0.30	0	1
Guest-host cultural distance	0.41	0.49	0	1.73
Guest-host cultural distance^s	0	1	-0.84	2.68
Guest rating	4.36	1.07	0	5
Guest rating^s	0	1	-4.06	0.59
Guest verification	0.87	0.33	0	1
Guest-host geographical distance (unit: 1000km)	0.89	1.75	0	9.37
Guest-host governance-quality distance	0.02	0.36	-0.68	1.05
Guest-host economic-development distance (unit:1000USD)	0.06	11.47	-75.11	78.01
Guest's total previous transactions	5.05	4.81	1	21
Guest prior transactions with the focal host	0.01	0.10	0	1
Guest home popularity	4.80	5.81	0	29
Guest with children	0.55	0.50	0	1
Guest age	45.29	10.49	21	72
Female guest requester	0.67	0.47	0	1
Host rating	3.50	1.99	0	5
Host's total previous transactions	4.27	4.60	0	18
Host home popularity	9.92	10.02	1	52
Host's coin balance (unit: 100)	11.64	6.18	0.1	18.11
Host-guest home price difference (unit: 100)	-0.20	0.77	-2.83	2.87
Advance notice of request	69	66	0	308
Duration of requested stay	6.32	6.02	1	61

Note: N=127,189; summary stats for variables in Column (3) of Tables 16A and 16B are similar to those in Columns (1), (2), and (4), so are not reported. ^{S} denotes standardized.

Table 15. Correlations

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Request approval	1														
2	Guest-host cultural distance	-0.04	1													
3	Guest rating	0.01	-0.01	1												
4	Guest verification	0.02	0.00	0.04	1											
5	Guest-host geographical distance	0.00	0.55	-0.01	0.00	1										
6	Guest-host governance-quality distance	-0.01	0.10	0.00	-0.05	0.15	1									
7	Guest-host economic-development distance	-0.00	0.02	-0.00	-0.03	0.12	0.75	1								
8	Guest's total previous transactions	0.04	-0.02	-0.07	0.14	-0.04	-0.01	0.00	1							
9	Guest prior transactions with the focal host	0.18	-0.03	0.00	0.00	-0.02	-0.01	0.01	0.05	1						
10	Guest home popularity	0.00	0.09	0.02	0.11	0.03	-0.03	0.01	0.16	0.00	1					
11	Guest with children	-0.02	-0.03	0.04	0.06	-0.06	-0.05	0.11	0.01	-0.02	0.00	1				
12	Guest age	0.06	0.01	0.02	0.12	0.06	0.02	-0.02	0.16	0.02	0.03	0.00	1			
13	Female guest requester	0.00	0.00	-0.02	-0.04	0.00	-0.01	0.04	-0.01	-0.01	-0.01	0.04	-0.09	1		
14	Host rating	-0.11	-0.04	-0.01	0.00	-0.03	-0.01	0.00	0.03	0.05	-0.02	0.00	0.00	0.01	1	
15	Host's total previous transactions	-0.07	-0.02	-0.01	0.00	-0.02	0.00	0.00	0.04	0.06	-0.02	-0.01	0.01	0.00	0.40	1
16	Host home popularity	-0.12	0.15	0.00	0.00	0.11	0.08	0.00	-0.01	-0.03	0.03	-0.02	0.02	0.01	0.09	0.16

Table 15 (Continued). Correlations

17	Host's coin balance	-0.04	0.05	0.00	0.01	0.05	0.01	0.01	0.03	0.01	0.00	0.00	0.02	0.00	0.07	0.06
18	Host-guest home price difference	0.02	-0.02	0.00	-0.07	-0.02	0.00	-0.01	-0.03	0.01	0.04	-0.12	-0.07	0.04	0.00	-0.01
19	Advance notice of request	-0.02	0.15	0.02	0.05	0.14	-0.04	0.05	-0.01	-0.02	0.02	0.11	0.07	-0.01	-0.01	-0.03
20	Duration of requested stay	-0.08	0.07	0.01	0.05	0.06	-0.07	0.07	-0.02	-0.03	0.05	0.10	0.03	-0.03	-0.04	-0.06
		16	17	18	19	20										
16	Host home popularity	1														
17	Host's coin balance	0.07	1													
18	Host-guest home price difference	-0.05	-0.01	1												
19	Advance notice of request	0.01	0.04	-0.01	1											
20	Duration of requested stay	-0.01	0.00	-0.02	0.35	1										

Note: N=127,189; Sample in Columns (1), (2), and (4) of Tables 4A and 4B. N=127,189. Correlations for variables in Column (3) are similar to these correlations, so are not reported.

Table 16A. Regression Results of Conditional Logit Models

DV: Request approval	(1)	(2)	(3)	(4)
Guest-host cultural distance^{s}	-0.0316*	-0.0315*	-0.0237*	-0.0778**
	(0.0155)	(0.0151)	(0.0119)	(0.0206)
Guest rating^{s}	0.0307**	0.0294*	0.0233*	0.0307**
	(0.0095)	(0.0123)	(0.0119)	(0.0095)
Guest verification	0.1640**	0.1640**	0.1601**	0.1702**
	(0.0542)	(0.0548)	(0.0438)	(0.0570)
Guest-host cultural distance^{s} × Guest rating^{s}		-0.0294**		
		(0.0089)		
Prior-host–host cultural distance^{s} × Guest rating^{s}			-0.0163*	
			(0.0080)	
Guest-host cultural distance^{s} × Guest verification				0.0531*
				(0.0215)
Prior-host–host cultural distance^{s}			-0.0412+	
			(0.0245)	
Guest-host geographical distance	0.0115	0.0115	0.0119	0.0114
	(0.0080)	(0.0080)	(0.0087)	(0.0081)
Guest-host governance-quality distance	-0.2361*	-0.2330*	-0.3269**	-0.2330*
	(0.1001)	(0.0987)	(0.0900)	(0.0987)
Guest-host economic-development distance	0.0007	0.0006	0.0025	0.0008
	(0.0034)	(0.0034)	(0.0038)	(0.0034)
Guest's total previous transactions	0.0136**	0.0136**	0.0151**	0.0136**
	(0.0021)	(0.0022)	(0.0029)	(0.0021)
Guest prior transactions with the focal host	2.9022**	2.9019**	2.9339**	2.9028**
	(0.0960)	(0.0959)	(0.1202)	(0.0963)
Guest home popularity	-0.0011	-0.0012	-0.0006	-0.0012
	(0.0032)	(0.0031)	(0.0031)	(0.0032)
Guest age	0.1418**	0.1418**	0.1445**	0.1417**
	(0.0217)	(0.0218)	(0.0298)	(0.0219)
Guest with children	-0.0343**	-0.0329**	-0.0352**	-0.0344**
	(0.0121)	(0.0120)	(0.0133)	(0.0120)
Female guest requester	0.0205**	0.0205**	0.0212**	0.0205**
	(0.0009)	(0.0009)	(0.0015)	(0.0009)
Host rating	0.0231	0.0230	0.0159	0.0229
	(0.0210)	(0.0210)	(0.0269)	(0.0210)
Host's total previous transactions	-0.1588**	-0.1588**	-0.1561**	-0.1588**
	(0.0069)	(0.0069)	(0.0082)	(0.0070)
Host home popularity	-0.0903**	-0.0903**	-0.0927**	-0.0903**
	(0.0055)	(0.0055)	(0.0067)	(0.0054)
Host's coin balance	-0.0112**	-0.0112**	-0.0126**	-0.0112**
	(0.0022)	(0.0022)	(0.0020)	(0.0022)
Host-guest home price difference	-0.0839**	-0.0840**	-0.0831**	-0.0839**
	(0.0037)	(0.0037)	(0.0046)	(0.0037)
Advance notice of request	0.0028**	0.0028**	0.0029**	0.0028**
	(0.0009)	(0.0009)	(0.0010)	(0.0009)
Duration of requested stay	-0.0939**	-0.0940**	-0.0907**	-0.0940**
	(0.0111)	(0.0111)	(0.0147)	(0.0110)
Observations	127,189	127,189	103,390	127,189

Notes: Conditional logit models with host fixed effects and year fixed effects. Robust standard errors clustered by host country in parentheses. ** p<0.01, * p<0.05, + p<0.1 (two-tailed tests). ^{S} denotes standardized. Model (3) excludes observations associated with guests having any prior hosts in countries not included in WVS or EVS because prior-host–host cultural distance is thus undefined.

Table 16B. Regression Results of Linear Probability Models

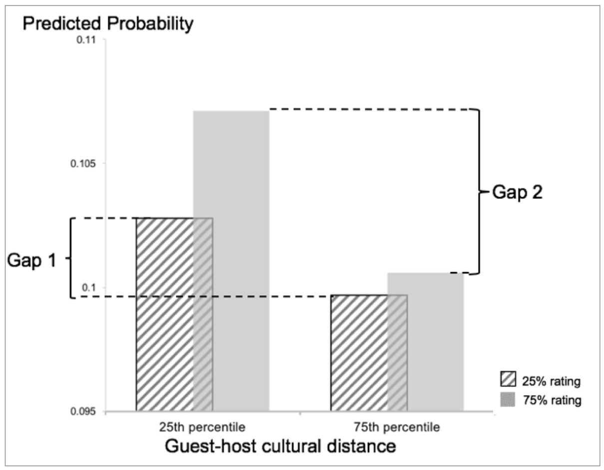
DV: Request approval	(1)	(2)	(3)	(4)
Guest-host cultural distance^{s}	-0.0021*	-0.0022*	-0.0017+	-0.0050**
	(0.0110)	(0.0011)	(0.0011)	(0.0015)
Guest rating^{s}	0.0024**	0.0025**	0.0022	0.0025**
	(0.0006)	(0.0008)	(0.0011)	(0.0006)
Guest verification	0.0129**	0.0128**	0.0132**	0.0129**
	(0.0044)	(0.0045)	(0.0037)	(0.0046)
Guest-host cultural distance^{s} × Guest rating^{s}		-0.0023**		
		(0.0007)		
Prior-host–host cultural distance^{s} × Guest rating^{s}			-0.0012*	
			(0.0006)	
Guest-host cultural distance^{s} × Guest verification				0.0033*
				(0.0014)
Prior-host–host cultural distance^{s}			-0.0031+	
			(0.0018)	
Guest-host geographical distance	0.0010	0.0010	0.0012	0.0010
	(0.0009)	(0.0009)	(0.0010)	(0.0009)
Guest-host governance-quality distance	-0.0195*	-0.0193*	-0.0277**	-0.0194*
	(0.0091)	(0.0090)	(0.0086)	(0.0089)
Guest-host economic-development distance	0.0001	0.0001	0.0002	0.0001
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Guest's total previous transactions	0.0013**	0.0013**	0.0014**	0.0013**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Guest prior transactions with the focal host	0.5261**	0.5260**	0.5406**	0.5261**
	(0.0136)	(0.0136)	(0.0173)	(0.0136)
Guest home popularity	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Guest with children	-0.0043**	-0.0042**	-0.0046**	-0.0044**
	(0.0012)	(0.0012)	(0.0017)	(0.0012)
Guest age	0.0017**	0.0017**	0.0018**	0.0017**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Female guest requester	0.0021	0.0021	0.0019	0.0021
	(0.0018)	(0.0018)	(0.0023)	(0.0018)
Host's rating	-0.0176**	-0.0176**	-0.0181**	-0.0176**
	(0.0011)	(0.0011)	(0.0012)	(0.0011)
Host's total previous transactions	-0.0087**	-0.0087**	-0.0088**	-0.0087**
	(0.0005)	(0.0005)	(0.0006)	(0.0005)
Host home popularity	-0.0004**	-0.0004**	-0.0005**	-0.0004**
	(0.0001)	(0.0001)	(0.0002)	(0.0001)
Host's coin balance	-0.0074**	-0.0074**	-0.0074**	-0.0074**
	(0.0004)	(0.0004)	(0.0005)	(0.0004)
Host-guest home price difference	0.0118**	0.0118**	0.0120**	0.0118**
	(0.0020)	(0.0020)	(0.0029)	(0.0020)
Advance notice of request	0.0002*	0.0002*	0.0002*	0.0002*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Duration of requested stay	-0.0091**	-0.0091**	-0.0097**	-0.0091**
	(0.0005)	(0.0005)	(0.0006)	(0.0005)
Observations	127,189	127,189	103,390	127,189

Notes: Linear probability models with host fixed effects and year fixed effects. Robust standard errors clustered by host country in parentheses. ** p<0.01, * p<0.05, + p<0.1 (two-tailed tests). ^{S} denotes standardized. Model (3) excludes observations associated with guests having any prior hosts in countries not included in WVS or EVS because prior-host–host cultural distance is thus undefined.

Model (1) of Table 16A includes direct effects to test H1, H2a, and H3a. The coefficient on *guest-host cultural distance* is negatively significant (β= -0.0316, $p<0.05$). This supports H1 that greater cultural distance is negatively associated with the occurrence of peer-to-peer transactions. A one-standard-deviation increase in *guest-host cultural distance* from the mean (0) corresponds to a 5-percent decrease of approval. Admittedly, the magnitudes of the effects of *guest-host cultural distance* on approval are small, but given that my setting is a peer-to-peer lodging platform which many people join in order to travel and to enjoy cross-cultural experiences—half the requests are for international trips—*guest-host cultural difference* is still significant. One can imagine the significant influence of cultural differences in other contexts. In addition, in Model (1), the coefficients on *guest rating* ($\beta= 0.0307$, $p<0.01$) and *guest verification* ($\beta= 0.164$, $p<0.01$) are positive and statistically significant. These results indicate higher probabilities of approval for more highly-rated guests and for guest who have undergone the verification process, supporting H2a and H3a.

Model (2) adds the interaction term *guest-host cultural distance* × *guest rating* to test H2b. The coefficient on this interaction term is negative and statistically significant ($\beta= -0.0294$, $p<0.001$), which supports H2b that predicted that the positive association between a process-based quality signal (guest rating) on a host's likelihood of accepting a request weakens as guest-host cultural distance increases. The positive and statistically significant coefficient on the interaction term provides additional support for H2b (see Table 16B, column (2)). Moreover, OLS results are helpful in interpreting the effect size: when *guest-host cultural distance* is held at its sample average, a one-standard-deviation increase in *guest rating* increases the probability of approval by 3.6 percent; when *guest-host cultural distance* is held at one standard deviation above its sample average, a one-standard-deviation increase in *guest rating* increases the probability by a mere 0.3 percent, a 92-percent difference. To illuminate this relationship, Figure 4 graphs the average predicted probability based on OLS results when *guest rating* and *guest–host cultural distance* are both at 25^{th} and 75^{th} percentiles, showing that compared to when high quality signals are absent (i.e., guest rating at 25^{th} percentiles), the gap between guests who are culturally proximate to the host and those who are culturally distant to the host is wider when high quality signals are present (Gap 2 > Gap 1).

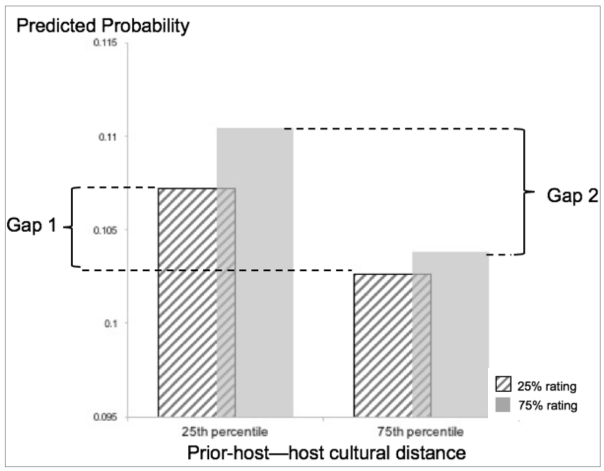
Figure 4. Guest rating and Guest-host cultural distance at 25th and 75th percentile



Model (3) adds to Model (1) the variable *prior-host–host cultural distance* and the interaction term *prior-host–host cultural distance* × *guest rating* to test H2c. Note that there are only 103,390 observations in Model (3) because *prior-host–host cultural distance* is undefined and observations are therefore dropped when any prior hosts are in countries not included in WVS or EVS. To avoid losing observations, *prior-host–host cultural distance* is thus not included in Models (1), (2), and (4); robustness tests including this variable in these three models yield largely identical results.

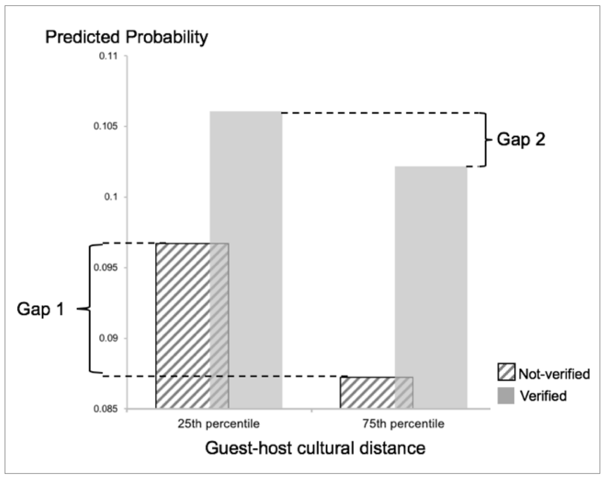
In Model (3), the coefficient on the interaction term *prior-host–host cultural distance* × *guest rating* is positive and statistically significant (β= -0.0163, p<0.05), which supports H2c that hypothesized that the positive influence of a process-based quality signal (i.e., guest rating) on a host's acceptance of a request weakens as prior-host–host cultural distance increases. Similarly, I re-estimate this specification as linear probability model, which provides additional support for H2c (see Table 16B, column (3)). Based on OLS results, when *prior-host–host cultural distance* is held at average, a one-standard-deviation increase in *guest rating* increases the probability of approval by 3.1 percent; when *prior-host–host cultural distance* is held at one standard deviation above the average, a one-standard-deviation increase in *guest rating* increases the probability by 1.4 percent, a 55-percent difference. To illuminate this relationship, Figure 5 graphs the average predicted probability based on OLS results when *guest rating* and *prior-host–host cultural distance* are both at 25th and 75th percentiles, showing that quality signals widen the gap between culturally disadvantaged and advantaged guests (Gap 2 > Gap 1).

Figure 5. Guest rating and Prior-host–host cultural distance at 25th and 75th percentile



Model (4) adds to Model (1) the interaction term *guest-host cultural distance* × *guest verification* to test H3b, and its coefficient is positive and statistically significant (β= 0.0531, $p<0.05$). This supports H3b that predicted that the positive influence of an institutional-based quality signal (guest verification) on the probability that a host accept a request is strengthened as guest-host cultural distance increases. Similarly, I re-estimate this specification as linear probability model, which provides additional support for H3b (see Table 16B, column (4)). Based on OLS results, when *guest-host cultural distance* is held at average, the probability of approval for verified guests is 18.4 percent higher than that for not-verified guests; when *guest-host cultural distance* is held at one standard deviation above the average, the probability of approval for verified guests is 23.1 percent higher than that for not-verified guests, a 26-percent difference. To illuminate this relationship, Figure 6 graphs the average predicted probability based on OLS results when *guest-host cultural distance* are held at 25th and 75th percentiles, showing that compared to when high quality signals are absent (i.e., not-verified guests), the gap between guests who are culturally proximate to the host and those who are culturally distant to the host is narrowed when institutional-based signals are present (Gap 2 < Gap 1).

Figure 6. Guest verification and Guest-host cultural distance at 25th and 75th percentile



Turning to control variables, across all models, hosts favor older guests and prior transaction partners, but not guest with children. As hosts receive more applications and have more transaction experience and higher coin balance, they become pickier[15].

Supplemental Analysis

In this section, I conduct additional tests to examine whether other country-level variables—such as geographical distance, governance-quality distance, and economic-development distance—bifurcate the effects of various quality signals in the same way that cultural distance does. Table 17 presents the interactions between three country-level variables

[15] Note that *guest-host governance quality* is highly correlated with *guest-host economic-development distance* (p >0.75). As robustness tests, I reestimate my main model omitting *guest-host governance-quality distance* and then, separately, omitting *guest-host economic-development distance*. This barely affects the coefficient on *guest-host governance-quality distance* (β=-0.2707, p<0.001) but makes the coefficient on *guest-host economic-development distance* negative and significant (β=-0.0069, p<0.001). Thus, the coefficient on *guest-host economic-development distance* is likely driven by multicollinearity and should be interpreted with caution.

and the two types of quality signal. Note that interactions between prior-host–host country-level distances and quality signals are not reported here because the results are largely identical with those reported in Columns (1), (3), and (5). Furthermore, because *guest-host governance-quality distance* and *guest-host economic-development distance* correlate at 0.78, I only include one of them to reduce multicollinearity, but including both yields identical results.

