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RESEARCH PAPER

Unlocking Online Reputation

On the Effectiveness of Cross-Platform Signaling in the Sharing Economy

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Abstract With the ever-growing popularity of sharing economy platforms, complementors increasingly face the challenge to manage their reputation on different platforms. The paper reports the results from an experimental online survey to investigate how and under which conditions online reputation is effective to engender trust across platform boundaries. It shows that (1) cross-platform signaling is in fact a viable strategy to engender trust and that (2) its effectiveness crucially depends on source–target fit. Implications for three stakeholders are discussed. First, platform complementors may benefit from importing reputation, especially when they have just started on a new platform and have not earned on-site reputation yet. The results also show, however, that importing reputation (even if it is excellent) may be detrimental if there occurs a mismatch between source and target and that, hence, fit is of utmost importance. Second, regulatory authorities may consider reputation portability as a means to make platform boundaries more permeable and hence to tackle lock-in effects. Third, platform operators may employ cross-platform signaling as a competitive lever.

Keywords Data portability · Digital platforms · Reputation · Sharing economy · Signaling theory · Trust

1 Introduction

Platforms for selling, renting, and servicing have become a popular alternative to conventional e-commerce channels (Van Alstyne et al. 2016; Sundararajan 2016). Services such as Airbnb for accommodation sharing, BlaBlaCar for ride sharing, eBay for commodity exchange, and Uber for on-demand mobility enable the exchange of spare resources among (private) individuals. At its core, a platform connects consumers (or *users*) to providers (or *complementors*) of products and services (Eisenmann et al. 2008). Platform-based businesses have raised billions in venture capital and exhibit strong market valuations [e.g., Uber: $69bn; Airbnb: $31bn; (Zijm et al. 2019)], often exceeding those of long-established industry incumbents. Recent studies on annual consumer spending (e.g., €17.2bn for resale goods; €6.6bn for renting accommodation), growth rates (50–100%), and overall market volume within the sharing economy (€570bn until 2025) underpin this development (EU 2017; PwC 2016).

Importantly, complementors need to establish a reputation on the platforms they operate on and a majority is active on multiple platforms (Hesse and Teubner 2019; Teubner et al. 2019). At that, they rely on the reputation they build *within* the boundaries of a specific platform. In view of the broad and highly specialized spectrum of platforms, complementors find themselves managing many separate reputations (Dakhlia et al. 2016). There is

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typically no technical integration across platforms, leading to friction, intransparencies, and increased transaction costs (Botsman 2012). Hence, the possibility to transfer reputation across platforms could provide substantial value to complementors. In particular, enabling such cross-platform signaling may help to overcome the inherent "cold start" problem when starting to use a new platform (Wessel et al. 2017). Also for platform operators, this strategy may constitute a competitive lever to win over complementors from other platforms (Eisenmann et al. 2006) and to enable them to facilitate additional transactions and enforce profitable prices early on (Wessel et al. 2017). Already back in the 1990s, Amazon.com allowed its complementors to import ratings from eBay but discontinued this service after eBay claimed that the ratings were *their* proprietary content (Resnick et al. 2000). As of 2019, several e-commerce platforms have indeed implemented import functions for user ratings from other platforms (e.g., Bonanza.com, Truegether.com). What is more, also the European Commission identifies cross-platform data and reputation portability as an important means to address issues of data ownership, lock-in effects, and platform competition (EU 2017, p. 93).

Here, however, the question arises whether (and if so, *how*) reputation is effective for engendering trust across platforms. Research on this matter, however, is scarce. While cross-platform signaling may be readily implemented *technically,* it is not clear whether reputation is actually transferable from a psychological perspective, that is, whether users will accept signals from external sources. Against this backdrop, we address the question of how and under which conditions online reputation represents an effective signal for trust-building across platform boundaries.

To do so, we develop and evaluate a research model in which we consider whether the availability of cross-platform reputation engenders users' trust in complementors. To this end, we draw on signaling theory (Dimoka et al. 2012; Spence 2002) and extend prior work on trust transfer (Chen and Shen 2015; Kelley 1973; Lim et al. 2006; Sia et al. 2009). Specifically, we assess how users evaluate prospective complementors when those have not collected any ratings on a specific (target) platform, but have gathered reputation on *another* (source) platform. We benchmark this scenario against two control conditions in which complementors have either gathered (1) reputation on the platform or (2) no reputation at all. In particular, we argue that users' perceptions of source–target *fit* promote the effectiveness of cross-platform reputation. To evaluate our hypotheses, we conduct an experimental online survey in which participants consider to transact with a prospective complementor.

The contribution of this paper is twofold. First, while previous research primarily considered reputation *within* a particular platform environment (Resnick and Zeckhauser 2002), our study delivers important insights into how user reputation may function *across* platforms. In particular, we show that the positive relationships between signal availability, trust, and purchasing intentions extend to cross-platform signaling. Moreover, we disentangle the effects of cross-platform reputation from the effect of the platform's trustworthiness (i.e., trust transfer). Second, we show that the effectiveness of cross-platform signaling hinges on users' perceptions of source–target fit. In doing so, we enrich the tenets of signaling theory by providing first evidence on the importance of these boundary conditions and expand its scope to multi-platform applications. We discuss our findings' practical and strategic implications for platforms, complementors, users, and regulatory authorities.

2 Theoretical Background and Related Work

2.1 Trust and Trust Transfer

Trust is commonly referred to as the willingness to accept vulnerability due to others' actions based on expectations about their intentions and skills (Gefen 2002; Gefen et al. 2000; Rousseau et al. (1998). It represents a critical construct for virtually all areas of e-commerce (Bolton et al. 2013; McKnight et al. 2002), and particularly for transactions between private individuals (Ert et al. 2016; Lu et al. 2010). Due to the inherent risks in Internet-facilitated transactions, users engage in transactions only if they believe that the other party will not exploit their vulnerability and behave opportunistically. This belief is conceptualized as a user's *trust in the complementor.* Due to its pivotal role for purchase intentions, researchers have explored a wide range of mechanisms (e.g., star ratings, escrow services) that platforms can implement towards this end (Chen et al. 2015; Pavlou and Gefen 2004).

