# RIF-Regressions and RIF-Decompositions:

## Implementation and Interpretation of Distributional Effects

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# Introduction

## What do you mean RIF?

## and what do you mean **distributional** effects??

# Introduction

- Unconditional quantile regressions (UQR) via RIF (Recentered Influence functions) was introduced by Firpo, Fortin, and Lemieux (2009) as a computationally simple strategy to estimate **Unconditional Partial Effects (UPE)** on quantiles, caused by **small** changes in distributions of characteristics.

- These are effects that would be measured across the **whole** distribution, but not for individual observations.

  - This is in contrast with standard **Conditional quantile regressions**, which focus on effects conditional on all characteristics being known.

- Since then, RIF-regressions have been used to analyze other statistics. See FFL(2018), Firpo and Pinto (2016), Chung and Vankerm (2018), Cowell and Flachaire (2007), Essama-Nssah and Lambert (2012) and Heckley et al (2016).

- Despite its popularity, however, the correct interpretation of RIF regressions and decomposition remain a challenge.

# CQR vs UQR

## What is the difference between Conditional and Unconditional effects?

# LR vs CQR : Visual analysis

Simulated Data | What LR does: | What CQR does: | But What UQR does?

# LR vs CQR : Visual analysis

Simulated Data | What LR does: | What CQR does: | But What UQR does?

# LR vs CQR : Visual analysis

Simulated Data | What LR does: | What CQR does: | But What UQR does?

# LR vs CQR : Visual analysis

Simulated Data | What LR does: | What CQR does: | **But What UQR does?**

- With LR and CQR, we can use coefficient estimations to identify how individual changes, or group specific changes will affect **expected** outcomes.

$$\frac{\partial y_i}{\partial x_{i1}} \; or \; \frac{\partial E(y_i|X)}{\partial x_1} \; or \; \frac{\partial Q(y_i|X,\theta)}{\partial x_1}$$

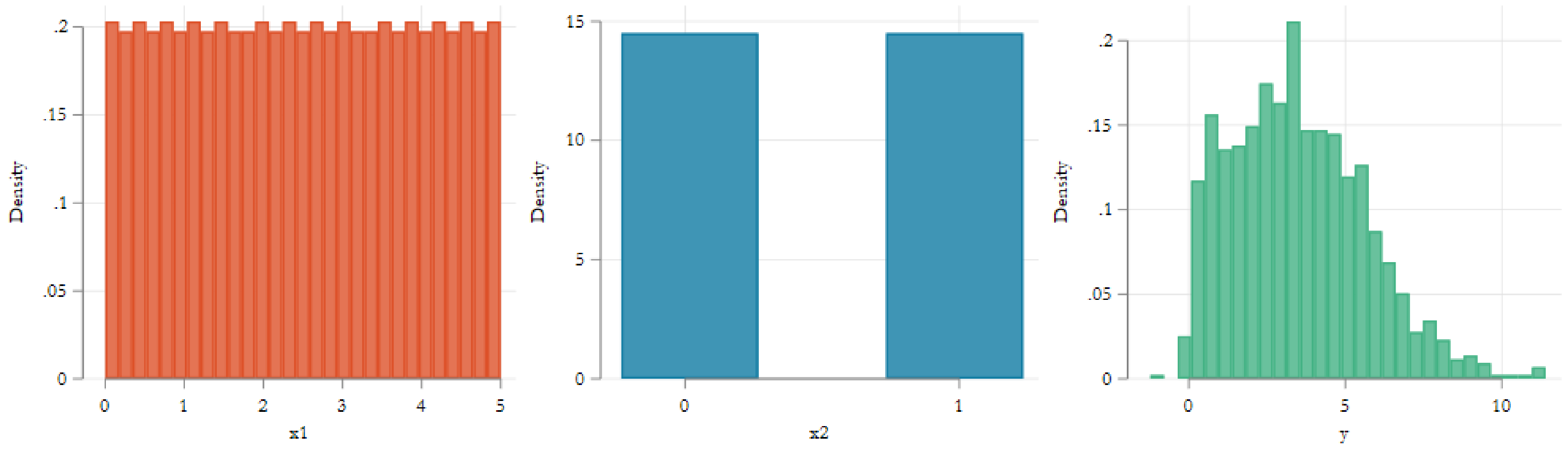
- But with **UQR** you can't measure the change on the distribution of individual values. (too small to be meaningful)

- Rather, we need to think in terms of distributional changes in $X's$, and how that will affect the change in the distribution of $y$ (but measured in quantiles)

# UQR: What it Does

UQR: From F(x1) and F(x2) to F(y) | UQR: D in x_1 | UQR: D in x_1 | UQR: Changes in x_2

