Automation risks of vocational training programs and early careers in NL

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Automation

- … will *change* job tasks, *destroy* jobs, *create* jobs
- … depending on (non)routine tasks, cognitive tasks
- … medium educated often work in routine/cognitive tasks with high automation risks

Automation probably changes social inequalities

- Automation is likely to further increase employment and income polarization (Autor, 2015; Goos et al., 2009, 2014)
- Wages in easier-to-automate jobs are lower (De La Rica et al., 2020; Nedelkoska & Quintini, 2018)
- Wages for abstract tasks have increased (Böhm, 2020; De La Rica et al., 2020).

Much unknown

- How does automation affect micro-level processes?
- How does automation affects school-to-work transition and early careers?
- Do social class, cognitive skills and personality traits compensate or worsen the effects?

Focus on VET

- Medium-skilled workers are the likeliest affected by technological change (Autor, 2015; Goos et al., 2009, 2014).
- VET is seen as a safety net for low qualified youth (Iannelli & Raffe, 2007; Shavit & Müller, 2000).
- But specificity of their skills might also be a disadvantage (cf. Forster et al., 2016; Hanushek et al., 2017).

VET graduates from programs that prepare for easier-to-automate jobs are less likely to have a successful STWT

- Employers might refrain from hiring graduates with skills that in their opinion will soon be obsolete
- Labor market entrants are outsiders (Lindbeck and Snower 2001)

Empirical strategy

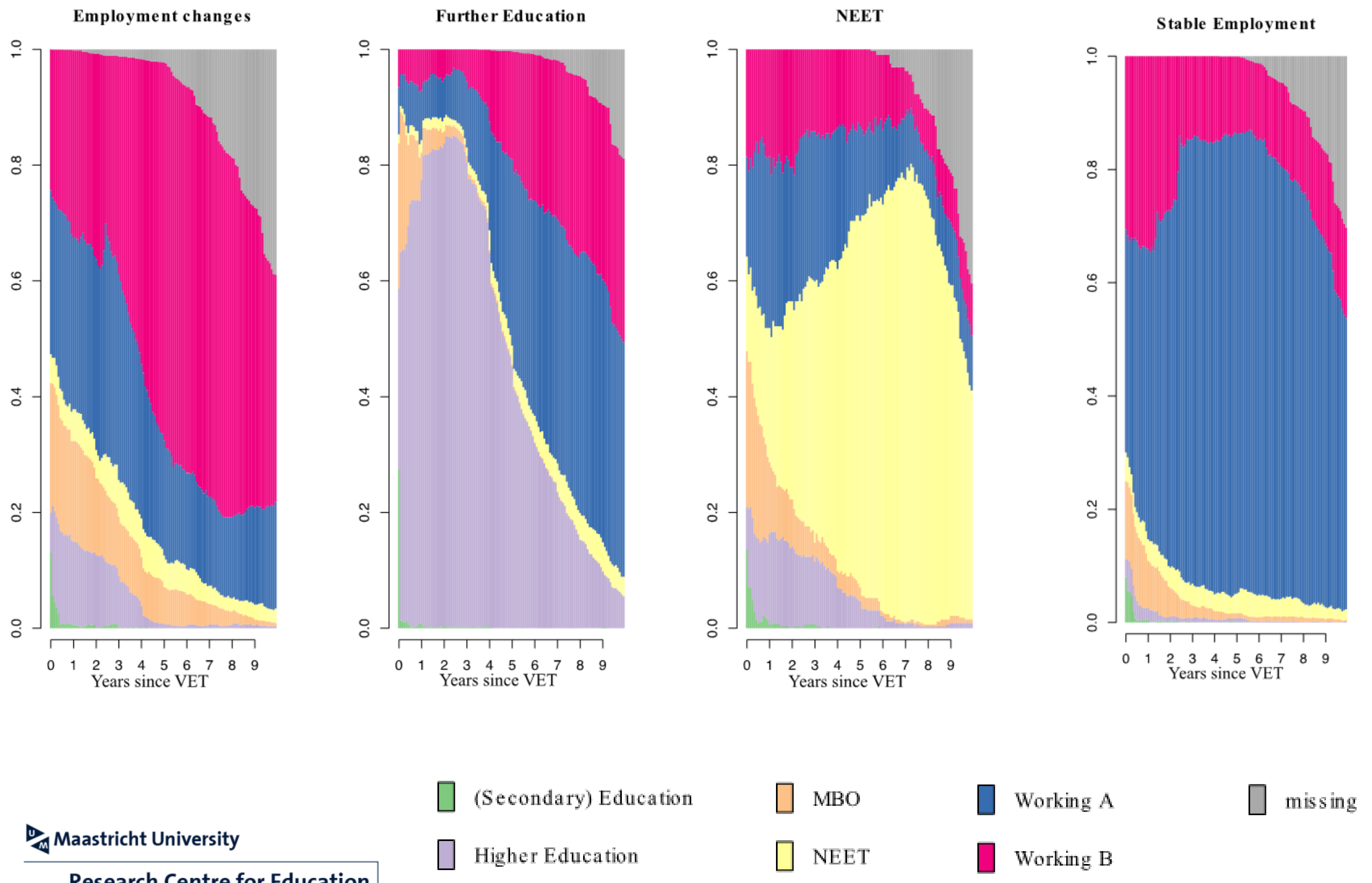
1. How to link automation risks to vocational training programs?
2. Sequence analyses to identify school-to-work trajectories
3. Multinomial regressions to link automation risks to trajectories
4. Growth curve models to link automation risks to starting wage and wage growth

