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Earnings volatility in Austria

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Abstract

This study analyzes earnings volatility in Austria from 1980 to 2018, providing a comprehensive view of individual income instability and its demographic and structural determinants. Using administrative data, we examine volatility trends by gender, age, earnings deciles, and employment interruptions. We find that earnings volatility has increased over time, with employment interruptions as a major driver, particularly among employees in low-skill sectors and the lower earnings deciles. Additionally, we observe significant gender differences, with women experiencing higher volatility, often linked to childbirth and family-related career interruptions. Through variance decomposition, we attribute the greater share of volatility to demographic changes, including the impact of migration, sectoral shifts, and the growing labor force participation of women.

JEL Classification: D31, E24, J13, J31, J62

Keywords: earnings volatility, employment interruptions, labor market dynamics

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1 Introduction

Earnings volatility is an indicator of economic instability and of central importance in macroeconomics, labour economics, the economics of the family, but also for social policy. (See e.g. Moffitt et al. (2022).) Given the importance of this indicator, many studies focus on the changes of earnings mobility over time. However, for the US, the empirical evidence is contradictory. Almost all studies for the US that rely on data from the PSID, the standard source for data to analyze earnings volatility, show rising volatility from the 1970s to the 1980s, and either no trend or a downward trend through the 1990s (Moffitt et al., 2022). In contrast, studies which use administrative data, e.g., Guvenen et al. (2014) find declining earnings volatility for men. Moffitt et al. (2022) conclude from a comparison of different data sources that the evidence shows no strong overall trend in earnings volatility among working men in the U.S. since the mid-1980s.

The availability of administrative data across countries and the conflicting results in estimating earnings volatility and inequality have motivated the Global Repository of Income Dynamics (GRID) project, which aims to provide harmonized cross-country analyses of earnings dynamics (GRID, 2023). Many recent studies have emerged from this initiative, revealing diverse trends in earnings volatility. For instance, Hoffmann et al. (2022) document an increase in earnings volatility between 1985 and 2017 for men and women in Italy, and Friedrich et al. (2022) for Sweden. Drechsel-Grau et al. (2022) find small increases in earnings volatility for both men and women in Germany since 2001. In contrast, Bell et al. (2022) report an increase for men but stable earnings volatility for women in the UK over similar periods.

We contributes to this effort by consistently estimating and interpreting earnings volatility trends using administrative data to examine annual earnings volatility in Austria between 1980 and 2018. We find greater earnings volatility in 2018 than in 1980 for both men and women, reflecting demographic and structural changes in the economy, such as migration and sectoral shifts. Consequently, we compare earnings volatility across cohorts and along their career paths. We find that men's earnings volatility is higher at younger ages and lower at older ages compared to older cohorts. For women, earnings volatility has shifted from younger ages to older ages due to later births. Additionally, we provide a detailed analysis of post-birth earnings volatility for women, as previous studies have often focused exclusively on men's earnings volatility (e.g., Shin and Solon (2011); Gottschalk et al. (1994)).

We use variance decomposition methods to detect the sources of earnings volatility, similar to Bloom et al. (2017) for the US and Cappellari and Jenkins (2014) for the UK. Employment interruptions cause most of the earnings volatility. For example, in 2012, 75% of overall earnings volatility was caused by 22% of employees whose employment was interrupted. The type of employment interruption matters, too: Employees with employment interruptions who also change firms experience higher earnings volatility than employees who have interruptions but stay with the same firm (recalls). Women's earnings are more volatile than men's, primarily because of employment interruptions that are related to birth and child care. Earnings volatility is similar for men and women in levels after age 45, and between men and women without children.

The probability of employment interruptions is lower for higher earnings, with the exception of employees in the top earnings decile. Employees at the bottom of the earnings distribution contribute much more to the overall earnings volatility than employees at the top. The bottom two earnings deciles account for about 40% of overall earnings volatility and the top two deciles for less than 15%. The contribution of employees at the lower end of the earnings distribution has been increasing since 2000. The results suggest that it is increasingly employees at the bottom of the earnings distribution, i.e., employees who are likely to be liquidity constrained, who have the greatest challenge to smooth their consumption.

The higher contributions to earnings volatility of employees with lower earnings coincides with sectoral changes in Austria where (relatively more stable) jobs in manufacturing declined from 32% in 1990 to 26% in 2015 and (relatively more unstable) jobs in the low skill services increased from 5% to 10%. The share of manufacturing jobs in the lowest earnings deciles declined, but it remained relatively stable for employees in the upper deciles of the earning distribution. The contribution of the manufacturing sector to annual earnings volatility declined from 22% in 1990 to 15% in 2014; the low skill service sector increased from 10% to 22%. In the low skill service sector, employees who work for employment agencies have exceptional high volatility; the agencies employ around

2.5% of all men, but they account for 12.5% of total earnings volatility. Our results suggest that changes in sectoral composition are more important than intra-sectoral changes in volatility.

