Hertie School

Exercise 4 (Discussion)

Cox and more

GRAD-E1322:
Applied Longitudinal Data Analysis

March, 8 2024

A Double Disadvantage? Minority Group, Immigrant Status, and Underemployment in the United States*

Gordon F. De Jong, *The Pennsylvania State University*
Anna B. Madamba, *TIAA-CREF*

Objective. This study documents the magnitude of four types of *under*employment experienced by both native-born minority and ethnic immigrant male and female workers in the United States and tests a "double disadvantage" economic outcome hypothesis that minority workers tend to be channeled into secondary-sector jobs and that immigrant workers face initial disadvantages in labor force assimilation. *Method.* Data for men and women aged 25–64 who are in the labor force and not attending school were derived from the 1990 Census Bureau Public Use Microdata Sample. Multinomial logistic regression procedures were used to estimate the effect of minority group membership and immigrant status on the odds of unemployment, part-time employment, working poverty, and job mismatch, relative to adequate employment. *Results.* Descriptive results showed greater overall underemployment among females than males. Blacks and Hispanics had higher unemployment and working-poverty rates compared to non-Hispanic whites and Asians, with job mismatch highest among Asians. Immigrant underemployment was greater than that of the native-born. Asians posted the largest disparity in immigrant versus native-born underemployment, and blacks had the smallest. Multivariate models showed that minority group effects were stronger than immigrant status effects in predicting underemployment. Increased likelihood of underemployment across the different minority groups versus non-Hispanic white workers was not fully accounted for by the expected influences of human-capital, demographic, industry, and occupational variables. *Conclusion.* The double disadvantage hypothesis of minority group *and* immigrant status is accepted only for Asian men and women with jobs mismatched to their skills and for Asian women, who are most likely to be unemployed or be among the working poor.

Practicing Intersectionality in Sociological Research: A Critical Analysis of Inclusions, Interactions, and Institutions in the Study of Inequalities*

Hae Yeon Choo
University of Wisconsin–Madison

Myra Marx Ferree
University of Wisconsin–Madison

In this article we ask what it means for sociologists to practice intersectionality as a theoretical and methodological approach to inequality. What are the implications for choices of subject matter and style of work? We distinguish three styles of understanding intersectionality in practice: group-centered, process-centered, and system-centered. The first, emphasizes placing multiply-marginalized groups and their perspectives at the center of the research. The second, intersectionality as a process, highlights power as relational, seeing the interactions among variables as multiplying oppressions at various points of intersection, and drawing attention to unmarked groups. Finally, seeing intersectionality as shaping the entire social system pushes analysis away from associating specific inequalities with unique institutions, instead looking for processes that are fully interactive, historically co-determining, and complex. Using several examples of recent, highly regarded qualitative studies, we draw attention to the comparative, contextual, and complex dimensions of sociological analysis that can be missing even when race, class, and gender are explicitly brought together.

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https://doi.org/10.1007/s13524-019-00773-3

Natives' Attitudes and Immigrants' Unemployment Durations

Check for updates

Sekou Keita[1] · Jérôme Valette[2]

Published online: 17 April 2019

Abstract
In this study, we investigate how the attitude of natives—defined as the perceived trustworthiness of citizens from different countries—affects immigrants' labor market outcomes in Germany. Evidence in the literature suggests that barriers to economic assimilation might be higher for some groups of immigrants, but the role of natives' heterogeneous attitudes toward immigrants from different countries of origin has received little attention. Using individual-level panel data from the German Socio-Economic Panel covering the years 1984 to 2014, we apply survival analysis methods to model immigrants' unemployment durations. We find that lower levels of trust expressed by natives toward the citizens of a given country, measured using Eurobarometer surveys, are associated with increased unemployment durations for immigrants from this country. We show that this result is not driven by origin-specific unobserved heterogeneity and that it is robust to different specifications and alternative explanations.

Keywords Immigrant workers · Unemployment duration · Discrimination

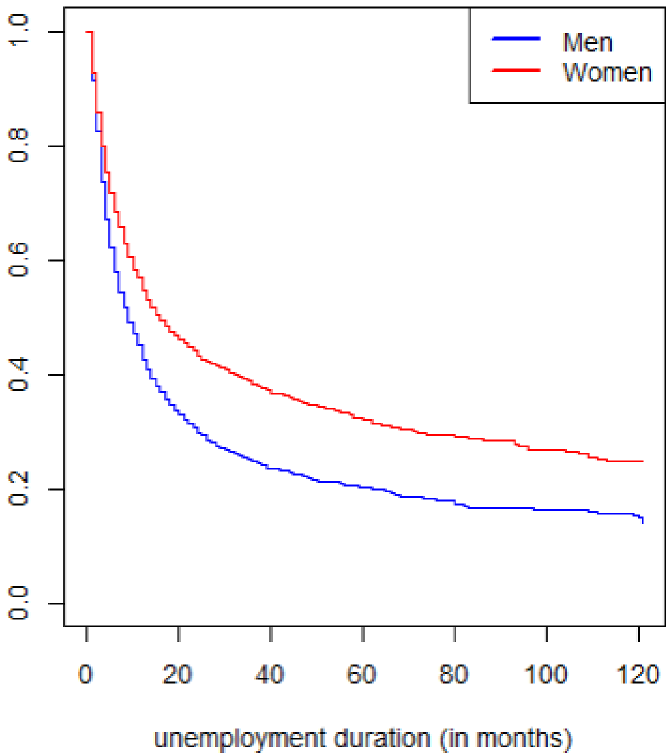
Marriage, Gender, and Class: The Effects of Partner Resources on Unemployment Exit in Germany