Table 17. Interactions of Guest-host Country Differences and Quality Signals

DV: Request approval	(1)	(2)	(3)	(4)	(5)	(6)
Guest-host governance-quality distance^s × Guest rating^s	-0.0006					
	(0.0009)					
Guest-host governance-quality distance^s × Guest verification		0.0056*				
		(0.0022)				
Guest-host economic-development distance^s × Guest rating^s			0.0003			
			(0.0009)			
Guest-host economic-development distance^s × Guest verification				0.0056*		
				(0.0027)		
Guest-host geographical distance^s × Guest rating^s					-0.0010	
					(0.0008)	
Guest-host geographical distance^s × Guest verification						0.0034+
						(0.0020)
Guest-host cultural distance^s	-0.0043	-0.0039	-0.0031	-0.0029	-0.0043	-0.0042
	(0.0033)	(0.0032)	(0.0037)	(0.0036)	(0.0029)	(0.0029)
Guest-host geographical distance^s	0.0017	0.0017	0.0005	0.0006	0.0017	-0.0013
	(0.0017)	(0.0018)	(0.0017)	(0.0018)	(0.0016)	(0.0020)
Guest-host governance-quality distance^s	-0.0063*	-0.0111**			-0.0069*	-0.0070*
	(0.0025)	(0.0035)			(0.0032)	(0.0032)
Guest-host economic-development distance^s			-0.0043	-0.0092*	0.0008	0.0009
			(0.0025)	(0.0039)	(0.0033)	(0.0033)
Guest rating^s	0.0024**	0.0025**	0.0024**	0.0024**	0.0025**	0.0024**
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Guest verification	0.0129**	0.0123**	0.0135**	0.0131**	0.0129**	0.0129**
	(0.0044)	(0.0036)	(0.0044)	(0.0037)	(0.0044)	(0.0046)
Guest's total previous transactions	0.0013**	0.0013**	0.0013**	0.0013**	0.0013**	0.0013**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Guest prior transactions with the focal host	0.5260**	0.5260**	0.5261**	0.5259**	0.5261**	0.5260**
	(0.0136)	(0.0135)	(0.0136)	(0.0136)	(0.0136)	(0.0136)
Guest home popularity	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Guest with children	-0.0043**	-0.0043**	-0.0041**	-0.0041**	-0.0043**	-0.0044**
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Guest age	0.0017**	0.0017**	0.0017**	0.0017**	0.0017**	0.0017**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Female guest requester	0.0021	0.0020	0.0022	0.0021	0.0021	0.0021
	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
Host rating	-0.0176**	-0.0176**	-0.0176**	-0.0176**	-0.0176**	-0.0176**
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Host's total previous transactions	-0.0087**	-0.0087**	-0.0087**	-0.0087**	-0.0087**	-0.0087**
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Host home popularity	-0.0004**	-0.0004**	-0.0004**	-0.0004**	-0.0004**	-0.0004**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Host's coin balance	-0.0074**	-0.0074**	-0.0074**	-0.0074**	-0.0074**	-0.0074**
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Host-guest home price difference	0.0118**	0.0118**	0.0117**	0.0117**	0.0118**	0.0118**
	(0.0020)	(0.0020)	(0.0020)	(0.0019)	(0.0020)	(0.0020)
Advance notice of request	0.0002*	0.0002*	0.0002**	0.0002**	0.0002*	0.0002*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Duration of requested stay	-0.0091**	-0.0091**	-0.0091**	-0.0091**	-0.0091**	-0.0091**
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Observations	127,189	127,189	127,189	127,189	127,189	127,189

Notes: Linear probability models with host fixed effects and year fixed effects. Robust standard errors clustered by host country in parentheses. ** $p<0.01$, * $p<0.05$, + $p<0.1$ (two-tailed tests). ^{S} denotes standardized.

Columns (1), (3), and (5) offer no evidence that guest rating is discounted as the governance-quality distance, economic-development distance, and geographical distance between host and guest increase. Columns (2), (4), and (6) show that the positive effect of guest verification by the platform is more pronounced as governance-quality distance, economic-development distance, and geographical distance increase. These results suggest, first, that institutional-based quality signals from platforms are particularly important for guests in remote or less-developed countries or countries with weaker governance quality, which further reveals the significance of platforms as legitimate institutional devices. Second, cultural distance is unique in devaluing process-based quality signals, a factor that influences the organizing of economic activities in global platform markets. While the rating system appears robust when quality information travels across countries that vary in economic and political development, it becomes malleable when it encounters cultural differences across countries.

DISCUSSION

This study reveals important insights about cultural bias and trust signals in global peer-to-peer platform markets, even in a marketplace for travelers where, ironically, enjoying cultural experiences is largely the point. Core to this research is the interplay between three bases of trust: cultural-similarity–based trust, process-based trust (operationalized as ratings), and institutional-based trust (operationalized as platform verification). I theorize that cultural dissimilarities impede trust such that culturally distant market participants are at disadvantaged positions. Process-based quality signals further widen the gap between advantaged and disadvantaged participants, but institutional-based quality signals narrow this gap. I find support for these hypotheses, suggesting the importance of distinguishing different types/sources of quality signals. Those findings advance our knowledge of evaluation bias and trust in peer-to-peer markets.

Scope Conditions

It is important to make explicit the scope condition that may delimit the generalizability of my findings before discussing their broader implications. In platform markets, the participant can be a seller or a buyer. My study focuses on the latter – evaluations of a *buyer's* (the guest) trustworthiness. The literature distinguishes trust in competence (e.g., ability or expertise) versus trust in motives (e.g., integrity, benevolence, honesty) (Mayer, Davis, and Schoorman 1995; Twyman, Harvey, and Harries 2008). In my study, the quality signals reflect more on the motives of the buyer. While this is meaningful for understanding whether buyers have equal opportunities in platform markets, it might also create a boundary condition for my theory because when it comes to evaluations of a *seller's* trustworthiness, people may also care about her competence (Cook, Cheshire et al. 2009). In that case, ratings and platform verification might not be directly comparable because the former could reflect her capacity to provide desirable goods or services, whereas the latter only indicates her motives. Thus, other forms of institutional-based signals such as expertise credentials may be more comparable to ratings. Future research could look into the distortion of process-based versus institutional-based signals in these contexts involving trust in competence.

Do Quality Signals Benefit or Punish Disadvantaged Groups?

The discrimination and double standards literature in sociology holds as a central tenet that people apply double standards towards disadvantaged groups and discount quality information about them (e.g., Bertrand and Mullainathan 2004; Foschi 2000; Heilman 2001; Ridgeway 2011). This suggests that quality information would actually punish individuals (guests) who are culturally distant from the audience (hosts) by giving a further advantage to advantaged individuals. However, the tradition of information economics contends that market signals can, at the margin, benefit the disadvantaged group (e.g., Arcidiacono et al. 2010; Lang and Manove 2011; Lendle et al. 2016). This suggests that quality information would benefit culturally distant individuals (guests) to a greater extent. Empirical work has provided evidence for both camps, which further fuels this theoretical debate.

Drawing on early works in the sociological theories of the product trust that categorize different sources of trust (Zucker, 1986), my study suggests that these different effects may be contingent on how different quality signals are produced and perceived: some are seen as generic and informative, while others are seen as idiosyncratic and thus discounted. Indeed, as my research shows, social bias persists in people's perception of quality signals: people discount self-dissimilar others' evaluations and discount evaluations made by self-dissimilar raters. However, this bias only occurs when quality signals are generated by prior partners, not when they are generated by platforms. These findings advance theories of double standards that emphasize how certain social groups face a higher bar such that they have to offer a stronger quality signal (Foschi, 2000; Lyness and Heilman 2006) by highlighting which sources of quality signal are more subject to this interference.

The finding that process-based quality signals can be discounted when cross social boundaries questions the efficacy of reference systems widely used in economic exchange relationships. The ever-increasing emphasis on process-based quality signals such as ratings or reference letters may further penalize culturally distant groups, such as international applicants or immigrants in the market. By contrast, quality signals cast by institutions may be less subject to cultural differences. This calls for renewed emphasis in many contexts on institutional-based quality signals that may avoid penalizing disadvantaged social groups. Findings from this study also suggest market-disadvantaged participants can benefit from strategically leveraging "proof sources" to reduce being penalized by double standards. Such participants may mitigate their disadvantage by deploying institutional-based quality signals or peer referees culturally proximate to the key audience.

Cultural Heterogeneity and Trust in Global Platform Markets

This study advances research on culture and trust in the global market. First, I directly theorize and test the role of cultural (dis)similarities between market actors in trust production. While shared cultural systems are frequently theorized in the trust literature (e.g., Zucker 1986), they are seldom the object of empirical study. The empirical literature on trust has surprisingly focused on trusting behaviors among people in one common societal culture (e.g., Buchan et al. 2002; Yamagishi and Yamagishi 1994). Research on global teams and international business does account for national cultural (dis)similarities (e.g., Chua et al. 2015; Guiso et al. 2009; Morosini et al. 1998), but largely in the context of conventional business organizations with elaborated organizational structures to guide interactions. The emerging scholarship of social bias in peer-to-peer platform markets has focused on one single country and thus ignored global cultural dynamics (Abrahao et al. 2017; Cui, Li, and Zhang 2016; Edelman, Luca, and Svirsky 2017).

My additional analysis further highlights the uniqueness of cultural differences compared to other country-level differences such as geographical distance, economic-development distance, and governance-quality distance. Of these, only cultural differences are shown to mitigate the strength of rating systems. Cultural heterogeneity is the hallmark of global markets (Appadurai 1990, 1996; Morley and Robins 2004; Scholte 2005) and continues to influence online dynamics despite the quality systems implemented to build a borderless market. Ironically, my setting is a global peer-to-peer lodging platform where experiencing cultural differences is largely the point. One can imagine the significant impact of cultural distance in other contexts.

Furthermore, my additional analysis suggests that institutional-based signals cast by platforms are also particularly important for guests in less-developed countries with weaker governance quality, which further reveals the significance of platforms as institutional devices. The finding from my main and additional analyses substantiates the proposition that formal modes of trust production are the sine qua non for modern markets in which transactions occur across heterogeneous social groups (Polanyi 1944; Shapiro 1987; Williamson 1985; Zucker 1983, 1986). Given the exponential growth of global markets, there would be a pressing demand for the institutional-based trust signals to supplement the compromised process-based trust signals.

Platform-based Trust

This study has implications for understanding and designing peer-to-peer platform markets. Practitioners and scholars have marveled at ratings systems enacted by peer participants as the cornerstone for platform markets (e.g., Bolton et al. 2004; Dellarocas 2003; Kollock 1999). A bulk of studies center on the efficacy and accuracy of rating systems—investigating, for example, whether ratings are accurate(e.g., Bolton et al. 2013; Dellarocas and Wood 2008), how ratings can influence pricing (Dellarocas 2003) and future online transactions (Kollock 1999; Luca 2016). Yet, few studies entertain the possibility that ratings systems are subject to social bias and of these few, virtually none examine this issue on a global scale. Despite all the hype for rating systems in platform markets, such optimism may be groundless.

Highlighting how social bias can discount ratings is important for understanding the limitations of rating systems and how those limitations may influence market participants' access to services and goods in these platform markets.

Furthermore, despite the scholarly attention on rating systems, it has been under-emphasized that platforms themselves have become legitimate evaluators. As peer-to-peer platform markets have expanded exponentially and transformed the economy, it is important to recognize the critical role of platforms as institutional devices. Millions of users bestow significant trust on platforms, granting them the power to produce institutional-based quality signals, which has prominent implications for the market order. My finding that quality signals cast by platforms are less subject to social bias and thus can facilitate transactions across geographical, cultural, economic, and political boundaries highlights that platforms ought to invest in the production of such quality signals, instead of focusing solely on rating systems. This is an under-emphasized "platform-based trust"—a type of institutional-based trust resting on the recognition that platforms are legitimate intermediaries. In the meantime, this research raises questions on how platforms should use their power of legitimatization and how they should be disciplined, which are critical questions for the growth of peer-to-peer platform markets.

CHAPTER 4.

Markers of Mission Commitment:

Career, Gender, and the Evaluation of Social Entrepreneurs

An ever-growing group of entrepreneurs are seeking to achieve social goals—such as alleviating poverty and addressing environmental problems—with a viable business model that allows them to sustain the operation of creating positive social impact. Such hybrid models of start-ups, coined social entrepreneurship, integrate both commercial and social welfare goals into their ventures, and engage in certain commercial activities (e.g., sales of products/services) for the purpose of better fulfilling their social missions. Over the past two decades, there has been an explosive growth of social entrepreneurship. According to a report by the European Commission, 1 out of 4 new businesses in the European Union is a social enterprise, and up to 1 out of 3 in France (Social Business Initiative 2014). In the UK, there are more than 470,000 social enterprises employing a total of 1.44 million people, with a third founded after 2007 (DCMS and BEIS 2017). In the United States, social enterprises are estimated to represent 3.5% of GDP, and 60% of them were created in 2006 or later (British Council 2013). In addition to governmental support, such growth of social enterprise is financially fueled by emerging impact investing funds as well as the ever-increasing group of crowd funders who contribute via crowdfunding platforms.

Despite its growing scale and social impact, researchers have recognized that the hybridity of social entrepreneurship creates unique challenges for social entrepreneurs (Battilana and Lee 2014, Pache and Santos 2013, Wry and York 2017). The dual missions require leaders of these organizations to organically integrate the commercial and social welfare logics and strike a balance between maintaining business competitiveness and maximizing social impact. In reality, the pressures to sustainably generate commercial benefits oftentimes suppress the pursuit of social goals in these ventures, a process referred to as “mission drift” (Ebrahim, Battilana, and Mair 2014; Grimes, Williams, and Zhao 2019). To this end, the social entrepreneurship literature has focused on how social entrepreneurs can assuage the social-commercial tension by leveraging various tactics in established hybrid organizations (Battilana and Dorado 2010; Pache and Santos 2010, 2013; Smith and Tracey 2016). However, it remains largely unexplored as to how the hybridity of social enterprise could encounter unique dynamics for the fundraising process of social entrepreneurship in comparison to the one of for-profit start-ups.

The entrepreneurship literature has extensively documented the decision-making process of investing in for-profit start-ups, and much attention has been focused on entrepreneurs’ human and social capitals that is critical for a new venture’s commercial viability (Baum and Silverman 2004; Burton et al. 2002; Colombo and Grilli 2005; Hsu 2007; Shane and Stuart 2002; Unger et al. 2011). However, researchers have realized that, for investing in social start-ups, new evaluation metrics are needed for “double-bottom-line investing, where the first line is financial and the second line is social” (Bugg-Levine, Kogut, and Kulatilaka 2012). In fact, some investors are becoming aware of the tension between the commercial and social goals even at an early stage of the hybrid venturing process (Wry and York 2017). Thus, beyond competence assessments, these investors who are particularly attentive to social entrepreneurship may also grapple with the uncertainty of an entrepreneur’s potential to deviate from the social mission for the sake of maximizing profits. Accordingly, this paper seeks to explore whether the perceived risk of mission drift influences investors’ decisions regarding financial support, and what factors shape such perceptions of potential mission drift and consequentially the investment decision in social start-ups.

In particular, we argue that social entrepreneurs' (a) nonprofit professional experience and (b) female identity serve as important signals that help alleviate potential investors' concerns about mission drift, thus leading to more favorable fundraising performance. As new ventures lack sufficient track records, investors tend to rely on the background information and other peripheral cues of the founder(s) to aid their investment decision (Baum and Silverman 2004; Burton et al. 2002; Higgins, Stephan, and Thursby 2011). We posit that, in the context of social entrepreneurship, prior nonprofit experience can establish an achieved, professional identity of the founder that signals dedication to fulfilling social mission, and the female identity is an ascribed, personal identity that is strongly associated with communal characteristics that describe a concern with the welfare of other people. Therefore, potential investors will perceive lower likelihood of mission drift and are more likely to invest in a social start-up when the founders have substantial nonprofit experience and are female.[16] Furthermore, accumulated research on signaling theory has established that positive signals in the same domain could potentially be substitutive in the eyes of external constituents (Albrecht 1981; Arthurs et al. 2009; Reuer, Tong, and Wu 2012). As founders' nonprofit professional experience and female identity essentially represent signals that both serve the same function of alleviating the concern over mission drift, we propose that they could to some extent be substitutive when influencing investors' evaluation of the social start-up. Specifically, the positive effect of nonprofit experience tends to be stronger

[16] We recognize that, with crowdfunders becoming an increasingly important body of investors for early-stage ventures, researchers have sought to unveil the extent to which the decision-making processes for crowdfunders and professional investors (such as angel investors and venture capitalists) are idiosyncratic. While some research established common findings in some aspects across crowdfunders and professional investors (Mollick and Nanda 2016), others found systematic differences (Li et al. 2017). Given the salience of mission drift in social enterprise and the lack of other objective data for professional investors to infer about mission drift, we do not theorize systematic differences across crowdfunders and professional impact investors in how their investment decisions are influenced by the founder's previous nonprofit experience and gender.

when the founder is a male, while the positive effect of female identity tends to be stronger when the founder has limited nonprofit experience.

We test these ideas in three studies. First, we conducted a field study of 451 social enterprise fundraising campaigns (Study 1) and found that ventures founded by entrepreneurs with nonprofit work experience and female social entrepreneurs are more successful than their counterparts. We then causally validated this relationship in two experimental studies by imitating a crowdfunding scenario in Study 2 and a professional venture capitalist investment scenario in Study 3, and further identified that it was mediated by investors' perceived risks of mission drift. In addition, across three studies, we consistently found that professional identity and gender identity are substitutive — one's effect is weaker at the presence of the other. Taken together, these findings support our proposition that professional identity and gender identity serve as markers of mission commitment for social entrepreneurs.

This paper makes three important contributions. First, this study expands the entrepreneurship scholarship that has been predominantly focusing on entrepreneurs' human and social capital (Baum and Silverman 2004; Burton et al. 2002; Colombo and Grilli 2005; Hsu 2007; Shane and Stuart 2002; Unger et al. 2011). It reveals that given the unique characteristics of social enterprises, there is a substantial shift of focus in the new venture evaluation process onto entrepreneurs' commitment to a venture's mission. Using two experimental studies, we are able to identify perceived risks of mission drift as an important mechanism influencing social entrepreneurs' fundraising outcomes. Second, our study moves beyond the existing literature's main focus on how established social enterprises handle the internal tension between social and commercial goals (Battilana and Dorado 2010; Pache and Santos 2010, 2013; Smith and Tracey 2016) and builds upon a handful of studies that have started to look into how critical external constituents such as early-stage investors assess social entrepreneurs (Cobb, Wry, and Zhao 2016; Lee, Adbi, and Singh 2020; Lee and Huang 2018; Yang, Kher, and Newbert 2020). Third, this paper provides new insight into the long-established female disadvantage in entrepreneurship such that female founders are in disadvantageous positions when seeking investments for new ventures (Becker-Blease and Sohl 2007; Brooks et al. 2014; Fay and Williams 1993; Guzman and Kacperczyk 2019). In the social enterprise context, however, we find that the gender advantage is reversed, such that female founders are preferred over male counterparts. Beyond revealing the female advantage, we also show that male founders can overcome their disadvantage by accumulating substantial nonprofit professional experience.

THEORY AND HYPOTHESES

Social Entrepreneurship and Mission Drift

Though social entrepreneurship is perceived as having the potential to solve problems extant in capitalist economies, it could complicate the mobilization of financial resources at an early stage (Bugg-Levine et al. 2012; Doherty, Haugh, and Lyon 2014). Pursuing both commercial success and social impact requires entrepreneurs to craft a delicate balance between the two goals. In theory, either goal could outweigh the other; but in reality, it is oftentimes the social goal that is marginalized. Although stories of heroic successful social entrepreneurs "changing the world" constitute a prominent feature of the academic literature on social entrepreneurship (Dacin, Dacin, and Tracey 2011), external constituents including investors, the media, and researchers are becoming vigilant about the dark side of social entrepreneurship.

There are entrepreneurs who focus on the symbolic management of social values to achieve their political and/or economic objectives and entrepreneurs who destroy (proactively or inadvertently) social goods as they pursue profitability or other objectives (Dacin et al. 2011).

Mission drift also occurs when entrepreneurs consistently allocate organizational resources to the development of commercial activities to increase profits, while they could have allocated such resources to scale-up their social impact and reach more people that need help (Ebrahim et al. 2014; Grimes et al. 2019; Ramus and Vaccaro 2017). The occurrence of mission drift could be a result of entrepreneurs' self-driven behaviors, or a compromise that entrepreneurs have to make given the pressure from certain stakeholders. While a venture's financial performance has a proven measurement, there are no established standards to measure their social performance(Dacin et al. 2011; Owen et al. 2000). The evaluation metrics often lack standardization and comparability, in contrast to financial performance. It is therefore difficult for stakeholders to objectively assess the social impact, giving rise to the prioritization of the financial goal over time (Grimes et al. 2019). All in all, the issue of "mission drift" has come to the front and center in social entrepreneurship as well as the evaluation process of potential investors.[17]

Signals are important under information asymmetry and uncertainty (Spence 1974). Because new ventures lack sufficient track records and because social impact lacks standard metrics for evaluation, investors are particularly likely to rely on social entrepreneurs' individual characteristics to gauge the prospect of a social venture's mission drift. In particular, identities[18], either ascribed or achieved, are highly observable and salient characteristics that could carry specific social meanings and subsequent behavioral expectations to affect the individuals' social

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[17] See an exemplar report at https://www.theguardian.com/small-business-network/2018/mar/12/social-enterprises-go-bust-all-the-time-how-the-sector-is-tackling-its-image-problem

[18] It is important to clarify that we use the term "identity" to refer to externally imposed categories or roles, and our approach is based in identity theory (Stryker and Burke 2000), according to which identities are "broadly recognized and meaningful categories that people apply to themselves and others as role players (e.g., doctor, lawyer, parent), group members (e.g., Asian, Catholic), and individuals (e.g., moral, powerful; Stryker and Burke 2000)." (Wry and York, 2017:438). This approach differs from other scholars that refer to identities as subjective knowledge, meaning, and experience (see Ramarajan 2014 for a review).

relations and external feedback (Stryker and Burke 2000). Social entrepreneurs' identities affect audience's perceptions about "who they are" and expectations about "what they will do" in a given situation, serving as important signals that could influence the evaluation of entrepreneurs (Thornton, Ocasio, and Lounsbury 2012; Wry and York 2017). In this study, we examine two identity signals associated with potential investors' evaluation of mission drift and their investment decision—professional identity (an achieved identity signaled by previous work experiences) and gender identity (an ascribed identity, i.e., gender roles)(Abrams and Hogg 1990; Merton 1957; Navis and Glynn 2011)

The two signals have generated substantial attention in entrepreneurship research especially in the venture selection and evaluation sphere. Entrepreneurs' professional experience is among the most frequently used criteria in venture capitalists' selection process (Baum and Silverman 2004; Hsu 2007; Unger et al. 2011). Research has also long established that female entrepreneurs are penalized by gender stereotypes and are less successful (Abraham 2020; Brooks et al. 2014; Guzman and Kacperczyk 2019; Kanze et al. 2018). While the previous literature documents the importance of successful business experience and the advantage of male identity in a new venture's fundraising, this study suggests that, in the context of social ventures, entrepreneurs with nonprofit work experience and female identity are preferred because of the concern over mission drift. Below, we elaborate on the direct and interactive effects of social entrepreneurs' nonprofit professional identity and female identity on their fundraising performance.

