EVROPSKÁ UNIE
Evropské strukturální a investiční fondy
Operační program Výzkum, vývoj a vzdělávání

MINISTERSTVO ŠKOLSTVÍ, MLÁDEŽE A TĚLOVÝCHOVY

Economics and Gender
Lecture 10

What can we learn from Uber?

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"The converging roles of men and women are among the grandest advances in society and the economy in the last century. But what must the last chapter contain for there to be equality in the labor market? It must involve changes in the labor market, especially how jobs are structured and remunerated to enhance temporal flexibility. The gender gap in pay would be considerably reduced and might vanish altogether if firms did not have an incentive to disproportionately reward individuals who labored long hours and worked particular hours." Goldin (2014)

EVOLUTION OF GENDER WAGE GAP (BLAU AND KAHN, 2017)

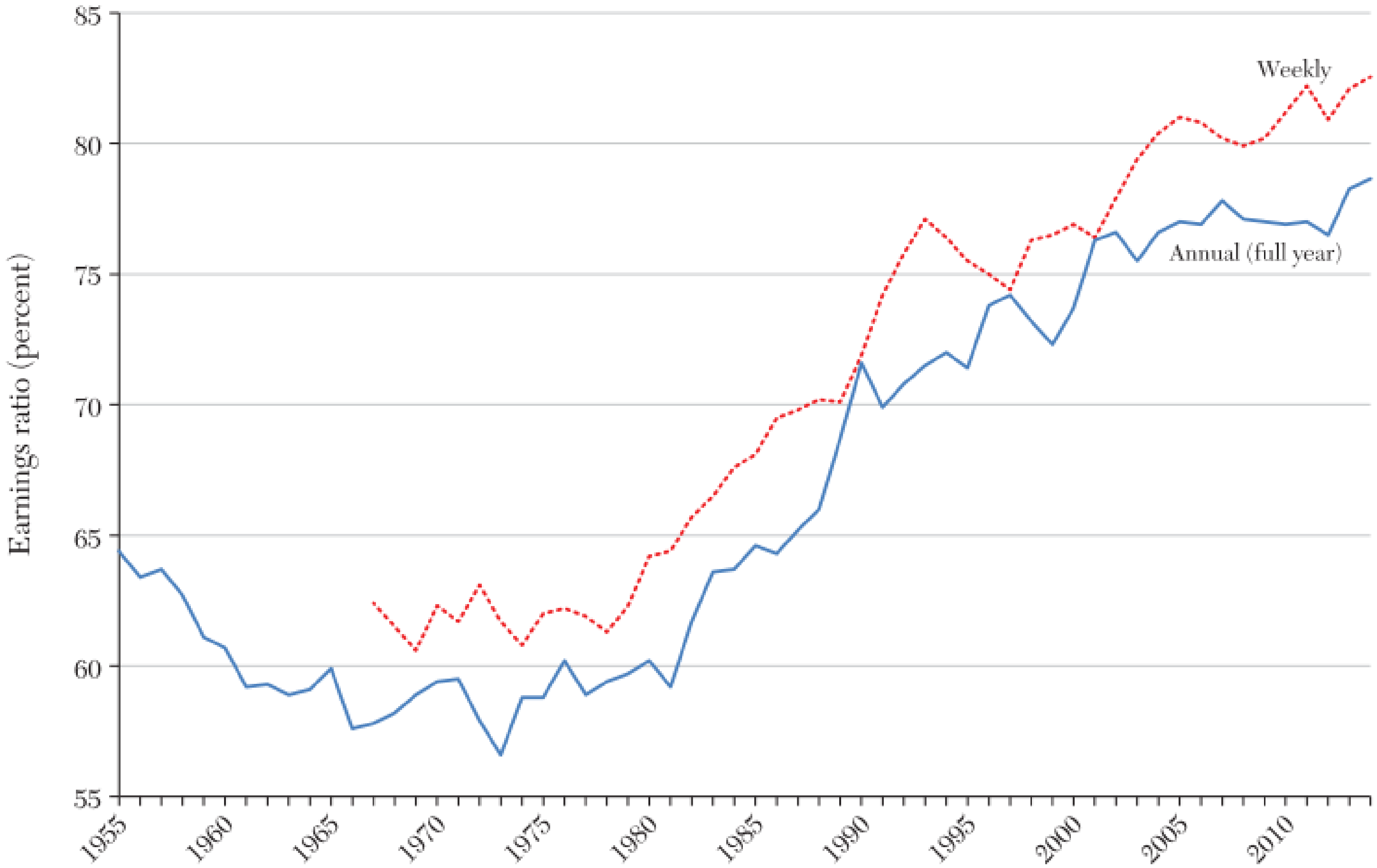


Figure 1. Female-to-Male Earnings Ratios of Full-Time Workers 1955–2014

Evolution of gender wage gap (Blau and Kahn. 2017)

