Employment, wages and inequality in India: An occupations and tasks based approach

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Technology and labour

- The impact of technology on labour
  - Skill biased technology change?
  - Technology displacing skilled workers?
  - Job polarization
- Autor, Levy and Murname (2003), Acemoglu and Autor (2011)
  - Task content of occupations to understand these trends
  - Which occupations are most likely to be affected by technology?

Technology and labour

- Tasks are classified based on whether they are:
  - Manual or cognitive
  - Routine or non-routine
- Various papers following this approach have classified occupations based on these task categories. Following Autor, Levy and Murname (2003), this paper creates four main categories: Non-routine manual(dropped), routine manual, routine cognitive and non-routine cognitive

Data Sources

- National Sample Survey Data: Employment-Unemployment Rounds
  - Rounds 61, 62, 64, 66, and 68, for the years 2005, 2006, 2008, 2010 and 2012 respectively
  - number of workers surveyed in these rounds vary from just over 375,000 to over 600,000
  - Each record is also assigned a sampling weight, which can be used as a multiplier to get information on all workers.
  - Details are available on each worker's principal activity, industry and occupation, education - both general and technical, gender, and wage among other variables

Data Sources

- O*NET:
  - Used to calculate task content of occupations
  - ONET database from its latest revision in 2010.
  - ONET database contains information on 974 occupations for which data has been collected from occupation experts. ONET Content Model defines an occupation as a set of variables called descriptors--contains 277 descriptors, describing different aspects of the job, and qualifications & interests of the workers.
  - Each descriptor is assigned a value along different scales for each occupation. There are 30 different types of scales as described in the ONET scales reference.

Task-content of occupations

- Task scores were calculated for each task type from ONET data.
- Table 1 describes the various measures that were used for task construction, along with the scale type. These measures were selected using Acemoglu and Autor (2011).
- The scale used was typically a product of the importance and level of each measure, where both values were first normalized to be between 0 and 1.
- The measures were added up for each task type and the scores were standardized to have mean zero and standard deviation 1.

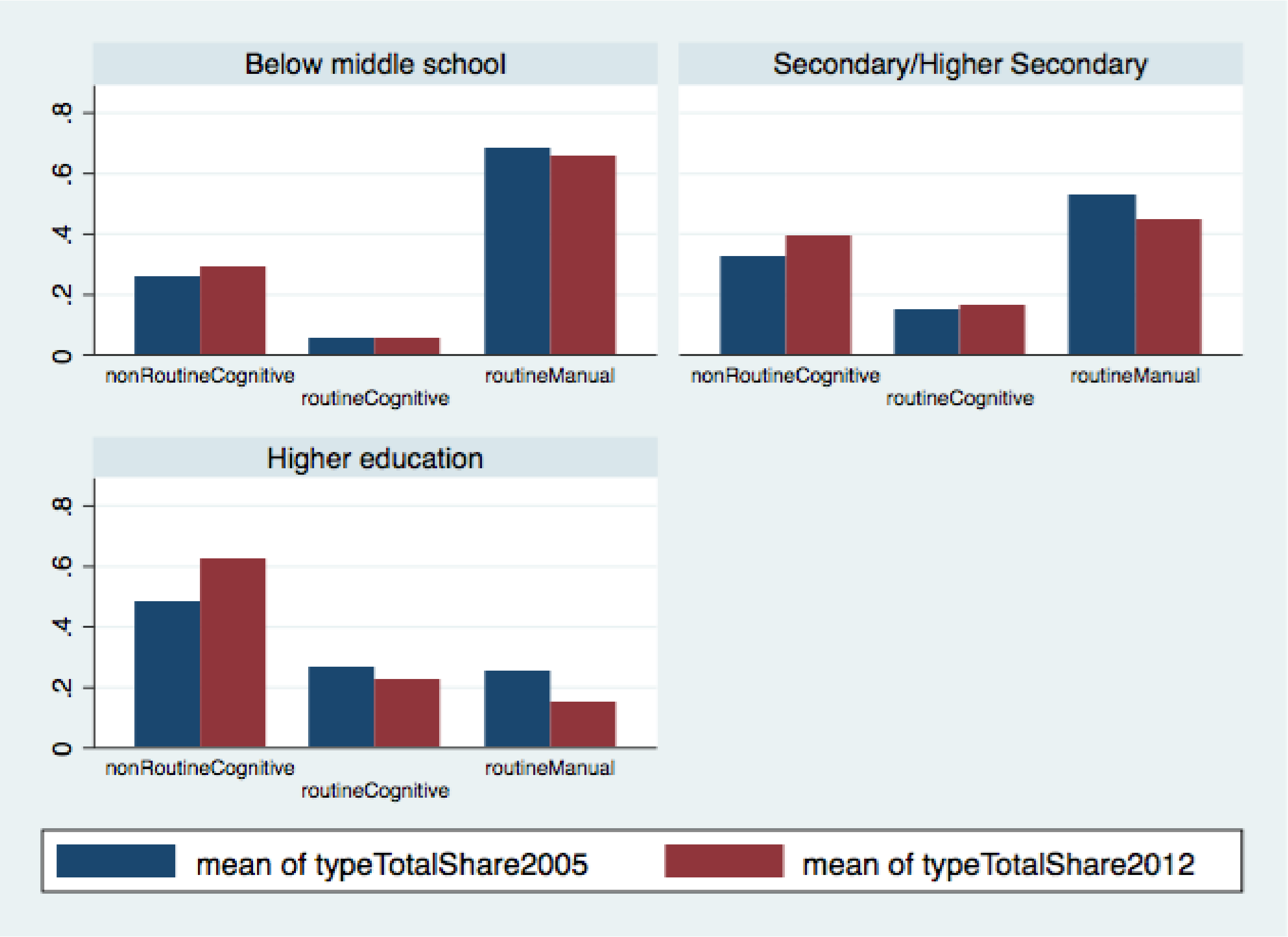
Table 1: ONET Task descriptions and scales