One important factor in this regard is the level of trust users have in the platform. Here, *trust transfer* refers to the notion that complementors "inherit" trustworthiness from the platform they operate on (Chen et al. 2015; Pavlou and Gefen 2004). This transference of trust is a "cognitive process in which one's trust in a familiar target can be transferred to another target by virtue of certain associations" (Chen et al. 2015, p. 264). Hence, everything else being equal, users are more likely to trust complementors if they trust the intermediary because "a trusted intermediary can also be expected to take steps to reduce buyer risk"

(Pavlou and Gefen 2004, p. 44).[1] Several studies have described how trust transfer is realized in cases of missing information on a particular actor (Chen and Shen 2015; Chen et al. 2015; Lim et al. 2006; Pavlou and Gefen 2004). For e-commerce, it was found that users' trust transfers from an e-commerce platform (*trust source*) to complementors on the platform (*trustees*) (Chen et al. 2015; Pavlou and Gefen 2004; Verhagen et al. 2006). The process of trust transfer from platforms to complementors has been studied for several contexts, including Taobao (Chen et al. 2015) and other e-vendor websites (Kim 2014), typically finding positive effects. Similarly, several studies specifically considering *Airbnb*, *Uber*, and *eBay* showed that trust in a platform is an effective driver of trust in complementors and purchase intentions (Han et al. 2016; Hong and Cho 2011; Mittendorf 2017; Verhagen et al. 2006).

2.2 Reputation

Beyond the platform's trustworthiness, presumably the most important factor for the formation of trust in complementors is their reputation. We refer to *reputation* as a complementor's accumulated and documented evaluation by prior transaction partners (Jarvenpaa et al. 2000; Kim et al. 2004). The success of an individual seller, host, or driver crucially depends on how well they are regarded by potential users (e.g., buyers, guests, passengers). To allow for reputation to establish, platforms employ various systems (Jøsang et al. 2007; Resnick et al. 2000). Typically, these systems let parties rate each other (Jøsang 2007, p. 209). By accumulating the individual experiences of previous transactions, such ratings lend themselves well for user assessment (Havakhor et al. 2016). Also, by employing simplified numerical logics (such as star ratings), aggregated scores provide an intuitive measure (Zervas et al. 2015). While the intricacies of user ratings, in particular positivity bias ("reputation inflation"), are subject to ongoing discussion, they have become table stakes on many platforms (Gutt et al. 2019). Consequently, designing and understanding reputation systems and their implications for online marketplaces "has become a first-order question in the digital economy" (Filippas et al. 2018, p. 2).

2.3 Signaling Theory

The formation of trust based on reputation is often explained by signaling theory (Akerlof 1970; Riegelsberger et al. 2005; Spence 2002). The main rationale of the theory posits that one party can reduce another's uncertainty by providing a signal. This assumes two parties with (at least partially) diverging interests and asymmetric information. This scenario is typical for buyer–seller and user–complementor relations where the buyer/user cannot assess a product's or service's quality prior to the transaction (Ghose 2009).

To reduce information asymmetry, complementors can send different types of signals. One type relies on the assessment by a third party such as prior transaction partners (Basoglu and Hess 2014; Donath 2007; Dunham 2011; Ma et al. 2017). User ratings thus represent common and relatively reliable signals. Extant research has shown that ratings function as an antecedent of trust in various contexts, including online sales (Kim et al. 2008, 2004) and accommodation sharing (Ert et al. 2016). The importance of signals for trust and the realization of transactions becomes particularly clear when considering the information asymmetry on such platforms (Ert et al. 2016). As such, users face considerable levels of economic and social exposure, for instance, when sharing a car or flat for many hours or even days (Hawlitschek et al. 2016a). In this regard, reputation is found to be particularly important for service provision as the delivered quality will very much hinge on the complementor's skills, goodwill, and integrity (Dimoka et al. 2012).

2.4 Cross-Platform Signaling

While there has been extensive research on the importance of signals for reputation *within* a given, enclosed platform environment, the question of whether and how reputation exerts an *influence across platforms* has received only little research attention thus far. Several scholars conducted requirement analyses and proposed mathematical models of how to aggregate reputation from dispersed sources (Grinshpoun et al. 2009; Mishra 1995; Pingel and Steinbrecher 2008). Further, there have been attempts to evaluate such models based on empirical data (Gal-Oz et al. 2010) and to predict trust in one context based on the reputation scores from another context (Kokkodis and Ipeirotis 2016; Venkatadri et al. 2016). For instance, in the context of crowd work, it has been shown that a worker's performance can be predicted by prior, category-specific feedback scores, suggesting cross-context transferability of peer-based online reputation (Kokkodis and Ipeirotis 2016). Similarly, it has been proposed to leverage user data from social media platforms (e.g., Facebook, Twitter) to make inferences about user legitimacy and hence to distinguish trustworthy from untrustworthy users on other platforms (Venkatadri et al. 2016). Most recently, Otto et al. (2018) considered the effect of star ratings from an external platform for ride sharing, finding support for the

[1] In this regard, quality control mechanisms such as Uber's policy to expel drivers with a rating below 4.6 stars or Airbnb's background checks on new hosts provide a rationale for the effectiveness of trust transfer (Airbnb 2017; BusinessInsider 2015).

cross-platform effectiveness of online reputation. Importantly, they focus on one specific combination of source platform (accommodation sharing) and target platform (ride sharing). For a conceptual and more comprehensive overview of cross-platform signaling, we refer to Hesse and Teubner (2019).