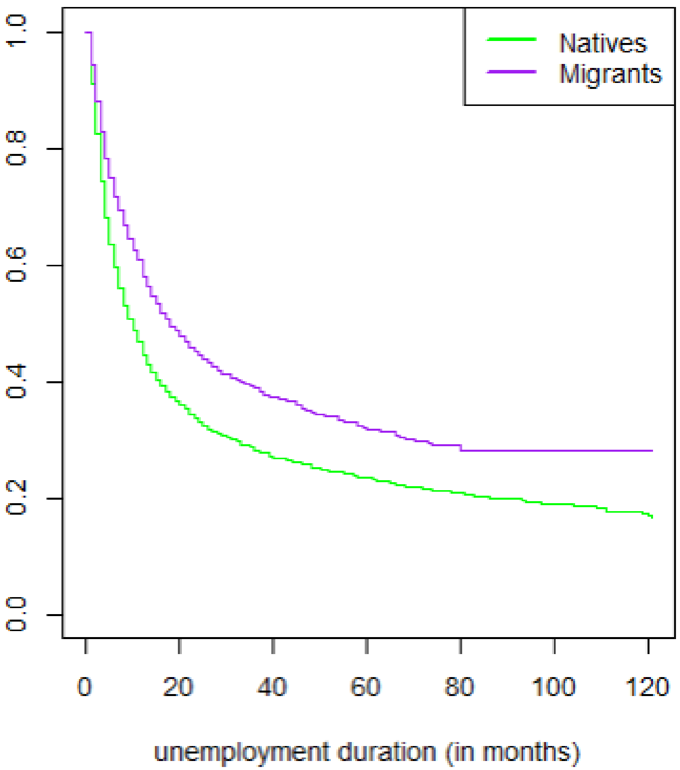
Marita Jacob, *University of Cologne*
Corinna Kleinert, *Institute for Employment Research, Nuremberg*

Research on social inequality and the family has indicated that partners are relevant to individuals' labor market decisions. Unemployment is a particularly interesting issue in the partnership context because the ensuing loss of income may affect the entire family. Against this background, we examine how singles and couples differ in terms of unemployment duration and how a partner's income and labor market–related resources influence re-employment. Considering the gender and class differences in labor market participation, we are particularly interested in variations in partner support between men and women in differing economic circumstances.

Using data from the German Socio-Economic Panel (GSOEP), we find that cohabitation accelerates re-employment, whereas marriage increases the prospect of re-employment only for men. More specifically, the partner's labor market resources facilitate re-employment. Although partner income has no effect in absolute terms, unemployed men and women who were formerly minor earners refrain from re-entering paid work. This pattern is more pronounced among low- and medium-income couples than among high-income families. Unemployment thus strengthens patterns of inequality both between and within couples.

Survival Function: Transition out of unemployment





Compositional Effects

Results from Cox Model, HR

Characteristic	Model01 HR[1]	Model01 95% CI[1]	Model01 p-value	Model02 HR[1]	Model02 95% CI[1]	Model02 p-value	Model03 HR[1]	Model03 95% CI[1]	Model03 p-value
Sex									
Men	—	—		—	—		—	—	
Women	0.68	0.66, 0.71	<0.001	0.68	0.65, 0.71	<0.001	0.68	0.66, 0.71	<0.001
Migration background									
Migrants	—	—		—	—		—	—	
Natives	1.57	1.50, 1.64	<0.001	1.39	1.32, 1.45	<0.001	1.36	1.30, 1.43	<0.001
AGECAT									
17-24	—	—		—	—		—	—	
25-29	1.28	1.19, 1.38	<0.001	1.12	1.04, 1.20	0.003	1.12	1.04, 1.21	0.002
30-39	1.09	1.02, 1.17	0.008	0.91	0.85, 0.97	0.004	0.92	0.86, 0.98	0.014
40-59	1.02	0.95, 1.09	0.6	0.82	0.77, 0.88	<0.001	0.86	0.80, 0.92	<0.001
50-64	0.62	0.58, 0.67	<0.001	0.49	0.46, 0.53	<0.001	0.52	0.48, 0.55	<0.001
Education									
1-low				—	—		—	—	
2-medium				1.96	1.84, 2.08	<0.001	1.94	1.83, 2.07	<0.001
3-high				2.45	2.27, 2.64	<0.001	2.34	2.17, 2.52	<0.001
Health status									
1-Big worries							—	—	
2-Some worries							1.44	1.36, 1.52	<0.001
3-No worries							1.42	1.33, 1.50	<0.001

[1] HR = Hazard Ratio, CI = Confidence Interval

Model1:

- Women‘s rate of leaving unemployment is 32% lower than men‘s.

A RATE IS NOT A PROBABILITY

WRONG: The likelihood is higher by 57%

Results from Cox Model, HR

Characteristic	Model01			Model02			Model03		
	HR[1]	95% CI[1]	p-value	HR[1]	95% CI[1]	p-value	HR[1]	95% CI[1]	p-value
Sex									
Men	—	—		—	—		—	—	
Women	0.68	0.66, 0.71	<0.001	0.68	0.65, 0.71	<0.001	0.68	0.66, 0.71	<0.001
Migration background									
Migrants	—	—		—	—		—	—	
Natives	1.57	1.50, 1.64	<0.001	1.39	1.32, 1.45	<0.001	1.36	1.30, 1.43	<0.001
AGECAT									
17-24	—	—		—	—		—	—	
25-29	1.28	1.19, 1.38	<0.001	1.12	1.04, 1.20	0.003	1.12	1.04, 1.21	0.002
30-39	1.09	1.02, 1.17	0.008	0.91	0.85, 0.97	0.004	0.92	0.86, 0.98	0.014
40-59	1.02	0.95, 1.09	0.6	0.82	0.77, 0.88	<0.001	0.86	0.80, 0.92	<0.001
50-64	0.62	0.58, 0.67	<0.001	0.49	0.46, 0.53	<0.001	0.52	0.48, 0.55	<0.001
Education									
1-low				—	—		—	—	
2-medium				1.96	1.84, 2.08	<0.001	1.94	1.83, 2.07	<0.001
3-high				2.45	2.27, 2.64	<0.001	2.34	2.17, 2.52	<0.001
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3-No worries							1.42	1.33, 1.50	<0.001

[1] HR = Hazard Ratio, CI = Confidence Interval

Model1:

- Women‘s rate of leaving unemployment is 32% lower than men‘s.
- The rate of leaving unemployment for natives is 57% higher than the rate of migrants.