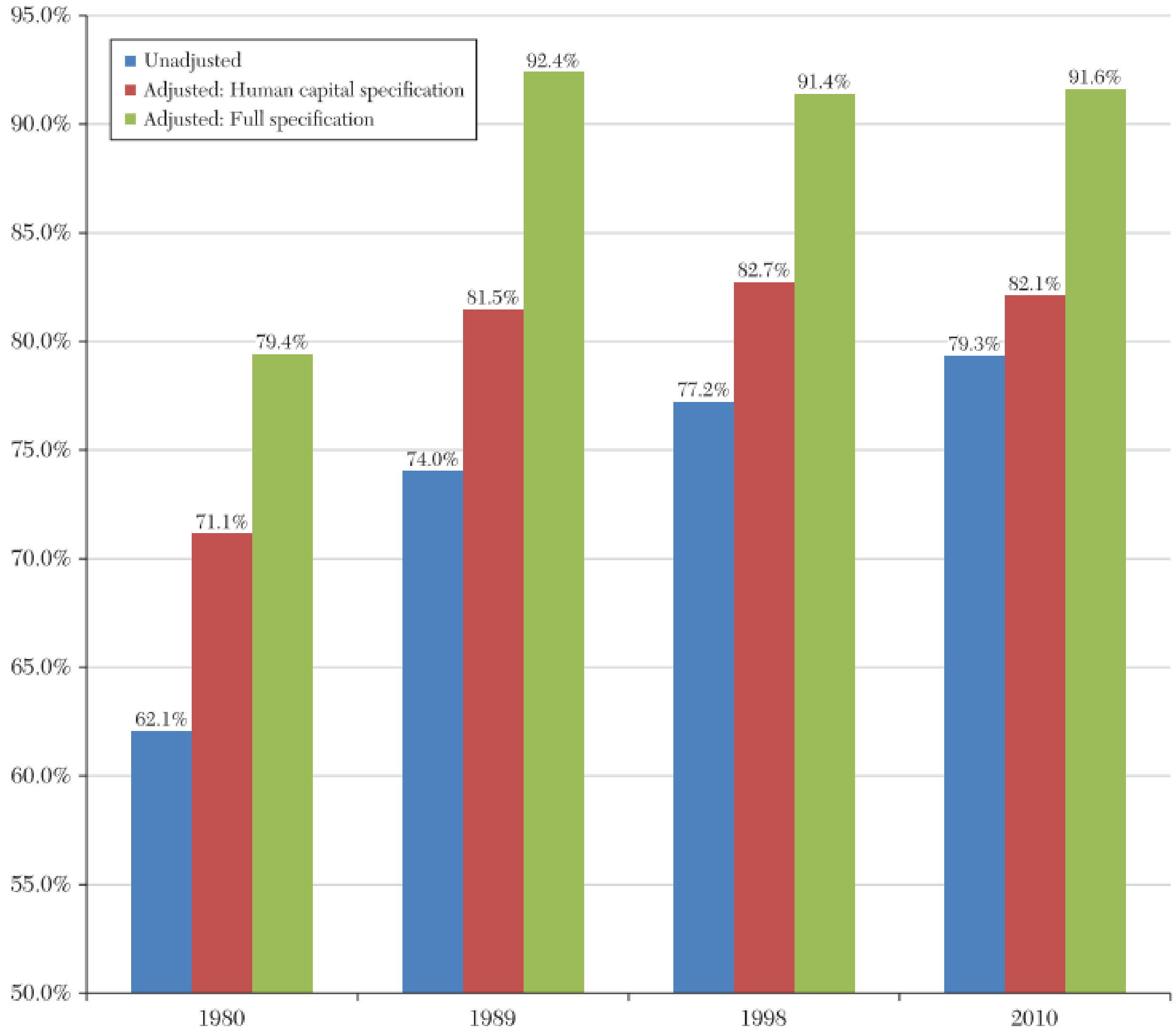


Figure 2. Female to Male log Wage Ratio, Unadjusted and Adjusted for Covariates (PSID)

EVOLUTION OF GENDER WAGE GAP (BLAU AND KAHN, 2017)

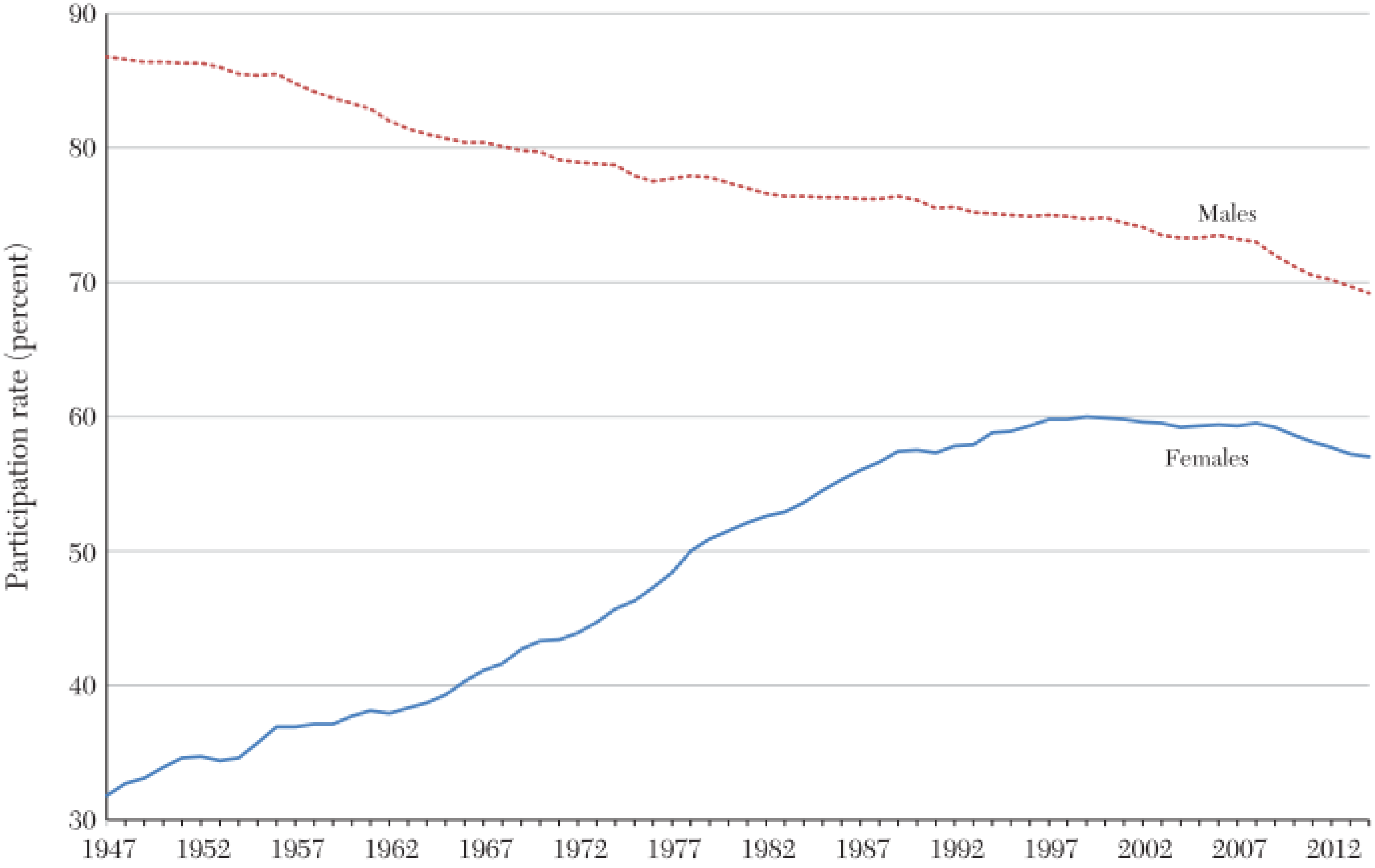


Figure 3. Trends in Female and Male Labor-Force Participation Rates, 1947–2014 (age sixteen and over)

LABOR FORCE PARTICIPATION (GREENWOOD ET AL. 2017)

