The Gender Pay Gap in the Gig Economy:

Evidence from over a Million Rideshare Drivers

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Will job flexibility close the gender pay gap?

The Gender Wage Gap Today:

- Female wages 88% of males in similar jobs (Blau and Kahn, 2017)
- Gap associated with fewer hours, weaker continuity of work, especially in middle-age when gaps largest (Bertrand et al. (2010); Blau and Kahn (2017))

Possible mechanism: job-flexibility penalty

- Imperfect worker substitution creates convex hours-earnings relationship (Goldin, 2014)
- Tech making workers more substitutable: removes flexibility penalty?

Will job flexibility close the gender pay gap?

Market for Uber drivers as a laboratory:

- Work is highly flexible, workers highly substitutable
- Unique setting with transparent compensation, highly detailed data
- Rules out "traditional forces"
  - Pay negotiation and promotions
  - Premium for working long hours
  - Direct gender discrimination by consumers
  - Job sorting

Gender pay gap for Uber drivers

$20.04

$21.28

Preview of results

Entire gap explained by where drivers work, experience, driving speed

- Where to drive: gender gap in location of work driven by differences in where men/women lives & women avoiding areas with bars and crime.
- Experience: women work fewer hours per week, higher attrition rates from Uber. Avg male has more experience $\rightarrow$ more productive than avg female
- Speed: men drive faster. Faster rides $\rightarrow$ more rides per hour $\rightarrow$ higher pay

Gender gap in experience likely important for gender wage gaps in many jobs

- Poor quality experience data $\rightarrow$ undervalue on-the-job learning in gender pay gaps
- With standard experience measure (polynomial in age), Uber drivers appear to earn a "long hours premium"
- Long hours correlated with more experience $\rightarrow$ overestimate "long hours premium"

Preview of results

Flexibility/substitutability unlikely to fully close gender wage gap

- Gig work commoditizes labor, making workers more substitutable $\rightarrow$ no convex returns to long hours
- Gig economy flexibility will not close the gender gap if a) long hours premium is proxy for experience and b) men and women differ in the types of gig work they complete

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National gender pay gap

Decomposing the gender pay gap, Chicago
- When/where drivers work
- Experience
- Speed

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Data on all US UberX/Pool drivers

National data

- Driver-week level data for UberX drivers in the US, 01/2015-03/2017
- 1,877,252 drivers, 513,417 of whom are female (27.3%)
  - 24.9 million driver-weeks in 196 cities

Gross earnings

- Earnings are gross of costs (e.g. gas, depreciation, Uber commission)
- Drivers paid by fixed formula – for each ride: base fare plus per-minute, per-mile rate, times any surge multiplier
- Drivers get various additional incentives (e.g., a small bonus for a certain number of trips in a week)

Driver earnings formula

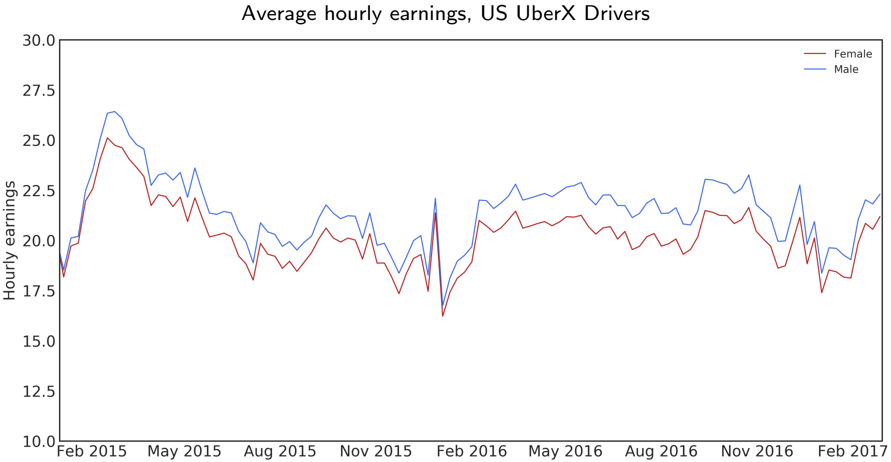
Driver earnings per hour are:

$$hourlyEarnings = \underbrace{60 * \left(SM * \left(r_b + d_1 r_d + \frac{r_t d_1}{s}\right) + I\right)}_{\text{trip earnings}} \Bigg/ \underbrace{\left(w + \frac{d_0 + d_1}{s}\right)}_{\text{time 'producing' trips}}$$

where

$$\begin{aligned} r_b &= \text{Base fare} & d_1 &= \text{On trip distance} \\ r_d &= \text{Per mile fare} & s &= \text{Speed} \\ r_t &= \text{Per minute fare} & w &= \text{Wait time for dispatch} \\ d_0 &= \text{Distance to pickup} & I &= \text{Incentive pay} \\ SM &= \text{Surge multiplier} & & \end{aligned}$$

Gender pay gap at Uber



Note: Data based on average hourly earnings across all driver-weeks for a given week. Earnings are pre-commission or other costs.

