Comments on "On the Asymmetrical Sensitivity of the Distribution of Real Wages to Business Cycle Fluctuations" by Rodrigo Barrela, Eduardo Costa, and Pedro Portugal

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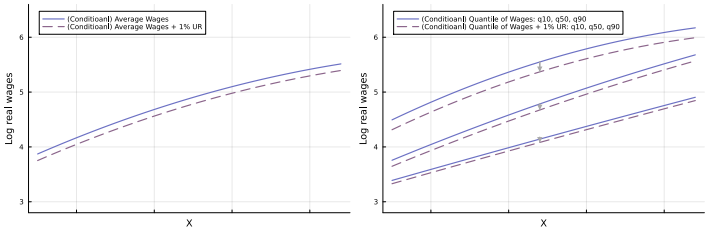
Summary

- Wage cyclicality: Business cycle (BC) $\overset{?}{\Rightarrow}$ Wages
  - Aggregate data based empirical work show conflicting results, suffering composition bias
  - Individual-level data generally conclude procyclical effect on wages, studying average effect
- This paper
  1. Characterizes the heterogenous impact of the BC along the conditional real wage distribution
  2. Investigates the sources of the (asymmetrical) real wage cyclicality
- Portuguese matched employer-employee admin data 1986-2021 (Relatório Único/Quadros de Pessoal) : High quality data with rich information on both firms and workers
  - mandatory survey, all private firms in the manufacturing and services sectors, no wage floor
  - Sample: full time, 18-64, > 80% national minimum wage, CBA covered (85% of the workforce), services and manufacturing sectors, job titles > 10 workers
  - 7,225,931 workers, 765,618 firms, and 52,342,436 worker-firm observations

Heterogenous impact of the BC along the conditional real wage distribution

- By moving away from conventional regression models to quantile models



(a) Conventional regression model (b) Conditional quantile regression

- They find: 1% ↑ in UR, 1.3% ↓ (90_{th} percentile), and 0.8% ↓ (10_{th} percentile) in real hourly wage implying wage inequality attenuated during recession
  - Stronger effect for the new hire (both in cyclicality and asymmetry)
  - By gender (male with larger procyclicality, similar asymmetry pattern across genders)
  - By edu (high edu with larger procyclicality and no sign of asymmetry)
- Wage composition: asymmetry not solely caused by cyclicality of minimum wages (P50 and P90 not similar), asymmetrical reactions hold for bargained wage and cushion wage

Quantile Regression with FE to Correct Composition Bias (Machado and Silva, 2019)

- Potential composition changes: low ability workers lose job, low-paying firms exit
  $\Rightarrow$ the estimator for the UR coefficient is bias
- Control individual & firm FE in the quantile regression model

$$w_{it} = UR_{t-1}\gamma^l + \phi_i^l + \phi_f^l + \underbrace{(UR_{t-1}\gamma^s + \phi_i^s + \phi_f^s)u_{it}}_{R_{it}}, \quad \text{where } E(u_{it}) = 0, E(|u_{it}|) = 1$$

$$\Leftrightarrow \quad Q_w(UR_{t-1}, \phi_i, \tau) = UR_{t-1}\gamma^l + \phi_i^l + \phi_f^l + (UR_{t-1}\gamma^s + \phi_i^s + \phi_f^s)q(\tau), \quad \text{where } q = F_u^{-1}$$

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$$Q_w(UR_{t-1}, \phi_i, \tau) = UR_{t-1}\left(\gamma^l + \gamma^s q(\tau)\right) + \left(\phi_i^l + \phi_i^s q(\tau)\right) + \left(\phi_f^l + \phi_f^s q(\tau)\right), \quad \text{where } q = F_u^{-1}$$

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- Method of Moments-Quantile Regression
  (1) $\hat{\gamma}^l, \hat{\phi}_i^l, \hat{\phi}_f^l$: reg w_{it} on UR_{t-1}, individual and firm dummies (Guimaraes and Portugal 2010)
  (2) $E\left(|R_{it}| \middle| UR_{t-1}, \phi_i\right) = (UR_{t-1}\gamma^s + \phi_i^s + \phi_f^s) \Leftrightarrow$

$$|R_{it}| = UR_{t-1}\gamma^s + \phi_i^s + \phi_f^s + \epsilon_{it}, E(\epsilon_{it}|UR_{t-1}, \phi_i) = 0$$

  $\hat{\gamma}^s, \hat{\phi}_i^s, \hat{\phi}_f^s$: reg $|\hat{R}_{it}|$ on UR_{t-1}, individual and firm dummies
  (3) $\hat{q}(\tau)$: simply check different quantiles of $\hat{R}/(UR_{t-1}\hat{\gamma}^s + \hat{\phi}_i^s + \hat{\phi}_f^s)$

Sources of the asymmetric real wage cyclicality

- Composition bias: adding FE of individual, firm, and match levels (Machado and Silva, 2019)
  - Important to correct composition bias: stronger procyclicality for stayers (low ability and low pay firms exit), no distinct wage reaction for stayers and new hires (match to worse jobs)
  - Not significant effect on asymmetrical reactions
- Heterogeneous reactions among firms/CBAs: Focusing on larger and perennial firms/CBA
  - Evidence of heterogeneous reactions to UR (countercyclical: 25% firms, 18% CBAs)
  - Asymmetry within firm/CBA: firms and CBAs tend to provide a lower degree of insurance to BC fluctuations to higher paid individuals
- Potential underlying economic models: complementarities between labor skills and capital $\Rightarrow$ demand for higher wage workers increases in expansions (Lindquist 2004 and Dolado et al. 2021).