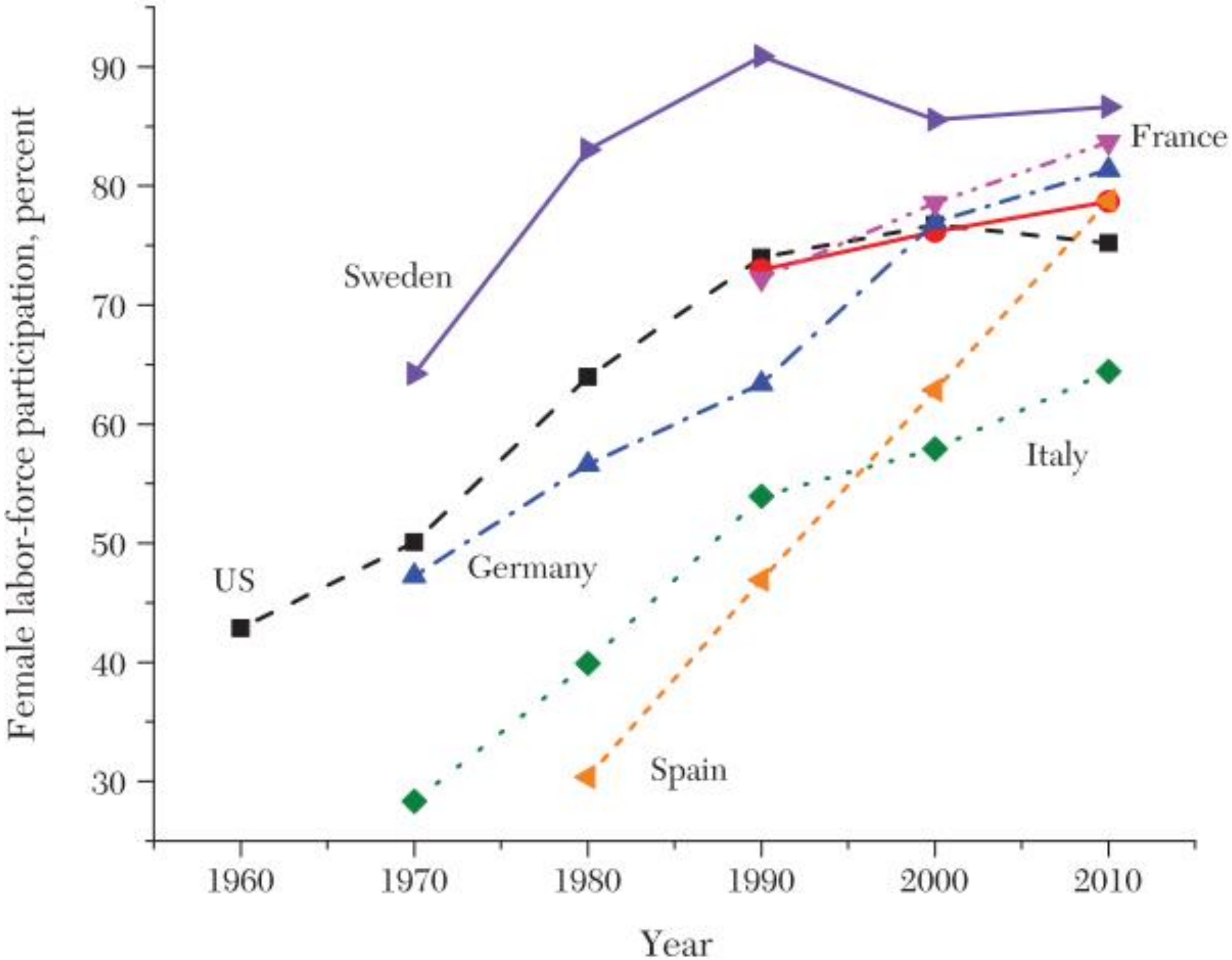


Figure 2. Female Labor-Force Participation, the United States and Western Europe, 1960–2010

LABOR FORCE PARTICIPATION – CHILDREN? (GREENWOOD ET AL. 2017)

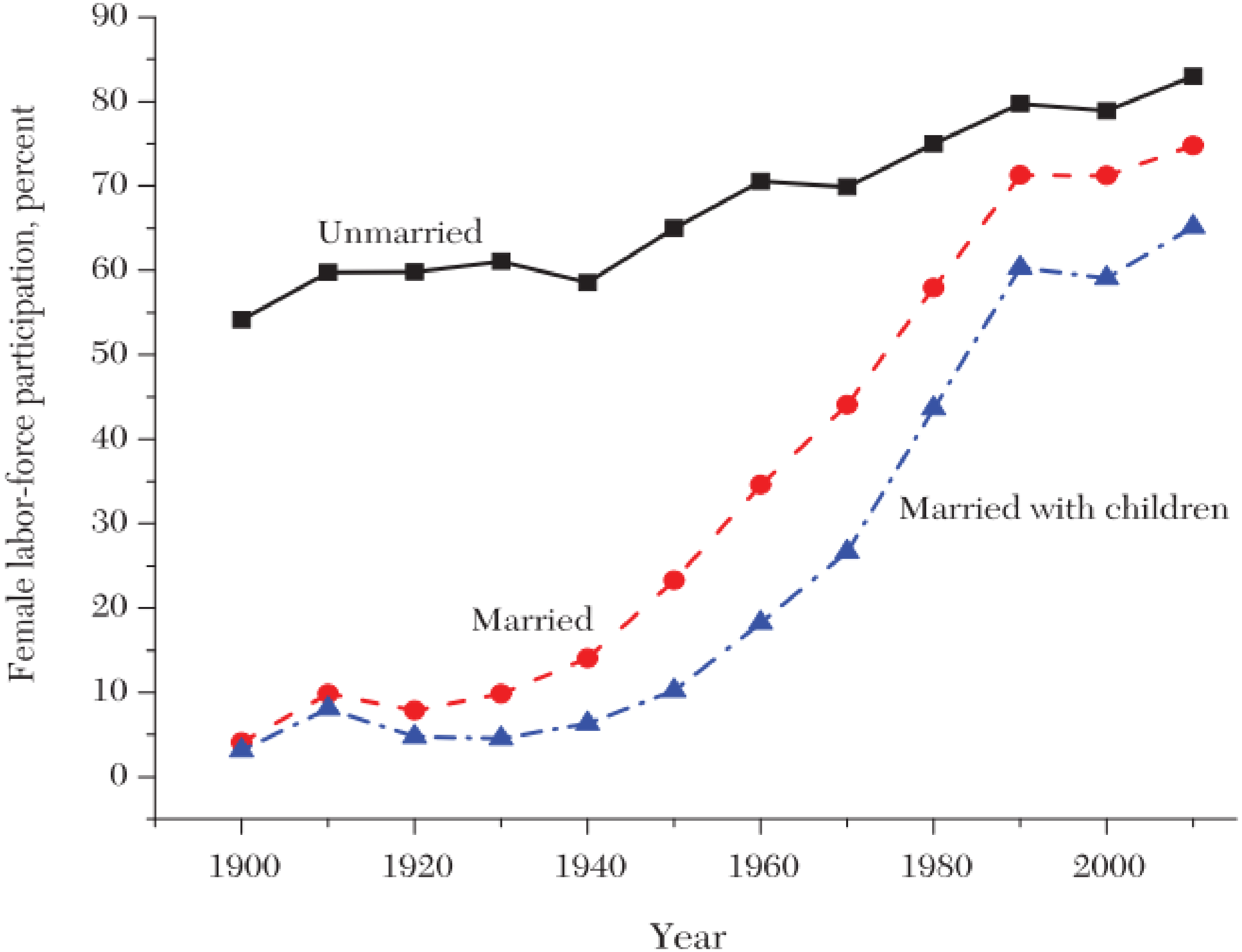


Figure 1. US Female Labor-Force Participation, 1900–2010

Labor force participation – children? (Greenwood et al. 2017)

