Decomposition Methods in the Social Sciences GESIS Training Course January 29 – February 1, 2024, Cologne

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5. Difference-in-difference decompositions

Contents



- 2 Example analysis
- 3 Juhn-Murphy-Pierce 1991 decomposition
- 4 Example analysis



Difference-in-difference decompositions

- Up to now we were concerned with a single outcome differential (e.g. a gender wage gap) at a specific point in time and in a specific region or population.
- Often, however, comparisons over time or between countries or regions are of interest.
 - ► How did the gender wage gap change over time and how much of this change is due to changes with respect to covariates?
 - How would the gender wage gap in country A look like if it had the wage structure of country B?
- One way of analyzing changes over time or between populations is to compare separate decomposition results. Some questions, however, require a "double" or "difference-in-difference" decomposition.
- A very famous application of such methodology, for example, is the "Swimming upstream" paper by Blau and Kahn (1997).



3 Juhn-Murphy-Pierce 1991 decomposition

4 Example analysis

5 Interventionist approach (Kröger/Hartmann)

Smith-Welch decomposition

(Smith and Welch 1987, also see e.g. Heckman et al. 2000, Kröger and Hartmann 2021)

• Given is a linear model

$$Y^{gt} = X^{gt}\beta^{gt} + \epsilon^{gt}, \quad \mathsf{E}(e^{gt}|X^{gt}) = 0$$

for two groups, g = m, f (males and females), at two time points, t = 0, 1.

 Using the male coefficients, β^{mt}, as reference, the decomposition of the group difference in average Y at time t can be written as

$$\Delta^{\mu t} = (ar{X}^{mt} - ar{X}^{ft})eta^{mt} + ar{X}^{ft}(eta^{mt} - eta^{ft}) = \Delta^{\mu t}_X + \Delta^{\mu t}_S$$

• We are now interested in decomposing the change in the wage gap over time.

Smith-Welch decomposition

• Let $\Delta \bar{X}^t = \bar{X}^{mt} - \bar{X}^{ft}$ and $\Delta \beta^t = \beta^{mt} - \beta^{ft}$. Using the male coefficients from the first time point, β^{m0} , as reference, this double decomposition can be written as

$$d\Delta^{\mu} = \Delta^{\mu 1} - \Delta^{\mu 0} = \left\{ (\Delta \bar{X}^1 - \Delta \bar{X}^0) \beta^{m 0} + \Delta \bar{X}^1 (\beta^{m 1} - \beta^{m 0}) \right\} \\ + \left\{ \bar{X}^{f 1} (\Delta \beta^1 - \Delta \beta^0) + (\bar{X}^{f 1} - \bar{X}^{f 0}) \Delta \beta^0 \right\} \\ = d\Delta^{\mu}_{\chi} + d\Delta^{\mu}_{S}$$

• Interpretation:

 $(\Delta \bar{X}^1 - \Delta \bar{X}^0) \beta^{m0}$

$$\Delta \bar{X}^1 (\beta^{m1} - \beta^{m0})$$

main endowments effect: shows how the wage gap changed because men and women became more similar or dissimilar in X (negative, if they became more similar; positive, if they became more dissimilar) secondary endowments effect due to change in reference wage structure over time

Smith-Welch decomposition

 $\bar{X}^{f_1}(\Delta\beta^1 - \Delta\beta^0)$ primary coefficients effect: effect of change in wage structure difference between men and women (negative, if coefficients became more similar; positive, if coefficients became more dissimilar)

 $(\bar{X}^{f1} - \bar{X}^{f0})\Delta\beta^0$

secondary coefficients effect due to change in reference endowments over time

- Of course, various other types of decompositions are possible depending on the choice of the reference group and the reference year. The index problem of the standard OB decomposition is now a double index problem, which can make it hard to keep an overview.
- See help smithwelch for a systematic discussion. It starts with the threefold decomposition and then shows how the formulas change if a reference group and/or a reference year is introduced. Of course, reference groups/years can also be results from pooled or averaged models. See Kröger and Hartmann (2021) for further variants of difference-in-differences decompositions.



