# Why do online taxi drivers accept very few rides? Evidence from Tap30.

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**Abstract**

In this paper, using a search and matching model, I show how learning of the mean parameter of a normal wage distribution affects the ride acceptance behavior of drivers working in online taxi platforms. I show that high expectation regarding the mean value of wage distribution leads drivers to accept fewer rides. Moreover, as time passes by, the belief is corrected and more offers will be accepted. In order to empirically show learning in drivers' behavior, I use a dataset from Tap30, an Iranian ride hailing company. I run two tests in order to quantitatively measure this effect. First, I check whether more experienced drivers' acceptance rate rises more sharply compared to that of inexperienced ones. Second, I test whether rejected offers for every accepted proposal in certain time slots of the day shows a pattern of learning for those drivers who are longer active in the market. The first test does not indicate any learnings while the second one shows an effect consistent with the implications of the model. However, the identification of this effect is subject to further analysis.

**Keywords:** Search and matching, Learning, Kalman filter, Online taxi platform, Labor supply in online markets, Service refusal.

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# Section 1: Introduction

With the emergence of online taxi platforms, new questions about the behavior of drivers and passengers in such markets have emerged. A key point in increasing the efficiency of these markets is raising participation of the drivers. In this regard, what penalty must be imposed to drivers who cancel a matched ride offer is of great importance. This policy raises the rejection cost for drivers and provides incentives for more ride acceptances. A higher acceptance rate, the percentage of accepted offers out of all ride proposals, is desirable in many aspects. First, higher acceptance rate translates to lower waiting time for the passengers to be matched to a driver. Second, it provides more revenue, improves reputation, and leads to more efficient allocations for the platform. Having said the benefits, the outcome for the drivers is not clear. On one hand, they can have more ride offers and higher revenues in the long run. On the other hand, they may bear a cost in the sense that they are forced to accept ride that would have been rejected otherwise if it was not for the punishment.

Pioneer ride hailing companies such as Uber and Lyft have a mechanism for punishing drivers who reject ride proposals. However, "Tap30", an Iranian online taxi platform, does not have such a mechanism for punishing drivers.[1] Moreover, in contrast to conventional online taxi platforms in the U.S. and Canada, Tap30 provides almost all information of a ride for the drivers. Therefore, as rejection has no cost, drivers wait for desired proposals and reject other offers without any worries. Consequently, acceptance rates are quite low in Tap30.

In this paper, I *indirectly* study how providing more information for the drivers on top of having no costs for rejection leads to having a low acceptance rate. More specifically, I show how learning, in the sense that rejecting offers helps finding perhaps better ones, affects the behavior of online taxi drivers in accepting/rejecting ride proposals. I write a search and matching model which includes the process of learning of the mean parameter of the wage distribution. The model indicates that the higher the expectation of drivers towards ride offers is, the lower acceptance rate will be. Moreover, it says that the earnings of a driver will be lower due to this avarice. Finally, I try to spot this learning effect in the data using two approaches. However, I have not successfully identified this pattern in this draft yet.

# Section 2: Literature Review

In this section I will briefly review the literatures related to the question discussed in this paper.

In the seminal work of Camerer et al. (1997), the authors argue that the wages of New York City cabdrivers are correlated within days but are uncorre-

[1] It should be noted that Tap30 *does* punish drivers who have accepted a ride offer but have cancelled it before passenger pickup.

lated between different days. This paper estimates wage elasticities of experienced and inexperienced cabdrivers and shows that the wage elasticity of inexperienced drivers is close to $-1$. Meaning, that they make decisions on a daily basis without intertemporal labor substitution and target a level income while working. In contrast, due to different methods and measurements, Farber (2005) shows that daily income effects are small and leaving the market happens after a daily hours of work has been reached by a driver. Farber (2008) empirically shows that this reference level of income varies substantially. Moreover, Crawford and Meng (2011), using a reference based model with rational expectations, further proves that New York taxi drivers target hours of work instead of income level.

In order to show how well a driver is able to distinguish good ride offers from bad ones while in the market, I include learning into the partial equilibrium job search model of McCall (1970). In the context of search and matching models, Felli and Harris (1996) studies wage determination in the presence of firm-specific human capital in continuous time using Brownian motion. Using a similar method, based on a job-matching model of the labour market, and Moscarini (2005) embeds a microeconomic job matching model in a macroeconomic equilibrium search environment among many others. The discrete time approach, which is adopted in this paper, uses a Kalman filter. The Kalman filter is a recursive algorithm for computing the mathematical expectation of a hidden state vector, conditional on observing a history of another vector of noisy signals on the hidden state. Interested readers may see Hamilton (1994) and Kim et al. (1999) for diverse applications.

# Section 3: The Model

I have assumed the simplest model to describe the learning process. I assume that the distribution for wage offers is $w_t \sim N(\mu, \sigma^2)$, where the driver knows that the distribution is normal and knows the true variance, $\sigma^2$.[2] However, she does not know the true mean parameter, therefore, she has a prior on the mean denoted by $\mu_0$ which is updated according to Bayes' rule.[3] In the next part of the paper, I will describe the model.

[2] Although the wage distribution is usually considered to have a log normal form since wages can not be negative, in order to bypass the complexities of the modeling in the learning process I avoid this assumption. It should be noted that the conclusions are the same under each assumption.

[3] The learning process, not discussed in this draft, is modeled by implementing a Kalman filter.

## 3.1 Search and Matching

Using the search and matching literature, I write a simple model to investigate the behavior of the drivers. I borrow the model of McCall (1970) to show the tradeoff decision of drivers between earning a wage and waiting to learn the true wage distribution. A driver who has started working has a prior belief, $\mu_0$, regarding the mean of the wage distribution, $\mu$. Depending on how much higher (lower) her belief from the true parameter is, she might reject (accept) more offers. Thus, the acceptance rate is directly affected in the tradeoff between accepting/rejecting ride offers and waiting to learn the true wage distribution. If a driver accepts a ride offer, in form of job wage in my model, she will be employed for 2 periods.[4] Then she must come back to the unemployment state in order to receive another offer. Technically, if the driver accepts an offer at time $t-1$ with wage $w_{t-1}$, she will be in state $W$ at time $t$ according to (1),

$$W(\hat{\mu}_{t-1}, w_{t-1}) = w_{t-1} + w_{t-1} + \mathbb{E}_{t-1}[U(\hat{\mu}_{t+2}, w_{t+2})], \tag{1}$$

where $\hat{\mu}_{t-1}$ is driver's belief regarding the mean parameter at time $t-1$ which is reflected in the expectation operator for calculation of future value of going back to unemployment. Note that if employed at time $t$, the latest offer received is $w_{t-1}$. Additionally, in the unemployment state $U$, a driver receives an unemployment benefit (which can be negative or positive) and waits to see the latest draw from the wage distribution and decides whether to accept or reject this offer according to her updated belief as shown in (2),

$$U(\hat{\mu}_t, w_t) = b + \mathbb{E}_t[J(\hat{\mu}_{t+1})]. \tag{2}$$

$J(\hat{\mu}_{t+1})$, defined in (3) and used in (2), is the value of receiving an offer in time $t$.

$$J(\hat{\mu}_{t+1}) = max\{W(\hat{\mu}_t, w_t), U(\hat{\mu}_{t+1}, w_{t+1})\}. \tag{3}$$

Notice that I have not assumed any discount factors since in the context of online taxi drivers, the duration of validity of each value function can be considered to be hours, days, or a couple of weeks at most. Consequently, discounting seems not to be of any importance. Note, that the value functions of employment status depend on the latest wage offer received and subjective belief regarding the mean of the wage distribution in any time $t$ while the value function of having an offer depends only on .

The expectation sign's time index explains with which wage offer the value functions are calculated. The expectation in employment state, $W$, at time $t$, is taken over the updated distribution using the last wage offer received, $w_{t-1}$.

