Peer Effects in Working Hours

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Motivation

Long working hours and overtime work are omnipresent in many industries (& academia), but our understanding of the reasons behind it is insufficient. Why do people work so long? Do they stay because they have work so much work to do, to impress their boss, or to compete for promotion? Or does the mere presence of others make them feel bad about leaving? This project presents a first attempt at gathering and analyzing observational data of people's (and their peers') working hours.

Existing literature

Working Hours and Overtime Work - Paul Lim

- Widespread variation in hours worked across the World: OECD countries work 1,744 hours per year on average. Mexico (2,255) and Korea (2,024) at the top work significantly more than France (1,514) and Germany (1,356).
- What constitutes overtime work differs markedly across countries, but it is common for actual working hours to be above hours agreed upon (e.g. Canadians work 1.7 hours overtime per week on average).

Effects of Long Working Hours - Defne Ozkan

- **Productivity**. E.g. Pencavel (2015): relationship between working hours and productivity non-linear such that below a threshold, output is proportional to hours and above this threshold, output rises at a decreasing rate.
- **Health.** E.g Shields (1999): long hours correlated with increasing risk of certain health behaviors: cigarette consumption, unhealthy weight gain, depression.
- **Income & Happiness.** Pouwels, Siegers and Vlasblom (2008): Longer working hours positive for income, but negative for happiness. Basic models underestimate the effect of income on happiness by not including working hours.

Peer Effects at Work - Yeeling Tse

- **Workplace productivity.** Positive effects on productivity for filling envelopes (Falk & Ichino (2006)), supermarket cashiers (Mas & Moretti (2009)), swimmers (Yamane (2015)) and negative effects for fruit pickers via incentive scheme (Bandiera, Barankay, & Rasul (2005)).

Model

Model framework to estimate the effect of peers in duration of stay or departure time: **1)** Assume arrival times for 200 persons in a 2-hour window are drawn from a uniform distribution, i.e. $U(0, 120)$. **2)** Assign seats sequentially by arrival time: given 40 tables and 8 seats per table, have them pick randomly, without replacement. **3)** Every person's stay duration is drawn from a normal distribution with mean of 60 minutes and standard deviation of 15 minutes, i.e. $\mathcal{N}(60, 15)$. **4)** For every person, we check if they had a neighbor present with them during their stay at the library. If yes, we add 20% to their departure time due to *peer effects*.

This yields a model data set with built-in peer effects, parameterized with: length of interval (ex. 120 mins.), mean and SD for the normal duration of stay (ex. 60, 15 mins.), the increase in duration of stay due to peer effects (ex. 20 percent). We use this model data set in the *bootstrap* hypothesis test described in the empirical section to assess the effectiveness of this test.

Data and Empirical

Rishab developed a simple but extensive API in Python to collect observational data and monitor peer effects. Some important methods of the API are given below:

API Important Functionalities

Table(A, "Moffit")	Creates new table A in Moffit
A.addPerson(2) **A.addPerson(3)**	Adds person 2 and 3 to Table A
A.addBreak(2)	Person 2 leaves for a break
A.endBreak(2)	Person 2 comes back from break
A.known(1, [2, 3])	Person 1 knows person 2 and 3 on Table A
A.removePerson(1)	person 1 departs permanently
showTables()	Shows all active tables in our current session
quitSession()	Ends our observation session

The API automatically records the accurate time, keeps track of active tables and people, and creates the dataset as seen in the image below.

	ID	Person	Table	Library	Arrival	Departure	Num_Breaks	Break_Start	Break_End	Neighbors
0	5657	2	A	Moffit	2019-03-23 18:20:02.703347	2019-03-23 18:33:47.097748	0	[]	[]	[(5, 7808)]
1	7808	5	A	Moffit	2019-03-23 18:20:02.705239	2019-03-23 18:42:29.331629	1	[datetime.datetime(2019, 3, 23, 18, 20, 3, 781...	[datetime.datetime(2019, 3, 23, 18, 30, 23, 76...	[(2, 5657)]
2	7657	1	B	Stacks	2019-03-23 18:25:41.342617	2019-03-23 18:37:07.846707	1	[datetime.datetime(2019, 3, 23, 18, 27, 36, 35...	[datetime.datetime(2019, 3, 23, 18, 37, 7, 846...	[(3, 7477), (6, 6146)]
3	7477	3	B	Stacks	2019-03-23 18:27:35.896722	2019-03-23 18:42:29.331629	2	[datetime.datetime(2019, 3, 23, 18, 27, 36, 35...	[datetime.datetime(2019, 3, 23, 18, 37, 7, 846...	[(1, 7657), (6, 6146)]
4	6146	6	B	Stacks	2019-03-23 18:34:10.473014	2019-03-23 18:42:29.331629	0	[]	[]	[(1, 7657), (3, 7477)]