Juhn-Murphy-Pierce 1991 decomposition

4 Example analysis

5 Interventionist approach (Kröger/Hartmann)

Example analysis (using smithwelch by Jann 2005b)

```
. use gsoep-extract, clear
(Example data based on the German Socio-Economic Panel)
(.keep if inlist(wave,1995,2015)
(23,792 observations deleted)
. keep if inrange(age, 25, 55)
(8,147 observations deleted)
. generate lnwage = ln(wage)
(2,734 missing values generated)
. generate expft2 = expft"2
(56 missing values generated)
. generate byte t = wave==2015 // 0 = 1995, 1 = 2015
```

```
. generate byte female = sex==2 // 0 = male, 1 = female
```

```
. summarize lnwage yeduc expft expft2 t female
```

Variable	Obs	Mean	Std. dev.	Min	Max
lnwage	8,277	2.71872	. 483595	1.108563	4.86638
yeduc	10,735	12.04332	2.700811	7	18
expft	10,955	12.21353	9.640926	0	40.5
expft2	10,955	242.1094	305.9972	0	1640.25
t	11,011	.6637908	.4724329	0	1
female	11,011	.5466352	. 497843	0	1

```
. drop if missing(lnwage,yeduc,expft) // remove unused observation (2,940 observations deleted)
```

```
. svyset psu [pw=weight], strata(strata)
```

```
Sampling weights: weight
```

```
VCE: linearized
```

```
Single unit: missing
```

```
Strata 1: strata
```

```
Sampling unit 1: psu
```

```
FPC 1: <zero>
```

• Outcome by time point and gender

```
. svy: mean lnwage if !missing(yeduc, expft), over(t female)
(running mean on estimation sample)
Survey: Mean estimation
Number of strata = 15 Number of obs = 8,071
Number of PSUs = 2,459 Population size = 23,859,887
Design df = 2,444
```

	Mean	Linearized std. err.	[95% conf.	interval]
c.lnwage@t#female				
0 0	2.84812	.0132636	2.822111	2.874129
0 1	2.627384	.0186491	2.590815	2.663954
1 0	2.862735	.0164148	2.830547	2.894923
1 1	2.657428	.0151483	2.627723	2.687132

• Characteristics by time point and gender

. svy: mean yeduc expft if !missing(lnwage), over(t female) (running mean on estimation sample) Survey: Mean estimation Number of strata = 15 Number of obs = 8,071 Number of PSUs = 2,459 Population size = 23,859,587 Design df = 2,444

	Mean	Linearized std. err.	[95% conf. interval]
c.yeduc@t#female			
0 0	12.04901	.0924429	11.86774 12.23029
0 1	11.79327	.091392	11.61406 11.97249
1 0	12.7098	.0980728	12.51749 12.90212
1 1	12.94121	.0904373	12.76387 13.11855
c.expft@t#female			
0 0	17.49546	.3094411	16.88867 18.10226
0 1	12.39256	.3700076	11.667 13.11812
1 0	17.17692	.3427645	16.50478 17.84906
1 1	10.79882	.2760263	10.25755 11.34009

• OB decomposition in 1995

. oaxaca lnwage yeduc (experience: expft expft2) /// if t==0, by(female) weight(1) nodetail svy > Blinder-Oaxaca decomposition Number of strata = 4 Number of obs = Population size = 11,707,370 Number of PSUs = 794 Design df = Model = linear Group 1: female = 0N of obs 1 = 1,486 Group 2: female = 1 N of obs 2 = explained: (X1 - X2) * b1

unexplained:	X2 *	(b1	- b2)
--------------	------	-----	-------

lnwage	Coefficient	Linearized std. err.	t	P> t	[95% conf.	interval]
overall						
group_1	2.84812	.013042	218.38	0.000	2.822519	2.873721
group_2	2.627384	.0178997	146.78	0.000	2.592248	2.662521
difference	.2207358	.0206432	10.69	0.000	.1802138	.2612579
explained	.0758792	.0115696	6.56	0.000	.0531684	.0985899
unexplained	.1448567	.0216315	6.70	0.000	.1023946	.1873188

2,609

1.123

790

• OB decomposition in 2015

. oaxaca lnwage yeduc (experience: expft expft2) /// > if t==1, by(female) weight(1) nodetail svy Blinder-Oaxaca decomposition Number of strata = 15 Number Number of PSUs = 2,037 Populat Design Model

```
Group 1: female = 0
Group 2: female = 1
    explained: (X1 - X2) * b1
    unexplained: X2 * (b1 - b2)
```

