**Building Trust in the Sharing Economy**

by

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# Thesis and Importance of the Issue: The Sharing Economy

The sharing economy presents the world with a dynamic solution to a complex problem; there is a finite supply of resources in the world and an ever increasing demand to allocate these resources in the most efficient way possible. This system of resource allocation is defined as a “socio-economic system built around the sharing of human and physical assets”. By utilizing information technology, individuals and corporations can reuse, distribute and share their excess capacity of goods and services. However, as with early online marketplaces such as Ebay and Amazon, building trust in these sharing economy platforms will be key to the widespread adoption of the sharing economy. In this paper, I will explore how being a member of an auto club or verifying your account with Facebook Connect impacts the likelihood of a driver accepting ride requests on Carpooling.com. This will enable us to explore how online social networks (Facebook Connect) and offline networks (auto clubs) affect the trust between drivers and riders.

Over the last decade the sharing economy has grown to include many applications such as peer-to-peer lending, car sharing, accommodation pooling, and labor redistribution. It encompasses a wide range of businesses and notably includes Airbnb (which lets owners rent out their extra rooms) and Uber (which connects drivers and riders for car transportation services). These services help connect those with excess supply to demand in order to more effectively utilize existing space and cars that otherwise may have gone unused. In many industries the sharing economy has disintermediated existing players by offering more personalized choices, prompt service via mobile apps, or by increasing the value proposition of an existing service.

The emergence of the sharing economy has been aided by a variety of factors including a growing global population, the adoption of mobile phones/social media, rising income inequality, and the need to maximize value following the global financial crisis. As the world’s population has grown from 2.5 billion in 1950 to 7.2 billion today, the necessity for the sharing the world’s resources has grown. In recent years, the increase in mobile phone, social media, and internet use has facilitated the real time exchange of information amongst multiple parties with more than 1.6 billion mobile internet users worldwide in 2014. Beyond this, global income inequality has increased with the world’s gini coefficient up from 0.38 in the early 1970s to 0.47 in the late 2000s as fewer people hold more and more wealth. Lastly, following the global financial crisis of 2008 more and more people are in favor of sharing resources with 52% of Americans reporting in 2013 that they rented, borrowed, or leased an item in the last 2 years that is typically bought.

These aforementioned factors have facilitated the growth of the sharing economy from next to nothing 15 years ago to a $26 billion dollar opportunity in 2014. Despite this progress, the sharing economy is still working to overcome many setbacks: platforms are facing increasing regulatory scrutiny, trust is difficult to build amongst anonymous peers on new platforms, and philosophical debates are emerging about the validity of sharing as a viable alternative to private ownership. This paper will focus on building trust in the sharing economy by utilizing a case study of an existing platform, Carpooling.com, and overlaying it with studies on trust in more traditional online marketplaces. Building trust will be vital to the future of the sharing economy since 70% of consumers cited their lack of trust as the main reason for avoiding collaborative consumption services.

Trust in the sharing economy is similar to traditional online marketplaces such as eBay and Amazon in that it utilizes the power of the internet to connect buyers and sellers. However a key difference is the physical sharing of goods and real life interaction of the two parties in the sharing economy. With traditional online marketplaces, trust was built through centralized and scalable review systems enabled by the emergence of the internet and personal computing. With the sharing economy, these review systems are in place but are being supplemented with new features in order to increase trust. These features include connections to social media accounts such as Facebook Connect, verification of membership in offline groups such as auto clubs, and verified government ID checks. Since traditional online marketplaces did not involve face to face interaction, offline identity was not as important as it is with the sharing economy. This is why some of the new features of trust in the sharing economy involve offline validation of a person’s identity.

Since the sharing economy is so new, very little academic work exists on it which makes an exciting but difficult topic to address. This paper will seek to answer how some of these new trust features of the sharing economy such as social media validation and auto club memberships affect the likelihood that a given ride request is confirmed on Carpooling.com’s website. My hypothesis is that drivers with Facebook Connect and/or auto club memberships will see an increase in the likelihood that their booking is accepted. On the other hand, I believe that for users who do not use the features they will be less likely to accept bookings given the relative lack of transparency and information. By analyzing how these new features impact booking frequency and acceptance rates I hope to offer a recommendation for other sharing economy platforms to build trust.

