# Decomposition Methods in Economics to Assess which Covariates Matter

Anabela Carneiro

Data Science and Statistics Webinar

23rd February 2021

# Roadmap

- Motivation
- Oaxaca-Blinder Decomposition
- Gelbach Decomposition
- Empirical Exercise

# Motivation

Decomposition methods in Economics aim to answer questions such as (Firpo et al., 2011):

- What are the most relevant factors that explain pay differences between men and women? Natives and Immigrants?
- What are the most relevant factors that explain wage inequality increases?
- What are the sources of the wage losses of displaced workers?
- The seminal papers by Oaxaca (1973) and Blinder (1973) with the aim of understanding the sources of the gender wage gap, became notorious in labor economics

# The Oaxaca-Blinder Decomposition

- How much of the gender wage gap could be attributed to differences in human capital (education and experience), occupational choices, industry?
- In this framework, the "unexplained" part of the gender gap is often attributed to labor market discrimination
- An extensive set of methodological papers aimed at refining and extending the OB decomposition (Freeman (1984), Juhn et al. (1993), DiNardo et al. (1996), Machado & Mata (2005), Firpo et al. (2009))

# The Oaxaca-Blinder Decomposition

- Let $w_{Ai}$ and $\mathbf{x}_{Ai}$ be respectively the wage and vector of observable characteristics of individual $i$ belonging to the reference group A.

- The wage equation relative to this group is:

$$\ln w_{Ai} = \mathbf{x}_{Ai}\boldsymbol{\beta}_A + u_{Ai} \tag{1}$$

- Similarly, the wage equation relative to group B is:

$$\ln w_{Bj} = \mathbf{x}_{Bj}\boldsymbol{\beta}_B + u_{Bj} \tag{2}$$

# The Oaxaca-Blinder Decomposition

- The regression model implies that the raw wage differential can be written as:

$$\Delta\overline{w} = \overline{\ln w_A} - \overline{\ln w_B} = (\overline{\mathbf{x}}_A - \overline{\mathbf{x}}_B)\widehat{\boldsymbol{\beta}}_A + \overline{\mathbf{x}}_B(\widehat{\boldsymbol{\beta}}_A - \widehat{\boldsymbol{\beta}}_B) \tag{3}$$

- The first term of the decomposition, $(\overline{\mathbf{x}}_A - \overline{\mathbf{x}}_B)\widehat{\boldsymbol{\beta}}_A$, represents the "explained" component of wage differences between groups, also called the *composition effect*.

- The second term, $\overline{\mathbf{x}}_B(\widehat{\boldsymbol{\beta}}_A - \widehat{\boldsymbol{\beta}}_B)$, represents the "unexplained" component, also called the *wage structure effect*. It measures, for group B, the differences of return to characteristics due to membership in this group.

# The Oaxaca-Blinder Decomposition

- The portion explained by discrimination using the Blinder-Oaxaca method depends on the reference group chosen.
- If B is the reference group instead of A, the explained part of the differences in average values of the wage logarithms is $(\bar{\mathbf{x}}_A - \bar{\mathbf{x}}_B)\widehat{\boldsymbol{\beta}}_B$.
- As $\overline{\ln w_A} - \overline{\ln w_B}$ is independent of the decomposition, the unexplained part changes according to the reference group.
- If group B is the reference group instead of group A, then $\Delta\overline{w} = (\bar{\mathbf{x}}_A - \bar{\mathbf{x}}_B)\widehat{\boldsymbol{\beta}}_B + \bar{\mathbf{x}}_A(\widehat{\boldsymbol{\beta}}_A - \widehat{\boldsymbol{\beta}}_B)$.