We run the following procedure to estimate the effect of *peers* on features of working hours. First, we aggregate all actual pairs of neighbors from our observational ($n = 196$) or model data (size n) and calculate a test statistic such as the average of the difference in departure times. This is the observed value of our test statistic. We then repeat the following a 1,000 times:

1. We create a similar vector of size n that consists of random of pairs of persons who could have been a valid pair according to their arrival and departure times.
2. We calculate the test statistic for this set of pairs and continue this procedure.

Finally, we plot the density of this statistic for the simulated random pairs, construct a 95% confidence interval and compare our observed value from actual pairs with this interval.

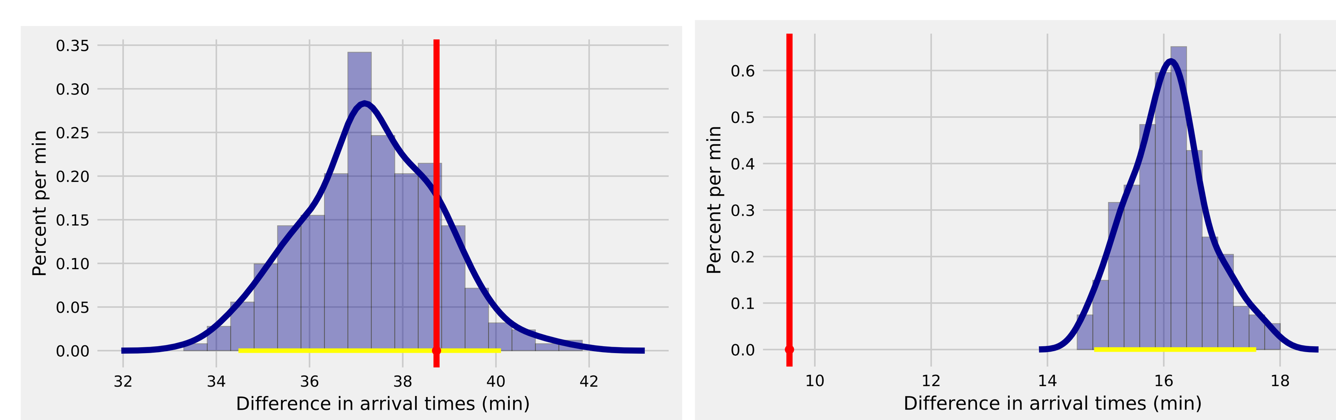

Fig. 1: Difference in arrival times. (left) Model data, (right) Empirical data

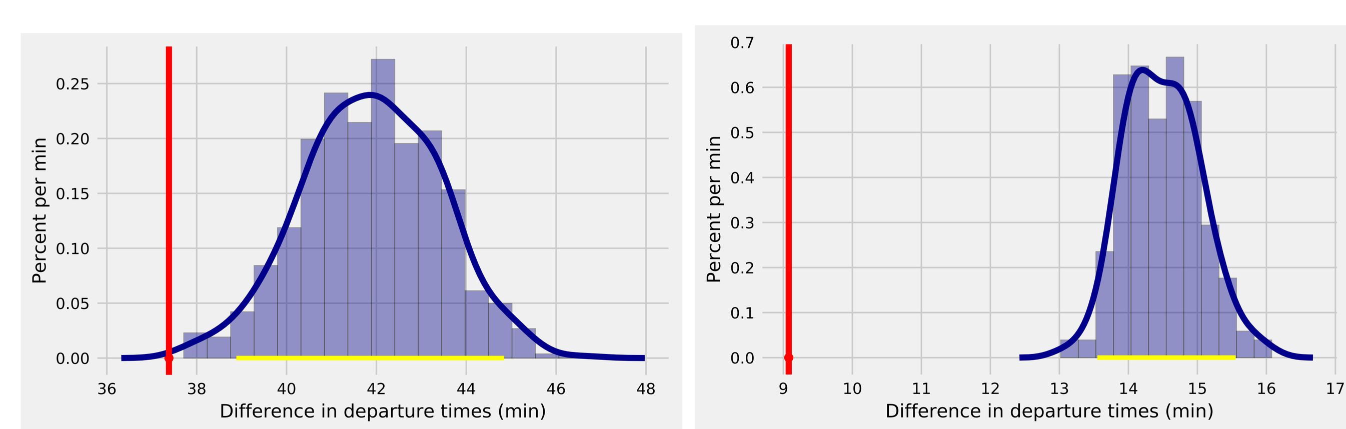

Fig. 2: Difference in departure times. (left) Model data, (right) Empirical data

Conclusion

We develop a first approach to observe working hours in the library setting and one potential methodology to assess potential peer effects in working hours.

The data suggests that actual "table neighbors"' arrival and departure times are much more correlated than are those of simulated, random "table neighbors". These results have clear limitations as of now, among others the low number of observations, a limited number of observation durations (resulting in top- and bottom-coding of duration times), imperfect measures of social ties, manual data input errors and confounding factors (such as class schedules etc.).

