Gender Blind is NOT Gender Neutral: Gender Disparities in Chinese Ride-sharing Platforms *

Yanan Jia† Yuheng Zhao‡ Wenyu Zhou §

This version: Dec 2024

Abstract

This paper highlights that the difference in exploiting destination information between male and female drivers perpetuates gender earning inequality in the ride-hailing industry. Using order-level data in December 2018 in Hangzhou City, we find a 3.5% hourly earning gap across genders. The gender earning gap is larger for platforms displaying the destination information to drivers before accepting the ride. We argue this difference is caused by gender differences in the utilization of destination information. Male drivers tend to be more experienced and are more likely to select more lucrative rides. Consistently, we observe greater gender disparities in speed and distance on platforms that disclose destination information. Moreover, when dividing the sample into drivers with and without permanent driver licenses, we find the hourly gender earning gap is more pronounced among drivers without permanent driver licenses, lending support to our proposed mechanism.

Keywords: gender disparity, gig economy, information, experience, ride-hailing drivers

JEL Codes: J30, J16, D63

*We are indebted to Dilip Mookherjee and Kevin Lang for their invaluable guidance and encouragements throughout this project. We would also like to thank David Lagakos, Siddharth George, Benjamin Marx, and Zihan Hu, Kexin Zhang for helpful conversations and comments. All errors remain our own.

†Yanan Jia (Renmin University of China): jiayanan@ruc.edu.cn

‡Yuheng Zhao (Renmin University of China): zhaoyuheng@ruc.edu.cn, corresponding author

§Wenyu Zhou (Zhejiang University): wenyuzhou@zju.edu.cn

1 Introduction

What sustains a gender earning gap in a gig economy like the ride-hailing industry if the pay formula and matching algorithm are gender-blind? This paper emphasizes that the difference in exploiting destination information between male and female drivers may play an important role in perpetuating gender earning inequality.

In contrast to traditional labor markets, the burgeoning gig economy in the past decades is featured great worker flexibility in the form of short-term contracts and freelance work. It is possible that the gig economy could generate a new path towards an equal labor market across genders by dividing work into small pieces and allowing easy substitution of work across workers.

By exploiting order-level data in December 2018 in Hangzhou City, China, we document a 3.5% hourly earning gap across genders, controlling for time and area to work as well as driver age. In addition, we find a difference across platforms. For platforms that display destination information to drivers prior to accepting the ride, the gender earnings gap is larger than for platforms that do not show destination information.

We argue that the differences are caused by the fact that different genders exploit the destination information differently. When passengers make ride requests, nearby drivers receive a pop-up notification and have the option to accept or decline the ride. Experienced drivers can gauge whether the ride is desirable or not from the destination information. By selecting the more desirable rides, drivers get higher or lower hourly earnings depending on their rule of selection.

There are three potential ways that destination information can impact the choice and income of drivers. (1) **Speed**: if a route passes through areas with heavy traffic, it may be less profitable due to slower speeds; (2)**Distance**: a longer journey is generally more profitable, and drivers can estimate the distance of a journey if both origin and destination information are provided ; (3)**Avoidance of unsafe areas**: females may choose to avoid unsafe areas when destination information is provided. If orders in unsafe areas have higher compensation, a gender preference could also contribute to the earnings gap.

Our hypothesis is based on the assumption that there is no selection of ride-hailing drivers on different platforms. While driver allocation is not entirely random, we ap-

proach this issue from two perspectives. First, we contend that the gender earnings disparity is unlikely to be attributable to selection bias. The rationale behind this assertion is that drivers' platform choices are governed by factors such as revenue sharing and order volume, which are gender-blind by design. Second, in our primary analysis we account for several gender-specific variables that may influence the hourly income, such as work time and area. Nevertheless, we cannot rule out the possibility of selection bias concerning unobserved variables.

Regarding the channels of speed and distance, our research suggests that male drivers, who tend to be more experienced in driving, may use more information when deciding whether to accept or reject a ride based on their experience, leading to higher male hourly earnings. Conversely, in the channel of avoidance of unsafe areas, female drivers use more information based on their preferences, which could result in lower female hourly earnings.

We show evidence that providing destination information leads to larger differences in speed and distance across genders. We find that on platforms that provide destination information, male drivers drive 2.49% faster than female drivers, while the difference is negligible on platforms that do not provide destination information. Male drivers also tend to have longer trips when they use platforms that provide destination information.