1. Automation risks and vocational training programs

Frey & Osborne data (SOC 4-digit) → ISCO 2-digit → Dutch LFS → Weighted average → Estimated automation risk of VET programs

Weighted average of the automation risk of the most frequent 50% of ISCO 2-digit occupations within each Dutch education code

2. Sequence analyses



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3. Multinomial regressions

	Employment Changes	Further Education	NEET	Stable Employment
Automation risk	-0.01	0.01	-0.00	-0.00
Field of diploma, ref.cat.: Blue Collar				
Services	-0.02	0.09***	0.01	-0.07***
Gender, ref.cat.: Male				
Female	-0.03	-0.07***	0.04***	0.06***
Immigration backgr., ref.cat. No				
Yes	-0.02	0.10***	0.03***	-0.11***
Level, ref. cat.: MBO3				
MBO4	-0.13***	0.31***	-0.02***	-0.16***
N (Persons)	3248			
BIC	7634.9			
McFadden Pseudo R^2	0.086			

Controlled for: cognitive ability and personality, and parental education, homeownership, household income
Source: Statistics Netherlands, own calculations.
* p <0.1 ** p <0.05 *** p <0.01

4. Growth curve models

DV: Real log hourly wage	GC1	GC2	GC3	GC4
Intercept	2.567***	2.567***	2.567***	2.652***
Years since VET	0.038***	0.038***	0.038***	0.038***
Automation Risk		-0.039***	-0.035***	-0.045***
Years since VET X Automation Risk			-0.001*	-0.001*
Gender, ref.cat.: Male				
Female				-0.000
Immigration backgr., ref.cat. No				
Yes				-0.040***
Field of diploma, ref.cat.: Blue Collar				
Services				-0.070***
Level, ref. cat.: MBO3				
MBO4				-0.021***
Variance components				
Between	0.048***	0.047***	0.047***	0.045***
Within	0.013***	0.013***	0.013***	0.013***
Random slope (Years)	0.001***	0.001***	0.001***	0.001***
Covariance intercept-slope	-0.529***	-0.546***	-0.546***	-0.552***
BIC	-27789.2	-27913.8	-27906.8	-27949.7
ICC	0.782	0.778	0.778	0.772
N (Person-years)	30281	30281	30281	30281
N (Persons)	3400	3400	3400	3400

Controlled for: cognitive ability and personality, and parental education, homeownership, household income

