Impact of working Overtime on Attrition

Why do we care about overtime and attrition?

"Employee turnover is expensive. Replacing an employee who quits costs, on average, 21% of their annual pay."

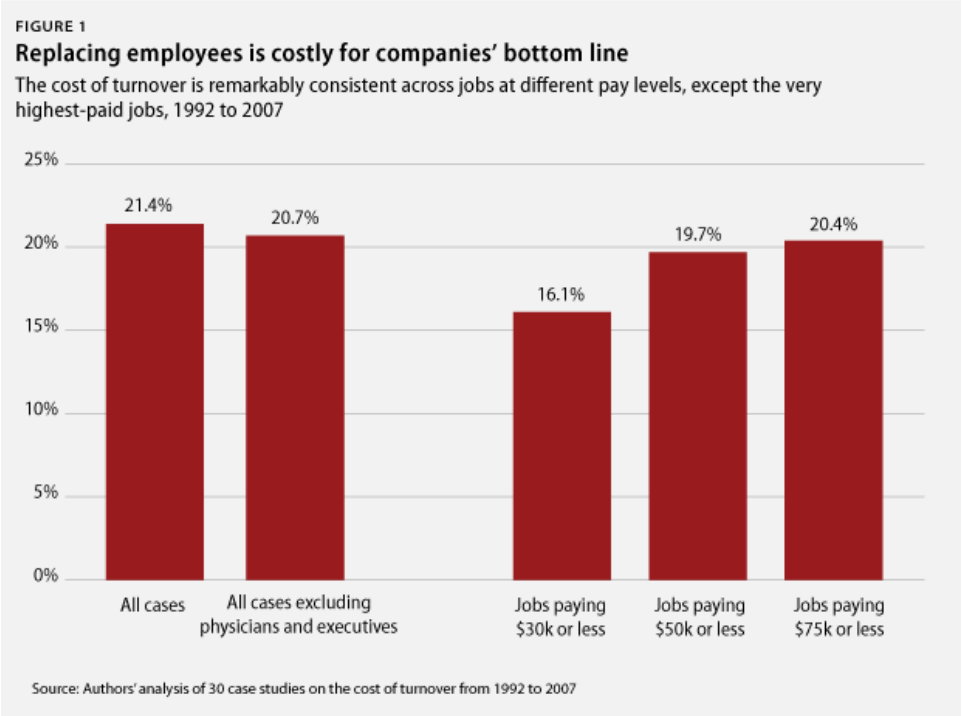
- *There Are Significant Business Costs to Replacing Employees, 2012*

"Long hours and heavy work loads are fueling turnover … burnout was driving up to 50% of annual turnover"

- *Feeling Burned Out at Work?, 2017*

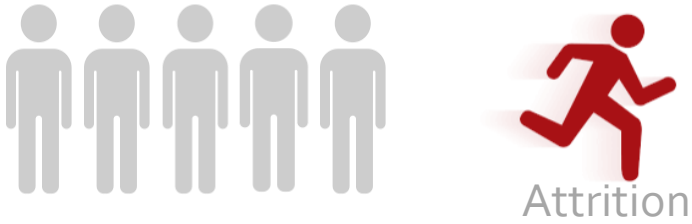
".. Highest voluntary attrition across sectors was seen in the IT services sector at 21.9%"