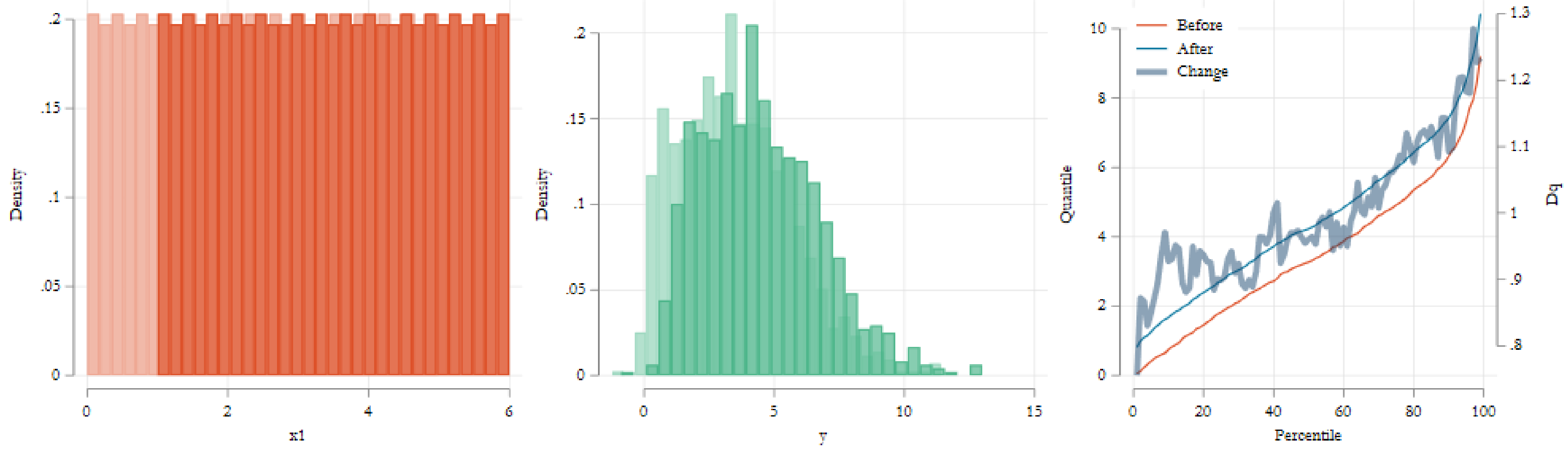
- In the current example, $F(Y)$ depends on the distribution of 3 other factors: $F(x_1)$, $F(x_2)$, $F(e)$. But, we assume $F(e)$ is independent, thus can be ignored.
- Thus, we can change the distribution of both $x_1$ or $x_2$!



# UQR: What it Does

UQR: From F(x1) and F(x2) to F(y) | **UQR: D in x_1** | UQR: D in x_1 | UQR: Changes in x_2

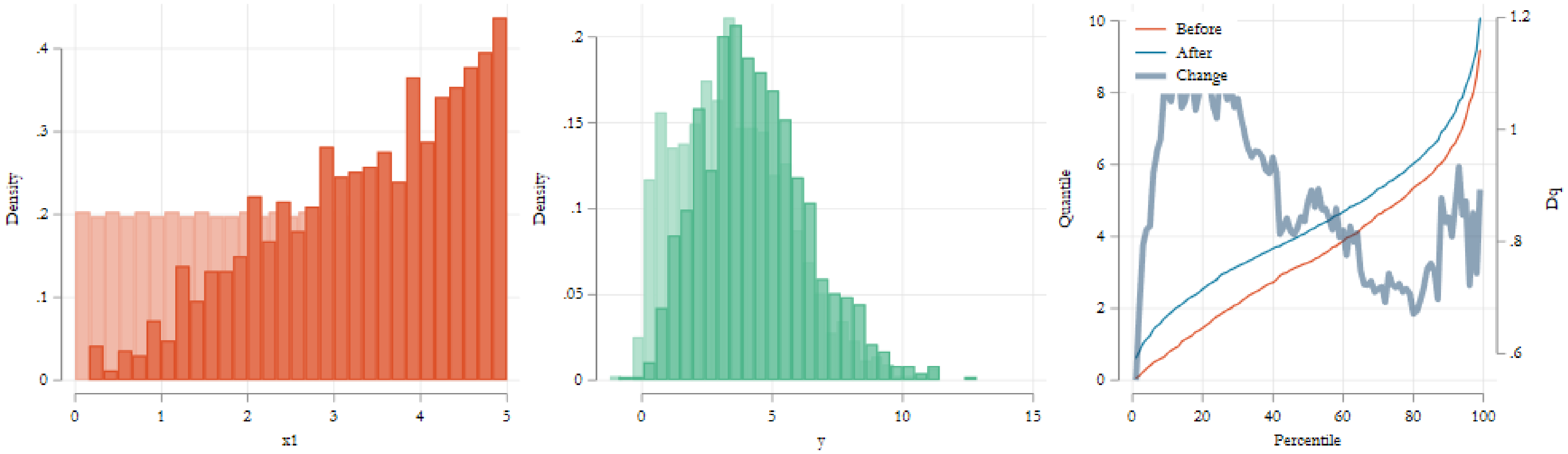
- The simplest kind of change could be one when the whole distribution shifts (change in means)



# UQR: What it Does

UQR: From F(x1) and F(x2) to F(y) | UQR: D in x_1 | **UQR: D in x_1** | UQR: Changes in x_2

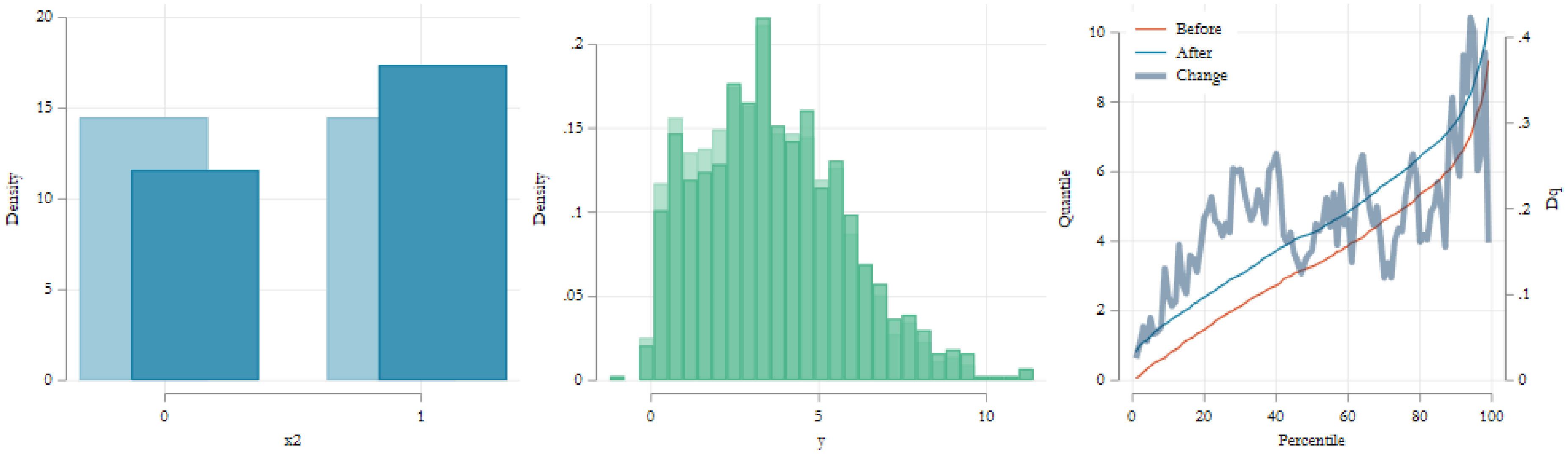
- But other kind of distributional changes could also be considered



# UQR: What it Does

UQR: From F(x1) and F(x2) to F(y) | UQR: D in x_1 | UQR: D in x_1 | **UQR: Changes in x_2**

- If $x_2$ is discrete, One may want to consider changes in proportions or shares of $1's$.



