ВЫСШАЯ ШКОЛА ЭКОНОМИКИ

НАЦИОНАЛЬНЫЙ ИССЛЕДОВАТЕЛЬСКИЙ
УНИВЕРСИТЕТ

Staffing Requirements Forecasting on Saint-Petersburg Labour Market

Draft

Andrei A. Ternikov

Motivation

Topic Evidence

Labour Market Phenomena

- Digitalization and automation on labour market
- Growing number of vacancies (new professions)
- Skill-set broadening (combination of skills)

Practical Side

- Ambivalent "methodology" of staffing requirement forecasting
- Demand from State labour authorities

Scientific Side

- New methodology (labour market supply-demand modelling)
- Model calibration on real data (use of "big" data)

Researches' Features

- Macro-level analysis
- Supply-side analysis

Foreign Research

Alsultanny Y. A., Congregado E., Giesecke J. A., Johnston B., Scheffler R. M., Wilke R. A.

Russian Market Research

Гуртов В. А., Голубенко В. А., Сигова С. В., Питухин Е. А., Мороз Д. М., Астафьева М. П., Putilov A. V., Bugaenko M. V., Timokhin D. V.

Gap

Micro-analysis of labour market data; staffing requirement determining & forecasting

Aim

Build a medium-term forecast of staffing requirements in the labour market of St. Petersburg

Hypotheses

- Expected expansion of the set of skills of a potential employees
- An increase in the number of vacancies that do not require binding to a specific industry under OKVED (industry codes)
- There is no expected drop in demand for workers in technical specialities who have received a secondary specialized education, despite the automation of production processes

Novelty

- The use of an extensive dataset (data of labour committee and HeadHunter), processed using machine learning methods (keyword extraction and automatic classification by professions, specialities and industries by codifier)
- Predicting the need for personnel (creation and testing of analytical and econometric models) taking into account changes in skill-sets of potential employees on Russian data

Methodological Base

Supply-demand models (CES-functions), time-series models calibration, machine learning techniques (non-structural features extraction & data classification)

Data

- HeadHunter CV $\approx$1.5M (2015-2017 + history)
- HeadHunter vacancies $\approx$60k (2015-2017)
- Committee dataset (2016-2017)

Done

- Vacancies codes assigned (accuracy $\approx$60%)
- Skills (text) lemmatized
- Education and profession assigned (generally)
- Set of simple ARIMA predictions for each vacancy built and weighted to official statistics data

Q&A