# Gelbach Decomposition - Motivation

- It is widely common in empirical research to estimate multiple specifications of a linear regression model to evaluate the "robustness" of the coefficient on some variable of interest, $X_1$, as various covariates, $\mathbf{X}_2$, are added to the base specification
- Or to account for the "effects" on the coefficient of $X_1$ as one moves from a base specification that has no covariates, $\mathbf{X}_2$, to the full specification that includes both $X_1$ and $\mathbf{X}_2$
- Example: cross-group gaps in wages (e. g., Altonji & Blank, 1999; Lang & Manove, 2006, Carneiro et al., 2012)

# Immigrant-native wage gap in Portugal: POLS (Carneiro, Fortuna & Varejão, 2012, JPE)

**Pooled OLS wage regression (selected estimates), 2003-2008**

**Dependent variable: log of the real hourly wage**

| | (1) | (2) | (3) |
|---|---|---|---|
| Male sample (N=7,706,548) | | | |
| Immigrant | -0.28643 | -0.19083 | -0.08249 |
| | (0.00164) | (0.00167) | (0.00152) |
| Years Since Migration | 0.01423 | 0.01089 | 0.00530 |
| | (0.00051) | (0.00048) | (0.00047) |
| Years Since Migration squared | -0.00009 | -0.00003 | -0.00004 |
| | (0.00002) | (0.00002) | (0.00002) |
| Concentration of Immigrants | | -0.24440 | -0.18876 |
| R-squared | 0.438 | 0.490 | 0.590 |
| Female sample (N=6,060,863) | | | |
| Immigrant | -0.17755 | -0.10620 | -0.04398 |
| | (0.00168) | (0.00167) | (0.00144) |
| Years Since Migration | 0.00561 | 0.00422 | 0.00087 |
| | (0.00056) | (0.00052) | (0.00047) |
| Years Since Migration squared | 0.00019 | 0.00019 | 0.00013 |
| | (0.00003) | (0.00003) | (0.00003) |
| Concentration of Immigrants | | -0.22967 | -0.14982 |
| | | (0.00283) | (0.00245) |
| R-squared | 0.500 | 0.549 | 0.637 |

Notes: Worker-cluster robust standard errors in parentheses. Specification 1 includes controls for the worker's age (and age squared), immigrant status, years since migration, schooling achievement, and time and region effects. Specification 2 further controls for three employer characteristics: size, industry, and immigrant concentration at the workplace. Specification 3 adds controls for worker tenure (and tenure squared), and skill- categories.

# Sequence Dependence

- As pointed out by Gelbach (2016, p. 529): "Comparing coefficient estimates from specifications in which covariates are added sequentially to a base model does not generally identify population parameters of interest.";
- In an insightful paper published in JOLE, Gelbach (2016) proposes a detailed decomposition based on the omitted variable bias formula that allows to unambigously disentangle the contibution of each ommited variable for the change in the coefficient of the variable of interest.

# Gelbach Decomposition - Gender Wage Gap

- Consider we are interested in estimating the gender wage gap
- We start by estimating the following model

$$\ln wage_{it} = \beta_o + \beta_1^{base} female_i + u_{it}$$

- $\beta_1^{base} = E(\ln wage_{it} \mid female = 1) - E(\ln wage_{it} \mid female = 0)$
- This may correspond to a biased measure of the gender wage gap as males and females may differ in other characteristics that also affect wages.

# Gelbach Decomposition - Gender Wage Gap

- Let's add those factors to the base model

$$\ln wage_{it} = \beta_o + \beta_1^{full} female_i + \beta_2^{full} educ_i + \beta_3^{full} exper_{it} + u_{it}$$

- $\beta_1^{base} \neq \beta_1^{full}$
- How much of the change in $\beta_1$ can be attributed to *exper* and how much can be attributed to *educ*?

- How much of the male-female wage gap is explained by gender differences in experience and education?

# Gelbach Decomposition - Gender Wage Gap

- Researchers often solve this problem by estimating an intermediate model

$$\ln wage_{it} = \beta_o + \beta_1^{educ} female_i + \beta_2^{educ} educ_i + u_{it}$$

- and then attribute the difference $\beta_1^{base} - \beta_1^{educ}$ to differences in education across the groups
- and the difference $\beta_1^{educ} - \beta_1^{full}$ to differences in labor market experience
- This is incorrect, as the order in which covariates are added can affect the accounting - order/sequence dependence
- Only if the variable *female* is orthogonal to *educ* and *exper* will the order be irrelevant