Why stop at quantiles ?

# Why stop at quantiles ?

Given the simulated data, we do not need to stop at **only** analyzing quantiles. We can, in fact, analyze changes in ANY statistic.

| | Original | After dx1 | After dx2 | Change dX1 | Change dX2 |
|---|---|---|---|---|---|
| Mean | 3.487 | 4.673 | 3.673 | 1.186 | 0.186 |
| Variance | 4.620 | 5.327 | 4.822 | 0.707 | 0.202 |
| SD | 2.150 | 2.308 | 2.196 | 0.159 | 0.046 |
| Skewness | 0.543 | 0.527 | 0.506 | -0.016 | -0.037 |
| Kurtosis | 3.031 | 2.998 | 2.940 | -0.033 | -0.091 |
| CV | 0.616 | 0.494 | 0.598 | -0.123 | -0.019 |

dX1: Change in the Mean of X1 in 1 unit

dX2: Change in the proportion of X2 in 10pp

## what about Quantile Treatment effects (QTE)?

# What about QTE?

Story Effect

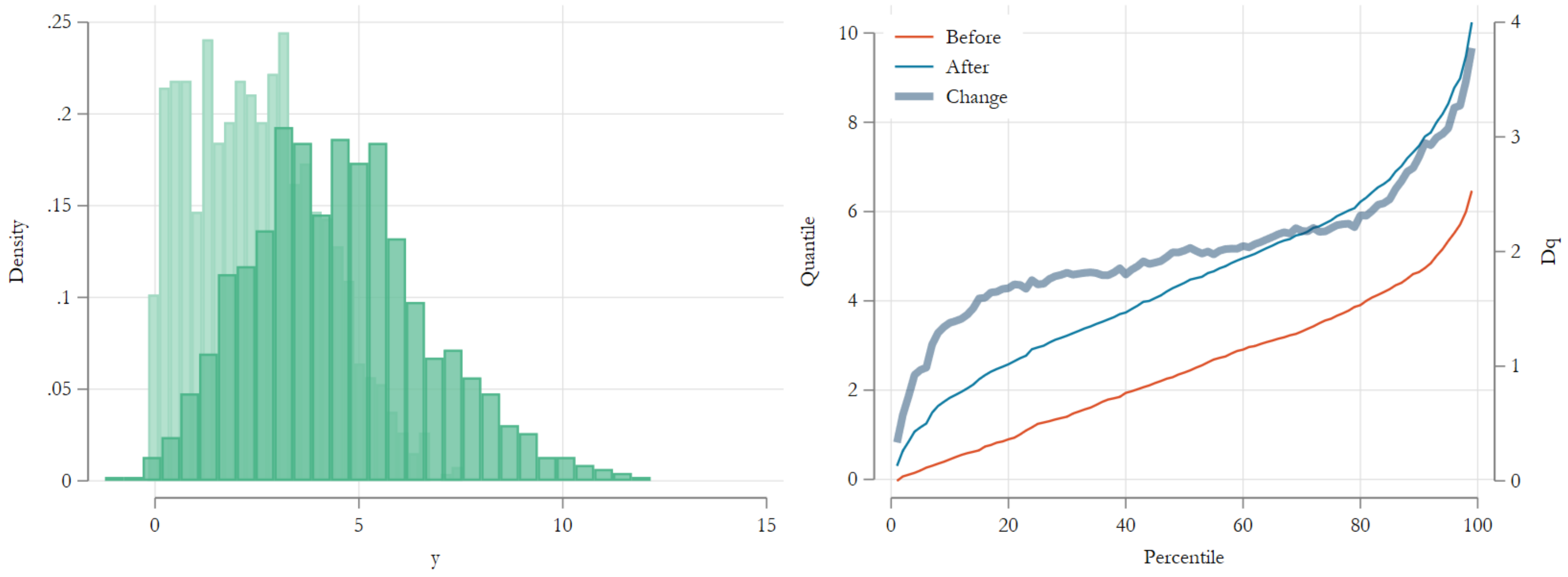
QTE can be understood as an extreme case of UQR, but also similar to CQR.

- CQR because you compare two distributions conditional on one [categorical] variable changin ( $x_2 = 0 \; vs \; x_2 = 1$ ), everything else constant (at some values).
- UQR because the distributions are unconditional on everything else, (conditional on distributions) making 2 changes to the distribution. (all $x_2$ to 0 and to 1)

With QTE you are making the thought experiment of comparing distributions when everyone is "treated" vs "untreated" (ATE). Although ATT or ATU are also feasible.

# What about QTE?

Story | Effect



# How are these effects estimated?

In the previous slides I have shown the intuition behind what it means to estimate Unconditional effect caused by changes in the distribution of $X's$.

The estimation of the effects or unconditional quantiles are *NOT* approximations. They are the true effects, because I know the data generating process exactly.

In real world applications we need to use approximations:

- Flexible multivariate modeling and Simulations/imputation (Machado and Mata, 2005).
  - Computationally intensive. Multiple Qreg or Flex Het Reg.
- Reweighting approaches (DiNardo, Fortin and Lemieux, 1996).
  - Two step approach. Logit $\rightarrow$ Comparing statistics of interest
- Local Approximations (Firpo, Fortin and Lemieux, 2009).
  - via RIF's!