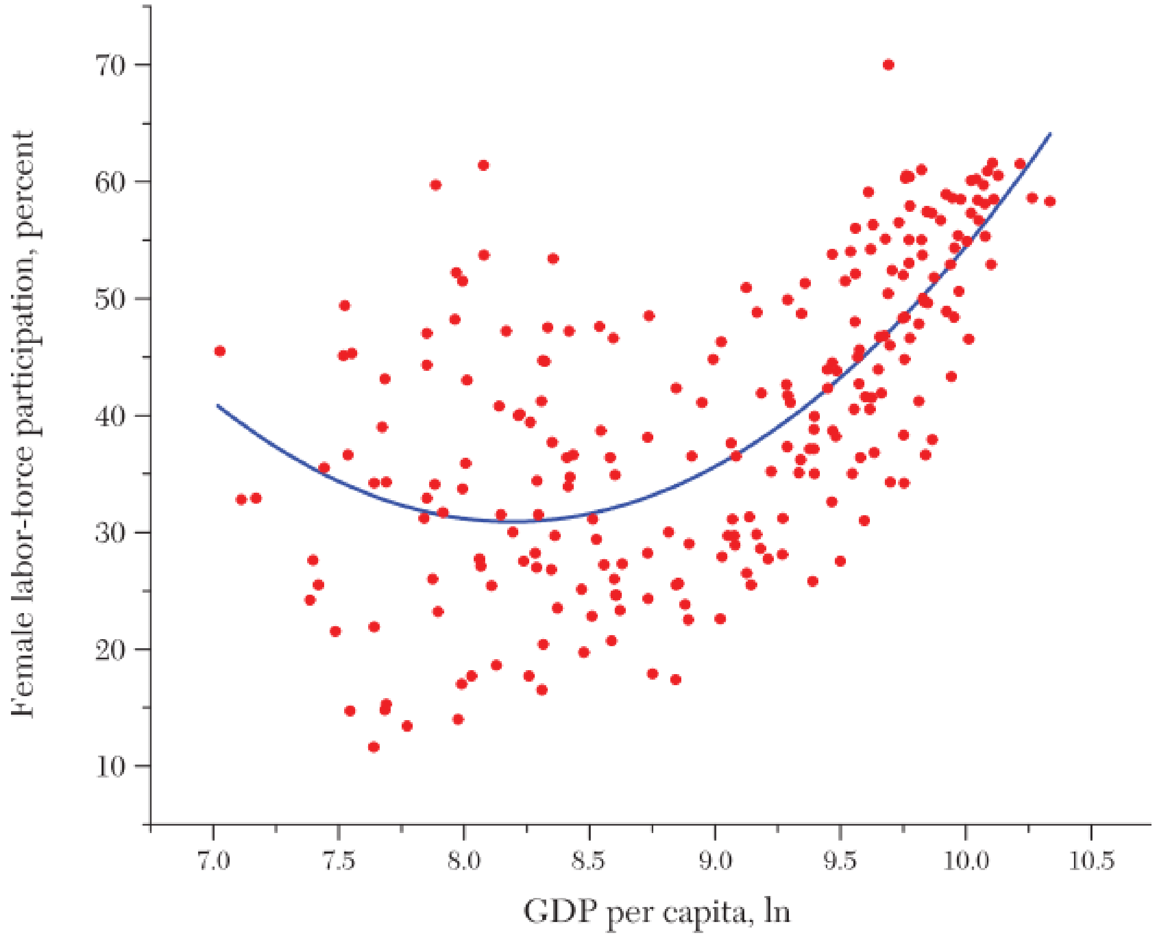


Figure 4. Economic Development and Female Labor-Force Participation for a Panel of Countries, 1890–2005

MOTIVATION

- women earn 88 cents on the dollar as compared to similar men in similar jobs (Blau and Kahn (2017))
- Most of remaining wage gap explained by fewer hours worked and weaker continuity of labor force participation
- work hours and disruption in labor force participation dramatically lower wages due to a "job-flexibility penalty„
  - imperfect substitution between workers can lead to a convex hours-earnings relationship

MOTIVATION (COOK ET AL, 2018)

- „gig“ economy
  - labor markets that divide work into small pieces
  - offer those pieces of work to independent workers in real-time with low barriers to entry
  - M-Turk, Uber, …
- Size
  - 15% of U.S. workers primarily do independent work
  - 30% do some independent work
- Female workers may be interested
  - flexible hours and transparent compensation
  - opportunity to make equal pay to their male counterparts (Hyperwallet 2017)

Uber

UBER

- American multinational transportation network company (TNC)
  - peer-to-peer ridesharing,
  - ride service hailing
  - Also food delivery, bicycle-sharing system
- As of 2019, Uber is estimated to have 110 million worldwide users
  - 69% US share in passenger transport
  - 25% food delivery
- Criticised by taxi drivers, dynamic pricing etc

HOW IT WORKS (COOK ET AL, 2018)

- software connects riders with drivers willing to provide trips at posted prices
- Riders can request a trip through a phone app
  - this request is then sent to a nearby driver
  - driver can either accept or decline the request during a short time window after seeing the rider's location
  - Declined => sent to another driver
  - (+ more variants)
- full discretion regarding when and where to work
- No employee benefits (healthcare, overtime, …)
- Transparent pay – fixed formula
  - Base rate + per-minute, per-distance, mutlipliER of demand
- Ratings of drivers

DRIVER EARNINGS (COOK ET AL, 2018)

- base fare r_b + a per-mile r_d + per-minute rate r_t
  - $1.70 base + $0.20 per minute + $0.95 per mile
  - Chicago 2017
  - High-demand bonus multiplier *SM*
- Additional incentives *I*
  - E.g. Completing a set of rides per week
  - (Under 9% of pay per hour)
- Effective hourly earnings *p(.)*

$$p(\cdot) = 60 * \left(\frac{SM\left(r_b + d_1 r_d + 60 * \frac{d_1 r_t}{s}\right) + I}{w + 60 * \frac{d_0 + d_1}{s}} \right)$$

DATA (COOK ET AL, 2018)

- all driver-weeks for drivers in the U.S. from January 2015 to March 2017
- Uber's "peer-to-peer services," UberX and UberPOOL
  - Rest excluded – different pay structure of limits
- 1,877,252 drivers
  - 513,417 female (27.3%)
- 24.9 million driver-weeks in 196 „cities"
- total earnings and hours worked for each driver-week
  - (gross) hourly earnings= total payout / hours worked
  - Not including costs of gas etc.

