Measuring Labour Market Disruption in the UK, 1960–2020

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Abstract

Artificial intelligence (AI) could soon redefine the nature of work across large segments of the workforce. To identify the scope of current and future labour market disruption, real-time indicators are desired for timely policy responses. Previous work has suggested occupational churn as a measure of labour market disruption. For the first time, we applied the methodology to another national economy, facilitated by verified AI-generated crosswalks. We analysed the labour market of the UK across seven decades, the longest consecutive time period available. We found that the historical pattern of labour market disruption in the UK mirrors that of the US, and that the 21st century has the most stable labour markets on record. Motivated by this consistent pattern of churn across countries, we suggest adopting occupational churn as the default measure of labour market disruption. We propose modifications to existing data releases to allow close monitoring of labour markets amidst continued AI adoption.

1 Introduction

The rapid adoption of AI raises concerns about the stability of the labour market as truly powerful AI could in principle automate segments of the economy. To address these concerns, indicators on labour market stability are desired to inform policymakers on timely policy responses. One such measure is churn.

Deming et al. (2025) introduced churn as a measure of historical labour market volatility and defined it as the sum of the absolute differences in shares of occupation groups between time periods. In this paper, we measure labour market volatility using occupational churn over seven decades and offer explanations for the observed historical pattern of churn. By demonstrating the soundness of occupational churn as an indicator when applied the UK, we highlight this indicator's potential as a cross-country measure of labour market volatility when continually assessing the impact of AI on the labour market.

Our findings show that churn in the UK closely mirrors that of the US. In particular,

1. the most recent decades (2000s-2020s) have the most stable labour market on record;
2. historically high churn in the late 20th century was largely driven by the decline in blue collar work and the steady rise of professional jobs;
3. the 2020s saw growth in high skill jobs with a decline in low, middle skill jobs and unemployment.

A current discussion on AI adoption is the potential substantial decrease in the number of entry-level jobs. Entry-level jobs require less expertise, are more repetitive and thus more susceptible to automation. As entry-levels jobs are typically filled by young workers, a diminishing supply of entry-level jobs will likely cause an increase in youth unemployment. Historically, youth unemployment has been linked to societal unrest, increased crime rates and in some cases, regime changes through the supply of rioters (Prince et al., 2018). Measuring churn for young workers, we find that

1. churn for young workers in recent decades (2000s-2020s) have exceeded that of the overall workforce;
2. blue collar jobs for young workers fell in parallel to the overall workforce, but the corresponding share that was lost was redistributed across services, sales, professional jobs and unemployment.

In Section 2, we present our methodology to harmonize occupations across the seven decades of UK census data with AI-assisted crosswalk generation. In Section 3.1, we present our findings on decadal occupational churn for UK. In remaining sections, we propose canonical analysis from that of Deming et al. (2025) to investigate the mechanisms underlying the occupation churn observed in the UK. Section 3.2 analyse churn by breaking down in occupation groups. Section 3.3 does so with skill groups. Section 3.4 repeats the analysis on the subset of young workers. We end with a discussion in Section 4 and a proposal to adopt occupation churn as a monthly labour market disruption indicator.

2 Methods

To measure labour market disruption, Deming et al. (2025) introduced churn as the sum of the absolute differences in shares of occupation groups between time periods. We adapt this definition but with one addition: the inclusion of unemployed people as a group. This is done to address a risk present in the previous methodology: if all groups uniformly shed off workers (a plausible scenario due to improved productivity from continued AI adoption), then the effect on churn will be minimal. We account for this effect by including unemployed people in our measure of churn as a distinct occupation group.

Note that churn is unitless. If two different countries use the same occupation codes, their churn can be compared to each other.

2.1 Data Sources

We collect occupation share data for each decade from 1960-2020 from the UK census through the UK Data Service. This is the longest consecutive time period when census data is available in the UK. No census data is available between 1912 and 1960. Each census file is an individual sample dataset. We remove students, retirees, institutionalised persons and inactive persons from our analysis. For the remainder, we mark each person as either employed or unemployed (see Table 2). For more details on the data sources, see section 5.1.1 of the appendix.

2.2 Calculating Churn

Occupations are coded differently across census years. Furthermore, some occupations are present in older census but are not coded in later years or are folded together into a group with other occupations. Similarly, some modern occupations do not have corresponding codes in earlier census. To make comparison possible, we harmonise the occupation groups between census. Since the 1981 census has the least number of distinct occupation groups (17 groups), we harmonize all occupations across census to the 1981 occupation codes. To facilitate with harmonising the groups, some of which has hundreds of unique values, we used OpenAI's o3 model (OpenAI (2025)) to generate crosswalks between each census year and the 1981 occupation codes. We then manually verified these crosswalks and made one change in the 1991 crosswalk on mapping professionals to the correct code. After converting all occupations into 1981-coded, we calculate the churn between these 17 occupation codes across the seven decades. For more details, see Section 5.1.2 in the appendix.

2.3 Occupation Groups and Skill Groups

We obtained the distribution of occupation groups from decadal census provided by the UK Data Service and harmonised it to 19 1980-standardised occupation codes. See the appendix (Section 5) for more information on the methodology.