[4] The choice of number of periods to be employed is arbitrary. In general, a driver can be at work for $n$ periods where $n$ indicates the severity of the tradeoff between two choices. However, in order to preserve the simplicity of the model and deriving a reasonable analytical solution I assume that $n = 2$.

Moreover, the expectation in unemployment state, $U$, at time $t$, is taken over the updated distribution using the last wage offer received, $w_t$. The updating process is done exploiting a Kalman filter. It is worth mentioning that the driver's best guess regarding the mean parameter at any future time is the same as her updated belief in the current time. It is important to point out that since $W(\hat{\mu}_t, w_{t-1})$ is increasing in wage, we have a cutoff strategy. Therefore, a reservation wage $R$ exists at times of the decision making such that rides offering a wage below that amount are rejected and rides offering a wage above that are accepted.

Since the drivers work reasonable hours during any time interval (days, weeks) and go out of the market for some time and then come back, the nature of our problem is of a finite-lived agent. Therefore, in order to capture different periods of activity with different characteristics, I assume that there exists a time $T$ that the driver makes the last decision of accepting/rejecting a ride offer and then leaves the market. Thus, I use backward induction to solve the model analytically. I start from the last period and recursively write the equations until I see a pattern. The derivation of the analytical solution is discussed in the Appendix. The reservation wage formula is shown in (4).

$$\forall t < T - 2 : R_t = \frac{J_{t+1} - J_{t+3}}{2} \tag{4}$$

Intuitively, the formula derived for the reservation wage shows that the decision of a driver regarding accepting/rejecting a ride offer depends on the opportunity cost of accepting the ride at hand and going to work for 2 periods (and later coming back to unemployment) for waiting for an offer in the next period.

# Section 4: Simulation

I have simulated the model discussed so far in order to study the behavior of a driver in this environment. In doing so, I assume that $w \sim N(10, 9)$ is the true wage distribution while the unemployment benefit $b$ is equal to 5. I investigate two scenarios. In either scenario, the driver is in the market for 30 periods. Every period a wage is randomly drawn from the true wage distribution.[5] If the driver is already employed in a period, she will miss seeing the wage offer in that period, therefore, no learning happens and her belief will remain the same. However, if she is unemployed, she sees the offer, updates her belief and decides whether to accept the ride.

First, I assume that the driver's initial belief regarding the mean parameter is $\mu_0 = 25$. The result is shown in Figure (3). It can be seen that initially, due to her wrong belief, the reservation wage is high and she won't accept some of the rides that would have been accepted if she knew the true mean of wage distribution. As time passes, seeing some offers, her belief starts to converge to the true parameter

[5] The draws in both cases are the same so that we are able to compare the results.

and the driver's behavior gets closer to what she would have done if she knew the true parameter. Due to this wrong belief, total earnings of the driver are lower in comparison to the case in which she knows the true mean.

In the other case, I assume that the driver's initial belief regarding the mean parameter is $\mu_0 = 2$. The behavior of the driver under this assumption is shown in Figure (4). Contrary to the previous case, this time due to her lower expectations regarding the average of wage draws she accepts more offers than she would have accepted if she knew the true parameter. In this case, total earnings are slightly higher compared to the case in which she knows the true parameter. However, one should be cautious in interpreting the effect of accepting more offers on accumulated earnings.

The result of a Monte Carlo simulation with 1000 runs of different wage draws for each case is provided in Figures (5) and (6) for the high and low belief cases, respectively.

# Section 5: Empirical Study

## 5.1 Data

I use the ride proposals data of Tap30, an online taxi platform in Iran.[6] This dataset includes every ride offer proposed in the city of Mashhad from passengers to drivers in Mehr 1398. In this study I focus on the behavior of the drivers only. For every offer, Tap30 provides the driver with full characteristics of the ride, including destination, ride ETA, ride distance, distance from passenger, and pickup ETA. Interestingly, in contrast to similar foreign ride hailing platforms, Tap30 does not punish drivers for rejecting a proposed ride offer. The only penalty imposed to the drivers is when a ride which has been accepted (by the driver) is cancelled by the driver. In that case, the driver will be charged 2000 Tomans. Also, no non-monetary punishments are in effect.[7] A brief summary of variables is shown in Table (1).

In order to identify the effect of learning, I decompose each day's time into 6 different slots (numbers in parenthesis are percentage of observations):

- 12 A.M. - 6 A.M. (3%)
- 6 A.M. - 10 A.M. (15%)
- 10 A.M. - 2 P.M. (25%)
- 2 P.M. - 5 P.M. (17%)
- 5 P.M. - 8 P.M. (19%)
- 8 P.M. - 12 A.M. (20%)

[6] For privacy issues, I have normalized the numbers reported in this paper. The attention must be on the variations only.

[7] For instance, depriving the driver from receiving more ride offers in the next minutes. For more reading, see Maruthasalam et al. (2018).

I've assumed that the wage distribution is (somehow) similar in each slot of a working day in a week. For example, 5 P.M. - 8 P.M. slot's wage distribution in Mondays remains the same during the month.[8] In Figure (7) the density of ride offers during Mehr across hours of day time is shown. Furthermore, the acceptance rate in different times of the day is depicted in Figure (8).

I have divided the drivers into three types: *low*, *medium*, and *high*, with respect to their active days in a month. I call a driver active if her total earnings within a day exceeds 30000 Tomans. Also, size of each group is one-third of the whole dataset. The acceptance rate for different groups of drivers is shown in Figure (9). Interestingly, as the number of working days increases, (average) daily total earnings increases too, according to Figure (10).

In order to better see the difference between drivers with (probably) higher experience to those who have not been in the market enough to learn the wage distribution, I ignore the medium cluster.[9] The histogram of working days of active drivers is shown in Figure (11). Additionally, the trend of acceptance rate variation within the day is depicted in Figure (12) for type low and high drivers.

## 5.2 Evolution of acceptance rate

In this part, I discuss the tests I have done in order to recognize the learning in drivers' behavior. Unfortunately, it should be noted that after doing several tests I was not able to identify such effect. However, I will discuss two of the tests I have done in the following lines. In the first, no learning is found to be present, while in the other, a (possibly) learning can be seen in the behavior of the drivers.

Initially, I investigate the trend of acceptance rate variation during Mehr 1398. As can be seen in Figure (13), the drivers who are less active during the month start at a lower rate of acceptance but end up accepting more ride offers on average at the end of the month. Table (2) column (1) shows the regression of acceptance/rejection of offers on time. I have controlled for day fixed effects, weekday fixed effects, and interaction of those two on top of fraction of accepted rides in accepting a ride. Fraction of accepted rides and fraction of income in a day captures the effects of different behavior of a specific driver regarding acceptance during a working day and income targeting. In column (2), I cut the data into the first 26 days as the first day of the last week was a day-off.[10] In column (3), I ran the same test for the three full weeks within Mehr 1398 (from $6^{th}$ to $26^{th}$). Figures (14) and (15) visually provide the changes in the results of columns (2) and (3), respectively. Unfortunately, I was not able to obtain any causal ef-

[8] Although this assumption is not accurate, it was the best I could do. I have controlled for different characteristics of days in regressions to mitigate the flaws of this assumption to the best possible extent.

[9] In almost all aspects of the study the medium type drivers behave somewhat in between low and high drivers.

[10] Mehr $27^{th}$, a Saturday, was Arba'een.

fect out of these tests. If anything, these tests indicate the opposite of what my model implied! Specifically, they indicate that not only the average acceptance for (probably) more experienced drivers is lower, but the slope with which they learn the distribution is also lower. Additionally, I ran the same test for different time slots in a similar setting in Table (3) (I pooled the data treating each slot as a block of observations for itself). Even though the regression coefficients are not statistically significant, one is not able to identify any meaningful pattern of learning. Compared to the baseline slot which is 1, the slope for slots 2 and 3 are larger for high type drivers while the slope for slots 4, 5, and 6 are negative.