To establish the relative importance of different factors, we decompose the variance of hourly earnings into variances of speed, distance, time and area fixed effects, and driver age. Our analysis reveals that among these factors, speed explains around 62.62% of the variance in hourly earnings and distance explains around 13.12% of the variance; the sets of time and area fixed effects and driver age can only account for 2.23% of the variance. This suggests that, compared to other controls, speed has a dominant impact on hourly earnings.

Regarding the mechanism of female avoidance of unsafe places, we argue that it is unlikely to be related to the enlarged gender earning gap that is attributable to the revealing of destinations. We have already shown that area fixed effects can only explain a small share of the variance in hourly earnings, and controlling for area fixed effects (origins and destinations) does not significantly impact the gender earning gap. Additionally, if female drivers avoid areas with more bars, they may end up driving faster due to the typically congested traffic conditions in these areas, which is inconsistent

with our findings on speed.

Our study contributes to several strands in the literature. First among these is gender earning gaps. Despite the considerable progress made over the last century towards gender convergence in the labor market, a gender wage gap of 12% persisted (Blau and Kahn, 2017). This gender wage gap is widely believed to be attributable to the "job-flexibility penalty," as women tend to work fewer hours and experience more disruption in their labor force participation (Bertrand, Goldin and Katz, 2010; Goldin, 2014). Bolotnyy and Emanuel (2022) have shown that among Boston MBTA drivers, the gender earnings gap can be explained by the fact that female operators take fewer hours of overtime and more unpaid time off than male operators. Our study extends this literature by providing new evidence that the difference in exploiting destination information between males and females can influence the drivers' selection of requests in the ride-hailing industry, leading to a gender earning gap even if the pay formula and matching algorithm are designed to be gender-blind.

Second, this paper is relevant to the growing literature on the social economic consequence of gig economy (Berger, Chen and Frey, 2018; Chen et al., 2019; Guda and Subramanian, 2019; Cook et al., 2021; Angrist, Caldwell and Hall, 2021; Liu, Brynjolfsson and Dowlatabadi, 2021; Liu et al., 2023). The extent to which the gig economy can mitigate discrimination and reduce inequality among workers is a hotly debated topic. Despite the topic's significance, there is limited empirical evidence about gender disparities in the gig economy because of a paucity of data. To the best of our knowledge, we provide the first evidence of the gender earning gap in the ride-hailing industry within the context of a developing country. Our findings suggest that platform regulations, such as concealing destination information from drivers, can help reduce the gender earning gap by addressing the difference in exploiting destination information between genders.

Finally, we add new evidence to the well-established literature on taxi drivers' labor supply behaviors (Camerer et al., 1997; Chou, 2002; Farber, 2005; Crawford and Meng, 2011; Farber, 2015; Thakral and Tô, 2021). By revealing the heterogeneity in gender earning gaps across platforms with different policies on information revealing and its interaction with demographic characteristics, this paper enriches our understanding of the labor supply dynamics of ride-hailing drivers, highlighting the role of information utilization in shaping economic behaviors and decision-making processes among

independent contractors.

In a paper close to our study, Cook et al. (2021) examine the gender earning gap in the US ride-hailing industry. They find a 7% gender earning gap among US Uber drivers and attribute it entirely to three factors: experience, preferences and constraints regarding where to work, and preferences for driving speed. In our settings, the time and area to work can only explain a small part of the gender earning gap. While both studies suggest that the selection of profitable orders is an important factor contributing to the gender earning gap, our study emphasizes that in Hangzhou, this selection is driven by the difference in exploiting destination information between genders.

2 Conceptual framework

The following parsimonious model demonstrates how revealing the destination to drivers leads to a larger gender earning gap by enabling male drivers to select more desirable orders and enhancing male drivers' speed, allowing for gender preferences for working at night and gender disparities in speed, conditional on route and time.[1]

We consider a sequential choice problem where a driver determines the working time, order type, and driving speed when working for the platform. The driver can be male ($g = m$) or female ($g = f$). In the first period, the driver chooses which time to drive $t \in \{D, N\}$. In the second period, the driver receives two requests. He or she chooses (1) which request to accept and (2) the effort e to spend on speed.

We use backward induction to solve the sequential problem. First, suppose the choice of time $t \in \{D, N\}$ is fixed. There are two possible states: $\omega \in \{1, 2\}$, where $\omega = i$ indicates that the i-th request is "good" while the other is "bad". A good request indicates that the traffic is good and thus good for improving speed, while a bad one indicates a heavy traffic jam that will slow down the speed. How the request types affect the driving speed will be specified later. It is worth noting that the states of requests are determined by the location, time, and weather. Ex-ante, each state realizes with probability 0.5.[2] A driver would receive a message (i.e. signal realization) $m \in \{m_1, m_2\}$ when a request arrives. We consider the following information structure, where ρ_g is

[1] In the model, the role played by gender preferences for taking trips to unsafe areas is similar to that played by working at night.