Results from Cox Model, HR

	Model01			Model02			Model03		
Characteristic	**HR**[1]	**95% CI**[1]	**p-value**	**HR**[1]	**95% CI**[1]	**p-value**	**HR**[1]	**95% CI**[1]	**p-value**
Sex									
Men	—	—		—	—		—	—	
Women	0.68	0.66, 0.71	<0.001	0.68	0.65, 0.71	<0.001	0.68	0.66, 0.71	<0.001
Migration background									
Migrants	—	—		—	—		—	—	
Natives	1.57	1.50, 1.64	<0.001	1.39	1.32, 1.45	<0.001	1.36	1.30, 1.43	<0.001
AGECAT									
17-24	—	—		—	—		—	—	
25-29	1.28	1.19, 1.38	<0.001	1.12	1.04, 1.20	0.003	1.12	1.04, 1.21	0.002
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40-59	1.02	0.95, 1.09	0.6	0.82	0.77, 0.88	<0.001	0.86	0.80, 0.92	<0.001
50-64	0.62	0.58, 0.67	<0.001	0.49	0.46, 0.53	<0.001	0.52	0.48, 0.55	<0.001
Education									
1-low				—	—		—	—	
2-medium				1.96	1.84, 2.08	<0.001	1.94	1.83, 2.07	<0.001
3-high				2.45	2.27, 2.64	<0.001	2.34	2.17, 2.52	<0.001
Health status									
1-Big worries							—	—	
2-Some worries							1.44	1.36, 1.52	<0.001
3-No worries							1.42	1.33, 1.50	<0.001

[1] HR = Hazard Ratio, CI = Confidence Interval

Model1:

- Women‘s rate of leaving unemployment is 32% lower than men‘s.
- The rate of leaving unemployment for natives is 57% higher than the rate of migrants.
- There is a hump-shaped effect of age. Very young and very old repsondents are subject to longer episodes of unemployment.

Results from Cox Model, HR

	Model01			Model02			Model03		
Characteristic	**HR**[1]	**95% CI**[1]	**p-value**	**HR**[1]	**95% CI**[1]	**p-value**	**HR**[1]	**95% CI**[1]	**p-value**
Sex									
Men	—	—		—	—		—	—	
Women	0.68	0.66, 0.71	<0.001	0.68	0.65, 0.71	<0.001	0.68	0.66, 0.71	<0.001
Migration background									
Migrants	—	—		—	—		—	—	
Natives	1.57	1.50, 1.64	<0.001	1.39	1.32, 1.45	<0.001	1.36	1.30, 1.43	<0.001
AGECAT									
17-24	—	—		—	—		—	—	
25-29	1.28	1.19, 1.38	<0.001	1.12	1.04, 1.20	0.003	1.12	1.04, 1.21	0.002
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Education									
1-low				—	—		—	—	
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Health status									
1-Big worries							—	—	
2-Some worries							1.44	1.36, 1.52	<0.001
3-No worries							1.42	1.33, 1.50	<0.001

[1] HR = Hazard Ratio, CI = Confidence Interval

Model 2:

- Education has a positive effect on leaving unemployment:
  - Medium education (compared to low education) increases the rate of leaving unemployment by 96%.
  - For the highly educated, the rate is increased by 145% (compared to the lowly educated).

- After controlling for education, the effect size of migration status declines compared to model 1, suggesting that education attainment can explain some differences between migrants and natives.

Results from Cox Model, HR

Characteristic	Model01			Model02			Model03		
	HR[1]	95% CI[1]	p-value	HR[1]	95% CI[1]	p-value	HR[1]	95% CI[1]	p-value
Sex									
Men	—	—		—	—		—	—	
Women	0.68	0.66, 0.71	<0.001	0.68	0.65, 0.71	<0.001	0.68	0.66, 0.71	<0.001
Migration background									
Migrants	—	—		—	—		—	—	
Natives	1.57	1.50, 1.64	<0.001	1.39	1.32, 1.45	<0.001	1.36	1.30, 1.43	<0.001
AGECAT									
17-24	—	—		—	—		—	—	
25-29	1.28	1.19, 1.38	<0.001	1.12	1.04, 1.20	0.003	1.12	1.04, 1.21	0.002
30-39	1.09	1.02, 1.17	0.008	0.91	0.85, 0.97	0.004	0.92	0.86, 0.98	0.014
40-59	1.02	0.95, 1.09	0.6	0.82	0.77, 0.88	<0.001	0.86	0.80, 0.92	<0.001
50-64	0.62	0.58, 0.67	<0.001	0.49	0.46, 0.53	<0.001	0.52	0.48, 0.55	<0.001
Education									
1-low				—	—		—	—	
2-medium				1.96	1.84, 2.08	<0.001	1.94	1.83, 2.07	<0.001
3-high				2.45	2.27, 2.64	<0.001	2.34	2.17, 2.52	<0.001
Health status									
1-Big worries									
2-Some worries							1.44	1.36, 1.52	<0.001
3-No worries							1.42	1.33, 1.50	<0.001

[1] HR = Hazard Ratio, CI = Confidence Interval

Model 3:

- Poor (subjective) health is a strong predictor for long unemployment duration.
- However, health differences do not seem to explain much of the differences in unemployment duration between migrants and natives.

*   **   ***

Model Fit: Is Model 2 better than Model 2

```
Likelihood ratio test

Model 1: SUBSET02$Surv ~ SEX01 + MIG + AGECAT + EDU
Model 2: SUBSET02$Surv ~ SEX01 + MIG + AGECAT + EDU + WORRY
  #Df LogLik Df  Chisq Pr(>Chisq)
1   8 -93682
2  10 -93589  2 186.46  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> 
```

Do I have to report p-value and Test-statistics?

APA-recommendations: https://www.socscistatistics.com/tutorials/chisquare/default.aspx

How to Report a Chi-Square Test Result (APA)

The APA requirements for citing statistical test results are quite precise, so you need to pay attention to the basic format, and also to the placing of brackets, punctuation, italics, and the like.

This is the basic format for reporting a chi-square test result (where the color red means you substitute in the appropriate value from your study).

X^2 (degress of freedom, *N* = sample size) = chi-square statistic value, *p* = *p* value.

Example

Imagine we conducted a study that looked at whether there is a link between gender and the ability to swim. We might report the results like this:

A chi-square test of independence was performed to examine the relation between gender and the ability to swim. The relation between these variables was significant, X^2 (1, *N* = 84) = 8.9, *p* = .0029. Women were more likely than men to be able to swim.

Other Examples

The proportion of subjects who reported being depressed did not differ by marriage, X^2 (1, *N* = 104) = 1.7, *p* > .05.

There is a significant relationship between the two variables. Hipsters are more likely than non-hipsters to own an IPhone, X^2 (1, *N* = 54) = 6.7, *p* < .01.

A chi-square test of independence showed that there was no significant association between gender and chocolate preference, X^2 (2, *N* = 88) = 2.1, *p* = .35.

STATISTICAL ERRORS

P values, the 'gold standard' of statistical validity, are not as reliable as many scientists assume.