To visualise the historical dynamics across occupation shares, we combine the 17 occupation codes into six occupation groups as in Deming et al. (2025). We mapped the occupations from each census file the the six occupation groups, yielding seven crosswalks for seven decades. We first generated the 1981 crosswalk with o3 (see Table 4). Using that as an example, we prompted Claude Code with the example inserted to generate the crosswalks for the remaining six decades. See 5.1.3 for more details.

We do the same to code the occupations in each census to high-, middle-, or low-skilled jobs. See 5.1.4 for more details.

2.4 Young Workers

We segment the population into those between 16 and 24 and repeat our analysis from the previous sections on churn, occupation groups, and skill groups. See Section 5.1.5 in the appendix for more details.

3 Results

3.1 Occupation Churn as a Labour Market Disruption Indicator

In Figure 1, we plot the occupation churn of employed person in England and Wales from 1960s to 2010s.

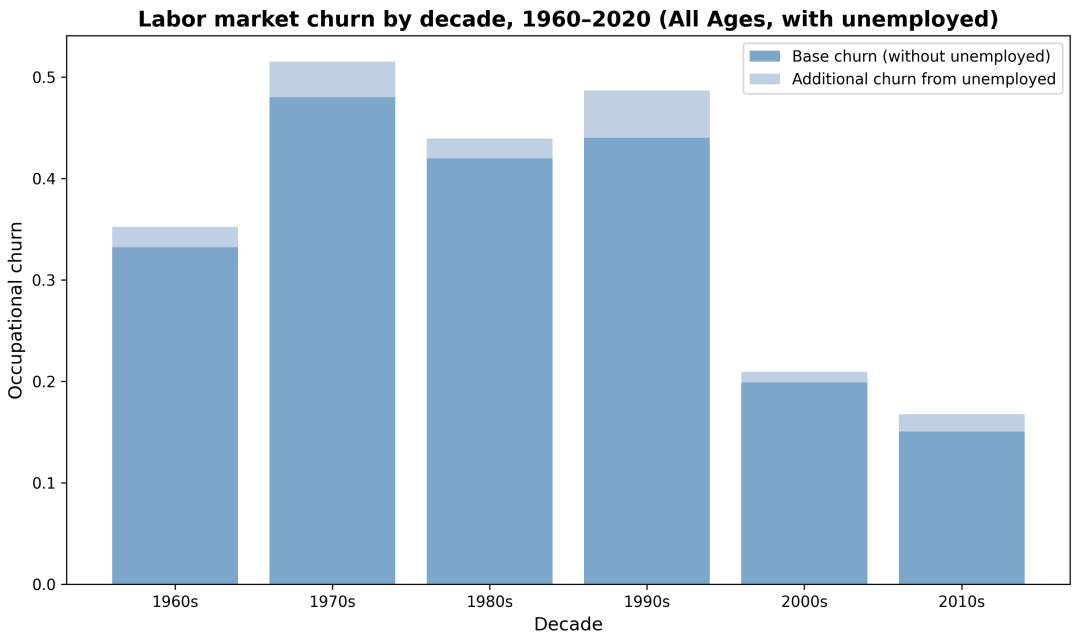

Figure 1: Labour market churn by decade, 1960–2020

Mirroring the pattern of churn in the US (see Figure 9), we found that the two most recent decades of the 21st century had the most stable labour market on record. From the 1970s to the 1990s, the UK saw significant occupational churn - more than twice of the magnitude observed in the 2000s. Although unemployment was higher before the 21st century, we note in Figure 1 that unemployment does not explain the full magnitude of higher churn observed before the 21st century. We now turn to an explanation behind the

observed trend on labour market churn by investigating the share of occupation groups over time.