[2] We do not consider cases where both orders are good or bad bacause they are irrelevant to our mechanism.

the accuracy of signals received by gender g.

$$\rho_g = P_g(m_1 \mid \omega = 1) = P_g(m_2 \mid \omega = 2) \geq 0.5 \tag{1}$$

Since the prior distribution is uniform, the posterior $P_g(\omega = i \mid m_i) = \rho_g$ for $i \in \{1, 2\}$.

The driver's choice contains two dimensions: $a \in \{1, 2\}$ stands for whether to choose the first or second request and $e \geq 0$ stands for the effort to spend on speed. The speed s is jointly determined by both dimensions. Given an accepted request, a unit of extra effort e accelerates the speed by ke. If the accepted request matches the true state (i.e., $a = \omega$), the speed is further increased by one unit (normalized). The analytic form of the speed is given by

$$s = \begin{cases} 1 + ke & \text{if } a = \omega; \\ ke & \text{if } a \neq \omega. \end{cases} \tag{2}$$

Let $\pi(s)$ be the income for driving at speed s and $c_g(e)$ be the cost of exerting effort e for a driver with gender g. Given the information structure specified above, the driver's optimization problem is

$$\max_e \rho_g \cdot \pi(1 + ke) + (1 - \rho_g) \cdot \pi(ke) - c_g(e). \tag{3}$$

Assume linear income π with slope ξ and quadratic cost with a gender-dependent parameter $c_g(e) = \psi_g e^2$. The optimizer to the problem above is given by

$$e^* = \frac{\xi k}{2\psi_g}. \tag{4}$$

The corresponding value function is

$$V(g) = \xi \rho_g + \frac{\xi^2 k^2 e}{4\psi_g}, \tag{5}$$

which is dependent on gender g. The first term represents the information rent for obtaining more precise signals.

Now we consider the first-period choice, where the driver determines to drive at day (D) or night (N). If the driver drives during the day, the net payoff is simply her optimized profit $V_D(g) = V(g)$. If he or she drives during the night, the net payoff is random:

$$V_N(g) = \begin{cases} V(g) + \bar{V} & \text{if no accident happens;} \\ V(g) + \underline{V} & \text{if an accident happens.} \end{cases} \tag{6}$$

Here, $\bar{V}$ represents the premium for driving at night; $\underline{V}$ represents the loss if an accident happens. Assume an accident happens with probability ϵ and $(1-\epsilon)\bar{V} + \epsilon\underline{V} > 0$. Assume the driver has a constant absolute risk aversion (CARA) utility index with risk coefficient $r \geq 0$; then the driver's expected utility at time t is

$$EU_t = \mathbb{E}_t\{-\exp[-rV_t(g)]\}. \tag{7}$$

If $EU_D \geq EU_N$, then the driver drives during the day; otherwise driving occurs at night. Assume the risk coefficient among males r_m is uniformly distributed over $[r_0, r_0 + r_1]$ and the risk coefficient among femailes r_f is uniformly distributed over $[r_0', r_0' + r_1]$, where $r_0 \leq r_0'$. Then the fraction of male driving at night will be higher than that of females driving at night.

When destination information is revealed, male drivers are more likely than female drivers to receive signal m_1 when the first request is in a good state and receive m_2 when the second request is in a good state because they are more experienced. That is, under these conditions, male drivers would have a higher accuracy of signal, wherein ρ_m is high while ρ_f is low (close to 0.5). An increase in the accuracy of signal ρ_g does not influence the optimal effort, but it leads to a higher expected speed.

$$\frac{\partial \mathbb{E}_\omega s*}{\partial \rho_g} > 0, \quad \frac{\partial e*}{\partial \rho_g} = 0 \tag{8}$$

This conceptual framework has three implications: (1) Gender preference disparity for working at night (and similarly for unsafe areas) and gender difference in speed, conditional on the route and time, lead to gender earning gaps in the ride-hailing industry even if the pay formula and matching algorithm are gender-blind; (2) On platforms that show the destination before a request is accepted, the gender speed gap is larger if males possess more information due to their advantage in experience; (3) The gender

gap would be smaller if both genders exploit the information similarly. In one subgroup, the drivers with permanent driving licenses, both genders are familiar with the traffic condition, and both are able to choose the more profitable requests if destination information is provided. Therefore, we have the following hypotheses:

H1: There is a gender earning gap among ride-hailing drivers.