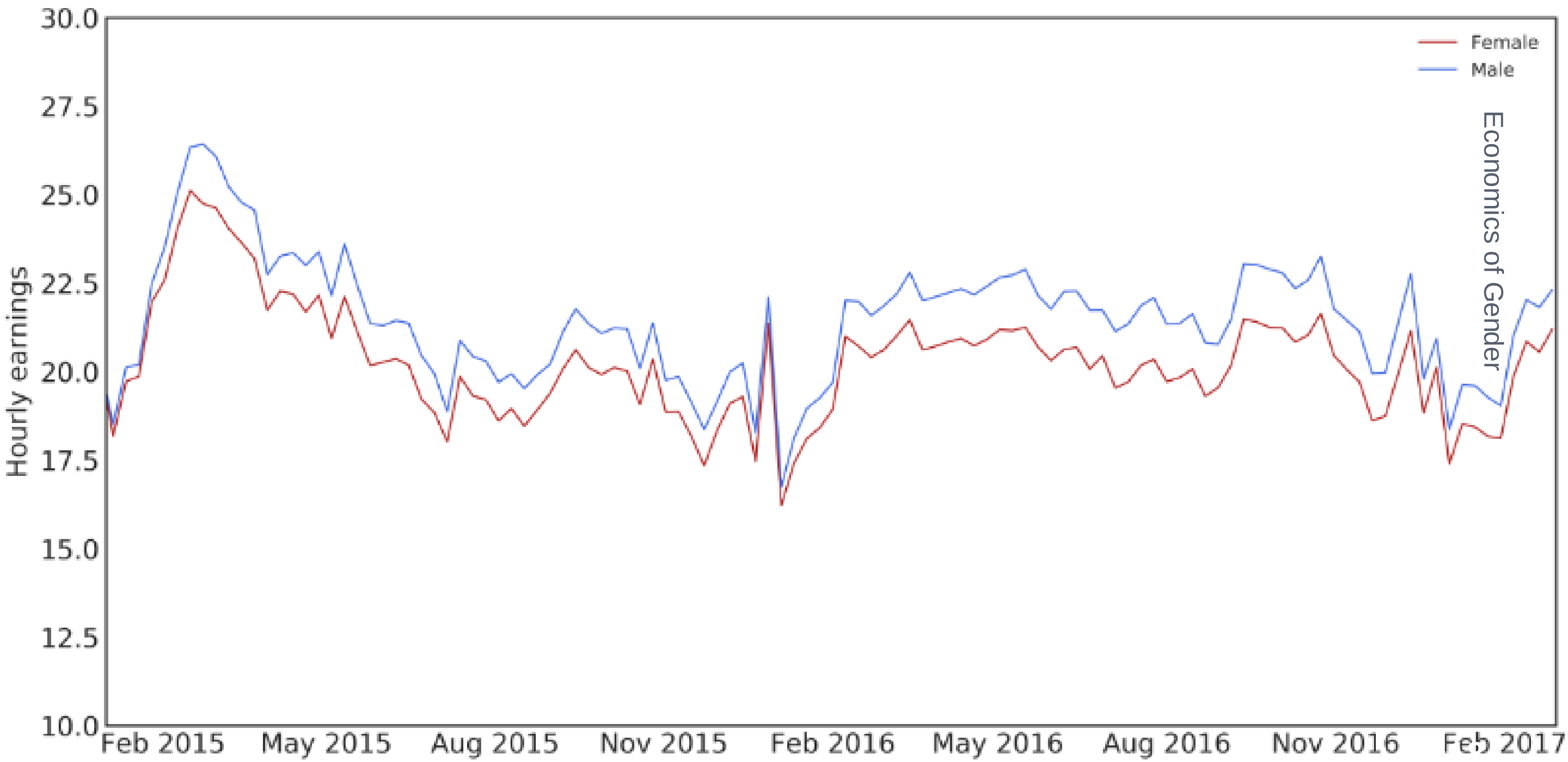
DATA – SUMMARY STATS (COOK ET AL, 2018)

	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

Data – Summary Stats (Cook et al, 2018)

- Active drivers gross an average of $375 per week and $21 per hour
- 60% of those who start ends 6M later
- Men make app. 50% more per week than women
  - work 50% more hours per week
- men make over $1/hour more, less likely to leave

AVERAGE HOURLY EARNINGS DEVELOPMENT (COOK ET AL, 2018)



ESTIMATES – MINCER EQ. (COOK ET AL, 2018)

- Standard approach

$$\ln(Earnings_{dt}) = \beta_0 + \beta_1 isMale_d + \rho X_{dt} + \epsilon_d$$

	(1) log(weekly earnings)	(2) log(weekly earnings)	(3) log(hourly earnings)	(4) log(hourly earnings)
isMale	0.4142	0.4092	0.0702	0.0653
	(0.002)	(0.002)	(0.001)	(0.001)
Intercept	4.9737	4.9208	2.9280	2.8849
	(0.002)	(0.002)	(0.001)	(0.001)
City	X	X	X	X
Week		X		X
N	24,877,588	24,877,588	24,877,588	24,877,588
Drivers	1,877,252	1,877,252	1,877,252	1,877,252
R^2	0.125	0.136	0.199	0.239

Men earn 7% more per hour for same job

ESTIMATES – MINCER EQ. (COOK ET AL, 2018)

- men make 7% more per hour !!
  - Same or more than MBAs, pharmacists
  - Smaller than economy-wide estimates
- Same job
- setting where work assignments are made by a gender-blind algorithm
- the pay structure is tied directly to output and not negotiated

- Why? – decomposition, focus on Chicago

Estimates – Mincer Eq. - Chicago (Cook et al, 2018)

	(1) log(weekly earnings)	(2) log(hourly earnings)
isMale	0.4315	0.0485
	(0.007)	(0.001)
Intercept	5.0487	3.1151
	(0.009)	(0.001)
Week	X	X
N	1,604,627	1,604,627
Drivers	120,019	120,019
R^2	0.038	0.110

Estimates Decomposition - Chicago (Cook et al, 2018)

- driver-hour = full hour block with some trip activity
  - total gross pay and hours worked for each driver-hour
  - Can look at where and when driver worked (geo-hash)
- Data
  - January 2015 to March 2017
  - 120,223 drivers (30.2% Female)
  - 33.0 million driver-hours
- implied hourly earnings in a driver-hour = total earnings for trips in that hour / minutes worked*60
- incentive earnings paid for achieving weekly trips target spread uniformly across minutes worked

Estimates Decomposition - Chicago (Cook et al, 2018)

	Men	Women	Difference
w – Wait time (min)	8.223	8.218	-0.005
	(0.008)	(0.019)	
d_0 – Accepts-to-pickup distance (mi)	0.485	0.500	0.015
	(0.000)	(0.001)	
d_1 – Trip distance (mi)	5.035	4.875	0.160
	(0.003)	(0.006)	
s – Speed (mph)	19.532	18.760	0.772
	(0.006)	(0.012)	
SM – Surge multiplier	1.051	1.046	0.005
	(0.000)	(0.000)	
I – Incentive payout ($)	0.903	0.818	0.085
	(0.001)	(0.002)	
Total per-trip payout ($)	10.142	9.841	0.301
	(0.004)	(0.008)	

Estimates Decomposition - Chicago (Cook et al, 2018)

	(1)	(2)	(3)	(4)	(5)	(6)
isMale	0.0356	0.0302	0.0261	0.0220	0.0210	0.0210
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
riderCancellations						-0.0478
						(0.000)
driverCancellations						-0.0302
						(0.0003)
Intercept	3.0862	3.0912	3.0946	3.0980	3.0989	3.1081
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Week	X	X	X	X	X	X
Hour of week		X		X	X	X
Geohash			X	X	X	X
Geohash*hour of week					X	X
N	11,572,163	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	0.164

ESTIMATES DECOMPOSITION - CHICAGO (COOK ET AL, 2018)