# So why do we need RIF's?

- From the three strategies I described above, the first two can be very computationally intensive.
- In contrast, RIF regressions provide a faster approach to get **Local linear approximations** of changes in distributions.
- The approach, however, is not without limitations:
  - All changes are related to **small** location shifts in the distribution of explanatory variables (change in means)
  - Larger changes will create poor approximations of the effects
- One must keep this in mind when analyzing and interpreting estimation results

But what are RIFs (Recentered Influence functions) ?

# Building blocks: IF $\rightarrow$ RIF

# Building Blocks: Some Notation

To understand what (R)IF's are, we first need to establish some notation:

1) We are interested on analyzing **distributional** statistics $v$ , which summarize some aspect or property of the data of interest y .

2) To calculate any distributional statistic, we need to know $F_y$ or $f_y$ . (the distribution).

3) And if we assume that $y_i = g(x_i, e_i)$, we need $e_i$ to be fully independent from $x$.

4) $F_y$ can also be written as a weighted mean of all conditional distributions:

$$F_y = F(y) = \int F_{Y|x} f_x dx$$

$$F_{y|x} = F(y|x) = \int F(y|x, e) f_e \, de$$

# Building Blocks: What are Influence Functions (IF's)?

Influence functions are *directional* derivatives of how would $v(F_y)$ change when $F_y$ changes, at the margin.

$$IF(v(F_y), \partial F_y) = \frac{\partial v(F_y)}{\partial F_y}$$

However this definition of distribution change is too *broad*. Thus, for the formal definition of IF's, we need to redefine the definition of a change:

$$G_y^c = \varepsilon 1_{y \geq c} + (1-\varepsilon) F_y$$

Thus the IF is defined by:

$$IF(y, v(F_y)) = lim_{\varepsilon \to 0} \frac{v(G_y^c) - v(F_y)}{\varepsilon}$$

> what is the rate of change (slope) that would be caused by a change in the distribution of $Y$, that gives more weight to $y = c$?

# Building Blocks: Recentered Influence Functions

FFL (2009) proposes using an modification of IF, called recentered influence functions (RIF).

$$RIF(c, v(F_y)) = v(F_y) + IF(c, v(F_y))$$

Which has the nice properties

$$E\left[RIF(y_i, v(F_y))\right] = v(y)$$

$$N^{-1}Var\left[RIF(y_i, v(F_y))\right] = Var(v(F_y))$$

My interpretation: A **RIF** is the contribution of a single observation to the construction of the distributional $v$.

# Building Blocks: RIF and Regression

So how does a RIF regression work?

- First: we are interested in analyzing potential changes in $v(F_y)$
- Second: $v(F_y)$ can be approximated as the unconditional mean of RIF's:

$$v(F_y) = \int RIF(y, v(F_y)) f_y dy$$

- Third: the unconditional distribution $F_y$ can be written as a weighted mean of conditional distributions:

$$v(F_y) = \iint RIF(y, v(F_y)) F_{y|x} dy \; f_x dx = \int E\left[RIF(y, v(F_y))|X\right] f_x dx$$

# Building Blocks: RIF and Regression

Based on the last expression, there are two ways one can use to **simulate** changes on the statistic $v(F_y)$.

1) One either assumes changes in $f_x$ (long way (reweighting))

2) One models $E\left[RIF(y, v(F_y))|X\right]$ using linear regressions, And average "predicted" changes in the RIF.

$$RIF(y, v(F_y)) = \beta_0 + \beta_1 x + e$$

> Small changes in $X's$ will be reflected as changes in the RIF, which can be interpreted as potential changes in the distributional Statistic $v(F_y)$.

**Why Small?**

If $\Delta F_x \rightarrow 0$, then $F_y' \sim F_y$ and you do not need to Re-estimate the RIF.

$$RIF(y, v(F_y')) \sim RIF(y, v(F_y)) + \beta_1$$

For large changes, however, this may not hold.

# RIF-Regression: Interpretation

RIF regressions imply using a model specification as follows:

$$RIF(y, v(F_y)) = \beta_0 + \beta_1 x + e$$

- Standard approach, Obtain partial derivatives, and interpret:

$$\frac{\partial RIF_i}{\partial x_i} = \beta_1 \; or \; \frac{\partial E(RIF_i|X)}{\partial x} = \beta_1$$

  But this is a change in the RIF for observation $i$. Or all groups where $X = x$.

Effect of $v$ is too small to be meaningful. (What proportion of the sample experience the change?)

# RIF-Regression: Interpretation

- Better Approach: Aggregate and obtain a better interpretations:

$$v(F_y) = \int E\left[RIF(y, v(F_y))|X\right] f_x dx$$

$$\frac{\partial v(F_y)}{\partial \bar{x}} = \int \frac{\partial E(RIF|X)}{\partial x} f_x dx$$

  Or:

$$v(F_y) = \beta_0 + \beta_1 \bar{x} \rightarrow \frac{\partial v(F_y)}{\partial \bar{x}}$$

But the only "simulation" we can impose is a change in the distribution of $X$ that increases the mean in 1 unit. (FFL: Location shift)

unless:

$$RIF_i = \beta_0 + \beta_1 x + \beta_2 (x - \bar{x})^2 + e \rightarrow v(F_y) = \beta_0 + \beta_1 \bar{x} + \beta_2 \hat{\sigma}^2$$