In this paper I will start by reviewing previous literature on online reputation systems, trust in online marketplaces, and the effect of online reviews on the price and volume of transactions. I will then provide specific data on Carpooling.com to provide insight on how trust is built in the sharing economy and how these new methods affect the likelihood a ride booking is accepted. Next I will analyze this data in the context of prior research to highlight the similarities and differences between trust in online marketplaces and the sharing economy. Finally, I will move on to discuss my findings to recommend further areas of research and the policy implications of my research.

# Survey of Previous Literature on Trust & Online Marketplaces

In this section I work through the prior academic work done on reputation systems, trust, and feedback mechanisms to frame the issue of trust in the sharing economy. Beyond this, I work to provide interesting parallels and potential areas to explore in comparison with traditional online marketplaces such as eBay and Amazon. The availability of previous research on the sharing economy itself is limited due to its recent emergence and as such the majority of literature surveyed for this thesis focuses on the traditional online marketplaces like eBay and Amazon. Many academic papers have been written on online reputation systems, trust in online marketplaces, building trust, and the impact of online reputations. These include papers on the topics of:

* Value of reputation on eBay (Resnick, Zeckhauser, Swanson, & Lockwood, 2006)
* Impact of text review on transaction price on Amazon (Ghose, Ipeirotis, & Sundararajan, 2007)
* Ratings impact on company revenue on Yelp (Luca, 2011)
* Effect of initial negative reviews on eBay (Cabral & Hortaçsu, 2010)
* Review reporting bias on eBay (Dellarocas & Wood, 2008)
* Empirical investigation of review manipulation and market conditions that increase manipulation (Mayzlin, 2012)
* Optimal review aggregation using accuracy, stringency, and reputation on Yelp (Dai, 2012)
* The impact of subjectivity and objectivity on usefulness of reviews for producers and consumers (Ghose, 2007)
* The impact of partner, stranger, or feedback networks on transaction frequency (Bolton, 2004)
* Online reputation vs offline reputation systems (Dellarocas, 2003)
* What leads to trust versus trustworthiness (Glaeser, Laibson, Scheinkman, & Soutter, 2000)
* Benefits and impact of the institutionalization of trust in online marketplaces (Pavlou, 2004)

I will seek to establish how prior studies have measured, investigated, and defined trust in order to explore how applicable these methods are for the sharing economy (specifically carpooling). I hypothesize that given the close proximity of the interaction/resource sharing of the sharing economy, the social connections and social profiles are key for building trust; the sharing economy is being built at a time when trust can easily be built through credible channels such as Facebook. The following discussion will take prior works and highlight how each of them can be utilized in order to explore their application to the sharing economy.

The first area of discussion is how ratings impact transaction price, what the effect of text on transaction price is, and how an increase in ratings impacts overall revenue. These studies all seek to quantify the impact of their respective rating systems on the marketplace and are applicable to the sharing economy. Resnick et al. discovered that the market on eBay rewarded sellers an estimated 8.1% more in purchase price if they had an established reputation when compared to new sellers. Beyond this, it was found by Ghose that by using text as a transaction predictor with price you can be more accurate than simply using the seller rating. Finally, Luca discovered that when Yelp restaurants (independent, not chain) obtain an increase of one star their overall revenue is impacted positively by 5-9%. When looking at the sharing economy I think the most exciting and relevant application of these studies is to look at how a seller or driver’s (the one with control of the resource) rating impacts the price at which they contract. I believe that in order to gain share or build up trust, early adopters are forced to undercut on price and then eventually can charge a market rate once they have established themselves as a reputable person. By looking at new users and how they transact in comparison with established users (frequency, price point, review characteristics), the behavior of establishing and building trust can be explored. In my opinion, since the sharing economy is a sharing of resources, as opposed to simply transacting on resources, building trust is more important to the transaction than traditional online marketplaces. This could cause an incentive to build reputation at a discount in order to win over future business and customers.

