



Dynamics of Skill Demand and Mismatch in the Dutch Labor Market: Evidence from Online Job Postings and VET Curricula

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ABSTRACT

We study the dynamics of skill demand for recent vocational education graduates over time, across sectors of education and occupational domains. Our analyses combine approximately 7 million online job postings (2021–2023), 109,789 graduate survey responses (2022–2024), and national VET curriculum data (2016–2021) in the Netherlands. Using online job postings, we classify a comprehensive set of required skills into six O*Net skill categories: basic, social, technical, systems, complex problem-solving, and resource management skills. We document substantial heterogeneity in skill requirements across occupations. Linking these data with skill supply measures derived from vocational education curricula, we find a positive correlation between skill supply and demand across occupations. Furthermore, we construct an individual-level measure of skill mismatch and show that higher measured mismatch is associated with greater self-reported mismatch and lower monthly earnings and hourly wages. Consistent with prior literature, our findings suggest that skill mismatch contributes to wage differences.

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Skills2Capabilities, a Horizon Europe study, is about understanding how skills systems need to develop if they are to assist people to make labour market transitions – i.e. between jobs, employers or sectors – and thereby reduce the level of skill mismatch which might otherwise arise.

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Introduction

The increasing pace of technological change, digitalization, and structural transformation such as the energy transition of the economy, have altered the task composition of work and shifted the relative demand for skills across occupations (Autor et al., 2003; Acemoglu and Autor, 2011; Goos et al., 2014; Acemoglu and Restrepo, 2018). The diffusion of digital technologies has increased the need for digital skills, ranging from the use of devices and communication platforms to big data analytics and information management (Shakina et al., 2021). In addition, the growing complexity of production and organizational structures has heightened the value of socio-emotional and behavioral (SEB) skills, which are often discussed as transversal skills within the capabilities approach, including teamwork, cooperation, creativity, and social engagement (Weinberger, 2014; Deming, 2017; Soto et al., 2024). Embodying workers with the skills and capabilities will make them resilient to changes in the demand. In this context, characterizing the dynamics of skill demand is essential for understanding the macroeconomic environment and for informing the content of curricula in education to ensure they evolve according to labor market needs.

In this paper, we investigate the extent to which the curricula of education programs match employers' skill demands. We focus on vocational education and training (VET) because of the tight link between education programs and occupations. Vocational education also represents a sizable segment of the student population in the Netherlands, with a share of 15- to 19-year-old students close to 40% in OECD countries OECD (2023). We combine three unique sources of data for the Netherlands. First, using data for the near-universe of job postings, we quantify employers' demand for skills. Second, we use curriculum data to quantify the supply of VET skills, and to investigate the extent to which this supply matches job demand. Third, we use large-scale survey data among graduates to investigate their perceived mismatch and relate it to the likely mismatch between the skills in curricula and skills demanded by employers.

In the Netherlands and other western countries, employers are struggling to fill vacancies, largely due to a shortage of suitable skilled applicants and historically low unemployment rates (OECD, 2023; IMF, 2024). This underscores the importance of quantifying skill demand and understanding the implications of skill mismatch in the Dutch labor market. A central empirical challenge lies in measuring skill mismatch. Guvenen et al. (2020) provide a theoretical framework for analyzing multidimensional skill mismatch and the dynamics of workers' human capital accumulation choices. Most empirical studies, however, rely on self-reported measures of mismatch, typically capturing discrepancies in educational level or field of study (Desjardins and Rubenson, 2011; Pellizzari and Fichen, 2017; McGuinness et al., 2018). Such measures focus exclusively on employees' perceptions and therefore fail to account for shifts in employer demand, variations within occupations, or the matches of skill content between the study programs and occupations. We go beyond this and exploit online job postings and curriculum data, next to subjective measures, to shed novel light on quantitative aspects of the mismatch.

We use a comprehensive dataset of online job postings from JobDigger, covering nearly all publicly posted vacancies in the Netherlands from 2021 to 2023, with detailed information on job titles, required skills, industry sector, and experience level. We focus on secondary vocational education

and training (VET) graduates who enter employment directly, as this group constitutes a major segment of the working population (Statistics Netherlands, 2022), and the standardized VET curricula in the Netherlands enable consistent skill measurement across programs. To examine the alignment between skills taught in education programs and those demanded by employers, we classify the wide variety of skill mentions in both job posting texts and vocational curricula into six broad skill categories that capture the main dimensions of labor market competencies defined by O*Net: basic skills, social skills, technical skills, systems skills, complex problem-solving skills, and resource management skills. These categories are grounded in the task-based literature that links technological change to shifts in the relative demand for different types of skills (Deming, 2017). We measure the degree of alignment using Euclidean distance metrics, capturing how far the skills emphasized in education diverge from those demanded in the labor market, where a larger distance indicates a greater mismatch. Our analysis focuses on newly graduated vocational education students, answering how employer skill demands evolve over time, how closely curricula align with those demands, and whether greater skill mismatches are associated with self-reported skill mismatch and wage outcomes.¹

The analysis reveals clear seasonal dynamics in labor demand, with job postings peaking in mid-year and declining during the winter months, a pattern that remains stable across years. The relative importance of skill categories is also highly persistent across seasons, although the demand for technical and complex problem-solving skills has increased slightly over the past three years. Patterns in the distribution of social and technical skills across sectors align closely with intuitive expectations: social-intensive sectors such as education emphasize interpersonal skills, whereas technical-intensive sectors such as construction rely more heavily on technical skills, lending credibility to our skill-demand classification. At the occupational level, skill mismatch varies substantially, with sales and services managers exhibiting the highest degree of mismatch and pharmaceutical technicians and construction managers the lowest. Moreover, the measured skill mismatch is strongly correlated with self-reported skill mismatch. A one-unit increase in the measured skill mismatch corresponds to a 19.6 percentage point increase in the self-reported mismatch, but this effect disappears once industry and occupation fixed effects are added. The self-reported skill mismatch is largely explained by the differences between industries and occupations. As for the wage outcomes, a one-unit increase in measured skill mismatch is associated with a 30.1 percentage decrease in monthly wage and a 22.3 percentage decrease in hourly wage. Together, these findings underscore the stability and structure of skill demand in the Dutch labor market while highlighting the significant wage penalties associated with skill mismatch.