Next steps? Collect more data, refine observational techniques and ways to measure and assess peer effects, extend to other work settings.

Second Project: Intergenerational Mobility & Loss Aversion

How does loss aversion over social status/rank affect intergenerational mobility? In this project, Yeeling simulated a model with two generations and the following features: 100 parents each have one child. Parents are randomly ranked (rank p) from 1 to 100, with 100 being the highest rank. A child's initial rank c_0 depends on its parent's rank (weight q) and a random draw (weight $1-q$). Each child can exert effort e to climb ranks. Children exert effort optimally, according to the following utility functions under the two alternative models:

Model 1: $u = v(c_0 + e) - \frac{e^{1+\gamma}}{1+\gamma}$

Model 2: $u = v(c_0 + e) - \frac{e^{1+\gamma}}{1+\gamma} + \omega v(c_0 + e - p)1_{(c_0+e \geq p)} + \omega\lambda v(c_0 + e - p)1_{(c_0+e<p)}$

After children exert effort, their final ranks are determined by ranking according to $c_0 + e$. We simulate each model a 1,000 times and plot the distribution of the intergenerational correlation in final ranks (between parents and their children's final rank), comparing the two models for different assumptions on q. The portrayed simulations assume $v = 20$, $\gamma = 1.25$, $\lambda = 2$, $\omega = 1$.

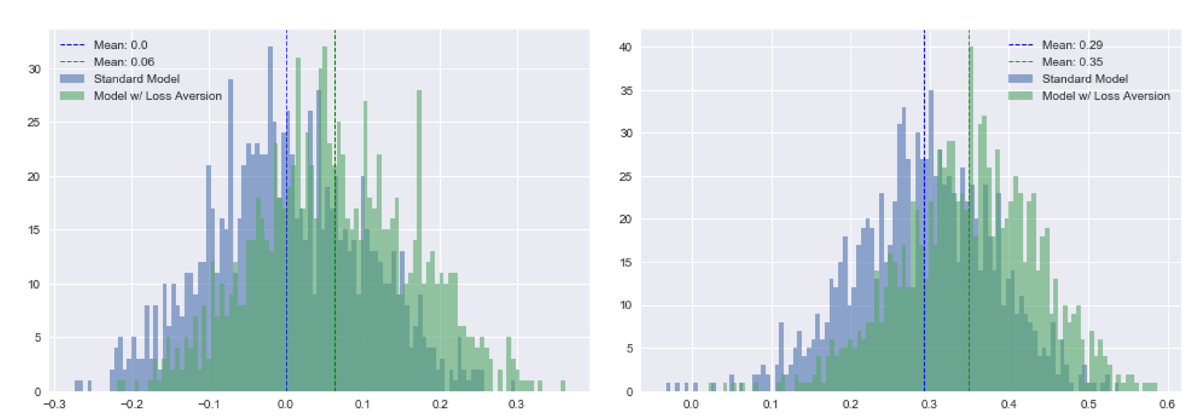

Fig. 3: Intergenerational Rank Correlation (left) $q = 0$ (right) $q = 0.25$

This little exercise shows that loss aversion over social ranks has the potential to increase the correlation between parents' and children's ranks and thus to lower social mobility. What's next? 1) Empirical analysis of potential status concerns & intergenerational mobility, 2) Enriching the model & simulation.