Next, the studies by Cabral and Dellarocas focus on how an initial negative rating impacts a seller’s growth rate and the consequence of being unable to see how many transactions went unrated. In Cabral’s study, sellers are found to transact -8% less after their first negative review compared to a rate of 5% before this review which demonstrates how even one negative review can impact a seller immensely. Beyond this, Dellarocas discusses how the lack of transaction reviews on eBay is not taken into account for a sellers reputation and how oftentimes negative reviews are only used when the problems are severe. These behaviors are important to the sharing economy, because unlike eBay, a person sharing their car or home will share the same car or home as opposed to simply selling the good and being done with the actual object in question. Similar to eBay, I believe that an initial negative review will impact a seller, but in the case of the sharing economy it could be a worse effect. This is due to the fact that when sharing their car or home, a negative review could imply a safety hazard or potential negative experience. With the buyer not left with any tangible good, any lukewarm review is sure to deter buyers as opposed to eBay where a neutral review is not as detrimental. The lack of reviews as seen on eBay is a bigger problem for the sharing economy; I believe that given the nature of these transactions (sharing a resource for a limited time), buyers are more inclined to leave reviews even when the transaction is neutral. This is because oftentimes eBay buyers are upset over the shipping time, quality of product, or promptness of response as opposed to the sharing economy where neutral concerns have a more direct impact on the buyer’s experience.

Beyond this, the studies consider the manipulation/aggregation of reviews, how the setup of the system affects market transactions, and the impact of word subjectivity on the usefulness of reviews. It was found that hotels located near each other are more prone to fake 1 and 2 star reviews if they are on TripAdvisor due to no booking being required. In the case of Yelp, Dai et. al showed that in order to maximize the value of reviews the effect of change in quality over time, the stringency of reviews, and reputational concerns must be factored in (Dai, 2012). Beyond this, based on the product (electronics, food items, clothing, etc.) an optimal review ranking system can be determined by mining for the correct mix of subjectivity and objectivity; with producers it is more important to view subjective facts while consumers prefer a mix of both subjective and objective reviews. Bolton et. al discovered that trust and trustworthiness are underprovided as the positive externalities and are not internalized by each buyer (Bolton, 2004). Again we find a plethora of interesting applications to the sharing economy: the impact of fake or review gaming, optimal review aggregation, difference in preferred content of reviews, and a scheme to ensure review posting. With the sharing economy and new platforms like Airbnb and Uber, it is important to optimize the review aggregation, incentivize posting, and avoid fake or malicious reviews. The most interesting area, in my opinion, is how review aggregations should differ for the sharing economy. Since these studies mainly focused on online marketplaces, the real life aspect of the sharing economy places more importance on accuracy and promptness (inherently subjective terms). I would like to look at how Airbnb reviews over time lead to a higher or lower utilization rate as well as how a person who improves their performance tracks. Beyond this, with systems like Lyft and Uber, making feedback both required and reciprocal, the system can increase the amount of reviews.

Lastly, the other three studies focus on how to differentiate between building trust and trustworthiness as well as how online reputation systems fundamentally differ from traditional word of mouth networks. Glaeser et al. highlighted how in order to determine whether someone is trusting you should ask about prior trusting behaviors; on the other hand, in order to determine whether someone is trustworthy, you should ask them if they trust others. With Dellarocas, it was discovered that online trust reputation systems have a unique set of challenges and opportunities when compared to word of mouth systems: their ability to scale quickly, the problem where early reviewers are subject to more risk, the capacity to exploit information processing, the ability to easily switch names/accounts, and the chance to use a PageRank like function to use social capital as a ranking system. Lastly, Pavlou et al. found that the most effective ways to increase a buyer’s trust in an online marketplace was to ensure trust in the intermediary and the perceived usefulness of the rating system. Based on these findings, the sharing economy should try and establish trust in early users and a survey would be useful in asking about their trust of others. It is likely that they are trusting people, since there is a selection bias in the set of people who are likely to share their own resources with others. However, on the flip side, these individuals should be trustworthy themselves, and in order to test for this it will be useful to examine the characteristics of early adopters to elicit if trust is easier to build between similar parties (nationality, gender, race, etc). Based on the challenges and opportunities mentioned by Dellarocas, it is useful to examine how these are being exploited with the sharing economy and the influence they have on trust. The main area of interest here is how the inability to change names due to social accounts effects trust as well as the ability to explore how a PageRank like function would serve to highlight users with high reviews and high social interconnectedness. In regards to Pavlou, it would be interesting to measure trust in the platforms themselves and look at failed platforms. This would allow an investigation into the impact of a user’s perceived trust in the system and rating system on the growth and success of the platform.