Number of obs	= 5,462
Population size	= 12,152,217
Design df	= 2,022
Model	= linear
N of obs 1	= 2,642
N of obs 2	= 2,820

lnwage	Coefficient	Linearized std. err.	t	P> t	[95% conf.	interval]
overall						
group_1	2.862735	.0162749	175.90	0.000	2.830818	2.894652
group_2	2.657428	.0149503	177.75	0.000	2.628108	2.686747
difference	.2053074	.0204701	10.03	0.000	.1651628	.245452
explained	.0904872	.0151554	5.97	0.000	.0607654	.120209
unexplained	.1148202	.0211416	5.43	0.000	.0733585	.1562819

- Estimate outcome models by time point and gender; these model will be used as input to the Smith-Welch decomposition.
 - . svy: regress lnwage yeduc expft expft2 if female==0 & t==0 (output omitted)
 - . estimates store male_t0
 - . svy: regress lnwage yeduc expft expft2 if female==1 & t==0 (output omitted)
 - . estimates store female_t0
 - . svy: regress lnwage yeduc expft expft2 if female==0 & t==1
 (output omitted)
 - . estimates store male_t1
 - . svy: regress lnwage yeduc expft expft2 if female==1 & t==1
 (output omitted)
 - . estimates store female_t1

• Overview of models.

. esttab male_t0 female_t0 male_t1 female_t1, nogap mti nonum r2

	male_t0	female_t0	male_t1	female_t1
yeduc	0.0567***	0.0586***	0.0829***	0.0789***
	(9.51)	(9.63)	(14.88)	(14.91)
expft	0.0318***	0.0206**	0.0357***	0.0313***
1	(5.62)	(3.11)	(6.04)	(6.36)
expft2	-0.000614***	-0.000373	-0.000593***	-0.000541***
1	(-4.09)	(-1.93)	(-3.79)	(-3.67)
_cons	1.855***	1.769***	1.430***	1.404***
-	(20.65)	(20.61)	(14.96)	(18.93)
N	1486	1123	2642	2820
R-sq	0.145	0.123	0.280	0.277

t statistics in parentheses

* p<0.05, ** p<0.01, *** p<0.001

• Smith-Welch decomposition

. smithwelch male_t0 female_t0 male_t1 female_t1, reference(1) benchmark(1) Decompositions of individual differentials:

	D	E	C
Sample 1	.2207358	.0758792	.1448567
Sample 2	.2053074	.0904872	.1148202

Difference in (components of) differentials:

dD	dE	dC
 0154284	.014608	0300365

Decomposition of difference in differentials:

	D	E	С
dE dC		0087573 0105462	

```
D = differential / difference in component of differential
E = part of D due to differences in endowments
C = part of D due to differences in coefficients
```

• Detailed Smith-Welch decomposition

. smithwelch male_t0 female_t0 male_t1 female_t1, reference(1) benchmark(1) ///

```
> detail(schooling=yeduc, experience=expft*)
```

Decompositions of individual differentials:

Sample 1	D	E	С
schooling experience _cons	0084441 .1426075 .0865725	.0144885 .0613907 0	0229326 .0812168 .0865725
Total	.2207358	.0758792	. 1448567
Sample 2	D	E	С
schooling experience _cons	.0328791 .1466832 .0257451	0191954 .1096826 0	.0520745 .0370006 .0257451
Total	.2053074	.0904872	.1148202

Difference in (components of) differentials:

	dD	dE	dC
schooling	.0413232	0336838	.0750071
experience	.0040757	.0482919	0442162
_cons	0608274	0	0608274

	0454004	01/608	0200265
Total	0154284	.014608	0300365

Decomposition of difference in differentials:

.

dE	D	E	C
schooling experience _cons	0336838 .0482919 0	0275985 .0188412 0	0060853 .0294507 0
Total	.014608	0087573	.0233653
dC	D	E	C
schooling experience _cons	.0750071 0442162 0608274	0022322 0083139 0	.0772393 0359022 0608274
Total	0300365	0105462	0194903

D = differential / difference in component of differential

- E = part of D due to differences in endowments
- C = part of D due to differences in coefficients



3 Juhn-Murphy-Pierce 1991 decomposition

4 Example analysis

5 Interventionist approach (Kröger/Hartmann)

Juhn-Murphy-Pierce 1991 decomposition (Juhn et al. 1991)

- Juhn et al. (1991) use an alternative setup by considering changes in the residual variance.
- The argument is that the gender wage gap will be large if the residual variance, that is, the variance of wages once controlling for observables such as education or work experience, is large.
- Conceptually, the residual variance can be viewed as the price of unobservables. The idea is, that there may be differences between men and women in such unobservables. If the prices increase, the gender wage gap will increase as well.
- For example, Blau and Kahn (1997) use the method in an analysis in which they argue that the gender wage gap would have declined more than it actually did, hadn't there been a strong increase in general wage inequality that had nothing to do with gender.