BY REGINA NUZZO

For a brief moment in 2010, Matt Motyl was on the brink of scientific glory: he had discovered that extremists quite literally see the world in black and white.

The results were "plain as day", recalls Motyl, a psychology PhD student at the University of Virginia in Charlottesville. Data from a study of nearly 2,000 people seemed to show that political moderates saw shades of grey more accurately than did either left-wing or right-wing extremists. "The hypothesis was sexy," he says, "and the data provided clear support." The *P* value, a common index for the strength of evidence, was 0.01 — usually interpreted as 'very significant'. Publication in a high-impact journal seemed within Motyl's grasp.

But then reality intervened. Sensitive to controversies over reproducibility, Motyl and his adviser, Brian Nosek, decided to replicate the study. With extra data, the *P* value came out as 0.59 — not even close to the conventional level of significance, 0.05. The effect had disappeared, and with it, Motyl's dreams of youthful fame[1].

It turned out that the problem was not in the data or in Motyl's analyses. It lay in the surprisingly slippery nature of the *P* value, which is neither as reliable nor as objective as most scientists assume. "*P* values are not doing their job, because they can't," says Stephen Ziliak, an economist at Roosevelt University in Chicago, Illinois, and a frequent critic of the way statistics are used.

For many scientists, this is especially worrying in light of the reproducibility concerns. In 2005, epidemiologist John Ioannidis of Stanford University in California suggested that most published findings are false[2]; since then, a string of high-profile replication problems has forced scientists to rethink how they evaluate results.

At the same time, statisticians are looking for better ways of thinking about data, to help scientists to avoid missing important information or acting on false alarms. "Change your statistical philosophy and all of a sudden different things become important," says Steven Goodman, a physician and statistician at Stanford. "Then 'laws' handed down from God are no longer handed down from God. They're actually handed down to us by ourselves, through the methodology we adopt."

DALE EDWIN MURRAY

OUT OF CONTEXT

P values have always had critics. In their almost nine decades of existence, they have been likened to mosquitoes (annoying and impossible to swat away), the emperor's new clothes (fraught with obvious problems that everyone ignores) and the tool of a "sterile intellectual rake" who ravishes science but leaves it with no progeny[3]. One researcher suggested rechristening the methodology "statistical hypothesis inference testing"[3], presumably for the acronym it would yield.

The irony is that when UK statistician Ronald Fisher introduced the *P* value in the 1920s, he did not mean it to be a definitive test. He intended it simply as an informal way to judge whether evidence was significant in the

Moving to a World Beyond "$p < 0.05$"

Some of you exploring this special issue of *The American Statistician* might be wondering if it's a scolding from pedantic statisticians lecturing you about what *not* to do with *p*-values, without offering any real ideas of what *to do* about the very hard problem of separating signal from noise in data and making decisions under uncertainty. Fear not. In this issue, thanks to 43 innovative and thought-provoking papers from forward-looking statisticians, help is on the way.

1. "Don't" Is Not Enough

There's not much we can say here about the perils of *p*-values and significance testing that hasn't been said already for decades (Ziliak and McCloskey 2008; Hubbard 2016). If you're just arriving to the debate, here's a sampling of what not to do:

- Don't base your conclusions solely on whether an association or effect was found to be "statistically significant" (i.e., the *p*-value passed some arbitrary threshold such as $p < 0.05$).
- Don't believe that an association or effect exists just because it was statistically significant.
- Don't believe that an association or effect is absent just because it was not statistically significant.
- Don't believe that your *p*-value gives the probability that chance alone produced the observed association or effect or the probability that your test hypothesis is true.
- Don't conclude anything about scientific or practical importance based on statistical significance (or lack thereof).

Don't. Don't. Just…don't. Yes, we talk a lot about don'ts. The *ASA Statement on p-Values and Statistical Significance* (Wasserstein and Lazar 2016) was developed primarily because after decades, warnings about the don'ts had gone mostly unheeded. The statement was about what not to do, because there is widespread agreement about the don'ts.

Knowing what not to do with *p*-values is indeed necessary, but it does not suffice. It is as though statisticians were asking users of statistics to tear out the beams and struts holding up the edifice of modern scientific research without offering solid construction materials to replace them. Pointing out old, rotting timbers was a good start, but now we need more.

Recognizing this, in October 2017, the American Statistical Association (ASA) held the Symposium on Statistical Inference, a two-day gathering that laid the foundations for this special issue of *The American Statistician*. Authors were explicitly instructed to develop papers for the variety of audiences interested in these topics. If you use statistics in research, business, or policymaking but are not a statistician, these articles were indeed written with YOU in mind. And if you are a statistician, there is still much here for you as well.

The papers in this issue propose many new ideas, ideas that in our determination as editors merited publication to enable broader consideration and debate. The ideas in this editorial are likewise open to debate. They are our own attempt to distill the wisdom of the many voices in this issue into an essence of good statistical practice as we currently see it: some do's for teaching, doing research, and informing decisions.

Yet the voices in the 43 papers in this issue do not sing as one. At times in this editorial and the papers you'll hear deep dissonance, the echoes of "statistics wars" still simmering today (Mayo 2018). At other times you'll hear melodies wrapping in a rich counterpoint that may herald an increasingly harmonious new era of statistics. To us, these are all the sounds of statistical inference in the 21st century, the sounds of a world learning to venture beyond "$p < 0.05$."

This is a world where researchers are free to treat "$p = 0.051$" and "$p = 0.049$" as not being categorically different, where authors no longer find themselves constrained to selectively publish their results based on a single magic number. In this world, where studies with "$p < 0.05$" and studies with "$p > 0.05$" are not automatically in conflict, researchers will see their results more easily replicated—and, even when not, they will better understand *why*. As we venture down this path, we will begin to see fewer false alarms, fewer overlooked discoveries, and the development of more customized statistical strategies. Researchers will be free to communicate all their findings in all their glorious uncertainty, knowing their work is to be judged by the quality and effective communication of their science, and not by their *p*-values. As "statistical significance" is used less, statistical thinking will be used more.

The *ASA Statement on P-Values and Statistical Significance* started moving us toward this world. As of the date of publication of this special issue, the statement has been viewed over 294,000 times and cited over 1700 times—an average of about 11 citations per week since its release. Now we must go further. That's what this special issue of *The American Statistician* sets out to do.