Given the previously mentioned literature on trust and rating systems, this thesis will focus on how social features such as auto club membership and Facebook Connect affect the likelihood that a ride is booked. Based on Dellaroca’s research on utilizing social capital to build trust I will work to answer how these features serve as an effective proxy for social capital. This social capital stems from the users who are either members of the ADAC auto club or connect their Facebook profiles to their account via Facebook Connect. This auto club contains over 18 million members in Germany (out of 82 million) and given the nature of the service, carpooling, I believe it will serve as an effective means to build trust between users. The ADAC offers all sorts of services including roadside assistance, travel/traffic information, financing assistance, and car rental services. Facebook Connect is an easy way for users to connect their social network identity to their account. Users who use Facebook Connect are not enabling others to see their Facebook profile but allowing the platform to verify their willingness to connect their Carpooling.com account with their Facebook account. By studying how these features impacts the success in bookings it will become easier to recommend strategies for other sharing economy platforms to build trust in their own systems. If these features increase the likelihood a ride is accepted then we can recommend other platforms implement similar strategies to decrease barriers to adoption and increase trust in the platform and between users.

# Data from Carpooling.com and Research Methodology

The source of the data used for research in this paper is from Carpooling.com, one of Europe’s most popular carpooling companies. The company facilitates carpooling in over 40 countries and in 7 different languages. For the past 10 years the company has grown from its roots in Germany to expand across Europe and is currently working to expand in the United States. The platform is based on their website booking system as well as their mobile app for both Android and iOS. Drivers post their route information including departure location, destination, date, time, number of seats available, as well as price per seat. The information is then posted to a sortable list where riders can look up potential routes and book rides. The riders have the ability to see information on drivers including their smoking status, Facebook Connect status, auto club membership status, verified phone number, and car make/model. Once a ride is posted and a rider makes a booking request, the driver then chooses to accept or reject the ride. The data used for this study contains all rides requested, booked, and other options available at the time of booking (train and bus).

Given their German roots, the company provided me with data from their top 10 most popular routes (see Figure 1) in Germany from +/- 3 weeks from April 2nd, 2014. The total population represents 23,312 booking requests with 13,277 unique passengers and 4,438 unique drivers. Based on the information provided the top routes over this time frame included Berlin to Hamburg and Hamburg to Berlin. This makes sense given their status as Germany’s most populous cities and close proximity via car (~3 hours). Based on the table below, it becomes apparent that even within the most popular routes there is variation on the likelihood that a ride gets accepted after it is requested. In general, the percentage is around 70% with the notable exception being the routes to and from Halle/Salle. One potential reason for this higher booking rate is the fact that this route only contains one bus alternative (while others include 3+) so drivers are more likely to receive more requests and accept higher rates of riders.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Departure City** | **Destination City** | **Count of Rides Rejected** | **Count of Rides Accepted** | **% Accepted** |
| Berlin | Hamburg | 1,063 | 3,113 | 74.55% |
| Berlin | Munich | 625 | 1,621 | 72.17% |
| Berlin | Dresden | 564 | 1,515 | 72.87% |
| Berlin | Leipzig | 597 | 1,192 | 66.63% |
| Berlin | Halle/Salle | 242 | 1,175 | 82.92% |
| Dresden | Berlin | 576 | 1,437 | 71.39% |
| Halle/Salle | Berlin | 198 | 1,164 | 85.46% |
| Hamburg | Berlin | 1,105 | 2,712 | 71.05% |
| Leipzig | Berlin | 572 | 1,238 | 68.40% |
| Munich | Berlin | 700 | 1,903 | 73.11% |