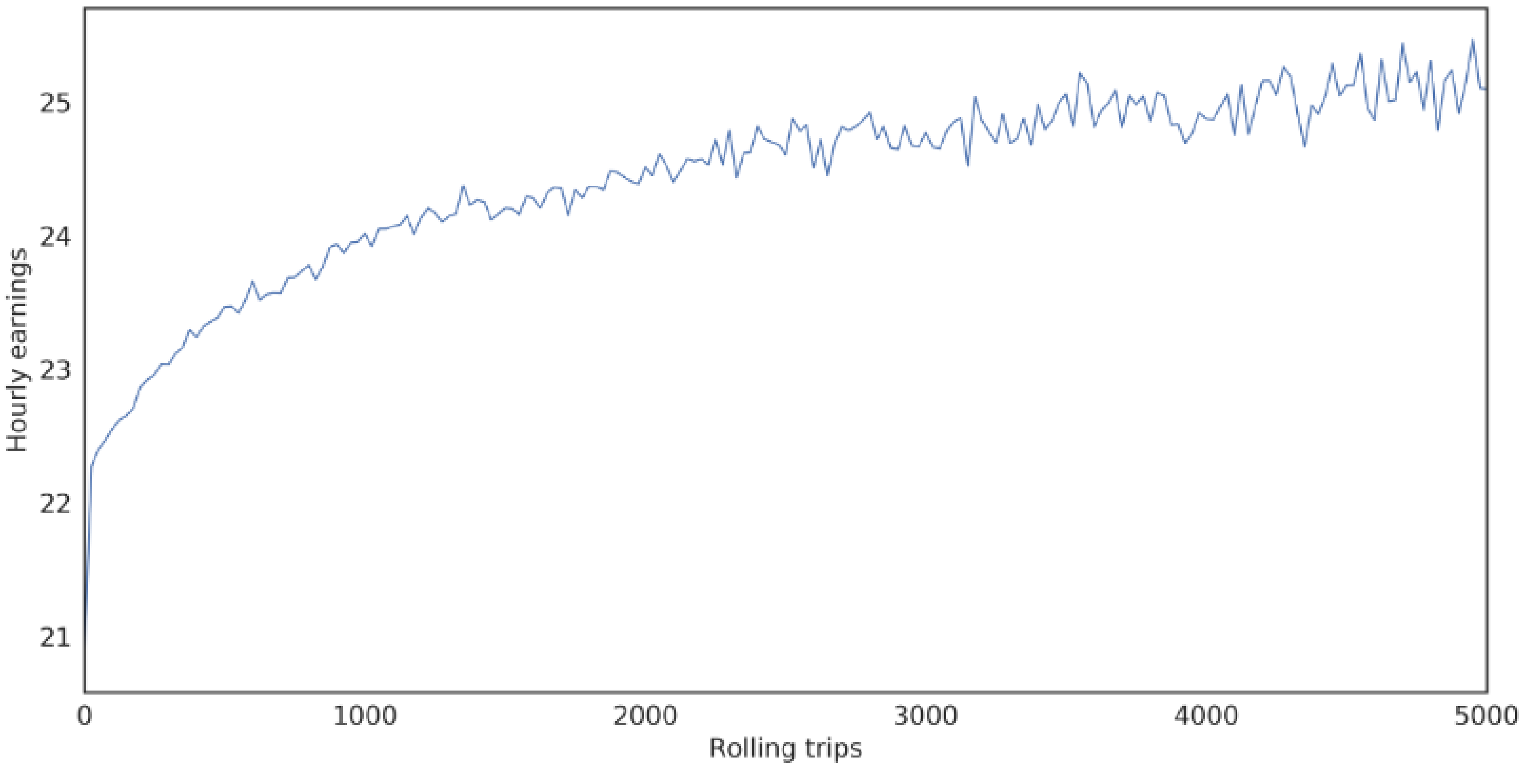
- baseline Chicago gender pay gap of 3.6% at the driver-hour level, controlling only for overall conditions in a given week
- hour of week controls eliminate 14% of the gender pay gap
  - hour-within-week preference differences are a small part of the gender gap
- Column 3 - controls for top fifty geohashes
  - removes about 25% of the gender pay gap
  - men drive in areas with higher pay
- Column 4 - "where and when“ combined
  - 1/3 of gap removed
- Column 6 – customer discrimination
  - No contribution to gender gap
- Remaining 2.1% gender gap is small to other gaps
  - Large for the same job at the same time and same place

Returns to experience (Cook et al, 2018)

- gender differences in experience may matter
  - Bertrand 2010
- Uber uses an assignment algorithm to offer trips to drivers, drivers use GPS, and drivers are not customarily paid a tip
  - Small role of experience expected
- However, many variables under control
  - Choosing when and where to work