ONET Id	Description	Scale
Non-routine cognitive		
4.A.2.a.4	Analyzing Data or Information	Importance * Level
4.A.2.b.2	Thinking Creatively	Importance * Level
4.A.4.a.1	Interpreting the Meaning of Information for Others	Importance * Level
4.A.4.a.4	Establishing and Maintaining Interpersonal Relationships	Importance * Level
4.A.4.b.4	Guiding, directing and motivating subordinates	Importance * Level
4.A.4.b.5	Coaching and developing others	Importance * Level
Routine cognitive		
4.C.3.b.4	Importance of Being Exact or Accurate	Context
4.C.3.b.7	Importance of Repeating Same Tasks	Context
4.C.3.b.8	Structured versus Unstructured Work (reverse)	Context
Routine manual		
4.C.3.d.3	Pace Determined by Speed of Equipment	Context
4.C.2.d.1.i	Spend Time Making Repetitive Motions	Context
4.A.3.a.3	Controlling Machines and Processes	Importance * Level

Task-content of occupations

- A concordance was obtained between the ONET occupation classification and ISCO 1988 classification. The NCO 2004 for India is based on the ISCO 1988 classification, which allows us to merge these scores at the 3 digit level for Indian occupation data.

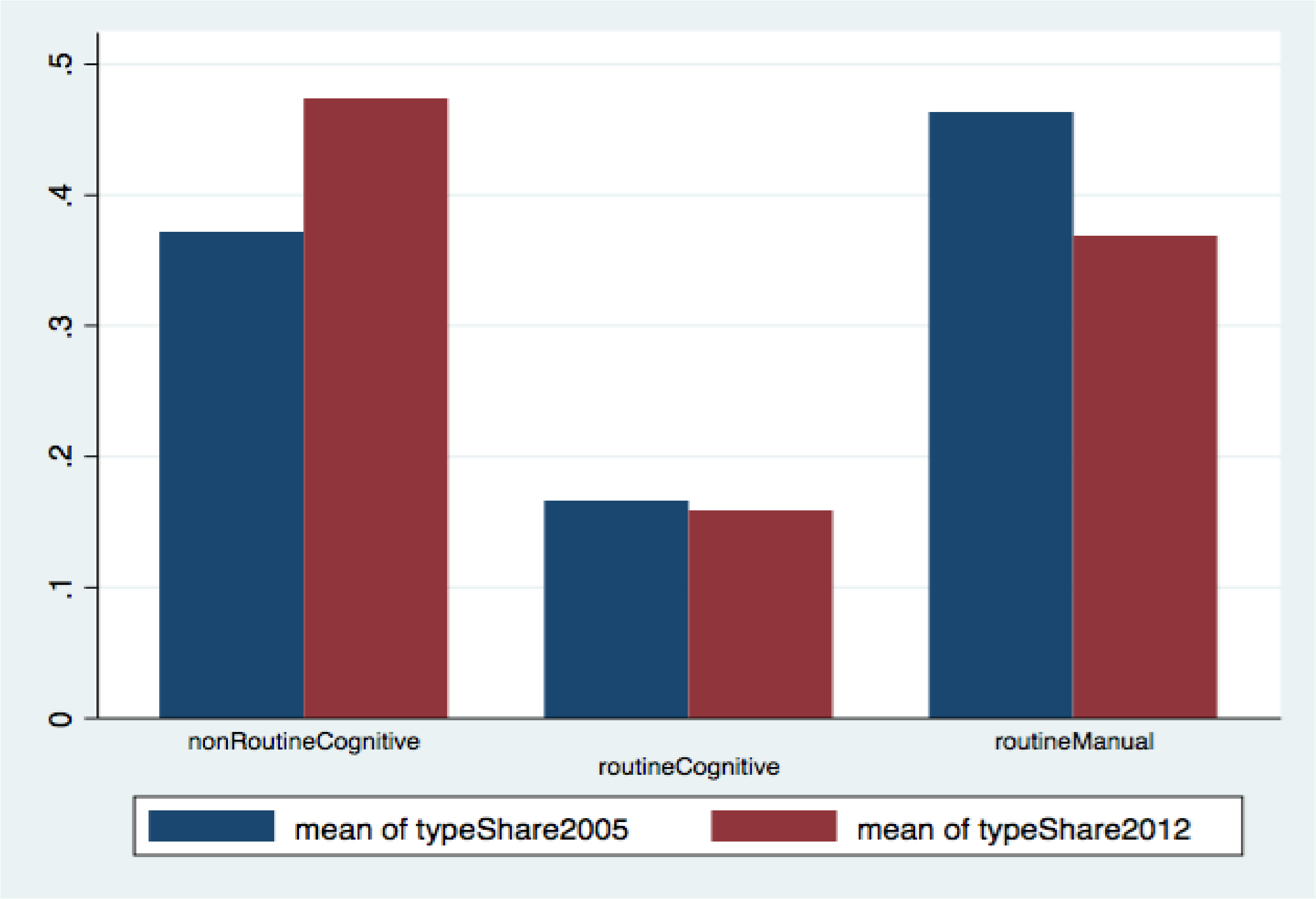
Share of employment for types of occupation by level of education