Figure 1

Beyond the city to city data, it is also useful to take a deeper look at the make-up of drivers, their characteristics and booking rates. As the table below shows (figure 2), 41.1% of drivers in this data set do not have a social connection or auto club membership. On the other hand, 46.3% of the drivers have no social connect feature but are members of auto clubs. The first interesting takeaway from figure 2 is the fact that those drivers with no social connection or auto club membership end up with 32% of their requests not booked. On the other hand, those drivers with both social connection and auto club membership ended up with only 14% of their rides not booked. While the sample set is smaller for those with both features (1,457 versus 10,548) it is still interesting to observe that drivers with two measures of trust enabled are less likely to reject bookings. Another interesting point is how those drivers with social connection but no auto club membership exhibit a low average number of rides. This could be due to the fact that these drivers are more casual drivers (not auto club members) who choose to use the Facebook Connect feature to verify their social identity.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **User Traits** | **Not Booked** | **Booked** | **Total** | **Ratio (Not booked/Total)** | **Driver count** | **Avg Rides** |
| No social connection |  | | | | | |
| No auto club | 3,420 | 7,128 | 10,548 | 32% | 1,826 | 5.71 |
| Auto Club | 2,363 | 8,011 | 10,374 | 23% | 2,053 | 5.05 |
| Social connection |  | | | | | |
| No auto club | 260 | 673 | 933 | 28% | 557 | 1.61 |
| Auto Club | 199 | 1,258 | 1,457 | 14% | 310 | 4.70 |

Figure 2

The importance of April 2nd is that it is the day when the website altered how their ride booking page looked. Prior to the change, the ride booking page did not contain information on a driver’s auto club membership (figure 3). After the change, the ride booking page was updated to contain this feature along wither other features including the status of a verified phone number and verified driver’s license (figure 4). This paper will focus on how this change in being able to see the auto club membership altered the likelihood that a ride was accepted before and after this change. With a distinct change in how users view the driver on this date it serves a useful event study for how behavior changed given the change in trust features visible on the ride booking page. Beyond this event study we will look at how Facebook Connect and auto club membership predict the likelihood of a booking acceptance throughout the time period. This provides us with another measure of how trust is built between users beyond simply what users see in a ride booking page.