For another test, I have grouped each days' data into the 6 previously defined slots. In each slot, define fraction of acceptance for a slot to be the acceptance rate of offers received so far to the total acceptance rate in that slot. Intuitively, I want to see how the behavior of a driver regarding accepting/rejecting an offer changes as she spends more time being in the market. Following this intuition, I test whether an increase in the fraction of acceptance induces more acceptance rate in Table (4). The column settings are similar to those in the previous Tables. The coefficient of interest is that of 'driver_type='High' * time * frac_acc_slot's. This coefficient says that acceptance rate of type high drivers increases on average as time passes in a slot, perhaps indicating that learning is in effect. Although, it should be noted that the identifiability of such effect is subject to many controversial questions!

# Section 6: Conclusion

In this paper, I wrote a search and matching model which incorporated learning behavior of the drivers regarding acceptance of ride proposals, then, with the intuition derived from the model I tried to identify this effect in the data. In the model, I showed that starting from a higher assessment regarding the mean of the wage distribution, the driver accepts fewer rides and her accumulated income is lower compared to the case that the true mean parameter is known. Although I was not able to properly *identify* this effect in the data, the second test I provided shows that perhaps a learning is present in the behavior of the drivers. The identification and further tests will be included in future drafts.

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# Appendix

## Analytical Solution of the Model

Here, the backward induction method discussed is shown for derivation of an analytical solution for the model. For simplicity in writing, I dropped the arguments of the value functions and I have indexed each with time only. The last period in which the driver has the option of deciding between accepting or rejecting the ride is denoted by $T$. Suppose unemployment benefits after $T$ are equal to zero and no more wage offers will be received.

$$t = T : \begin{cases} W_T = 2w, \\ U_T = b, \\ J_{T+1} = 0. \end{cases}$$

$$t = T-1 : \begin{cases} W_{T-1} = 2w, \\ U_{T-1} = b + \mathbb{E}_{T-1}\, J_T, \\ J_T = max\{2w,\ b\}, \\ R_T = \frac{b}{2}. \end{cases}$$

$$t = T-2 : \begin{cases} W_{T-2} = 2w + \mathbb{E}_{T-3}\, U_T = 2w + b, \\ U_{T-2} = b + \mathbb{E}_{T-2}\, J_{T-1}, \\ J_{T-1} = max\{2w,\ b + \mathbb{E}_{T-2}\, J_T\}, \\ R_{T-1} = \frac{b+J_T}{2}. \end{cases}$$

$$t = T-3 : \begin{cases} W_{T-3} = 2w + \mathbb{E}_{T-4}\, U_{T-1}, \\ U_{T-3} = b + \mathbb{E}_{T-3}\, J_{T-2}, \\ J_{T-2} = max\{2w + b,\ U_{T-2}\}. \end{cases}$$

Writing the equations of $t = T - 3$ in another form:

$$t = T-3 : \begin{cases} W_{T-3} = 2w + b + \mathbb{E}_{T-4}\, J_T, \\ U_{T-3} = b + \mathbb{E}_{T-3}\, J_{T-2}, \\ J_{T-2} = max\{2w + b,\ b + \mathbb{E}_{T-3}\, J_{T-1}\}, \\ R_{T-2} = \frac{J_{T-1}}{2}. \end{cases}$$

$$t = T-4: \begin{cases} W_{T-4} = 2w + b + \mathbb{E}_{T-5}\, J_{T-1}, \\ U_{T-4} = b + \mathbb{E}_{T-4}\, J_{T-3}, \\ J_{T-3} = max\{2w + b + \mathbb{E}_{T-4}\, J_T,\ b + \mathbb{E}_{T-4}\, J_{T-2}\}, \\ R_{T-3} = \frac{J_{T-2} - J_T}{2} \end{cases}$$

$$t = T-5: \begin{cases} W_{T-5} = 2w + b + \mathbb{E}_{T-6}\, J_{T-2}, \\ U_{T-5} = b + \mathbb{E}_{T-5}\, J_{T-4}, \\ J_{T-4} = max\{2w + b + \mathbb{E}_{T-5}\, J_{T-1},\ b + \mathbb{E}_{T-5}\, J_{T-3}\}, \\ R_{T-4} = \frac{J_{T-3} - J_{T-1}}{2} \end{cases}$$

Comparing the formulas derived for $R_{T-4}$ and $R_{T-3}$, one can see that they are the same expect for one shift in time. The form of the pattern in the reservation wage is clear: $\forall t < T-2 : R_t = \frac{J_{t+1} - J_{t+3}}{2}$.[11]

[11] In general, with $n$ periods, we have $\forall t < T-n : R_t = \frac{J_{t+1} - J_{t+n+1}}{n}$. The intuition is similar.

# Figures and Tables

Convergence of driver's belief to the true mean parameter

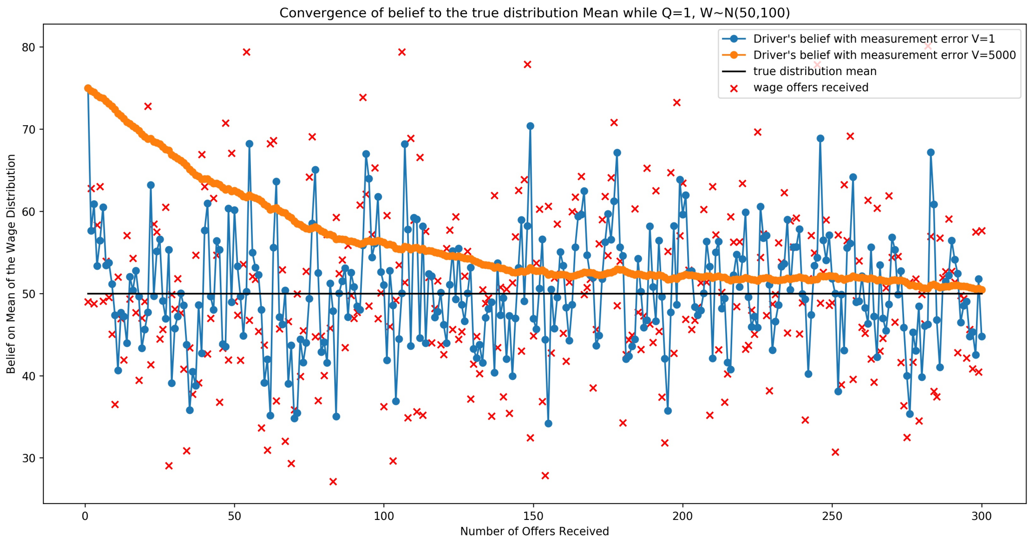


**Figure 1:** In this figure, the red 'x' signs indicate the random draws of a normal distribution with $\mu = 10, \sigma^2 = 9$ which act as measurement signals while $Q = 0.5$. Two extreme cases for measurement error, V, are shown. In the orange line, which indicates $V = 5000$, the belief takes longer to converge to the true parameter, however, once it does the volatility of the updated belief is small. On the other hand, in the light blue line, which indicates $V = 1$, the belief quickly converges to the true parameter, however, it is very volatile since every measurement signal has a lot of information due to low measurement error and keeps changing a lot.