Furthermore, we show that demographic trends in the working population have strong implications for the earnings volatility. The increase in the share of young employees linked to the large baby boomer cohorts was accompanied by a sizable increase in volatility levels. Similarly, in the periods when large numbers of immigrants entered the Austrian labor market earnings volatility was greater than in other periods. The relatively more volatile earnings of immigrants emerged in a period which saw an overall decrease in earnings volatility of native employees. Furthermore, fertility and family policies that affect mothers' labor market attachment have sizable effects on earnings volatility.

When we compare the earnings volatility across cohorts, we find that younger men's earnings are more volatile at younger ages and less volatile at older ages compared to older cohorts. For women, earnings volatility has shifted from younger ages to older ages due to later births. Younger generations of mothers have become increasingly more likely to return to the labor market than women of older generations, especially mothers who have only one child. The earnings volatility of women that is associated with their first child has declined for younger generations due to less volatility in employment duration and despite greater volatility in daily earnings.

2 Data

We use data from the Austrian Social Security Database (ASSD) which is a large employer-employee dataset that covers the universe of all private sector employees from 1972 to 2021 (Zweimüller et al., 2009). Information on earnings are derived from the social security basis which corresponds to gross earnings except for those who earn less than the minimum (€4,110 p.a. in 2010) or earn more than the maximum social security basis (€57,540 p.a. in 2010).[1] Employees pay social security contributions only if their earnings exceed the minimum and up to the maximum contribution base and we therefore do not observe bottom and top earnings. Therefore, we complement the social

[1] Thresholds are set annually and their growth is plotted in Figure 2.

security data with tax records from the Austrian Ministry of Finance.[2] The additional data are from pay slips which employers have to submit to the tax authority for each of their employees. A pay slip contains information on the exact employment period, gross earnings, payroll tax, and social security contributions. The use of these uncensored data has a clear advantage over social security contributions, but is only available from 1994 to 2012. For our main analysis, we use the earnings measure from the social security data because all major trends can be reproduced using both data sets. We present outcomes using both data sources whenever differences are sizable. All monetary variables are deflated to 2010 price levels using the Personal Consumption Expenditure Deflator (Statistik Austria, 2024*a*).

In our analysis, we focus on blue-collar and white-collar employees who are 25 to 55 years old. Earnings for the self-employed, farmers, civil servants, and marginally employed are not observed and we exclude the self-employed, the farmers, and the civil servants. We restrict our sample to employees who have a minimum degree of labor market attachment: Employees who earned at least the minimum social security contribution basis (€366 in 2010)) in at least three months in two consecutive years. For the analyses which are based on pay slip data, we exclude observations with earnings of more than €1.4 million per year. We exclude employees who work more days in marginal employment than in regular employment in a given year. To reduce the impact of early career and retirement dynamics, we constrain our sample to 25 to 55 year old persons and drop the first and the last year of their employment. The sample restrictions reduce the number of observations in the raw data by around 15% and the final sample contains 1.30 million persons in 1980 and 1.92 million persons in 2018.

Demographic variables such as year of birth and sex are available for all observations, as well as the birth of children and spells of parental leave. The migration status of employees is however not consistently available. Due to the importance of migration in explaining labor market developments, we derive the migration status indirectly from the age, the year of the first labor market record, and the education level. All individuals who had their first labor market status before age 19 are considered native persons. Approximately a third of a birth cohort enter the labor market as

[2] Figure 1 shows the distribution of the social security basis compared to gross earnings retrieved from uncensored pay slips for the year 2000.

apprentices at age 15. We classify employees with a high school diploma ("Matura") as immigrants if they have their first record after age 21 and tertiary educated employees as immigrants if their first record is after age 24 for women and 25 for men.[3] This indicator is imperfect and categorizes immigrants who arrive at young ages as natives and natives who have their first labour market record relatively late as immigrants. Furthermore, we can only categorize employees if their first labour market status was recorded after 1960. Employees who had entered the labour market before 1960 are categorised as natives. In 1980, only 4% of all employees did not have Austrian citizenship, but until 2020, this number increased to 17%. Figure 24 shows that we capture well the changes in the stock of immigrants when comparing our sample to official census data. Furthermore, the classification is only possible until 2015 as we have no information on education for new labour market entrants after 2015.

We aggregate NACE 1-digit sectors with similar activities and earnings to different categories. We define the public sector (O public administration, P education, Q health), high skill services (H Transport, J Information and communication, K financial services, L real estate, M Science and technical services), low skill services (I Food and tourism, N other services), the primary sector (A agriculture and forestry, B mining, D energy), manufacturing (C manufacturing), and construction (F construction). The low skill service sector had median annual earnings of €23,500 for men in 2018 and €17,400 for women — around 40% less than the median earnings in the high skill service sector for men and women. The median public service job paid around 14% less than the median job in the high skill service sector.