- *IBM article, 2017*

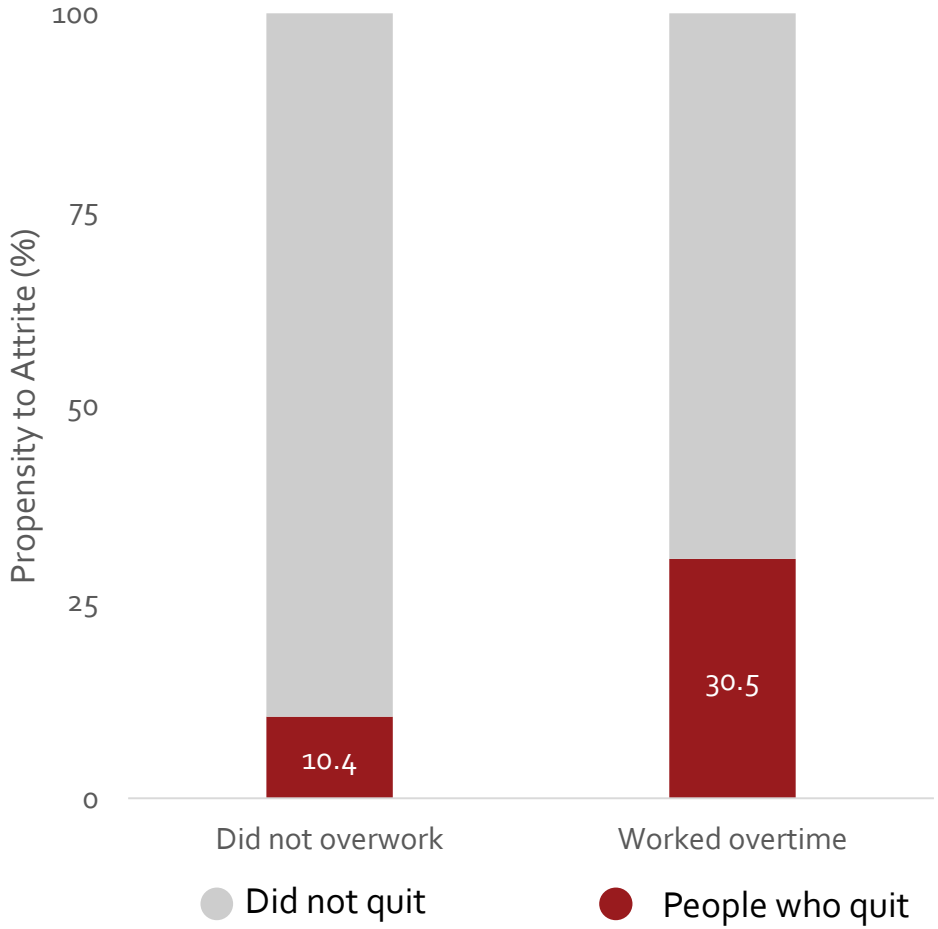


We use the IBM HR dataset to study the impact of overtime on attrition

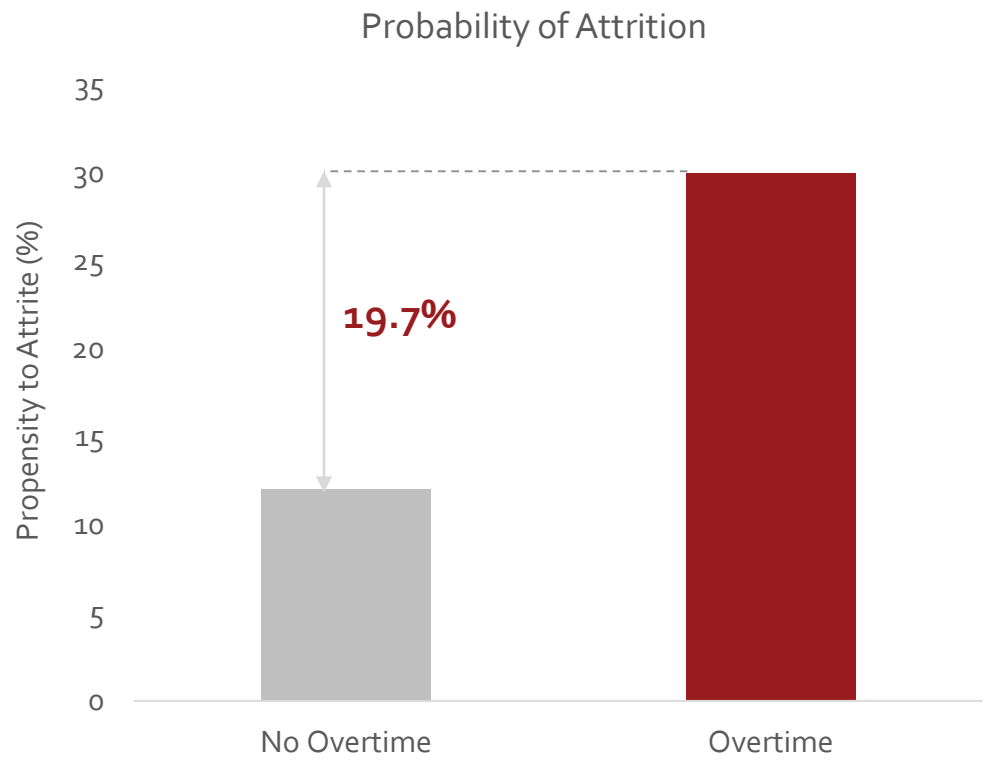
HR dataset is a cross-sectional dataset containing **employee**, **work-life** and **job related** data