# Gelbach Decomposition - Omitted variable bias formula

- Gelbach (2016) provides a solution based on the omitted variable bias formula:
  1. Estimate the full model by OLS and obtain: $\widehat{\beta}_1^{full}, \widehat{\beta}_2^{full}, \widehat{\beta}_3^{full}$

$$\widehat{\beta}_2^{full}\widehat{\Gamma}_{educ} + \widehat{\beta}_3^{full}\widehat{\Gamma}_{exper} = \widehat{\beta}_1^{base} - \widehat{\beta}_1^{full}$$

# Gelbach Decomposition - Omitted variable bias formula

- Gelbach (2016) provides a solution based on the omitted variable bias formula:
  1. Estimate the full model by OLS and obtain: $\widehat{\beta}_1^{full}, \widehat{\beta}_2^{full}, \widehat{\beta}_3^{full}$
  2. Use OLS to estimate two auxiliary regressions of *educ* on *female* and of *exper* on *female* and then recover the estimates $\widehat{\Gamma}_{educ}$ and $\widehat{\Gamma}_{exper}$, respectively.

$$\widehat{\beta}_2^{full}\widehat{\Gamma}_{educ} + \widehat{\beta}_3^{full}\widehat{\Gamma}_{exper} = \widehat{\beta}_1^{base} - \widehat{\beta}_1^{full}$$

# Gelbach Decomposition - Omitted variable bias formula

- Gelbach (2016) provides a solution based on the omitted variable bias formula:
  1. Estimate the full model by OLS and obtain: $\widehat{\beta}_1^{full}, \widehat{\beta}_2^{full}, \widehat{\beta}_3^{full}$
  2. Use OLS to estimate two auxiliary regressions of *educ* on *female* and of *exper* on *female* and then recover the estimates $\widehat{\Gamma}_{educ}$ and $\widehat{\Gamma}_{exper}$, respectively.
  3. The male-female wage gap attributable to educ is $\widehat{\beta}_2^{full}\widehat{\Gamma}_{educ}$ and to experience is $\widehat{\beta}_3^{full}\widehat{\Gamma}_{exper}$

$$\widehat{\beta}_2^{full}\widehat{\Gamma}_{educ} + \widehat{\beta}_3^{full}\widehat{\Gamma}_{exper} = \widehat{\beta}_1^{base} - \widehat{\beta}_1^{full}$$

# Gelbach Decomposition - Omitted variable bias formula

- Hence, the contribution of each variable are the mean male-female gap in *educ* and *exper* ($\widehat{\Gamma}_{educ}$ and $\widehat{\Gamma}_{exper}$), scaled by each regressor's impact on wages ($\widehat{\beta}_2^{full}$ and $\widehat{\beta}_3^{full}$), respectively.
- Consider the population regression model:

$$Y = X_1\beta_1 + X_2\beta_2 + \varepsilon$$

- Assuming that $E[\varepsilon \mid X] = 0$,where $X = [X_{1,}X_2]$
- Under these assumptions, the OLS estimator for the full model is $\widehat{\beta} = (X^{'}X)^{-1}X'Y$ is consistent

# Gelbach Decomposition - Omitted variable bias formula

- Now, consider the coefficient on $X_1$ from the base specification that ignores $X_2$.The estimator of $\beta_1$ is

$$\widehat{\beta}_1^{base} = (X_1'X_1)^{-1}X_1'Y$$

- whose probability limit is

$$p\lim \widehat{\beta}_1^{base} = \beta_1 + p\lim(X_1'X_1)^{-1}X_1'X_2\beta_2$$

$$\text{or } \beta_1^{base} = \beta_1 + \Gamma\beta_2 = \beta_1 + \delta$$

- where $\Gamma$ is the matrix of coefficients from projecting the columns of $X_2$ on the columns of $X_1$.