Half-Life and prediction standard deviation (for 25 steps) in learning

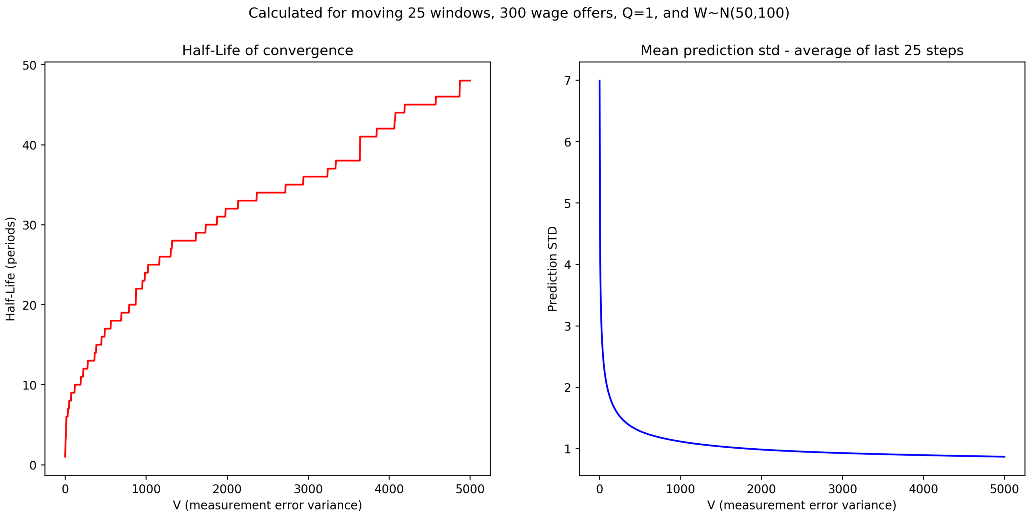


**Figure 2:** this figure shows that with an increase in measurement error, the driver's belief takes longer to convergence to the true value, but the standard deviation of the moving 25 windows of the belief decreases (the kinks in the left figure are due to the fact that we are working in discrete time.). Note that the lower bound of the standard deviation is equal to the initial variance of the prior, $P_0$. Also note that, the qualitative figure of the standard deviation depends on the number of chosen windows to calculate the standard deviation.

| | count | mean | sd |
|---|---|---|---|
| Normalized_Accept | | 1 | 1.275611 |
| Normalized_Max_Income | | 1 | .5322069 |
| Normalized_Max_Offers | | 1 | .549145 |
| Drivers | 7,726,256 | | |

**Table 1:** Summary of variables

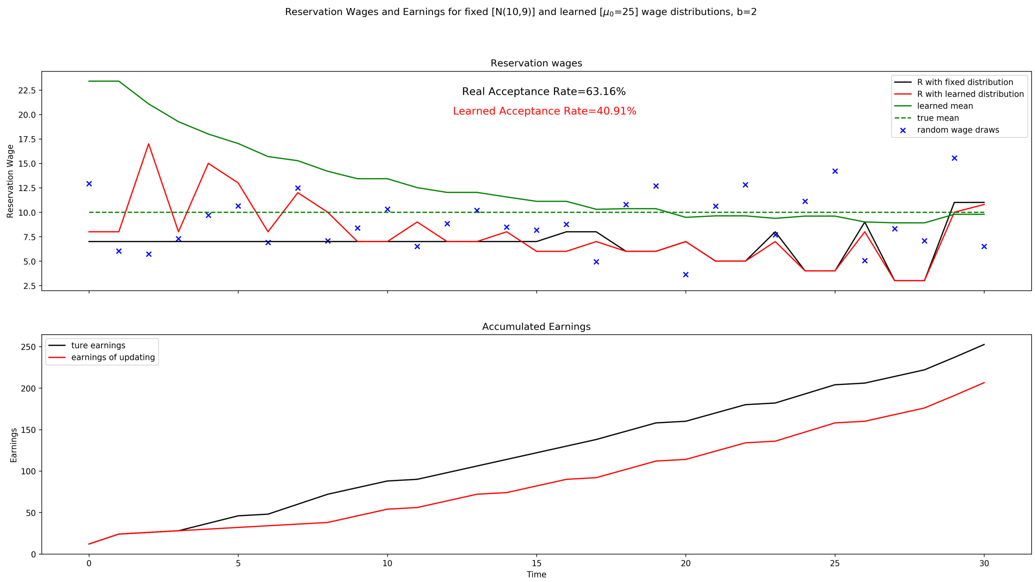


**Figure 3:** Evolution of reservation wage and earnings with $\mu_0 = 25$. When the prior of the driver is high above the true parameter, the reservation wage is higher than what would have been if she knew the true mean. In this case, the driver misses offers between real and learned reservation wages (those between red and black lines). Consequently, the acceptance rate will be lower (41% versus 63%).

| | (1) | (2) | (3) |
|---|---|---|---|
| | Accepted | Accepted | Accepted |
| time | 0.00289$^{***}$ | 0.000755$^{*}$ | 0.00367$^{***}$ |
| | (0.000258) | (0.000309) | (0.000430) |
| driver_type='High' | -0.0137 | -0.00457 | -0.00157 |
| | (0.0103) | (0.0104) | (0.0111) |
| driver_type='High' * time | -0.00155$^{***}$ | -0.00126$^{***}$ | -0.00146$^{***}$ |
| | (0.000249) | (0.000296) | (0.000403) |
| frac_acc_day | -0.0669$^{***}$ | -0.0626$^{***}$ | -0.0819$^{***}$ |
| | (0.0127) | (0.0134) | (0.0163) |
| driver_type='High' * frac_acc_day | -0.0517$^{***}$ | -0.0517$^{***}$ | -0.0516$^{***}$ |
| | (0.00639) | (0.00666) | (0.00717) |
| time * frac_acc_day | -0.00115$^{***}$ | -0.00295$^{***}$ | -0.00204$^{***}$ |
| | (0.000339) | (0.000404) | (0.000546) |
| Constant | 1.582$^{***}$ | 1.596$^{***}$ | 1.529$^{***}$ |
| | (0.00858) | (0.00895) | (0.0105) |
| Observations | 4175741 | 3727262 | 3098271 |
| Adjusted $R^2$ | 0.059 | 0.058 | 0.056 |
| Controlled for weekday, driver type, interaction of weekday and driver type, price, ride ETA, pickup ETA, ride distance, pickup distance, max income in day, and fraction of income within day. | | | |

Standard errors in parentheses
$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

**Table 2:** Regressing acceptance on time and fraction of acceptance. Standard errors are clustered at driver-weekday level. 'Accepted' is a dummy variable indicating whether a ride proposal has been accepted (=1) or rejected =0) by a driver. Coefficients of interest are highlighted.

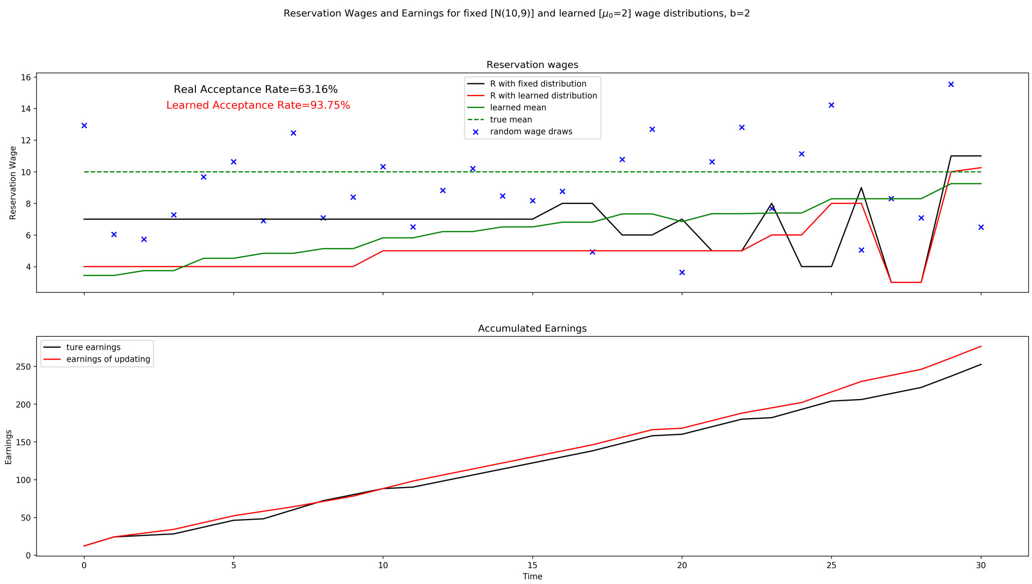


**Figure 4:** Evolution of reservation wage and earnings with $\mu_0 = 2$. When the prior of the driver is below the true parameter, the reservation wage is lower than what would have been if she knew the true mean. In this case, the driver accepts offers between real and learned reservation wages (those between red and black lines). Consequently, the acceptance rate will be higher (94% versus 63%).