This paper makes a novel contribution by providing the first unified measurement of skill mismatch that jointly exploits text data from both the demand and supply sides of the labor market. Existing research using online job postings has documented shifts in employer skill demand driven by technological change and organizational restructuring (Beaudry et al., 2016; Deming and Kahn, 2018; Hershbein and Kahn, 2018; Forsythe et al., 2020; Atalay et al., 2020; Modestino et al., 2020;

¹ The self-reported measures are obtained from graduate survey.

Azar et al., 2020; Acemoglu et al., 2022; Loll and Wessling, 2025), showing that digitalization has increased demand for cognitive and analytical skills while automation has increased the value of interpersonal and communication skills. Other studies link vacancy-based skill measures to wage inequality, highlighting how evolving skill requirements shape earnings distributions (Deming, 2017; Mueller et al., 2024). Within the search and matching framework, recent work further examines how job seekers sort into occupations and how employers screen or discriminate through job postings (Banfi and Villena-Roldan, 2019; Kuhn and Shen, 2023). On the supply side, a growing literature quantifies the skill content of educational curricula and links early skill formation to labor market outcomes (Langer and Wiederhold, 2023; Lipowski et al., 2024; Buehler et al., 2024; Cnossen et al., 2025). However, these strands of research remain disconnected: no existing study has directly related the skills demanded by employers to those supplied through formal education. This paper bridges that gap by combining text-derived data from both job postings and curricula to enable a multidimensional, scalable comparison of skills across sectors and occupations. By linking this measured mismatch to wage outcomes, we connect descriptive skill analytics to economic implications, revealing how misalignments between education and employer needs translate into systematic pay differentials.

The remainder of the paper is structured as follows. Section 2 describes the data sources and preprocessing procedures, including the classification of skills, the construction of the measured skill mismatch, and the empirical strategy. Section 3 presents the main descriptive evidence, focusing on the dynamics of skill demand and the degree of skill mismatch between occupations and educational programs. Section 4 discusses policy implications, outlines the study's limitations, and concludes.

Data & Methodology

Online Job Ads Data

Our primary data source is a database of online job postings provided by JobDigger,² a recruitment technology firm that systematically collects and archives employment postings from Dutch online sources. JobDigger continuously scrapes and standardizes postings from approximately 1,700 unique websites, including major job boards such as Indeed.nl, Jobbird, Uitzendbureau.nl, Werkzoeken.nl, and Nationale Vacaturebank.nl, as well as a wide range of company career pages. According to the provider, the dataset covers roughly 95 percent of all vacancies posted online in the Netherlands, offering a near-universe view of employer demand. Each job posting record includes detailed information on the advertised occupation (4 digit ISCO), industry classification (SBI), job source, skill requirements, and contract characteristics, such as working hours, contract type, and where available, wage information. The dataset is preprocessed to remove duplicates and standardized across sources, ensuring high-quality micro-level job posting data. The JobDigger data have previously been employed in studies of vacancy dynamics in the Netherlands (Abdullah, 2021; de Groot et al., 2021; Pillar et al., 2022; Vermeulen and Amaros, 2024).

² For further information, please see: <https://www.jobdigger.nl/jobdigger-data/data-voor-analysedoeleinden/>

The raw delivery comprised roughly 14 million job postings spanning the years 2021–2023. To focus on vacancies relevant to upper-secondary VET graduates (MBO level), we restrict the sample to postings that require no more than an MBO qualification (no explicit formal education requirement also included) and that do not specify prior work experience. Postings without explicit education or experience requirements are retained under the assumption that they target entry-level or lower-skill positions. These restrictions yield a final analytical sample of approximately 7 million unique postings, representing about 52 percent of the original dataset and covering nearly all occupations employing MBO-educated workers. The final data set provides a uniquely detailed and representative picture of skill demand for vocational-level jobs in the Dutch labor market, allowing us to examine both cross-sectional and sectoral variation in required skills across occupations and industries.

Curriculum Data

Our second data source consists of nationally standardized curricula for all Dutch upper-secondary VET (MBO) programs, obtained from the Foundation for cooperation on Vocational Education, Training and the Labour Market (SBB).³ SBB is responsible for developing, updating, and maintaining MBO curricula to ensure consistency between educational training and industry needs. These curricula have been publicly available since 2012 and are organized by education program identifiers (CREBO codes), each of which specifies a set of learning objectives and skill components described in the *Core Tasks* section. The standardization of the Dutch VET system ensures that national curricula are uniform across schools, eliminating local variation in training content. Additionally, each skill is formally assessed upon completion, and these examinations are standardized nationally to guarantee consistent certification standards. SBB maintains a legally mandated updating process: each curriculum is reviewed at least every five years. This institutionalized process ensures that curricula evolve systematically with labor market trends. We treat these curricula as a unified and nationally representative measure of the skill supply provided by vocational education, harmonized across years and programs to enable direct comparison with vacancy-based skill demand. In this paper, to match with the time span of job posting data, we use the curriculum data from 2016 to 2021. For detailed description of MBO curriculum data and the updates, please refer to Zhu et al. (2024).

Graduate Survey Data

The analysis draws on data from a nationally representative survey conducted among MBO graduates,⁴ which collects detailed information on employment status, wage information, self-reported skill mismatch, and demographic characteristics such as age, gender, and ethnicity, approximately 1.5 years after graduation. More specifically, self-reported skill mismatch is identified by the question “Connection current position to training”, and graduates report “good or sufficient” or “mediocre or bad”. The wage information is identified by self-reported monthly wage and working hours. By linking unique education program identifiers (CREBO codes) recorded in the survey with the start dates of the education program, we are able to match each graduate to the

³ See: <https://www.s-bb.nl>.

⁴ For more information, see the project page at <https://www.jobmbo.nl/monitor/>.

specific education program they completed and the associated skill content. We restrict attention to those who entered the labor market directly after completing MBO studies. Because the job posting data span 2021 – 2023, we limit the survey data to responses corresponding to this period (2022 – 2024). After applying restrictions to include only employed graduates aged 16–26 with valid skill supply and demand measures, the analytical sample comprises 45,784 individuals (42% of the full sample).⁵

Skill Measurement

We measure skills on both the demand and supply sides of the Dutch labor market using a harmonized classification based on the O*NET content model, which provides a standardized framework for grouping related skills under the same concept. Table 1 presents the six skill domains and corresponding examples. Each skill text extracted from a job posting or curriculum description is mapped to one of these domains, ensuring direct comparability across data sources.