We see that people **who worked overtime have a higher attrition rate**

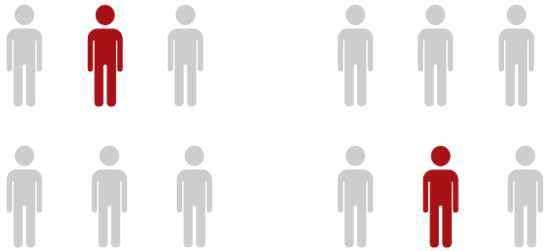


Based on our analysis, we infer that working overtime increases probability of leaving by 19.7%

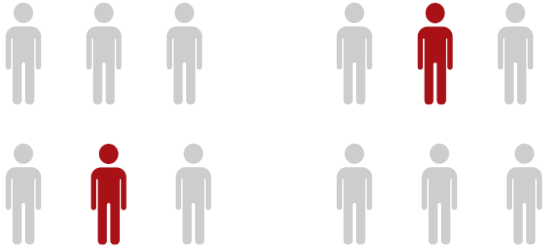


We cannot randomly make employees work overtime, and overtime status may depend on other factors

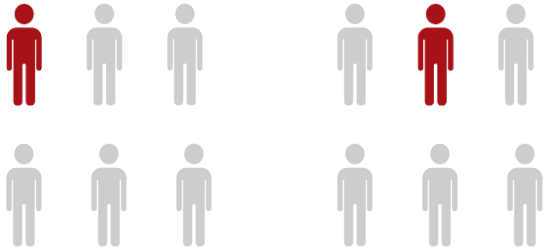
What would we ideally do?



Yes No



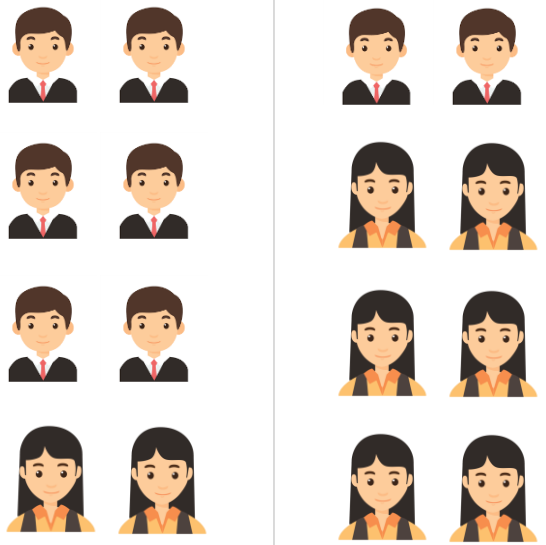
Male Female



Higher Lower

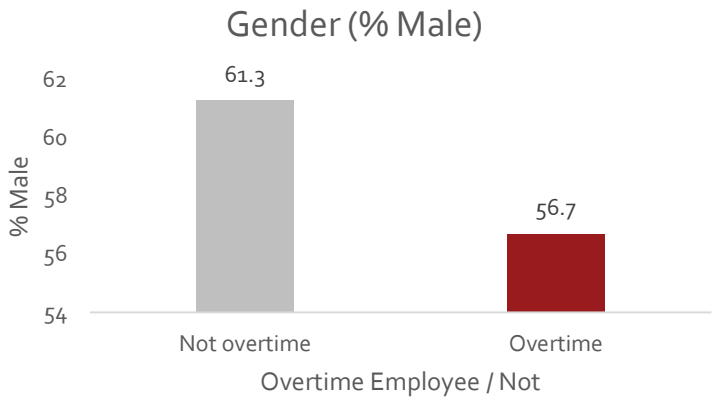
Do they leave more often then others?