3.2 Share of Occupation Groups

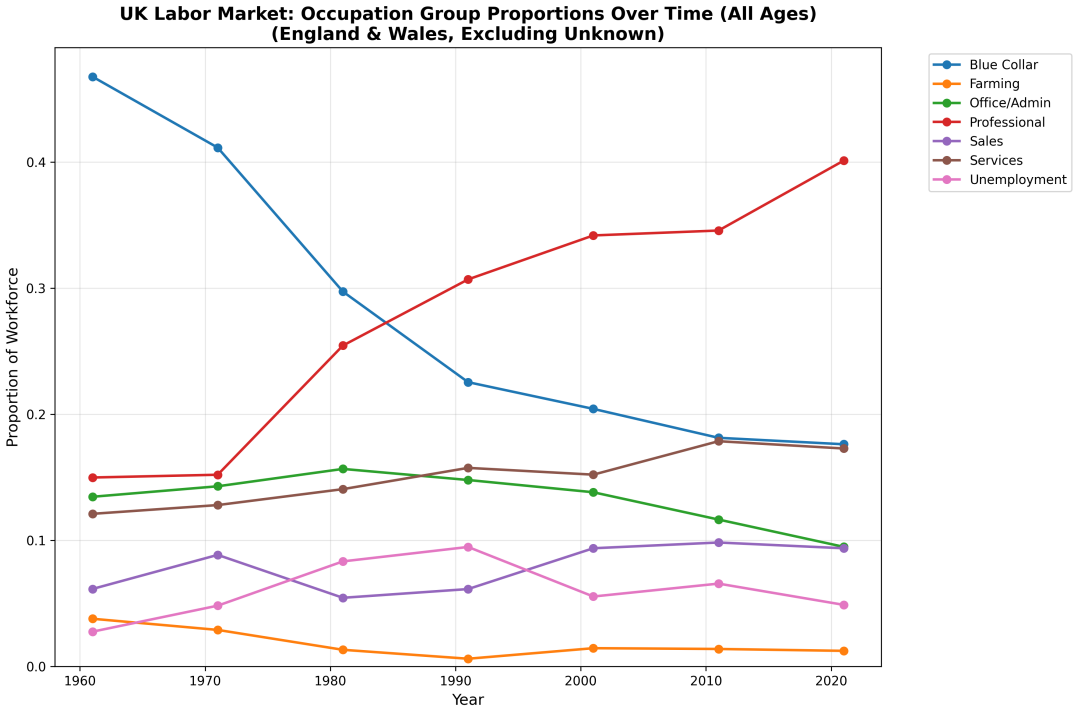

Figure 2: Occupation group proportions over time

In Figure 3, we grouped occupations into six main groups as in Deming et al. (2025) and plotted their share across decades alongside unemployment. We found a rapid decline in blue collar share which more than halved throughout the seven decades on record (46% → 18%, −4.7% per decade) that was counteracted with a strong rise of professional occupations (15% → 40%, +4.2% per decade) which more than doubled. Professionals overtook blue collar jobs as the dominant group in 1980-1990. Office and administrative jobs almost halved after a peak in 1980 (16% → 9%), while services (12% → 17%) and sales jobs (6% → 9%) grew. Farming continued its decline and more than halved (3.7% → 1.2%). These trends are in close agreement to that observed in the US as in Deming et al. (2025).

We thus attribute the high churn observed pre-2000 in Figure 1 to be largely driven by the rapid decline in blue collar work observed in Figure 2. The magnitude of decline exceeds more than 5.4% per decade for each subsequent pair of decades up to 1990, and less than 2.4% per decade on and after 2000. During the decline of blue collar work up to 1990, we also observe a steady rise of unemployment (2.7% → 9.4%).

Although the professional occupation group is currently the dominant group in the UK

and has seen continued growth, we note that it is also the most exposed to AI adoption (Mark Muro, Jacob Whiton, Robert Maxim).

3.3 Share of Skill Groups

We now analyse the share of occupation by their designation as low-skill, middle-skill, or high-skill groups. See the appendix (Section 5) for details on methodology and grouping. We plot our results in Figure 3.

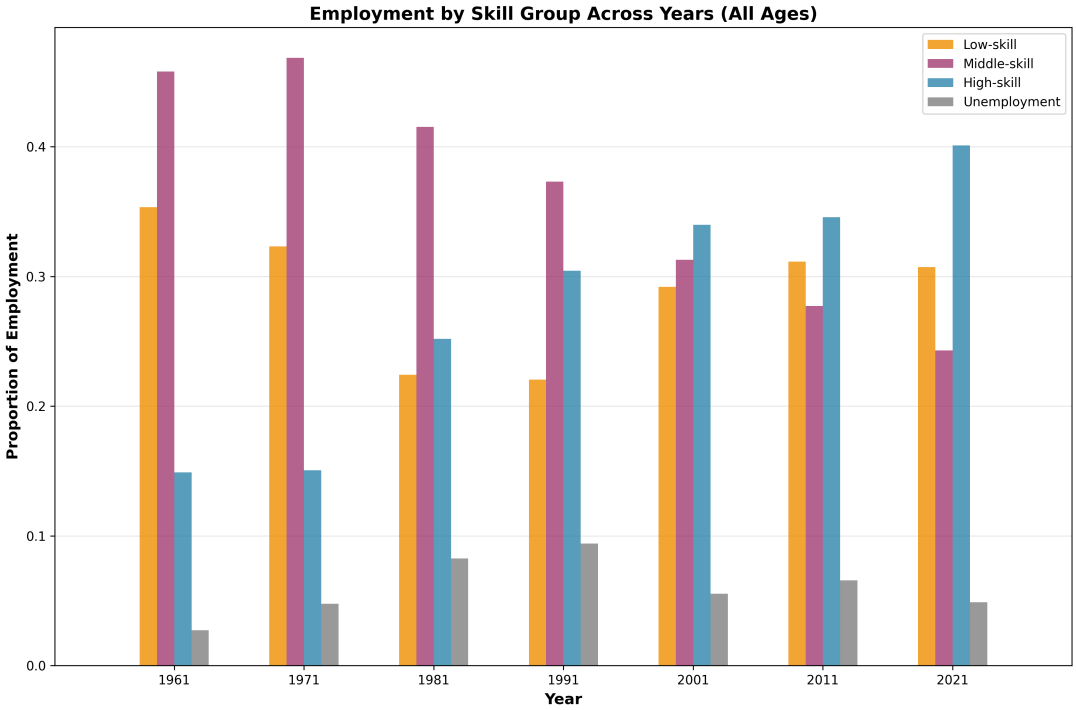

Figure 3: Occupation group proportions over time. "Additional churn from unemployment" is the difference between the churn calculated with employment and without.

Parallel to the decline of the blue collar work and the rise of professionals, we find a steady decline of middle-skilled jobs (46% → 24%) and a steady rise of high-skill jobs (15% → 40%). Low-skill jobs fluctuated with a dip in 1991 (35% → 22% → 31%).