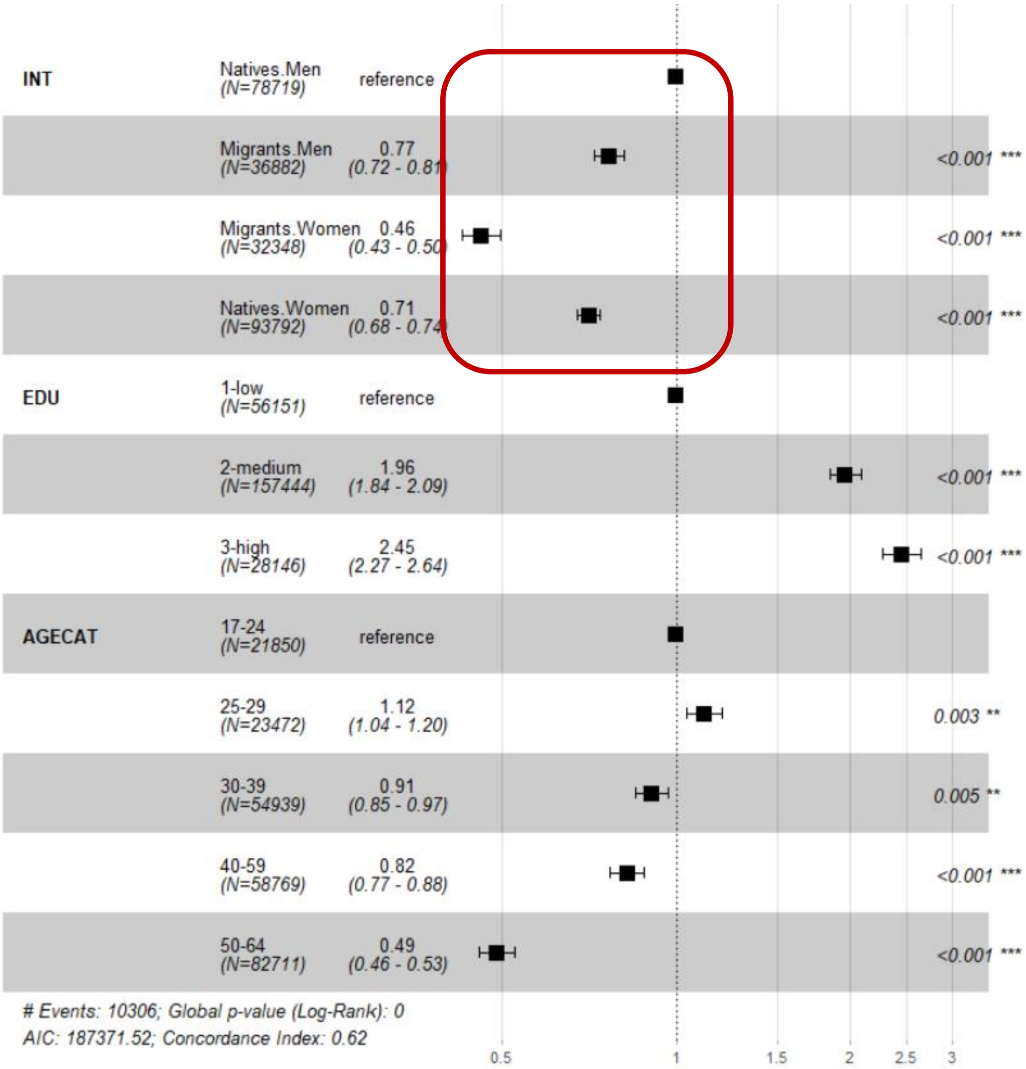
To get to the do's, though, we must begin with one more don't.

https://www.nature.com/articles/506150a.pdf

https://www.tandfonline.com/doi/full/10.1080/00031305.2019.1583913

Interaction Effects

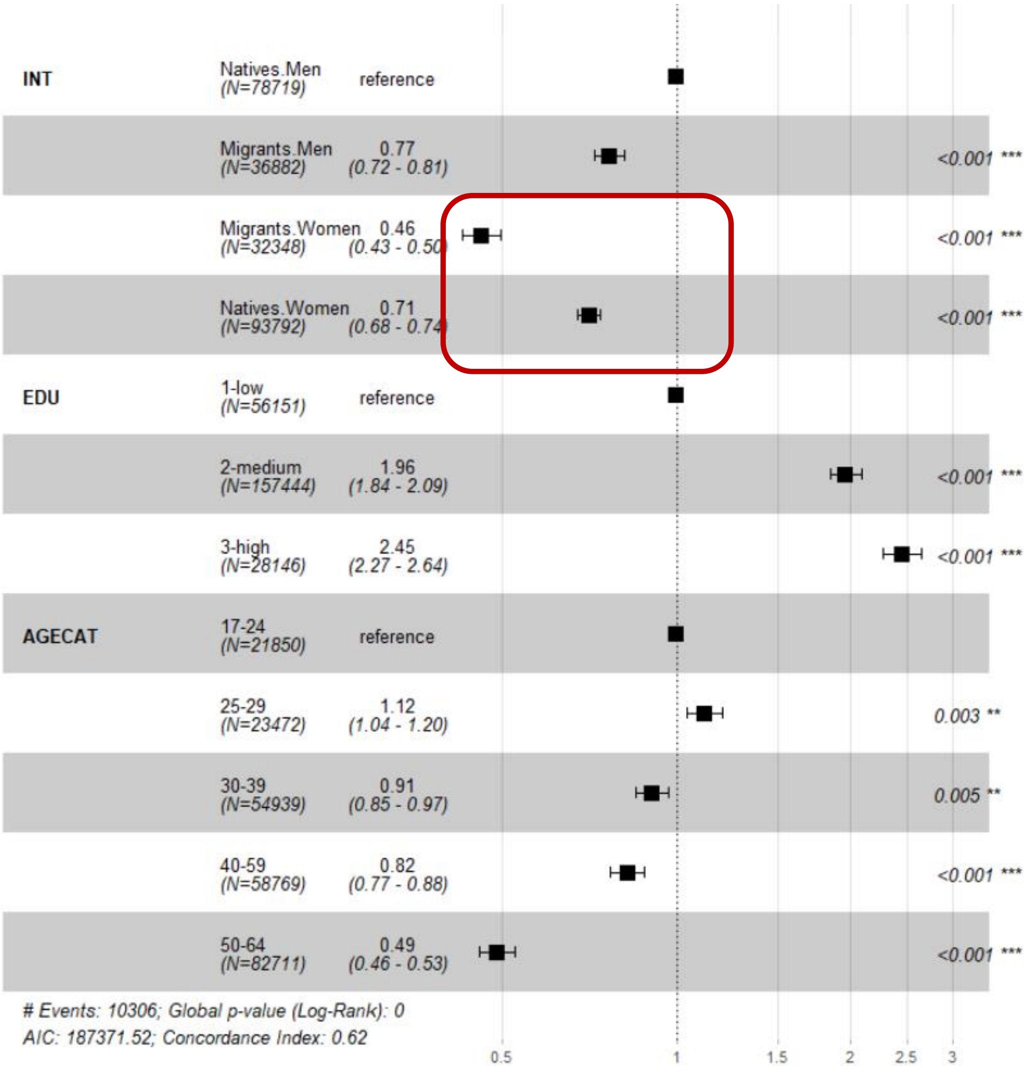
Transition out of unemployment, hazard ratios