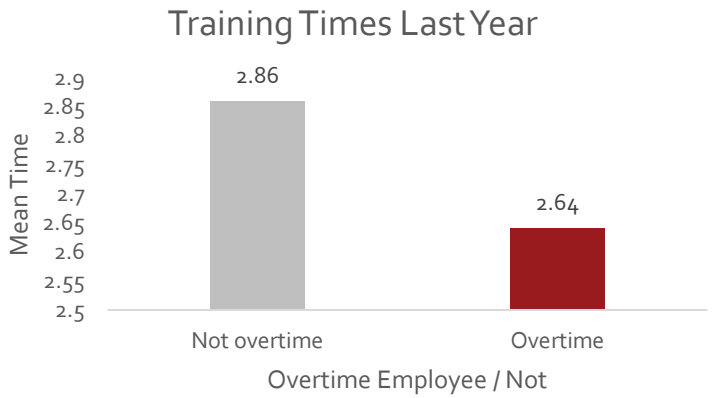
In real world, randomization does not work the same way, and these groups might not be similar

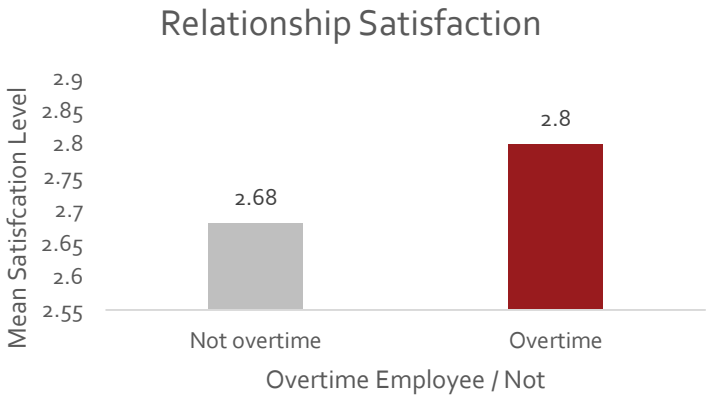


Possible that men work overtime than women

Employees working overtime differ in gender, satisfaction and training distribution