In sum, prior research has thus far either completely neglected the role of user perception or was limited to one specific platform combination. As we show in this paper, however, the effectiveness of cross-platform signaling does not only rely on the mere existence of reputation but also on users' perception of how well its origin matches the target context. Hence, this study differs from previous studies in that it directly evaluates cross-platform signaling from a user-centered perspective and accounts for platform-specific differences as well as the boundary condition of source–target fit.

3 Hypotheses Development

In the following, we develop our hypotheses for users' trust with cross-platform signaling (Fig. 1). Extending the literature on trust transfer, we consider trust in the complementor as a result of a cross-platform signal's availability (H_1) and user perceptions of source–target fit between the involved platforms (H_2). Given the large and consistent body of evidence with regard to the concept of trust transfer and the positive relation between trust and purchase intentions, we consider these relations as sufficiently established and refrain from stipulating separate hypotheses. Appendix A (available online via http://link.springer.com) provides definitions and items of all constructs.

3.1 Relation Between Cross-Platform Signal Availability and Trust in Complementor (H_1)

For users of sharing economy platforms, trust in complementors can be interpreted as the positive belief in the complementors' ability, integrity, and benevolence (Hawlitschek et al. 2016b). According to signaling theory, the availability of a reliable signal (e.g., a user rating from a prior transaction in the reputation system of a platform) can reduce uncertainty and thus help to foster trust. Now, given that a complementor operates on several platforms and has collected positive ratings on at least one of those platforms, we suggest that these ratings can, to some extent, be leveraged as cross-platform signals. As reputation systems summarize ratings from past transactions with various users (Jøsang et al. 2007), they convey a certain amount of generalizable information on skills, goodwill, and integrity that is likely to be considered as relevant on other sharing platforms as well. For successful service provision on various sharing platforms, there may hence exist an intuitive set of properties, skills, and attitudes which would benefit complementors within basically any platform (e.g., reliability, communication skills, cleanliness, etc.). We thus suggest that the general availability of positive reputational information – independent from its source platform or context – represents a meaningful signal and thus positively influences trusting beliefs.

H_1 Cross-platform signal availability is associated with increased trust in the complementor.

3.2 Relation Between Source–Target Fit and Trust in Complementor (H_2)

The way in which a reputational signal creates meaning needs to be considered against the context it is evaluated in (Hendrikx et al. 2015). When investigating how a complementor's reputation on a (source) platform serves as a signal for users to trust them on a different (target) platform, it is hence important to take potential contextual differences between source and target into account. In other words, just because a complementor is able to refer to an existing reputation may not necessarily imply that this reputation will also be perceived as a *meaningful* signal, applicable to the target platform. *Source–Target Fit* refers to the user's perception of how applicable a signal from the source platform is for transactions on the target platform (i.e., perceptions of consistency or congruency between the target and source domain) (Aaker and Keller 1990; Dens

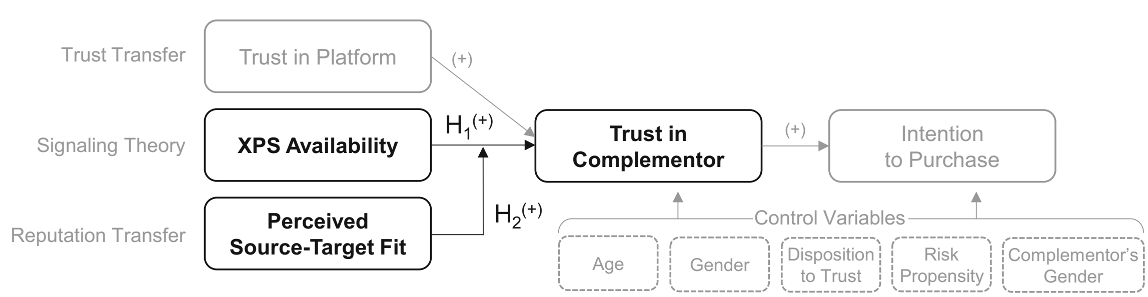


Fig. 1 Conceptual research model. *Note*: XPS = cross-platform signaling

and De Pelsmacker 2010). Perceived fit was identified "as the prime determinant of success" for the extension of business activities to new contexts (Arikan et al. 2016, p. 930). High levels of fit may exist for platforms from the same or similar domains or when the associated operations, tasks, and requirements are perceived as similar, that is, when there exists some degree of overlap or comparability. From the theoretical perspective, the psychological concept of *categorization* underpins this reasoning. Categorization refers to a cognitive heuristic to deal with (overwhelmingly) large amounts of stimuli (Boush and Loken 1991). Categorization, in this sense, represents a process of cognitive "pigeonholing" to structure and simplify one's environment (Shaw 1990). When facing a novel instance, which, however is associated with a known category, "the attitude associated with that category can be transferred to the new instance" (Boush and Loken 1991, p. 18). Naturally, high levels of fit are likely to be reflected in similar cognitive categorization. Conversely, a lack of fit may result in ineffectiveness of reputation for building trust within the target context (Dong et al. 2007). In this vein, Aaker and Keller (1990) stated that "if the fit is incongruous, the extension may be regarded as humorous or ridiculous" (p. 30).

We argue that a similar cognitive categorization takes place when users assess the applicability of an existing reputation score for the trustworthiness of that complementor on a different platform. In particular, the personal qualities of being regarded as a well-reputed driver on Uber, for instance, may be perceived as well-transferable to other ride sharing platforms, whereas being regarded as a well-reputed eBay seller may be seen as less transferable to accommodation sharing. A higher level of fit suggests that the original skills and personal characteristics which were responsible for building a reputation on platform A in the first place, will be *applicable* on platform B too – as the tasks, challenges, and requirements on B are similar to those of A. We hence posit:

H_2 Higher levels of source–target fit are associated with increased trust in the complementor.