# Gelbach Decomposition - Omitted variable bias formula

- $\delta = \Gamma\beta_2$ is the omitted variable bias from excluding $X_2$ when estimating $\beta_1$, and is non-zero if $E[X_1 X_2] \neq 0$
- It also suggests a natural decomposition of the difference between the base and full model coefficients on $X_1$

$$\begin{aligned} \delta &= \Gamma_1\beta_{2,1} + ... + \Gamma_k\beta_{2,k} \\ \delta &= \beta_1^{base} - \beta_1 \end{aligned}$$

# Gelbach Decomposition - Stata Codes

```
. *base model*
. reg lwage fem

      Source |       SS           df       MS      Number of obs   =     4,165
-------------+----------------------------------   F(1, 4163)      =    491.72
       Model |  93.6914807         1  93.6914807   Prob > F        =    0.0000
    Residual |  793.213421     4,163  .190538895   R-squared       =    0.1056
-------------+----------------------------------   Adj R-squared   =    0.1054
       Total |  886.904902     4,164  .212993492   Root MSE        =    .43651

------------------------------------------------------------------------------
       lwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         fem |  -.4744661   .0213967   -22.17   0.000     -.516415   -.4325171
       _cons |   6.729774     .00718   937.29   0.000     6.715697     6.74385
------------------------------------------------------------------------------
```

# Gelbach Decomposition - Stata Codes

```
. *fulll model*
. reg lwage fem ed exp

      Source |       SS           df       MS      Number of obs   =     4,165
-------------+----------------------------------   F(3, 4161)      =    698.84
       Model |  297.147867         3  99.0492891   Prob > F        =    0.0000
    Residual |  589.757034     4,161  .141734447   R-squared       =    0.3350
-------------+----------------------------------   Adj R-squared   =    0.3346
       Total |  886.904902     4,164  .212993492   Root MSE        =    .37648

------------------------------------------------------------------------------
       lwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         fem |  -.4358154   .0185376   -23.51   0.000    -.4721589   -.3994719
          ed |   .0752953   .0021448    35.11   0.000     .0710903    .0795003
         exp |   .0118283   .0005476    21.60   0.000     .0107547    .0129019
       _cons |   5.523389   .0324625   170.15   0.000     5.459745    5.587033
------------------------------------------------------------------------------
```

# Gelbach Decomposition - Stata Codes

```
Decomposition of changes in coefficients on x1 vars:

       fem

into parts due to these groups:

g1 = ed

g2  = exp
```

| lwage | Coef. | Std. Err. | z | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| fem | | | | | | |
| g1 | -.0008109 | .0102937 | -0.08 | 0.937 | -.0209862 | .0193644 |
| g2 | -.0378397 | .0065713 | -5.76 | 0.000 | -.0507192 | -.0249602 |
| __TC | -.0386507 | .0109806 | -3.52 | 0.000 | -.0601721 | -.0171292 |

# Gelbach Decomposition - Gender Wage Gap

Decomposition of the Gender Wage Gap (Gelbach, 2016)

| | Base Model Coef. estimate | Full Model Coef. estimate | Change (1)-(2) | Decomposition of the change into: *educ* | *exper* |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | $-0.47447$ | $-0.43581$ | $-0.038651$ | $-0.00081$ | $-0.03784$*** |
| | | | | (0.01029) | (0.00657) |

Note: *** significant at the 1% level.

# Immigrant-native wage gap in Portugal: Gelbach Decomposition (Carneiro, Fortuna & Varejão, 2012, JPE)

Immigrants at new destinations: how they fare and why

**Table 2** Decomposition of the immigrant-native wage gap variation between specifications 1 and 3 (contribution of covariates omitted in specification 1)

| | Male sample | | Female sample | |
|---|---|---|---|---|
| | Coefficient | SD | Coefficient | SD |
| Concentration of immigrants | –0.0436* | (0.0005) | –0.0278* | (0.0005) |
| Size | –0.0001 | (0.0003) | –0.0020* | (0.0003) |
| Industry | –0.0300* | (0.0003) | –0.0161* | (0.0004) |
| Tenure | –0.0631* | (0.0005) | –0.0491* | (0.0003) |
| Qualification levels | –0.0670* | (0.0005) | –0.0388* | (0.0006) |
| Total | –0.2038* | (0.0009) | –0.1337* | (0.0010) |

Notes: The figures reported in the last row ('Total') are estimates of the difference of the wage gap between immigrants and natives obtained with specifications 1 and 3 (and the corresponding robust standard errors); they are equal to the arithmetic difference between the estimated coefficients of the Immigrant variable reported in Table 1. All other figures in the coefficients' columns are interpreted as the absolute contribution of the corresponding covariate for the observed change in the estimated coefficient of the Immigrant variable from specifications 1 to 3. For details, see Gelbach (2009)