# Example: rifhdreg

Panel Panel

```
ssc install rif, replace
ssc install qregplot, replace
use http://fmwww.bc.edu/RePEc/bocode/o/oaxaca.dta, clear

rifhdreg  lnwage educ exper tenure female [pw=wt], rif( q(10) )
Linear regression                                Number of obs     =      1,434
                                                 F(4, 1429)        =      18.53
                                                 Prob > F          =     0.0000
                                                 R-squared         =     0.1057
                                                 Root MSE          =     1.2185
------------------------------------------------------------------------------
             |               Robust
      lnwage | Coefficient  std. err.      t    P>|t|     [95% conf. interval]   Mean
-------------+----------------------------------------------------------------
        educ |   .1202519   .0176049     6.83   0.000     .0857177    .1547861   11.5
       exper |   .0265787   .0045188     5.88   0.000     .0177145     .035443   12.7
      tenure |   .0058231   .0039389     1.48   0.140    -.0019035    .0135497    7.8
      female |  -.0895745    .082585    -1.08   0.278    -.2515753    .0724262   45.8%
       _cons |   1.040692   .2704888     3.85   0.000     .5100938    1.571289
------------------------------------------------------------------------------
Distributional Statistic: q(10)
Sample Mean    RIF q(10) :  2.7635 -> 10th : 15.85
1pp increase women  -> -0.00089 log points ~ -0.089% wage decline At 10th
```

# Example: rifhdreg

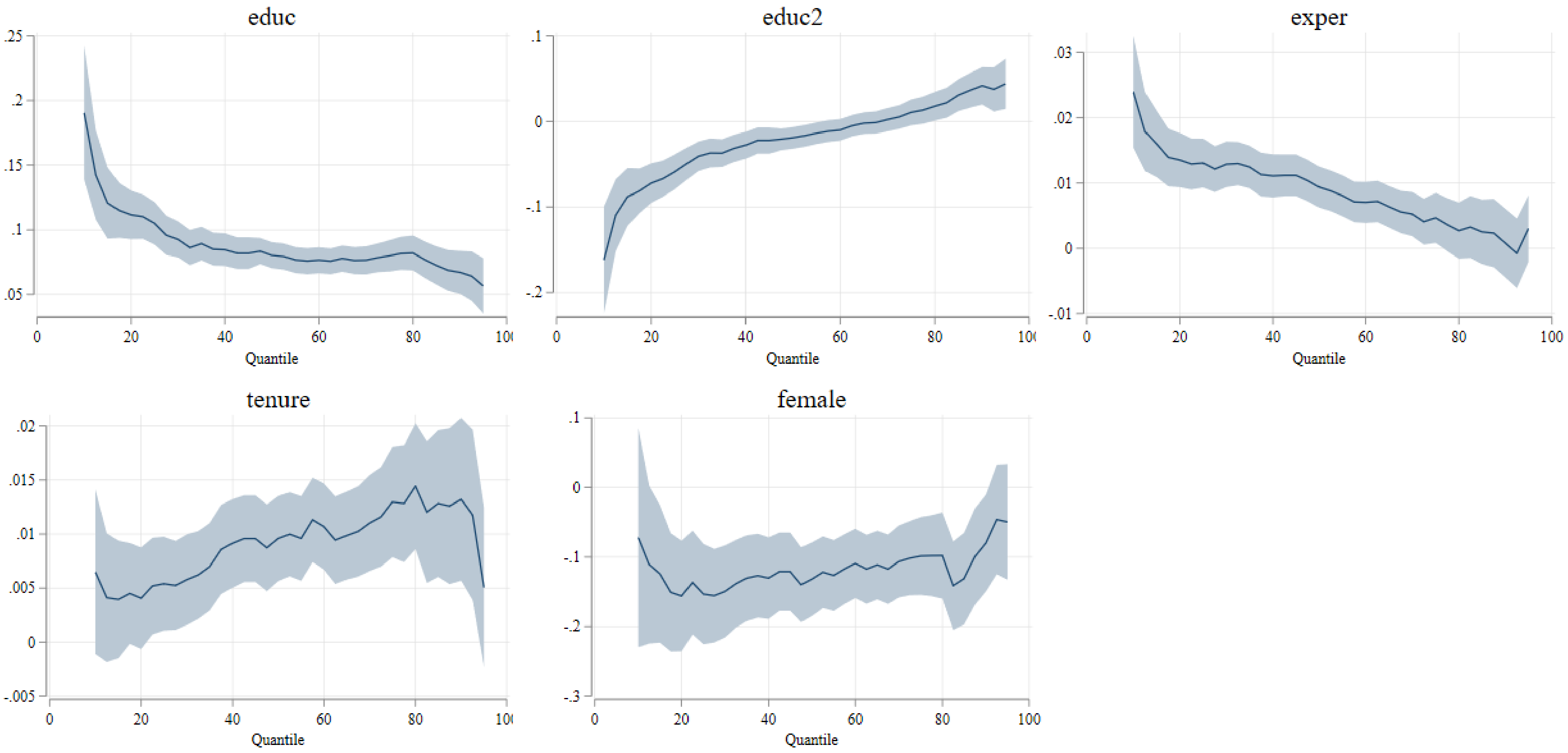
Panel Panel

```
sum educ if lnwage!=. [aw=wt]
gen educ2=(educ-r(mean))^2
sum educ2 if lnwage!=. [aw=wt]
replace educ2=educ2/r(mean)
rifhdreg  lnwage educ educ2 exper tenure female [pw=wt], rif( q(10) )
Linear regression                               Number of obs     =      1,434
                                                F(5, 1428)        =      17.87
                                                Prob > F          =     0.0000
                                                R-squared         =     0.1458
                                                Root MSE          =     1.1913

------------------------------------------------------------------------------
             |               Robust
      lnwage | Coefficient  std. err.      t    P>|t|     [95% conf. interval]   Mean
-------------+----------------------------------------------------------------
        educ |   .1905978    .026438     7.21   0.000     .1387363    .2424594   11.5
       educ2 |  -.1621495   .0319977    -5.07   0.000     -.224917   -.099382    1    <- Std Variance
       exper |   .0239944   .0043647     5.50   0.000     .0154326    .0325562   12.7
      tenure |   .0065056   .0038795     1.68   0.094    -.0011046    .0141159    7.8
      female |  -.0717937   .0804414    -0.89   0.372    -.2295898    .0860024   45.8%
       _cons |   .4142694   .3241888     1.28   0.202    -.2216679    1.050207
------------------------------------------------------------------------------
Distributional Statistic: q(10) -> 10th : 15.85
10% increase in Educ variance -> -.016 Log points ~ 1.6% wage decline of the 10th per
```