We further plot the *change* in skill group share in Figure 4. The decades 1971-1991 saw a period of net high-skill growth, where shares of low-skill and middle-skill groups dropped, while unemployment rose. The growth of high-skill jobs occurs again in 2011-2021 , but with a drop in unemployment. Skill polarisation occurred in 1991-2001, where both low-skill and high-skill jobs grew, while middle-skill jobs decreased. These trends mirror that in the US as in Deming et al. (2025), where net high-skill growth occurred in the 1980s and 1990s, followed by skill polarisation in 2000s. The US also saw net high-skill growth in 2016-2022.

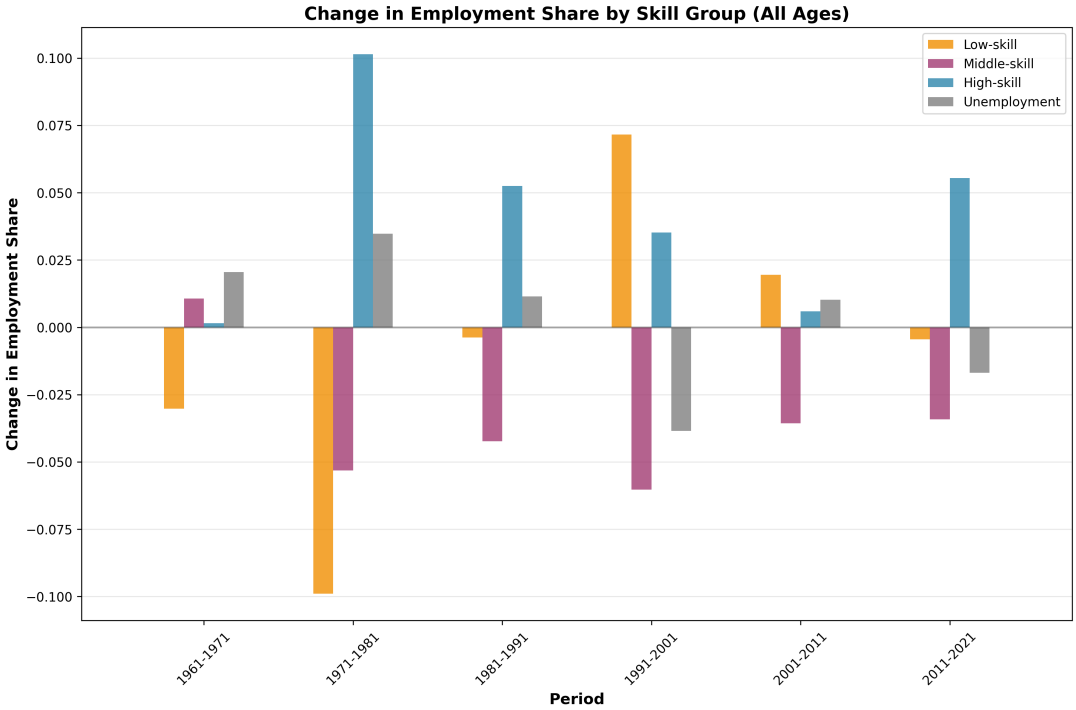

Figure 4: Skill group growth over time

3.4 Young Workers and Fresh Graduates

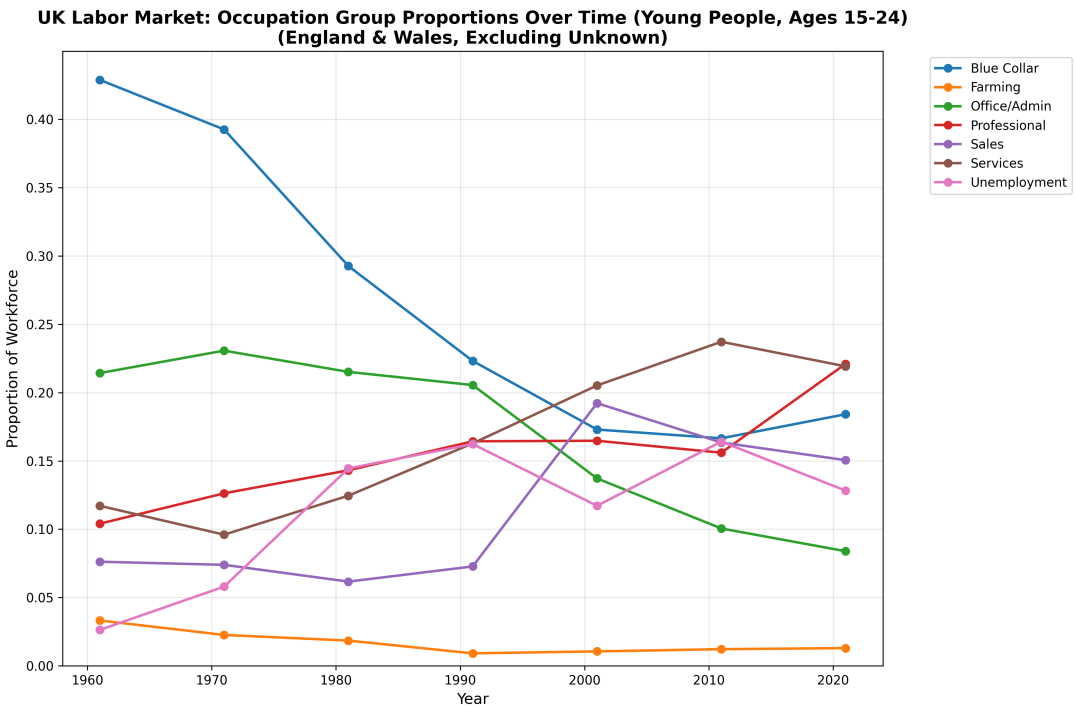

Figure 5: Occupation group proportions over time, young people

In Figure 5, we find similar trends to Figure 2, noticeably that of a decline of blue collar jobs. However, the rise of professional jobs are not as substantial, likely because many