H2: The gender earning gap would be larger on platforms that provide destination information to drivers before they accept offers.

H3: The differences in the gender earning gap across platforms would be smaller for drivers with permanent driving licenses.

3 Data and empirical strategy

3.1 Data

Our analysis is based on a comprehensive panel dataset of ride-hailing drivers in Hangzhou, which is the third largest city in China's Yangtze River Delta, known for its established ride-hailing market. The ride-hailing data were obtained from the Bureau of Transformation in Hangzhou and cover the period December 1-31, 2018. The administrative sample includes detailed travel information like pick-up time, drop-off time, pick-up location, drop-off location, driving distance, deadhead distance, trip revenue, as well as driver information and vehicle information from 16,284,444 trips and 46,627 drivers. For each ride-hailing driver, we have detailed information about gender, age, and completed trip orders. Using these data, we construct the following variables:

(1) **Hourly earning**: the transaction-level income divided by the sum of wait times and time spent on trips; (2) **Time spent on trip**: the difference between arrival time and departure time; (3) **Wait time**: the time between completing a previous trip and picking up a passenger for a new trip; (4) **Speed**: the driving miles divided by trip time; (5) **Location**: the geohash[3] dummy constructed by longitudes and latitudes of origins and destinations; and (6) **Experience**: the driver's age or time since obtaining a driver license.

[3]Geohash is a hierarchical spatial data structure that subdivides space into buckets of grid shape. A geohash is a unique identifier of a specific region on the Earth.

3.2 Empirical strategy

To quantify the gender earning gap, we consider the following baseline specification:

$$y_{ijt} = \beta \cdot \textit{Female}_{it} + X_j^\top \gamma + \delta \lambda_i + \theta_{w,t} + \omega_{o,d} + c + \epsilon_{ijt}, \tag{9}$$

where y_{ijt} is the outcome, which can be driver i's hourly earning on transaction j on the time t; $\textit{Female}_{it}$ is the dummy variable for gender; X_j is a vector of transaction-level control variables, including speed during the trip and distance of the trip; λ_i is the individual-level control variables, including a driver's experience proxied by age or time since obtaining a driver license; $\theta_{w,t}$ is the day-of-the-week fixed effect and hour fixed effects; $\omega_{o,d}$ is the origin and destination fixed effects; and c is the intercept term. ϵ_{it} is the residual that is clustered at the individual level.

We divide our sample into two sub-groups: ride-hailing drivers on platforms that provide destination information before accepting the request; and drivers on platforms that do not provide destination information. If male drivers are able to choose more profitable requests when they have more information, we expect them to have higher hourly earnings and drive faster. Therefore, we expect that the magnitude of β would be larger for drivers on platforms that provide destination information.

There might be alternative explanations for the larger gender earning gap on platforms that provide destination information. One alternative mechanism is that females may choose to avoid less desirable but more profitable requests when the destination is provided. In this case, the enlarged gender earning gap is due to females' use of information based on gender differences in preference rather than males' use of information based on gender differences in experience (Bolotnyy and Emanuel, 2022).

To address this concern, we divide ride-hailing drivers into those with and without permanent driver licenses. We assume that both genders with permanent driver licenses are familiar with the road and traffic conditions. Hence, when destination information is provided, both genders have similar information. If the enlarged gender earning gap is due to experienced male drivers' use of information, we would expect to see a smaller gender earning gap among drivers with permanent driver licenses than among drivers without permanent driver licenses when platforms that provide destination information are used.

4 Empirical results

Table 1 presents the gender daily earning gap within the ride-hailing industry. Column 1 indicates that, on average, female ride-hailing drivers in Hangzhou earned 9.43% less per day than their male counterparts. Column 2 controls the number of hours spent on the trip and wait time. Wait time is based on the time between completing the previous trip and picking up passengers for a new trip. We replace the wait time with the average wait time of the driver on the same day when the former is greater than 30 minutes. Controlling for working hours significantly reduced the gender daily earning gap to 3.91%. In columns 3 and 4, we control the day-of-week fixed effects and the experience by adding age and square of age to the regression, respectively. Column 5 includes all aforementioned controls and fixed effects, and the results are largely consistent. The subsequent empirical analysis focuses on the remaining gender earning gap of 4.44% in Column 5. To account for transaction-specific characteristics, such as destination and hour-fixed effects, we examine hourly income, which we will elaborate on in the subsequent paragraphs.