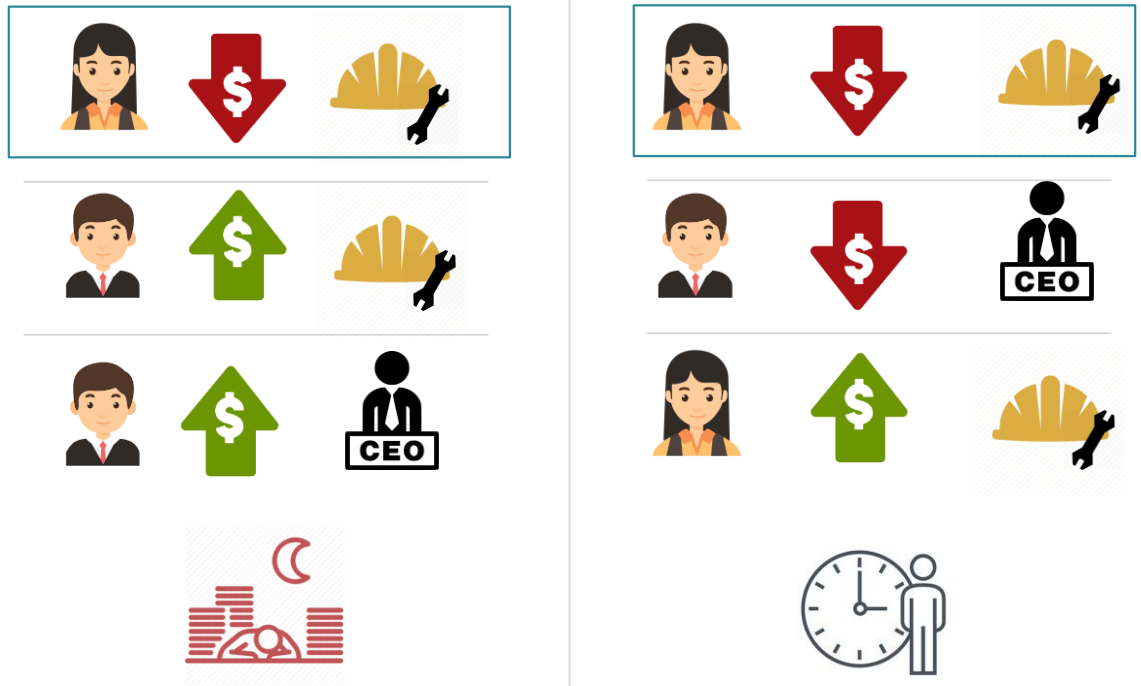






… and hence we have to match attributes from the groups to find out the impact of only over-time status on attrition

We use propensity score matching to pseudo-randomize groups such that the only difference between them is that they worked overtime



The only thing different between these groups was that they worked overtime or not

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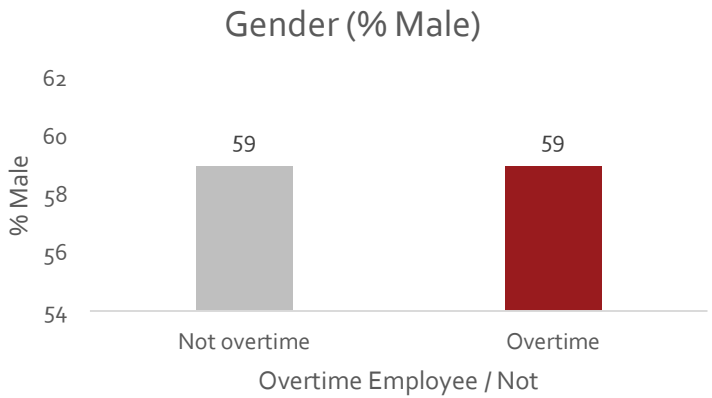
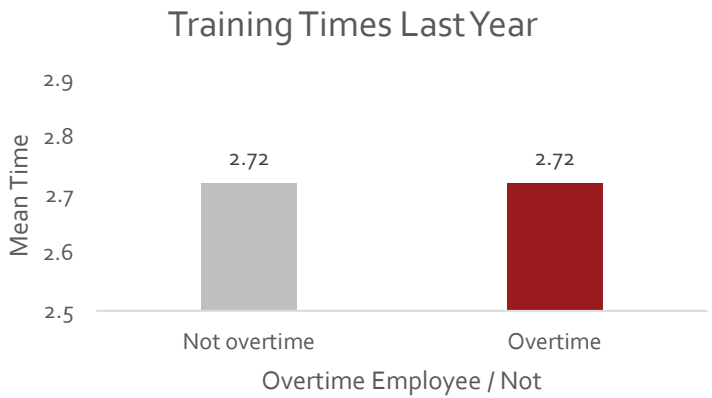
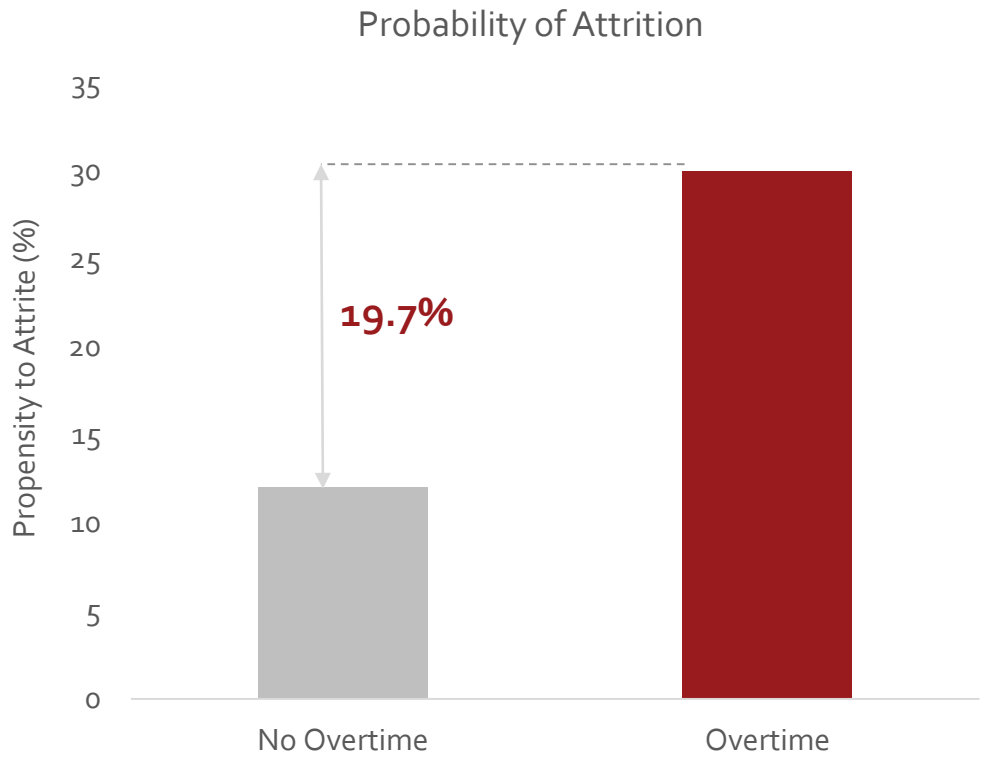
Once we randomize, we now have even groups with only difference being one group worked overtime

