

## EUROPEAN CONFERENCE ON QUALITY IN OFFICIAL STATISTICS 2024 ESTORIL - PORTUGAL



# Estimating Non-Regular Earings for Micro Organizations

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#### Agenda

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- 2. Data Chjaracteristics and Panel Structure
- 3. Process of estimation
- 4. Outlier detection
  - 1. First Stage
  - 2. Second stage
  - 3. Raw aggregates
- 5. Sample Adjustments
  - 1. Weighting and Calibration
  - 2. Comparison
- 6. Summary



#### Introduction

- Target of the method
  - Non-Regular earnings are need for some earnings statistics
- Reason for developing
- Used data
  - Surveys are too burdenful for both sides
  - Administrative data is very helpful vs unknown sample characteristics at the end
- Difficulties for estimating
- Generalizable solution?

#### **Data Characteristsics**

- Sources are from:
  - National Tax Authority
  - Hungarian State Treasury
- Cross sectional years cover 4.7 million observations.
- Merge 4 year on unique identifiers results in 1.6 million observations
  - These are people who didn't change ISCO codes and organization, join or exit the labor market
  - Obviously this should leave out two age class the young and the elderly
  - Another difference we observe is some ISCO codes tend to be under represented (phisycal jobs)
    - Either coming from the previous step and these are the ISCO codes the have young or elderly mainly working in them.
    - There could be ISCO categories where people jump between organizations or change ISCO categories.
- Finally keep only micro organizations

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#### Heterogeneity analysis I

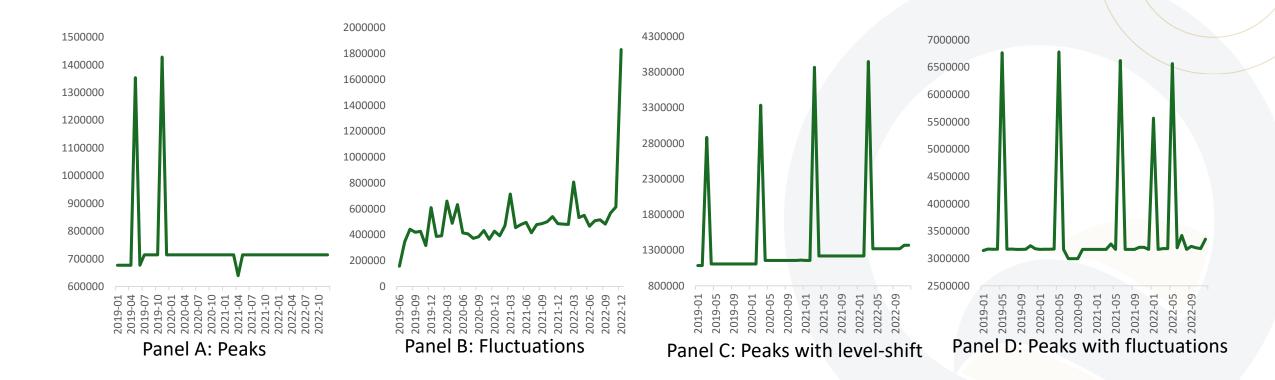
Age categories	Panel	Year 2019	Year 2020	Year 2021	Year 2022
< 25	0.5%	14.8%	10.4%	10.4%	10.7%
25-35	12.0%	22.7%	22.3%	22.3%	21.9%
35-45	25.9%	28.3%	26.9%	25.7%	24.7%
45-55	37.1%	22.6%	25.1%	26.2%	26.7%
55-65	23.3%	10.9%	14.0%	14.0%	14.3%
65 <	1.3%	0.6%	1.24%	1.5%	1.8%

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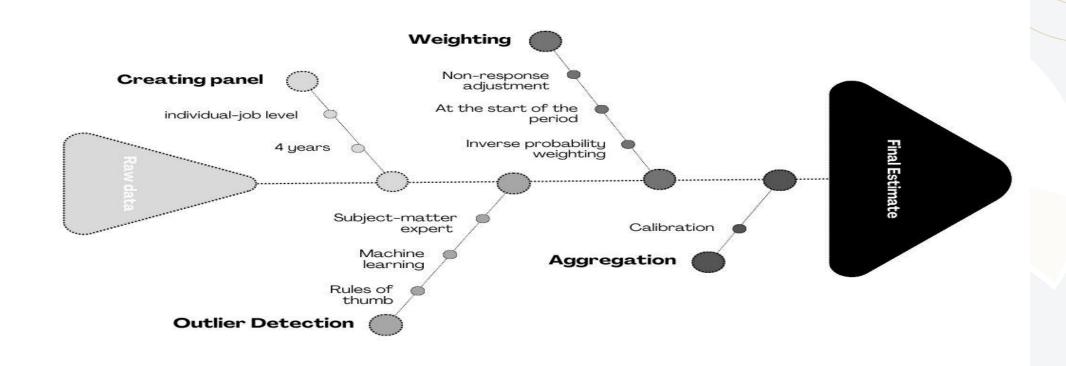
#### Heterogeneity analysis II

