Hiring and the Dynamics of the Gender Gap

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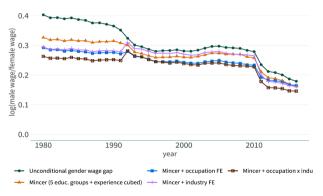
NBER SI Labor Studies 2023 - Discussion (Nina Roussille)

Canonical definitions of the gender pay gap

- Starting from the raw pay gap, researchers have typically been interested in its decomposition between:
 - The explained gap, i.e pay disparities that reflect differences in observable characteristics such as education and experience.
 - * For instance, even for a given level of education (e.g. college degree), women tend to sort into less lucrative majors (HR vs. engineering).
 - ★ This can in part explain why women are paid lower wages than men.
 - ▶ The **unexplained** gap, i.e the residual gap once we have accounted for all observables.

Explained vs. unexplained gender pay gap in Germany





• Because unexplained vs. explained components have very different interpretations, it is crucial to get the decomposition right.

Getting this decomposition right is hard!

- The validity of the explained vs. unexplained decomposition relies heavily on whether researchers have access to the right controls.
- In studies using administrative data (e.g. PSID, IAB), the controls are fairly coarse
 - e.g. education is controlled for with years of schooling and degree level, labor market history is accounted for with years of experience.
- If the available observables were more granular/exhaustive, would the conditional gender pay gap be different?

This paper proposes a novel angle

- Instead of defining the object of interest as the pay gap between **similarly qualified** men and women...
- ... they define it as the pay gap between men and women in similar jobs.
 - ▶ Gender equality defined as "Equal Pay for Equal Work", as opposed to Equal Pay for Equal Observables → clever way to sidestep the "right individual controls" problem
- **Research question:** Do men and women achieve systematically different outcomes when matched to the same job vacancy opportunity?
- Why hasn't this been done before?!

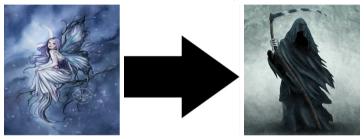
Identification strategy: Intuition

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- This paper's strategy: unexpected deaths create a pool of vacancies that firms did not not expect to have (ala Jäger and Heining (2022)).
- **Identification assumption:** the job does not change *differentially* by gender during the transition between the deceased and new worker.

Identification strategy

What problem does their strategy solve compared to simply using all job switches?

- It is usually hard in admin data to disentangle job replacement from job creation.
 - ▶ The exogenous death of the worker helps make the case that the next hire fills the same job.
- Even if one could disentangle job replacement from job creation in admin data, using endogenous replacements would be problematic:
 - Prior worker characteristics/wages might not be a good proxy for job characteristics (either worker was fired or left for better pay, etc.).
 - ▶ This would make it hard to use gender differences in the wage change between the previous and new worker as a benchmark to compute the gender wage gap.

Identification strategy: some thoughts

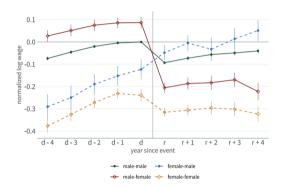
- While the job opening is exogenous, the decision to hire a new worker and the scope of their work is not:
 - ► The newly hired worker may take on more/less responsibility than the previous one (ex post restructuring).
- Importantly for the topic of interest of this paper (gender gaps), the decision to hire a man or a woman as a replacement is not random:
 - e.g. hiring the same or opposite gender of the deceased worker is inherently a decision of the team the person is hired into.
 - e.g. the firm's decision to hire a certain gender may be correlated with its financial health (e.g. shrinking firm may hire women **because** they are cheaper.)
 - ► Possible tests: show there is no correlation between hiring decision and proxies for firm growth (e.g. number of employees, profits etc...) and/or local labor market tightness

Main result: Really stark gender gap!

Mean log wage by transition group

Plotting raw group mean by relative event time and associated standard error

 Normalizing Male-Male to 0 at event time 0



 Headline finding: female replacements have starting wages that are on average 20 log points lower than their male counterparts

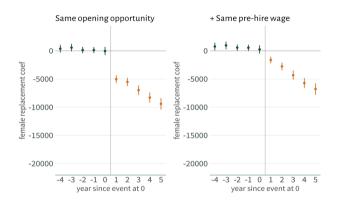
Main result: some thoughts

The main figure features three interesting patterns:

- Magnitude of the gender gap in hiring opportunities: its size (20%) is 1.5 times larger than the residual pay gap in Germany (13%) and about the size of the raw gender pay gap (18%).
- Sign of the wage change between deceased and replacement worker: most replacements lead to negative wage changes. Is that indicative of different Xs between deceased and new hire? Or of large firm-specific human capital? Would that be true if we looked at all replacements?
- <u>Dynamics</u>: the wage growth post-hire differs by gender. Differential learning on the job?
 <u>Negotiation</u>? Discrimination?

Key role of the previous wage

Earnings difference by replacement gender



• Suggests policies that limit the ability of firms to ask questions about salary history and/or salary expectations could play a key role in decreasing the gender pay gap .

Conclusion

- Identifying firms that offer different wages to men and women for the same job is highly policy-relevant:
 - Unequal Pay for Equal Work and has been outlawed by the Equal Pay Act of 1963 in the US and is regulated in many European countries
 - ► This paper is a big step towards identifying bad actors in the eye of the law!
- This paper calls for more holistic approaches (e.g. going beyond controlling for worker characteristics) in understanding the different components of the gender gap (eg Bronson and Thoursie (2021)).