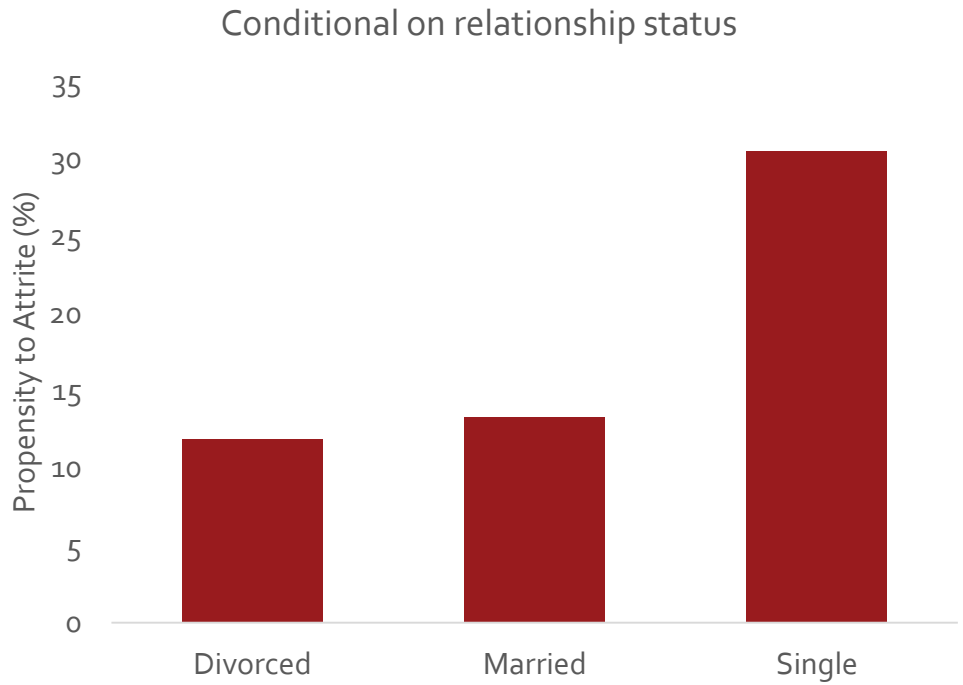




We found that employees that work overtime have 18.2% higher chance of leaving as compared to employees who do not