*Significant at 1%

# The Sources of the Wage Losses of Displaced Workers (Raposo, Portugal & Carneiro, 2021, JHR)

- Sample (*Quadros de Pessoal* data set):
  - Treatmet group: 25 cohorts of workers who lost their jobs between 1988 and 2014 due to firm closure

# The Sources of the Wage Losses of Displaced Workers (Raposo, Portugal & Carneiro, 2021, JHR)

- Sample (*Quadros de Pessoal* data set):
  - Treatmet group: 25 cohorts of workers who lost their jobs between 1988 and 2014 due to firm closure
  - Control group: individuals who were employed in firms that did not close in the 1986-2016 period

# The Sources of the Wage Losses of Displaced Workers (Raposo, Portugal & Carneiro, 2021, JHR)

- Methodology:
  - High-dimensional FE model that accounts for worker, firm, job title, and match quality effects (returns to time-invariant characteristics of the worker-firm match)

$$w_{it} = \alpha_i + \lambda_{J(i,t)} + \theta_{F(i,t)} + \psi_{iF(i,t)} + \gamma_t + \boldsymbol{\beta}\mathbf{X}_{it} + \sum_{k \geq -m} D_{it}^k \delta_k + \mu_{it}$$

# The Sources of the Wage Losses of Displaced Workers (Raposo, Portugal & Carneiro, 2021, JHR)

- Methodology:
  - High-dimensional FE model that accounts for worker, firm, job title, and match quality effects (returns to time-invariant characteristics of the worker-firm match)

$$w_{it} = \alpha_i + \lambda_{J(i,t)} + \theta_{F(i,t)} + \psi_{iF(i,t)} + \gamma_t + \boldsymbol{\beta}\mathbf{X}_{it} + \sum_{k \geq -m} D_{it}^k \delta_k + \mu_{it}$$

  - Builds on Gelbach (2016) methodology, which appeals to the omitted variables bias formula, to compute a detailed decomposition of the contribution of each fixed effect to the change in the estimate of the displacement dummies.

# Earnings Losses of displaced workers in Portugal: OLS Solution (Raposo et al., 2021, JHR)

Table 3: Wage loss estimates

| | $\hat{\delta}_k^{ols}$ | SE | $\hat{\delta}_k^{base}$ | SE | $\hat{\delta}_k^{full}$ | SE |
|---|---|---|---|---|---|---|
| | (1) | | (2) | | (3) | |
| Specification 1 | | | | | | |
| $D_{-10}$ | -0.218 | (0.003) | 0.061 | (0.002) | 0.003 | (0.001) |
| $D_{-9}$ | -0.178 | (0.003) | 0.061 | (0.001) | 0.008 | (0.001) |
| $D_{-8}$ | -0.183 | (0.003) | 0.044 | (0.001) | 0.000 | (0.001) |
| $D_{-7}$ | -0.135 | (0.003) | 0.042 | (0.001) | 0.005 | (0.001) |
| $D_{-6}$ | -0.122 | (0.003) | 0.067 | (0.001) | 0.032 | (0.001) |
| $D_{-5}$ | -0.159 | (0.002) | 0.032 | (0.001) | -0.002 | (0.001) |
| $D_{-4}$ | -0.171 | (0.002) | 0.024 | (0.001) | -0.004 | (0.001) |
| $D_{-3}$ | -0.176 | (0.002) | 0.021 | (0.001) | -0.003 | (0.001) |
| $D_{-2}$ | -0.181 | (0.002) | 0.018 | (0.001) | -0.002 | (0.001) |
| $D_{-1}$ | -0.185 | (0.002) | 0.015 | (0.001) | -0.003 | (0.001) |
| $D_0$ | -0.213 | (0.002) | 0.009 | (0.001) | -0.008 | (0.001) |
| $D_1$ | -0.156 | (0.004) | -0.013 | (0.001) | -0.024 | (0.001) |
| $D_2$ | -0.219 | (0.003) | -0.018 | (0.001) | -0.011 | (0.001) |
| $D_3$ | -0.241 | (0.003) | -0.029 | (0.001) | -0.005 | (0.001) |
| $D_4$ | -0.240 | (0.002) | -0.039 | (0.001) | -0.002 | (0.001) |
| $D_5$ | -0.268 | (0.003) | -0.048 | (0.001) | 0.001 | (0.001) |
| $D_6$ | -0.294 | (0.003) | -0.056 | (0.001) | 0.002 | (0.001) |
| $D_7$ | -0.334 | (0.003) | -0.062 | (0.001) | 0.005 | (0.001) |
| $D_8$ | -0.377 | (0.003) | -0.072 | (0.001) | 0.006 | (0.001) |
| $D_9$ | -0.373 | (0.003) | -0.072 | (0.001) | 0.011 | (0.001) |
| $D_{10}$ | -0.349 | (0.003) | -0.067 | (0.001) | 0.013 | (0.001) |
| $R^2$ | 0.11 | | 0.89 | | 0.92 | |
| Specification 2 | | | | | | |
| Pre-displacement | -0.218 | (0.003) | 0.026 | (0.000) | 0.000 | |
| Post-displacement | -0.178 | (0.003) | -0.046 | (0.000) | 0.000 | |
| $R^2$ | 0.11 | | 0.89 | | 0.92 | |
| Specification 3 | | | | | | |
| Net | -0.106 | (0.002) | -0.072 | (0.000) | 0.000 | |
| $R^2$ | 0.11 | | 0.89 | | 0.92 | |