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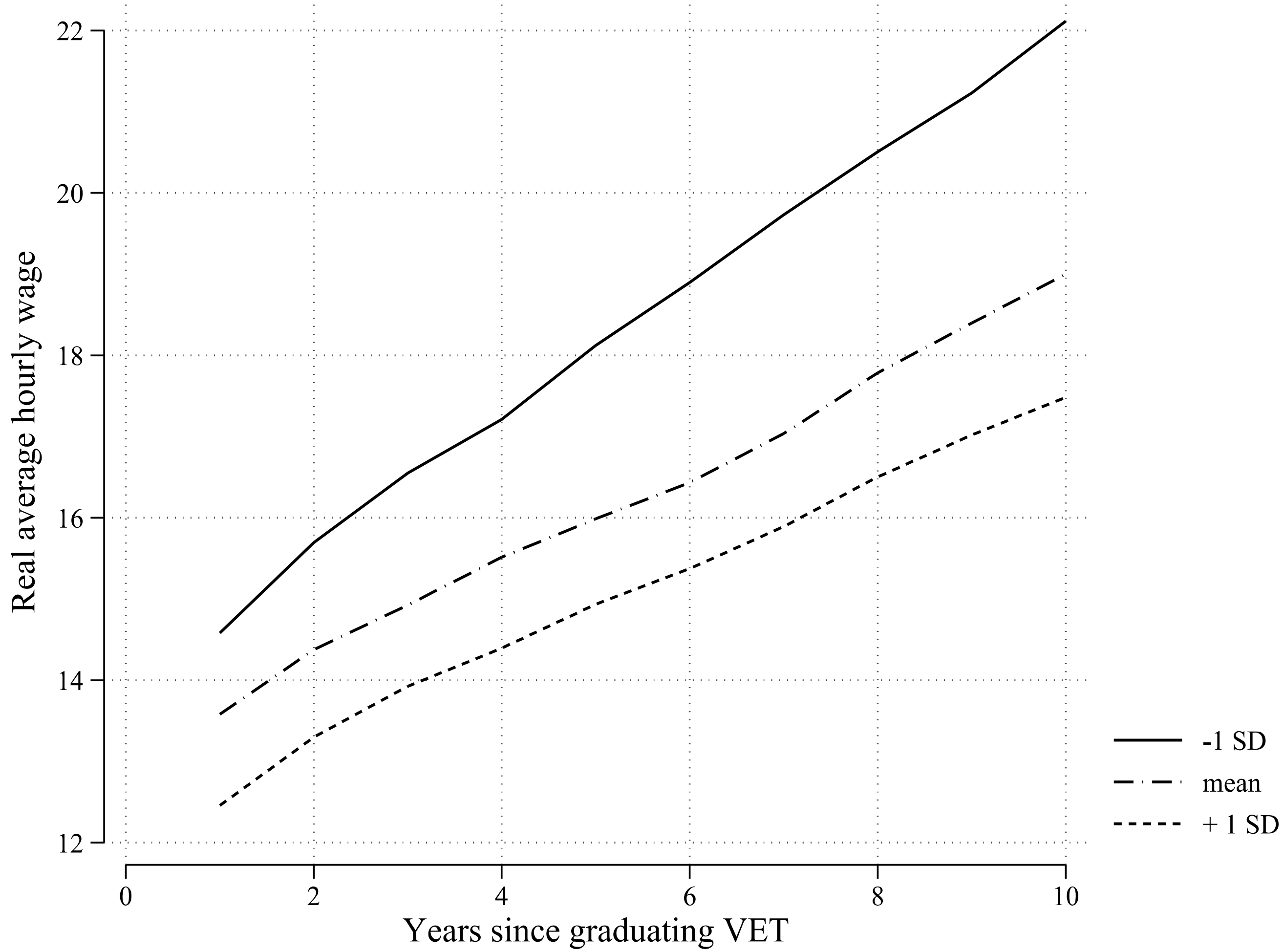
Average wage profiles of vocational education graduates by tertials of automation risk.



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Remain vigilant but do not overdo!

- Automation risk is not (yet) driving young graduates out of employment
- Lower starting wages for easier-to-automate VET programs, nothing found for wage growth