ISCO categories	Panel	Year 2019	Year 2020	Year 2021	Year 2022
CO	0.0%	1.0%	0.7%	0.8%	0.0%
C1	10.8%	6.9%	7.1%	7.0%	7.4%
C2	18.0%	14.7%	15.1%	15.8%	15.5%
C3	16.4%	15.2%	15.5%	16.4%	15.7%
C4	6.6%	7.1%	7.0%	6.9%	7.2%
C5	10.7%	10.7%	10.7%	10.4%	10.6%
<b>C6</b>	0.8%	0.7%	0.7%	0.7%	0.7%
C7	12.4%	9.3%	9.2%	8.7%	8.7%
C8	14.6%	13.2%	13.0%	12.7%	12.9%
<b>C9</b>	9.5%	21.1%	21.0%	20.4%	21.2%

### Typical earnings time series



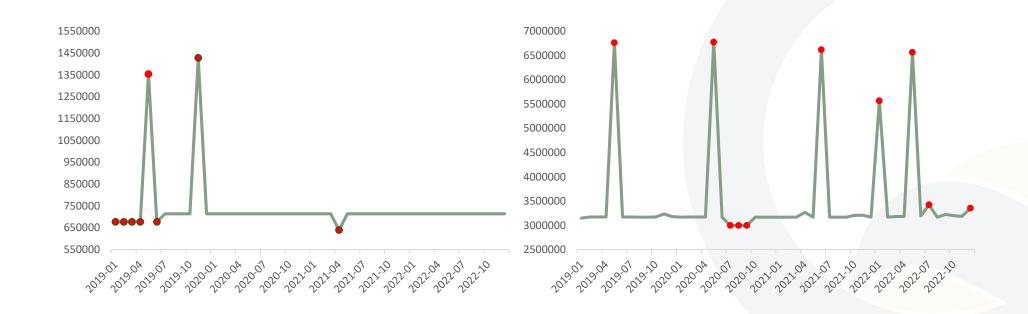
#### **Process of estimation**



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#### First stage of outlier detection

 This stage uses mainly random forest based isolation to detect outliers in the previously seen time series in a unsupervised fashion.



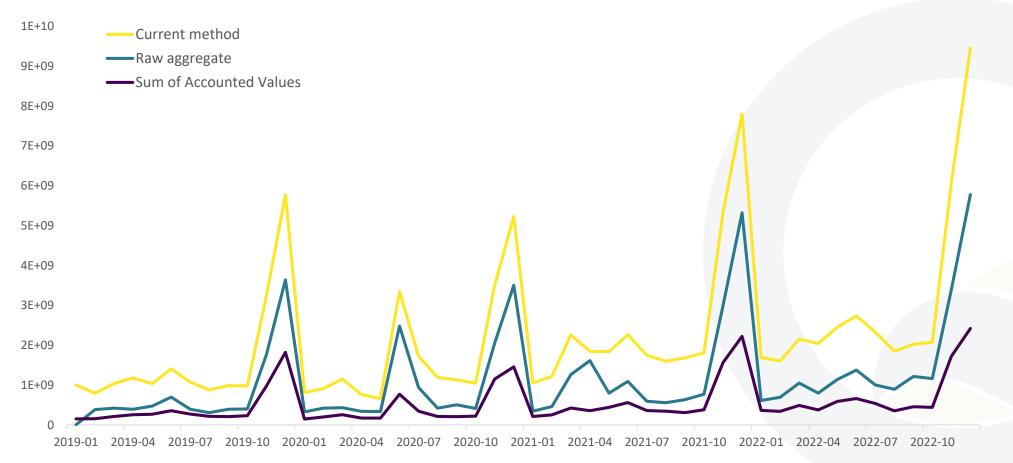
#### Second stage of outlier detection

- This stage uses mainly subject matter expert knowledge to define filters after the first stage to be more precise on classifying outlier points as non-regular earning values.
- 1. Retroactive Raises: commonly used in Hungary

$$D_{RR} = \left(\frac{w_t - \overline{w}_{t-1,t-n}}{m_t * \overline{w}_{t-1,t-n}} < p\right)$$

- 2. Regulatory one-time payouts: These are not included by definition, subject matter experts identify when and in what amount it happend to which ISCO categories.
- 3. Small and Regular Fluctuations: Usually should be fluctuation in earnings due to per piece rate or performance wages.
  - Generally small fluctionations < 70-80 EUR, in January larger ones.