Professional Identity: Founder's Nonprofit Experience and Fundraising Performance

Most entrepreneurs have experience working in other organizations prior to founding a new firm (Dobrev and Barnett 2005; Kacperczyk 2012; Sørensen and Fassiotto 2011).

Entrepreneurs' past work experiences form the basis of the founding conditions (Beckman and Burton 2008; Fern, Cardinal, and O'Neill 2012; Zheng, Devaughn, and Zellmer-Bruhn 2016), provide access to critical resources (Hallen 2008; Sørensen and Fassiotto 2011), and importantly, influence how investors evaluate entrepreneurs (Delmar and Shane 2006; Hoang and Gimeno 2010). As extensively documented in the literature, in conventional venture investing, investors view entrepreneurs' professional experiences as markers of business competence and effective leadership—they signal entrepreneurs' expertise, skills, and social capital, which reduce investors' concerns about venture failures (Baum and Silverman 2004; Burton et al. 2002; Gulati and Higgins 2003). Thus, the more work experience with prominent employers the entrepreneurs have, the more likely investors would invest in them (Burton et al. 2002).

In the case of social entrepreneurs, however, we argue that some investors may place more emphasis on the social entrepreneurs' prior nonprofit experience, not only because social entrepreneurs with a nonprofit background presumably have domain expertise and resources that could advance a venture's social impact, but, perhaps more importantly, because of some investors' concern over entrepreneurs drifting from their social missions. A significant body of research has shown that social imprints—defined as entrepreneurs' early emphasis on accomplishing the organization's social mission—are critical to avoid it (Battilana et al. 2015). Taking this further, we posit that external evaluators who are attentive to organizations' social performance would be vigilant about founders' early commitment to advancing social welfare, which might be reflected in their prior professional choices. Thus, entrepreneurs' prior experience in the nonprofit sector might serve as a strong signal that could relieve external evaluators' concern over social mission drift.

First, unlike ad-hoc framing strategies that can be perceived as inauthentic (Rudman and Glick 1999), professional identities are developed via substantial work time in organizations and are viewed as authentic credible signals. Professional identities help external audiences define who a person is and whether their behavior is consistent with their claims (Stryker and Burke 2000)—such consistency can elicit perceived authenticity and gain favorable evaluations (Luthans and Avolio 2003; Simons 2002). With substantial nonprofit work experience, social entrepreneurs can establish an authentic professional identity that is viewed as socially-oriented and thus aligned with a hybrid venture's social welfare goal. In comparison, founders with substantial for-profit experience yet a lack of nonprofit experience may establish a professional identity that is viewed as economic and profit-oriented (Battilana and Dorado 2010; Glynn 2000), which may indicate a higher risk of the founder prioritizing financial goals over social goals when the two conflict (i.e., mission drift). Social entrepreneurs with nonprofit work experience thus may appear authentic because their past professional behaviors appear consistent with their current claims of adhering to the social mission. This perceived authenticity alleviates investors' concern for mission drift at the very beginning.

Second, in addition to authenticity, professional identity signals predictability for future decisions and behaviors. In organizational work environments, individuals internalize a set of norms and guidance regarding how the work is to be performed, and these behavioral prescriptions become automatic and rigid (DiRenzo 1977). Decision-makers thus could infer how a person would react in a given situation from her professional identity. In the context of start-ups, venture development processes are likely to be imbued with hurdles and pivots, and entrepreneurs' reactions and choices may differ. The external audience may expect that social entrepreneurs with exposure to only commercial working environments are predisposed to commercial practices, leading them to be more likely to lose sight of the social welfare goal in their decision-making. These behavioral expectations exacerbate investors' concern for mission drift during the future venture development process.

Thus, social entrepreneurs with nonprofit professional experience may be perceived as more authentic and more predictable, and thus are more likely to adhere to their social missions. This alleviates external constituents' mission drift concerns and consequently gains favorable fundraising outcomes. We hypothesize that:

H1a: Social entrepreneurs with nonprofit work experience will raise more funds than those with only for-profit experience.

H1b: Perceived risk of mission drift mediates the positive relationship between social entrepreneurs' nonprofit work experience and fundraising performance.

Personal Identity: Founder's Female Identity and Fundraising Performance

While achieved identities such as professional identities are highly salient signals that might influence entrepreneurs' venture evaluation process, entrepreneurship literature has shown that ascribed identities such as gender can also affect how entrepreneurs are evaluated by external constituents. Indeed, extensive literature has documented the "female disadvantage" in entrepreneurship (Abraham 2020; Brooks et al. 2014; Guzman and Kacperczyk 2019; Kanze et al. 2018) due to gender stereotypes — entrepreneurship is viewed as a male-preserved field and the stereotypical female characteristics are incongruent with the image of competent business leaders (Eagly and Karau 2002; Heilman, Block, and Martell 1995). Specifically, women are generally regarded as more communal (e.g., care for other's welfare), and men more agentic (e.g., assertive and controlling) (Eagly and Karau 2002). These general gender stereotypes produce unfavorable bias against females in traditional entrepreneurial processes.

Despite the widely documented female disadvantage in the conventional venturing process, recent research shows that the gender gap is reduced when a conventional for-profit start-up is framed as having a social impact (Lee and Huang 2018). Taking this further, we argue that in the case of hybrid ventures, gender stereotypes can work to the benefit of women such that female social entrepreneurs will be evaluated more favorably, resulting in a "female advantage." First, women are stereotypically seen as communal, understanding and nurturing; thus, external evaluators might expect female social entrepreneurs to be more likely to stay adhere to a venture's social welfare goal when they are facing the tradeoffs between financial and social goals. This alleviates external evaluators' concern for mission drift in the future venturing process.

Second, female leaders are expected to exhibit a more inclusive leadership style characterized by more collaboration, communication, and less hierarchy (Eagly and Johnson 1990; Rosener 1995). This feminine leadership style is critical for social enterprises that face a dilemma in allocating their resources and balancing social and commercial performance. People expect female leaders to be more able to lead an inclusive team and solve diverse concerns more effectively than their male counterparts (Post 2015) and building an inclusive decision-making space is shown to be critical for the success of a hybrid venture (Battilana et al. 2015). Thus, female social entrepreneurs might be seen as more likely to successfully handle social-commercial conflicts and avoid mission drift than their male counterparts.

Thus, in the case of social entrepreneurship, we propose that gender stereotypes will work to the advantage of women, as they will be perceived to be less likely to drift from a venture's social mission, thus making female social entrepreneurs preferred in the eyes of investors. We hypothesize that:

H2a: Female social entrepreneurs will raise more funds than male social entrepreneurs.

H2b: Perceived risk of mission drift mediates the positive relationship between social entrepreneurs' female identity and fundraising performance.

The Substitutive Effects of Nonprofit Professional Experience and Female Identity

While the majority of prior research studies entrepreneurs' work background and gender in isolation, external constituents such as investors typically view an entrepreneur as a total package, making it important to understand how these two critical factors are perceived in combination. We argue that these two signals could be, to some extent, substitutive with each other in influencing fundraising performance; that is, the positive effect of one signal may diminish at the presence of the other.

First, positive signals in the same domain could be substitutive because they offer redundant benefits and mechanically compromise each single signal's value. The value of a signal is a function of level of adverse selection risk that decision-makers face; this, in turn, is influenced by the presence or absence of other signals that provide similar information benefits (Spence 1974). If other signals are lacking, the risk of adverse selection is more severe, and the value of a particular signal will be greater. For example, in their study of new venture's formation of future strategic alliance, Ozmel et al.(2013) showed that the value of one signal—a venture's tie to prominent VCs, diminishes with the another signal—new venture's prominence in alliance network, because both signals provide somewhat similar information. In the context of our study, signals associated with nonprofit professional experience and female identity serve the same function of alleviating investors' concern over mission drift. If a social entrepreneur does not have either signal, impact investors face greater adverse selection risk and uncertainty due to the mission drift concern. Thus, the value of the signals associated with entrepreneurs' professional background and gender will be greater when the other signal is absent. If, on the other hand, one signal is present—for example, the entrepreneur has substantial professional experience in the nonprofit sector and hence the new venture has differentiated itself from others with no such prospects, investors face a lower risk of adverse selection. Therefore, the value of signals about having female founders decreases.

Second, researchers of cognitive attention and signal sets have also proposed the sufficiency argument—if one credible signal is sufficient for decision-makers in some contexts, they would pay less attention to additional signals to save cognitive resources, dimming those signals' valence (Drover et al. 2018). For example, Albrecht (Albrecht 1981) noted that, interviewers often rely on educational background to infer a job applicant's productivity but less so in the presence of other credible signal such as internal reference. In another case, Arthur et al (Arthurs et al. 2009) showed that, to ensure IPO success, owners oftentimes choose a longer lockup period to signal a firm's long-term viability, but less so when they have other signals such as prestigious underwriting backing to provide for potential investors with the assumption that multiple signals might not be necessary if one is sufficient.

Both professional experience and gender identity have strong signaling value, and the aforementioned prior research examining these two factors in isolation implicitly argues each is sufficient in influencing investors' decision-making. In the context of our study, a socially-oriented professional identity is developed via substantial work time and long-term dedication in nonprofit organizations—a strong signal that is more authentic than other ad-hoc framing strategies or self-claiming commitment toward social goals. This signal could be sufficient in shaping some investors' perceived mission drift and venture attractiveness, diming the valence of entrepreneurs' gender signal. On the other hand, the gender signal could also be sufficient for some investors as gender stereotypes have been shown to have strong and lasting effects across various contexts. Female social entrepreneurs already benefit from the society's gender stereotypes by being perceived as caring, social-welfare-oriented, and less subject to mission drift. Thus, when look at female social entrepreneurs' profiles, signals associated with their professional identity are, at the margin, less salient. By contrast, male entrepreneurs—as they carry the stereotypes of being aggressive, ambitious, and forceful—could gain more from the nonprofit signal to overcome their gender disadvantage.

Thus, we posit that founder's nonprofit work experience and female identity can be to some extent substitutive when influencing decision-makers' perception over mission drift and decision of funding, such that the positive effect of one weakens at the presence of the other. That is, the signaling value of nonprofit experience is more pronounced for male entrepreneurs, and the positive effect of female identity is stronger for entrepreneur with only for-profit experience. We hypothesize that:

H3a: Nonprofit experience and female identity negatively interact to influence fundraising performance, such that the positive effect of one diminishes at the presence of the other.

H3b: Perceived risk of mission drift mediates the interactive effect of founder's nonprofit experience and female identity on fundraising performance.

Overview of Studies

We conducted three studies to test our hypotheses. In Study 1, we examined social enterprise fundraising campaigns in three crowdfunding platforms to test the main effects and interactive effects (H1a, 2a, and 3a). We then conducted two experimental studies (Study 2 & 3) to (a) provide causal evidence on the effects of founder's nonprofit experience and gender on fundraising performance, and (b) test perceived risk of mission drift as the mediating mechanism of the proposed effects (H1b, 2b, and 3b). Study 2 adopted a crowdfunding context and investigated participants' evaluation of social entrepreneurs in the position of crowdfunders, while Study 3 put participants in the role of professional impact investors and examined if our findings hold when participants have the mindset of making professional investment.

Study 1: A Field Study of Crowdfunding Campaigns

Sample and Procedures

A growing number of social entrepreneurs have resorted to crowdfunding platforms to fund their ventures at the nascent stage, including generic platforms that span across various types of fundraising causes such as Indegogo.com and specialized platforms that are exclusively for social enterprises and nonprofit organizations. We took several steps to identify ventures on these platforms that meet the definition of social enterprises and attract socially-aware investors.

First, we thoroughly identified and compared 11 of the most well-known generic and specialized crowdfunding platforms, and decided to focus solely on three platforms, *Kickstarter*, *StartSomeGood*, and *Pozible*, because they provide the most comprehensive publicly available information on entrepreneurs and their ventures (see Appendix A for details). We scraped information on fundraising campaigns since the inception of these three platforms up to February 2020. Specifically, we scraped 908 campaigns in the Public Benefit category on *Kickstarter*, 211 campaigns in the Social Enterprise category on *Start-Some-Good*, and 287 campaigns in the Social Enterprise category on *Pozible*. Campaigns in these categories are likely to attract socially-aware investors.

Second, we manually screened these campaigns and excluded those that did not meet the definition of social enterprises. The authors independently coded 60 projects and then discussed together to agree upon four screening criteria: (1) the campaign aims to support a business with *continuous* operations, instead of individual activities or one-off charitable events; (2) the campaign has a valid business model to support its social mission without fully relying on charitable donations; (3) the campaign aims to support a business that has social missions, and does not exist purely for profit; (4) the campaign has a clearly identified individual(s) as its founder(s). We then hired and trained 4 research assistants to identify social enterprises from the entire database following these criteria. Each campaign was coded by two research assistants independently (the inter-rater reliability is 84%). Authors then cross-checked each case and discussed the controversial cases to reach an agreement. We identified 451 fundraising campaigns in total (197 from *Kickstarter*, 146 from *Start-Some-Good*, and 108 from *Pozible*).

Third, we coded a founder's work experience and gender via information on the campaign website, such as pictures and videos, and their social media pages (i.e., LinkedIn and Facebook). Out of the 451 campaigns, 344 disclosed founder prior work experience via campaign website or founders' social media pages, including 44 with founders' prior work experience only in the nonprofit sector, 149 only in the for-profit sector, and 151 in both. We created a dummy variable, *founder with nonprofit experience*, with "1" indicating that the campaign disclosed that (at least one of) the founder(s) had professional work experience in the nonprofit sector. We also created a dummy variable, *founder work experience not disclosed* to distinguish campaigns lacking founder work information. In addition, 411 campaigns disclosed founder gender information, 185 were founded solely by men, 160 solely by women, and 66 by both men and women. We created a dummy variable, *female founder*, with "1" indicating that the venture disclosed (at least one of) the founder(s) being female. We also created a dummy variable *founder gender not disclosed* to distinguish campaigns lacking founder gender information.

Results

We tested whether there is an association between a campaign's founder's work experience and gender and the total amount of funding a venture is able to raise (logged; unit: USD); a campaign is the unit of analysis. Following prior studies (Greenberg and Mollick 2017; Younkin and Kuppuswamy 2017), we controlled for a set of influential variables identified in prior studies of crowdfunding: the total number of words (logged) and the total number of pictures in the project description (logged), fundraising goal (logged; unit: USD), and whether this campaign is foreign— that is, the campaign's main target sites are in countries other than the platforms' primary users' countries. Lastly, we included year fixed effects and platform fixed effects to control for unobserved time and platform effects. Table 18 reports summary statistics and correlations, and Table 19 OLS regression results with robust standard errors.

Table 18. Summary Statistics and Correlations

		M	S.D.	Min	Max	1	2	3	4	5	6	7	8	9
1	Total fund raised (logged)	8.27	2.87	0	13.26	-								
2	Founder with nonprofit experience	0.43	0.50	0	1	0.39	-							
3	Female founder	0.50	0.50	0	1	0.10	0.18	-						
4	Number of words in description (logged)	6.72	0.80	0	8.67	0.28	0.11	-0.01	-					
5	Number of pictures in description (logged)	2.03	1.06	0	4.26	0.41	0.16	0.00	0.44	-				
6	Fundraising goal (logged)	9.48	1.15	5.70	12.61	0.45	0.08	-0.09	0.28	0.34	-			
7	Foreign venture	0.31	0.46	0	1	-0.19	-0.04	-0.04	-0.02	-0.07	-0.06	-		
8	Founder work experience not disclosed	0.24	0.43	0	1	-0.19	-0.49	-0.17	-0.20	-0.18	-0.19	-0.04	-	
9	Founder gender not disclosed	0.09	0.28	0	1	-0.10	-0.27	-0.31	-0.06	-0.09	-0.02	-0.09	0.56	-

Note: N=451. Summary stats and correlations of the subsample (N=344) are largely similar so are not reported for simplicity.

Table 19. OLS Regression Results

DV: *Total amount of funding raised (logged)*	(1)	(2)	(3)	(4)	(5)	(6)
Founder with nonprofit experience		1.575**	1.958**		1.675**	2.217**
		(0.186)	(0.275)		(0.176)	(0.287)
Female founder		0.564**	0.879**		0.618**	1.176**
		(0.180)	(0.283)		(0.184)	(0.334)
Nonprofit experience X Female founder			-0.689*			-1.010**
			(0.346)			(0.385)
Number of words in description (logged)	-0.066	0.013	0.013	-0.219	-0.141	-0.161
	(0.122)	(0.125)	(0.125)	(0.144)	(0.167)	(0.165)
Number of pictures in description (logged)	0.725**	0.615**	0.620**	0.738**	0.602**	0.632**
	(0.121)	(0.114)	(0.114)	(0.142)	(0.127)	(0.127)
Fundraising goal (logged)	0.406**	0.493**	0.493**	0.497**	0.620**	0.621**

Table 19 (Continued). OLS Regression Results

	(0.098)	(0.093)	(0.092)	(0.114)	(0.104)	(0.102)
Foreign venture	-0.964**	-0.810**	-0.789**	-0.839**	-0.638**	-0.591**
	(0.232)	(0.212)	(0.212)	(0.259)	(0.223)	(0.218)
Founder work experience not disclosed	-0.089	0.816*	0.783*			
	(0.303)	(0.338)	(0.341)			
Founder gender not disclosed	-0.882†	-0.540	-0.353			
	(0.520)	(0.543)	(0.572)			
Observations	451	451	451	344	344	344
R-squared	0.540	0.606	0.609	0.541	0.649	0.657

Note: platform fixed effects and year fixed effects are included in all models; robust standard errors in parentheses; ** $p<0.01$, * $p<0.05$, † $p<0.1$

Models (1) – (3) are estimated on the full sample, and Models (4)-(6) on the sample excluding campaigns not disclosing the work or gender information of their founder(s) as robustness tests. Model (1) reports coefficients on control variables — campaigns that have more pictures, higher fundraising goals, and are local are likely to receive more funds. In Model (2), the statistically significant positive coefficient on *founder with nonprofit experience* (B = 1.575, $p < 0.01$) suggests that campaigns that disclosed that the founder or at least one of the founders had previously worked in nonprofit sectors raised significantly more—specifically, 3.8 times more (= exp (1.575)-1)—funding than others campaigns that do not have such nonprofit-experience signals, supporting H1a. H1a is also supported by Model (5).

The statistically significant positive coefficient on *female founder* (B = 0.564, $p < 0.01$) suggests that campaigns that disclosed having at least one female founder raised significantly more—specifically, 76% more (= exp (0.564)-1)—funding than other ventures that do not have such female-founder signals, supporting H2a. H2a is also supported by Model (5).

Model (3) adds the interaction term, *Nonprofit experience* X *Female founder* (B = -0.689, $p < 0.05$), suggesting a significant interaction between nonprofit experience and female identity. Pairwise comparison of predictive margins reveals that among campaigns that have founders with nonprofit-experience signals, those that have female-founder signals raised an average of 9.1 log dollars while others without female-founder signals an average of 9.3 log dollars, a statistically insignificant difference ($F=0.90$, $p>0.1$). Thus, a gender gap is not observed among social entrepreneurs that disclosed their professional experience in the nonprofit sector. By contrast, among campaigns without nonprofit-experience signals, those that do not have female-founder signals only raised an average of 7.2 log dollars while others with female-founder signals an average of 8.0 log dollars, a statistically significant difference ($F=9.67$, $p<0.05$). Female identity is more positively associated with fundraising performance when nonprofit-experience signals are absent.

In addition, among campaigns that have female-founder signals, those without nonprofit-experience signals raised an average of 8.0 log dollars whereas others that have nonprofit-experience signals raised an average of 9.3 log dollars, a statistically significant difference ($F=29.64$, $p<0.01$). By contrast, among campaigns that do not have female-founder signals, those without nonprofit-experience signals raised an average of 7.2 log dollars whereas others that have nonprofit-experience signals raised an average of 9.1 log dollars, a statistically significant difference ($F=50.66$, $p<0.01$). Having nonprofit work experience is more positively associated with fundraising performance when campaigns do not have female-founder signals. In conclusion, results in Model (3) support H3a, as with Model (6).

Study 2: An Experiment Test in Crowdfunding Context

Study 2 was conducted to provide causal evidence on the findings of Study 1 via experimental manipulation. This experiment also enabled us to test the perceived risk of mission drift as the mediating mechanism of the effects found in Study 1. This between-person experiment adopted a crowdfunding context and investigated participants' evaluation of social entrepreneurs in the position of crowdfunders.