Table 1: Raw daily gender earning gap in the Hangzhou ride-hailing industry

	(1)	(2)	(3)	(4)	(5)
VARIABLES	ln(Daily income)				
Female	-0.0943***	-0.0391*	-0.0392*	-0.0443*	-0.0444*
	(0.0294)	(0.0235)	(0.0235)	(0.0234)	(0.0234)
ln(Workhour)		0.796***	0.795***	0.794***	0.794***
		(0.00525)	(0.00527)	(0.00521)	(0.00522)
Age				0.0173***	0.0173***
				(0.00417)	(0.00417)
Age_sq				-2.16e-04***	-2.16e-04***
				(5.56e-05)	(5.56e-05)
Mean of dependent variable	5.921	5.921	5.921	5.921	5.921
Day of week FE	No	No	Yes	No	Yes
Observations	87,461	87,461	87,461	87,461	87,461
R-squared	0.001	0.675	0.675	0.676	0.676

Note: Standard errors in parentheses are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1. The sample used consists of daily-level observations for ride-hailing drivers in Hangzhou City in December 2018. The dependent variable is the daily earning of drivers who work for at least one hour during a given day. The work hour is measured by the sum of the hours spent on the trip and the wait time. Wait time is based on the time between completing the previous trip and picking up a passenger for a new trip. We replace the wait time with the average wait time of the driver on the same day if it is greater than 30 minutes.

Table 2 presents the findings on the raw gender hourly earning disparity that only controls for gender dummy. Hourly income is measured by the earning of one transaction over the sum of hours spent on the trip and wait time. Column 1 shows that female ride-hailing drivers in Hangzhou on average earned 2.39 yuan (approximately 0.35 dollars) less per hour than their male counterparts. Column 2 shows that the gender earning gap is about 3.71%, which is smaller than the 7% gender earning gap in Cook et al. (2021). Columns 3 and 4 use an alternative measure of hourly income that replaces the wait time with 0 if the wait time is greater than 30 minutes. The estimated absolute and relative gender earning gaps are 2.24 yuan and 3.48%, respectively, which are close to the findings in columns 1 and 2, suggesting that our results are not sensitive to specific measurements.

Table 2: Raw hourly gender earning gap in Hangzhou's ride-hailing industry

VARIABLES	(1) Hourly inc measure 1	(2) Hourly inc measure 1	(3) Hourly inc measure 2	(4) Hourly inc measure 2
	Income	ln(Income)	Income	ln(Income)
Female	-2.386***	-0.0371***	-2.239***	-0.0348***
	(0.557)	(0.009)	(0.522)	(0.008)
Mean of dependent variable	72.54	4.234	74.47	4.257
Day of week FE	No	No	No	No
Hour FE	No	No	No	No
Origin and destination FE	No	No	No	No
Observations	560,727	560,727	560,727	560,727
R-squared	0.000	0.000	0.000	0.000

Note: Standard errors in parentheses are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1. The sample used consists of transaction-level observations for ride-hailing drivers in Hangzhou City in December 2018. The dependent variable is the average hourly earning measured by the earning of the transaction over the sum of the hours spent on the trip and the wait time. Wait time is based on the time between completing the previous trip and picking up a passenger for a new trip. In columns 1 and 2, we replace the wait time with the average wait time of the driver on the same day if the wait time is greater than 30 minutes. In columns 3 and 4, we replace the wait time with 0 if it is greater than 30 minutes.

Table 3 gradually adds controls and fixed effects from column 2 to column 5. Column 1 has the same specification as Table 2 column 2. Column 2 of Table 3 controls the day-of-week fixed effects and hour fixed effects, which decreases the gender earning gap by 0.14 percentage points (3.77% of the raw gap). Column 3 controls the origin fixed effects and destination fixed effects measured by dummies of geohash, which decreases the gender earning gap by 0.15 percentage points (4.04% of the raw gap). Column 4 controls the experience by adding age and square of age to the regression, which increases the gender earning gap by 0.06 percentage points (1.62% of the raw gap). Column 5 includes all the mentioned controls and fixed effects, which decrease the gender earning gap by 0.2 percentage points (5.39% of the raw gap). Overall, the results in Table 3 suggest that work time, work area, and experience across genders can

only explain a small part of the raw gender earning gap.