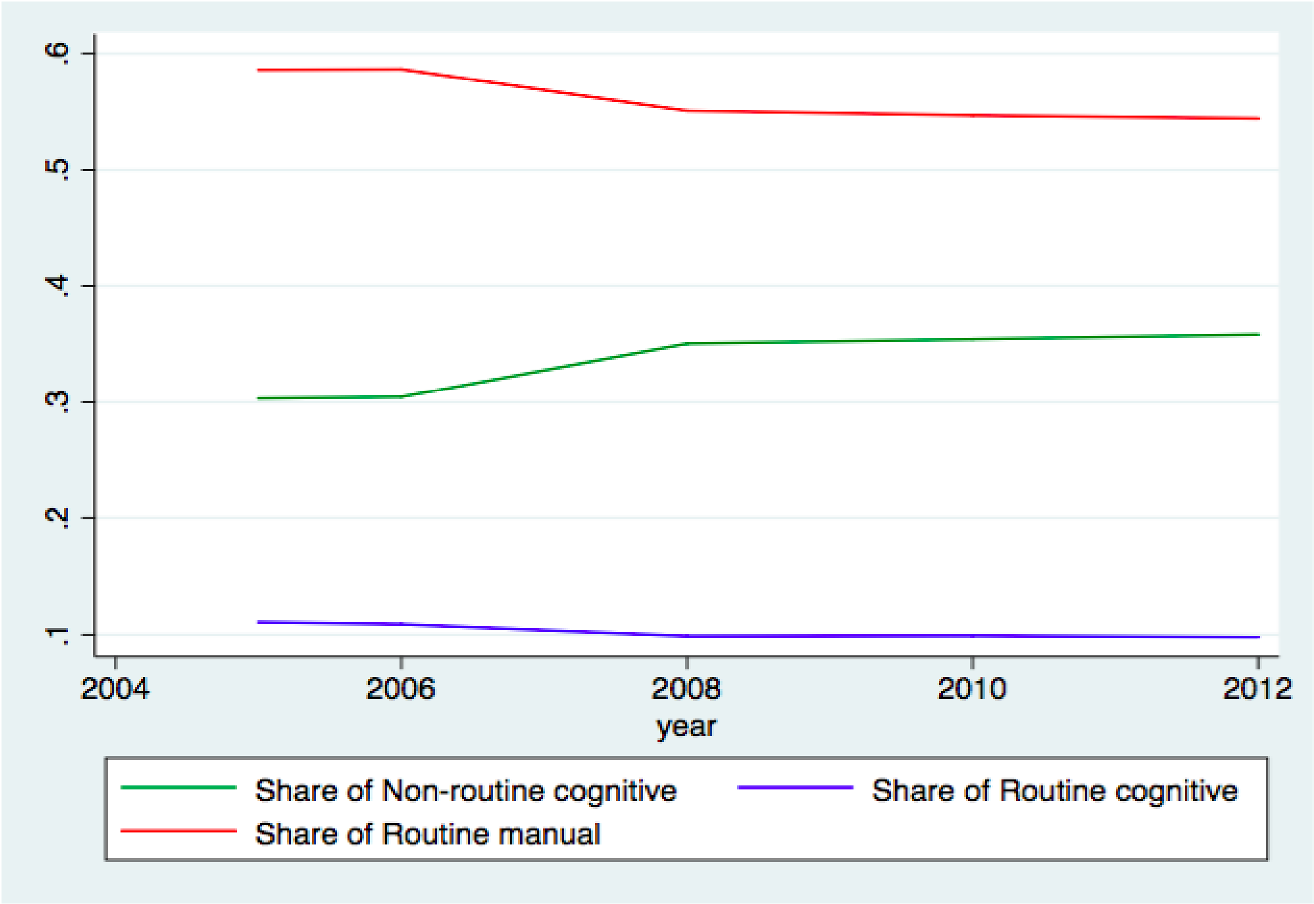
Task-content of occupations and skills

- Low skilled workers are primarily engaged in routine manual tasks
- High skilled workers are primarily engaged in non-routine cognitive tasks