Participants and Procedures

We recruited 900 participants through Amazon Mechanical Turk (hereafter referred to as Mturk). Prior research stated that the internal and external validity of experiments using Mturk subjects are comparable with those using subjects from traditional pools (Berinsky, Huber, and Lenz 2012). Participants were told that they would read a crowdfunding page of a social enterprise start-up and were subsequently asked to evaluate the venture and the founder. Participants were randomly assigned to read one of six versions of a crowdfunding page in a 2 (founder's gender: male or female) by 3 (founder's previous work experience: for-profit only, has both for-profit and nonprofit, and nonprofit only) experimental design. Each version (see Appendix B for the full pitch) started by a brief description of what a social enterprise is, followed by a crowdfunding campaign featuring NYBakery—a real-world New-York-based bakery seeking to provide jobs to individuals who face barriers to employment and support them for their future employment. Texts and pictures were provided to describe how this organization fulfills its social mission (via open hiring and training programs) and how its business model generates revenues to support its long-term operations. Following this, we presented the profile of the Founder/CEO, where we manipulated the founder's gender and previous work experience.

We manipulated founder's gender with two names: Ashley for female and Andrew for male[19]. We manipulated founder's previous work experience by providing different profiles: for-profit experience only, mixed experience, and nonprofit experience only (see Appendix A for detailed descriptions). In the for-profit-only group, Ashley/Andrew worked at the Ernest Gourmet Food Company (Publicly traded) during 2004-2009, and at the Acquis Consulting Group (Private) during 2009-2015. In the nonprofit-only group, Ashley/Andrew worked at the Institute for Youth Development (Nonprofit) during 2004-2009, and at the Common Good

[19] Although pictures of entrepreneurs may manipulate founder gender in a more vivid way, we did not use pictures because there could be unintended differences incurred in addition to gender, such as attractiveness and warmth.

Initiative (Nonprofit) during 2009-2015. In the mixed-experience group, Ashley/Andrew worked at the Ernest Gourmet Food Company (Publicly traded) during 2004-2009, and at the Common Good Initiative (Nonprofit) during 2009-2015. We provided similar job responsibilities—yet tailored to different positions—across for-profit and nonprofit organizations.

Next, to strengthen participants' impression of the social enterprise and the founder, we asked two open-ended questions about their opinions on the start-up and the founder, respectively. Then, participants answered questions on (a) the perceived risk of mission drift, (b) the perceived founder's competence, (c) intended support to this campaign. In the end, participants indicated their age, gender, race, education, and were debriefed about the deceptive lottery.

Measures

Perceived Risk of Mission Drift. Although the notion of mission drift has been discussed in depth in the literature (e.g., Ebrahim et al. 2014; Grimes et al. 2019), there's a lack of quantitative research on—and thus a lack of existing scale to capture—perceived risk of mission drift. Nonetheless, this stream of theoretical and qualitative work provides us with a rich theoretical foundation to inductively derive three measuring items that reflect the key aspects of the perceived risk of mission drift. Specifically, we asked participants: "Based on your first impression of the Founder/CEO of this social venture, Ashley/Andrew, to what extent do you agree/disagree with the following statements: (a) He/she is trustworthy in using the corporate money only to serve the social purpose; (b) To him/her, making profits is a means to serve the social purpose, not a goal; (c) If there's a conflict between making more profits and serving the social purposes better, he/she will prioritize the social mission over profiting making". Participants responded based on a 5-point Likert scale (1=strongly disagree to 5 = strongly agree). We reverse-coded these items to obtain the score for perceived risk of mission drift. The Cronbach's alpha is 0.79.

Perceived Founder's Competence. As discussed, previous studies have shown that perceived leader's competence is an important factor in potential investors' decisions of support. Thus, we include it as a controlling mediating mechanism. Following the established scale (Fiske et al. 2002), we asked participants: "Based on your first impression of the Founder/CEO of this social venture, Ashley/Andrew, to what extent do you agree/disagree with the following statements (1=strongly disagree to 5 = strongly agree): (a) He/she is capable of running the startup efficiently; (b) He/she is competent in leading this startup, and (c) He/she has what it takes to lead this startup". The Cronbach's alpha is 0.95.

Financial Support. We presented participants with the following deceptive statement: "By completing this task, you will automatically be entered into a lottery. Five out of every hundred participants will win a bonus ($50). Now before entering the lottery, you can decide whether you want to support this social startup by donating some or all of the $50. Our research team will transfer the money you choose to donate to them. Please indicate the amount you would like to contribute below (from 0 to $50). If you win the lottery, you will receive the bonus with the amount of 50 minus how much you decide to donate. If you do not win the lottery, your intended donation will be invalid." After participants indicated the amount they would like to contribute, we asked them to provide a brief rationale underlying their decision. We designed the lottery for two reasons. First, it is less arbitrary than asking for a hypothetical contribution that has no real monetary loss. Second, because the lottery winnings would be in excess of earned participation money, it better mimics real world crowdfunders using their extra money to contribute to campaigns they like.

Other control variables. Although the randomized assignment of participants into experimental groups evens out individual differences across groups, we control for participants' demographic characteristics for more conservative tests, including their gender, race, age, and education level, which might influence their perception of the founder and the start-up (Greenberg and Mollick 2017) (See Appendix D for detailed measures).

Results

We took several steps to assure the quality of data for analysis. First, we dropped 19 participants who spent less than 5 minutes (half of the median completion time, 10 minutes) because they might not read the materials carefully. Second, we excluded 186 participants who failed either of the two manipulation check questions asking the founder's gender (female or male) and previous work experience (for-profit only, nonprofit only, and mixed). Third, in our deceptive lottery, we asked participants to provide their Mturk ID so that we can transfer the award if they win the lottery. We excluded 10 participants who did not provide their Mturk ID and thus might not believe the lottery design. Fourth, to better mimic real world crowdfunders using extra money to support campaigns, we dropped 77 participants who explicitly said in self-reported supporting decision rationales that they liked the venture but could not contribute due to financial constraints and the need for every bit of possible money. Thus, we had 608 valid participants, with a valid response rate of 68%. Among the 608 participants, 56% were female; regarding age, 38% were between 25-34, 23% between 35-44, and 27% between 45-64; regarding education, 31% had some college or associate's degree, 42% had bachelor's degree, and 17% had advanced degree; regarding race, 80% were white. Summary statistics and correlations are in Table 20, and interaction/mediation analyses in Table 21.

Table 20. Summary Statistics and Correlations

		Mean	S. D	1	2	3	4	5	6	7	8	9
1	Female founder [a]	0.47	0.50	-								
2	Founder Work Experience [b]	0.74	0.44	-0.02	-							
3	Support	22.01	13.82	0.11	0.10	-						
4	Perceived Risk of Mission Drift	2.21	0.95	-0.11	-0.20	-0.23	-					
5	Perceived Leader Competence	6.24	0.88	0.06	0.09	0.17	-0.50	-				
6	Participant Age	2.80	1.04	-0.01	0.00	0.10	-0.08	0.06	-			
7	Participant Gender [a]	0.56	0.50	-0.07	0.01	0.01	-0.08	0.12	0.08	-		
8	Participant Education	3.64	0.89	0.01	-0.02	0.03	0.10	-0.23	-0.03	-0.06	-	
9	Participant Race [c]	0.80	0.40	0.01	-0.03	0.04	0.03	0.02	0.17	-0.01	0.02	-

Note. N=608; a: 1 = female, 0 = male; b: 1 = has nonprofit experience, 0 = for-profit experience only; c: 1 = white, 0 = others.

Table 21. Interaction and Mediation Analysis

	DV: Support			DV: Perceived Risk of Mission Drift	
	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	8.70*	19.45**	16.37**	2.51**	2.49**
	(3.44)	(3.45)	(3.68)	(0.21)	(0.23)
Control variables					
Participant Age	1.37*	1.08*	1.16*	-0.07	-0.07
	(0.54)	(0.53)	(0.53)	(.36)	(0.04)
Participant Gender [a]	0.25	-0.25	-0.19	-0.14	-0.14
	(1.12)	(1.10)	(1.10)	(0.08)	(0.08)
Participant Education	0.67	0.80	0.94	0.09*	0.09*
	(0.62)	(0.61)	(0.61)	(0.04)	(0.04)
Participant Race [c]	1.06	1.12	1.34	0.09	0.09
	(1.39)	(1.37)	(1.36)	(0.09)	(0.09)
Independent variables					
Founder Gender [a]	7.41**	2.32*	6.74**	-0.23**	-0.22
	(2.19)	(1.10)	(2.15)	(0.07)	(0.15)
Founder Nonprofit	6.23**	2.07	4.94**	-.43**	-.42**
Experience [b]	(1.76)	(1.27)	(1.75)	(0.09)	(0.12)
Interaction					
Founder Gender *	-5.91*		-5.95*		-0.01
Nonprofit Experience	(2.55)		(2.50)		(0.17)
Mediator					
Perceived Risk of Mission		-3.07**	-3.07**		
Drift		(0.60)	(0.59)		
R-squared	0.043	0.076	0.084	0.074	0.074

Note. N=608; ** p<0.01, * p<0.05, † p<0.1
a: 1 = female, 0 = male; b: 1 = has nonprofit experience, 0 = for-profit experience only; c: 1 = white, 0 = others.

Founder's Nonprofit Experience (H1a & 1b). The ANOVA with support amount as the DV shows that there are significant differences across three groups (for-profit only, nonprofit only, and mixed) (F = 4.90, p <0.01), but Scheffe post-hoc analysis further showed that the mixed experience and nonprofit-only groups do not significantly differ from each other. Thus, for further analysis, we combined the two into the "has-nonprofit-experience" group. ANCOVA (with all controls variables)[20] shows that the has-nonprofit-experience group (Mean = 22.86, S.E.

[20] Conclusions of significance remain unchanged without the control variables for all the analyses of Study 2.

= 0.65) garners significantly higher support than the for-profit-only group (Mean = 19.54, S.E. = 1.10), F = 6.79, p <0.01, supporting H1a. Furthermore, founders with nonprofit experience are associated with lower perceived risk of mission drift (Model 4 in Table 4: B = -0.43, S.E. = 0.09, p <0.01), which is negatively related to support amount (Model 2 in Table 4: B = -3.07, S.E. = 0.60, p <0.01). Bootstrapping indirect effect analysis shows that founder's nonprofit experience has a significant indirect effect on funds raised via perceived risk of mission drift (indirect effect = 1.31, S.E. = 0.38, 95% Boot CI = [0.67. 2.18]), supporting H1b.

Founder's Gender (H2a & 2b). ANCOVA with support as the DV across the two gender groups shows that the female founder group (Mean = 23.58, S.E. = 0.81) garners significantly higher support than the male founder group (Mean = 20.62, S.E. = 0.77), F = 7.05, p <0.01, supporting H2a. Furthermore, female founders are associated with lower perceived risk of mission drift (Model 4 in Table 4: B = -0.23, S.E. = 0.07, p <0.01), which is negatively related to support amount (Model 2 in Table 4: B = -3.07, S.E. = 0.60, p <0.01). Again, indirect effect analysis shows that founder's female identity has a significant indirect effect on funds raised via perceived risk of mission drift (indirect effect = 0.69, S.E. = 0.28, Bootstrapped 95% CI = [0.25, 1.35]), supporting H2b[21].

Interaction (H3a and 3b). We conducted interaction and mediation analyses following (Hayes 2013). The interactive effect of founder's nonprofit experience and gender on raised funds is significant and negative (Model 1 in Table 4: B = -5.91, S.E. = 2.55, p < 0.05). Specifically, nonprofit experience only benefits male entrepreneurs (B = 6.24, S.E. = 1.76, p <0.01, 95% CI = [2.77, 9.70]), but not female entrepreneurs (B = 0.33, S.E. = 1.83, p >0.10, 95% CI = [-3.26, 3.92]), as illuminated in Figure 7. Also, women outperform men among

[21] Analysis show that neither nonprofit experience nor gender is significantly related to participant's perceived founder competence. Thus, we exclude the possibility of perceived competence as a mediating mechanism.

entrepreneurs tend to raise more funds than male entrepreneurs when the founder does not have nonprofit experience (B = 7.41, S.E. = 2.19, p <0.01, 95% CI = [3.10, 11.72]), but this gender gap disappears among entrepreneurs having nonprofit experience (B = 1.50, S.E. = 1.29, p > .10, 95% CI = [-1.03, 4.03]), as illuminated in Figure 8.

Figure 7. Conditional Effects of Founder Nonprofit Work Experience on Funding Amount Across Founder Gender

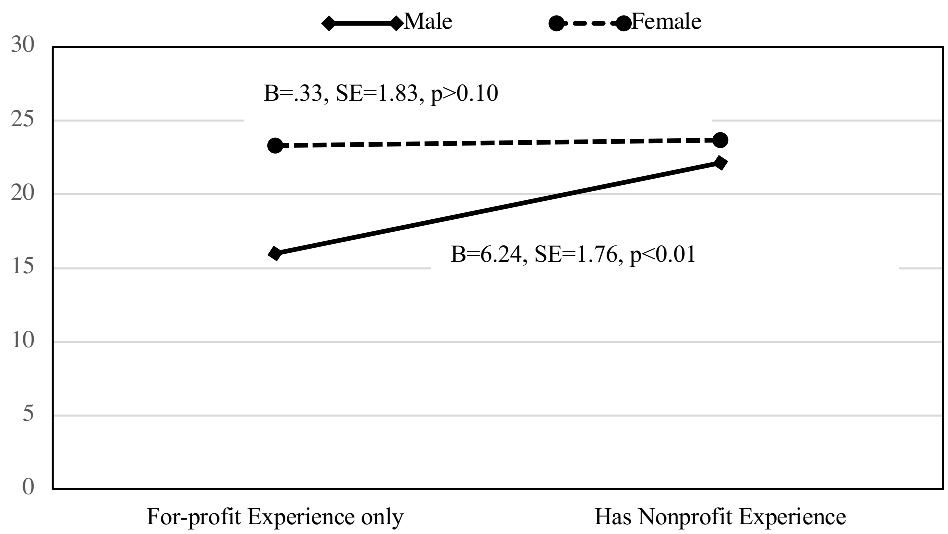
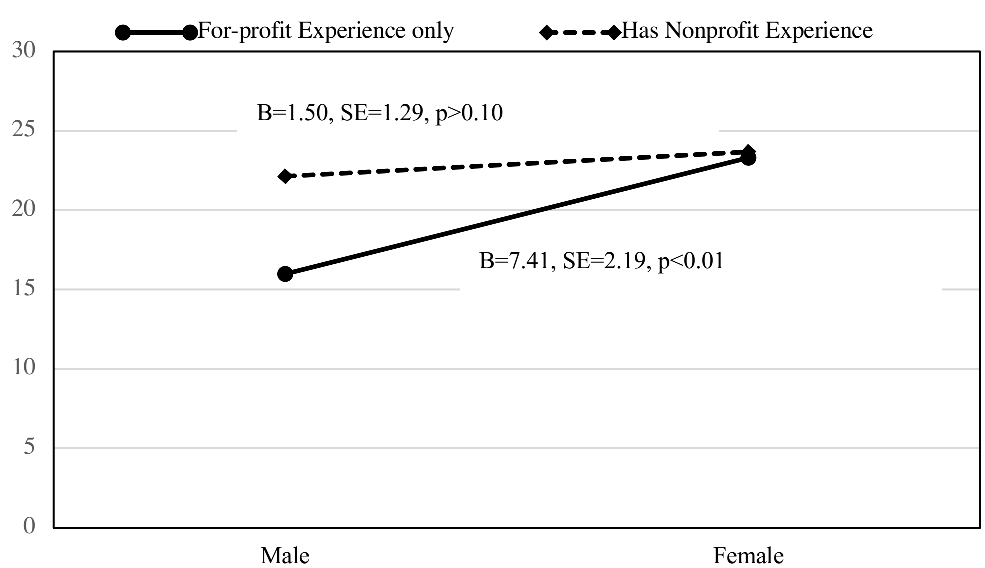


Figure 8. Conditional Effects of Founder Gender on Funding Amount Across Founder Experience



Thus, founder's nonprofit experience and female identity are substitutive in garnering funds, supporting H3a. However, we did not find support for H3b—the interaction between founder's nonprofit experience and gender on perceived mission drift is not statistically significant as shown in Model 5.

Study 3: An Experiment Test in Professional Investing Scenario

Study 3 was conducted to triangulate and corroborate our findings in previous two studies. In Study 3, we investigate whether investors in a professional investment mindset would evaluate social entrepreneurs differently from being crowdfunders. Furthermore, the bakery industry in Study 2 might be perceived as more aligned with female stereotypes, so in this study we used a start-up case in another industry that is more gender-neutral. In addition, we recruited participants from another platform, Prolific, which is dedicated to connecting researchers and participants, whereas MTurk is a generic out-sourcing platform that include many task types for different purposes.

Participants and Procedure

We recruited 480 participants via Prolific. Participants are in management positions or professional consultants with at least 3 years' fulltime work experience[22]. Participants were told that they would play the role of a junior partner in a venture capital firm that seeks to invest in an early-stage social enterprise, read a pitch, and assess its potential as an investment target. It was also stated that their decisions will be shared with senior partners. Participants were randomly assigned to read one of six versions of a pitch in a 2 (founder's gender: male or female) by 3

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[22] In an ideal design we would have a sample of professional impact investors, which we unfortunately were not able to secure access to. To remedy this, we recruited participants who were in management positions or were professional consultants with at least 3 years fulltime work experience. Moreover, we tested and controlled for the participants' financial acumen. Last, we address this as a potential limitation of our paper in our discussion and encourage future research to test our findings with professional impact investors.

(founder's work experience: for-profit only, has both for-profit and nonprofit, and nonprofit only) experimental design. The pitch (see Appendix C for the full pitch) was from Yellow Brick Road, a social enterprise that features an online platform connecting employers seeking employees with community college students[23]. Following the demonstration of YBR's goals and business models, we presented the profile of the Founder/CEO and we manipulated the founder's gender and work experience with the same materials as Study 2. Participants then answered two open-ended questions about their opinions on the start-up and the founder, and filled out a questionnaire including the perceived risk of mission drift, the founder's perceived competence, their decision of investment, and demographic information, etc.

Measures

Perceived risk of mission drift and *Perceived founder competence* are as measured in Study 2.

Amount of Investment. We captured a social entrepreneur's fundraising performance by asking participants, as a junior partner in a venture capital firm, how much they would decide to invest in the featured social enterprise: "We understand that an investor will only make an informed decision of investment after hearing how the entrepreneurs address their concerns and questions. But we are interested in your gut feeling of investing in this company given the presented information. Assuming that the entrepreneurs have addressed your questions to your satisfaction, how much (in thousands) would you invest in this company under the budget of $500,000 designated by your firm?"

Other control variables. In addition to age, gender, race, and education, we further assessed the participants' prevention focus and financial acumen because they may influence

[23] This pitch was part of a social enterprise pitch competition in a prestigious business school in the Northeast of the United States. We obtained the entrepreneurs' approval to adapt their pitch materials for academic use.

investors' decisions (Kanze et al. 2018, Smith and Chae 2017) (see Appendix D for detailed measures).

Results

Similar to Study 2, we took several steps to assure the quality of data for analysis. First, we dropped 28 participants who spent less than 7 minutes (half of the median completion time,14 minutes). Second, we excluded 86 participants who failed either of the two manipulation check questions asking the founder's gender and previous experience. Different from Study 2, we excluded 7 participants who failed the financial acumen test—those who failed all three finance questions might either not have the basic knowledge of finance or economics to make sound decisions as an investor or not pay attention to the questions. In the end, we had 359 participants, with a valid response rate of 75%. Among the359 participants, 58% of them were female; regarding age, 44% were in the age group of 25-34, 31% in 35-44, and 21% in 45-64; regarding education, 60% had some college or an associate's degree, 27% had bachelor's degree, and 7% had advanced degree; regarding race, 88% were white. Summary statistics and correlations are in Table 22, and interaction/mediation analyses in Table 23.

Table 22. Summary Statistics and Correlations

		Mean	S. D	1	2	3	4	5	6	7	8	9	10	11
1	Founder Gender [a]	0.52	0.50	-										
2	Founder Work Experience [b]	0.67	0.47	0.04	-									
3	Support (in thousands)	168.25	98.85	0.10	0.15	-								
4	Perceived Risk of Mission Drift	3.03	0.93	-0.11	-0.36	-0.24	-							
5	Perceived Leader Competence	5.47	0.92	-0.10	0.02	0.30	-0.40	-						
6	Participant Prevention Focus	5.85	0.79	-0.02	0.00	0.09	-0.11	0.19	-					
7	Participant Finance Acumen	2.55	0.63	-0.02	0.04	-0.00	-0.02	-0.08	-0.13	-				
8	Participant Age	2.73	0.87	-0.01	-0.05	-0.06	-0.05	-0.11	0.07	0.14	-			
9	Participant Gender [a]	0.58	0.49	0.19	0.05	0.04	-0.05	0.08	0.02	-0.29	0.06	-		
10	Participant Education	4.33	0.75	0.09	0.01	0.01	0.01	-0.05	-0.04	0.07	0.02	0.13	-	
11	Participant Race [c]	0.88	0.32	-0.04	-0.07	-0.08	-0.07	0.07	0.03	-0.06	0.11	0.13	0.04	-

Note. N = 359. a: 1 = female, 0 = male; b: 1 = has nonprofit experience, 0 = for-profit experience only; c: 1 = white, 0 = others.