Summary statistics US drivers

	All	Men	Women
Weekly earnings	$376.38	$397.68	$268.18
Hourly earnings	$21.07	$21.28	$20.04
Hours per week	17.06	17.98	12.82
Trips per week	29.83	31.52	21.83
6 month attrition rate	68.1%	65.0%	76.5%
Number of drivers	1,873,474	1,361,289	512,185
Number driver/weeks	24,832,168	20,210,399	4,621,760
Number of Uber trips	740,627,707	646,965,269	93,662,438

Note: Values are based on all UberX/UberPOOL driver-weeks in the US from January 2015 - March 2017. The percent of drivers who are female varies across city; to mitigate composition effects, we weight averages at the city level by *total* number of drivers in a city, rather than by number of male (or female) drivers. 6 month attrition rate is defined as the percent of drivers who are no longer active 26 weeks after their first trip. We consider drivers to be active on a given date if they complete another trip within another 26 weeks of that date. For calculating attrition rate, we subset to drivers who completed their first trip between Jan 2015 and March 2016 to allow us to fully observe whether they are inactive, per the definition above, 26 weeks after they join.

Baseline regression: $6 - 7\%$ national pay gap

For driver d in week w, we regress

$$logHourlyEarnings_{d,w} \sim isMale_d + controls$$

	All US				Chicago	
	Weekly earnings		Log hourly earnings		Log weekly earnings	Log hourly earnings
isMale	0.4142	0.4092	0.0702	0.0653	0.4315	0.0485
	(0.002)	(0.002)	(0.001)	(0.001)	(0.007)	(0.001)
Intercept	4.9737	4.9208	2.9280	2.8849	5.0487	3.1151
	(0.002)	(0.002)	(0.001)	(0.001)	(0.009)	(0.001)
City	X	X	X	X		
Week		X		X	X	X
N	24,877,588	24,877,588	24,877,588	24,877,588	1,604,627	1,604,627
R^2	0.125	0.136	0.199	0.239	0.038	0.110

Note: This table documents the gender pay gap for all US cities from January 2015 to March 2017. Data are at the driver-week level; weekly earnings is the entire pay for a given week, while hourly earnings is the pay divided by hours worked in the week. Standard errors (clustered at the driver-level) in parentheses.

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More granular analysis using Chicago data

Focusing on one city: Chicago

- Allows far more granular data at *driver-hour level*, and can include details on driver behavior, such as
  - Where a driver drives
  - Time of day and day of week
  - # lifetime trips and tenure to-date
  - Average speed during that hour
  - Rider/driver cancellations
- Chicago drivers from January 2015 - March 2017. 120,223 drivers (30.2% female). 34.9 million driver/hours

We later replicate in San Francisco, Houston, Atlanta, Detroit, and Boston.

Parameters from the earnings function differ by gender

	Men	Women	Difference (Men - Women)
w – Wait time (min)	5.857	5.920	-0.063
	(0.00158)	(0.00346)	
d_0 – Accepts-to-pickup distance (mi)	0.569	0.580	-0.011
	(0.00044)	(0.00054)	
d_1 – Trip distance (mi)	5.108	5.070	0.038
	(0.00098)	(0.00223)	
s – Speed (mph)	18.262	17.634	0.628
	(0.00152)	(0.00333)	
SM – Surge multiplier	1.116	1.105	0.011
	(0.00005)	(0.00010)	
I – Incentive payout ($)	0.594	0.624	-0.030
	(0.00026)	(0.00062)	

Note: Averages are per-trip based on trips completed in Chicago. For wait time and accepts-to-pickup distance, averages are based on trips from May 2016 - March 2017 due to limitations in the underlying raw data. All other averages are based on data for the entire sample. Wait time is based on time between either coming online or completing previous trip and picking up passenger for new trip. Trip distance is based on actual route taken; however, accepts-to-pickup distance is the Haversine distance between corresponding coordinates. The gender composition of drivers changes over time; to correct for this, we re-weight observations in each week of data by (total trips)/(trips by that gender). Standard errors reported in parentheses.

Wage gap in Chicago: fully explained & no evidence of discrimination

	(1)	(2)	(3)	(4)
isMale	0.0356	0.0355	−0.0018	−0.0018
	(0.003)	(0.003)	(0.002)	(0.002)
riderCancellations		-0.0091		-0.0238
		(0.000)		(0.000)
driverCancellations		0.0078		-0.0158
		(0.003)		(0.002)
Intercept	3.0862	3.0869	1.7346	1.7452
	(0.003)	(0.003)	(0.003)	(0.004)
Driver experience			X	X
Log driving speed			X	X
Week	X	X	X	X
Hour of week			X	X
Geohash			X	X
N	11,572,163	11,572,163	11,572,163	11,572,163
R^2	0.039	0.039	0.266	0.267

Note: This table documents both the gender pay gap in hourly earnings with and without controls for experience, location, time, speed, and cancellations. Driver experience is measured by a driver's lifetime trips completed prior to a given date, where lifetime trips is binned into 0-100 trips, 100-500 trip, 500-1000 trips, 1000-2500 trips, and >2500 trips. Driving speed is the speed driven while on trip in a given driver-hour. Standard errors (clustered at the driver-level) in parentheses.