4 Method

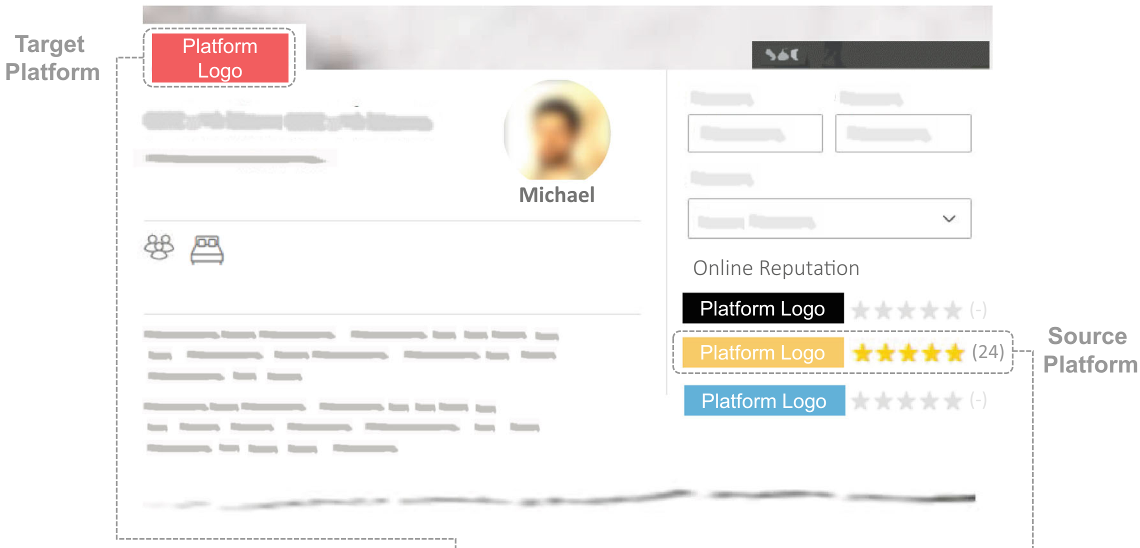
To evaluate our hypotheses, we conduct an experimental online survey in which participants take the role of prospective users (i.e., buyers, guests, or passengers) deciding whether or not to engage in a transaction with a prospective complementor (i.e., driver, host, or seller). We consider three main treatment conditions. First, in the "no signal" control condition (CTR^{no}), the complementor has not accumulated any ratings at all. Second, in the cross-platform signaling (XPS) scenario, the complementor has not accumulated any ratings on the (target) platform, but on another (source) platform. Third, in an additional control condition (CTR^{yes}), the complementor has accumulated ratings on the respective target platform. Figure 2 illustrates this treatment design, wherein the cells on the diagonal represent the CTR^{yes} control conditions and the lower row represents the CTR^{no} control conditions. All other cells represent the various XPS conditions with the respective combinations of source and target platform. We employ a between subjects design, that is, any subject is exposed to exactly one of the treatment conditions. We provide an overview of all main variables across treatments in Appendix B.

To create variety with regard to our focus variables and to avoid the limitations associated with constraining the study to one specific platform, we consider four platforms. To present participants with easy-to-relate-to scenarios, we consider the platforms *Airbnb* (accommodation sharing), *BlaBlaCar* (ride sharing), *eBay* (commodity exchange), and *Uber* (taxi service). Note that this selection of platforms also promises some degree of variance with regard to fit between platforms which is an important condition in order to study its effect on trust. Within the XPS treatment, we consider all 12 combinations of source and target platforms.

4.1 Stimulus Material

Each participant sees one complementor profile on one of the four target platforms and is asked to consider it. To minimize confounding effects, the stimulus material is presented in view of the following design considerations.

1. The overwhelming majority of ratings on most platforms are five stars (Abramova et al. 2017; Gutt and Kundisch 2016). Since our study addresses cross-platform signaling for complementors and these are not likely to actively take "bad" ratings along to a different platform, we focus on 5 star scores. Moreover, also in the control condition with ratings on the respective platforms (CTR^{yes}), a rating score of five stars is used. While this represents a natural starting point for future research, we deliberately focus on this practically most relevant scenario.
2. In order to create a reasonably realistic scenario and also to charge the displayed rating score with sufficient reliability, the rating score is based on 24 reviews. This number is informed by prior research and represents the 75%-quantile within Airbnb ratings (Teubner et al. 2017).
3. The introductory text describes the scenario verbally: (a) "The user has received 24 reviews on «target



Treatment Configuration		Target platform			
		Airbnb	BlaBlaCar	eBay	Uber
Source platform	Airbnb	CTR^{yes}	XPS	XPS	XPS
	BlaBlaCar	XPS	CTR^{yes}	XPS	XPS
	eBay	XPS	XPS	CTR^{yes}	XPS
	Uber	XPS	XPS	XPS	CTR^{yes}
	—	CTR^{no}	CTR^{no}	CTR^{no}	CTR^{no}

Fig. 2 Stimulus material and treatment design. *Note:* Treatment configuration: CTR^{no} = lower bound control condition with no signal at all; CTR^{yes} = upper bound control condition with signal available on target platform; XPS = cross-platform signaling; for publication, platform logos have been replaced by placeholders

platform»" (CTR^{yes}), (b) "The user has not received any ratings or reviews on «target platform» yet. However, the user's «source platform» profile with 24 reviews is linked up" (XPS), (c) "The user has not received any reviews or ratings on «target platform» yet." (CTR^{no}). The placeholders are filled by the respective platform names.

4. Profile images were found to affect users' perceptions and decisions (Ert et al. 2016). Since we focus on the effects of transaction-based reputation, profile image effects should be minimized. We contend that to create vivid and engaging scenarios, such basic elements should, however, not be omitted entirely. The displayed profile images are hence blurred, avoiding confounding effects due to factors such as attractiveness, visual trustworthiness, or similarity. To control for potential gender effects induced by the stimulus material, both male and female profiles are used. The displayed names are drawn from a set of common first names.