Table 23. Interaction and Mediation Analysis

	DV: Support			DV: Perceived Risk of Mission Drift	
	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	64.04	197.13**	168.15**	4.61**	4.85**
	(59.03)	(63.20)	(64.89)	(0.51)	(0.52)
Control Variables					
Participant Age	-5.77	-7.43	-6.94	-0.05	-0.05

Table 23 (Continued). Interaction and Mediation Analysis

	(6.06)	(5.98)	(5.97)	(0.05)	(0.05)
Participant Gender [a]	6.43	5.67	6.11	-0.01	-0.02
	(11.31)	(11.16)	(11.12)	(0.10)	(0.10)
Participant Education	2.14	0.93	2.41	0.03	0.01
	(7.00)	(6.86)	(6.88)	(0.06)	(0.06)
Participant Race [c]	-19.67	-25.64	-25.14	-0.25†	-0.25†
	(16.23)	(16.09)	(16.03)	(0.14)	(0.14)
Participant Prevention	11.94†	9.17	9.41	-0.12*	-0.12*
Focus	(6.55)	(6.50)	(6.47)	(0.06)	(0.06)
Participant Finance	3.73	2.60	3.05	-0.03	-0.03
Acumen	(8.81)	(8.69)	(8.66)	(0.08)	(0.08)
Independent Variables					
Founder Gender [a]	49.85**	12.56	39.80*	-0.19*	-0.48**
	(18.08)	(10.43)	(18.00)	(0.09)	(0.16)
Founder Nonprofit	54.63**	13.12	34.66*	-0.72**	-0.93**
Experience [b]	(15.73)	(11.66)	(16.44)	(0.10)	(0.14)
Interaction					
Founder Gender *	-49.55*		-40.51†		0.42*
Nonprofit Experience	(22.08)		(21.85)		(0.19)
Mediator					
Perceived Risk of		-22.77**	-21.49**		
Mission Drift		(5.97)	(5.97)		
R-squared	0.061	0.085	0.094	0.160	0.172

Note. N = 359. ** p<0.01, * p<0.05, † p<0.1

a: 1 = female, 0 = male; b: 1 = has nonprofit experience, 0 = for-profit experience only; c: 1 = white, 0 = others.

Founder's Nonprofit Experience (H1a & 1b). The ANOVA with investment amount as the DV shows that there are significant differences across three groups (for-profit only, nonprofit only, and mixed) (F=4.45, p<0.05). Same with findings in Study 2, Scheffe post-hoc analysis further showed that the mixed experience and nonprofit-only groups do not significantly differ from each other (Mean difference =7.98, S.E.= 11.86, p=0.82). Thus, we combined the two into the "has-nonprofit-experience" group. ANCOVA (with all control variables) shows that the has-nonprofit-experience group (Mean = 177.96, S.E. = 6.30) garners significantly higher investment than the for-profit-only group (Mean = 148.15, S.E. = 9.08), F=7.23, p<0.01, supporting H1a. Furthermore, founders with nonprofit experience are associated with lower perceived risk of mission drift (Model 4 in Table 6: B= -0.72, S.E. = 0.10, p <0.01), which is negatively related to amount of investment (Model 2 in Table 6: B = -22.77, S.E. = 5.97, p <0.01). Bootstrapping indirect effect analysis shows that founder's nonprofit experience has a significant indirect effect on investment amount via perceived risk of mission drift (indirect effect = 16.28, S.E. = 4.77, Boot 95% CI = [7.48, 26.30]), supporting H1b.

Founder's Gender (H2a and 2b). ANCOVA (with all control variables) shows that the amount of investment for female founder group is not significantly higher than the male founder group ($p = 0.10$). However, among the control variables, only *prevention focus* is marginally significantly related to decision of investment. To save degrees of freedom for our analysis, we reconducted ANCOVA only controlling for prevention focus—this test shows that female founder group (Mean = 177.55, S.E. = 7.17) garners marginally higher investment than the male founder group (Mean = 158.01, S.E. = 7.52), $F = 3.54$, $p = 0.06$. Also, ANOVA without control variables yields the same significance level. As such, we claim that H2a was marginally supported. Female founders are associated with lower perceived risk of mission drift (Model 4 in Table 6: $B = -0.19$, S.E. = 0.09, $p < 0.05$). Bootstrapping indirect effect analysis shows that founder's female identity has a significant indirect effect on funds raised via perceived risk of mission drift (indirect effect = 4.26, S.E. = 2.34, Boot 95% CI = [0.11, 9.34]), supporting H2b[24].

Interaction (H3a and 3b). We conducted interaction and mediation analyses following (Hayes 2013). The interactive effect of founder's nonprofit experience and gender on attracting investment is significant and negative (Model 1 in Table 6: $B = -49.55$, S.E. = 22.08, $p < 0.05$). Specifically, nonprofit experience only benefits male entrepreneurs ($B = 54.63$, S.E. = 15.73, $p < 0.01$, 95% CI = [23.69, 85.57]), but not female entrepreneurs ($B = 5.08$, S.E. = 15.44, $p = 0.74$, 95% CI = [-25.29, 35.45]). Also, women outperform men among entrepreneurs when the entrepreneurs do not have nonprofit experience ($B = 49.85$, S.E. = 18.08, $p < 0.01$, 95% CI = [14.29, 85.41]), but this gender gap disappears among entrepreneurs with nonprofit experience ($B = 0.30$, S.E. = 12.83, $p = 0.98$, 95% CI = [-24.93, 25.52]). To sum up, female identity and

[24] Similar to Study 2, ANOVA results in unreported supplementary tests show that neither founder's nonprofit experience nor gender is significantly related to participant's perceived competence of the founder. Thus, we exclude the possibility of perceived founder's competence as a mediating mechanism.

nonprofit experience are substitutive in attracting investment—one's effect decreases at the presence of the other, supporting H3a

Furthermore, the interactive effect of founder gender and nonprofit experience on perceived risk of mission drift is significant (Model 5 in Table 6: B = 0.42, S.E. = 0.19, $p < 0.05$). Specifically, nonprofit experience of the entrepreneurs is more effective in reducing perceived risk over mission drift for men (B = -0.93, S.E. = 0.14, $p < 0.01$, 95% CI = [-1.20, -.66]) than for women (B = -0.51, S.E. = 0.14, $p < 0.01$, 95% CI = [-0.78, -.024]). Conditional indirect effect analysis shows that, nonprofit experience has a more positive indirect effect on fundraising performance for men (indirect effect = 19.97, Boot S.E. = 6.52, 95% Boot CI = [8.39, 33.34]) than for females (indirect effect = 10.93, Boot S.E. = 4.09, 95% Boot CI = [3.71, 19.76]). Also, entrepreneurs' female identity reduces perceived risk over mission drift only when the entrepreneurs do not have nonprofit experience (B = 39.80, S.E. = 18.00, $p < 0.05$, 95% CI = [4.41, 75.20]), and women are not significantly advantaged over men in relieving concern over mission drift when they both have nonprofit experience (B = -0.71, S.E. = 12.62, $p = 0.96$, 95% CI = [-25.52, 24.11]). Conditional indirect effect analysis shows that, female identity has a significantly positive indirect effect on fundraising performance (via perceived risk of mission drift) when the entrepreneurs do not have nonprofit experience (indirect effect = 10.04, Boot S.E. = 4.62, 95% Boot CI = [2.34, 20.30]), but the indirect effect is not significant when the entrepreneurs have nonprofit experience (indirect effect = 1.01, Boot S.E. = 2.42, 95% Boot CI = [-3.89, 6.03]). Thus, H3b is supported.

DISCUSSIONS

Outsiders search for signals to make inferences about a nascent venture's potential. While conventional investors heed signals of entrepreneurs' competence, investors attentive to social entrepreneurs might view these signals differently. We theorize that social entrepreneurs' two identities—nonprofit work experience and female identity—may be perceived as positive signals by investors and reduce their concerns about mission drift in social ventures, resulting in better fundraising performance. We also propose that these two identity signals are substitutive—the signaling effect of one diminishes at the presence of the other. Three empirical studies corroborate our hypotheses. While our field study using 451 crowdfunding campaigns (Study 1) supports the hypothesized effects of social entrepreneurs' nonprofit experience and gender on fundraising performance, two experimental studies (Studies 2 and 3) provide further evidence that such favorable evaluation on two identities is channeled through less risk of mission drift perceived by investors.

Theoretical and Practical Implications

This study extends the entrepreneurship scholarship to account for the unique features of social entrepreneurship; we shift the focus of entrepreneur evaluation literature from human and social capital to mission commitment by investigating how external constituents evaluate social entrepreneurs, an increasingly influential group in the entrepreneur population. The entrepreneurship literature, which predominantly looks at for-profit start-ups, stresses various signals for entrepreneurs' human and social capital in evaluation processes (Colombo and Grilli 2005; Delmar and Shane 2006; Unger et al. 2011). Our paper shows that, given their unique characteristics, social enterprises are viewed as requiring unique qualities of social entrepreneurs beyond the traditional stereotype of a successful entrepreneur. There is a substantial shift of focus in the evaluation process of social entrepreneurs, including the emphasis on commitment to a venture's social mission. Specifically, we highlight two markers of commitment—professional identity and gender identity—that significantly affect external investors' decisions by influencing their perceived risks of social entrepreneurs' drifting away from social missions.

We also expand the emerging social entrepreneurship literature by shedding light on some indicators in external constituents' evaluation matrix of social entrepreneurs in the early venturing process. To this end, this literature has focused on how social entrepreneurs assuage the tension between social and commercial goals using various "playbooks" in established hybrid organizations (Battilana and Dorado 2010; Pache and Santos 2010, 2013; Smith and Tracey 2016). Yet, we know little about early venturing processes, and we lack insight into how critical external constituents such as early-stage investors view social entrepreneurs. Wry and York (2017), in their theory paper, delineated how identities influence social entrepreneurs making decisions related to the recognition and pursuit of hybrid venture opportunities. Our study, taking this further, reveals that identities can influence how social entrepreneurs are viewed by external constituents. These insights are also important for social entrepreneur practitioners because they consequently affect whether social entrepreneurs can obtain key resources.

Our findings also highlight an important mechanism, commitment to social mission, that explains why external investors favor social entrepreneurs with nonprofit professional experience and women. As an emerging yet underdeveloped field, current literature on mission and mission drift has focused either on what organizational mission statements are (Bartkus and Glassman 2008; Kenneth and Baetz 1998; Pearce and David 1987) or how they *actually* cope with hybrid goals, which give rise to mission drift (Battilana et al. 2015; Battilana and Dorado 2010; Pache and Santos 2013; Wry and Zhao 2018) As theoretically proposed by Grimes et al (Grimes et al. 2019), mission drift is also a perception "with regard to audience evaluations of the organization's authenticity and responsiveness". With empirical evidence, we show that investors may foresee the occurrence of mission drift and thus preempt such risk by selecting social entrepreneurs who they believe can adhere to a venture's social goal. *Perceived* risks of mission drift by these critical external constituents, therefore, can influence whether social entrepreneurs can obtain key external resources. As such, we add a more nuanced understanding to the mission drift phenomenon in hybrid organizations by uncovering key stakeholders' decision-making patterns rather than looking for institutional or intra-organizational forces driving such situations (Battilana and Dorado 2010; Ebrahim et al. 2014; Zhao and Wry 2016)

This paper provides new insight on the long-established female disadvantage in entrepreneurship — empirical research extensively documented that female entrepreneurs raise less capital (Becker-Blease and Sohl 2007; Brooks et al. 2014; Guzman and Kacperczyk 2019), have limited resource access (Castellaneta, Conti, and Kacperczyk 2020), and receive gendered feedback (Balachandra et al. 2019; Eddleston et al. 2016; Kanze et al. 2018; Malmström, Johansson, and Wincent 2017), resulting in underperformance (Coleman and Robb 2009; Jennings and Brush 2013). In the social enterprise context, however, we find that the gender pattern is reversed such that female social entrepreneurs are preferred over male counterparts; gender stereotypes advantage female social entrepreneurship by reducing external evaluators' concern for mission drift. Such a pattern implies that, in the venturing process, gender (dis)advantage may not be context-free, adding to a growing body of literature in this strand (Abraham 2020; Johnson, Stevenson, and Letwin 2018; Lee and Huang 2018).

Finally, beyond revealing the female advantage, we provide evidence that male social entrepreneurs can overcome this male disadvantage by accumulating substantial nonprofit professional experience. These findings provide important practical insights for men seeking a career transition into social entrepreneurship: for one, gaining professional nonprofit experience before funding a new hybrid venture might benefit their optics. Furthermore, for male social entrepreneurs that cannot substantially change their career images, assembling a leadership team including female social entrepreneurs might also reduce the negative gendered perception of being less committed to social missions. More broadly, our findings suggest that when social entrepreneurs appeal to potential constituents, they may emphasize those identities that align well with associated mission statements or signal additional social mission commitment if their innate identities seem confrontational with investors' expectations.

Limitations and Future Directions

There are several limitations in our study. First, there is a wide range of investors including traditional capital market investors and philanthropic donors at the two ends of the spectrum, with social impact investors in the middle (Trelstad 2016); and, even within the social impact investor category, there are diverse players including for-profit funds, investment partners fund, and government-based institutions, which each have different investment logics (Cobb et al. 2016; Pahnke, Katila, and Eisenhardt 2015). We focus solely on investors that seek both financial and social returns and are vigilant about the risk of mission drift; other investors that lean heavily towards financial returns might react differently.

Second, relatedly, some studies reveal common investment decisions across amateur crowdfunders and professional investors (Mollick and Nanda 2016) while others show systematic differences (Li et al. 2017). In the professional venture investment scenario in Study 3, we recruited participants who were in management positions or were professional consultants with at least 3 years fulltime work experience, and we tested and controlled for their financial acumen. An experiment study with professional impact investors would be ideal. Furthermore, online experiments cannot fully resemble real-world decision-making scenarios, although we conducted several procedures to imitate real-world situations and assure the quality of data, such as presenting real business cases to participants and running several manipulation checks. Experiments in the field would be ideal when opportunity allows.

Conclusion

Our study suggests the need to look beyond the traditional research focus on competence signals of entrepreneurs and attend to how signals for mission commitment can be critical in social entrepreneurship. Given the unique tension between social and business goals in social enterprises, we show that social entrepreneurs' nonprofit professional identity and female identity can substitutively alleviate investors' concerns for mission drift, garnering more funds in early-stage social ventures. This study contributes to the literature on entrepreneurship and organizational signaling, and has implications for entrepreneur practitioners.

CHAPTER 5.

CONCLUSION

Peer-to-peer platforms differ greatly from conventional modes of economic organization. In his seminal essay, *Neither market nor hierarchy: Network forms of organization*, Powell (1990) compared three modes of organization—market, hierarchy, and network. Discretely coordinated markets among individual entrepreneurs and hierarchically organized firms have been conceived as alternative means for organizing economic activities by transaction cost economists (Coase 1937; Williamson 1975), while economic sociologists such as Powell challenge the market-hierarchy continuum and view networks as a third mode of economic organization that hinges on relationships and norms.

Peer-to-peer platforms are neither hierarchies, networks, nor traditional peer-to-peer offline markets; they are highly organized by algorithms with information distribution boosted by modern technologies. Platforms promise efficiency, transparency, and accessibility that the three traditional modes of economic organization may not fully deliver. The rise of these platform markets therefore creates opportunities for developing economic sociological theories that have largely focused on either hierarchies or networks. The three empirical chapters in my dissertation each look at a platform-related phenomenon and my work suggests that efforts to engineer a platform market with efficiency, transparency, and accessibility are subject to social interferences. Specifically, my work reveals the unintended consequences of instituting a performance evaluation system (Chapter 2) and the presence of social biases in exchange partner selection despite these prospective partners potentially having similar performance information (Chapters 3 & 4).

Through an in-depth study of a peer-to-peer lodging platform, Chapter 2 shows that concerns regarding these post-hoc evaluations could influence whom one chooses to transact with at the outset. Market participants seek to reduce their anxiety about evaluations made by transaction partners by selecting partners with *inferior* market standing—who they presume are more likely to be satisfied with their offerings and will thus be more likely to provide positive evaluations. Findings from Chapter 2 reveal unintended consequences of the evaluation systems of platform markets. Evaluation systems are designed to reduce quality information asymmetry among platform users; yet, they encourage gaming behaviors that lead to "rating inflation", causing the failure of these evaluation systems. The platform literature has shown that market participants under-report negative ratings for fear of retaliatory negative ratings (e.g., Fradkin, Grewal, and Holtz 2018) and submit reciprocal ratings (Bolton et al. 2013; Diekmann et al. 2014) causing ratings on many platforms to become overwhelmingly positive (Hu et al. 2009). Unlike those studies focusing on post-hoc strategies, my research reveals the dynamics of selection even before a transaction occurs and provides another explanation for rating inflation in platform markets. My work opens an upstream conversation on the consequences of installing an evaluation system, and these insights may benefit platform companies.

Chapter 3 reveals the presence of cultural bias where it might be least expected to be, a global peer-to-peer lodging platform that was launched with a claim of benefiting people who desire cross-cultural travel experiences. My analyses of over one million lodging requests exchanged among these users reveal that hosts are less likely to approve requests from culturally distant guests. Furthermore, I find that the effect of ratings weakens as the cultural distances between a host and a guest, and between a host and a guest's prior host(s), increase, further widening the gap in host acceptance of culturally proximate versus culturally distant guests. In contrast, the effect of platform verification enhances as the cultural distance between a host and a guest increases, thus narrowing the gap in host acceptance of culturally proximate versus culturally distant guests. This study casts light on the debate over whether quality signals benefit advantaged or disadvantaged groups. Furthermore, while practitioners and scholars have marveled at ratings systems enacted by peer participants as the cornerstone for platform markets (Bolton et al. 2004; Dellarocas 2003; Kollock 1999), it has been under-emphasized that platforms themselves have become legitimate evaluators. My finding that quality signals cast by platforms are less subject to social bias and thus can facilitate transactions across geographical, cultural, economic, and political boundaries highlights that platforms ought to invest in the production of such quality signals, instead of focusing solely on rating systems.

Chapter 4 shows the presence of social biases associated with career background and gender among crowdfunders, as evidenced by one field study of 451 social entrepreneurs' fundraising campaigns on crowdfunding platforms, one lab-based experimental study imitating crowdfunding campaigns, and one lab-based experimental study imitating professional venture capital investments. This research suggests that social entrepreneurs' nonprofit work experience and female identity can help alleviate potential investors' concern over mission drift, and in turn garner more financial support. Moreover, nonprofit work experience and female identity are substitutive of each other; that is, the positive effect of one diminishes at the presence of the other. This chapter reveals that social factors could distort crowdfunders' judgement, and specifically in the evaluation process of social entrepreneurs, crowd investors emphasize entrepreneurs' commitment to a venture's social mission. This research also presents some evidence that these evaluation biases among crowdfunders might also exist in professional investing scenarios. It expands the crowdfunding literature and the general entrepreneurship scholarship in general, which predominantly looks at for-profit start-ups (e.g., Colombo and Grilli 2005; Delmar and Shane 2006; Greenberg and Mollick 2017)

Understanding the nature of economic organization and the varieties of capitalism is a founding interest of economic sociology; peer-to-peer platform markets provide an opportunity to revisit existing theories and generate new insights, given their unique features that are different from conventional networks, hierarchies, or discrete peer-to-peer transactions. As the studies in this dissertation illustrate, despite the efforts to engineer a highly-functioning market, how economic transactions on these platforms eventually unfold are subject to social processes. Some system designs such as a performance evaluation system may encourage gaming and lead to unintended consequences such as rating inflation. Social biases towards certain social groups that are prevalent offline remain despite platforms' efforts to increase transparency. It is apparent that the peer-to-peer platform is far from being an efficient, transparent, and assessible market as it promises, yet solutions to these issues have only begun to be explored.

With its focus on the behavior of individual market participants on peer-to-peer platforms, this dissertation goes beyond an organizational scholar's traditional central focus, organizations, but essentially investigates the same core question—the organization of economic activities. In recent years, scholars across fields including information science, economics, political science, and in this case, economic sociology and organizational theory, have come to understand peer-to-peer platforms from different but complementary perspectives. It is my hope that this research contributes to this broader intellectual and practitioner community.

REFERENCES

Abraham, Mabel. 2020. "Gender-Role Incongruity and Audience-Based Gender Bias: An Examination of Networking among Entrepreneurs." *Administrative Science Quarterly* 65(1):151–80.

Abrahao, Bruno, Paolo Parigi, Alok Gupta, and Karen S. Cook. 2017. "Reputation Offsets Trust Judgments Based on Social Biases among Airbnb Users." *Proceedings of the National Academy of Sciences* 114(37):9848–53.

Abrams, Dominic Ed, and Michael A. Hogg. 1990. *Social Identity Theory: Constructive and Critical Advances.* Springer-Verlag Publishing.

Ai, Chunrong, and Edward C. Norton. 2003. "Interaction Terms in Logit and Probit Models." *Economics Letters* 80(1):123–29.

Albrecht, James W. 1981. "A Procedure for Testing the Signalling Hypothesis." *Journal of Public Economics* 15(1):123–32.

Allison, Paul D. 2009. *Fixed Effects Regression Models*. Los Angeles: SAGE.

Anteby, Michel. 2010. "Markets, Morals, and Practices of Trade: Jurisdictional Disputes in the U.S. Commerce in Cadavers." *Administrative Science Quarterly* 55(4):606–38.

Antràs, Pol, and Davin Chor. 2013. "Organizing the Global Value Chain." *Econometrica* 81(6):2127–2204.

Appadurai, Arjun. 1990. "Disjuncture and Difference in the Global Cultural Economy." *Theory, Culture & Society* 7(2–3):295–310.

Appadurai, Arjun. 1996. *Modernity at Large Cultural Dimensions of Globalization*. Minneapolis (Minn.): University of Minnesota Press.

Arcidiacono, Peter, Patrick Bayer, and Aurel Hizmo. 2010. "Beyond Signaling and Human Capital: Education and the Revelation of Ability." *American Economic Journal: Applied Economics* 2(4):76–104.

Arthurs, Jonathan D., Lowell W. Busenitz, Robert E. Hoskisson, and Richard A. Johnson. 2009. "Signaling and Initial Public Offerings: The Use and Impact of the Lockup Period." *Journal of Business Venturing* 24(4):360–72.