- Roughly, middle-high skilled workers mainly engaged in routine cognitive tasks

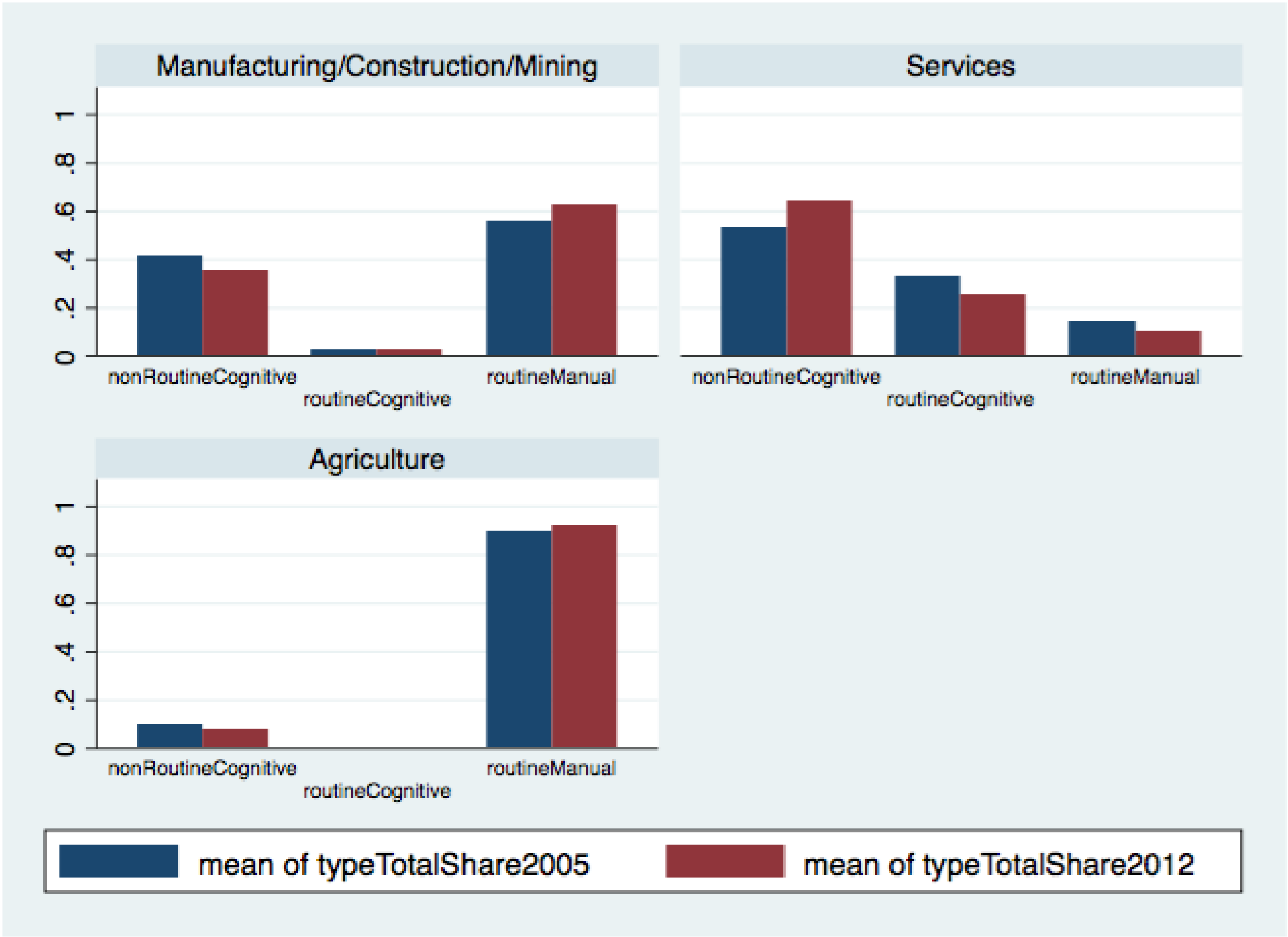
Share of employment in the three occupation categories