# Earnings Losses of displaced workers in Portugal: OLS solution (Raposo et al., 2021, JHR)

| | | Decomposition of the wage loss into | | | | | |
|---|---|---|---|---|---|---|---|
| | Wage loss | Firm FE | | Match quality FE | | Job title FE | |
| | $\hat{\delta}_k^{base} - \hat{\delta}_k^{full}$ | $\hat{\tau}_k^{\theta}$ | SE | $\hat{\tau}_k^{\psi}$ | SE | $\hat{\tau}_k^{\lambda}$ | SE |
| Specification 1 | | | | | | | |
| $D_{-10}$ | 0.058 | 0.016 | (0.000) | 0.014 | (0.000) | 0.028 | (0.001) |
| $D_{-9}$ | 0.053 | 0.016 | (0.000) | 0.013 | (0.000) | 0.023 | (0.000) |
| $D_{-8}$ | 0.044 | 0.015 | (0.000) | 0.011 | (0.000) | 0.018 | (0.000) |
| $D_{-7}$ | 0.037 | 0.013 | (0.000) | 0.011 | (0.000) | 0.013 | (0.000) |
| $D_{-6}$ | 0.035 | 0.011 | (0.000) | 0.010 | (0.000) | 0.014 | (0.000) |
| $D_{-5}$ | 0.034 | 0.012 | (0.000) | 0.009 | (0.000) | 0.012 | (0.000) |
| $D_{-4}$ | 0.028 | 0.010 | (0.000) | 0.008 | (0.000) | 0.010 | (0.000) |
| $D_{-3}$ | 0.024 | 0.008 | (0.000) | 0.007 | (0.000) | 0.008 | (0.000) |
| $D_{-2}$ | 0.020 | 0.006 | (0.000) | 0.007 | (0.000) | 0.007 | (0.000) |
| $D_{-1}$ | 0.018 | 0.005 | (0.000) | 0.007 | (0.000) | 0.006 | (0.000) |
| $D_0$ | 0.017 | 0.005 | (0.000) | 0.006 | (0.000) | 0.005 | (0.000) |
| $D_1$ | 0.011 | 0.014 | (0.000) | -0.006 | (0.001) | 0.003 | (0.000) |
| $D_2$ | -0.007 | 0.006 | (0.001) | -0.008 | (0.001) | -0.004 | (0.000) |
| $D_3$ | -0.024 | -0.003 | (0.001) | -0.011 | (0.000) | -0.010 | (0.000) |
| $D_4$ | -0.037 | -0.011 | (0.001) | -0.012 | (0.000) | -0.014 | (0.000) |
| $D_5$ | -0.049 | -0.017 | (0.001) | -0.015 | (0.000) | -0.017 | (0.000) |
| $D_6$ | -0.058 | -0.023 | (0.001) | -0.015 | (0.000) | -0.020 | (0.000) |
| $D_7$ | -0.067 | -0.026 | (0.001) | -0.018 | (0.000) | -0.023 | (0.000) |
| $D_8$ | -0.078 | -0.031 | (0.001) | -0.020 | (0.001) | -0.028 | (0.000) |
| $D_9$ | -0.083 | -0.031 | (0.001) | -0.021 | (0.001) | -0.031 | (0.000) |
| $D_{10}$ | -0.080 | -0.027 | (0.001) | -0.020 | (0.001) | -0.033 | (0.000) |
| $R^2$ | | 0.96 | | 0.99 | | 0.99 | |
| Specification 2 | | | | | | | |
| Pre-displacement | 0.026 | 0.008 | (0.001) | 0.008 | (0.001) | 0.010 | (0.001) |
| Post-displacement | -0.046 | -0.014 | (0.002) | -0.015 | (0.001) | -0.017 | (0.001) |
| $R^2$ | | 0.96 | | 0.99 | | 0.99 | |
| Specification 3 | | | | | | | |
| Net | -0.072 | -0.022 | (0.001) | -0.023 | (0.001) | -0.027 | (0.001) |
| $R^2$ | | 0.96 | | 0.99 | | 0.99 | |