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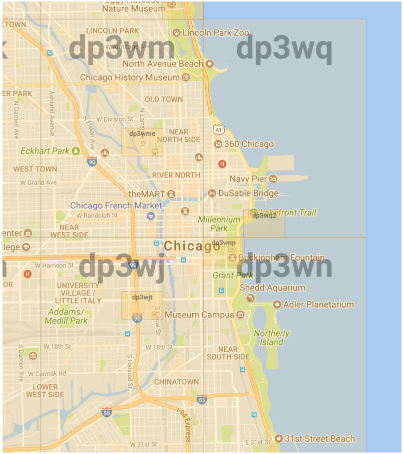
Controlling for when/where drivers work

When

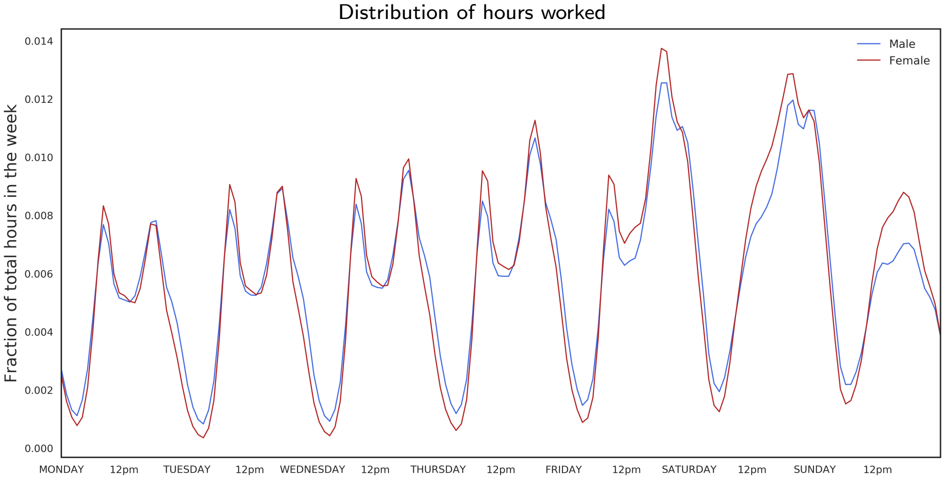
For each driver-hour, we include a dummy for the hour of week (168 total hours)

Where

We use geohashes to control for where drivers work. For each hour, we track which geohashes drivers had a trip start within. We restrict to the top 50 geohashes in the greater Chicago area, which accounts for 89.2% of all trips

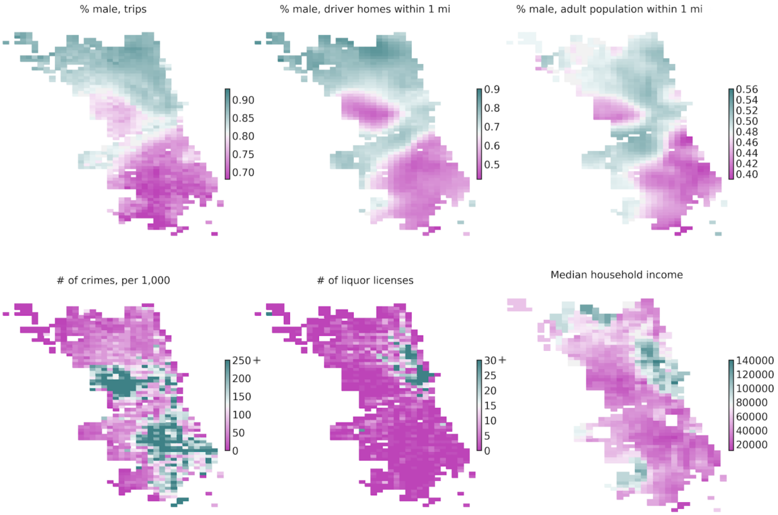


Men tend to drive late nights more



Note: This figure shows percent of time drivers spend in a certain hour. Data are constructed by dividing hours worked in a given hour by men/women by the total hours worked by men/women

Driving location correlated with home, crime



Driver's home location predicts driving locations

Dependant Variable: Log male share of rides within geohash

	(1)	(2)	(3)
Log share of driver homes male (within 1mi)	0.6667		0.7175
	(0.010)		(0.016)
Log # of crimes per 1,000pp		-0.0866	0.0334
		(0.009)	(0.006)
Log # of liquor licenses		0.1366	0.0653
		(0.011)	(0.007)
Log median household income		0.1495	-0.0374
		(0.027)	(0.016)
Log share adult census pop. male (within 1mi)		0.3833	-0.1396
		(0.053)	(0.032)
Intercept	0.9180	0.0587	1.0748
	(0.011)	(0.311)	(0.180)
N	1,014	1,014	1,014
R^2	0.774	0.435	0.815

Note: Data are at the geohash level. The outcome variable is the log share of rides within a geohash that were completed by men.

Adding Where/when controls

	(1)	(2)	(3)	(4)	(5)
isMale	0.0356	0.0302	0.0261	0.0220	0.0210
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Intercept	3.0862	3.0912	3.0946	3.0980	3.0989
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Week	X	X	X	X	X
Hour of week		X		X	X
Geohash			X	X	X
Geohash*hour of week					X
N	11,572,163	11,572,163	11,572,163	11,572,163	11,572,163
R^2	0.039	0.099	0.092	0.143	0.161

Note: Data are at the driver-hour level. Geohash controls are a vector of dummies for whether a driver had a trip (or Pool chain) start in a given geohash in that hour. Standard errors (clustered at the driver-level) in parentheses.