Share of employment by type of occupation



Share of employment for types of occupation for each sector



Decomposing changes in employment shares in occupations

- Are the changes driven by changing shares of employment between industries or is it the changing composition of occupations within industries that are mainly responsible for these trends?

$$\Delta E_{jt}=\Delta E_t^B + \Delta E_t^W$$

$$\Delta E_{jt} = \Sigma_k\, \Delta E_{kt}\lambda_{jk} + \Sigma_j \Delta\lambda_{jkt}E_k$$

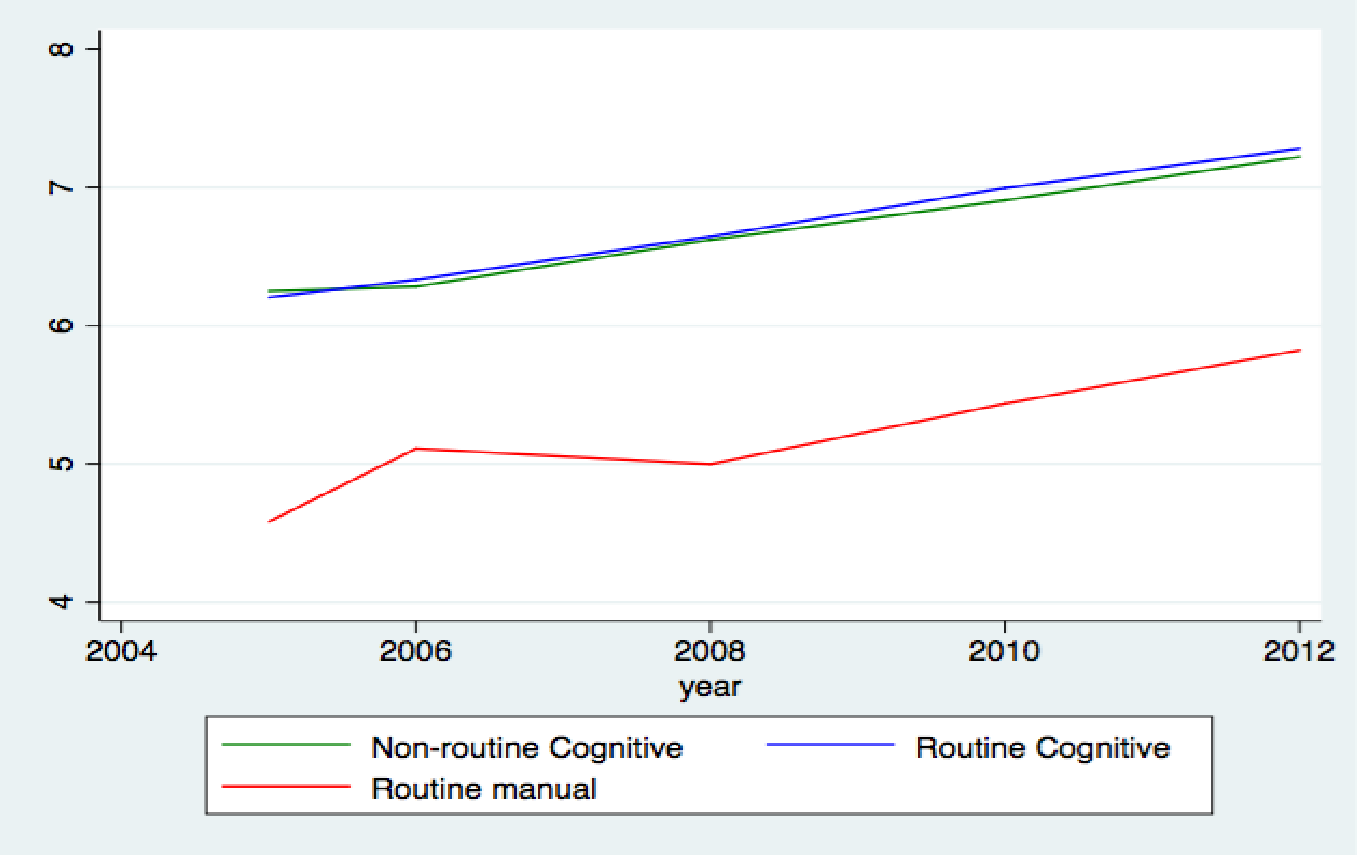
Decomposition of change in share of employment by occupation type between 2005-2012