professional jobs would require more years of expertise, as in management. We do see a large jump in professional share of youth employment from 2010 to 2020 (16% → 22%, +8%). We suggest a follow-up study to verify if this trend of increasing professional share holds up in 2025. The change in shares for other occupation groups are also more substantial than that of the general working population: office and administration (21% → 8%, −13%) services (12% → 22%, +10%), sales (7% → 15%, +8%).

In Figure 6, we find that although churn has decreased for the general working population since 1990, the churn for young workers exceeds that of the general working population since. For the decade 2010-2020, churn for the working population was 0.17, while it was 0.28 for young workers. Recent decades thus show that the labour market is more disruptive for youth workers than for the general population.

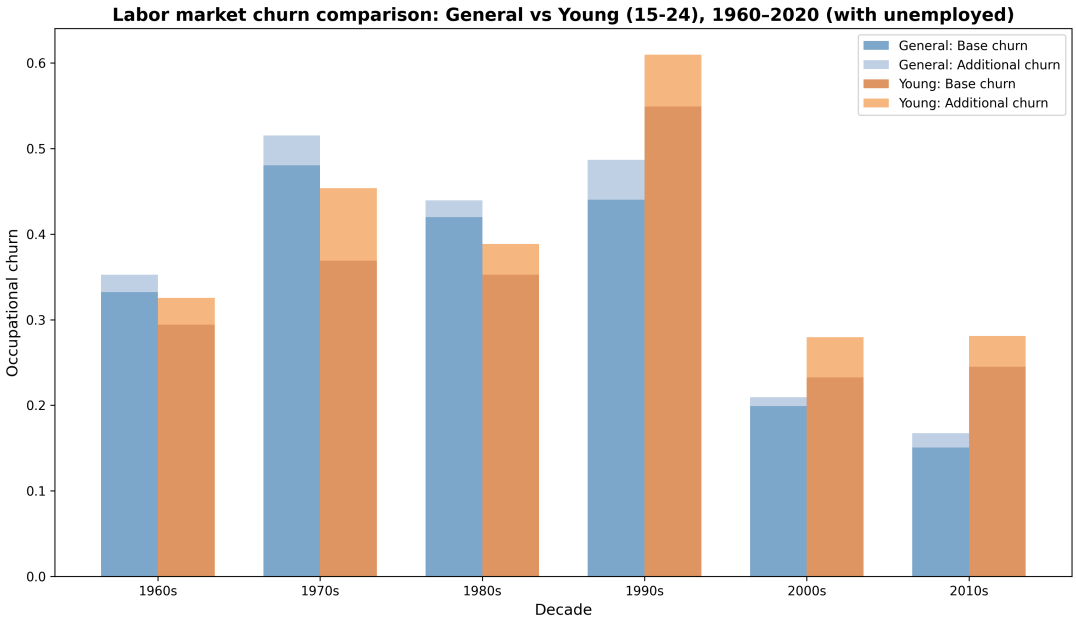

Figure 6: Churn comparison between the working population and the young workers

In Figure 7, we plot for young workers the skill group shares across decades. We find a decrease in middle-skilled jobs as in Figure 3, mirroring the decline of blue collar jobs in Figure 5. In contrast to Figure 3 however, high-skill jobs grew slower than of the general working population, echoing the finding in Figure 5 that professional jobs are growing slowly. It is emphasised that skill polarization has occurred when comparing youths from 1961 to 2021, as the share of both low-skill, high-skill and unemployed youths grew at the expense of middle-skill jobs.

4 Discussion and Limitations

Churn can be calculated for young workers, and we found it to be higher than that of general population and that high-skill jobs are lagging in growth among young workers.

Figure 7: Skill group proportions over time, young people

We recommend follow-up research on the share of high-skill or professional jobs in youth employment in the present to provide clarity on whether the upward trend continues.

Currently, the key limitation for occupational churn is its reliance on decadal census. To improve the frequency of updates from decades to monthly, we propose adapting existing monthly labour force data releases with occupation group shares to enable the monthly computation of occupational churn as a real-time indicator. For the UK government, this could be done with modifications through Labour Force Survey single-month estimates, (i.e. the X01 dataset) (Office for National Statistics, 2025b) by releasing estimates of occupational group shares. In the US, this could be done with similar modifications to the Current Population Survey (CPS) (US Census Bureau, 2025).

5 Conclusion

Occupational churn offers a universally comparable indicator of labour market disruption across countries and over time. Using seven decades of UK census data, we show that the historical trajectory of labour market change closely mirrors that of the US: high disruption during the late 20th century, followed by unprecedented stability in the 21st. We also find that youths in the 21st century experience consistently higher volatility than the general workforce, highlighting a group at particular risk as AI adoption accelerates.

While the reliance on decadal census data currently limits the timeliness of churn measurement, we propose adapting monthly labour force surveys to include occupational

shares, enabling churn to function as a real-time, scalable early-warning system. Such an indicator would allow policymakers to track the pace of AI-driven disruption, anticipate risks such as rising youth unemployment, and design timely interventions to preserve labour market stability.