• Consider a model

 $Y^{gt} = X^{gt}\beta^t + \epsilon^{gt}$

for two groups, g = m, f (males and females), at two time points, t = 0, 1, where β^t are some reference regression parameters (non-discriminatory prices of observables).

• The model can also be expressed as

$$Y^{gt} = X^{gt}\beta^t + r^{gt}\sigma^t$$

where σ is a reference residual standard deviation (non-discriminatory prices of unobservables) and $r = (Y - X\beta^t)/\sigma^t$ is a standardized residual.

• Thus, the equation now has a two-component error term. The residuals are expressed as a function of the general residual inequality at time *t* and the positions of the residuals in the residual distribution.

• The mean outcome differential between men an women at time *t* can then be decomposed as follows:

$$\begin{aligned} \Delta^{\mu,t} &= \bar{Y}^{mt} - \bar{Y}^{ft} = (\bar{X}^{mt} - \bar{X}^{ft})\beta^t + (\bar{r}^{mt} - \bar{r}^{ft})\sigma^t \\ &= \Delta^{\mu}_X + \Delta^{\mu}_S \end{aligned}$$

- The first term is the "predicted gap" and the second term is the "residual gap". They are equal to the "explained" part and the "unexplained" part in a standard OB decomposition using β^t as reference coefficients.
- Let $\Delta \bar{X}^t = (\bar{X}^{mt} \bar{X}^{ft})$ and $\Delta \bar{r}^t = (\bar{r}^{mt} \bar{r}^{ft})$. Given two time points t = 0 and t = 1 the change in the outcome differential can then be written as

$$egin{aligned} \Delta^{\mu,1} - \Delta^{\mu,0} &= (\Delta ar{X}^1 eta^1 - \Delta ar{X}^0 eta^0) + (\Delta ar{r}^1 \sigma^1 - \Delta ar{r}^0 \sigma^0) \ &= d\Delta^{\mu}_X + d\Delta^{\mu}_S \end{aligned}$$

• The change in the "predicted gap" can be further decomposed as

$$d\Delta^{\mu}_{X} = (\Delta \bar{X}^1 - \Delta \bar{X}^0)\beta^0 + \Delta \bar{X}^0(\beta^1 - \beta^0) + (\Delta \bar{X}^1 - \Delta \bar{X}^0)(\beta^1 - \beta^0)$$

where the first term is the main "observed quantities" effect due to a change in gender differences in X, the second term is a secondary effect due a change in "prices" for observed quantities, and the third term is an interaction term.

• Likewise, the change in the "residual gap" can be decomposed as

$$d\Delta_S^{\mu} = (\Delta \bar{r}^1 - \Delta \bar{r}^0)\sigma^0 + \Delta \bar{r}^0(\sigma^1 - \sigma^0) + (\Delta \bar{r}^1 - \Delta \bar{r}^0)(\sigma^1 - \sigma^0)$$

where the first term is the so-called "gap effect" due to changes in the group differences in residual positions (i.e. changes in the group differences in "unobserved quantities" and changes in discrimination), the second term is the part due to changes in residual inequality (i.e. changes in "prices" for unobserved quantities), and the third term is again an interaction term.

• Similar to other decompositions, it is common practice to use the "prices" of one of the years as the reference prices (or use some average or pooled results). For example, if we use t = 0 as the reference, the decomposition simplifies to:

$$d\Delta_X^{\mu} = (\Delta \bar{X}^1 - \Delta \bar{X}^0)\beta^0 + \Delta \bar{X}^1(\beta^1 - \beta^0)$$
$$d\Delta_S^{\mu} = (\Delta \bar{r}^1 - \Delta \bar{r}^0)\sigma^0 + \Delta \bar{r}^1(\sigma^1 - \sigma^0)$$

- Furthermore, a detailed decomposition can be obtained for the components of dΔ^μ_X in the usual way (but obviously not for dΔ^μ_S).
- Note that results for $d\Delta_X^{\mu}$ are the same as for the Smith-Welch decomposition (if using the same setup). For $d\Delta_S^{\mu}$ only the total is the same; that is, Smith-Welch and Juhn-Murphy-Pierce lead to a different breakup of $d\Delta_S^{\mu}$.