Occupation Type	Industry∆	Occupation ∆	Total ∆
Non-routine Cognitive	2.28	2.1	4.46
Routine Cognitive	1.19	-2.15	-0.96
Routine Manual	-3.42	-0.08	-3.5

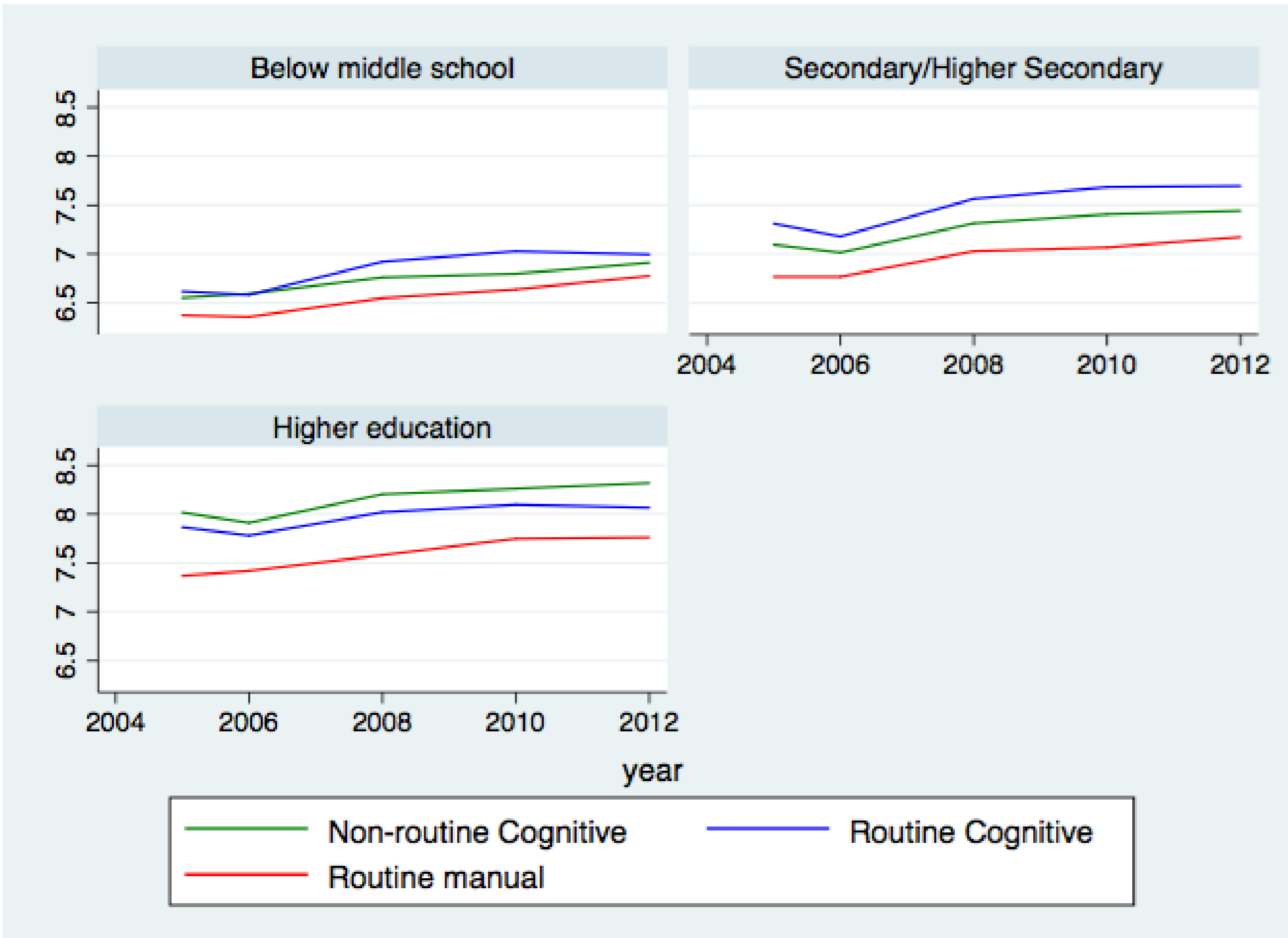
Decomposition of change in share of employment by occupation between 2005-2012