# Example: rifhdreg

```
qregplot educ educ2 exper tenure female, hole(4) col(3) xsize(10) ysize(5) q(10(2.5)95)
```



# Example: rifhdreg

| | (1) gini | (2) Std | (3) IQRatio8020 |
|---|---|---|---|
| educ | -1.971*** | -0.0772*** | -0.0756** |
| | (0.404) | (0.0180) | (0.0237) |
| educ2 | 3.039*** | 0.100*** | 0.193*** |
| | (0.515) | (0.0227) | (0.0292) |
| exper | -0.406*** | -0.0123*** | -0.0239*** |
| | (0.0746) | (0.00226) | (0.00589) |
| tenure | 0.0560 | -0.000158 | 0.0205** |
| | (0.0871) | (0.00168) | (0.00696) |
| female | 3.097* | 0.0275 | 0.140 |
| | (1.438) | (0.0442) | (0.101) |
| _cons | 49.16*** | 1.521*** | 2.817*** |
| | (4.873) | (0.206) | (0.293) |
| N | 1434 | 1434 | 1434 |
| rifmean | 26.27 | 0.590 | 2.064 |

Standard errors in parentheses

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

# What about QTE?

# QTE via RIF

- As mentioned, Standard RIF regressions cannot be used to estimate "treatment" effects.
    - Changes in treatment Status is a large distributional change.
- However, one can use a modified version of RIF, conditioning only on 1 variable (treatment)

$$RIF(y|D) = \beta_0 + \beta_1 D + \beta_2 x + e$$

$$RIF(y|D=1) \times D + (1-D) \times RIF(y|D=0) = \beta_0 + \beta_1 D + \beta_2 x + e$$

- Thus we simply need to estimate the RIF Separately for treated and untreated groups, while controlling for other factors.
    - Other factors can be controlled linearly, with interactions, or IPW, or both.

# Example: QTE via RIF

code Plots Other

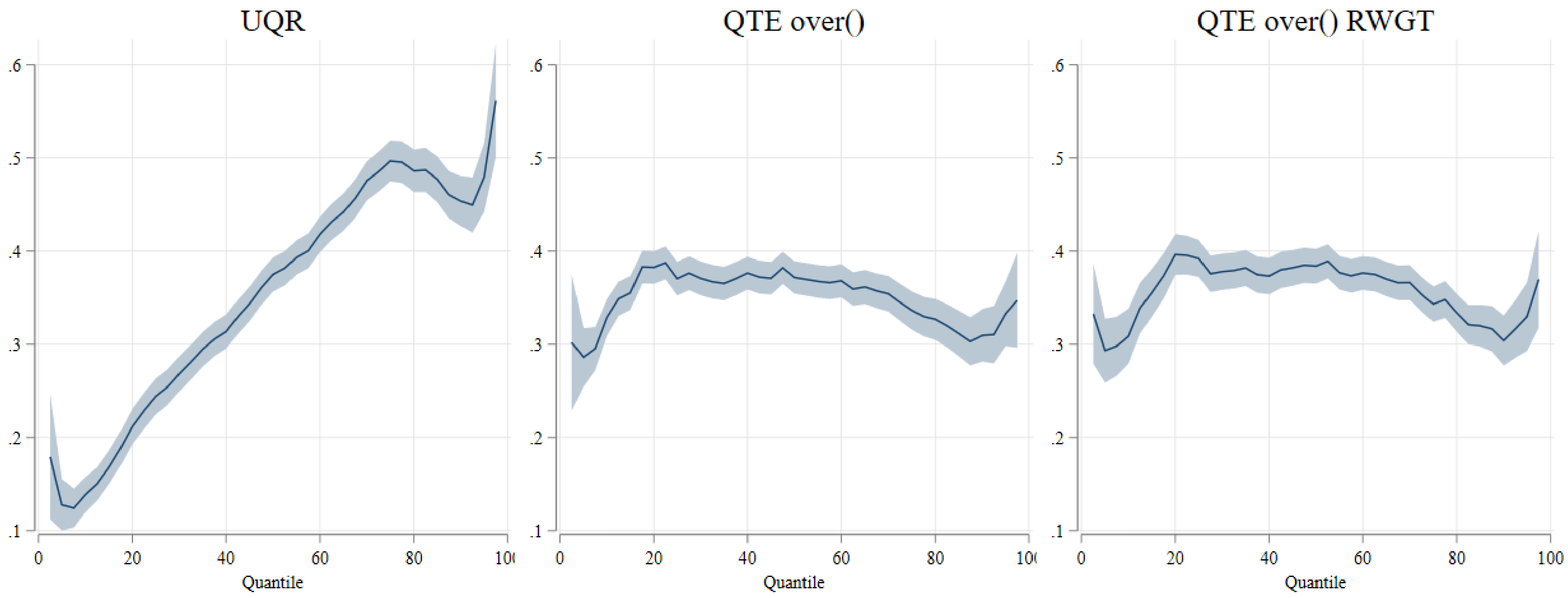
```
webuse nlswork, clear
  UQREG
rifhdreg ln_wage collgrad age i.race nev_mar union c_city ttl_exp, rif(q(10))
qregplot collgrad, q(2.5(2.5)97.5) name(m1, replace)

  QTE with Over()
rifhdreg ln_wage collgrad age i.race nev_mar union c_city ttl_exp, rif(q(10))  ///
   over(collgrad)
qregplot collgrad, q(2.5(2.5)97.5) name(m2, replace)

  QTE with Over() and RWGT
rifhdreg ln_wage collgrad age i.race nev_mar union c_city ttl_exp, rif(q(10)) ///
   over(collgrad) rwlogit( age i.race nev_mar union c_city ttl_exp)
qregplot collgrad, q(2.5(2.5)97.5) name(m3, replace)
```