- Compared to native men, migrant men‘s rate of leaving unemployment is reduced by 23%.
- Compared to native men, migrant women‘s rate of leaving unemployment is reduced by 40%.
- Compared to native men, native women‘s rate of leaving unemployment is reduced by 29%.

Note: Interpretation of HR of categorical variables is always in relation to the referency category.

Transition out of unemployment, hazard ratios



- Compared to native women, migrant women‘s rate of leaving unemployment is reduced by 35%

[Calculation 1-(0.46/0.71)=0.35]

Is the difference betweeen migrant women and native women significant?

Note: Interpretation of HR of categorical variables is always in relation to the referency category.

Family Context & Unemployment

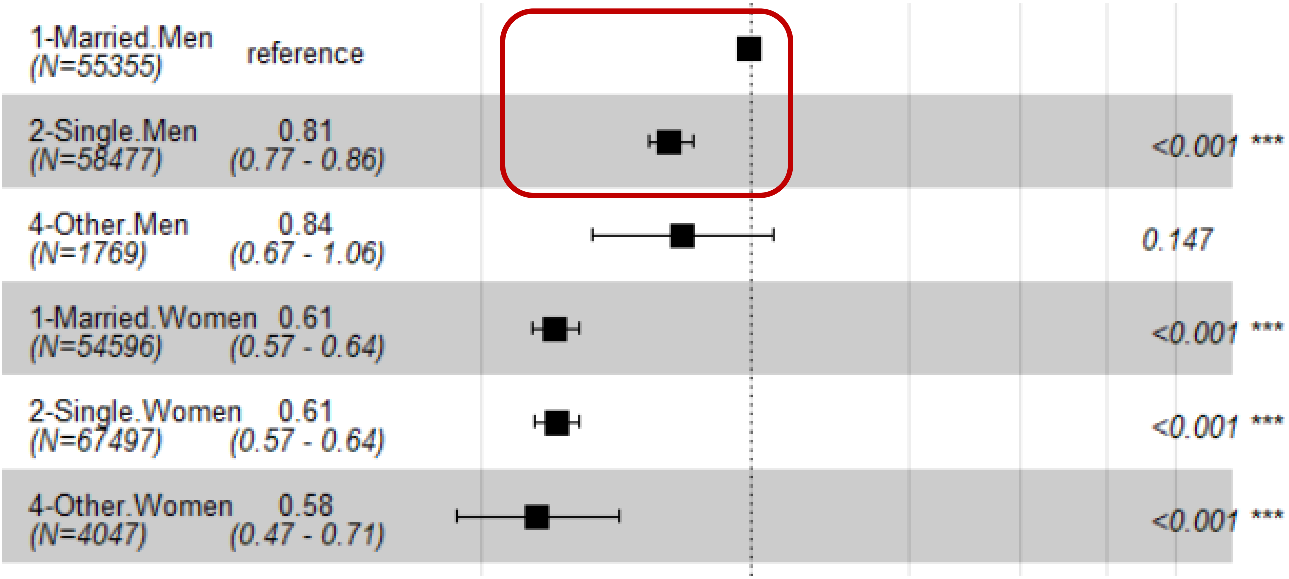
Marriage, Gender, and Class: The Effects of Partner Resources on Unemployment Exit in Germany

Marita Jacob, *University of Cologne*
Corinna Kleinert, *Institute for Employment Research, Nuremberg*

Research on social inequality and the family has indicated that partners are relevant to individuals' labor market decisions. Unemployment is a particularly interesting issue in the partnership context because the ensuing loss of income may affect the entire family. Against this background, we examine how singles and couples differ in terms of unemployment duration and how a partner's income and labor market–related resources influence re-employment. Considering the gender and class differences in labor market participation, we are particularly interested in variations in partner support between men and women in differing economic circumstances.

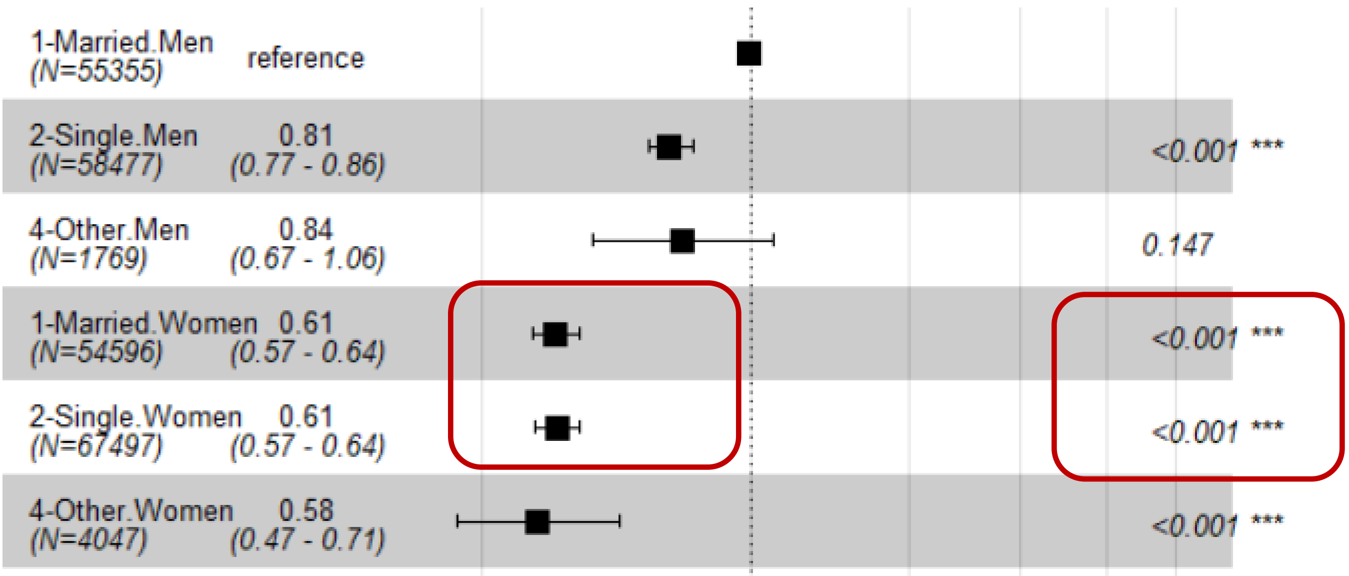
Using data from the German Socio-Economic Panel (GSOEP), we find that cohabitation accelerates re-employment, whereas marriage increases the prospect of re-employment only for men. More specifically, the partner's labor market resources facilitate re-employment. Although partner income has no effect in absolute terms, unemployed men and women who were formerly minor earners refrain from re-entering paid work. This pattern is more pronounced among low- and medium-income couples than among high-income families. Unemployment thus strengthens patterns of inequality both between and within couples.