Occupation	IndustryΔ	Occupation Δ	Total Δ
Legislators, Senior officials and managers	0.78	3	3.78
Professionals	0.82	0.86	1.689
Technicians and Associate Professionals	0.63	0.03	0.66
Clerks	0.35	0.06	0.41
Service workers and Shop & market sales workers	1.33	-2.56	-1.23
Skilled Agricultural and fishery workers	-6	0.85	-5.151
Craft and trade related workers	2.29	-0.40	1.89
Plant and machine operators and assemblers	0.49	0.45	0.94
Elementary occupations	-0.56	-2.43	-2.99

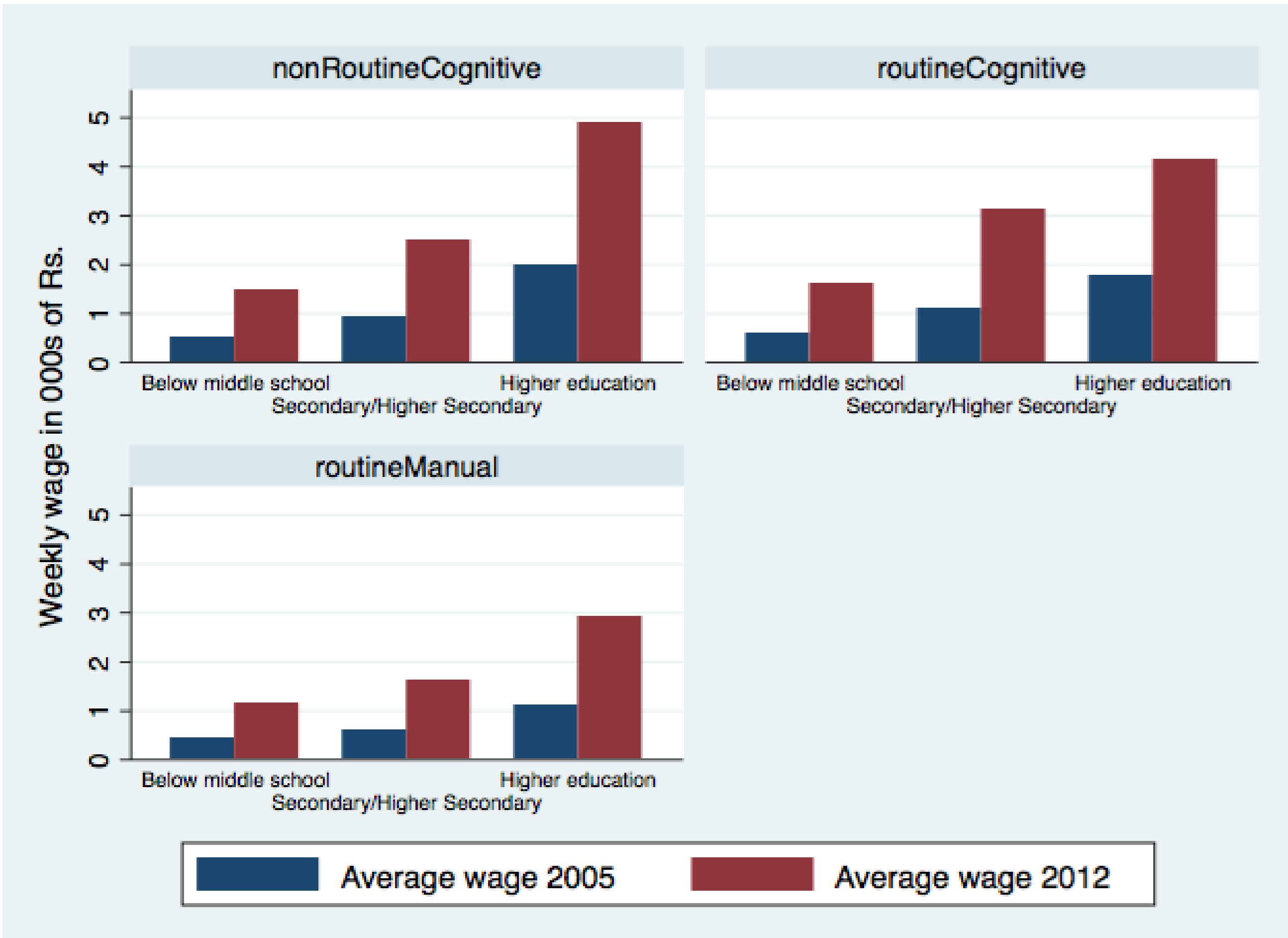
Trends in wages by type of occupation



Change in wages for types of occupation by level of education



Change in wages for levels of education by types of occupation



Occupational Specialization and Average Wages

- Following Acemoglu and Autor (2011) create cohorts based on their gender, education, age and region
- In order to group workers based on their occupational specialization, we calculate the share of workers in each of these groups in non-routine cognitive, routine cognitive and routine manual occupations ($\gamma_{sejk}{}^{NRC}$, $\gamma_{sejk}{}^{RC}$, $\gamma_{sejk}{}^{RM}$)
- Include ϑe, ϑj *and* ϑk, which are education, age and region fixed effects

Occupational Specialization and Average Wages

$$\log w_{sejkt} = \beta_1 * \gamma_{sejk}{}^{NRC} * t_i + \beta 2 * \gamma_{sejk}{}^{RC} * t_i + t_i + \vartheta_e + \vartheta_j + \vartheta_k + e_{sejkt}$$

$$\gamma_{sejk}{}^{NRC} + \gamma_{sejk}{}^{RC} + \gamma_{sejk}{}^{RM} = 1$$

Dependent Variable: Log (Average daily wage)	Male	Female
Share of routine cognitive 2005*2005	0.378*** (0.0721)	0.802*** (0.195)
Share of routine cognitive 2005*2006	0.219** (0.0712)	0.315 (0.222)
Share of routine cognitive 2005*2008	0.203** (0.0668)	-0.0348 (0.164)
Share of routine cognitive 2005*2010	0.444*** (0.0772)	0.666** (0.286)