Comments

- Very nice paper, pleasure to read!
- Present new and interesting empirical evidence using high quality data, highly relevant for structural modeling
- Apply novel estimation method
- Deep investigation into sources

Two main comments:

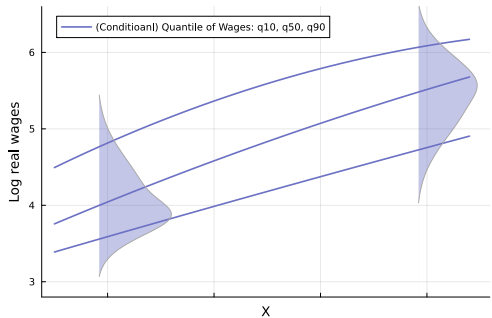
1. Interpretation of the asymmetrical reactions of high- and low-wage workers
   (a) I will first explain what is captured by the quantile model
   (b) I will discuss potential extensions to the quantile model
2. Connection to nonparametric methods

Interpretation of High and Low Wage Workers

- The quantile regression model (let's temporarily ignore new hires)

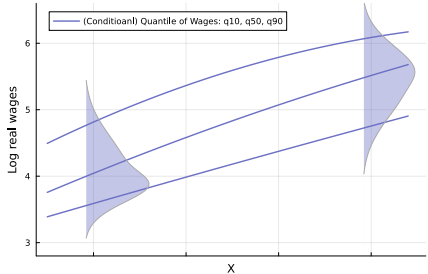
$$w_{it} = Q_w(UR_{t-1}, \underbrace{z_{it}, \phi_i, \phi_f}_{X_{it}}, \tau_{it}) \tag{1}$$

  where z_{it} includes age, tenure, edu, gender, and a time trend, and $\tau_{it} \sim U(0,1)$
- Given a certain UR_{t-1}, workers can earn high or low wages due to two different factors
  (1) Their own **profile** X_{it}: high or low edu, experienced or not, high ability or not, etc.
  (2) **Stochastic** term: τ_{it}



Interpretation of High and Low Wage Workers: Luckiness?

- What is the captured "*asymmetrical reactions of high- and low-wage workers*" to UR in this model?



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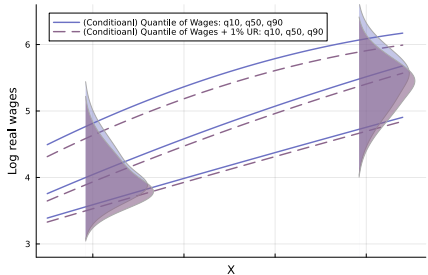

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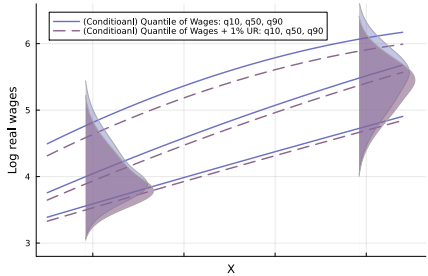

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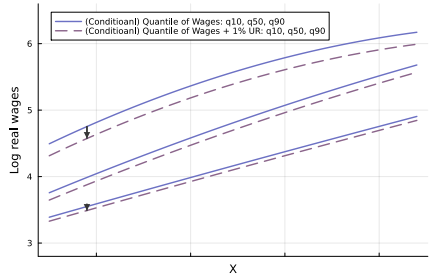

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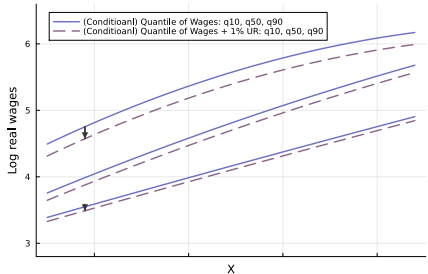

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- After netting out X, the residual seems more like *fluctuations* rather than heterogeneity: without persistence, today's high-wage workers ($\tau = 0.9$) can be low-wage workers in the next period too

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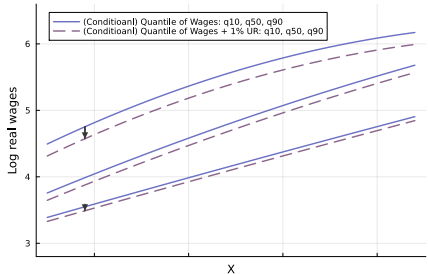

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$\Rightarrow$ Comparison of luckiness across BC, better be lucky during expansion rather than recession.