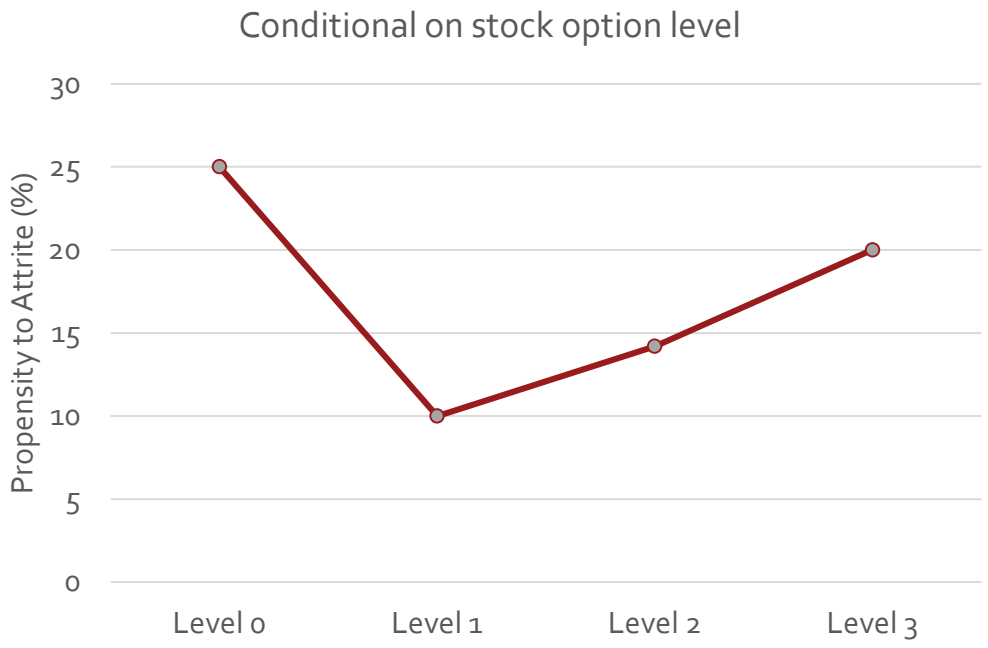


Single people are more likely to leave the firm when worked overtime



Mid level employees have higher willingness to stay, and stock options play a role in employee's leaving decision

Stock options are an effective strategy to check employ attrition even when working overtime



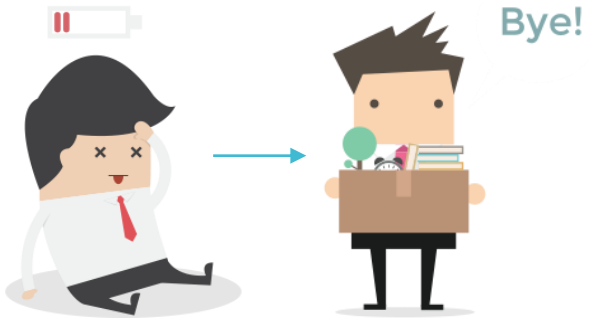
Employees more acceptable to working over time in their mid – level career growth time

We make multiple assumptions while doing this analysis

Interference

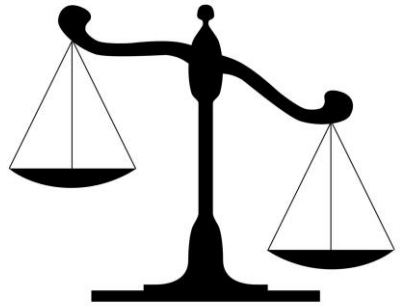
Employee interactions can lead to over-worked employees influencing others

Temporal Precedence



Since, employee's who quit can no longer work, we can always assume X before Y

No endogeneity



Sample is representative of population
No measurement error
All drivers are taken into consideration

Limitations and next steps

Limitations

- There are multiple factors that are not observed in the dataset, that might have an impact on both working overtime and decision to leave, for example, presence of student loans
- We lose records during the matching process, thereby reducing the dataset by 50%

Next steps

- Use a panel data to understand impact over time
- Use number of hours worked overtime instead of an overworked flag
- Understand the effect for low performing employees as well