"Where" effects fully explained by residence, crime, and bars

	All Chicago data			City of Chicago only	
	(1)	(2)	(3)	(4)	(5)
isMale	0.0302	0.0261	0.0220	0.0434	0.0026
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
Log # of crimes per 1,000pp					0.0043
					(0.003)
Log # of liquor licenses					0.0675
					(0.003)
Intercept	3.0912	3.0946	3.0980	3.1199	1.7117
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Week	X	X	X	X	X
Hour of week	X		X		X
Geohash		X	X		
Driver home geohash					X
Experience bins					X
Log speed					X
N	11,572,163	11,572,163	11,572,163	7,969,988	7,969,988
R^2	0.099	0.092	0.143	0.062	0.306

Note: Data are at the driver-hour level. Geohash controls are a vector of dummies for whether a driver had a trip (or Pool chain) start in a given geohash in that hour. Standard errors (clustered at the driver-level) in parentheses.

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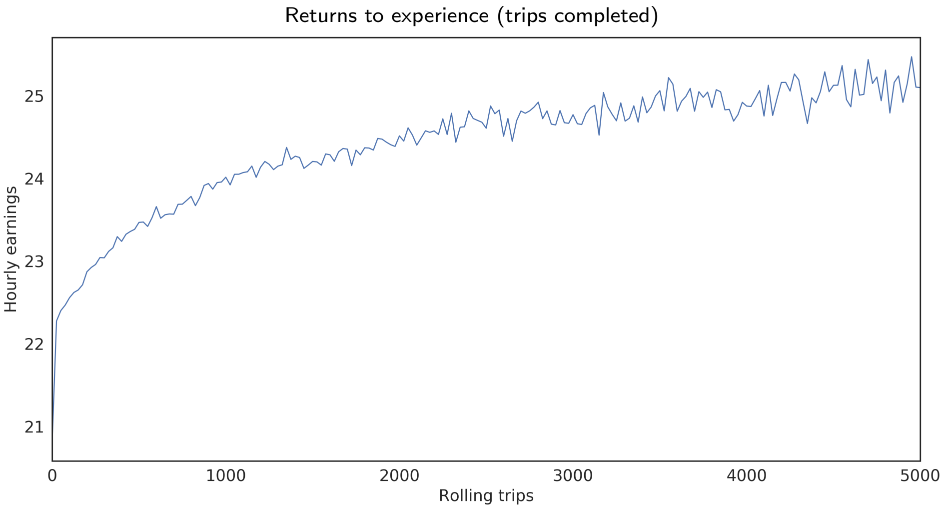
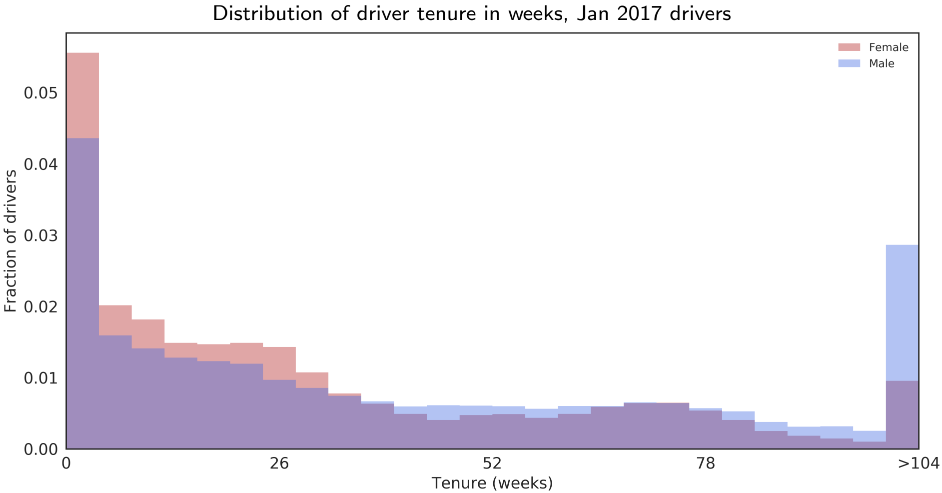
Substantial returns to experience



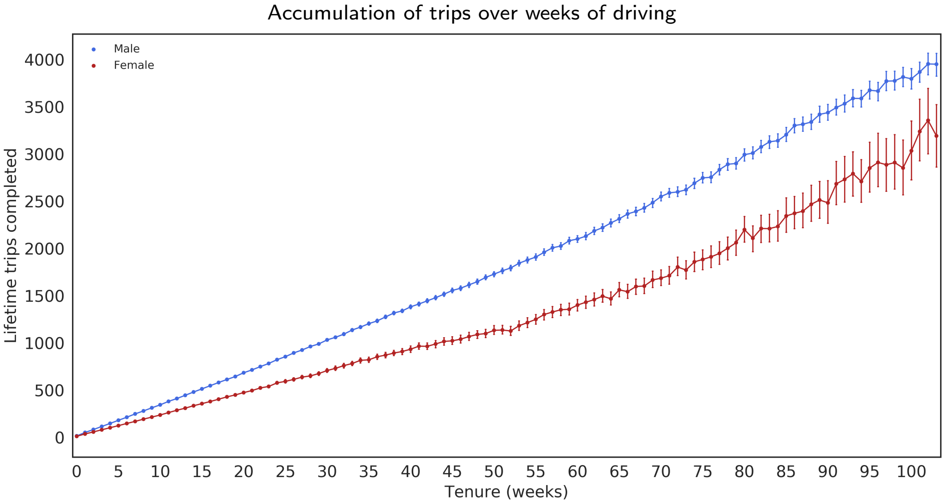
Note: This figure shows how earnings increase as drivers have completed more trips on the platform. Trips completed is binned by 25 to smooth the plot and have sufficient observations per group.