RETURNS TO EXPERIENCE

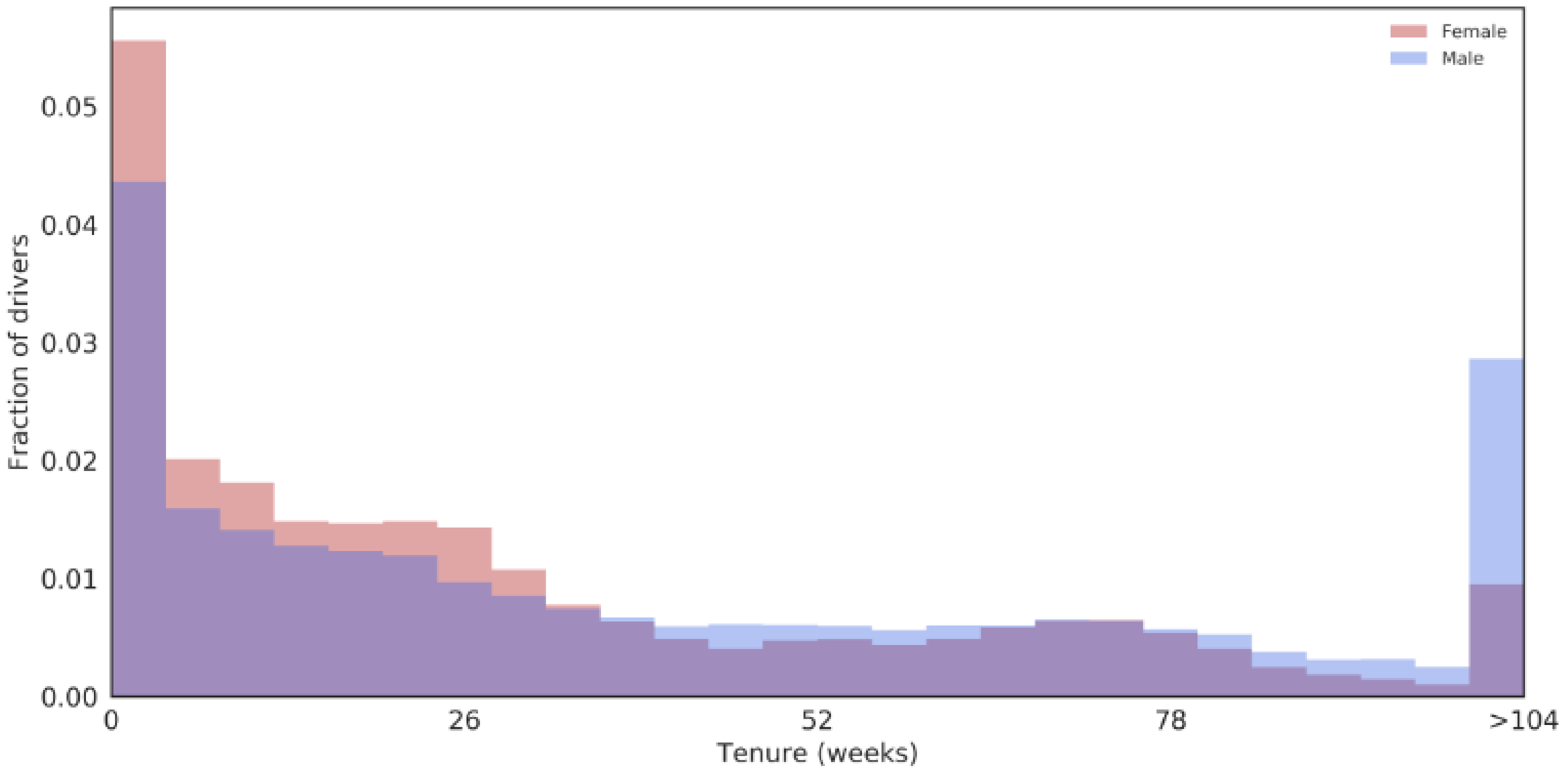
Figure 4: Returns to experience



Note: This figure shows the average earnings of drivers with a given number of rolling trips completed prior to a day of work; rolling trips are binned into buckets of 25 trips completed. Data include all Chicago drivers from January 2015 to March 2017.

MEN LAST LONGER (COOK ET AL, 2018)

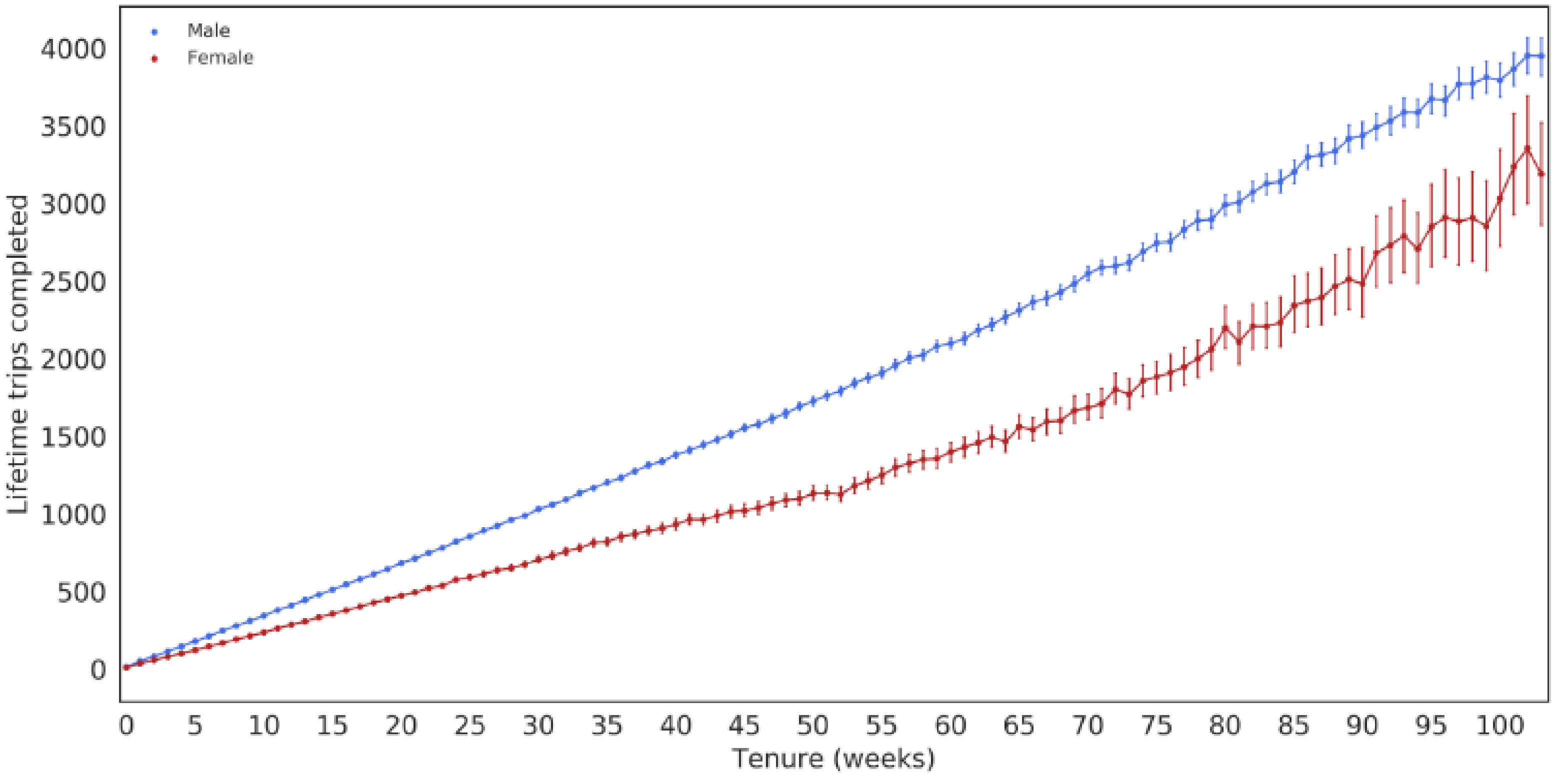
Figure 2: Distribution of driver tenure, January 2017



Note: This figure shows the average weeks of tenure for drivers that completed a trip in January 2017; we limit to a single month to avoid composition effects. Tenure is measured as the number of weeks since a driver's first completed trip.

MEN WORK MORE (COOK ET AL, 2018)

Figure 3: Accumulation of trips over weeks of driving



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.

RETURNS TO EXPERIENCE IN REGRESSIONS (COOK ET AL, 2018)

Table 6: Returns to experience

	(1)	(2)	(3)	(4)
isMale	0.0138	0.0083	0.0129	0.0081
	(0.003)	(0.003)	(0.003)	(0.002)
Trips completed: 100-500	0.0530	0.0497	0.0357	0.0339
	(0.001)	(0.001)	(0.001)	(0.001)
Trips completed: 500-1000	0.0773	0.0747	0.0512	0.0495
	(0.002)	(0.002)	(0.002)	(0.001)
Trips completed: 1000-2500	0.1001	0.0990	0.0650	0.0638
	(0.002)	(0.002)	(0.002)	(0.002)
Trips completed: >2500	0.1391	0.1390	0.0877	0.0860
	(0.004)	(0.003)	(0.003)	(0.003)
Intercept	3.0228	3.0294	3.0528	3.0581
	(0.002)	(0.001)	(0.003)	(0.001)
Week	X	X	X	X
Hour of week		X		X
Geohash			X	X
Geohash*hour of week				X
N	11,572,163	11,572,163	11,572,163	11,572,163
R^2	0.048	0.107	0.096	0.165

Note: This table expands on the regressions in Table 5 by adding controls for a driver's experience. Experienced is measured as trips completed before a given day of work. Drivers with fewer than 100 completed trips are the excluded category. The outcome variable is log of hourly earnings. Standard errors (clustered at the driver-level) in parentheses.