Share of routine cognitive 2005*2012	0.273*** (0.0714)	0.270 (0.191)
Share of non-routine cognitive 2005*2005	0.412*** (0.0605)	0.267** (0.107)
Share of non-routine cognitive 2005*2006	0.273*** (0.0656)	0.220* (0.119)
Share of non-routine cognitive 2005*2008	0.347*** (0.0624)	0.268** (0.111)
Share of non-routine cognitive 2005*2010	0.394*** (0.0629)	0.155 (0.129)
Share of non-routine cognitive 2005*2012	0.313*** (0.0644)	0.0797 (0.119)
Constant	5.819*** (0.312)	6.221*** (0.193)
Year FE	Yes	Yes
Observations	9344	3483
R^2	0.7969	0.7105

Occupational Specialization and Average Wages

- We find that for all years, returns to workers specializing in routine cognitive tasks and non-routine cognitive tasks increase more than workers specializing in routine manual tasks for all years of our data, especially for males.
- For males, the coefficients on non-routine cognitive tasks are higher for almost all years as compared to routine-cognitive tasks, showing that the returns for non-routine cognitive tasks are increasing more than returns to routine cognitive tasks.
- For females, the returns to routine-cognitive tasks are higher than the returns to non-routine cognitive tasks for most years.
- One possible interpretation is that since routine cognitive tasks have already reached a plateau in terms of automation, the workers still engaged in these tasks earn increasing returns as compared to routine manual tasks wherein occupations continue to shrink due to increased automation.

Conclusion

- Economic policy that seeks to guarantee education and employment needs to take into account the fact that most middle-skilled occupations, which are likely to be routine cognitive or routine manual will be largely automated in the near future