4.2 Procedure, Measures, and Sample

Altogether, 408 participants were recruited by email from a student subject pool as platforms are particularly attractive to young, well-educated, and tech-savvy users (EU 2017; Mittendorf et al. 2019). Five respondents were removed from the dataset as they did not pass attention checks. The final sample hence includes 403 participants (111 female, 292 male, mean age = 24.42 years). A more detailed overview of the sample and its allocation to the treatment conditions is provided in Appendix B. The sample size was determined along the following considerations. Our experiment constitutes a between-subjects design with three different treatment conditions (CTR^{no}, CTR^{yes}, XPS). Participants were randomly allocated to these three main treatments. However, it needs to be considered that our design also involves different source–target platform combinations as sources of variation for users' perceived source–target fit. As shown in Fig. 2, there are 4 (CTR^{no}) + 4 (CTR^{yes}) + 12 (XPS) = 20 cells, that is, combinations. Assuming an effect size of d = .25, α = .05, and power = .80, this requires a sample size of 360 to compare these cells (Faul et al. 2007). Our sample size hence surpasses this requirement by a margin of about

10%. The number of participants per treatment conditions reflects the notion that the number of cells in the XPS condition is three times larger than in each of the two control conditions. Overall, the XPS conditions comprise 241 participants, where both the CTR^{yes} and the CTR^{no} conditions comprise 81 participants each.

As an incentive for participation, 22 randomly selected respondents received a cash payoff (2 × €50; 20 × €20). After clicking on the survey link in the invitation email, and providing informed consent to take part, participants were introduced to the scenario. Then, participants saw the randomly generated profile in the upper part of the screen. Questionnaire items were displayed in random order in the lower part of the screen in blocks of eight items. To operationalize our theoretical constructs, we adapted validated scales. Appendix A provides a summary of all constructs and items. In addition to the model's main constructs, we assess participants' gender, risk propensity (Dohmen et al. 2011), disposition to trust (Gefen 2000), and familiarity with the respective platform (Gefen and Straub 2004) as control variables.

5 Results

5.1 Manipulation Checks

To confirm that our manipulation yielded a range of responses with regard to trust in platform and source–target fit, Fig. 3 compares these values for the different platforms and combinations. Individual trust in platform ranges between 1 and 7, that is, on the full range of the 7-point Likert scales (mean = 4.61; standard deviation = 1.27). Similarly, individual fit values range between 1 and 7 (mean = 4.34; standard deviation = 1.53).

Note that source–target fit values only exist for the XPS condition (241 observations). To test whether our manipulation (i.e., source- and target platform) successfully created different levels of perceived source–target fit, we grouped the values in the XPS condition by the four source and target platforms (Airbnb, BlaBlaCar, eBay, Uber), yielding 4 × 3=12 different conditions. A one-way ANOVA reveals significant variation with regard to this factor ($F(11, 229) = 5.76$, $p < .001$). A post hoc Tukey test reveals that, in short, there are 11 (out of the 66 possible) significant differences between groups, the largest of which are between BlaBlaCar/Uber and eBay/Uber ($\Delta = 2.72$, $p < .001$) as well as between Uber/BlaBlaCar and eBay/Uber ($\Delta = 2.15$, $p < .001$). Table 1 shows all average values of source–target fit for the various combinations of source- and target platform in the XPS conditions.

Importantly, the degree of perceived source–target fit is somewhat sensitive to direction. One could argue in favor of a symmetric degree of fit based on the assumption that it emerges (inter alia) from common requirements. These may be based on skills, traits, attitudes, and the like. If, now, two platforms require a certain skill, a reputation earned in one should be effective as a signaling device within the other – and vice versa. However, it appears unlikely that the sets of required skills, traits, and attitudes will be exactly congruent. Hence, cases in which the required properties for one platform represents a subset of the other are easily conceivable ($A \subset B$). In such cases, source–target fit would be higher in one ($B \rightarrow A$) than in the other direction. In fact, the data confirm that a high degree of source–target fit from platform A to B (e.g., Uber → eBay: 3.98) does not necessarily imply equally high fit for the reverse (e.g., eBay → Uber: 2.96). To underpin this asymmetry of source–target fit statistically, we re-arranged the data from Table 1 and correlated each fit value (from A to B) with its opposite counterpart (i.e., from B to A). This correlation on aggregated level with all possible platform combinations ($n = 6$) is insignificant (Pearson's $r(4) = .77$, $p = .073$). Given that this analysis is based on 6 pairs of platforms only, we ran an additional Spearman correlation test, yielding similar results (Spearman's $r = .75$, $p = .08$). Similarly, when randomly pairing *individual users* of opposing source–target combinations, a correlation between the respective fit levels is also insignificant (Pearson's $r_{\emptyset}(107) = .164$, $p = .088$; based on 2,000 runs).

5.2 Testing Hypothesis H_1

To evaluate H_1, we benchmark trust in the complementor in the cross-platform signaling condition against the two control conditions. As shown in Fig. 4, trust in the complementor is markedly higher in the CTR^{yes} condition ($M = 4.93$, $SD = 0.99$) and markedly lower in the CTR^{no} condition ($M = 3.77$, $SD = 1.20$) than it is in the cross-platform signaling condition ($M = 4.21$, $SD = 1.09$). Noteworthy, this observation is (by and large) consistent across platforms. A two-way between-subjects 3 (CTR^{no}, XPS, CTR^{yes}) × 4 (Airbnb, BlaBlaCar, eBay, Uber) ANOVA confirms this visual assessment. We observe a significant effect of treatment on trust ($F(2, 397) = 23.80$, $p < .001$). In support of H_1, a post hoc Tukey test confirms that XPS yields significantly higher levels of trust than CTR^{no} ($\Delta = .44$, $p < .01$). Given the 1-to-7 points Likert scale, this amounts to 38% of the difference between on-site reputation and having no reputation at all (CTR^{yes}–CTR.