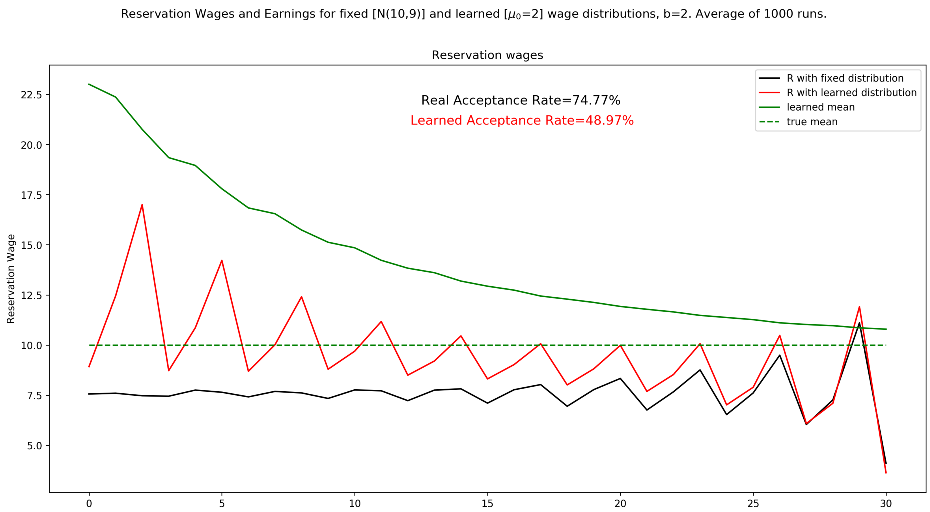


**Figure 5:** Monte Carlo simulation with 1000 different wage draws for the high belief case.

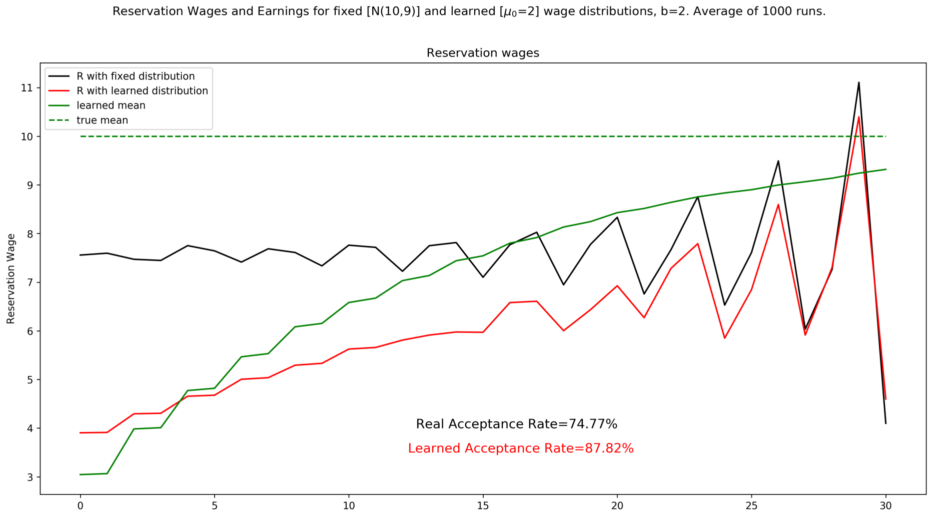


**Figure 6:** Monte Carlo simulation with 1000 different wage draws for the low belief case.

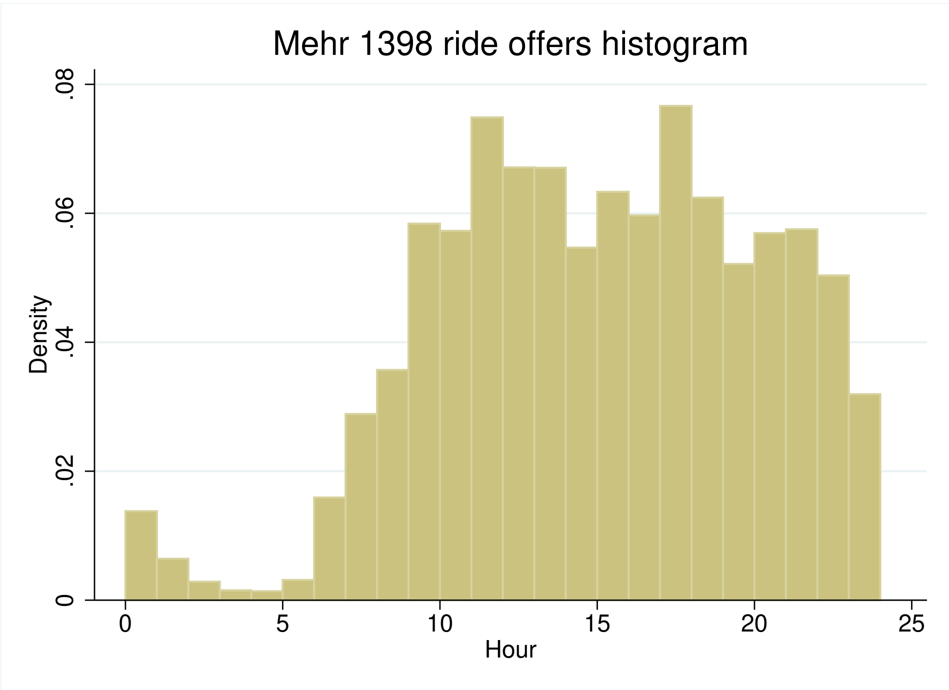


**Figure 7:** Density of Mehr's ride proposals across day time

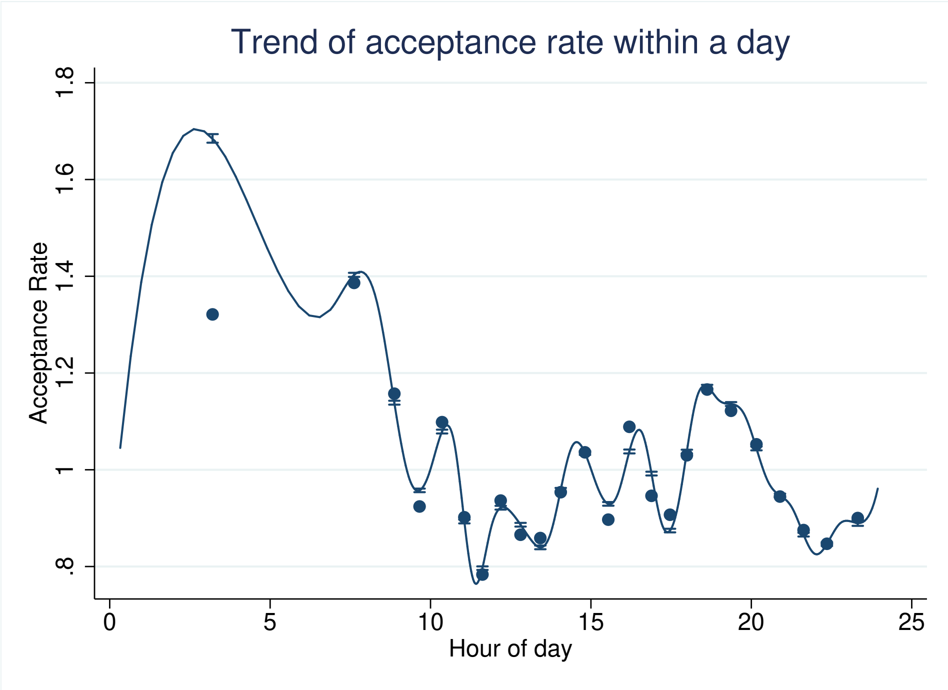


**Figure 8:** Acceptance rate trend within a day (average of 30 days)

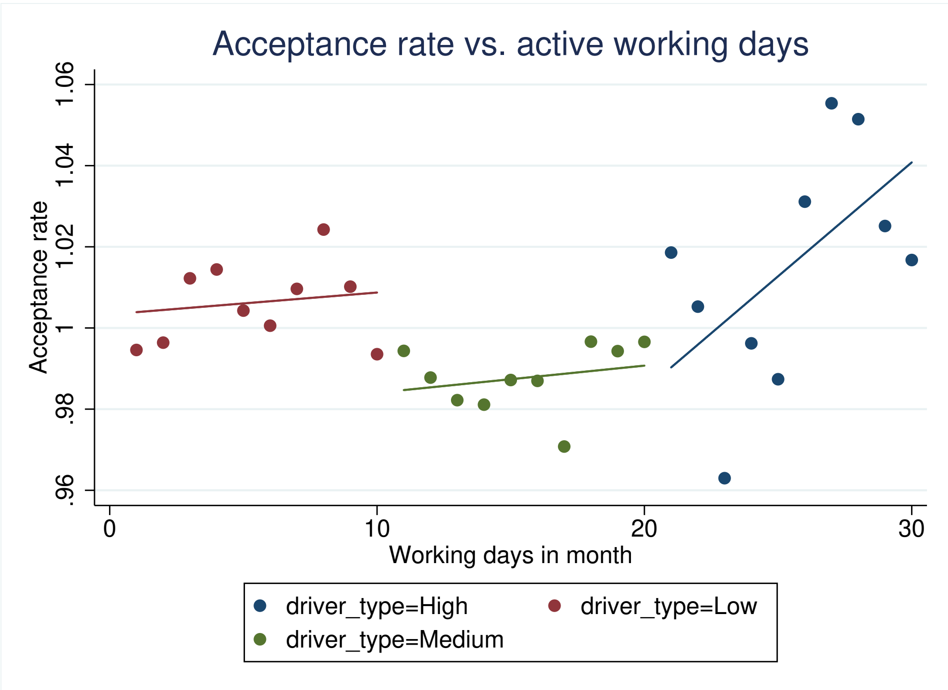


**Figure 9:** Acceptance rate for different groups of drivers

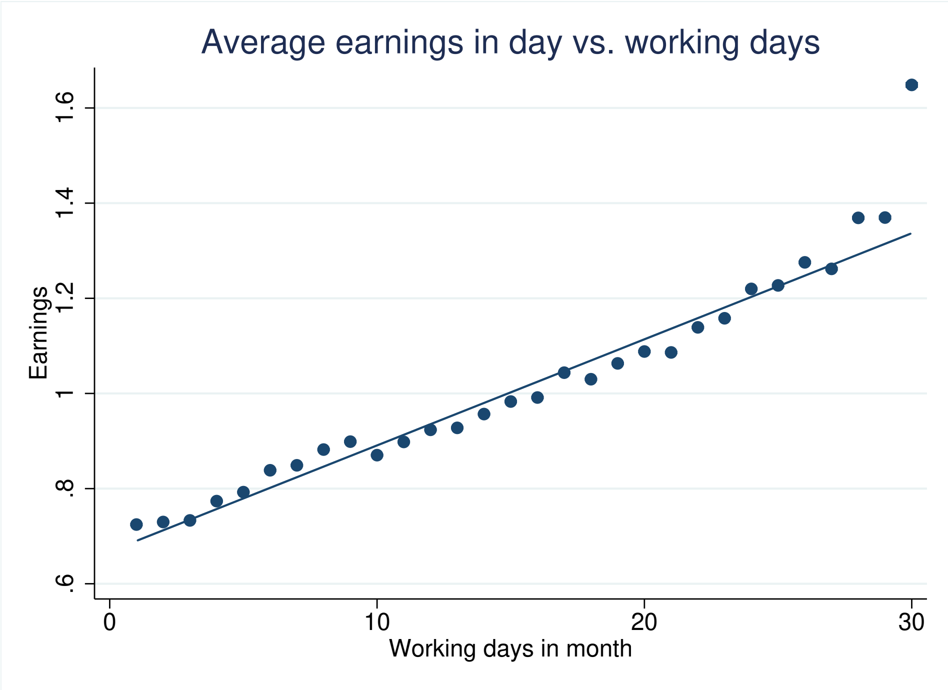


**Figure 10:** Average earnings in day versus working days in month

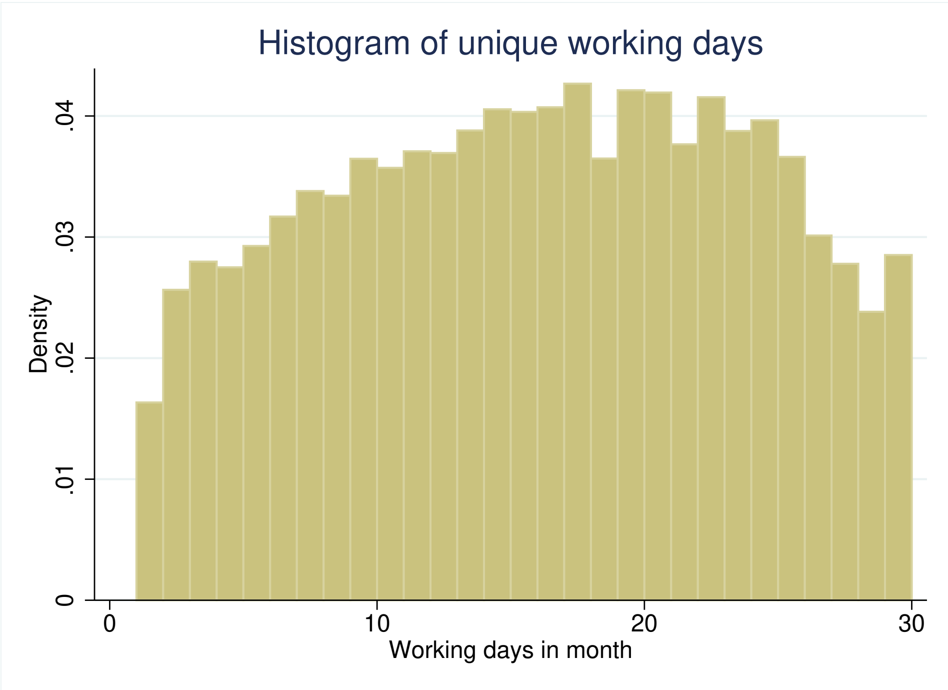


**Figure 11:** Histogram of active drivers' working days

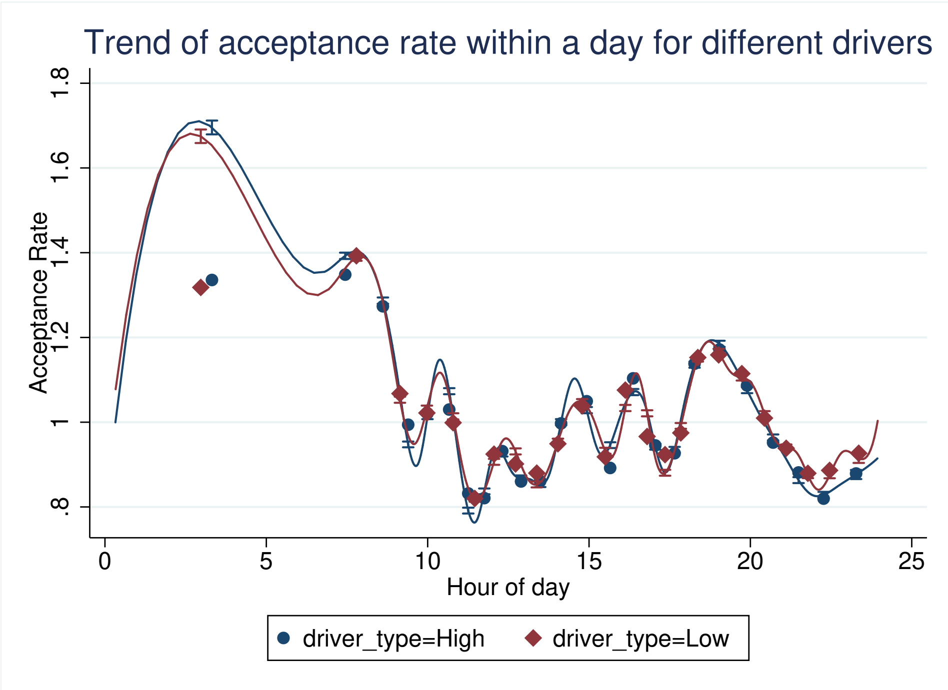


**Figure 12:** Acceptance rate trend within a day for type low and high drivers (average of 30 days)

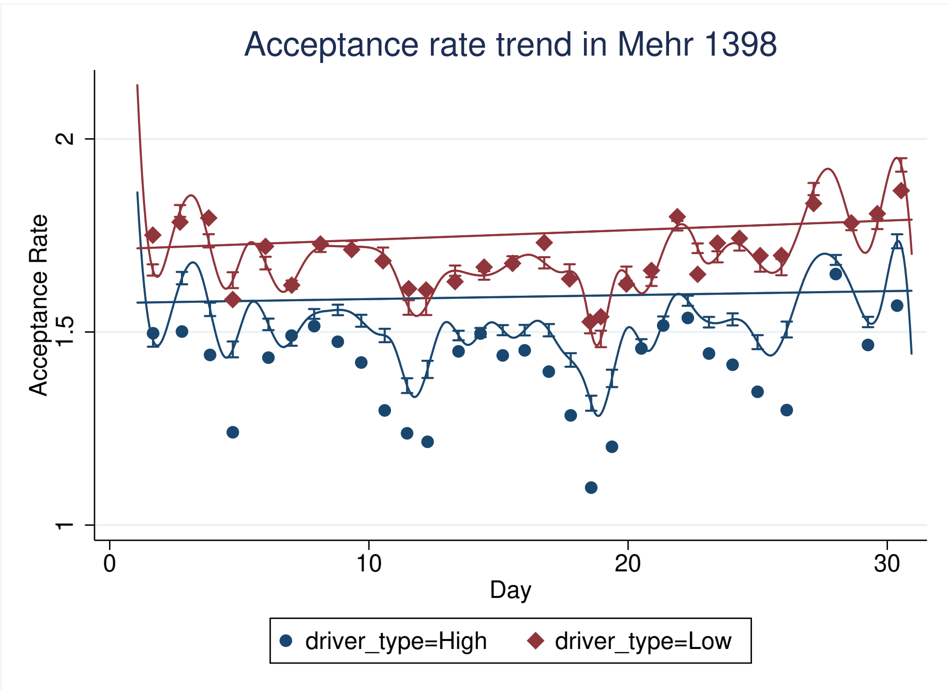


**Figure 13:** Acceptance rate trend in Mehr 1398.

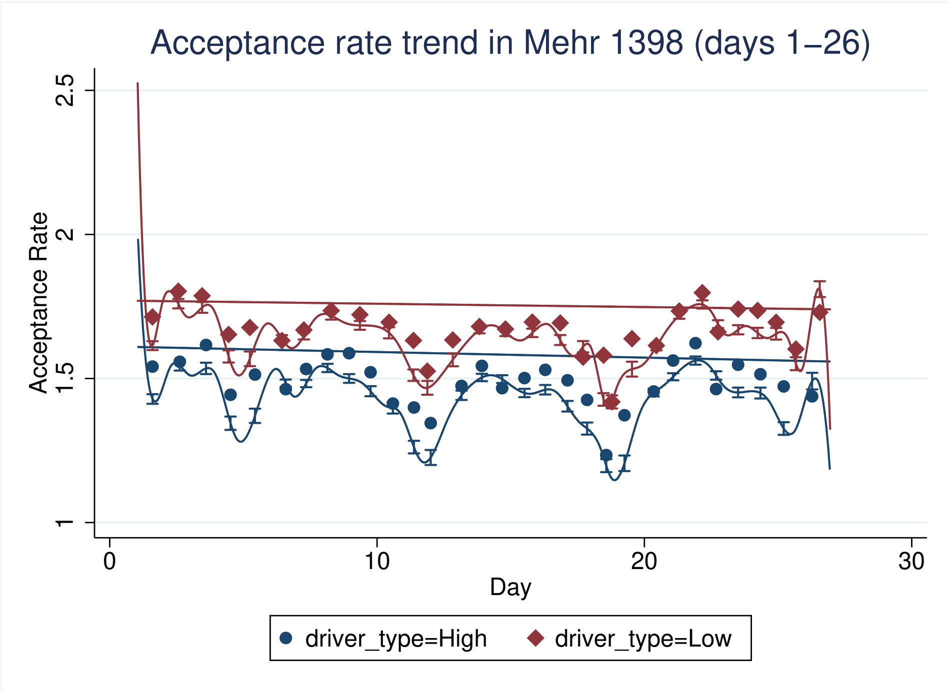


**Figure 14:** Acceptance rate trend in Mehr 1398 (dropping last incomplete week).

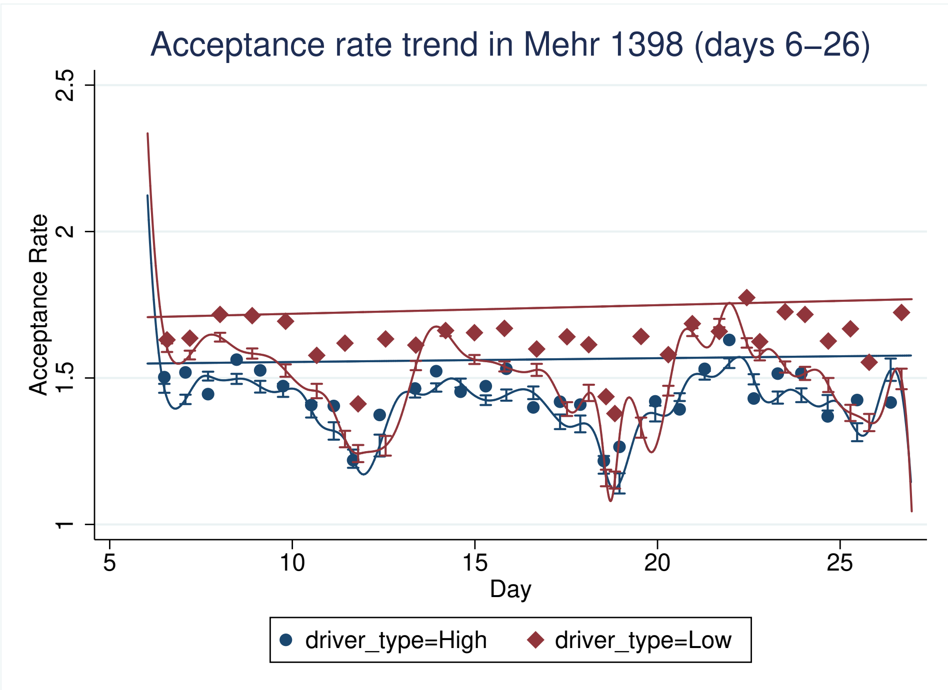


**Figure 15:** Acceptance rate trend in Mehr 1398 (dropping first and last incomplete week).

| | (1) Accepted | (2) Accepted | (3) Accepted |
|---|---|---|---|
| time | 0.00281** | 0.00464*** | 0.00930*** |
| | (0.00105) | (0.00126) | (0.00180) |
| driver_type='High' | -0.0260 | -0.0160 | -0.00644 |
| | (0.0301) | (0.0311) | (0.0466) |
| driver_type='High' * time | -0.00214 | -0.00230 | -0.00290 |
| | (0.00159) | (0.00181) | (0.00258) |
| slot=2 | -0.290*** | -0.279*** | -0.248*** |
| | (0.0217) | (0.0230) | (0.0355) |
| slot=3 | -0.729*** | -0.693*** | -0.670*** |