Table 1. The O*NET content model (worker requirement)

Skills Domain	Keywords (Contents)
Basic Skills	Reading comprehension, active listening, writing, speaking, mathematics, science, critical thinking (logic and reasoning), active learning, learning strategies, monitoring
Social Skills	Social perceptiveness, coordination, persuasion, negotiation, instructing, service orientation
Complex Problem-Solving Skills	Complex problem-solving
Technical Skills	Operations analysis, technology design, equipment selection, installation, programming, operations monitoring, operation and control, equipment maintenance, troubleshooting, repairing, quality control analysis
Systems Skills	Judgment and decision-making, systems analysis, systems evaluation
Resource Management Skills	Time management, management of financial resources, management of material resources, management of personnel resources

Notes: Data retrieved from National Center for O*NET Development. *O*NET OnLine*. April 29, 2024, from <https://www.onetonline.org/>.

Skill Extraction from the Job Postings

Skill extraction from the job postings relies on multi-stage natural language processing (NLP) pipelines implemented in Python (version 3.13.5). JobDigger compiles a list of skills detected in the population of job postings, which allows us to directly perform classification on the dictionary of skills. In total, there are 15,845 distinct skills. The raw data of extracted skills is multi-language

⁵ This age restriction ensures comparability with early-career labor market entrants targeted in the vacancy dataset. The age distribution in the full sample is presented in Appendix Figure 1. Keeping graduates aged 16-26 remains 81% of the sample.

(including Dutch, German, and English), and hence we translate all the non-English skill texts into English using deep-translator (version 1.11.4). After translation and text cleaning, candidate skill texts were matched to a pre-defined dictionary categories derived from O*NET taxonomies (as in Table 1) using embedding-based similarity matching. The classification was conducted using a semi-supervised machine learning model that combined a manually defined category set with large volumes of unlabeled text. Contextual embeddings, derived from the pre-trained language model “all-MiniLM-L6-v2”, were used to capture semantic relationships between skill texts, and a label-propagation algorithm assigned probabilistic class memberships to one of the six skill dimensions. For low-confidence predictions, we manually reviewed the affected skills and assigned them to the most appropriate category. When skills exhibited cross-category characteristics, they are also assigned to the predicted category that with the highest probability. This process ensured consistent classification criteria rather than subjective judgment. Manual inspection of low-confidence predictions ensures consistent classification accuracy across categories. The examples of classification and the corresponding probability score can be found in Table 2.

Formally, each job posting is thus represented as a normalized skill vector, $s_j = \{s_{j,1}, s_{j,2}, s_{j,3}, s_{j,4}, s_{j,5}, s_{j,6}\}$, where $s_{j,i}$ denotes the relative importance of skill i for job posting j . More specifically:

$$s_{j,i} = \frac{N_{S_{j,i}}}{N_{TotalSkills_j}}$$

where $N_{S_{j,i}}$ denotes the total number of specific skill i within job posting j ; $N_{TotalSkills_j}$ denotes the total number of skills within job posting j . Aggregating these vectors by ISCO 4-digit occupation yields occupational skill profiles, capturing the composition of employer skill demand for entry-level positions targeting at MBO graduates.

Table 2. An Illustration of Skill Classification

Skills	Predicted Category	Score	Low Confidence
Unpredictable situations	Complex Problem-Solving Skills	0.4058	FALSE
Problem-solving capacity	Complex Problem-Solving Skills	0.7329	FALSE
Literature	Basic Skills	0.3722	FALSE
Reading comprehension	Basic Skills	0.6122	FALSE
Speaking skills	Social Skills	0.7195	FALSE
Presentation skills	Social Skills	0.6550	FALSE
Pharmaceutical Patient Care	Resource Management Skills	0.2378	TRUE
Catering industry	Resource Management Skills	0.4062	FALSE
Automation policy	Technical Skills	0.3463	FALSE
Management of Electrical Installations	Technical Skills	0.4619	FALSE
Capacity tests	Systems Skills	0.3091	FALSE

Notes: This table illustrates the skill classification procedure applied to job posting texts. Each row shows an example of an extracted skill mention, the predicted skill category based on the O*NET taxonomy, and the associated model confidence score. “Low confidence = TRUE” indicates that the model’s posterior probability of category assignment falls below the 0.30 threshold. We selected 0.30 as a conservative cutoff that balances quality control with feasibility, capturing predictions where the model provides no strong preference for any category. The examples are presented for illustrative purposes only and do not represent the full sample distribution.

Skill Extraction from the Curricula

On the supply side, skill information is extracted from the standardized Dutch MBO curricula. Each MBO educational program contains textual descriptions of competencies, which specify the skills to be acquired during training. These descriptions were processed and mapped onto the same O*NET taxonomy to ensure comparability with the job posting data. Because the curricula do not specify teaching hours or credit weights for each skill, we treat total instructional intensity as fixed within education levels and interpret relative frequency as relative importance, reflecting trade-offs in emphasis rather than absolute training intensity. For program p , it has skill vector $s_p = \{s_{p,1}, s_{p,2}, s_{p,3}, s_{p,4}, s_{p,5}, s_{p,6}\}$, where $s_{p,i}$ denotes the relative importance of skill i for program p . The construction of relative importance is the same as in job posting skill vector construction. This yields the skill vector for each curriculum that is directly comparable to the job posting-based vectors. For detailed information of curriculum structure and skill measurements in Dutch curricula, please refer to Zhu et al. (2024).

Measuring Skill Mismatch

To quantify skill mismatch between the education system and the labor market, we compute distance-based indices comparing skill vectors from curricula and job postings at the corresponding occupational level. Specifically, an occupation is identified when graduates report that their current job is aligned with their field of study. Conditional on holding such a matched position, we are able to link each graduate’s occupation to the corresponding study program they completed, and thus we have the skill vectors from both supply and demand side. We use Euclidean distance to capture absolute gaps in skill intensity:

$$SkillMismatch_o = \sqrt{\sum_i^6 (s_{o,p,i} - s_{o,j,i})^2}$$

where $SkillMismatch_o$ indicates the level of skill mismatch for occupation o ; $s_{o,p,i}$ indicates the relative importance of skill i for education program p that translates into occupation o ; and $s_{o,j,i}$ indicates the relative importance of skill i for job posting j that aggregated to occupation o . This metric captures the magnitude of misalignment between educational skill supply and employer skill demand. A larger Euclidean distance reflects a greater overall gap in the intensity of skill in the education and labor market, for instance, that curricula place proportionally less weight on technical or social skills relative to employer requirements. Occupations with high skill mismatch values are expected to have employees whose skill portfolios are less aligned with job

requirements, potentially translating into higher self-reported mismatch on the job, and lower wage outcomes.