One interesting finding here is that, in contrast to the overall trust-promoting effect of reputation transfer, importing an eBay rating to Uber yields *lower* trust than not having any rating at all – even though the imported

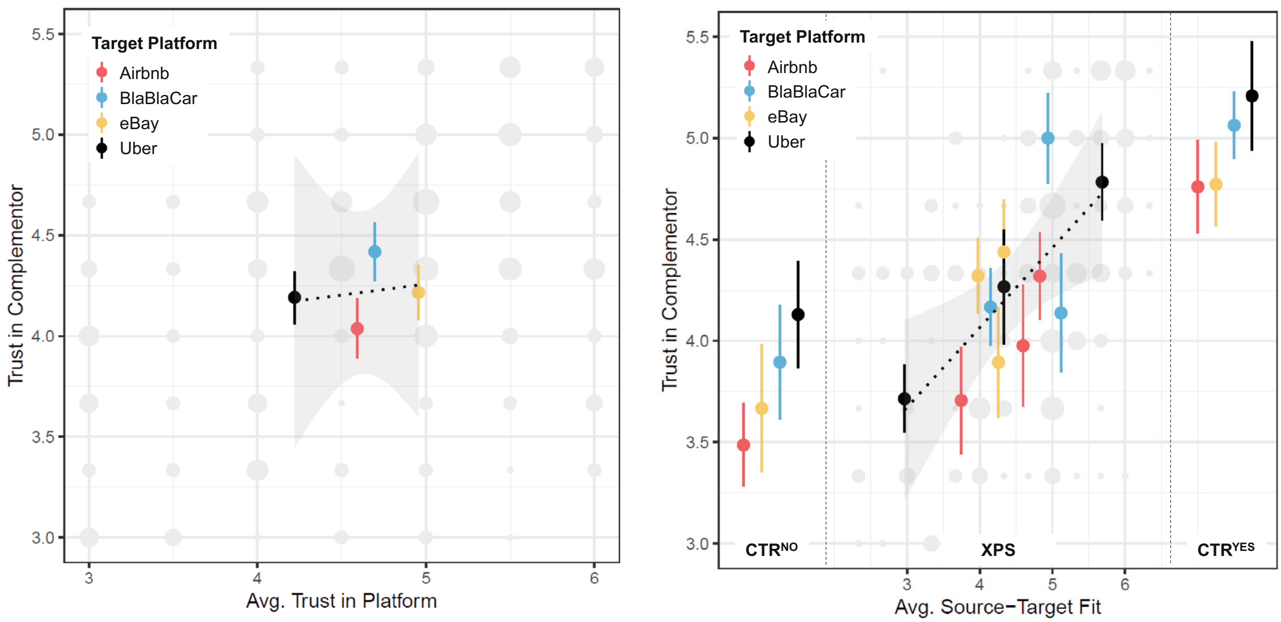


Fig. 3 Manipulation checks for trust in platform and source–target fit. *Note*: Colored dots indicate mean values; standard errors indicated by error bars. Both x- and y-axis reflect 7-point Likert scales. Linear estimate and 95% confidence interval indicated by dotted line and grey area. CTR^{NO} = no reputation was displayed; CTR^{YES} = reputation stems from the target platform itself; XPS = cross-platform signaling

Table 1 Average values for source–target fit in the cross-platform signaling condition

Source/target	Airbnb	BlaBlaCar	eBay	Uber
Airbnb	–	4.94 (1.21)	4.33 (1.70)	4.33 (1.49)
BlaBlaCar	4.83 (1.44)	–	4.26 (1.54)	5.68 (1.39)
eBay	4.60 (1.30)	4.15 (1.41)	–	2.96 (1.29)
Uber	3.75 (1.45)	5.12 (0.80)	3.98 (1.36)	–

Standard deviation in parentheses; n = 241 (out of 403)

reputation is a straight 5-star rating. Note that this case also yields the overall lowest value of source–target fit (eBay → Uber: 2.95). We will come back to this peculiar finding in the discussion.

5.3 Testing Hypothesis H_2

Now, to evaluate H_2, we zoom in on the treatment condition with cross-platform signaling. Specifically, we use covariance-based structural equation modeling (CB-SEM)

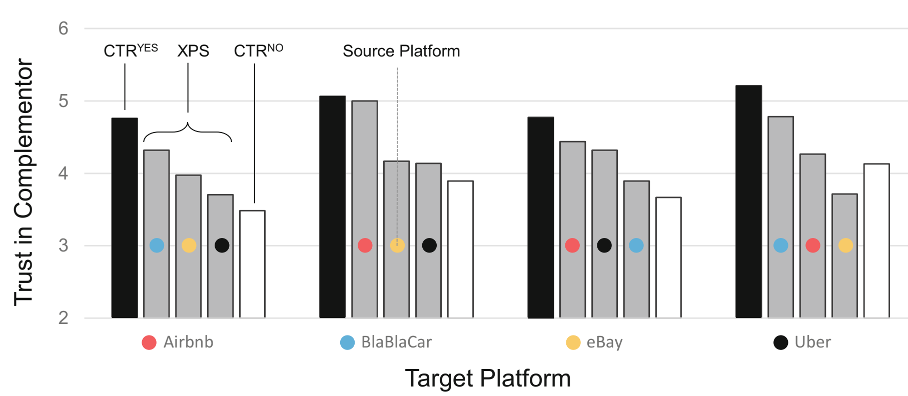


Fig. 4 Average values of trust in complementor compared between cross-platform signaling and control conditions. *Note*: Colored dots within the grey bars indicate source platform. CTR^{NO} = no reputation was displayed; CTR^{YES} = reputation originated from the target platform itself; XPS = cross-platform signaling

Table 2 Construct descriptives, reliability measures, and correlations

	Descriptives		Composite reliability	Cronbach's alpha	AVE	Correlation matrix			
	Mean	SD				1	2	3	4
Intention to purchase (1)	5.13	1.31	.97	.96	.92	–			
Trust in complementor (2)	4.21	1.09	.86	.75	.67	.70	–		
Trust in platform (3)	4.61	1.27	.90	.78	.82	.47	.49	–	
Source–target fit (4)	4.34	1.53	.96	.93	.88	.56	.65	.31	–

AVE average variance extracted, *SD* standard deviation; n = 241 (out of 403)

to evaluate this part of the research model (R, *lavaan*). Note that for the assessment of H_2, only the XPS treatment conditions apply since the concept of source–target fit is not meaningful when there is no source platform (such as the case in the control conditions). Hence, the number of observations for testing H_2 is 241 rather than 403, which represents the sum of all participants in the XPS cells in Fig. 2. Table 2 provides construct descriptives, reliability measures, and correlations.