Men on platform for longer time



Note: This figure shows the number of weeks on the platform for all drivers who completed a trip in January 2017

Men accumulate experience more quickly



Note: This figure shows the average number of lifetime trips completed for drivers of a certain tenure. Tenure is based on the number of weeks since a driver completed their first trip. The data only include driver-weeks with >0 trips.

Controls for experience shrink pay gap to under 1%

	(1)	(2)	(3)	(4)
isMale	0.0138	0.0083	0.0129	0.0085
	(0.003)	(0.003)	(0.003)	(0.002)
Trips completed: 100-500	0.0530	0.0497	0.0357	0.0334
	(0.001)	(0.001)	(0.001)	(0.001)
Trips completed: 500-1000	0.0773	0.0747	0.0512	0.0494
	(0.002)	(0.002)	(0.002)	(0.001)
Trips completed: 1000-2500	0.1001	0.0990	0.0650	0.0648
	(0.002)	(0.002)	(0.002)	(0.002)
Trips completed: $>$2500	0.1391	0.1390	0.0877	0.0890
	(0.004)	(0.003)	(0.003)	(0.003)
Intercept	3.0228	3.0294	3.0528	3.0570
	(0.002)	(0.001)	(0.003)	(0.001)
Week	X	X	X	X
Hour of week		X		X
Geohash			X	X
N	11,572,163	11,572,163	11,572,163	11,572,163
R^2	0.048	0.107	0.096	0.146

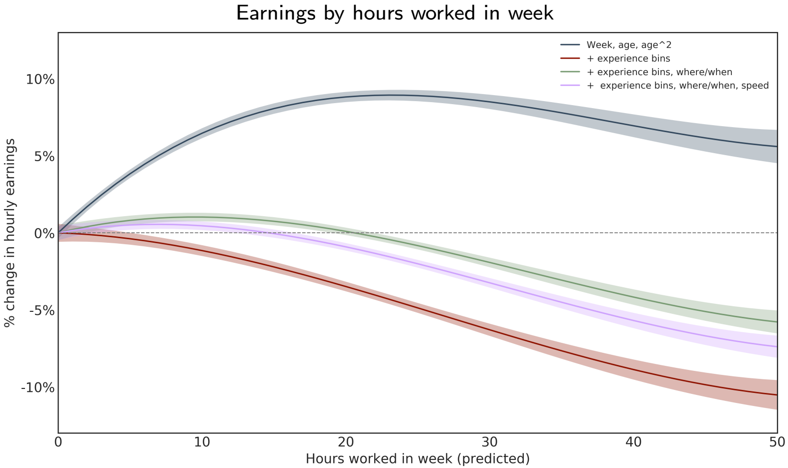
Note: Data are at the driver-hour level. Trips completed is based on lifetime trips before a given day of work. Standard errors (clustered at the driver-level) in parentheses.

In appendix: Learning curves identical for men and women Cohort

Returns to experience vs job-flexibility penalty

- Working few hours per week, weak job continuity $\rightarrow$ women gain experience slower than men $\rightarrow$ gender pay gap due to productivity differences
- Standard datasets measure experience imprecisely (age $-$ yrs of edu)
- What looks like a job-flexibility penalty may be proxy for return to experience
- Role of job-flexibility penalty vs. returns to experience policy relevant:
  - Tech to make jobs flexible may not improve gender wage gap if gap driven by productivity value of experience
  - Need tech to "flatten the learning curve" to close gender gap
  - Need broader changes in time-use by gender to equate experience

Return to long hours for Uber drivers?



Note: This figure graphs the effect on earnings of different values of driving intensity, defined by how often they are predicted to drive in the week of observation (predicted based on hours driven in past weeks) using a regression of log hourly earnings on cubic predicted hours worked. Drivers in their first week of work are not included. "Experience bins" and "where/when" controls are the same as those used throughout the paper. Shaded region represents 95% confidence interval based on standard errors clustered at the driver-level.