Transition out of unemployment, hazard ratio



- Unmarried men encounter a lower rate of leaving unemployment than married men.
- Unmarried and married do not seem to differ.

Transition out of unemployment, hazard ratio



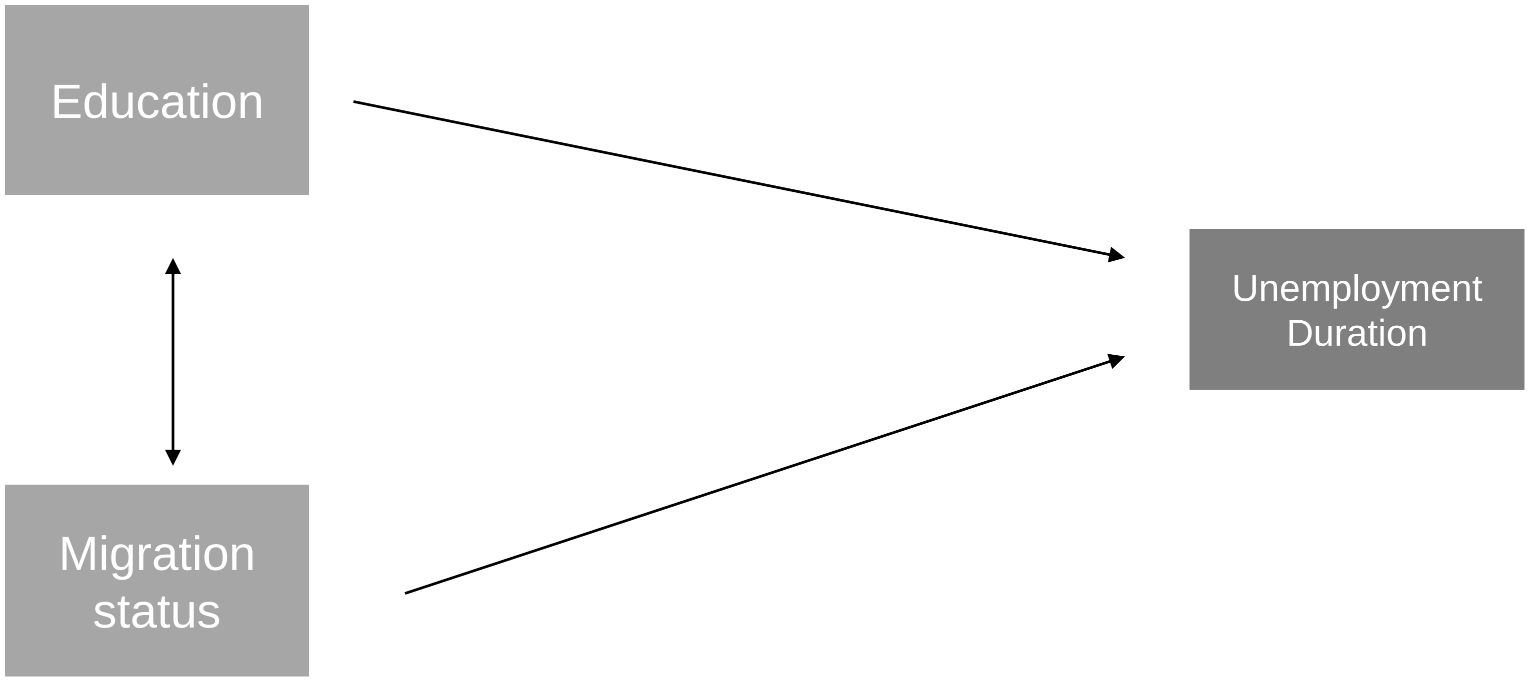
- Unmarried and married women do not seem to differ.

Is the difference significant?

Limitations

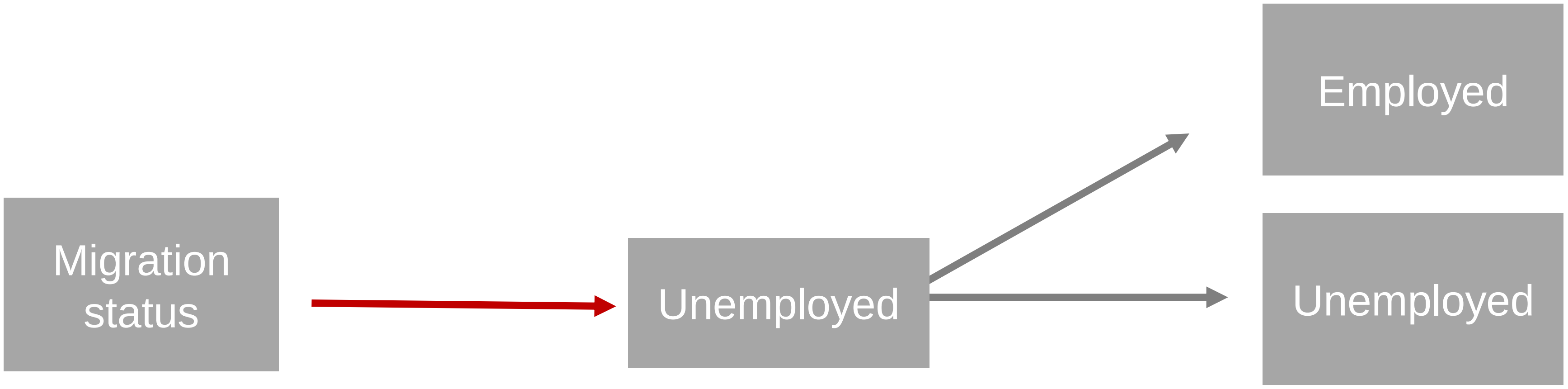
Omitted variable bias

- Education
- Work experience
- Household income/partner income
- Language proficiency, ethnicity, duration of stay in country



Selected Sample

- Natives are less likely than migrants to become unemployed.
- Those natives who are unemployed may be negatively selected. This negative selection may increase their unemployment duration.
- Accounting for selection should increase the differences between migrants and natives.