| | (0.0202) | (0.0214) | (0.0334) |
| slot=4 | -0.705*** | -0.646*** | -0.638*** |
| | (0.0206) | (0.0218) | (0.0339) |
| slot=5 | -0.793*** | -0.709*** | -0.696*** |
| | (0.0205) | (0.0216) | (0.0337) |
| slot=6 | -0.841*** | -0.797*** | -0.782*** |
| | (0.0208) | (0.0220) | (0.0342) |
| slot=2 * time | -0.00246* | -0.00370** | -0.00568** |
| | (0.00117) | (0.00140) | (0.00196) |
| slot=3 * time | 0.00113 | -0.00239 | -0.00392* |
| | (0.00108) | (0.00130) | (0.00184) |
| slot=4 * time | 0.000962 | -0.00446*** | -0.00529** |
| | (0.00110) | (0.00132) | (0.00187) |
| slot=5 * time | 0.00202 | -0.00551*** | -0.00666*** |
| | (0.00110) | (0.00131) | (0.00186) |
| slot=6 * time | -0.000978 | -0.00517*** | -0.00630*** |
| | (0.00111) | (0.00133) | (0.00188) |
| driver_type='High' * slot=2 | -0.0972** | -0.0907** | -0.118* |
| | (0.0320) | (0.0332) | (0.0499) |
| driver_type='High' * slot=3 | -0.0865** | -0.0835** | -0.0974* |
| | (0.0303) | (0.0314) | (0.0476) |
| driver_type='High' * slot=4 | -0.0707* | -0.0751* | -0.0766 |
| | (0.0310) | (0.0321) | (0.0485) |
| driver_type='High' * slot=5 | -0.0752* | -0.0859** | -0.0868 |
| | (0.0309) | (0.0320) | (0.0483) |
| driver_type='High' * slot=6 | -0.116*** | -0.118*** | -0.108* |
| | (0.0314) | (0.0325) | (0.0488) |
| driver_type='High' * slot=2 * time | 0.00312 | 0.00253 | 0.00396 |
| | (0.00173) | (0.00198) | (0.00279) |
| driver_type='High' * slot=3 * time | 0.00111 | 0.000810 | 0.00152 |
| | (0.00164) | (0.00186) | (0.00265) |
| driver_type='High' * slot=4 * time | -0.000328 | 0.00000644 | 0.0000282 |
| | (0.00166) | (0.00190) | (0.00270) |
| driver_type='High' * slot=5 * time | -0.00000512 | 0.000887 | 0.000841 |
| | (0.00166) | (0.00189) | (0.00269) |
| driver_type='High' * slot=6 * time | -0.000337 | -0.000254 | -0.000797 |