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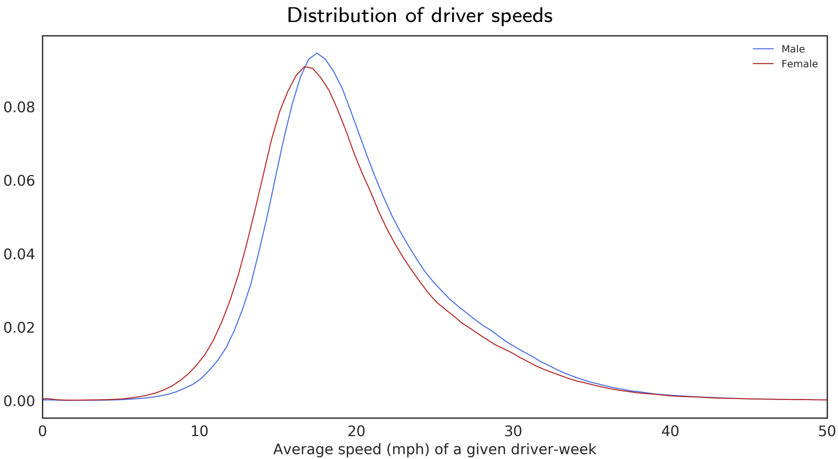
Driving speed: pay structure rewards speed

Uber per minute and per mile rates may be balanced in such a way that there could be an advantage to driving fast

- In Chicago, drivers are paid only \$0.20 per minute, but \$0.90 per mile. Other cities are even more skewed – Baltimore pays \$0.11 per minute and \$1.15 per mile
- Faster driving is a productive trait (conditional on same number of accidents...)
- We calculate driver speed in a given hour based on trip duration and distance traveled on trip in that hour

Men drive faster than women



Note: Data are at the driver-week level. Speed is calculated by dividing total trip distance by total trip time in a given driver-week.

Speeding is not a learned behavior (much)

$$logSpeed_{d,h} \sim isMale_d + controls$$

	(1)	(2)
isMale	0.0236	0.0218
	(0.002)	(0.002)
Trips completed: 100-500		0.0039
		(0.001)
Trips completed: 500-1000		0.0075
		(0.001)
Trips completed: 1000-2500		0.0096
		(0.002)
Trips completed: $>$2500		0.0110
		(0.002)
Intercept	2.9174	2.9119
	(0.001)	(0.001)
Week	X	X
Geohash*hour of week	X	X
N	11,572,163	11,572,163
R^2	0.352	0.352

Note: Data are at the driver-hour level. Speed is calculated as distance on trip over time on trip for the given driver-hour.

Speed explains remaining gender gap

	(1)	(2)	(3)	(4)
isMale	0.0256	0.0106	0.0016	−0.0018
	(0.004)	(0.002)	(0.002)	(0.002)
logSpeed	0.2677	0.4552	0.2715	0.4544
	(0.002)	(0.001)	(0.002)	(0.001)
Intercept	2.3084	1.7704	2.2293	1.7346
	(0.003)	(0.004)	(0.005)	(0.004)
Week	X	X	X	X
Hour of week		X		X
Geohash		X		X
Experience bins			X	X
N	11,572,163	11,572,163	11,572,163	11,572,163
R^2	0.101	0.263	0.111	0.266

Note: Data are at the driver-hour level. Speed calculated as trip distance over trip duration in a given hour. Standard errors (clustered at the driver-level) in parentheses.

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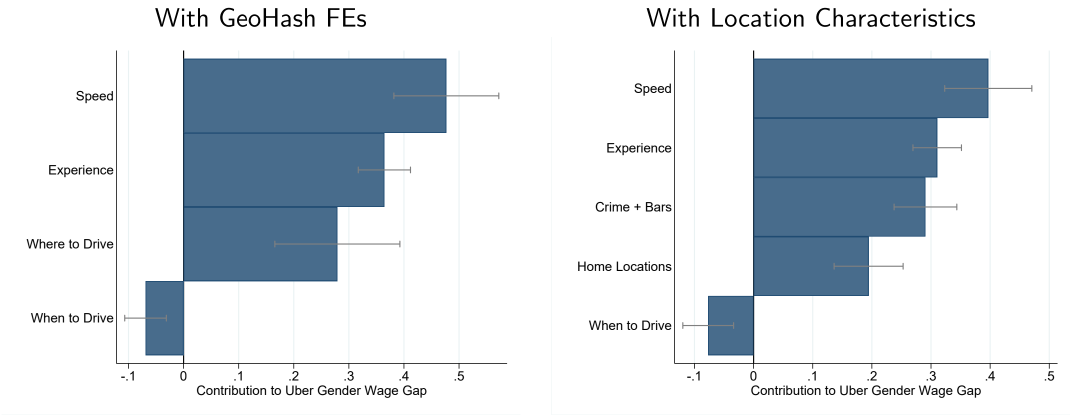
Speed, experience, and location drive pay gap



Decomposition following Gelbach (2016)

Results qualitatively similar in other cities

	Chicago	San Francisco	Boston	Houston	Detroit	Atlanta
Number of drivers	120,223	110,189	72,130	42,194	24,130	64,200
Percent female	30.2%	25.6%	19.8%	26.7%	26.6%	41.9%
Baseline wage gap	0.0356	0.0980	0.0520	0.0327	0.0361	0.0313
	(0.003)	(0.006)	(0.005)	(0.004)	(0.004)	(0.003)
Controls for when, where	0.0220	0.0619	0.0345	0.0156	0.0173	0.0153
	(0.002)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)
Controls for experience, when, where	0.0085	0.0255	0.0134	0.0022	0.0112	0.0045
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Controls for speed, when, where, experience	-0.0018	0.0165	0.0052	-0.0145	0.0024	-0.0022
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Gelbach – when	-0.0691	-0.0032	-0.0262	-0.0886	0.1108	0.0172
	(0.0193)	(0.0055)	(0.0240)	(0.0296)	(0.0183)	(0.0250)
Gelbach – where	0.2791	0.0183	0.1455	0.1741	0.1270	0.2064
	(0.0579)	(0.0262)	(0.0443)	(0.0169)	(0.0357)	(0.0201)
Gelbach – experience	0.3645	0.4151	0.3829	0.4088	0.2529	0.3681
	(0.0241)	(0.0226)	(0.0536)	(0.0535)	(0.0601)	(0.0381)
Gelbach – speed	0.4770	0.4330	0.4202	0.9923	0.4719	0.5609
	(0.0485)	(0.0395)	(0.0287)	(0.1024)	(0.0536)	(0.0570)