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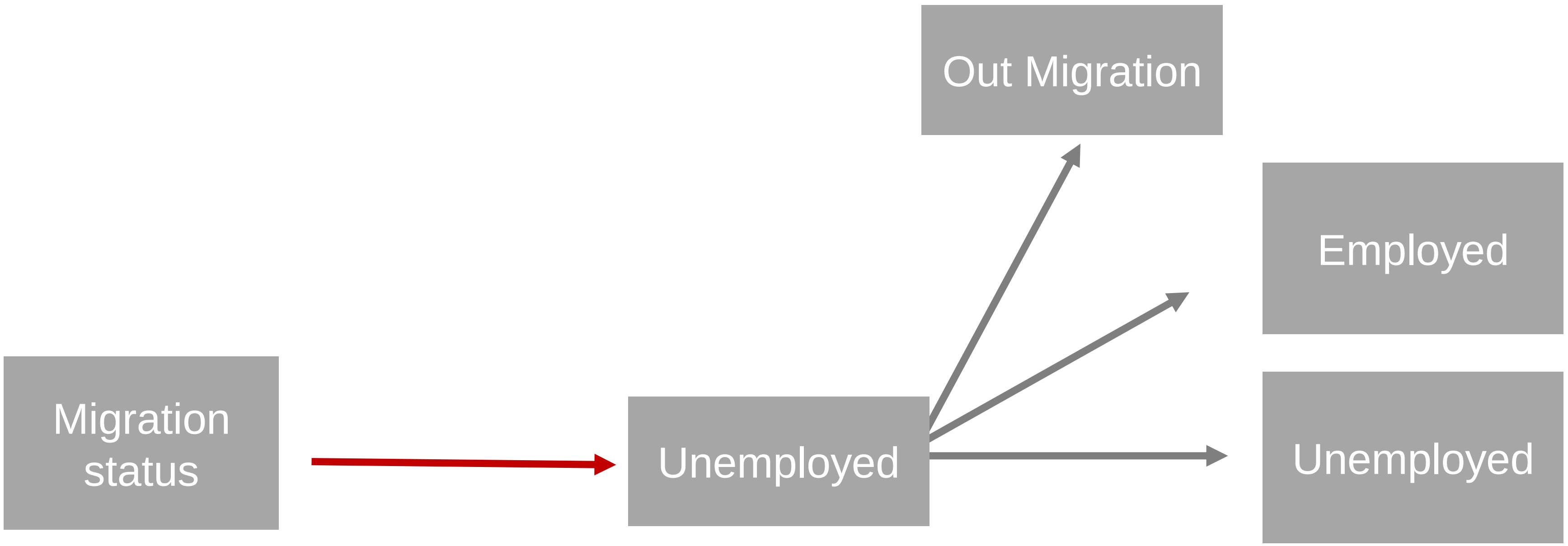
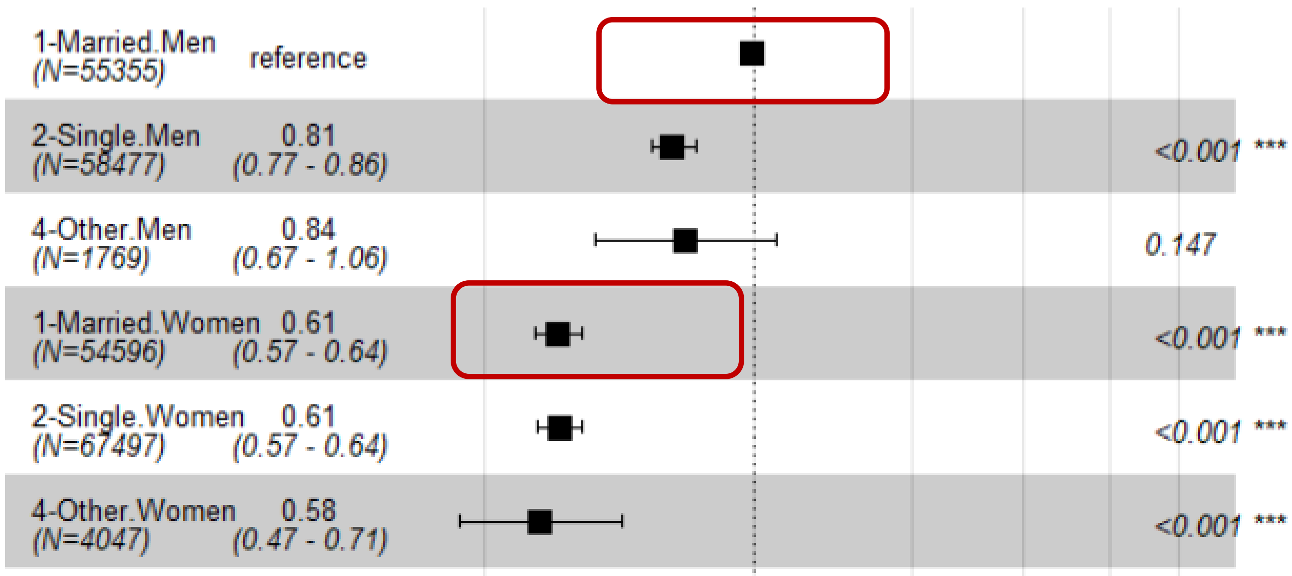


Transition out of unemployment, hazard ratio

Causal?



Proportionality Assumption

- Natives who are unemployed for a long period of time may be a particular group with very poor labor market prospects.

- The rate to leave unemployment may narrow down between natives and migrants with increasing duration of unemployment.