Audia, Pino G., and Sebastien Brion. 2007. "Reluctant to Change: Self-Enhancing Responses to Diverging Performance Measures." *Organizational Behavior and Human Decision Processes* 102(2):255–69.

Balachandra, Lakshmi, Tony Briggs, Kim Eddleston, and Candida Brush. 2019. "Don't Pitch Like a Girl!: How Gender Stereotypes Influence Investor Decisions." *Entrepreneurship Theory and Practice* 43(1):116–37.

Bartkus, Barbara R., and Myron Glassman. 2008. “Do Firms Practice What They Preach? The Relationship between Mission Statements and Stakeholder Management.” *Journal of Business Ethics* 83(2):207–16.

Battilana, Julie, and Silvia Dorado. 2010. “Building Sustainable Hybrid Organizations: The Case of Commercial Microfinance Organizations.” *Academy of Management Journal* 53(6):1419–1440.

Battilana, Julie, and Matthew Lee. 2014. “Advancing Research on Hybrid Organizing – Insights from the Study of Social Enterprises.” *The Academy of Management Annals* 8(1):397–441.

Battilana, Julie, Metin Sengul, Anne-Claire Pache, and Jacob Model. 2015. “Harnessing Productive Tensions in Hybrid Organizations: The Case of Work Integration Social Enterprises.” *Academy of Management Journal* 58(6):1658–85.

Baum, Joel A. C., and Brian S. Silverman. 2004. “Picking Winners or Building Them? Alliance, Intellectual, and Human Capital as Selection Criteria in Venture Financing and Performance of Biotechnology Startups.” *Journal of Business Venturing* 19(3):411–36.

Becker, Gary Stanley. 1957. *The Economics of Discrimination*. Chicago: The University of Chicago Press.

Becker-Blease, John R., and Jeffrey E. Sohl. 2007. “Do Women-Owned Businesses Have Equal Access to Angel Capital?” *Journal of Business Venturing* 22(4):503–21.

Beckman, Christine M., and M. Diane Burton. 2008. “Founding the Future: Path Dependence in the Evolution of Top Management Teams from Founding to IPO.” *Organization Science* 19(1):3–24.

Bennett, V. M., L. Pierce, J. A. Snyder, and M. W. Toffel. 2013. “Customer-Driven Misconduct: How Competition Corrupts Business Practices.” *Management Science* 59(8):1725–42.

Berger, Joseph, Bernard P. Cohen, and Morris Zelditch. 1972. “Status Characteristics and Social Interaction.” *American Sociological Review* 37(3):241–55.

Berinsky, Adam J., Gregory A. Huber, and Gabriel S. Lenz. 2012. “Evaluating Online Labor Markets for Experimental Research: Amazon.Com’s Mechanical Turk.” *Political Analysis* 20(3):351–68.

Berry, Heather, Mauro F. Guillén, and Nan Zhou. 2010. “An Institutional Approach to Cross-National Distance.” *Journal of International Business Studies* 41(9):1460–80.

Bertrand, Marianne, and Sendhil Mullainathan. 2004. “Are Emily and Greg More Employable than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination.” *American Economic Review* 94(4):991–1013.

Biernat, Monica, and Diane Kobrynowicz. 1997. "Gender- and Race-Based Standards of Competence: Lower Minimum Standards but Higher Ability Standards for Devalued Groups." *Journal of Personality and Social Psychology* 72(3):544–57.

Bolton, Gary, Ben Greiner, and Axel Ockenfels. 2013. "Engineering Trust: Reciprocity in the Production of Reputation Information." *Management Science* 59(2):265–85.

Bolton, Gary, Elena Katok, and Axel Ockenfels. 2004. "How Effective Are Electronic Reputation Mechanisms? An Experimental Investigation." *Management Science* 50(11):1587–1602.

Bolton, Patrick, Xavier Freixas, and Joel Shapiro. 2012. "The Credit Ratings Game." *The Journal of Finance* 67(1):85–111.

Bonikowski, Bart. 2010. "Cross-National Interaction and Cultural Similarity: A Relational Analysis." *International Journal of Comparative Sociology* 51(5):315–48.

Branzei, Oana, Ilan Vertinsky, and Ronald D. Camp. 2007. "Culture-Contingent Signs of Trust in Emergent Relationships." *Organizational Behavior and Human Decision Processes* 104(1):61–82.

Brewer, Paul A. 2007. "Operationalizing Psychic Distance: A Revised Approach." *Journal of International Marketing* 15(1):44–66.

British Council. 2013. *The Scale of Social Enterprise*.

Bromiley, Philip. 1991. "Testing a Causal Model of Corporate Risk Taking and Performance." *The Academy of Management Journal* 34(1):37–59.

Bromley, Patricia, and Walter Powell. 2012. "From Smoke and Mirrors to Walking the Talk: Decoupling in the Contemporary World." *The Academy of Management Annals* 6(1):483–530.

Brooks, Alison Wood, Laura Huang, Sarah Wood Kearney, and Fiona E. Murray. 2014. "Investors Prefer Entrepreneurial Ventures Pitched by Attractive Men." *Proceedings of the National Academy of Sciences* 111(12):4427–31.

Buchan, Nancy R., Rachel T. A. Croson, and Robyn M. Dawes. 2002. "Swift Neighbors and Persistent Strangers: A Cross-Cultural Investigation of Trust and Reciprocity in Social Exchange." *American Journal of Sociology* 108(1):168–206.

Bugg-Levine, Antony, Bruce Kogut, and Nalin Kulatilaka. 2012. "A New Approach to Funding Social Enterprises." *Harvard Business Review* 90(1/2):118–23.

Burt, Ronald S. 1978. "Cohesion Versus Structural Equivalence as a Basis for Network Subgroups." *Sociological Methods & Research* 7(2):189–212.

Burton, M. Diane, Jesper B. Sørensen, and Christine M. Beckman. 2002. "Coming from Good Stock: Career Histories and New Venture Formation." Pp. 229–62 in *Social structure and organizations revisited*. Emerald Group Publishing Limited.

Buunk, Abraham P., and Frederick X. Gibbons. 2007. "Social Comparison: The End of a Theory and the Emergence of a Field." *Organizational Behavior and Human Decision Processes* 102(1):3–21.

Castellaneta, Francesco, Raffaele Conti, and Aleksandra Kacperczyk. 2020. "The (Un) Intended Consequences of Institutions Lowering Barriers to Entrepreneurship: The Impact on Female Workers." *Strategic Management Journal*.

Castellucci, Fabrizio, and Gokhan Ertug. 2010. "What's in It for Them? Advantages of Higher-Status Partners in Exchange Relationships." *Academy of Management Journal* 53(1):149–66.

Chatterji, Aaron K., and Michael W. Toffel. 2010. "How Firms Respond to Being Rated." *Strategic Management Journal* n/a-n/a.

Chen, Ya-Ru, Joel Brockner, and Jerald Greenberg. 2003. "When Is It 'a Pleasure to Do Business with You?' The Effects of Relative Status, Outcome Favorability, and Procedural Fairness." *Organizational Behavior and Human Decision Processes* 92(1):1–21.

Chua, Roy Y. J., Michael W. Morris, and Shira Mor. 2012. "Collaborating across Cultures: Cultural Metacognition and Affect-Based Trust in Creative Collaboration." *Organizational Behavior and Human Decision Processes* 118(2):116–31.

Chua, Roy Y. J., Yannig Roth, and Jean-François Lemoine. 2015. "The Impact of Culture on Creativity: How Cultural Tightness and Cultural Distance Affect Global Innovation Crowdsourcing Work." *Administrative Science Quarterly* 60(2):189–227.

Chung, Seungwha (Andy), Harbir Singh, and Kyungmook Lee. 2000. "Complementarity, Status Similarity and Social Capital as Drivers of Alliance Formation." *Strategic Management Journal* 21(1):1–22.

Coase, R. H. 1937. "The Nature of the Firm." *Economica* 4(16):386–405.

Cobb, J. Adam, Tyler Wry, and Eric Yanfei Zhao. 2016. "Funding Financial Inclusion: Institutional Logics and the Contextual Contingency of Funding for Microfinance Organizations." *Academy of Management Journal* 59(6):2103–31.

Coleman, James S. 1990. *Foundations of social theory*. Cambridge, Mass.: Harvard University Press.

Coleman, Susan, and Alicia Robb. 2009. "A Comparison of New Firm Financing by Gender: Evidence from the Kauffman Firm Survey Data." *Small Business Economics* 33(4):397.

Colombo, Massimo G., and Luca Grilli. 2005. "Founders' Human Capital and the Growth of New Technology-Based Firms: A Competence-Based View." *Research Policy* 34(6):795–816.

Cook, Karen S., and Russell Hardin. 2001. "Norms of Cooperativeness and Networks of Trust." Pp. 327–47 in *Social norms*, edited by M. Hechter and K. D. Opp. New York: Russell Sage Foundation.

Cook, Karen S., Russell Hardin, and Margaret Levi. 2005. *Cooperation without Trust?* New York: Russell Sage Foundation.

Cook, Karen, Chris Snijders, Vincent Buskens, and Coye Cheshire. 2009. *ETrust: Forming Relationships in the Online World*. New York: Russell Sage Foundation.

Correll, Shelley J., Cecilia L. Ridgeway, Ezra W. Zuckerman, Sharon Jank, Sara Jordan-Bloch, and Sandra Nakagawa. 2017. "It's the Conventional Thought That Counts: How Third-Order Inference Produces Status Advantage." *American Sociological Review* 82(2):297–327.

Cowen, Amanda P. 2012. "An Expanded Model of Status Dynamics: The Effects of Status Transfer and Interfirm Coordination." *Academy of Management Journal* 55(5):1169–86.

Cowen, Emory L. 1952. "The Influence of Varying Degrees of Psychological Stress on Problem-Solving Rigidity." *The Journal of Abnormal and Social Psychology* 47(2, Suppl):512–19.

Cui, Ruomeng, Jun Li, and Dennis Zhang. 2016. "Reducing Discrimination with Reviews in the Sharing Economy: Evidence from Field Experiments on Airbnb." *SSRN Working Paper*.

Cyert, Richard M., and James G. March. 1963. *A Behavioral Theory of the Firm*. Engelwood: Prentice-Hall.

Dacin, M. Tina, Peter A. Dacin, and Paul Tracey. 2011. "Social Entrepreneurship: A Critique and Future Directions." *Organization Science* 22(5):1203–13.

Davis, Gerald F. 2016. "Can an Economy Survive Without Corporations? Technology and Robust Organizational Alternatives." *The Academy of Management Perspectives* 30(2):129–40.

Dawes, Robyn M., Jeanne McTavish, and Harriet Shaklee. 1977. "Behavior, Communication, and Assumptions about Other People's Behavior in a Commons Dilemma Situation." *Journal of Personality and Social Psychology* 35(1):1–11.

DCMS, and BEIS. 2017. *Social Enterprise: Market Trends 2017*.

Dellarocas, Chrysanthos. 2003. "The Digitization of Word of Mouth: Promise and Challenges of Online Feedback Mechanisms." *Management Science* 49(10):1407–24.

Dellarocas, Chrysanthos, and Charles A. Wood. 2008. “The Sound of Silence in Online Feedback: Estimating Trading Risks in the Presence of Reporting Bias.” *Management Science* 54(3):460–76.

Delmar, Frédéric, and Scott Shane. 2006. “Does Experience Matter? The Effect of Founding Team Experience on the Survival and Sales of Newly Founded Ventures.” *Strategic Organization* 4(3):215–47.

Diekmann, Andreas, Ben Jann, Wojtek Przepiorka, and Stefan Wehrli. 2014. “Reputation Formation and the Evolution of Cooperation in Anonymous Online Markets.” *American Sociological Review* 79(1):65–85.

Dinesen, Peter Thisted, and Kim Mannemar Sønderskov. 2015. “Ethnic Diversity and Social Trust: Evidence from the Micro-Context.” *American Sociological Review* 80(3):550–73.

DiRenzo, G. J. 1977. “Socialization, Personality, and Social Systems.” *Annual Review of Sociology* 3(1):261–95.

Dobrev, Stanislav D., and William P. Barnett. 2005. “Organizational Roles and Transition to Entrepreneurship.” *Academy of Management Journal* 48(3):433–49.

Doherty, Bob, Helen Haugh, and Fergus Lyon. 2014. “Social Enterprises as Hybrid Organizations: A Review and Research Agenda.” *International Journal of Management Reviews* 16(4):417–36.

Duguid, Michelle M., Denise Lewin Loyd, and Pamela S. Tolbert. 2010. “The Impact of Categorical Status, Numeric Representation, and Work Group Prestige on Preference for Demographically Similar Others: A Value Threat Approach.” *Organization Science* 23(2):386–401.

Eagly, Alice H., and Blair T. Johnson. 1990. “Gender and Leadership Style: A Meta-Analysis.” *Psychological Bulletin* 108(2):233.

Eagly, Alice H., and Steven J. Karau. 2002. “Role Congruity Theory of Prejudice toward Female Leaders.” *Psychological Review* 109(3):573.

Ebrahim, Alnoor, Julie Battilana, and Johanna Mair. 2014. “The Governance of Social Enterprises: Mission Drift and Accountability Challenges in Hybrid Organizations.” *Research in Organizational Behavior* 34:81–100.

Eddleston, Kimberly A., Jamie J. Ladge, Cheryl Mitteness, and Lakshmi Balachandra. 2016. “Do You See What I See? Signaling Effects of Gender and Firm Characteristics on Financing Entrepreneurial Ventures.” *Entrepreneurship Theory and Practice* 40(3):489–514.

Edelman, Benjamin, Michael Luca, and Dan Svirsky. 2017. “Racial Discrimination in the Sharing Economy: Evidence from a Field Experiment.” *American Economic Journal: Applied Economics* 9(2):1–22.

Eisenhardt, Kathleen M., and Behnam N. Tabrizi. 1995. "Accelerating Adaptive Processes: Product Innovation in the Global Computer Industry." *Administrative Science Quarterly* 40(1):84–110.

Elfenbein, Hillary Anger, and Nalini Ambady. 2003. "When Familiarity Breeds Accuracy: Cultural Exposure and Facial Emotion Recognition." *Journal of Personality and Social Psychology* 85(2):276–90.

Espeland, Wendy Nelson, and Michael Sauder. 2007. "Rankings and Reactivity: How Public Measures Recreate Social Worlds." *American Journal of Sociology* 113(1):1–40.

Espeland, Wendy Nelson, and Michael Sauder. 2016. *Engines of Anxiety: Academic Rankings, Reputation, and Accountability*. New York: Russell Sage Foundation.

Espeland, Wendy Nelson, and Mitchell L. Stevens. 1998. "Commensuration as a Social Process." *Annual Review of Sociology* 24(1):313–43.

Evans, Jody, and Felix T. Mavondo. 2002. "Psychic Distance: The Construct and Measurers." *American Marketing Association. Conference Proceedings; Chicago* 13:308.

Fay, Michael, and Lesley Williams. 1993. "Gender Bias and the Availability of Business Loans." *Journal of Business Venturing* 8(4):363–76.

Fern, Michael J., Laura B. Cardinal, and Hugh M. O'Neill. 2012. "The Genesis of Strategy in New Ventures: Escaping the Constraints of Founder and Team Knowledge." *Strategic Management Journal* 33(4):427–47.

Festinger, Leon. 1954. "A Theory of Social Comparison Processes." *Human Relations* 7(2):117–40.

Foschi, Martha. 2000. "Double Standards for Competence: Theory and Research." *Annual Review of Sociology* 26(1):21–42.

Foschi, Martha, Larissa Lai, and Kirsten Sigerson. 1994. "Gender and Double Standards in the Assessment of Job Applicants." *Social Psychology Quarterly* 57(4):326–39.

Fradkin, Andrey, Elena Grewal, Dave Holtz, and Matthew Pearson. 2015. "Bias and Reciprocity in Online Reviews: Evidence From Field Experiments on Airbnb." Pp. 641–641 in *Proceedings of the Sixteenth ACM Conference on Economics and Computation*, *EC '15*. New York, NY, USA: ACM.

Fradkin, Andrey, Elena Grewal, and David Holtz. 2018. "The Determinants of Online Review Informativeness: Evidence from Field Experiments on Airbnb." *SSRN Electronic Journal*.

Freeman, John H., and Pino G. Audia. 2006. "Community Ecology and the Sociology of Organizations." *Annual Review of Sociology* 32(1):145–69.

Garcia, Stephen M., Hyunjin Song, and Abraham Tesser. 2010. "Tainted Recommendations: The Social Comparison Bias." *Organizational Behavior and Human Decision Processes* 113(2):97–101.

Glynn, Mary Ann. 2000. "When Cymbals Become Symbols: Conflict Over Organizational Identity Within a Symphony Orchestra." *Organization Science* 11(3):285–98.

Goffman, Erving. 1959. "The Presentation of Self in Everyday Life." *Garden City, NY: Anchor*.

Goffman, Erving. 1967. *Interaction Ritual: Essays on Face-to-Face Behavior.* Garden City, N.Y.: Doubleday.

Gould, Roger V. 2002. "The Origins of Status Hierarchies: A Formal Theory and Empirical Test." *American Journal of Sociology* 107(5):1143–78.

Gould, Roger V. 2003. *Collision of Wills: How Ambiguity about Social Rank Breeds Conflict*. Chicago, Ill.; London: University of Chicago Press.

Greenberg, Jason, and Ethan Mollick. 2017. "Activist Choice Homophily and the Crowdfunding of Female Founders." *Administrative Science Quarterly* 62(2):341–74.

Greene, William. 2010. "Testing Hypotheses about Interaction Terms in Nonlinear Models." *Economics Letters* 107(2):291–96.

Greene, William H. 2003. *Econometric Analysis*. Upper Saddle River, N.J.: Prentice Hall.

Greve, Henrich R. 1998. "Performance, Aspirations, and Risky Organizational Change." *Administrative Science Quarterly* 43(1):58–86.

Grimes, Matthew G., Trenton Alma Williams, and Eric Yanfei Zhao. 2019. "Anchors Aweigh: The Sources, Variety, and Challenges of Mission Drift." *Academy of Management Review* 44(4):819–45.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales. 2009. "Cultural Biases in Economic Exchange?" *The Quarterly Journal of Economics* 124(3):1095–1131.

Gulati, Ranjay, and Martin Gargiulo. 1999. "Where Do Interorganizational Networks Come From?" *American Journal of Sociology* 104(5):1439–93.

Gulati, Ranjay, and Monica C. Higgins. 2003. "Which Ties Matter When? The Contingent Effects of Interorganizational Partnerships on IPO Success." *Strategic Management Journal* 24(2):127–144.

Guzman, Jorge, and Aleksandra (Olenka) Kacperczyk. 2019. "Gender Gap in Entrepreneurship." *Research Policy* 48(7):1666–80.

Hall, Edward Twitchell, and Mildred Reed Hall. 1990. *Understanding Cultural Differences:[Germans, French and Americans]*. Vol. 9. Intercultural press Yarmouth, ME.

Hallen, Benjamin L. 2008. "The Causes and Consequences of the Initial Network Positions of New Organizations: From Whom Do Entrepreneurs Receive Investments?" *Administrative Science Quarterly* 53(4):685–718.

Hayes, Andrew F. 2013. *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach*.

Heilman, Madeline E. 2001. "Description and Prescription: How Gender Stereotypes Prevent Women's Ascent Up the Organizational Ladder." *Journal of Social Issues* 57(4):657–74.

Heilman, Madeline E., Caryn J. Block, and Richard F. Martell. 1995. "Sex Stereotypes: Do They Influence Perceptions of Managers?" *Journal of Social Behavior and Personality* 10(4):237.

Higgins, Matthew J., Paula E. Stephan, and Jerry G. Thursby. 2011. "Conveying Quality and Value in Emerging Industries: Star Scientists and the Role of Signals in Biotechnology." *Research Policy* 40(4):605–17.

Hillmann, Henning, and Brandy L. Aven. 2011. "Fragmented Networks and Entrepreneurship in Late Imperial Russia." *American Journal of Sociology* 117(2):484–538.

Hoang, Ha, and Javier Gimeno. 2010. "Becoming a Founder: How Founder Role Identity Affects Entrepreneurial Transitions and Persistence in Founding." *Journal of Business Venturing* 25(1):41–53.

Hsu, David H. 2007. "Experienced Entrepreneurial Founders, Organizational Capital, and Venture Capital Funding." *Research Policy* 36(5):722–41.

Hu, Nan, Jie Zhang, and Paul A. Pavlou. 2009. "Overcoming the J-Shaped Distribution of Product Reviews." *Communications of the ACM* 52(10):144–47.

Ibarra, Herminia. 1992. "Homophily and Differential Returns: Sex Differences in Network Structure and Access in an Advertising Firm." *Administrative Science Quarterly* 37(3):422–47.

Jang, Sujin. 2017. "Cultural Brokerage and Creative Performance in Multicultural Teams." *Organization Science* 28(6):993–1009.

Jennings, Jennifer E., and Candida G. Brush. 2013. "Research on Women Entrepreneurs: Challenges to (and from) the Broader Entrepreneurship Literature?" *The Academy of Management Annals* 7(1):663–715.

Jiang, Crystal X., Roy YJ Chua, Masaaki Kotabe, and Janet Y. Murray. 2011. "Effects of Cultural Ethnicity, Firm Size, and Firm Age on Senior Executives' Trust in Their

Overseas Business Partners: Evidence from China." *Journal of International Business Studies* 42(9):1150–73.

Johnson, Michael A., Regan M. Stevenson, and Chaim R. Letwin. 2018. "A Woman's Place Is in The… Startup! Crowdfunder Judgments, Implicit Bias, and the Stereotype Content Model." *Journal of Business Venturing* 33(6):813–31.