Juhn-Murphy-Pierce 1991 decomposition: estimation

- Estimation of the components of $d\Delta^{\mu}_{X}$ is straightforward.
- Estimation of the components of $d\Delta_S^{\mu}$ is more involved and requires some discussion. Two approaches are used in the literature, a **parametric** approach and a **nonparametric** approach.
- Parametric
 - Since, by definition, $\epsilon^t = r^t \sigma^t$, expression $\Delta \bar{r}^t \sigma^t$ can simply be estimated as the mean difference in residuals ϵ between men an women at time *t*.
 - But what about expressions such as $\Delta \bar{r}^1 \sigma^0$?
 - ► An obvious solution is to estimate the residual standard deviation at time t = 0 and then multiply it by the mean difference in standardized residuals of t = 1.
- Nonparametric
 - The parametric approach is simple, but neglects changes in the distributional shape (apart from the variance).
 - ► The following nonparametric procedure has therefore been proposed.

Juhn-Murphy-Pierce 1991 decomposition: estimation

Let F^t() be the distribution function of the residuals at time t.
 Furthermore, let p^t represent the relative positions of the residuals in the residual distribution at time t, that is

 $p^{gt} = F^t(\epsilon^{gt})$ and thus $\epsilon^{gt} = Q^t(p^{gt})$

where $Q() = F^{-1}()$ is the quantile function (inverse of F()).

- The solution now is to apply the quantile function of one time point to the residual ranks of the other time point.
- For example, $\Delta \bar{r}^1 \sigma^0$ is estimated by assigning each individual at t = 1a percentile number corresponding to its position in the residual distribution of t = 1 (i.e., compute p^1), then using these relative ranks to derive hypothetical residuals given the t = 0 residual distribution (i.e. compute $Q^0(p^1)$), and finally taking the mean difference in these hypothetical residuals between men and women.
- The JMP 1991 procedure relies on some strong assumptions and is not free of critique (e.g. Yun 2009).



Juhn-Murphy-Pierce 1991 decomposition

Example analysis

5 Interventionist approach (Kröger/Hartmann)

Example analysis (using jmpierce2 by Jann 2005b)

- Estimate the outcome models to be used in the JMP 1991 decomposition.
 - jmpierce2 does not fully support models estimated with the svy prefix; this is why we just apply the weights rather than svy.
 - . regress lnwage yeduc expft expft2 [pw=weight] if female==0 & t==0 (output omitted)
 - . estimates store male_t0
 - . regress lnwage yeduc expft expft2 [pw=weight] if female==1 & t==0 (output omitted)
 - . estimates store female_t0
 - . regress lnwage yeduc expft expft2 [pw=weight] if female==0 & t==1
 (output omitted)
 - . estimates store male_t1
 - . regress lnwage yeduc expft expft2 [pw=weight] if female==1 & t==1
 (output omitted)
 - . estimates store female_t1

• Nonparametric JMP 1991 decomposition

. jmpierce2 male_t0 female_t0 male_t1 female_t1, reference(1) benchmark(1) Decomposition of individual differentials:

	raw dif-	quantity	residual
	ferential	effect	gap
Sample 1	.2207358	.0758792	.1448567
Sample 2	.2053074	.0904872	.1148202

Difference in (components of) differentials:

	D	E	U
Total	0154284	.014608	0300365

Decomposition of difference in predicted gap:

	E	Q	Р
Total	.014608	0087573	.0233653

Decomposition of diffence in residual gap:

	U	Q	Р
Total	0300365	0394444	.0094079

- D = difference in differential
- E = difference in predicted gap
- U = difference in residual gap
- Q = quantity effect
- P = price effect

• Parametric JMP 1991 decomposition

. jmpierce2 male_t0 female_t0 male_t1 female_t1, reference(1) benchmark(1) parametric Decomposition of individual differentials:

	raw dif-	quantity	residual
	ferential	effect	gap
Sample 1	.2207358	.0758792	.1448567
Sample 2	.2053074	.0904872	.1148202

Difference in (components of) differentials:

	D	E	U
Total	0154284	.014608	0300365

Decomposition of difference in predicted gap:

	E	Q	Р
Total	.014608	0087573	.0233653

Decomposition of diffence in residual gap:

	U	Q	Р
Total	0300365	0385607	.0085242

- D = difference in differential
- E = difference in predicted gap
- U = difference in residual gap
- Q = quantity effect
- P = price effect

• Detailed JMP 1991 decomposition

. jmpierce2 male_t0 female_t0 male_t1 female_t1, reference(1) benchmark(1) ///

> detail(schooling=yeduc, experience=expft*)

Decomposition of individual differentials:

	raw dif-	quantity	residual
	ferential	effect	gap
Sample 1	.2207358	.0758792	.1448567
Sample 2	.2053074	.0904872	.1148202

Difference in (components of) differentials:

	D	E	U
Total	0154284	.014608	0300365

Decomposition of difference in predicted gap:

	E	Q	Р
Total	.014608	0087573	.0233653
schooling experience	0336838 .0482919	0275985 .0188412	0060853 .0294507

Decomposition of diffence in residual gap:

	U	Q	Р
Total	0300365	0394444	.0094079

- D = difference in differential
- E = difference in predicted gap
- U = difference in residual gap
- Q = quantity effect
- P = price effect



Juhn-Murphy-Pierce 1991 decomposition

4 Example analysis

Interventionist approach (Kröger/Hartmann)

Interventionist approach (Kröger/Hartmann)

- Kröger and Hartmann (2021) give an overview of several difference-in-differences decompositions and propagate an easy to interpret interventionist approach.
- The approach is somewhat different from Smith-Welch and Juhn-Murphy-Pierce in that it does not try to provide separate breakups of the change/difference in the explained part and the change/difference in the unexplained part.
- Again, let there be two groups two groups, $g \in \{m, f\}$ (males and females), and two time points, $t \in \{0, 1\}$.
- The decomposition then asks:
 - 1. How does the group difference change if endowments are adjusted to the level of time 1, but coefficients are kept at their values of time 0 (endowments effect).
 - 2. How does the group difference change if coefficients are adjusted to the values of time 1, but endowments are kept at their level of time 0 (coefficients effect)

Interventionist approach (Kröger/Hartmann)

• That is, the decomposition is as follows:

$$\begin{split} \Delta E &= (\bar{X}^{m1} - \bar{X}^{m0})\beta^{m0} - (\bar{X}^{f1} - \bar{X}^{f0})\beta^{f0} \\ \Delta C &= \bar{X}^{m0}(\beta^{m1} - \beta^{m0}) - \bar{X}^{f0}(\beta^{f1} - \beta^{f0}) \\ \Delta I &= (\bar{X}^{m1} - \bar{X}^{m0})(\beta^{m1} - \beta^{m0}) - (\bar{X}^{f1} - \bar{X}^{f0})(\beta^{f1} - \beta^{f0}) \end{split}$$

- The sum of ΔE , ΔC , and ΔI is equal to the overall change in the group difference between time 0 and time 1.
- Primary interest lies in ΔE (endowments effect) and ΔC (coefficients effect). As usual, the interaction term ΔI is less straightforward to interpret.

Exercise 5

References

- Blau, F.D., L.M. Kahn (1997). Swimming Upstream: Trends in the Gender Wage Differential in the 1980s. Journal of Labor Economics 15(1):1–42.
- Heckman, J.J., T.M. Lyons, Petra E. Todd (2000). Understanding Black-White Wage Differentials. American Economic Review 90(2): 344-349.
- Jann, B. (2005a). jmpierce2: Stata module to compute trend decomposition of outcome differentials. Available from https://ideas.repec.org/c/boc/bocode/s448804.html.
- Jann, B. (2005b). smithwelch: Stata module to compute trend decomposition of outcome differentials. Available from http://ideas.repec.org/c/boc/bocode/s448805.html.
- Juhn, C., K.M. Murphy, Brooks Pierce (1991). Accounting for the Slowdown in Black-White Wage Convergence. In Marvin Kosters (Ed.), Workers and Their Wages (pp. 107–143). Washington, DC: AEI Press.
- Kröger, H., J. Hartmann (2021). Extending the Kitagawa-Oaxaca-Blinder decomposition approach to panel data. The Stata Journal 21(2):360–410.
- Smith, J.P., F.R. Welch (1989). Black Economic Progress After Myrdal. Journal of Economic Literature 27(2):519–564.
- Yun, M. (2009). Wage Differentials, Discrimination and Inequality: A Cautionary Note on the Juhn, Murphy and Pierce Decomposition Method. Scottish Journal of Political Economy 56(1):123–137.