Table 3: Hourly gender earning gap in the Hangzhou ride-hailing industry

	(1)	(2)	(3)	(4)	(5)
VARIABLES	ln(Hourly income)				
Female	-0.0371***	-0.0357***	-0.0356***	-0.0377***	-0.0351***
	(0.00899)	(0.00879)	(0.00844)	(0.00904)	(0.00828)
Age				0.00581***	0.00583***
				(0.00163)	(0.00156)
Age_sq				-7.94e-05***	-7.77e-05***
				(2.17e-05)	(2.06e-05)
Mean of dependent variable	4.234	4.234	4.234	4.234	4.234
Day of week FE	No	Yes	No	No	Yes
Hour FE	No	Yes	No	No	Yes
Origin and destination FE	No	No	Yes	No	Yes
Observations	560,727	560,727	560,727	560,727	560,727
R-squared	0.000	0.008	0.028	0.001	0.036

Note: Standard errors in parentheses are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1. The sample used consists of transaction-level observations for ride-hailing drivers in Hangzhou City in December 2018. The dependent variable is the average hourly earning measured by the earning of the transaction over the sum of the hours spent on the trip and the wait time. Wait time is based on the time between completing the previous trip and picking up a passenger for a new trip. We replace the wait time with the average wait time of the driver on the same day if it is greater than 30 minutes.

Table 4 divides the sample into drivers on platforms with and without destination information. Column 1 indicates that on platforms that reveal the destination to drivers prior to accepting requests, the gender earning gap is 2.48%, but this gap is only 1.21% for drivers on platforms without such information. The difference between the two types of platforms, although insignificant, suggests that drivers operating in platforms that disclose destinations might selectively choose requests to accept.[4]

[4]The gender earning gaps are smaller in both types of platforms compared to pooling them together, which might be caused by the difference in average gross income across platforms. We argue that the comparison of average gross income across platforms is less informative because the net income of each transaction is subject to the revenue shares between drivers and platforms.

Table 4: Hourly gender earning gap in platforms with and without destination information

	(1)	(2)	(3)	(4)
	ln(Hourly income)			
VARIABLES	Dest_on	Dest_off	Dest_on	Dest_off
Female	-0.0248***	-0.0121**	-0.0111**	-0.0101
	(0.00819)	(0.00518)	(0.00448)	(0.00625)
ln(Speed)			0.549***	0.506***
			(0.00646)	(0.00291)
Mean of dependent variable	4.125	4.256	4.125	4.256
Controls	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes
Origin and destination FE	Yes	Yes	Yes	Yes
Observations	93,907	466,814	93,907	466,814
R-squared	0.063	0.041	0.691	0.636

Note: Standard errors in parentheses are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1. The sample used consists of individual-day level observations for ride-hailing drivers in Hangzhou City in December 2018. The dependent variable is the average hourly earning measured by the earning of the transaction over the sum of the hours spent on the trip and the wait time. Wait time is based on the time between completing the previous trip and picking up a passenger for a new trip. We replace the wait time with the average wait time of the driver on the same day if it is greater than 30 minutes. Controls included are age and age square.

In the conceptual framework, we argue that platforms that reveal destination information to drivers have a larger gender gap because male drivers exploit their experience and select requests that allow them to drive faster. If that is the driving force, we would expect to see a smaller or negligible difference across different types of platforms once we control the speed. As in Table 4 columns 3 and 4, when we control the logarithm of speed, the gender earning gap in the platform with destination information decreases to 1.11%, while the gender earning gap in platforms without destination information remains largely unchanged. Moreover, the magnitude of the gender earning gaps is similar in different types of platforms after controlling the speed. Judging from columns 3 and 4, speed may explain between one-third to a half of the gender earning

gap (depending on whether pooling or separating specifications are used). However, a significant portion of the gender earning gap remains that cannot be explained. This could be due to a selection of vehicle brands and models, which can have a direct impact on hourly income.

Drivers on platforms that reveal the destination beforehand can infer several pieces of information regarding the attractiveness of potential ride requests: (1) the expected speed of the trip, which is predicated upon the particular route and traffic conditions; (2) the distance of the trip, which can be directly derived from the origin and destination information; and (3) the safety of the destination, a matter more likely to be of concern at night.

We decompose the variance of the logarithm of hourly earnings into five sets of factors: the logarithm of speed, the logarithm of distance, the origin fixed effects and destination fixed effects, the day of week fixed effects and hour fixed effects, and age fixed effects. Table 5 shows that the variance in speed accounts for approximately 62.62% of the total variance in hourly earnings, the variance in the distance accounts for 13.12% of the total variance; the fixed effects controlling for time, area, and experience only accounts for 2.23% of the total variance. This suggests that speed has more of a dominant effect on variance in hourly earnings than distance and other control variables. This is consistent with our findings in Table 3, which shows adding time and area fixed effects and experience only explains a small part of the raw gender earning gap.