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Appendix

5.1 Methodology

5.1.1 Data Sources

We collect the grouped occupation share of the population for each decade from 1960-2020 from the UK Census. We list them in the list below.

- Office for National Statistics (2024)
- Office for National Statistics (2025a)
- Cathie Marsh Centre for Census and Survey Research University of Manchester and Census Division Office for National Statistics (2023b)
- Cathie Marsh Centre for Census and Survey Research University of Manchester and Census Division Office for National Statistics (2023a)
- Office for National Statistics and Enhancing and Enriching Historic Census Microdata Project (EEHCM) (2023)
- Enhancing and Enriching Historic Census Microdata Project (EEHCM) and Office for National Statistics (2023b)
- Enhancing and Enriching Historic Census Microdata Project (EEHCM) and Office for National Statistics (2023a)

We assess each census data file through the UK Data Service. These census data contain individual samples and the sample size for each data file is summarised in Table 1.

Census Decade	Sample Size	Records in Sample
2021	5%	3.0 million
2011	2%	2.8 million
2001	3%	1.8 million
1991	2%	1.2 million
1981	5%	2.8 million
1971	5%	2.4 million
1961	5%	2.6 million

Table 1: Sample sizes and number of records for selected census decades

There are several constraints on the data sources:

Location constraints: The census data provided for 2011 and 2021 is limited to England and Wales. For comparability, we subset the census data for other years to England and Wales as well.

Temporal constraints: The UK Data Service does not provide access to census data between 1912 and 1960, so our current analysis from 1961 to 2021 is the longest possible spanning analysis that is contiguous with the 2020s. Census data is provided for 1851-1911, which presents a potential research direction to analyse churn further back into the labour market history of the UK.

Working population: We remove students, retirees, institutionalised persons and inactive persons from our analysis. For the remainder, we mark each person as either employed or not. For more details, see Table 2.

Year	Variable	Category Description	Decision
1961	`econpage`	0–3: Employed (full/part/family)	KEEP - employed
		4–5: Out of work (sick/other)	KEEP - unemployed
		6–9, -9: Inactive, student, retired, N/A	EXCLUDE
1971	`econpage`	0: In employment	KEEP - employed
		1–2: Out of employment (sick/other)	KEEP - unemployed
		3–7, -8, -9: Inactive, retired, student, missing	EXCLUDE
1981	`pactlw`	1–3: Job last week / waiting to start	KEEP - employed
		4: Seeking work	KEEP - unemployed
		0, 5–11, -8, -9: Inactive, students, missing	EXCLUDE
1991	`ECONPRIM`	1–5: Employees, self-employed, govt scheme	KEEP - employed
		6: Unemployed	KEEP - unemployed
		7–10: Students, sick, retired, other inactive	EXCLUDE
2001	`econact`	1–6: Employees, self-employed	KEEP - employed
		7–8: Unemployed (seeking/waiting)	KEEP - unemployed
		9–13, -9: Retired, student, inactive	EXCLUDE
2011	`ECOPUK`	1–6: Employees, self-employed	KEEP - employed
		7: Unemployed	KEEP - unemployed
		8–16, -9: Students, retired, inactive	EXCLUDE
2021	`economic_activity_status_17m`	1–6: Employees, self-employed	KEEP - employed
		7: Unemployed (seeking/waiting)	KEEP - unemployed
		8–16, -8: Full-time students, retired, inactive	EXCLUDE

Table 2: Summary of KEEP/EXCLUDE Decisions for Economic Activity Variables by Decade

5.1.2 Calculating Churn

To calculate churn, we harmonise the occupation groups between census. For each census, we take the column that provides the highest granularity on occupations. We list these columns in Table 3 and their description in the data dictionary.

We note that the census data files also contain industry orders, but our focus here is on the occupations which relates to the skills of the person employed. Since 1981 has the least number of unique values, we harmonize all occupation codes across census to that of 1981. A crosswalk is developed for each year other than 1981, and can be found at the project GitHub repository.

The crosswalks are first drafted by OpenAI's o3 model. For each crosswalk, we provided o3 with the prompt at 5.1.2

We then attach the section of the relevant column descriptions from the pair of data dictionaries to the prompt. We manually reviewed the resulting crosswalks and made one change in 1991 where instead of mapping code 6 (Other professionals) and 9 (Other associate professionals) to 16 (Miscellaneous), we map them to code 1 (Professional and related supporting management: senio national and local government managers).

After harmonising, we overwrite the 1981-standardised occupation codes for unemployed persons to -100 according to Table 2. This is because some of the occupation codes were for the most recent job, and an unemployed person could have that field populated. We then handle missing values. Codes -9 (not applicable) and -8 (missing) are only present in 1971 and 1991 (after the -100 overwrite), but they sum up to less than 1% of the remaining dataset. We drop these erroneous rows. Code 17 (Inadequately described and not stated) is present from 1961 to 1981 but they are each less than 1.5%. We also drop these rows because they are different from code 16 (Miscellaneous).

We then calculated the proportion of each 1981-standardised occupation group, followed by the churn. The "additional churn from unemployment" as displayed in Figure 1 is calculated by taking the difference between the churn calculated with employment and without.