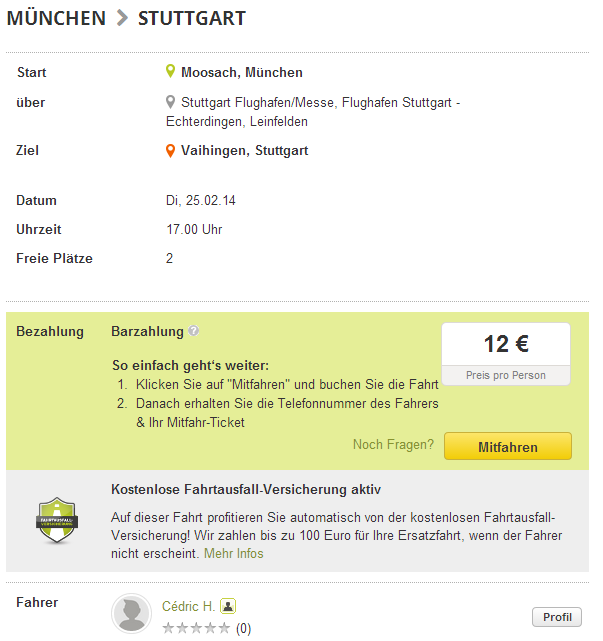


Figure 3

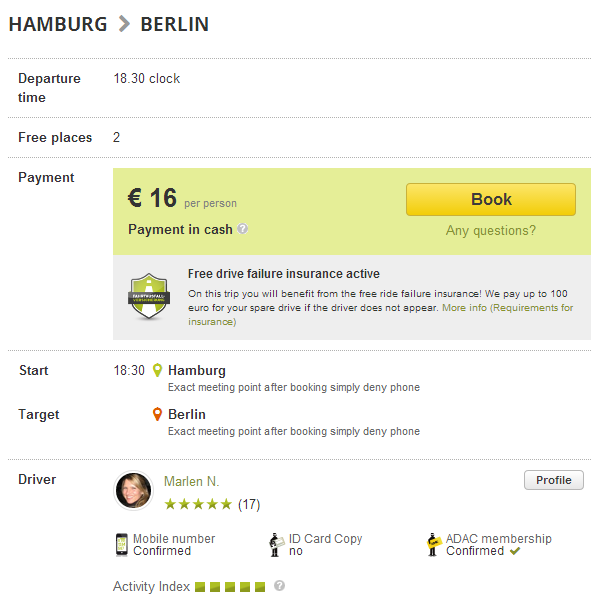


Figure 4

The methodology used to analyze the data was binary logistic regression. In this model, we are trying to model the outcome of a binary event where the outcome is either a booked ride (denoted as 1) or a denied booking request (denoted as 0). The input variables consist of other binary variables with value 1 if the feature is present and 0 if the feature is not present for the ride. These include Facebook Connect, auto club membership, whether the ride occurred before or after the change in driver profile, the presence of the same sex for driver/rider, and lastly if the rider and driver are both smokers. In addition to these binary input variables we consider continuous predictors such as the price difference of the ride compared to the routes average and a drivers rating on the platform. The price difference takes into account the impact of price on the likelihood a ride is booked since those that are cheaper are generally expected to be booked more often all else equal. The rating takes into account the users rating on the platform on a scale of 1 to 5 although most drivers have either a high (5), low (1) rating or no rating: 71% have 5 star ratings, 5% have 1 star ratings, and 18% have no rating.

Regression Model:

In this model we are given betas for each input variable as well as a constant that is used to predict outcome of our dependent variable. This outcome is the natural log of the odds of the event occurring divided by the odds of the event not occurring. This logit function is the dependent variable that the regression is run on using the independent variables mentioned earlier. The outcome and accuracy of this model will help us determine which independent variables (such as auto club membership) impact the probability of the dependent variable being 1 (a booking is accepted). This model also provides us with odds ratios which helps measure how fitted probability changes between the different values of our explanatory variable. A value near 1 for the odds ratio suggests the variable does not have a substantial effect on the outcome, while an odds ratio greater than 1 means the variable is associated with higher odds of the outcome. A value less than 1 means that an increase in the input decreases the likelihood that the event occurs.

# Analysis of Data

In the first step of analysis we force fit a regression based on all available input variables and then isolate the statistically significant (p < 0.05) ones to rerun the regression in order to improve the model. This exhaustive list of variables enables us to isolate the variables that are most predictive of the logit odds that a ride is booked. The results of the first regression (below in figure 5) isolate the driver’s auto club membership, driver’s social connect, price differential compared to average ride available, driver rating, and rider auto club membership as statistically significant. The variables that are not statistically significant include the change in ride booking page (denoted before/after change), same sex of driver/rider, both rider/driver smokers, drivers after the ride booking change with auto club membership (denoted driver,time,auto), drivers after the ride booking change with social connect (denoted driver,time,social), and rider social connect. As mentioned earlier, the odds ratio provides us with a helpful measure to explaining how the relevant variables impact the odds of the ride being booked. In this regression we see drivers in auto clubs and drivers with social connect have odds ratios of 1.7036 and 1.5149. This means that these two features have a substantial impact on the odds of a ride being booked relative to the other variables which is in line with our earlier finding that these drivers had the lowest percentage of rejected rides at 14%.

|  |  |  |  |
| --- | --- | --- | --- |
| **Variable** | **Beta** | **Odds Ratio** | **P-value** |
| Constant | 0.5379 |  | 0.000\*\* |
| Price difference | -0.01256 | 0.9875 | 0.026\*\* |
| Driver Rating | 0.06487 | 1.0670 | 0.000\*\* |
| Driver Social Connect | 0.4154 | 1.5149 | 0.000\*\* |
| Driver Auto Club | 0.5327 | 1.7036 | 0.000\*\* |
| Rider Auto Club | -0.1040 | 0.9012 | 0.015\*\* |
| Rider Social | -0.0535 | 0.9479 | 0.188 |
| Same sex of driver and rider | -0.0297 | 0.9708 | 0.322 |
| Driver and rider both smokers | -0.300 | 0.7406 | 0.337 |
| Drivers after the booking page change w/ social connect | -0.0636 | 0.9384 | 0.292 |
| Drivers after the booking page change w/ auto club membership | -0.004 | 0.9962 | 0.972 |
| Before or after the booking page change | 0.0343 | 1.0349 | 0.402 |

Figure 5 \*\*statistically significant

|  |  |
| --- | --- |
| **Goodness of Fit Test** | **p-value** |
| Deviance | 0.000 |
| Pearson | 0.527 |
| Hosmer-Lemeshow | 0.184 |

To test the fit of the model we use three of the goodness of fit tests, namely deviance, Pearson, and Hosmer-Lemeshow. These help us compare the difference between the observed outcomes of bookings with the predicted ones under our model. In this case, since p < 0.05 for the deviance we can reject the null hypothesis which means our model is not a good fit and other models should be explored. The Pearson test is >0.05 which means the null hypothesis cannot be rejected and the model could be considered a good fit under this test. Similarly, under the Hosmer-Lemeshow model our p value is >0.05 indicating this model is a good fit. Overall, it appears the initial model has substantial room for improvement which will we work on based on our findings of which variables were statistically important in the first regression.