Johnson-Spratt, Kim. 1998. "Housing Discrimination and Source of Income: A Tenant's Losing Battle Note." *Indiana Law Review* 32(2):457–80.

Jordan, Alexander H., and Pino G. Audia. 2012. "Self-Enhancement and Learning from Performance Feedback." *Academy of Management Review* 37(2):211–31.

Kacperczyk, Aleksandra J. 2012. "Opportunity Structures in Established Firms: Entrepreneurship versus Intrapreneurship in Mutual Funds." *Administrative Science Quarterly* 57(3):484–521.

Kanze, Dana, Laura Huang, Mark A. Conley, and E. Tory Higgins. 2018. "We Ask Men to Win and Women Not to Lose: Closing the Gender Gap in Startup Funding." *Academy of Management Journal* 61(2):586–614.

Kenneth, Christopher, and Mark Bart Baetz. 1998. "The Relationship between Mission Statements and Firm Performance: An Exploratory Study." *Journal of Management Studies* 35(6):823–53.

Kogut, Bruce, and Harbir Singh. 1988. "The Effect of National Culture on the Choice of Entry Mode." *Journal of International Business Studies* 19(3):411–32.

Kollock, Peter. 1994. "The Emergence of Exchange Structures: An Experimental Study of Uncertainty, Commitment, and Trust." *American Journal of Sociology* 100(2):313–45.

Kollock, Peter. 1998. "Social Dilemmas: The Anatomy of Cooperation." *Annual Review of Sociology* 24(1):183–214.

Kollock, Peter. 1999. "The Production of Trust in Online Markets:" Pp. 99–123 in *Advances in Group Processes*. Vol. 16. Greenwich, Conn.: JAI Press.

Kulik, Carol T., and Maureen L. Ambrose. 1992. "Personal and Situational Determinants of Referent Choice." *The Academy of Management Review* 17(2):212–37.

Kuwabara, Ko. 2015. "Do Reputation Systems Undermine Trust? Divergent Effects of Enforcement Type on Generalized Trust and Trustworthiness." *American Journal of Sociology* 120(5):1390–1428.

Lahey, Joanna N. 2008. "Age, Women, and Hiring an Experimental Study." *Journal of Human Resources* 43(1):30–56.

Lang, Kevin, and Michael Manove. 2011. "Education and Labor Market Discrimination." *American Economic Review* 101(4):1467–96.

Lee, Matthew, Arzi Adbi, and Jasjit Singh. 2020. "Categorical Cognition and Outcome Efficiency in Impact Investing Decisions." *Strategic Management Journal*.

Lee, Matthew, and Laura Huang. 2018. "Gender Bias, Social Impact Framing, and Evaluation of Entrepreneurial Ventures." *Organization Science* 29(1):1–16.

Lendle, Andreas, Marcelo Olarreaga, Simon Schropp, and Pierre-Louis Vézina. 2016. "There Goes Gravity: EBay and the Death of Distance." *The Economic Journal* 126(591):406–41.

Li, Junchao Jason, Xiao-Ping Chen, Suresh Kotha, and Greg Fisher. 2017. "Catching Fire and Spreading It: A Glimpse into Displayed Entrepreneurial Passion in Crowdfunding Campaigns." *Journal of Applied Psychology* 102(7):1075.

Li, Stan X., and Whitney Blair Berta. 2002. "The Ties That Bind: Strategic Actions and Status Structure in the US Investment Banking Industry." *Organization Studies* 23(3):339–68.

Locke, Richard M., Fei Qin, and Alberto Brause. 2007. "Does Monitoring Improve Labor Standards? Lessons from Nike." *Industrial & Labor Relations Review* 61(1):3–31.

Luca, Michael. 2016. "Reviews, Reputation, and Revenue: The Case of Yelp. Com." *Com (March 15, 2016). Harvard Business School NOM Unit Working Paper* (12–016).

Luca, Michael, and Georgios Zervas. 2016. "Fake It Till You Make It: Reputation, Competition, and Yelp Review Fraud." *Management Science* 62(12):3412–27.

Luchins, Abraham S. 1942. "Mechanization in Problem Solving: The Effect of Einstellung." *Psychological Monographs* 54(6):i–95.

Luthans, Fred, and Bruce J. Avolio. 2003. "Authentic Leadership Development." *Positive Organizational Scholarship* 241:258.

Lyness, Karen S., and Madeline E. Heilman. 2006. "When Fit Is Fundamental: Performance Evaluations and Promotions of Upper-Level Female and Male Managers." *Journal of Applied Psychology* 91(4):777–85.

Lynn, Freda B., Joel M. Podolny, and Lin Tao. 2009. "A Sociological (De)Construction of the Relationship between Status and Quality." *American Journal of Sociology* 115(3):755–804.

Macy, Michael W., and John Skvoretz. 1998. "The Evolution of Trust and Cooperation between Strangers: A Computational Model." *American Sociological Review* 63(5):638–60.

Magee, Joe C., and Adam D. Galinsky. 2008. "Social Hierarchy: The Self-Reinforcing Nature of Power and Status." *The Academy of Management Annals* 2(1):351–98.

Malmström, Malin, Jeaneth Johansson, and Joakim Wincent. 2017. "Gender Stereotypes and Venture Support Decisions: How Governmental Venture Capitalists Socially Construct Entrepreneurs' Potential." *Entrepreneurship Theory and Practice* 41(5):833–60.

March, James G., and Zur Shapira. 1992. "Variable Risk Preferences and the Focus of Attention." *Psychological Review* 99(1):172–83.

Mcfadden, Daniel. 1973. "Conditional Logit Analysis of Qualitative Choice Behavior." Pp. 105–42 in *Frontiers of Econometrics*, edited by P. Zarembka. New York: Academic Press.

Mendes, Wendy Berry, Jim Blascovich, Brian Lickel, and Sarah Hunter. 2002. "Challenge and Threat during Social Interactions with White and Black Men." *Personality and Social Psychology Bulletin* 28(7):939–52.

Merton, Robert K. 1968. "The Matthew Effect in Science: The Reward and Communication Systems of Science Are Considered." *Science* 159(3810):56–63.

Merton, Robert King. 1957. *Social Theory and Social Structure toward the Codification of Theory and Research.* Glencoe, Ill.: Free Press.

Mollick, Ethan, and Ramana Nanda. 2016. "Wisdom or Madness? Comparing Crowds with Expert Evaluation in Funding the Arts." *Management Science* 62(6):1533–53.

Morley, David, and Kevin Robins. 2004. *Spaces of Identity: Global Media, Electronic Landscapes and Cultural Boundaries*. London: Routledge.

Morosini, Piero, Scott Shane, and Harbir Singh. 1998. "National Cultural Distance and Cross-Border Acquisition Performance." *Journal of International Business Studies* 29(1):137–58.

Mortensen, Mark, and Tsedal B. Neeley. 2012. "Reflected Knowledge and Trust in Global Collaboration." *Management Science* 58(12):2207–24.

Mussweiler, Thomas. 2003. "Comparison Processes in Social Judgment: Mechanisms and Consequences." *Psychological Review* 110(3):472–89.

Mussweiler, Thomas, and Fritz Strack. 2001. "The Semantics of Anchoring." *Organizational Behavior and Human Decision Processes* 86(2):234–55.

Navis, Chad, and Mary Ann Glynn. 2011. "Legitimate Distinctiveness and the Entrepreneurial Identity: Influence on Investor Judgments of New Venture Plausibility." *Academy of Management Review* 36(3):479–499.

Neal, Derek A., and William R. Johnson. 1996. "The Role of Premarket Factors in Black-White Wage Differences." *Journal of Political Economy* 104(5):869–95.

Nissenbaum, Helen. 2004. "Will Security Enhance Trust Online, or Supplant It?" Pp. 155–88 in *Trust and Distrust in Organizations: Dilemmas and Approaches*. Vol. VII. New York: Russell Sage Foundation.

Obloj, Tomasz, and Todd Zenger. 2017. "Organization Design, Proximity, and Productivity Responses to Upward Social Comparison." *Organization Science* 28(1):1–18.

Ocasio, William. 1995. "The Enactment of Economic Adversity-a Reconciliation of Theories of Failure-Induced Change and Threat-Rigidity." *Research In Organizational Behavior: An Annual Series Of Analytical Essays And Critical Reviews* 17:287–331.

Olsson, A. 2005. "The Role of Social Groups in the Persistence of Learned Fear." *Science* 309(5735):785–87.

Orbell, John, and Robyn Dawes. 1981. "Social Dilemmas." *Progress in Applied Social Psychology* 1:37–66.

Owen, David L., Tracey A. Swift, Christopher Humphrey, and Mary Bowerman. 2000. "The New Social Audits: Accountability, Managerial Capture or the Agenda of Social Champions?" *European Accounting Review* 9(1):81–98.

Pache, Anne-Claire, and Filipe Santos. 2010. "When Worlds Collide: The Internal Dynamics of Organizational Responses to Conflicting Institutional Demands." *Academy of Management Review* 35(3):455–76.

Pache, Anne-Claire, and Filipe Santos. 2013. "Inside the Hybrid Organization: Selective Coupling as a Response to Competing Institutional Logics." *Academy of Management Journal* 56(4):972–1001.

Pahnke, Emily Cox, Riitta Katila, and Kathleen M. Eisenhardt. 2015. "Who Takes You to the Dance? How Partners' Institutional Logics Influence Innovation in Young Firms." *Administrative Science Quarterly* 60(4):596–633.

Pearce, John A., and Fred David. 1987. "Corporate Mission Statements: The Bottom Line." *Academy of Management Perspectives* 1(2):109–15.

Podolny, Joel M. 1994. "Market Uncertainty and the Social Character of Economic Exchange." *Administrative Science Quarterly* 39(3):458–83.

Polanyi, Karl. 1944. "The Great Transformation: The Political and Economic Origins of Our Time." *New York: Farrar & Rinehart Inc.*

Post, Corinne. 2015. "When Is Female Leadership an Advantage? Coordination Requirements, Team Cohesion, and Team Interaction Norms." *Journal of Organizational Behavior* 36(8):1153–75.

Powell, Walter W. 1990. "Neither Market nor Hierarchy: Network Forms of Organization." *Research in Organizational Behavior* 12:295–336.

Ramarajan, Lakshmi. 2014. “Past, Present and Future Research on Multiple Identities: Toward an Intrapersonal Network Approach.” *The Academy of Management Annals* 8(1):589–659.

Ramus, Tommaso, and Antonino Vaccaro. 2017. “Stakeholders Matter: How Social Enterprises Address Mission Drift.” *Journal of Business Ethics* 143(2):307–22.

Raub, Werner, and Jeroen Weesie. 1990. “Reputation and Efficiency in Social Interactions: An Example of Network Effects.” *American Journal of Sociology* 96(3):626–54.

Raz, Joseph. 1986. *The Morality of Freedom*. Oxford: Oxford University Press.

Resnick, Paul, and Richard Zeckhauser. 2002. “Trust among Strangers in Internet Transactions: Empirical Analysis of EBay’ s Reputation System.” Pp. 127–57 in *Advances in Applied Microeconomics*. Vol. 11. Bingley: Emerald (MCB UP).

Reuer, Jeffrey J., Tony W. Tong, and Cheng-Wei Wu. 2012. “A Signaling Theory of Acquisition Premiums: Evidence from IPO Targets.” *Academy of Management Journal* 55(3):667–83.

Ridgeway, C. L., and S. J. Correll. 2006. “Consensus and the Creation of Status Beliefs.” *Social Forces* 85(1):431–53.

Ridgeway, Cecilia L. 2011. *Framed by Gender: How Gender Inequality Persists in the Modern World*. New York: Oxford University Press.

Ridgeway, Cecilia L., Elizabeth Heger Boyle, Kathy J. Kuipers, and Dawn T. Robinson. 1998. “How Do Status Beliefs Develop? The Role of Resources and Interactional Experience.” *American Sociological Review* 63(3):331–50.

Rivera, Lauren A., and András Tilcsik. 2019. “Scaling Down Inequality: Rating Scales, Gender Bias, and the Architecture of Evaluation.” *American Sociological Review* 84(2):248–74.

Roberts, Peter W., Mukti Khaire, and Christopher I. Rider. 2011. “Isolating the Symbolic Implications of Employee Mobility: Price Increases after Hiring Winemakers from Prominent Wineries.” *American Economic Review* 101(3):147–51.

Rockstuhl, Thomas, and Kok-Yee Ng. 2008. “The Effects of Cultural Intelligence on Interpersonal Trust in Multicultural Teams.” *Handbook of Cultural Intelligence: Theory, Measurement, and Applications* 206–20.

Rosener, Judy B. 1995. *America’s Competitive Secret: Utilizing Women as a Management Strategy*. New York: Oxford University Press.

Roth, Louise Marie. 2004. “Bringing Clients Back In:” *The Sociological Quarterly* 45(4):613–35.

Rudman, Laurie A., and Peter Glick. 1999. “Feminized Management and Backlash toward Agentic Women: The Hidden Costs to Women of a Kinder, Gentler Image of Middle Managers.” *Journal of Personality and Social Psychology* 77(5):1004.

Salk, Jane E., and Oded Shenkar. 2001. “Social Identities in an International Joint Venture: An Exploratory Case Study.” *Organization Science* 12(2):161–78.

Sangiorgi, Francesco, and Chester Spatt. 2017. “Opacity, Credit Rating Shopping, and Bias.” *Management Science* 63(12):4016–36.

Sauder, Michael, and Wendy Nelson Espeland. 2009. “The Discipline of Rankings: Tight Coupling and Organizational Change.” *American Sociological Review* 74(1):63–82.

Sauder, Michael, Freda Lynn, and Joel M. Podolny. 2012. “Status: Insights from Organizational Sociology.” *Annual Review of Sociology* 38(1):267–83.

Schelling, Thomas C. 1960. *The Strategy of Conflict*. Cambridge (Mass.): Harvard University Press.

Schofer, Evan, and John W. Meyer. 2005. “The Worldwide Expansion of Higher Education in the Twentieth Century.” *American Sociological Review* 70(6):898–920.

Scholte, Jan Aart. 2005. *Globalization: A Critical Introduction*. Houndmills, Basingstoke; New York: Palgrave Macmillan.

Schor, Juliet B., Connor Fitzmaurice, Lindsey B. Carfagna, Will Attwood-Charles, and Emilie Dubois Poteat. 2016. “Paradoxes of Openness and Distinction in the Sharing Economy.” *Poetics* 54(February):66–81.

Schor, Juliet B., and Connor J. Fitzmaurice. 2015. “Collaborating and Connecting: The Emergence of the Sharing Economy.” in *Handbook of Research on Sustainable Consumption*. 410-425: Edward Elgar Publishing.

Schwartz, Shalom H. 1994. “Beyond Individualism/Collectivism: New Cultural Dimensions of Values.” Pp. 85–119 in *Cross-cultural research and methodology series*. Vol. 18. Thousand Oaks, CA: SAGE Publications.

Schwartz, Shalom H. 1999. “A Theory of Cultural Values and Some Implications for Work.” *Applied Psychology* 48(1):23–47.

Shane, Scott, and Daniel Cable. 2002. “Network Ties, Reputation, and the Financing of New Ventures.” *Management Science* 48(3):364–81.

Shane, Scott, and Toby Stuart. 2002. “Organizational Endowments and the Performance of University Start-Ups.” *Management Science* 48(1):154–70.

Shapiro, Carl. 1982. “Consumer Information, Product Quality, and Seller Reputation.” *The Bell Journal of Economics* 20–35.

Shapiro, Susan P. 1987. “The Social Control of Impersonal Trust.” *American Journal of Sociology* 93(3):623–58.

Sharkey, Amanda J., and Patricia Bromley. 2014. “Can Ratings Have Indirect Effects? Evidence from the Organizational Response to Peers’ Environmental Ratings.” *American Sociological Review* 0003122414559043.

Sharkey, Amanda J., and Balázs Kovács. 2018. “The Many Gifts of Status: How Attending to Audience Reactions Drives the Use of Status.” *Management Science* 64(11):5422–43.

Short, Jodi L., and Michael W. Toffel. 2010. “Making Self-Regulation More than Merely Symbolic: The Critical Role of the Legal Environment.” *Administrative Science Quarterly* 55(3):361–69.

Sidanius, James, and Felicia Pratto. 1999. *Social Dominance: An Intergroup Theory of Social Hierarchy and Oppression*. Cambridge: Cambridge University Press.

Simons, Tony. 2002. “Behavioral Integrity: The Perceived Alignment between Managers’ Words and Deeds as a Research Focus.” *Organization Science* 13(1):18–35.

Singh, Jitendra V. 1986. “Performance, Slack, and Risk Taking in Organizational Decision Making.” *Academy of Management Journal* 29(3):562–85.

Sitkin, Sim B., and Amy L. Pablo. 1992. “Reconceptualizing the Determinants of Risk Behavior.” *Academy of Management Review* 17(1):9–38.

Smith, Edward Bishop, and Kevin Gaughan. 2016. “Better in the Shadows? Media Coverage and Market Reactions to Female CEO Appointments.” *Academy of Management Proceedings* 2016(1):13997.

Smith, Wendy K., and Paul Tracey. 2016. “Institutional Complexity and Paradox Theory: Complementarities of Competing Demands.” *Strategic Organization* 14(4):455–66.

Social Business Initiative. 2014. *The Social Business Initiative Brochure*.

Sørensen, Jesper B., and Magali A. Fassiotto. 2011. “Organizations as Fonts of Entrepreneurship.” *Organization Science* 22(5):1322–31.

Spence, A. 1974. *Market Signaling: Informational Transfer in Hiring and Related Screening Processes*.

Stryker, Sheldon, and Peter J. Burke. 2000. “The Past, Present, and Future of an Identity Theory.” *Social Psychology Quarterly* 63(4):284–97.

Stuart, Toby E., Ha Hoang, and Ralph C. Hybels. 1999. “Interorganizational Endorsements and the Performance of Entrepreneurial Ventures.” *Administrative Science Quarterly* 44(2):315–49.

Tajfel, Henri. 1978. *Differentiation between Social Groups: Studies in the Social Psychology of Intergroup Relations*. London; New York: Published in cooperation with European Association of Experimental Social Psychology by Academic Press.

Thornton, Patricia H., William Ocasio, and Michael Lounsbury. 2012. *The Institutional Logics Perspective: A New Approach to Culture, Structure, and Process*. Oxford: Oxford University Press.

Thye, Shane R. 2000. "A Status Value Theory of Power in Exchange Relations." *American Sociological Review* 65(3):407–32.

Tiedens, Larissa Z., Miguel M. Unzueta, and Maia J. Young. 2007. "An Unconscious Desire for Hierarchy? The Motivated Perception of Dominance Complementarity in Task Partners." *Journal of Personality and Social Psychology* 93(3):402–14.

Tihanyi, Laszlo, David A. Griffith, and Craig J. Russell. 2005. "The Effect of Cultural Distance on Entry Mode Choice, International Diversification, and MNE Performance: A Meta-Analysis." *Journal of International Business Studies* 36(3):270–83.

Trapido, Denis. 2013. "Counterbalances to Economic Homophily: Microlevel Mechanisms in a Historical Setting." *American Journal of Sociology* 119(2):444–85.

Trelstad, Brian. 2016. "Impact Investing: A Brief History." *Capitalism & Society* 11(2).

Troyer, Lisa, and C. Wesley Younts. 1997. "Whose Expectations Matter? The Relative Power of First- and Second-Order Expectations in Determining Social Influence." *American Journal of Sociology* 103(3):692–732.

Tsui, Anne S., and Charles A. O'Reilly. 1989. "Beyond Simple Demographic Effects: The Importance of Relational Demography in Superior-Subordinate Dyads." *Academy of Management Journal* 32(2):402–23.

Tziner, Aharon, and Dov Eden. 1985. "Effects of Crew Composition on Crew Performance: Does the Whole Equal the Sum of Its Parts?" *Journal of Applied Psychology* 70(1):85–93.

Umphress, Elizabeth E., Kristin Smith-Crowe, Arthur P. Brief, Joerg Dietz, and Marla Baskerville Watkins. 2007. "When Birds of a Feather Flock Together and When They Do Not: Status Composition, Social Dominance Orientation, and Organizational Attractiveness." *Journal of Applied Psychology* 92(2):396–409.

Unger, Jens M., Andreas Rauch, Michael Frese, and Nina Rosenbusch. 2011. "Human Capital and Entrepreneurial Success: A Meta-Analytical Review." *Journal of Business Venturing* 26(3):341–58.

Webster, Murray, and Joseph M. Whitmeyer. 1999. "A Theory of Second-Order Expectations and Behavior." *Social Psychology Quarterly* 62(1):17–31.

Williamson, Oliver E. 1975. *Markets and Hierarchies*. New York: Free Press.

Williamson, Oliver E. 1981. "The Economics of Organization: The Transaction Cost Approach." *American Journal of Sociology* 87(3):548–77.

Williamson, Oliver E. 1985. *The Economic Institutions of Capitalism: Firms, Markets, Relational Contracting*. New York; London: Free Press ; Collier Macmillan.

Wilson, Robert. 1985. "Reputations in Games and Markets." *Game-Theoretic Models of Bargaining* 27–62.

Woolthuis, Rosalinde Klein, Bas Hillebrand, and Bart Nooteboom. 2005. "Trust, Contract and Relationship Development." *Organization Studies* 26(6):813–40.

Wry, Tyler, and Jeffrey G. York. 2017. "An Identity-Based Approach to Social Enterprise." *Academy of Management Review* 42(3):437–60.

Wry, Tyler, and Eric Yanfei Zhao. 2018. "Taking Trade-Offs Seriously: Examining the Contextually Contingent Relationship Between Social Outreach Intensity and Financial Sustainability in Global Microfinance." *Organization Science* 29(3):507–28.