Empirical Specification

To investigate the association between measured skill mismatch and labor market outcomes, we estimate the following fixed-effects model:

$$Y_{i,o,d,t} = \alpha + \beta \cdot SkillMismatch_{i,o,d,t} + \gamma' \cdot X_{i,o,d,t} + \delta_o + \tau_d + \lambda_t + \epsilon_{i,o,d,t}$$

where $Y_{i,o,d,t}$ denotes the outcome variable for individual i who works in occupation o in industry d in year t . The main outcomes of interest are (i) a binary indicator for self-reported skill mismatch and (ii) the logarithm of monthly earnings and hourly wages. The key explanatory variable, $SkillMismatch_{i,o,d,t}$, is our skill mismatch index, defined at the individual-year level and capturing the distance between employer skill demand (from job postings) and educational skill supply (from curricula). The control variable vector includes individual-level controls such as age and gender. The education level is restricted to the MBO level by construction. The specification includes industry fixed effects (τ_d) to account for time-invariant differences across sectors, occupation fixed effects (δ_o) to capture persistent occupational characteristics, and year fixed effects (λ_t) to control for macroeconomic conditions and time trends common to all workers. The coefficient of interest, β , measures the association between skill mismatch and labor market outcomes. Standard errors are clustered at the occupation–industry level.

Unlike the occupational-level mismatch index used in descriptive analyses, the individual-level measure combines the specific educational program with the average skill profile for that individual's occupation, providing greater within-occupation variation. Additionally, since we intend to examine the consequences of skill mismatch instead of describing occupational averages, our sample includes both educational matched individuals and educational mismatched individuals.

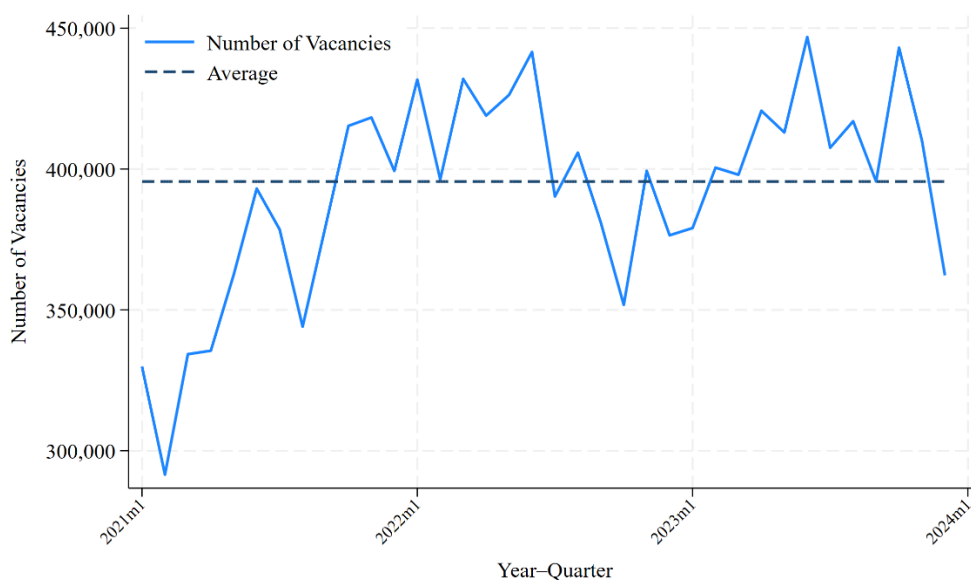
Descriptive Evidence

Dynamics of Skill Demand

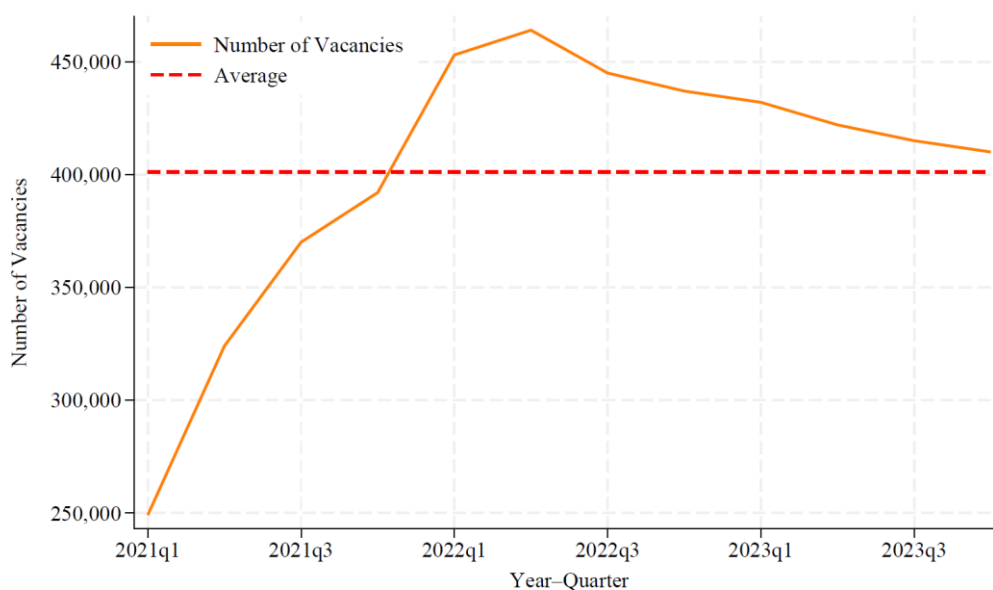
The analysis of online job postings reveals temporal and structural dynamics in Dutch labor demand. As we can see in the both panels in Figure 1, the number of postings reaches its lowest point in the first quarter of 2021 (January in panel (a)) and peaks in the second quarter of 2022 (around June in panel (a)), a pattern consistent across both JobDigger data and official vacancy statistics published by Statistics Netherlands (CBS) (Statistics Netherlands (CBS), 2024). The average number of job postings in the JobDigger data is approximately 400,000 per month, which closely matches the levels reported in the official statistics. Additionally, the overall temporal pattern is quite similar to the government's quarterly series, lending strong external validity to our dataset. As illustrated in Figure 1 panel (a), job postings exhibit a pronounced seasonal pattern over the 2021–2023 period, with activity peaking around mid-year and declining during the winter months. This recurring cycle likely reflects recruitment practices aligned with fiscal and academic calendars.