Table 5: Dominance analysis of factors that affect hourly earning

ln(Hourly income)	Donimance Stat.	Standardized Domin. Stat.	Ranking
ln(Speed)	0.6262	0.8032	1
ln(Distance)	0.1312	0.1682	2
Origin and destination FE	0.0146	0.0187	3
Day of week FE and hour FE	0.0064	0.0082	4
Age FE	0.0013	0.0016	5
Overall fit statistics	0.7796		

The sample used consists of transaction-level observations for ride-hailing drivers in Hangzhou City in December 2018. The dependent variable is the average hourly earning measured by the earning of the transaction over the sum of the hours spent on the trip and the wait time. Wait time is based on the time between completing the previous trip and picking up a passenger for a new trip. We replace the wait time with the average wait time of the driver on the same day if it is greater than 30 minutes.

Table Table 6 reports the results on the speed and the distance of the trip. Columns 1 and 2 show that on platforms that reveal the destination to drivers, males on average drive 2.49% faster than females; on platforms that do not show the destination this gap is negligible for drivers. Columns 3 and 4 show that male drivers on platforms with destination information take trips that on average are 3.55% longer, but female drivers take longer trips on platforms that do not show the destination.[5] The findings in Table 6 are consistent with our proposed mechanism that males are able to choose more lucrative requests when the destination information is revealed.

[5]The relationship between distance and hourly income should be regarded with caution. There is a positive correlation between hourly income and distance, but the mechanism is mainly driven by the higher speed of longer trips. Adjusting for speed reveals an inverse correlation between hourly income and distance.

Table 6: Gender mile and speed gap in platforms with and without destination information

	(1) Dest on	(2) Dest off	(3) Dest on	(4) Dest off
VARIABLES	ln(Speed)		ln(Distance)	
Female	-0.0249**	-0.0039	-0.0355***	0.0111**
	(0.0112)	(0.0087)	(0.0132)	(0.0049)
Mean of dependent variable	-5.691	-5.670	1.669	1.703
Controls	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes
Origin and destination FE	Yes	Yes	Yes	Yes
Observations	93,907	466,814	92,979	463,749
R-squared	0.088	0.097	0.145	0.158

Note: Standard errors in parentheses are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1. The sample used consists of transaction-level observations for ride-hailing drivers in Hangzhou City in December 2018. The dependent variable in columns 1 and 2 is speed, while in columns 3 and 4 it is miles driven. Speed is measured by the miles driven over the sum of hours spent on the trip and the wait time. Wait time is based on the time between completing the previous trip and picking up a passenger for the new trip. We replace the wait time with the average wait time of the driver on the same day if it is greater than 30 minutes. Controls included are age and age square.

If the difference in exploiting destination information is the dominant mechanism that explains the gender earning gaps across platforms, we would expect to observe smaller gender earning gaps for drivers who possess more information ex-ante. One group that may have sufficient information is drivers with permanent driving licenses, who are familiar with traffic conditions. Both male and female drivers with sufficient experience can leverage the destination information to decide which requests to accept. Consequently, we expect to see a smaller gender earning gap among drivers obtaining permanent driver licenses than among drivers with temporary driver licenses when platforms that provide destination information are used.

Table 7: Hourly gender earning gap in platforms with destination information for drivers with different experiences

	(1)	(2)	(3)	(4)
	ln(Hourly income) with destination on			
	By driver license type		By age	
VARIABLES	Permanent	Temporary	Senior	Junior
Female	-0.00497	-0.0265***	-0.0206*	-0.0320***
	(0.0102)	(0.00882)	(0.0113)	(0.0120)
Mean of dependent variable	4.116	4.126	4.121	4.129
Controls	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes
Origin and destination FE	Yes	Yes	Yes	Yes
Observations	11,365	82,322	49,919	43,986
R-squared	0.082	0.063	0.068	0.063

Note: Standard errors in parentheses are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1. The sample used consists of individual-day-level observations for ride-hailing drivers in Hangzhou City in December 2018. The dependent variable is the average hourly earning measured by the earning of the transaction over the sum of hours spent on the trip and the wait time. Wait time is based on the time between completing the previous trip and picking up a passenger for a new trip. We replace the wait time with the average wait time of the driver on the same day if it is greater than 30 minutes. Controls included are age and age square. Senior drivers are those older than 36.