Note: This table includes results from 5 other US cities. All numbers – except for the summary statistics and Gelbach decompositions – are the coefficients on isMale from our standard regressions, with controls: 'when' refers to hour of week, 'where' refers to geohashes, 'experience' refers to bins of lifetime trips, and 'speed' is the log average speed on trip for the given hour. All specifications also control for the calendar week. The outcome variable is log of hourly earnings. Observations are at the driver-hour level. For larger cities, regressions are run on subsets no smaller than 35% so that the full specification is more computationally tractable. Standard errors (in parentheses) clustered at the driver level.

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Gender differences in preferences/constraints external to labor market impacts labor supply choices, wages:

- Gendered differences in residential location, driving speed, safety risks lead to different labor supply decisions, creating gender productivity and wage gaps
- Equalizing these gender differences requires broad society changes, far beyond labor market

Premium pay for long hours proxies for returns to experience:

- Without high quality experience measures, can not disentangle long hours premium from on-the-job learning
- As work becomes commoditized and workers more substitutable, "long hours premium" should decline
- In Uber, what looks like long hours premium is actually on-the-job learning: fewer hours means fewer accumulated experience
- In broader economy, need better experience measures before suggesting that commoditizing jobs to lower long hours premium will narrow gender wage gap

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Distribution of driver race

	Men	Women
Likely Hispanic	18.52%	14.88%
Likely Black	20.02%	45.20%
Likely Asian	9.40%	2.21%
Likely White	52.06%	37.71%

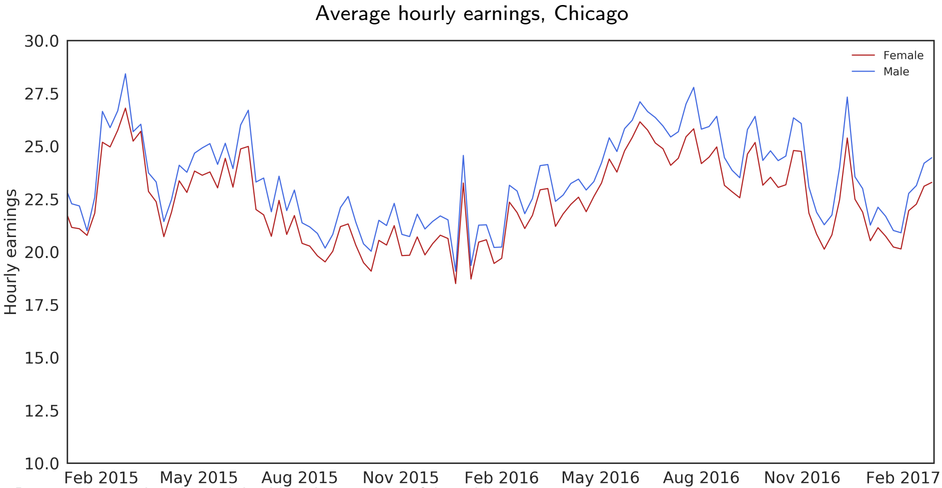
Note: This table presents the distribution of drivers across races. Race is imputed based on a driver's name and home census block; we define driver race based on the most probable race from the imputation.

Regressions with race controls

	(1)	(2)
isMale	0.0303	-0.0038
	(0.003)	(0.002)
Intercept	3.0850	1.9418
	(0.003)	(0.007)
Driver race	X	X
Week	X	X
Hour of week		X
Geohash		X
Experience bins		X
Log speed		X
N	11,572,163	11,572,163
R^2	0.040	0.259

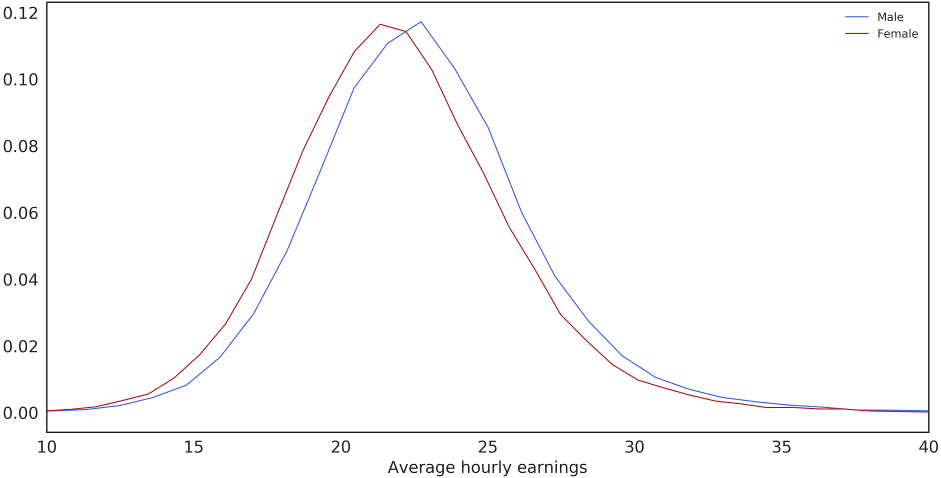
Note: Data are at the driver-hour level. rejectDispatch and cancelTrip are dummies for whether a driver rejected or canceled a trip in the given hour. Standard errors (clustered at the driver-level) in parentheses.