Now that we have isolated the variables that are statistically significant we rerun the regression with only those variables that were statistically significant to try and improve our model. In this model the values are similar to those of the previous but our goodness of fit tests have actually become worse with the Hosmer-Lemeshow now indicating the model is not a good fit (p<0.05). This means that we are more than likely missing a key variable in the model that would increase our ability to predict the likelihood of a booking being accepted.

|  |  |  |  |
| --- | --- | --- | --- |
| **Variable** | **Beta** | **Odds Ratio** | **P-value** |
| Constant | 0.5287 |  | 0.000\*\* |
| Price difference | -0.01236 | 0.9877 | 0.028\*\* |
| Driver Rating | 0.06501 | 1.0670 | 0.000\*\* |
| Driver Social Connect | 0.4121 | 1.5101 | 0.000\*\* |
| Driver Auto Club | 0.5022 | 1.6525 | 0.000\*\* |
| Rider Auto Club | -0.1041 | 0.9011 | 0.015\*\* |

Figure 6 \*\*statistically significant

|  |  |
| --- | --- |
| **Goodness of Fit Test** | **p-value** |
| Deviance | 0.000 |
| Pearson | 0.537 |
| Hosmer-Lemeshow | 0.000 |

# Research Conclusions and Areas for Further Research

The initial regression showed how the change in ride booking page actually had very little impact on the outcome of a ride booking. This suggests that incremental changes to a platform do not have a large impact on the transaction behavior of users; the features that became apparent on the ride booking page were already available on the user’s profile. In this case it would be useful to study how the initial implementation of Facebook Connect and auto club membership impacted the transaction behavior of users. By comparing how users transact before and after the availability of this information it will be easier to measure the true impact of these trust features on the likelihood that a ride gets booked. Despite the inconclusive evidence on how the change in the ride booking page impacted the platform, it is has become evident that both auto club membership and social connect for drivers are predictive variables when trying to predict the likelihood of a ride being accepted. However, as seen by the goodness of fit tests there is still room for predicting what exactly impacts the likelihood that a ride is booked on the Carpooling.com platform. When booking a ride there are a lot of variables that could impact an acceptance that were not modeled here including the timing of the booking relative to the ride time, number of previous rides driven, booking of multiple seats, and exogenous emergencies that prevent rides from occurring.

After answering these questions through our data and research it is useful to consider what other areas of trust in the sharing economy could benefit from this discussion. In terms of sharing resources within the sharing economy it would be interesting to study what 3rd party ID verifications (Facebook, LinkedIn, government ID, etc) are most impactful on trust between users. In addition to this, what information is included in a user’s profile should be studied in order to determine what features users look at when transacting so the platform can decrease barriers to adoption. With our data we were looking at a very unique measure of trust, auto club membership, which is largely not transposable to other countries. This means that cultural and social norms should be considered when analyzing how likely users are to trust a sharing economy platform since preconceived biases already exist.

The sharing economy is a distinct platform that has the potential to change how we utilize existing resources but this benefit will not come easily. As mentioned throughout this paper trust will be a huge barrier to overcome. Even the definition of trust in the sharing economy is up for debate. Going forward it would be useful to standardize this discussion or even advocate for a centralized system of user ratings and trust measuring (similar to Trust Cloud which already exists but not on a large scale). Platforms will need to consider how users perceive trust in the platform, trust in other users, as well as trust in the sharing economy itself before transactions become as easy and ubiquitous as eBay or Amazon. Consumers in the sharing economy are now sharing real life experiences and assets; the risk is greater than ever which is why trust must be measured, analyzed, and optimized. This paper serves as a case study on just one platform in one country but the implications are widespread. The sharing economy needs online social features like Facebook Connect and offline measures such as auto club memberships to increase trust between users.

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