Table 7 columns 1 and 2 show that on platforms that provide destination information, the gender earning gap for drivers with temporary driver licenses is 2.65%, but is negligible for drivers with permanent driver licenses. Columns 3 and 4 show the results of robustness checks by dividing the drivers into senior and junior groups by their age. The gender earning gap is 3.20% for junior drivers and 2.06% for senior drivers, albeit the coefficients are not statistically different.

5 Conclusion

Our study highlights that the difference in exploiting destination information between male and female drivers perpetuates gender earning inequality in the ride-hailing industry. Using order-level data collected in December 2018 from Hangzhou City, we find a 3.5% hourly earning discrepancy between genders. In addition, we find that the gender earning gap is larger for platforms that display the destination information to drivers before they accept a ride. We argue that this difference arises due to gender differences in the utilization of destination information. Male drivers tend to be more experienced and are more likely to select more lucrative rides. In line with this mechanism, we also observe a greater gender disparity in speed and distance on platforms that disclose destination information. Moreover, when dividing the sample into drivers with and without permanent driver licenses, we find the hourly gender earning gap is more pronounced among drivers without permanent driver licenses, lending support to our proposed mechanism.

References

Angrist, Joshua D, Sydnee Caldwell, and Jonathan V Hall. 2021. "Uber versus taxi: A driver's eye view." *American Economic Journal: Applied Economics*, 13(3): 272–308.

Berger, Thor, Chinchih Chen, and Carl Benedikt Frey. 2018. "Drivers of disruption? Estimating the Uber effect." *European Economic Review*, 110: 197–210.

Bertrand, Marianne, Claudia Goldin, and Lawrence F Katz. 2010. "Dynamics of the gender gap for young professionals in the financial and corporate sectors." *American economic journal: applied economics*, 2(3): 228–255.

Blau, Francine D, and Lawrence M Kahn. 2017. "The gender wage gap: Extent, trends, and explanations." *Journal of economic literature*, 55(3): 789–865.

Bolotnyy, Valentin, and Natalia Emanuel. 2022. "Why do women earn less than men? Evidence from bus and train operators." *Journal of Labor Economics*, 40(2): 283–323.

Camerer, Colin, Linda Babcock, George Loewenstein, and Richard Thaler. 1997. "Labor Supply of New York City Cabdrivers: One Day at a Time." *Quarterly Journal of Economics*, 112: 407–441.

Chen, M Keith, Peter E Rossi, Judith A Chevalier, and Emily Oehlsen. 2019. "The value of flexible work: Evidence from Uber drivers." *Journal of Political Economy*, 127(6): 2735–2794.

Chou, Yuan K. 2002. "TESTING ALTERNATIVE MODELS OF LABOUR SUPPLY: EVIDENCE FROM TAXI DRIVERS IN SINGAPORE." *The Singapore Economic Review*, 16: 17–47.

Cook, Cody, Rebecca Diamond, Jonathan V Hall, John A List, and Paul Oyer. 2021. "The gender earnings gap in the gig economy: Evidence from over a million rideshare drivers." *The Review of Economic Studies*, 88(5): 2210–2238.

Crawford, Vincent P., and Juanjuan Meng. 2011. "New York city cab drivers' labor supply revisited: Reference-dependent preferences with rational-expectations targets for hours and income." *American Economic Review*, 101: 1912–1932.

Farber, Henry S. 2005. "Is Tomorrow Another Day? The Labor Supply of New York City Cabdrivers." *Journal of Political Economy*, 113: 46–82.

Farber, Henry S. 2015. "Why you can't find a taxi in the rain and other labor supply

lessons from cab drivers." *Quarterly Journal of Economics*, 130: 1975–2026.

Goldin, Claudia. 2014. "A grand gender convergence: Its last chapter." *American Economic Review*, 104(4): 1091–1119.

Guda, Harish, and Upender Subramanian. 2019. "Your uber is arriving: Managing on-demand workers through surge pricing, forecast communication, and worker incentives." *Management Science*, 65(5): 1995–2014.

Liu, Meng, Erik Brynjolfsson, and Jason Dowlatabadi. 2021. "Do digital platforms reduce moral hazard? The case of Uber and taxis." *Management Science*, 67(8): 4665–4685.

Liu, Meng, Xiaocheng Tang, Siyuan Xia, Shuo Zhang, Yuting Zhu, and Qianying Meng. 2023. "Algorithm aversion: Evidence from ridesharing drivers." *Management Science*.

Thakral, Neil, and Linh T Tô. 2021. "Daily labor supply and adaptive reference points." *American Economic Review*, 111(8): 2417–2443.