Despite these seasonal fluctuations in the number of job postings, Figure 2 shows the composition of skill demand remains remarkably stable across time, suggesting that while the intensity of hiring responds to cyclical factors, the underlying structure of occupational and skill requirements in the Dutch labor market is persistent. While the relative importance of skill categories is largely stable, we observe a modest but consistent increase in the demand for technical and complex problem-solving skills. This trend aligns with the ongoing digitalization and technological upgrading of production processes, which require a workforce capable of managing more complex systems and analytical tasks (Autor et al., 2003; Acemoglu and Autor, 2011; Deming, 2017; Hershbein and Kahn, 2018).

Figure 1: Number of Job Postings across Time



(a) Monthly Number of Job Postings in the Netherlands (JobDigger)



(b) Quarterly Number of Job Vacancies in the Netherlands (Statistics Netherlands)

To further validate the classification of skills used in our analysis, we examine the joint distribution of social and technical skill intensity across sectors. The results shown in Figure 3 reveal intuitive and economically meaningful patterns: sectors characterized by interpersonal interaction and service provision exhibit a higher relative importance of social skills; in contrast, sectors emphasizing production, construction, and technical maintenance display stronger demand for technical skills. As shown in the Figure 3, education and healthcare sectors exhibit high social skill intensity, whereas construction and mining are characterized by strong technical orientation. The coherence of these sectoral patterns with occupational content supports the validity of our vacancy-based skill measures as indicators of employer skill demands.

Figure 2: Relative Importance of Skills across Time

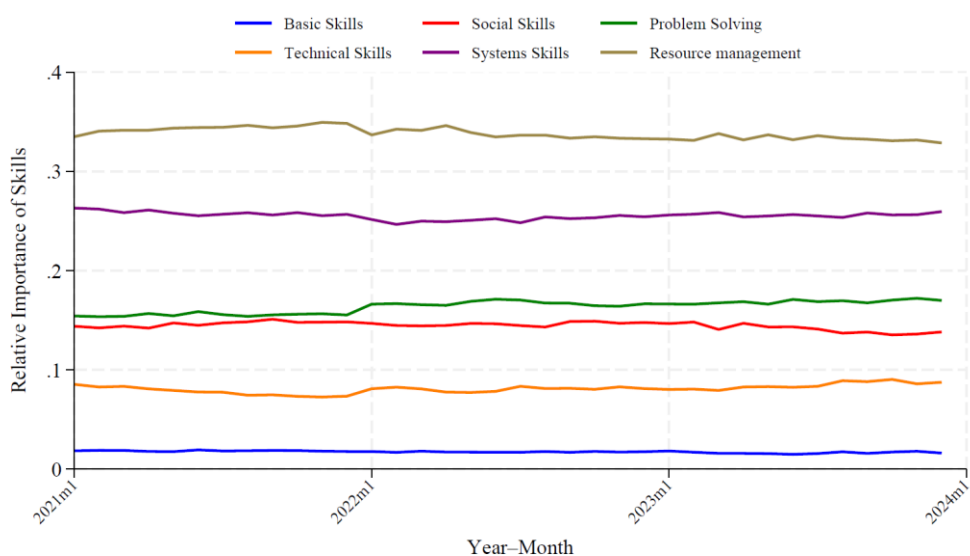
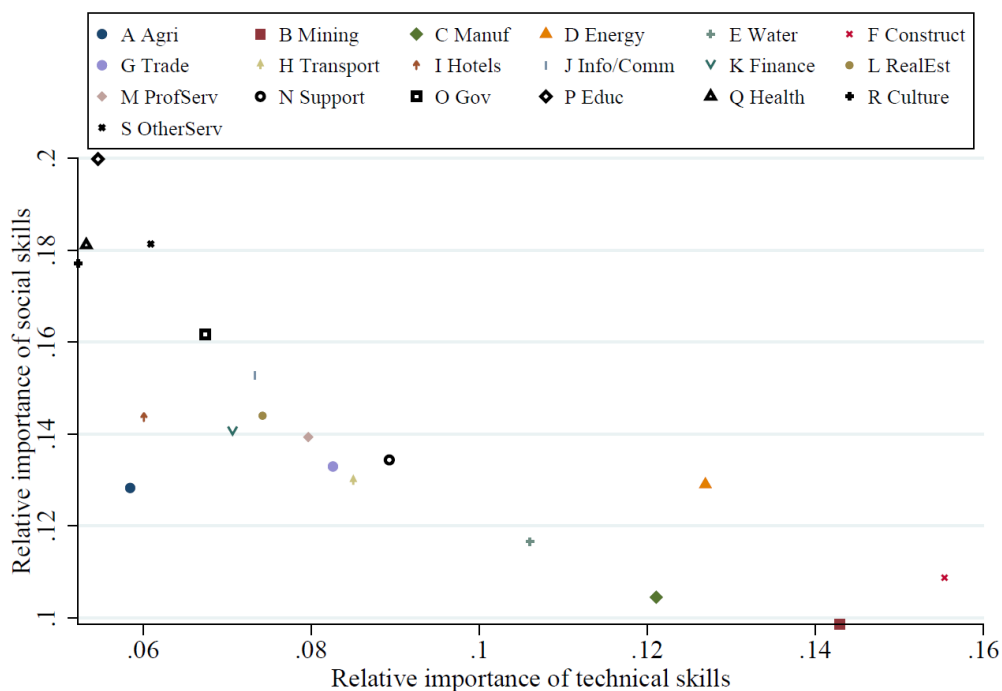


Figure 3: Relative Importance in Social vs. Technical Skills by Sectors



Skill Mismatches between Occupation and Education

Having established the structure and evolution of skill demand, we next assess the extent of alignment between the skills emphasized in VET and those demanded by employers. The analysis is restricted to graduates employed and to job postings that specify no prior work experience, ensuring comparability between educational skill supply and employer demand at the point of labor market entry.

We begin by examining the correlation of skills from both ends in entry-level occupations. Appendix Table 1 reports the correlations between the relative importance of skills in curricula and those extracted from job postings at the occupational level. The correlations are generally positive, which may suggest some alignment between vocational programs and labor market needs. Higher estimates for technical and social skills indicate that these areas might be particularly relevant in both curricular design and early-career labor demand. Taken together, the results suggest indicative evidence of coherence between vocational training and the skills required in related occupations.