The assessment of the measurement model indicated good fit with regard to conventional thresholds [Adjusted Goodness of Fit Index (AGFI) = .88; Comparative Fit Index (CFI) = .98; Tucker–Lewis Index (TLI) = .98; Root Mean Square Error of Approximation (RMSEA) = .04] (Hair et al. 2010). In line with H_2, we find that higher source–target fit is associated with higher levels of trust in the complementor in case a cross-platform signal is available ($\beta = .55$, $p < .001$). This effect can be considered as "large" (Urbach and Ahlemann 2010). Moreover, as expected, we find positive relations between users' trust in the platform and trust in complementor ($\beta = .31$, $p < .001$) as well as between trust and purchase intentions ($\beta = .80$, $p < .001$). Finally, there occurs no significant interaction between trust in platform and source–target fit on trust in the complementor.

5.4 Control Variable Analysis

We consider several control variables including age, disposition to trust, gender, familiarity with the platform, and risk propensity. Also, we control for the complementor's gender. We observe three significant effects. First, users' general disposition to trust is positively related to their trust in the complementor ($\beta = .25$, $p < .001$). Second, also risk propensity is positively associated with trust in the complementor ($\beta = .15$, $p < .01$). Third, female profiles are associated with increased trust ($\beta = .12$, $p < .01$). Importantly, the control variables only exert small and moderate effects (Urbach and Ahlemann 2010) and the main hypothesized relations are unaffected by using/removing the control variables in/from the model. Thus, the conclusions derived from this study do not critically hinge on individual sample characteristics such as age, gender, disposition to trust, and risk propensity.

6 Discussion

6.1 Summary of Results and Contribution

As the spectrum of the sharing economy has broadened from commodity exchange to a large variety of experience goods and services, complementors increasingly manage separate online identities. Reputation can be understood as part of their capital for attracting demand – or, more generally speaking – as a catalyst for transactions. Constraining reputation to a specific platform is hence at the charge of complementors, where it becomes "impossible for [them] to capitalize on their reputation [and] when they are moving to another platform, they are starting from scratch" (Scholz 2016, p. 20). This impedes the formation of trust, inhibits the realization of mutually beneficial transactions, and hence yields economic inefficiency. By studying the effectiveness of cross-platform signaling from a user psychology perspective, this study provides novel insights which we discuss in the following.

First, prior research has primarily focused on reputation and trust *within* confined platform boundaries (e.g., Ert et al. 2016). However, such studies did either not take into account the role of user perceptions (Grinshpoun et al. 2009; Mishra 1995; Pingel and Steinbrecher 2008) or the role of boundary conditions (Otto et al. 2018). Extending this research by considering various combinations of source and target platforms with varying levels of fit, we show that, overall, the availability of a rating score does in fact exert a trust-building effect *across* platform boundaries, ultimately translating into purchase intentions (H_1; see also Figs. 3, 4).

Second, by considering different source–target combinations, we shed light on how specifically reputation engenders trust. In particular, we show that the effectiveness of signals relies on users' perception of source–target fit between the respective platforms (H_2; see also Fig. 3, right-hand side). Most prior work on signaling within the sharing economy is based on an implicit assumption of (high) fit. However, the diversity of today's platform landscape necessitates an assessment that goes beyond this assumption and individual cases. Thereby, as we have seen, source–target fit can vary substantially, also concerning the *direction* of the source–target relation (see Table 1). This may be due to the specific sets of skills, traits, and attitudes responsible for successful provision in the different contexts (e.g., driving, care, punctuality, cleanliness, etc.). These sets may in part be distinct, overlapping, or one may represent a subset of another. It is straightforward to conclude that a good reputation for an activity requiring many skills/traits will flow well towards an activity with fewer or less complex requirements – but not the opposite way around. In such a case, the attitudes and skills represented by the (albeit excellent) ratings from one platform may simply not be of predictive value on another.

Interestingly, a low source–target fit can even yield *lower* levels of trust than not having any reputation at all (see Fig. 4; eBay to Uber). We can only speculate what causes this. One line of reasoning may be that users perceive that the complementor is *misleadingly* trying to capitalize on a reputation that is too remote from the intended context. Supporting this line of interpretation, there is evidence that misplaced objects or actions are often found to be perceived as aggravating or ridiculous (Aaker and Keller 1990). Similar to a company attempting to extend its product line to an entirely non-fitting domain,[2] complementors attempting to leverage their ratings on other platforms may fail miserably if the very idea of linking the contexts is perceived as being too far of a stretch.

Moreover, while a platform's trustworthiness itself also impacts trust between users and complementors, this relation does not moderate the effectiveness of cross-platform signaling, making reputation import strategies viable for less renowned, potentially less trusted entrant platforms. Control variable analysis indicates that our findings are robust against socio-demographic factors such as users' age, gender, and general trusting disposition.

6.2 Practical Implications

Beyond the theoretical lens, these results have important practical implications for complementors, platforms, and regulatory authorities. First of all, complementors can in fact benefit from referring to existing reputation by providing a link or reference within their profile. When doing so, they may want to emphasize similarities between contexts and applicability (e.g., highlighting the complementarity of skills).