Year	Column Name	Description	Unique Values
1961	`occ`	Occupation code	204
1971	`occord`	Occupation orders	29
1981	`dvocco`	Occupation order	17
1991	`OCCSUBMJ`	Occupation: SOC Sub-major Groups	23
2001	`socmin`	Standard Occupational Classification 2000 - minor	82
2011	`SOCMIN`	Standard Occupation Classification (3-digit)	91
2021	`occupation_105a`	Occupation (105 categories)	105

Table 3: Occupation-related variable names and their row counts by census year

Prompt

You are given two files below. Your task is to produce a crosswalk, where the rows from the first files are the keys. The crosswalk will be used to map data from the first file to the second file. Each file has Value and Label columns. The Value column gives the occupation code, and the Label is the description. For each row in the first file, find a row in second file that best corresponds to it. Output a resulting csv with 4 columns: firstValue, firstLabel, secondValue, secondLabel. Output a downloadable csv. You should match by reading the Label columns and manually match the rows.

5.1.3 Plotting Occupation Groups

We produce a crosswalk from 1981-standardised occupation code to occupation groups as in Deming et al. (2025). We develop our crosswalk by providing the prompt in 5.1.3 to o3 and attach the data description from the 1981 data dictionary and the crosswalk used in Deming et al. (2025). The resulting crosswalk is in Table 4.

We then use Claude Code to generate the occupation group mapping for each year, providing the above as an example for 1980. We drop those that didn't have a valid mapping, which are codes -8 and -9 (missing), and 330 for 1961, 26 for 1971 and 17 for 1981 (Inadequately described occupations). These "Unknown" occupation groups each make up less than 1.3% of each dataset.

Prompt

You are given two data sources below. The first one is the 1980 occupation codes. The second one is a grouping of codes from a different data sources. Use the second data source to come up with a mapping from the 1980 occupation codes to the major groups in the second data source. Create a downloadable csv that has two columns, 1980code and group.

1980 Code	Description	Group
1	Professional and related supporting management: senior national and local government managers	Professional
2	Professional and related in education, welfare and health	Professional
3	Literary, artistic and sports	Professional
4	Professional and related in science, engineering, technology and similar fields	Professional
5	Managerial	Professional
6	Clerical and related	Office/Admin
7	Selling	Sales
8	Security and protective service	Services
9	Catering, cleaning, hairdressing and other personal service	Services
10	Farming, fishing and related	Farming
11	Materials processing: making and repairing (excluding metal and electrical)	Blue Collar
12	Processing, making, repairing and related (metal and electrical)	Blue Collar
13	Painting, repetitive assembling, product inspecting, packaging and related	Blue Collar
14	Construction, mining and related not identified elsewhere	Blue Collar
15	Transport operating, materials moving and storing and related	Blue Collar
16	Miscellaneous	Services

Table 4: Mapping of 1980 occupation codes to broad occupational groups

5.1.4 Plotting Skill Groups

Similar to Section 5.1.3 above, we provide the prompt in 5.1.4 to o3, attach the column description from the 1980 data dictionary and the skill group table in Deming et al. (2025). The resulting crosswalk from 1981-standardised occupation codes to skill groups is at Table 5. We drop codes -8, -9, 17 from our plots. We plot 16 (Miscellaneous) as its own category as it includes both high and low skill occupations. One suggestion to further improve the accuracy of this plot is to map the occupation codes themselves from each year to the skill groups, without mapping them first to the 1981-standardized codes.

We then use Claude Code to generate the skill group mapping for each year, providing the above as an example for 1980. We drop the missing codes -8, -9, and inadequately described codes as per the section above. All years have less than 1.3% of such removed rows, while 1981 has 2.6% of them.

Prompt

You are given two files below. Your task is to produce a crosswalk, where the rows from the first files are the keys. The crosswalk will be used to map data from the first file to the second file. Each file has Value and Label columns. The Value column gives the occupation code, and the Label is the description. For each row in the first file, find a row in second file that best corresponds to it. Output a resulting csv with 4 columns: firstValue, firstLabel, secondValue, secondLabel. Output a downloadable csv. You should match by reading the Label columns and manually match the rows.

1980 Code	**Description**	**Group**
1	Professional and related supporting management: senior national and local government managers	High-skill
2	Professional and related in education, welfare and health	High-skill
3	Literary, artistic and sports	High-skill
4	Professional and related in science, engineering, technology and similar fields	High-skill
5	Managerial	High-skill
6	Clerical and related	Middle-skill
7	Selling	Middle-skill
8	Security and protective service	Low-skill
9	Catering, cleaning, hairdressing and other personal service	Low-skill
10	Farming, fishing and related	Low-skill
11	Materials processing: making and repairing (excluding metal and electrical)	Middle-skill
12	Processing, making, repairing and related (metal and electrical)	Middle-skill
13	Painting, repetitive assembling, product inspecting, packaging and related	Middle-skill
14	Construction, mining and related not identified elsewhere	Low-skill
15	Transport operating, materials moving and storing and related	Low-skill

Table 5: Mapping of 1980 occupation codes to major skill groups

5.1.5 Young Workers

We subset the data to those between 16-24-years-old. We include 15-year-olds in 1961 as they are banded together as 15-19 in the census data. See Table 6 for age bands in each

census files.