# The Sources of the Wage Losses of Displaced Workers (Raposo et al., 2021, JHR)

- Conclusions
  - Post-displacement monthly wages are, on average, 7.2 log points lower than pre-displacement wages;

# The Sources of the Wage Losses of Displaced Workers (Raposo et al., 2021, JHR)

- Conclusions
  - Post-displacement monthly wages are, on average, 7.2 log points lower than pre-displacement wages;
  - Sorting into lower paying job titles represents the largest component of the monthly wage loss of displaced workers, accounting for 37 percent of the total average monthly wage; firm and match effects account, respectively, for 31 and 32 percent of the total monthly wage loss;.

# References


- Altonji, J., Blank, R. (1999). "Race and Gender in the Labor Market.", in Handbook of Labor Economics, vol. 3C, ed. Orley Ashenfelter and David Card, 1-102. Amsterdam: Elsevier.
- Blinder, A. (1973). "Wage Discrimination: Reduced Form and Strucutural Estimates", Journal of Human Resources, 8: 436-455.
- Carneiro, A., Fortuna, N., Varejão, J. (2012). "Immigrants at New Destinations: How They Fare and Why", Journal of Population Economics, 25(3): 1165-1185.
- DiNardo, J., Fortin, N., Lemieux, T. (1996). "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach", Econometrica, 64: 1001-1044.
- Firpo, S., Fortin, N., Lemieux, T. (2009). "Unconditional Quantile Regressions", Econometrica, 77 (3): 953-973.
- Firpo, S., Fortin, N., Lemieux, T. (2011). "Decomposition Methods", in Handbook of Labor Economics, vol. 4A, ed. Orley Ashenfelter and David Card, 1-102. Amsterdam: Elsevier.

# References


- Freeman, R. (1984). "Longitudinal Analysis of the Effect of Trade Unions", Journal of Labor Economics, 2: 1-26.
- Gelbach, J. 2016. “When do covariates matter? And which ones, and how much?” Journal of Labor Economics, 34(2):509–543.
- Juhn, C., Murphy, K., Pierce, B. (1993). "Wage Inequality and the Rise in Returns to Skill", Journal of Political Economy, 101: 410-442.
- Lang, K., Manove, M. (2006). "Education and Labor-market Discrimination". NBER working paper n$^o$ 12257, National Bureau of Economic Research, Cambridge, MA.
- Machado, J., Mata, J. (2005). "Counterfactual Decompositions of Changes in Wage Distributions using Quantile Regression", Journal of Applied Econometrics 20 (4): 445-465.
- Oaxaca, R. (1973). “Male-female wage differentials in urban labor markets”, International Economic Review, 14: 693-709.
- Raposo, P., Portugal, P., Carneiro, A. (2021). “The Sources of the Wage Losses of Displaced Workers: The Role of the Reallocation of Workers into Firms, Matches, and Job Titles”, Journal of Human Resources.