Moreover, platforms can also leverage this information for their benefit. Platform operators may, for instance, provide an import function, allowing complementors to integrate external signals in a structured and reliable manner. In fact, the US-based e-commerce platforms Bonanza.com and Truegether.com offer such functions for importing ratings from eBay. Alike complementors, platforms may want to emphasize why and how imported signals are well-applicable to their own specific context.

In a more general sense, cross-platform signaling may mitigate platform lock-in, enable data ownership and portability, and hence stimulate competition in a domain that tends to develop monopolies due to the presence of positive network effects (Eisenmann et al. 2006). Hence, from a strategic perspective, cross-platform signaling may serve as a competitive lever to lower entry barriers, win over users and complementors from other (potentially competing) platforms, and facilitate multi-homing (Eisenmann et al. 2006). It may also help to overcome the platform-typical cold-start problem (i.e., complementors not being credible and trustworthy due to a lack of reputation) and hence represent a viable strategy for platform launch (Stummer et al. 2018). For non-competing platforms, bidirectional cross-platform signaling (i.e., "reputation sharing") may represent a mutually beneficial strategy of cooperation.

Naturally, such strategic considerations prompt questions of how platforms may and would counteract adversarial reputation transfers, that is, the use of reputation data from within their system without their consent. First, especially large incumbents who have already seized considerable market power may have little interest in letting other platforms "drain" their reputation data. Second, also the import side may be skeptical, especially when complementors reference to their reputation on a competing platform as such references may be regarded as an implicit means of advertisement. One potential way forward here could be that smaller platforms use cross-platform signaling to facilitate the entrance for new complementors by temporarily "borrowing" the trust users have in the referred platform. In this vein, to address the double-edged sword of reputation transfer, platforms could allow for cross-platform signaling only until the complementor has achieved a certain level of on-site reputation (e.g., five ratings/reviews), and then remove this possibility.

While the 2017 EU report emphasizes the potential upsides of reputation portability (EU 2017, p. 93), others have argued that consumer welfare could be impaired (Swire and Lagos 2013). Notwithstanding these considerations, the *EU General Data Protection Regulation* implemented in May 2018 has introduced a right of data

[2] See Zippo's attempt to market a women's perfume (Austin 2013); Who would not want to smell like lighter fluid?!

portability as one of its most notable features. In particular, Article 20 grants individuals the right "to receive the personal data concerning him or her, which he or she has provided to a controller, in a structured, commonly used and machine-readable format and have the right to transmit those data to another controller without hindrance from the controller to which the personal data have been provided" (European Parliament 2016, p. 144). While the regulation intends to reduce prohibitive switching costs, associated lock-in, and to ensure platform competition, it is not explicitly geared towards reputational data. Moreover, it targets personal data which was "produced" by individuals themselves (e.g., Facebook updates) (Kathuria and Lai 2018). An individual's transaction-based reputation, however, is not provided or produced by them, but by *other* individuals. For those individuals who have created this data (e.g., written a text review), it is rather unlikely that there occurs any demand for data portability (Kathuria and Lai 2018). Fundamentally, the notion of cross-platform signaling also raises the question *who actually owns* the reputational information (e.g., the complementor, the platform, the originator); a much and controversially discussed subject in jurisprudence (Graef 2016). We contribute to this debate by showing that cross-platform signaling is indeed effective. Hence, regulatory authorities may build on this finding and consider explicitly granting the right to transmit reputational information to other platforms.

6.3 Limitations and Future Research

Like any research, this study has limitations. As we point out in the following paragraphs, many of these limitations provide viable starting points for future work. First, while we operationalized reputation by means of a simple numerical score, most current sharing platforms provide further mechanisms and cues to build trust between users and complementors. Examples include text-based reviews, identity verification, and social network integration (Abramova et al. 2017). Since many platforms exhibit skewed distributions towards positive rating scores, we have focussed on the most common value (5 out of 5 stars). Future research may hence consider other, that is, lower rating scores. In this regard, however, it needs to be noted that a bad reputation is not likely to be carried along *deliberately* by any complementor – raising the intriguing question of involuntary reputation drag-along; similar to China's social scoring system (Campbell 2019).

Second, in addition to the focus on one *type* of reputational information, this study considers only one *source* at a time. However, users may have accounts and reputation scores on more than one other platform (Teubner et al. 2019). Importantly, this may include non-e-commerce platforms such as social or business networks and there may also exist reputation within the target platform *and* on other platforms. As we have focused on rather well-known platforms, future research may take less acquainted or completely unknown sources into account.

A further limitation relates to the present study's sample. Like many other studies, our research draws on a student-based subject pool, implying some limitation in diversity, especially with regard to age and education. For the purpose of studying peer-based platforms, this limitation may not be all too stark given that many (while of course not all) of those platforms' users lean towards the young and well-educated end (Akbar et al. 2016; EU 2017; Mittendorf et al. 2019).

Finally, as this paper has focussed on the user's perspective, future research should consider the determinants of cross-platform signaling from the opposite, that is, the complementor's perspective, as well. Given the different levels of economic exposure for users and complementors, the role of reputation may be quite different for this opposite perspective. Also, other boundary conditions beyond fit may be relevant when a complementor evaluates a user's request – given that a) the user's role is more passive but b) economic and/or social exposure for the complementor may be higher (e.g., on Airbnb).

7 Conclusion

As our study shows, reputation does transfer between platforms and it is up to the platform operators' information systems and their user interface design to allow for such transfers to occur. Compared to the control conditions of within-platform and non-existent signals, we find the overall levels of trust and purchase intentions to range between those poles for cross-platform signals. By connecting this finding to established theoretical concepts, this study contributes to a more thorough understanding of managing reputation across platforms and provides the means to leverage reputational capital for entering new ones. Based on the foundations of signaling theory, we show that users' perception of source–target fit represents an important driver of the effectiveness of cross-platform signaling. Consequently, our research supports scholars, complementors, platforms, regulators, and users in understanding, designing for, and maintaining trust within the sharing economy.

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