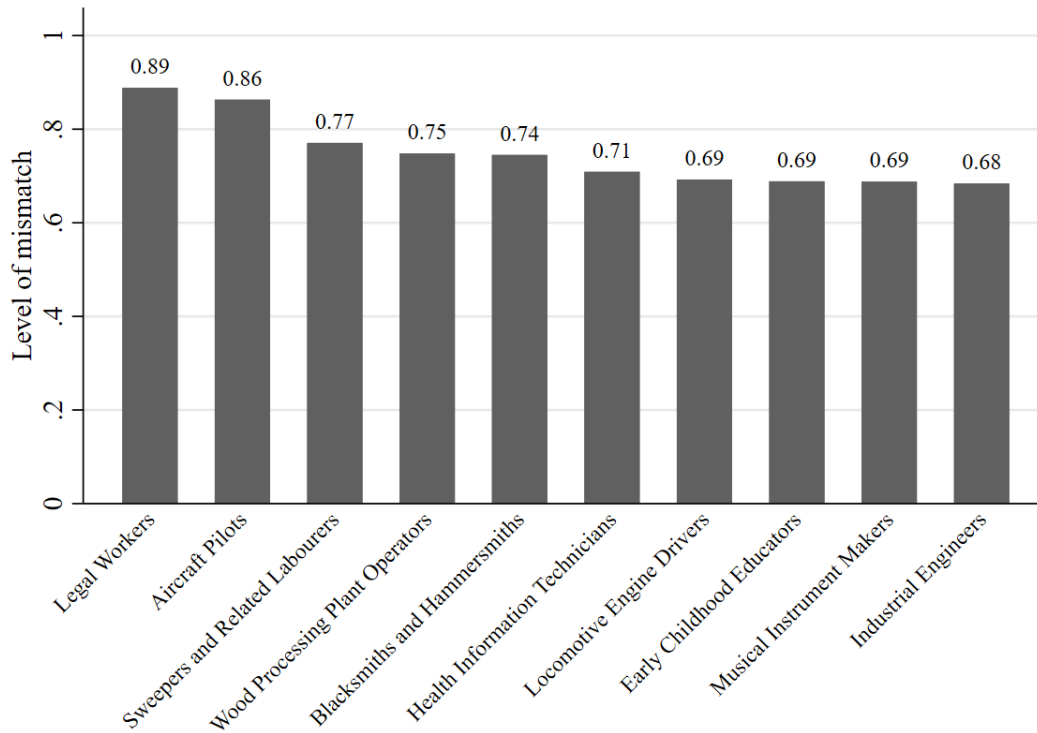
Using Euclidean distance to quantify the divergence between vacancy-based and curriculum-based skill vectors, we construct an occupational-level index of skill mismatch within each industry and track its evolution over time. The results reveal heterogeneity across occupations. As illustrated in Figure 4, the highest levels of measured mismatch are observed among legal workers, aircraft pilots, and sweepers, with the measured skill mismatch indices higher or equal to 0.75.⁶ In contrast, secondary education teachers, advertising and public relations, and sewing workers exhibit the lowest degrees of mismatch, with the measured skill mismatch indices lower than 0.28, indicating a closer correspondence between the skills taught in training programs and those demanded in the workplace. These patterns are aligned with our presumption that occupations with dynamic environments tend to experience faster shifts in required skill mixes, while technically regulated or task-stable professions maintain stronger alignment between educational preparation and job-specific requirements.

Labor Market Outcomes of Skill Mismatch

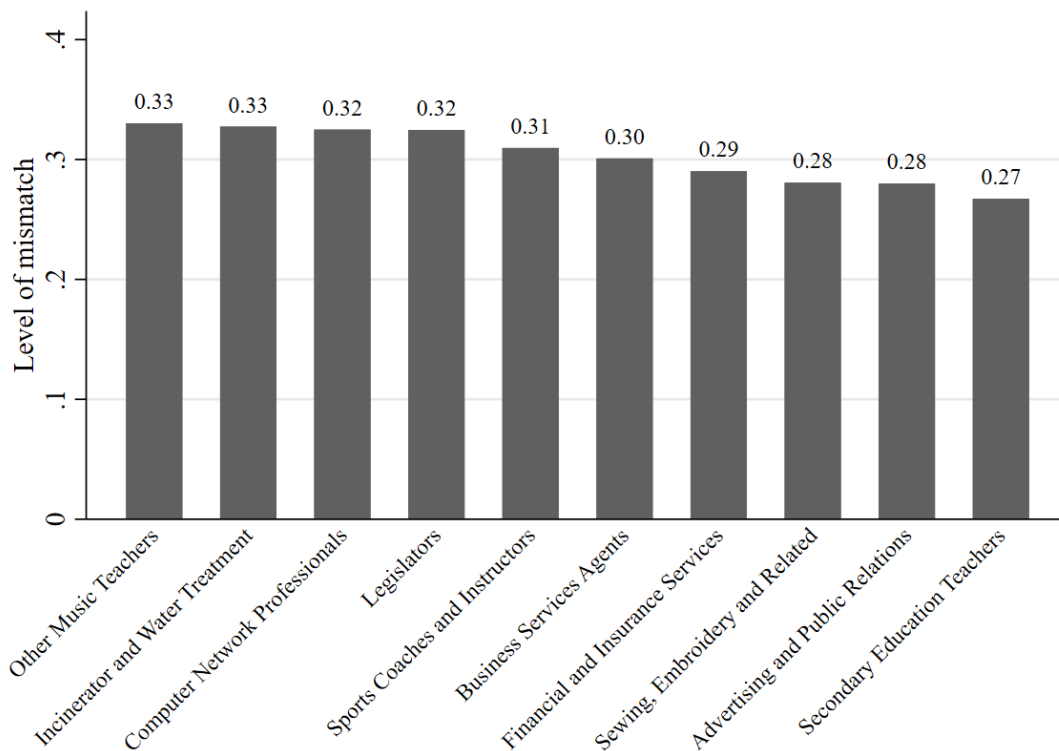
Table 3 presents summary statistics for our study sample. The average respondent is 21 years old, and 53% are female. The mean monthly wage amounts to approximately 2087 euros, corresponding to an average of 34 working hours per week and an implied hourly wage of 16 euros. 24% of employed graduates report skill mismatch, while 18% of them report field-of-study mismatch. As for our constructed skill mismatch index, graduates are on average measured with a 0.45 level of mismatch. In terms of educational background, the majority of respondents completed programs at MBO level 4, with smaller shares graduating from lower levels.