Xiao, Zhixing, and Anne S. Tsui. 2007. "When Brokers May Not Work: The Cultural Contingency of Social Capital in Chinese High-Tech Firms." *Administrative Science Quarterly* 52(1):1–31.

Yamagishi, Toshio, Karen S. Cook, and Motoki Watabe. 1998. "Uncertainty, Trust, and Commitment Formation in the United States and Japan." *American Journal of Sociology* 104(1):165–94.

Yamagishi, Toshio, and Midori Yamagishi. 1994. "Trust and Commitment in the United States and Japan." *Motivation and Emotion* 18(2):129–66.

Yang, Shu, Romi Kher, and Scott L. Newbert. 2020. "What Signals Matter for Social Startups? It Depends: The Influence of Gender Role Congruity on Social Impact Accelerator Selection Decisions." *Journal of Business Venturing* 35(2):105932.

Yinger, John. 1995. *Closed Doors, Opportunities Lost: The Continuing Costs of Housing Discrimination*. New York: Russell Sage Foundation.

Younkin, Peter, and Venkat Kuppuswamy. 2017. "The Colorblind Crowd? Founder Race and Performance in Crowdfunding." *Management Science* 64(7):3269–87.

Zelizer, Viviana A. 1989. "The Social Meaning of Money: 'Special Monies.'" *American Journal of Sociology* 95(2):342–77.

Zelizer, Viviana A. Rotman. 1994. *Pricing the Priceless Child: The Changing Social Value of Children*. Princeton, N.J.: Princeton University Press.

Zenger, Todd R., and CR Marshall. 2000. "Determinants of Incentive Intensity in Group-Based Rewards." *Academy of Management Journal* 43(2):149–63.

Zervas, Georgios, Davide Proserpio, and John Byers. 2015. "A First Look at Online Reputation on Airbnb, Where Every Stay Is Above Average." *SSRN Electronic Journal*.

Zhao, Eric Yanfei, and Tyler Wry. 2016. "Not All Inequality Is Equal: Deconstructing the Societal Logic of Patriarchy to Understand Microfinance Lending to Women." *Academy of Management Journal* 59(6):1994–2020.

Zheng, Yanfeng, Michael L. Devaughn, and Mary Zellmer-Bruhn. 2016. "Shared and Shared Alike? F Ounders' Prior Shared Experience and Performance of Newly Founded Banks." *Strategic Management Journal* 37(12):2503–20.

Zucker, Lynne G. 1983. "Organizations as Institutions." Pp. 1–47 in *Research in the Sociology of Organizations*. Vol. 2, edited by S. Bacharach. Greenwich, Conn.: JAI Press.

Zucker, Lynne G. 1986. "Production of Trust: Institutional Sources of Economic Structure, 1840–1920." *Research in Organizational Behavior* 8:53–111.

Zuckerman, Harriet. 1967. "Nobel Laureates in Science: Patterns of Productivity, Collaboration, and Authorship." *American Sociological Review* 32(3):391–403.

APPENDICES

Appendix A. Lists of Crowdfunding Platforms

Platforms	Founding year	The platform designates a category for social enterprises, nonprofits, or public-benefit-oriented projects.	The platform lists both successful and failed fundraising projects.	The platform provides detailed description of the fundraising projects.	The platform accepts funds from all individual investors, as opposed to only from professional investors.	The platform displays founder names and fundraising closing dates.	The platform has projects in various industries, as opposed to focusing on one specific industry.
Kickstarter.com	2009	√	√	√	√	√	√
Indiegogo.com	2007		√	√	√		√
StartSomeGood.com	2011	√	√	√	√	√	√
Pozible.com	2011	√	√	√	√	√	√
Chuffed.com	2013	√	√		√	√	√
GoFundMe.com	2010		√	√	√	√	√
Crowdfunder.com	2012		√	√	√	√	√
Mightycause.com	2007		/	/	√	/	/
CircleUp.com	2011		/	/		/	

Note: Cells with blank information indicate that the platform does not meet the standard listed in the first row of that column. We excluded several platforms for a couple of reasons. For example, Indiegogo, another leading generic crowdfunding platform, unfortunately does not designate a category for social enterprises, making the screening process strenuous given its large number of campaigns across all categories and our limited research resources. Also, it does not include the closing dates for the crowdfunding campaigns. GoFundMe and Mightycause are two popular sites to the public for its crowdfunding network but mainly focus on individual causes or nonprofit organizations. We also excluded Chuffed since there were only a limited number of projects that met the definition of social enterprise and the difficulty to identify the founder for most of them. We finally excluded CircleUp since they connect entrepreneurs with industrial experts or institutional investors, but not with individual amateurs, and are located in a narrow scope of businesses, i.e., consumer goods. CircleUp and MightyCause offer fee-based service only available to registered entrepreneurs for investor networking and thus are denoted with a "/" sign in the cells.

Appendix B. Experiment Materials for Study 2

Please read carefully through the public pitch of a start-up social enterprise and fill out the questionnaire below.

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What is a social enterprise?

Social enterprise is an innovative hybrid business model that aims to address social problems via business approaches. Both social missions and business missions are at its core. Traditional businesses seek to maximize economic profits, while traditional charitable organizations rely on donations to achieve social benefits. In contrast, social enterprises fulfill their social purposes and sustain operation via economic gains from business activities. Furthermore, all the economic gains left will NOT go to shareholders but only to further operations of the social enterprise.

Leaders of social enterprises have to strike a balance between social goals and business goals such that they do not compromise key aspects of its social missions in their efforts to generate revenues. In fact, it is not uncommon that some social enterprises, driven by the pursuit of financial profits, have shifted away from their original social missions.

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Below is the public pitch of a start-up social enterprise, NYBakery.

NYBakery

NYBakery, founded in 2015, is a social enterprise based in New York City. The founding mission of this social enterprise is to provide jobs to individuals who face barriers to employment in our first-rate bakery and support our trainees for their future employment.

How do we fulfill our social missions?

Open Hiring

Socially disadvantaged individuals who lack education credentials, work history, or language skills due to childhood poverty, family disruption, homelessness, or incarceration, are discriminated at work application and deprived of work training opportunities. We employ individuals who face these social barriers, and offer the supportive services the employee and the community need to thrive.

Training and Future Employment

NYBakery provides 12-Week training that teaches participants the fundamentals of Culinary & Pastry Arts, covering food and banquet prep. Program includes on-the-job-training and ServSafe Certification. Graduates are prepared to work in any restaurant, catering service, or food manufacturing facility. Culinary and Pastry Arts graduates are ideal employees for front or back of house in the food industry. They are ServSafe Certified, talented cooks and hardworking employees. Since 2016, we have 50 graduates from our training programs and 74% of graduates achieved employment!

How do we make profits to maintain operation?

Comprised entirely of people offered a job opportunity through Open Hiring, our bakers operate a first-rate food processing facility. We bake and ship brownies every day to many cafés and restaurants in Manhattan and produce award-winning brownies and cookies for sale online. We also provide Culinary & Pastry Arts training for the public for a fee, including 4-hour weekend class and online programs.








INCLUSIONS

We have the experience and know-how to create the perfect brownie add-ins for any dairy or non-dairy frozen dessert.

CORPORATE & SOCIAL GIFTING

Give a gift with meaning to clients and friends. Our customizable treats are perfect for all occasions.

WHOLESALE

Bulk and tray brownies and cookies available in your favorite flavor and sizes.

CONTRACT MANUFACTURING

Private label, contract manufacturing and packaging available for all products.

Our Founder & CEO: Andrew/Ashley

Before founding this venture, Andrew/Ashley has over-ten-years' work experience in for-profit organizations with expertise in business operation and management. Below is his/her resume.

2015-present, Founder and CEO, NYBakery

(Previous Experience: for-profit only)
2009-2015, Associate, Acquis Consulting Group (Private company)

- Designed new store-format strategies and new supply-chain strategies for supermarket chains
- Provided business operation solutions and procurement management with a focus on the food industry, delivered tailor-made planning tools to support decision making regarding procurement, scheduling and capacity planning.

2004-2009, Senior Manager, Ernest' Gourmet Food Company (Publicly traded company)

- Led key marketing and strategy initiatives, including brand campaigns and long-term business planning.
- Managed inventory system including documentation, communication, and deliver scheduling to support perishable warehouse environments.

(Previous Experience: nonprofit only)
2009-2015, Senior Manager for Community Development, Common Good Initiative (Nonprofit organization)

- Coordinated and assessed community food pantry services and homeless center operations, integrated the donation-redistribution channels.

- Managed relationships with corporations and fundraising events, engaged in major community-corporation integration projects.

2004-2009, Project Manager, Institute for Youth Development (Nonprofit organization)

- Managed a range of community-based projects including but not limited to care coordination, family continuation, and youth education workshops.
- Managed community-based employment support and career development projects.

(Previous Experience: has both for-profit and nonprofit experience)

2009-2015, Senior Manager for Community Development, Common Good Initiative (Nonprofit organization)

- Coordinated and assessed community food pantry services and homeless center operations, integrated the donation re-distribution channels.
- Managed relationships with corproations and fundraising events, engaged in major community-corporation integration projects.

2004-2009, Senior Manager, Ernest' Gourmet Food Company (Publicly traded company)

- Led key marketing and strategy initiatives, including brand campaigns and long-term business planning.
- Managed inventory system including documentation, communication, and deliver scheduling to support perishable warehouse environments.

Use of Funds

Although we have a solid business model to make profits and maintain operations in the long-term, we need financial support at this time to set up facilities and cover other short-term operational costs before we can make profits. To expand NYBakery, we need a few practical resources. Funds raised will be used for:

- Support for renting additional branch stores for NYBakery and workshop space for holding training sessions;
- Support for hosting marketing and social events to attract business partners who are potential employers of our students.

Please support NOW to help us create an inclusive society!

Appendix C. Experiment Materials for Study 3

Scenario:

You are a junior partner in a venture capital firm that is seeking to invest in an early-stage social enterprise. You received a pitch from Yellow Brick Road, a social enterprise that features an online platform connecting employers seeking employees with community college students. It aims to create clearer education pathways for students toward job security and better placement and to help employers finding potential employees that have the skillsets that they desire.

Please read through their pitch and assess its potential as an investment target for your company. Your evaluations and decisions will be shared with your senior partners.

What Is a Social Enterprise?

A social enterprise is a hybrid business model that aims to address social problems via business approaches. Both social missions and business missions are at its core. Traditional businesses seek to maximize economic profits, while traditional charitable organizations rely on donations to achieve social benefits. In contrast, social enterprises fulfill their social purposes and sustain operations via economic gains from business activities. Furthermore, all the economic gains left will NOT go to shareholders but only to further operations of the social enterprise. Leaders of social enterprises need to strike a balance between social goals and business goals such that they do not compromise key aspects of its social missions in their efforts to generate revenues. In fact, it is not uncommon that some social enterprises, driven by the pursuit of financial profits, have shifted away from their original social missions.

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Yellow Brick Road: Empowering Community College Education

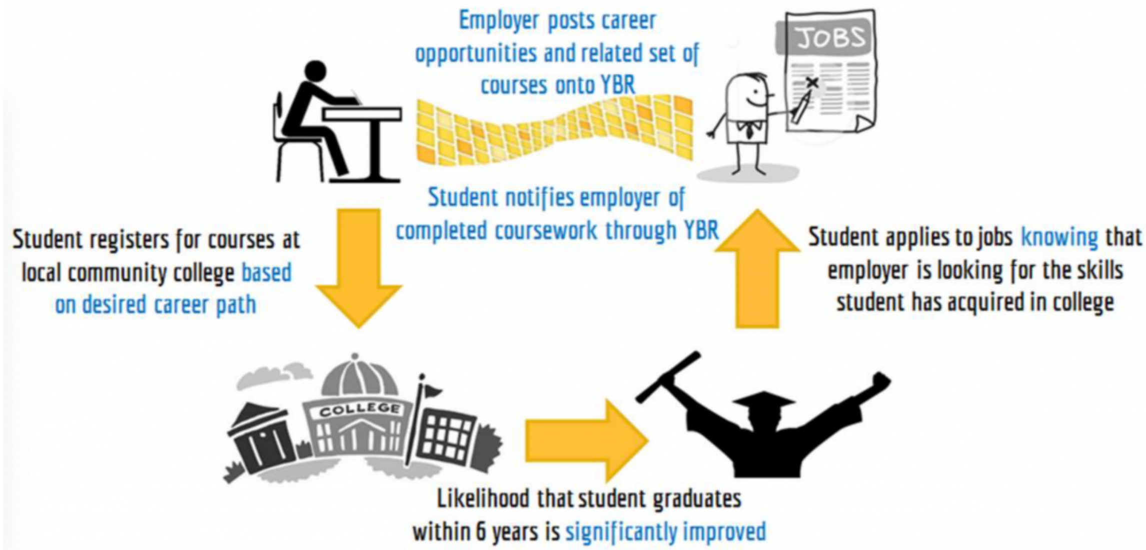
Problem

In the face of impossibly high four-year college tuition rates and unsustainable student debt loads, more attention is being focused on America's community colleges as an affordable solution for high-need students seeking economic empowerment. The economic returns for society at large are great: our government invests around $54,800 for each Associate's degree but gains an additional $142,000 in revenue from increased income tax payments as well as savings from decreased social service costs. There is a gross mismatch, however, between the promise of community colleges and their actual reality. Only 13% of low-income community college students earn an Associate's degree within six years. Faced with immediate economic needs and unclear pathways towards job security, too many students choose to leave the community college system without a degree and are unable to secure living wage employment.

Solution

Yellow Brick Road (YBR) is an online platform that connects employers seeking Associate-level employees with aspiring community college students, while also providing these students with a clear, visual pathway to economic security. High school seniors thinking of attending community college can search Yellow Brick Road for specific career opportunities posted by local employers. Once a position is selected, a career pathway specific to the employer is displayed. Therefore, we serve three types of stakeholders: students, community colleges, and employers (see Figure C1).

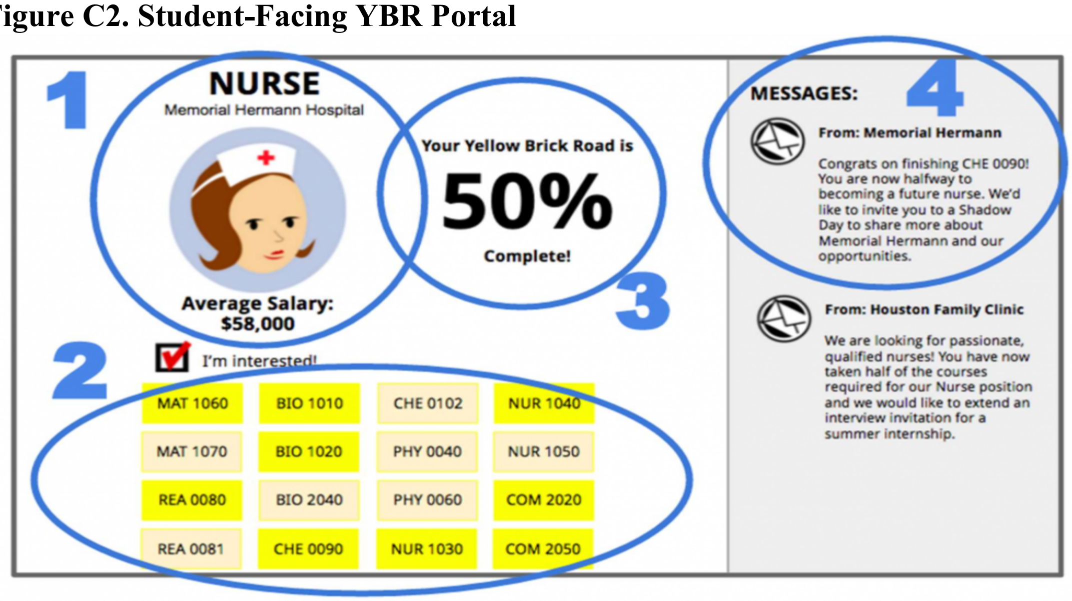
Figure C1. Yellow Brick Road Community College Experience for Students



The student-facing portal (Figure C2) contains information in 4 key sections:

- Position Details: On each job profile, students will be able to access pertinent information about the position including average salary, typical work schedule, and career advancement opportunities.
- The Yellow Brick Road: With each profile, a 'road' is laid out for the student. Each brick corresponds to a particular class the student must take at his/her local community college.
- Progress Tracker: Once a student satisfactorily completes a class, his/her reported progress is tracked on the site.
- Message Board: Employers are able to send pre-programmed and customized messages to students at various points in the 'road' completion to engage and motivate students through the journey.

Figure C2. Student-Facing YBR Portal



By specifying the classes a student must take for a particular career path and facilitating early matching of employers with future employees, Yellow Brick Road allows students to take greater ownership over their college education and engages employers to be motivating forces along the way.

Strategy

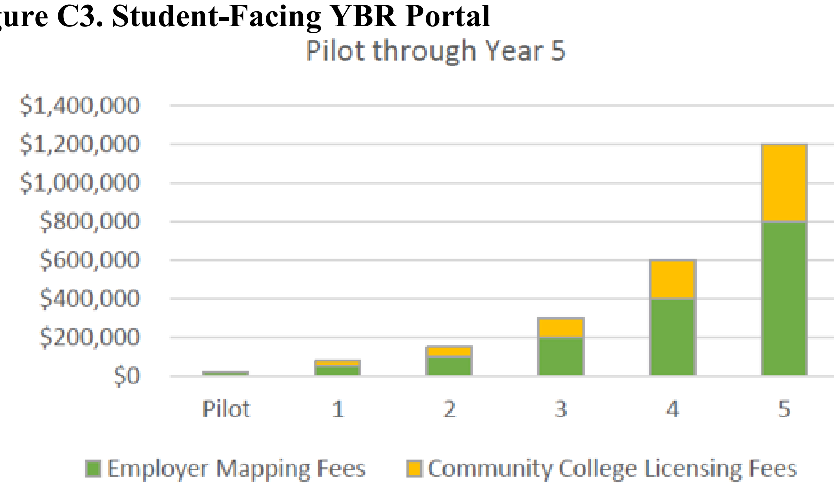
YBR will operate as a for-profit social enterprise to ensure sustainability and maximize growth potential. To ensure the cost is not a barrier to adoption and to remain consistent with our social mission, Yellow Brick Road will be offered as a free service to students to avoid financial burden and to increase adoption. Therefore, YBR's main sources of revenue will be community colleges and employers.

- **Community colleges** will be charged a flat licensing fee of $5,000 per campus per year to provide Yellow Brick Road to their students. Upon enrolling a campus, Yellow Brick Road will work with the administration to upload their course catalog to the platform in order to allow for the design of logical 'roads' based on the courses offered and local employers' hiring needs. Once a campus' course catalog is uploaded, the marginal cost of an additional student account is very low, which allows for the initial use of a flat rate pricing model, regardless of campus enrollment.
- **Employers** will pay $1,000 per career 'road' designed per college. Though employers will need to develop job descriptions for the roles they are hiring, the Yellow Brick Road team will provide the necessary expertise and coordination with the campus administration to map out the courses ('bricks') that define the 'road' to a specific job. This process will be arduous initially, but we anticipate a steep learning curve as the team builds relationships with community college administrators and better understands each college's offerings.

Financial Projections

Based on current assumptions of scale and usage, we anticipate achieving approximately $1.2M in annual revenue within 5 years, and we believe that this is a conservative view. Going forward, YBR will continue to explore additional pricing strategies and revenue opportunities and will also explore how to best capture the large opportunity represented by small to medium-sized enterprises in our target markets.

Figure C3. Student-Facing YBR Portal



Appendix D. Measures for Control Variables in Study 2 & 3

Your age is:

A. 24 and younger
B. 25-34
C. 35-44
D. 45-64
E. 65 and older

You are:

A. Male
B. Female

Your educational attainment is:

A. Less than high school
B. High school completion
C. Some college or associate's degree
D. Bachelor's degree
E. Advanced degree

You primarily identify as:

A. Asian
B. Black
C. Hispanic/Latino
D. White
E. Other

[Study 3 only: Participant's Prevention Focus]

Note: The scale below is adapted from Neubert et al.(2008), "Regulatory focus as a mediator of the influence of initiating structure and servant leadership on employee behavior", Journal of Applied Psychology, 93(6), 1220. This original scale of prevention focus is 9 items with 3 dimensions. We choose one item out of each dimension, thus having 3 items for our purpose. In choosing the item for each dimension, we choose the one with the highest factor loading in their reported exploratory factor analysis. The Cronbach's alpha is .64.

Please indicate to what extent the following statements describe you (1 strongly disagree, to 7 strongly agree)

A. At work, I focus my attention on completing my assigned responsibilities.
B. I concentrate on completing my work task correctly to increase my job security.
C. I do everything I can to avoid loss at work.

[Study 3 only: Financial Acumen Assessment]

Note: The scale below is adapted from Smith and Chae (2017), "The effect of organizational atypicality on reference group selection and performance evaluation", Organization Science, *28(6), 1134-1149.We choose three out of the original five items to reduce the length of our questionnaire.*

Suppose you had $100 in a savings account and the interest rate was 2 percent per year. After five years, how much do you think you would have in the account if you left the money to grow?

A. More than $102
B. Exactly $102
C. Less than $102
D. Do not know

Imagine that the interest rate on your savings account was 1 percent per year and inflation was 2 percent per year. After one year, would you be able to buy more than, exactly the same as, or less than today with the money in this account?

A. More than today
B. Exactly the same
C. Less than today
D. Do not know

Do you think that the following statement is true or false? "Buying a single company stock usually provides a safer return than a stock mutual fund."

A. True
B. False
C. Do not know