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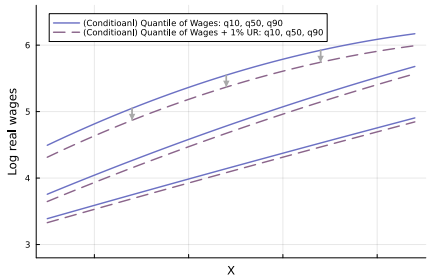

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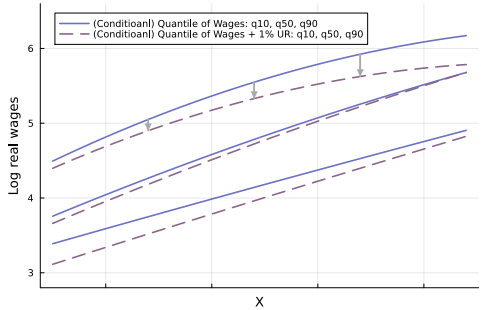
- We could easily allow for more flexible marginal effect, $\rho(\tau, X, UR_{t-1})$, by adding interactions, such as between UR and z_{it} (empirically supported by the edu, gender, firm/CBA exercises)



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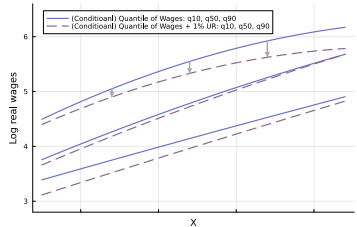

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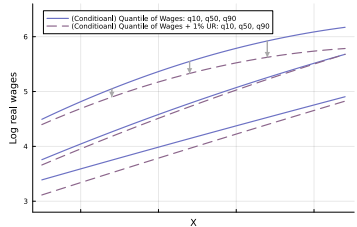

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$$\int \rho(\tau, z_{it}) f(z_{it}|\text{high wages}) dz \quad \text{and} \quad \int \rho(\tau, z_{it}) f(z_{it}|\text{low wages}) dz \tag{3}$$

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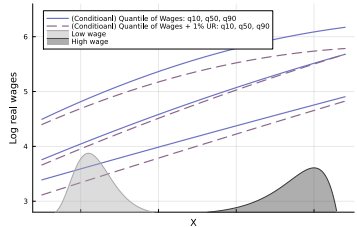

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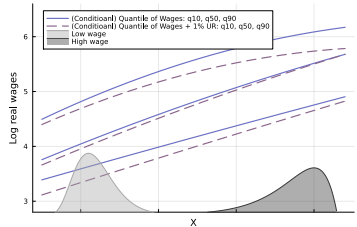

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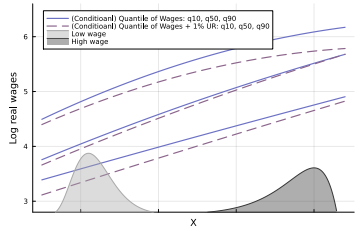

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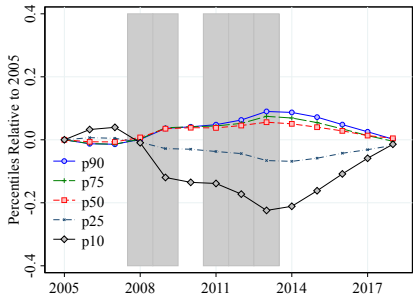
- By considering the heterogeneity across X, $\rho(\tau, X_i)$, better connect to structural models (e.g. Dolado et al. 2021 and Robin 2011) where skill/ability are usually defined based on X not τ.

Connection to Nonparametric Methods – Grid Projects

- Connection to recent literature put forward by Guvenen et al. (2021) and others using nonparametric approach producing statistics on income dynamics using admin data.
- Net out year and gender (edu) effects on log real wages and study the evolvement of percentiles



(a) Percentiles of the distribution of residualized log annual earnings, based on Arellano et al. (2022)

  - Not controlling for unobserved heterogeneities, annual earnings not hourly wages

Connection to Nonparametric Methods – Grid Projects

- In the case of no unobserved heterogeneity, the the location-scale representation becomes

$$w_{it} = Q_w(z_{it}, UR_{t-1}, \tau) = z'_{it}\beta^l + UR_{t-1}\gamma^l + (z'_{it}\beta^s + UR_{t-1}\gamma^s)q(\tau) \tag{3}$$

- The residual after the net-out step can be seen as the estimate of $R = (z'_{it}\beta^s + UR_{t-1}\gamma^s)q(\tau)$
- Plot the percentiles of the distribution of $\hat{R}$ by each year, this provides similar information to the equation (3) regarding relative changes between different τ with BC
  - We can pool all data together instead of fixing a specific z group because the marginal effect of UR is assumed to be the same across all z groups

- Also use Spanish data, Bonhomme and Hospido (2017) focus on aggregate shocks and inequality: increased inequality during recession

- Overall, nice paper to read!
- Very relevant research question on the topic that deserves more attention
- Promising paper for its excellent data, methodology and investigated mechanisms