⁶ Note that in Figure 4 panel (a), judges are not typical MBO occupations. However, there are MBO graduates that found a position classified as judge and hence exists in our analysis. This is in line with the observation that judge is one of the most mismatched occupation.

Figure 4: An Illustration of Measured Skill Mismatch



(a) Measured Most Skill Mismatched Occupations



(b) Measured Least Skill Mismatched Occupations

Table 3. Summary Statistics

Variable	Number of Obs.	Mean/Percent	Std. dev.	Min	Max
Graduation Year	45,784	2021.93	0.8180	2021	2023
Age	45,784	21.45	1.7955	16	26
Gender (Female = 1)	45,784	0.53	0.5286	0	1
Monthly Wage	42,682	2087.24	833.1909	1	9900
Working Hour	45,677	34.10	8.8737	0	95
Hourly Wage	42,572	16.00	11.6600	0.0042	586.5000
Self-report Skill Mismatch	45,784	0.24	0.4260	0	1
Self-report Education Mismatch	42,397	0.18	0.3820	0	1
Measured Skill Mismatch	45,582	0.45	0.1167	0.0280	1.1771
Education Program Level	89,240	3.27	0.9484	1	4
Level 1	1,112	2.43%			
Level 2	7,396	16.15%			
Level 3	11,698	25.55%			
Level 4	25,578	55.87%			

Table 4 reports the relationship between measured skill mismatch and self-reported skill mismatch among MBO graduates. In the most parsimonious specification without controls or fixed effects (Column 1), a one-unit increase in measured mismatch is associated with a 19.6 percentage point increase in the probability that a graduate reports being skill mismatched on her job (significant at 5%). Adding individual controls (Column 2) and sequentially including year fixed effects (Column 3) leaves the estimate unchanged. However, adding industry and occupation fixed effects (Columns 4–5) largely attenuates the effects and presents statistically insignificant results. This implies that the differences between industries and occupations contribute more to the self-reported skill mismatch instead of our constructed measure.

Table 4. Measured Skill Mismatch and Self-reported Skill Mismatch

	Self-reported Skill Mismatch				
	(1)	(2)	(3)	(4)	(5)
Measured Skill Mismatch	0.196**	0.184**	0.184***	0.078	-0.010
Robust S.E.	(0.0936)	(0.0937)	(0.0937)	(0.0827)	(0.0779)
Controls	NO	YES	YES	YES	YES
Year FE	NO	NO	YES	YES	YES
Industry FE	NO	NO	NO	YES	YES

Occupation FE	NO	NO	NO	NO	YES
R-squared	0.0030	0.0041	0.0042	0.0581	0.1589
No. of Observation	40,841	40,841	40,841	40,841	40,841

Notes: Each column reports estimates from an ordinary least squares regression of the outcome variable, self-reported skill mismatch, on the measured skill mismatch index. Column (1) presents the baseline specification without controls or fixed effects. Column (2) adds individual-level controls (age and gender). Column (3) further includes year fixed effects, while Columns (4) and (5) sequentially add industry and occupation fixed effects. Standard errors are clustered at the occupation–industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

In addition to the reported skill mismatch, we further examine the wage effects. Table 5 Panel A reports results for the monthly earning, while Panel B reports results for the hourly wage. Across both panels, the estimated coefficients on measured skill mismatch are negative and statistically significant, indicating that greater misalignment between the skills taught in education and those demanded in the labor market is associated with lower earning outcomes. Unlike the self-reported mismatch results, the magnitude of the earning penalty is relatively stable across specifications. The simple specification without controls or fixed effects yields the largest negative coefficient (approximately 42.8%, significant at the 1% level), while the fully specified model in Column (5) produces a smaller estimate of roughly 30.1%, about three fourth the size of the baseline effect. The sharpest reduction occurs with the inclusion of industry fixed effects, suggesting that a substantial portion of the raw association reflects systematic earning differences across industry with varying skill structures rather than within-occupation variation in mismatch itself. In the preferred full specification, the coefficient remains statistically significant at the 1% level, indicating that even after controlling for occupation, industry, and year, a one-unit increase in measured skill mismatch corresponds to an estimated 30.1% decline in monthly earning. This attenuation pattern implies that while part of the mismatch–earning relationship operates through occupational sorting, skill misalignment within occupations continues to exert a meaningful negative effect on early-career earnings.

Turning to Panel B, the pattern of estimates is quite similar to that observed in Panel A. The coefficients remain negative and highly statistically significant across all specifications, and their magnitudes decline as additional controls and fixed effects are introduced. The estimated hourly wage penalty in the fully specified model is roughly half the size of that in the simple regression without controls, again underscoring the role of occupational sorting in earning differences. Specifically, in the preferred full specification, a one-unit increase in measured skill mismatch corresponds to an estimated 22.3% decline in hourly wages. The results remain statistically significant at the 1% level.

Table 5. Measured Skill Mismatch and Wage Outcomes

	(1)	(2)	(3)	(4)	(5)
Panel A. (log) monthly earning					
Measured Skill Mismatch	-0.428***	-0.312***	-0.317***	-0.207***	-0.301***

Robust S.E.	(0.0774)	(0.0560)	(0.0572)	(0.0751)	(0.0387)
Controls	NO	YES	YES	YES	YES
Year FE	NO	NO	YES	YES	YES
Industry FE	NO	NO	NO	YES	YES
Occupation FE	NO	NO	NO	NO	YES
R-squared	0.0085	0.0763	0.0948	0.1500	0.2238
No. of Observation	38,739	38,739	38,739	38,739	38,739
<hr/>					
Panel B. (log) hourly wage					
Measured Skill Mismatch	-0.445***	-0.343***	-0.349***	-0.144**	-0.223***
Robust S.E.	(0.0785)	(0.0680)	(0.0688)	(0.0667)	(0.0326)
Controls	NO	YES	YES	YES	YES
Year FE	NO	NO	YES	YES	YES
Industry FE	NO	NO	NO	YES	YES
Occupation FE	NO	NO	NO	NO	YES
R-squared	0.0103	0.0638	0.0897	0.1637	0.2094
No. of Observation	38,633	38,633	38,633	38,633	38,633

Notes: Each column reports estimates from an ordinary least squares regression of the outcome variable, (log) monthly earning and (log) hourly wage, on the measured skill mismatch index. Column (1) presents the baseline specification without controls or fixed effects. Column (2) adds individual-level controls (age and gender). Column (3) further includes year fixed effects, while Columns (4) and (5) sequentially add industry and occupation fixed effects. Standard errors are clustered at the occupation–industry level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Discussion & Conclusion

Our results depict the full picture of dynamics of skill demand across time and industry and discuss its relation with labor market outcomes. We show the seasonal fluctuations in the number of job postings as well as the stable composition of skill demand over time, indicating the persistent structural patterns in Dutch labor demand. At the occupational level, the skills taught in MBO curricula are positively correlated with those required in job postings, suggesting that the vocational education system broadly aligns with skill requirements, particularly in terms of technical and social skills. However, the measured skill mismatch remains, leading to deteriorated labor market outcomes. Our analysis shows that individuals with higher measured skill mismatch are more likely to report skill mismatch and earn lower wages. Specifically, a 1 unit increase in measured mismatch is associated with a 30.1% percentage point lower monthly earning and a 22.3% percentage point lower hourly wage. These patterns persist after accounting for individual characteristics, industry, occupation, and year fixed effects.