# Example: QTE via RIF

code | Plots | Other



# Example: QTE via RIF

code Plots **Other**

| | Gini | TE-Gini | Std | TE-Std | IQRT | QTE-IQTR |
|---|---|---|---|---|---|---|
| collgrad | 5.517*** | -1.400* | 0.109*** | -0.009 | 0.574*** | -0.106*** |
| | (0.532) | (0.552) | (0.007) | (0.008) | (0.031) | (0.027) |
| age | 0.503*** | 0.380*** | 0.007*** | 0.006*** | 0.034*** | 0.022*** |
| | (0.048) | (0.049) | (0.001) | (0.001) | (0.003) | (0.002) |
| 1.race | | | | | | |
| 2.race | 1.125* | -0.064 | 0.017* | -0.004 | 0.244*** | 0.073** |
| | (0.488) | (0.506) | (0.007) | (0.007) | (0.028) | (0.024) |
| 3.race | 2.875 | 1.951 | 0.048 | 0.033 | 0.188 | 0.290** |
| | (1.990) | (2.063) | (0.028) | (0.028) | (0.116) | (0.100) |
| nev_mar | 1.756** | 1.296* | 0.039*** | 0.031*** | 0.103** | 0.104*** |
| | (0.557) | (0.578) | (0.008) | (0.008) | (0.032) | (0.028) |
| union | -0.767 | 0.482 | -0.015* | -0.002 | -0.001 | 0.046 |
| | (0.494) | (0.512) | (0.007) | (0.007) | (0.029) | (0.025) |
| c_city | -0.333 | -0.751 | -0.013* | -0.016* | -0.096*** | -0.058* |
| | (0.460) | (0.477) | (0.006) | (0.007) | (0.027) | (0.023) |
| ttl_exp | -0.074 | 0.161* | 0.000 | 0.003** | 0.012** | 0.023*** |
| | (0.062) | (0.064) | (0.001) | (0.001) | (0.004) | (0.003) |
| _cons | 9.830*** | 11.571*** | 0.213*** | 0.243*** | 0.857*** | 1.112*** |
| | (1.283) | (1.330) | (0.018) | (0.018) | (0.075) | (0.064) |
| **N** | 19215 | 19215 | 19215 | 19215 | 19215 | 19215 |
| rifmean | 26.508 | 24.563 | 0.468 | 0.437 | 2.171 | 2.000 |

# What about [K]OB Decompositions?

# RIF Decompositions

FFL(2018) proposes that it is possible to extend the use of RIF regressions to decomposition analysis, similar to what is commonly done with the Kitagawa-Oaxaca-Blinder decomposition.

They also suggest a refinement that introduces a reweighting step.

The logic is simple: As with RIF-regressions, simply swap the dependent variable with the corresponding RIF, and proceed as usual.

I would argue that KOB decompositions are in principle better at keeping the principles and assumptions of RIF-regressions:

- Analyze unconditional statistics, considering unconditional differences in distributions across two groups

However, Interpretation could be somewhat difficult.

# OB_RIF Decompositions

Step 1: RIF estimation

$$RIF_i(D=k) = \beta_{k0} + \beta_{k1}x_1 + \beta_{k2}x_2 + e_k \ \forall \ k = 0,1$$

Step 2: Express regressions in terms of unconditional means

$$F_{y|D=k} = F_y^k$$

$$E(RIF_i|D=k) = v(F_y^k) = \beta_{k0} + \beta_{k1}\bar{x}_1 + \beta_{k2}\bar{x}_2 = \bar{X}_k\beta_k = v( \ F^k_{y|x} \ , \ F^k_x)$$

This step explicitly says: group specific distributional statistics can be approximated as function of the Mean of the variables on control variables.

# OB_RIF Decompositions

Step 3: Decomposition

$$v(F_y^1) - v(F_y^0) = \bar{X}_1\beta_1 - \bar{X}_0\beta_0$$

$$v(F_y^1) - v(F_y^0) = (\bar{X}_1 - \bar{X}_0)\beta_0 + \bar{X}_1(\beta_1 - \beta_0)$$

$$v(F_y^1) - v(F_y^0) = \left[v(F^0_{y|x}, F^1_x) - v(F^0_{y|x},\ F^0_x)\right] + \left[v(F^1_{y|x}, F^1_x) - v(F^0_{y|x},\ F^1_x)\right]$$

Under certain assumptions, the last term can be use as a treatment effect on treated (k=1).

# OB_RIF Decompositions: Refinement

Using means may not be enough to capture differences in distributions across groups. Thus a better approach, Combine KOB with reweighted approach.

Step 1: logit/probit, and obtain IPW's

$$P(k=1|x) = G(X\beta)$$

Step 2: Estimate Auxiliary Regression (counterfactual) using IPW:

$$v\left(F^0_{y|x}, \tilde{F}^1_x\right) = \bar{X}^c_1\beta^c_0 \simeq \bar{X}_1\beta_0$$

$$v\left(F^1_{y|x}, \tilde{F}^0_x\right) = \bar{X}^c_0\beta^c_1 \simeq \bar{X}_0\beta_1$$

Step 3: Decomposition

$$\Delta X = \bar{X}^c_1\beta^c_0 - \bar{X}_0\beta_0 = (\bar{X}^c_1 - \bar{X}_0)\beta_0 + \bar{X}^c_1(\beta^c_0 - \beta_0)$$

$$\Delta\beta = \bar{X}_1\beta_1 - \bar{X}^c_1\beta^c_0 = \bar{X}_1(\beta_1 - \beta^c_0) + (\bar{X}_1 - \bar{X}^c_1)\beta^c_0$$

# OB_RIF Decompositions: Summary

In the RIF framework, we are attempting to determine what factors account for differences in the distribution between two groups: $\Delta v$.