| | (0.00167) | (0.00190) | (0.00270) |
| frac_acc_day | 0.114*** | 0.0930*** | 0.0707*** |
| | (0.0131) | (0.0140) | (0.0178) |
| driver_type='High' * frac_acc_day | 0.106*** | 0.107*** | 0.110*** |
| | (0.00875) | (0.00911) | (0.00980) |
| time * frac_acc_day | -0.000986* | -0.00111* | -0.000329 |
| | (0.000447) | (0.000532) | (0.000723) |
| Constant | 2.108*** | 2.072*** | 1.981*** |
| | (0.0205) | (0.0216) | (0.0331) |
| Observations | 4175741 | 3727262 | 3098271 |
| Adjusted $R^2$ | 0.078 | 0.077 | 0.076 |
| Controlled for weekday, driver type, interaction of weekday and driver type, price, ride ETA, pickup ETA, ride distance, pickup distance, max income in day, and fraction of income within day. | | | |

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

**Table 3:** Regressing acceptance on fraction of acceptance in slot. Standard errors are clustered at driver-weekday-slot level. 'Accepted' is a dummy variable indicating whether a ride proposal has been accepted (=1) or rejected =0) by a driver. Coefficients of interest are highlighted.

| | (1) Accepted | (2) Accepted | (3) Accepted |
|---|---|---|---|
| time | 0.00408*** | 0.00100** | 0.00432*** |
| | (0.000326) | (0.000387) | (0.000543) |
| frac_acc_slot | 0.326*** | 0.344*** | 0.304*** |
| | (0.0259) | (0.0279) | (0.0331) |
| time * frac_acc_slot | -0.00206*** | -0.00237*** | -0.000260 |
| | (0.000530) | (0.000630) | (0.000876) |
| driver_type='High' | -0.00492 | -0.00887 | 0.00336 |
| | (0.00894) | (0.00964) | (0.0139) |
| driver_type='High' * time | -0.00247*** | -0.00217*** | -0.00288*** |
| | (0.000481) | (0.000572) | (0.000772) |
| driver_type='High' * frac_acc_slot | -0.0433** | -0.0471** | -0.0566* |
| | (0.0144) | (0.0156) | (0.0227) |
| driver_type='High' * time * frac_acc_slot | 0.00162* | 0.00209* | 0.00281* |