#### Raw aggregates

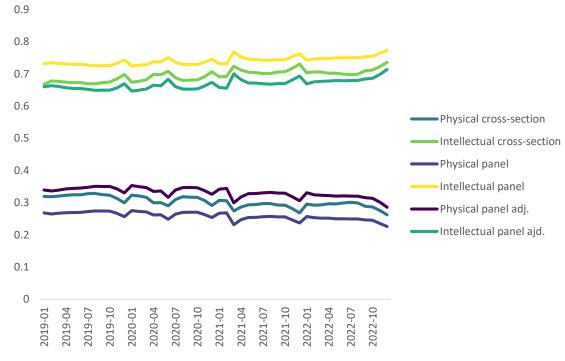


#### Weighting & Calibration

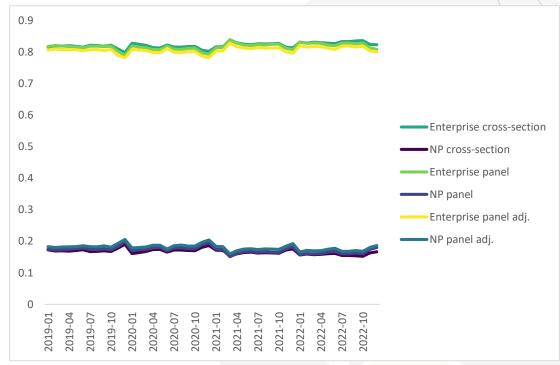
- Our ides is to make this similar to non-response adjustment.
  - Understanding differences between the panel samples and cross-sectional years.
  - Then use inverse probabilty weighting to correct the sample distributions
  - Calculated on the 1.6 million observations and not just for Micro organizations
- Targeted currently to achieve similarity to cross-sections in currently published important categories:
  - Type of organizations (entr., non-proit and gov. Body)
  - Type of job (physical, intellectual, unknown)
- Weights are calcuated from they 2019 cross-sectional data with logistic regression
  - Used variables: ISCO (4 digit), gender of employee and age category
- Calibration is done on each cross-sectional data using observation numbers
  - By variables: NACE (2 digit) and County codes

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#### Comparison of aggregated series



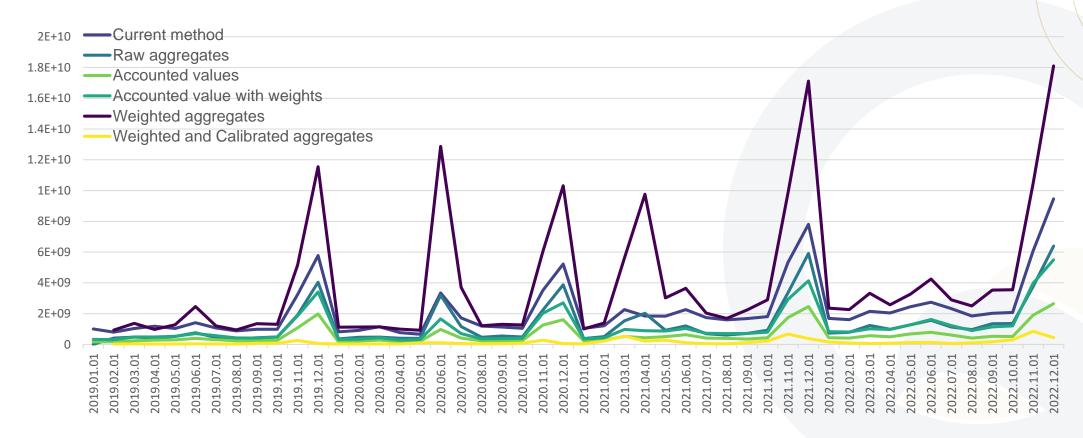
Panel A: Comparison of aggregated series by occupation types



Panel B: Comparison of aggregated series by organization types

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#### Comparison of all series



#### Summary

- Bottom up appraoch to reach Macro indicators.
- The problem of using unknown populations due to "BIG" data.
- The weighted results still have to be corrected to reach a level of index continuity and do not have a large revision.
- Possible improvements:
  - Calibration technique seems to be off
  - Outlier filtering not strict enough at peaks?
  - Weights should be corrected yearly?
  - Is there still a regulatory payout we did not find at 2021.04?
- Future of the method: If method provides acceptable results with small fluctuations from month-to-month, the method is easy generalizable to national level.



#### Thank you for your attention!





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