This may be explained by:

- Differences in distribution of characteristics: differences in means.
- Differences in "returns" to those characteristics: Differences in $\beta's$ as proxy for Conditional distributions. $F(Y|X,D)$.

This can be done using `oaxaca_rif`

# Example: Oaxaca RIF

```
use http://fmwww.bc.edu/RePEc/bocode/o/oaxaca.dta, clear;gen wage=exp(wage);
oaxaca_rif wage educ exper tenure [pw=wt], rif( q(50) ) by(female)

RIF    : q(50)
Group 1: female = 0 x1*b1                       N of obs 1      = 751
Group c: x1*b2                                  N of obs C      =           .
Group 2: female = 1 x2*b2                       N of obs 2      = 683
------------------------------------------------------------------------------
        wage | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
overall      |
     group_1 |   32.21719   .6021551    53.50   0.000     31.03698    33.39739
     group_2 |   26.31728   .5978081    44.02   0.000      25.1456    27.48897
  difference |   5.899902   .8485077     6.95   0.000     4.236857    7.562946
   explained |   2.394187   .4587227     5.22   0.000     1.495107    3.293267  (x1-x2)*b2
 unexplained |   3.505714   .7964557     4.40   0.000      1.94469    5.066739  ATT:x1*(b1-b2)
-------------+----------------------------------------------------------------
explained    |                                                                    M     F
        educ |    1.25169    .322888     3.88   0.000     .6188412    1.884539  (11.74-11.18)
       exper |   .6502986   .2382173     2.73   0.006     .1834013    1.117196  (13.74-11.46)
      tenure |   .4921986   .2726614     1.81   0.071    -.0422079    1.026605  ( 8.97- 6.39)
-------------+----------------------------------------------------------------
unexplained  |                                                                Diff in F_y|X
        educ |  -2.529993   3.086411    -0.82   0.412    -8.579247    3.519262
       exper |  -1.011601   1.330902    -0.76   0.447    -3.620122    1.596919
      tenure |   1.790919   1.120194     1.60   0.110    -.4046214    3.986459
       _cons |    5.25639   3.192297     1.65   0.100    -1.000397    11.51318  Diff b0
------------------------------------------------------------------------------
```

# Example: Oaxaca RIF

```
. oaxaca_rif wage educ exper tenure [pw=wt], rif( q(50) ) by(female) rwlogit(educ exper tenure)
Group 1: female = 0 x1*b1                         N of obs 1       = 751
Group c: X2~>rw~>X1 or x1*b2                      N of obs C       = 683
Group 2: female = 1 x2*b2                         N of obs 2       = 683

------------------------------------------------------------------------------
        wage | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
Overall      |
     group_1 |   32.21719   .5686022    56.66   0.000     31.10275    33.33163   Men
     group_c |   28.87179   .5911752    48.84   0.000     27.71311    30.03047   Men Paid as Women
     group_2 |   26.31728   .5556553    47.36   0.000     25.22822    27.40635   Women
 tdifference |   5.899902   .7950228     7.42   0.000     4.341685    7.458118
 t_explained |   2.554504   .8113205     3.15   0.002     .9643449    4.144663
t_unexplained |  3.345398   .8202418     4.08   0.000     1.737753    4.953042   ATT
-------------+----------------------------------------------------------------
explained    |
       total |   2.554504   .8113205     3.15   0.002     .9643449    4.144663
 p_explained |    2.06466   .3891674     5.31   0.000     1.301906    2.827414
  specif_err |   .4898437    .770001     0.64   0.525     -1.01933    1.999018 -> Need Review Specification
-------------+----------------------------------------------------------------    Polynomial Interactions
unexplained  |
       total |   3.345398   .8202418     4.08   0.000     1.737753    4.953042
   rwg_error |   .2952259   .3468002     0.85   0.395      -.38449    .9749418 -> Similar to Balance Test
p_unexplained |  3.050172   .7424254     4.11   0.000     1.595045    4.505299
------------------------------------------------------------------------------
```

# Example: Other Stats

```
                     q10             q90             gini        iqratio8020
overall
group_1            18.43***        52.87***        23.78***        1.979***   Men
                  (0.867)         (1.177)         (0.826)        (0.0603)
group_2            13.90***        43.65***        28.20***        2.011***   Women
                  (0.875)         (1.192)         (1.279)        (0.0692)
difference         4.531***        9.221***       -4.422**        -0.0316
                  (1.232)         (1.676)         (1.523)        (0.0918)
explained          2.531***        2.816***       -1.552*         0.00544
                  (0.623)         (0.832)         (0.622)        (0.0368)
unexplained        2.000*          6.405***       -2.869          -0.0370
                  (1.014)         (1.917)         (1.537)        (0.0929)
----------------------------------------------------------------------------
explained
educ               0.934**         1.803**        -0.360           0.0116
                  (0.305)         (0.574)         (0.361)        (0.0171)
exper              1.307**         1.192*         -0.956*         -0.0424
                  (0.419)         (0.499)         (0.414)        (0.0249)
tenure             0.290          -0.179          -0.237           0.0362
                  (0.228)         (0.518)         (0.395)        (0.0305)
unexplained
educ               5.519           5.549          -0.533          -0.111
                  (5.816)         (10.61)         (9.030)         (0.462)
exper             -1.610          -9.895***       -0.862          -0.218
                  (1.927)         (3.000)         (2.351)         (0.161)
tenure             0.430           6.813**         1.282           0.0155
                  (0.966)         (2.508)         (1.637)         (0.125)
_cons             -2.339           3.938          -2.757           0.276
                  (7.570)         (10.18)         (9.700)         (0.519)
```

# Conclusions

- In this presentation, I provided a general review of RIF regressions, implementation and interpretation.
- RIF, by default estimates effects at the margin (UPE). But can be used to estimate distributional effects (over() and oaxaca_rif)
- IPW can be combined with RIF to estimate Distributional TE. But Standard errors need correction
- The implementation is straight forward with the commands `rifhdreg` and `oaxaca_rif`

# Thanks you!

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