This paper advances the existing skill mismatch literature by quantifying skill mismatch using data-driven approaches linking education and labor market information. By combining large-scale text data from job postings and vocational curricula, we develop the first unified framework to measure

skill mismatch, offering an objective, scalable, and multidimensional measure grounded in real-time labor market dynamics. This paper not only complements recent work using online job posting data to document technological change and evolving skill requirements (Acemoglu et al., 2022; Azar et al., 2020; Mueller et al., 2024, Loll and Wessling, 2025), but also extends this line of research to the education system by exploiting curricula (Buehler et al., 2024; Langer and Wiederhold, 2023; Zhu et al., 2024; Lipowski et al., 2024; Cnossen et al., 2025). In this sense, the study bridges two previously disconnected strands of the literature and provides a methodological foundation for integrating real-time labor market intelligence into education and training policy design. Future research could extend this framework to more granular skill contents and incorporate longitudinal tracking of individuals to assess how education-acquired skills translate into career progression and wage trajectories.

Our results also highlight the need for more adaptive and evidence-based approaches to job training and vocational skill development. In the short term, policymakers can leverage real-time vacancy analytics to identify emerging skill gaps and guide the updating of vocational curricula and training modules. Targeted upskilling programs could help reduce skill mismatch and generate higher wage returns. In the longer term, integrating job posting data with administrative education and employment records would enable systematic monitoring of how educational investments translate into labor market outcomes, providing an empirical foundation for continuous curriculum adjustment and policy evaluation.

Online job posting data provide a valuable real-time lens on labor market dynamics but with limitations. First, it is not clear whether we could get the full coverage of labor demand, as not all employers recruit online and sectors such as small firms or public services are underrepresented (Hershbein and Kahn, 2018). Although our volume aligns closely with official statistics, those benchmarks are themselves largely web-scraped and unlikely to capture the full population of vacancies. Measurement errors may also arise from imperfect de-duplication, skill extraction, occupational classification, and skill classification, leading to biased estimate. Moreover, even if the technical procedures are correctly conducted, some firms may systematically list more skills than others, reflecting differences in recruitment practices rather than actual job content, which could bias the inferred relative importance of skill categories. To ensure comparability between skill supply and demand, we restrict attention to entry-level jobs suitable for MBO graduates, and thus our results could not be generalized to higher education graduates. It is not clear how a higher education certificate and work experience would re-scale the job requirements in job postings. In addition, basic skills are explicitly embedded in curricula but often implicit in job postings, as employers typically assume these competencies without listing them. Further research should shed light on providing a more generalizable view on dynamic skill demand in the labor market. Nonetheless, combining vacancy and curriculum data offers an unusually comprehensive view of skill alignment.

In sum, this paper develops novel framework to measure skill mismatch by linking online job postings with vocational curricula. The results show that educational and occupational skill profiles are correlated, yet measured skill mismatches persist and increase the likelihood of

perceived skill mismatch and lowering wages among new graduates. These findings demonstrate the value of vacancy analytics for monitoring skill demand dynamics and informing training design.

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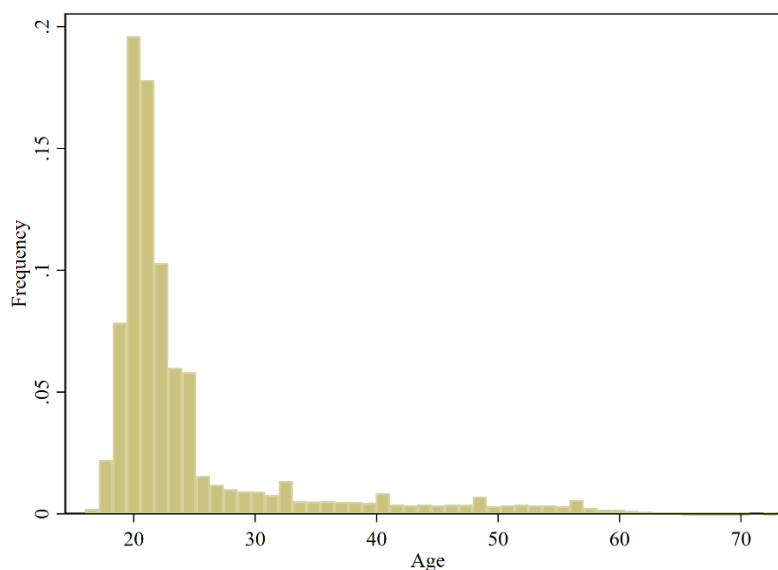
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Appendix

Appendix Figure 1: Distribution of Ages



Appendix Table 1. Correlation between Skills Learned at School and Skill Demand at Job

		Skills in Job Postings					
		basic	social	complex problem solving	technical	resource management	system
Skills in Curricula	basic	0.0238	0.0262	0.0388	-0.0137	-0.0386	-0.0086
	social	0.0293	0.1078	-0.0200	-0.0884	-0.0148	-0.0020
	complex problem solving	0.0202	0.1074	-0.0363	-0.1863	0.0566	0.0045
	technical	-0.0096	-0.0847	0.0499	0.2310	-0.1247	0.0070
	resource management	-0.0234	-0.0609	-0.0373	-0.0146	0.0917	-0.0037
	system	-0.0345	-0.0489	-0.0303	-0.0745	0.1156	-0.0002

Notes: This table reports pairwise correlations between the relative importance of skill categories in vocational education curricula and those observed in job posting data. Each cell shows the Pearson correlation coefficient between the corresponding skill dimensions across occupations. All variables are normalized measures of skill intensity based on the O*NET taxonomy.

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