Returns to experience in regressions (Cook et al, 2018)

- Column 1 - drivers who have completed over 2500 trips make nearly 14% more than those in their first 100 trips
  - gender earnings gap shrinks to 1.4% (1/3 of original)
- Column 2 - controls for hour of week
  - gap is further reduced to under 1%
  - Returns to experience important
- Column 3 - controls for location
  - do not reduce the gender gap but substantially reduce the returns to experience
- men and women are on different parts of the learning curve, which drives a large part of the gender earnings gap

RETURNS TO EXPERIENCE IN REGRESSIONS (COOK ET AL, 2018)

- drivers can affect their earnings also through strategic actions - rejecting dispatches and cancelling trips
  - If a rider is far, there is an additional cost
  - If likely to get a closer ride, makes sense to reject
  - high time-to-pickup ride may indicate an imbalance in supply and demand => soon higher multiplier
- Experience plays a role – learning when to cancel/not accept important
  - even with controls for strategic rejecting and canceling, drivers with over 2500 trips make 6.2% more than those in their first 100 trips

Returns to experience (Cook et al, 2018)

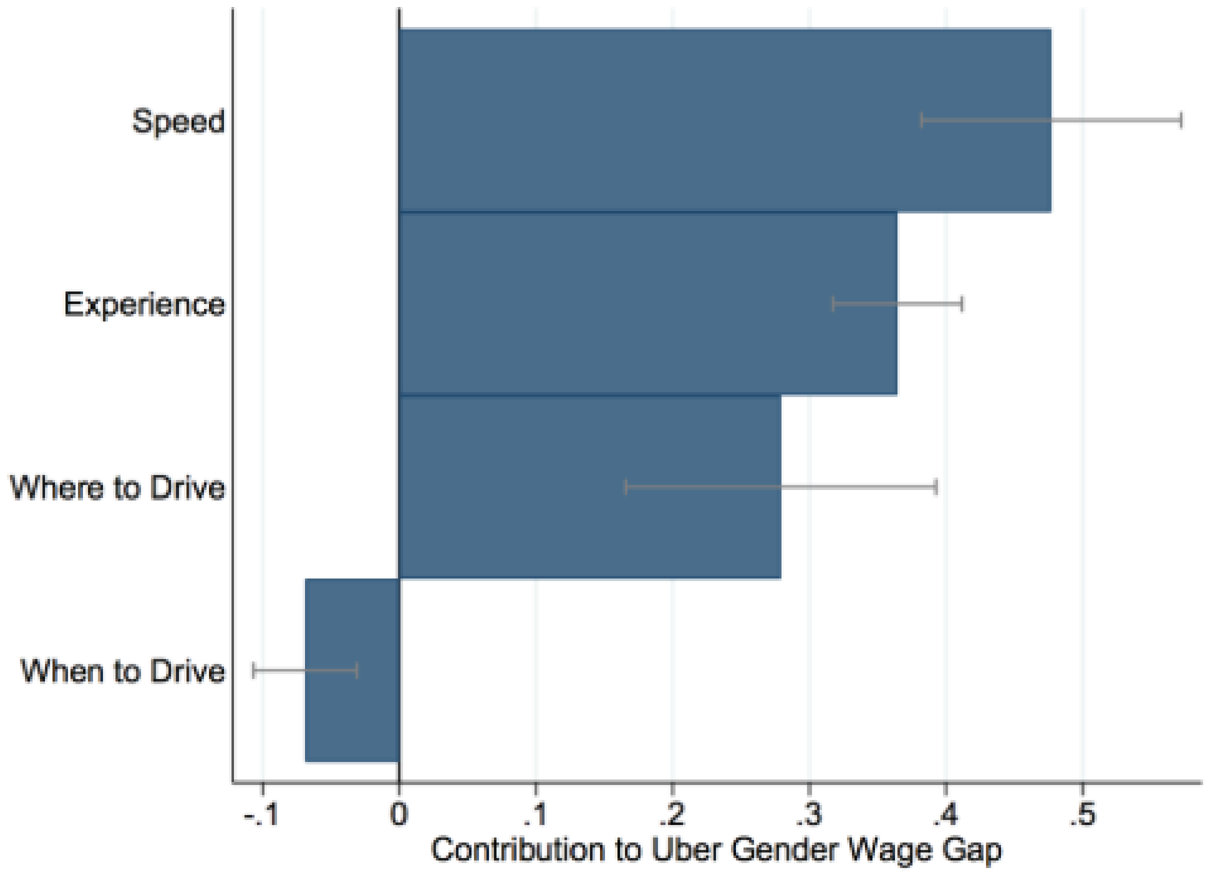
- even in this short-term gig economy environment, experience and gender differences in experience play out in a way that contributes substantially to the gender pay gap, as men and women are on different parts of the learning curve.
- relationship between experience and the gender pay gap for drivers is surprisingly similar to at least some traditional job environments

Returns to Speed (Cook et al, 2018)

- drivers earn a per-minute and a per-mile rate on each trip
- earnings- maximizing drivers would drive as slowly as possible
- Data: positive expected return to driving faster
- speed = distance on trip / time on trip in a given driver-hour
- Results: elasticity of 27% of speed on earnings
  - 1% increase in speed increases earnings by 0.27%
  - control for geohash and hour of week – 46%
  - Adding experience completely eliminates gap!

Overall decomposition

Figure 5: Gelbach decomposition



CONCLUSION

- surprising that they can fully explain the gap
  - returns to experience, a pay premium for faster driving, and preferences for where to drive
- surprising that there was a gender earnings gap to begin with
- men and women learn in a productive manner and at roughly the same rate
- even in the gender-blind, transactional, flexible environment of the gig economy, gender-based preferences can open gender earnings gaps

READING LIST

- Obligatory:
  - Cook, C., Diamond, R., Hall, J., List, J. A., & Oyer, P. (2018). The Gender Earnings Gap in the Gig Economy: Evidence from over a Million Rideshare Drivers. Working paper. https://web. stanford. edu/~ diamondr/UberPayGap.pdf
- Optional:
  - Blau, Francine D. and Lawrence M. Kahn, "The Gender Wage Gap: Extent, Trends, and Explanations," Journal of Economic Literature, 2017, 55, 789–865.
  - Azmat, Ghazala and Rosa Ferrer, "Gender Gaps in Performance: Evidence from Young Lawyers," Journal of Political Economy, October 2017, 125 (5), 1306–1355.
  - Madden, Janice Fanning, "Why Women Work Closer to Home," Urban Studies, 1981, 18 (2), 181–194.

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