| | (0.000787) | (0.000937) | (0.00127) |
| slot=2 | 0.0614*** | 0.0790*** | 0.0723*** |
| | (0.0162) | (0.0174) | (0.0190) |
| slot=3 | -0.375*** | -0.384*** | -0.393*** |
| | (0.0151) | (0.0162) | (0.0178) |
| slot=4 | -0.276*** | -0.287*** | -0.303*** |
| | (0.0155) | (0.0167) | (0.0183) |
| slot=5 | -0.416*** | -0.437*** | -0.446*** |
| | (0.0155) | (0.0167) | (0.0183) |
| slot=6 | -0.346*** | -0.347*** | -0.371*** |
| | (0.0156) | (0.0168) | (0.0184) |
| slot=2 * frac_acc_slot | -0.739*** | -0.781*** | -0.785*** |
| | (0.0262) | (0.0280) | (0.0312) |
| slot=3 * frac_acc_slot | -0.443*** | -0.455*** | -0.457*** |
| | (0.0247) | (0.0265) | (0.0296) |
| slot=4 * frac_acc_slot | -0.465*** | -0.482*** | -0.486*** |
| | (0.0253) | (0.0271) | (0.0302) |
| slot=5 * frac_acc_slot | -0.196*** | -0.210*** | -0.237*** |
| | (0.0253) | (0.0271) | (0.0303) |
| slot=6 * frac_acc_slot | -0.428*** | -0.454*** | -0.444*** |
| | (0.0251) | (0.0269) | (0.0301) |
| frac_acc_day | 0.0650*** | 0.0547*** | 0.0576*** |
| | (0.0122) | (0.0129) | (0.0141) |
| Constant | 1.950*** | 1.994*** | 1.930*** |
| | (0.0163) | (0.0175) | (0.0203) |
| Observations | 3495588 | 3122241 | 2595228 |
| Adjusted $R^2$ | 0.070 | 0.070 | 0.069 |
| Controlled for weekday, driver type, interaction of weekday and driver type, price, ride ETA, pickup ETA, ride distance, pickup distance, and maximum income within day. | | | |

Standard errors in parentheses

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

**Table 4:** Regressing acceptance on time and fraction of acceptance in different slots. Standard errors are clustered at driver-weekday-slot level. 'Accepted' is a dummy variable indicating whether a ride proposal has been accepted (=1) or rejected =0) by a driver. Coefficients of interest are highlighted.