Earnings



Note: Data is aggregated to the week-level based on earnings of driver-hours in a given week.

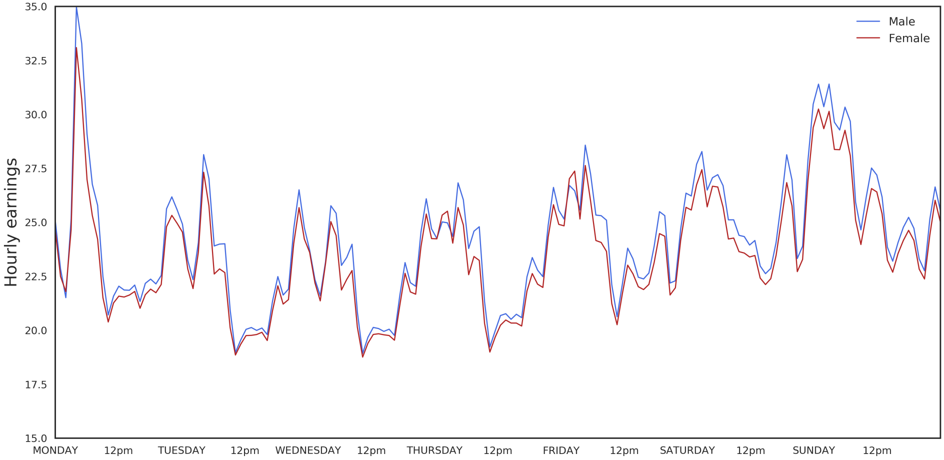
Earnings



0.12
0.10
0.08
0.06
0.04
0.02
0.00
10
15
20
25
30
35
40
Average hourly earnings
Male
Female

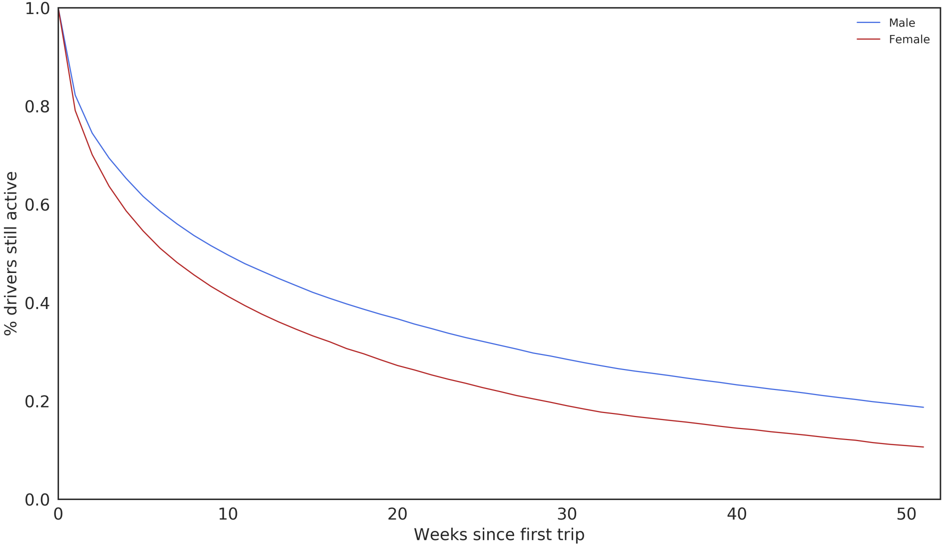
When drivers work

Earnings vary over course of the week, but the wage gap always present



Driver attrition

Men have lower attrition rates



Experience: differential learning

	(1)	(2)
isMale	0.0145	0.0096
	(0.002)	(0.002)
Trips completed: 100-500	0.0529	0.0343
	(0.003)	(0.002)
Trips completed: 500-1000	0.0768	0.0493
	(0.004)	(0.003)
Trips completed: 1000-2500	0.0995	0.0655
	(0.006)	(0.004)
Trips completed: $>$2500	0.1453	0.0919
	(0.014)	(0.009)
isMale*Trips completed: 100-500	−0.0004	−0.0006
	(0.003)	(0.003)
isMale*Trips completed: 500-1000	0.0004	−0.0002
	(0.004)	(0.004)
isMale*Trips completed: 1000-2500	0.0006	−0.0022
	(0.006)	(0.006)
isMale*Trips completed: $>$2500	−0.0069	−0.0067
	(0.0012)	(0.012)
Intercept	3.0223	3.0571
	(0.002)	(0.002)
Week	X	X
Geohash*hour of week		X
N	11,572,163	11,572,163
R^2	0.047	0.164

Note: Data are at the driver-hour level for Chicago drivers