Year	Column (verbatim)	Ages Included
1961	`quinage`	15–19, 20–24 (banded)
1971	`ageo`	16–24 (banded)
1981	`ageo`	16–24 (banded)
1991	`AGE`	16–24
2001	`age0`	16–24
2011	`AGE`	16–24
2021	`resident_age_74m`	16–24

Table 6: Age column names and included age ranges by census year

We include the skill-group growth plot in Figure 8.

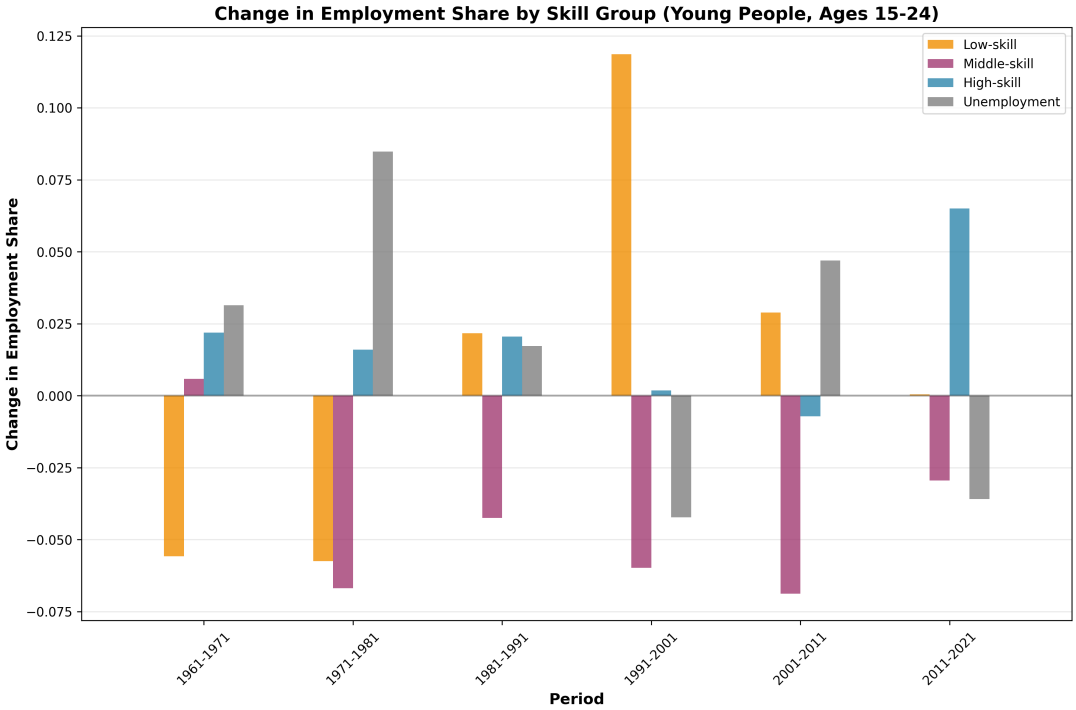

Figure 8: Skill group growth over time, young people

6 Additional Churn Figures

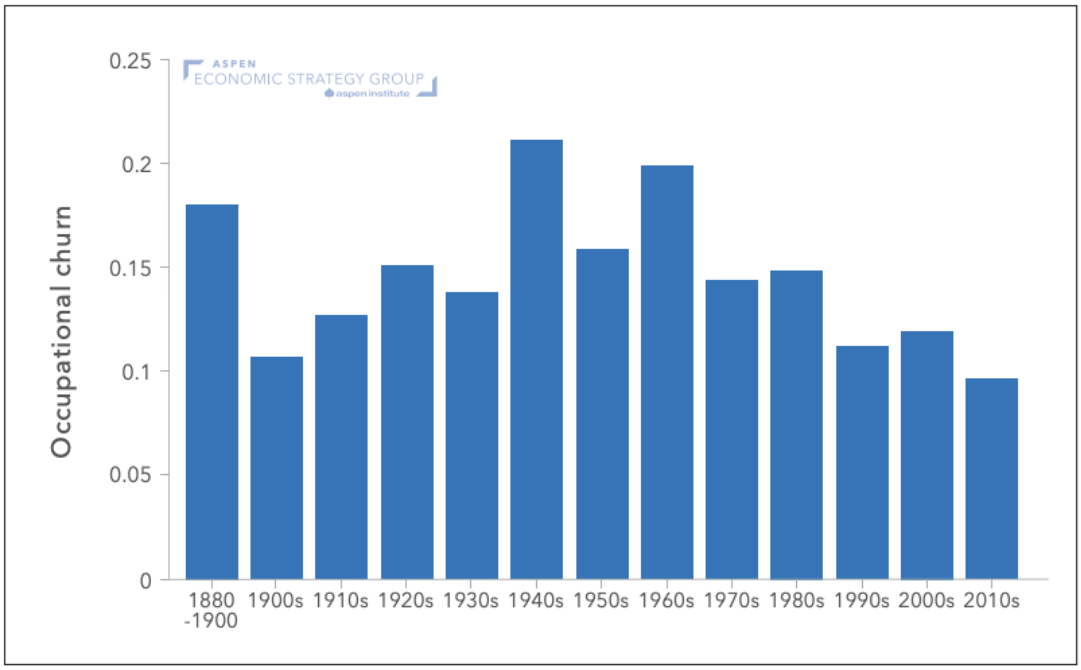

Figure 9: U.S. churn from 1880-2010, figure from Deming et al. (2025)