We define employment interruptions as non-employment periods of at least 8 days. Employees with a maximum of 7 days of non-employment are considered to be employed continuously. An employee is defined to have an employment interruption if she had an interruption in year t or year $t-1$, or both. To study the consequences of employment interruptions, we define the following types of interruptions: Recalled, firm changers, on parental leave, and a residual group of employees who cannot be allocated to one of the other groups. An employee is defined to be recalled if two consecutive employment spells with the same employer were interrupted by at least 14 days and

[3] Men are required to do military or alternative service and hence start tertiary education typically one year later than women of the same cohort.

up to half a year of non-employment. An employee has changed firms if she had two consecutive employment spells with different employers. If employees are recalled by their employer and also changed firms in a given year, they are allocated to the group of recalled. Employees who interrupted their employment by taking parental leave are in the group of parental leave, irrespective of other types of employment interruptions. (For example, they might have changed firms while on parental leave.) The type of employment interruptions is defined on the observations in year t and $t-1$. For example, an employee is categorized as recalled if she was recalled by her employer in year t or in year $t-1$, or both.

The residual group consists of employees who had no recorded earnings for at least one calendar year, for example, due to a change to self-employment or civil service, long-term unemployment, unpaid care work, education or temporary migration. Earnings deciles are based on the average daily earnings within the last two years conditional on year, sex, and age. We choose daily earnings instead of annual earnings to proxy potential earnings rather than labour market attachment.

3 Descriptive Statistics

3.1 Labour market dynamics and earnings

Table 1 shows descriptive statistics of our sample in 1985 and 2015. Overall, the working population has become older. In the 25 to 55 year age group, the average age of men and women has risen by 1.7 and 3 years. We want to highlight two major changes in the Austrian labor market: The large increase in women's labor force participation and the decline in manufacturing jobs. The number of women in our sample increased from 530,000 to 850,000, an increase of 60%. About 60% of this increase is due to higher participation of women who already lived in Austria prior to 1985 and the remaining 40% are due to a higher number of immigrants. The number of men increased by 24% to 945,000 and would have stayed constant without immigration.

Another remarkable change documented across many developed nations is the decline in manufacturing jobs (e.g., Berger and Frey, 2016). Sectoral data becomes fully available only in 1990. Of all women in employment, their share in manufacturing dropped from 20% in 1990 to 10% in 2015 (in absolute terms, their number dropped by 20,000 to 85,000). For men, their share of emplyoment in manufacturing dropped from 30% to 26%, although it increased in absolute numbers by 11,000 to 241,000. Over the same period, employment in the public sector (education and health care) and in the low skill service sector (tourism and food, other services such as rental and leasing, services to buildings, business support) increased for women and men. Additionally, employment in the wholesale and retail sector increased mainly for women.

The proportion of employees with at least one employment interruption in two years fell from 26% to 24% for men and from 26% to 22% for women, which is mainly due to fewer recalls for both men and women, and fewer interruptions for women due to childbirths and parental leave. Consistent with fewer employment interruptions, the average number of days in employment increased for women (336 to 341 days) and for men (341 to 342). At the same time, the proportion of employees who changed firms rose from 8.5% to 9.3% for men and 6.9% to 8.2% for women.

While the average employment duration increased, the number of employees experiencing at least one unemployment spell in a two-year period has increased from 10.6% to 13.5% for men and from 10% to 11.5% for women. The average number of days in unemployment (conditional on having an unemployment spell) has increased for men (from 74 to 75 days), but declined for women (from 84 to 79 days).

Between 1985 and 2015, average earnings have increased for men and women by 37% and 32% to €36,000 and €25,000. Daily earnings have increased by similar rates. The number of men earning above the maximum social security contribution basis dropped somewhat from 11 % in 1982 to 9% in 2015. This number remained stable for women at around 2%.

Figure 2 shows that earnings at the top of the distribution have been growing stronger than those at the bottom of the distribution up to 2015. However, the growth has been different for men and women: While men's earnings in the bottom decile grew by around 5% between 1981 and 2015, the earnings for women in the bottom decile increased by 30%. The earnings of the top 25% of women grew similar to median earners, however, the gains for the top 10% male employees were particularly strong.[4]

[4]Earnings dynamics at the top of the distribution are limited by the maximum social security contribution basis.

Table 1: Descriptive statistics.

	men				women			
	1985	2015	Δ 1985-2015	Δ 1985-2015,%	1985	2015	Δ 1985-2015	Δ 1985-2015,%
Earnings, employment duration								
Annual earnings	28,054.78	35,671.60	7,616.82	27.15	19,111.05	25,235.61	6,124.56	32.05
Daily earnings	81.86	103.50	21.64	26.43	56.94	74.06	17.12	30.07
Maximum SSC (share)	0.11	0.09	-0.02	-13.94	0.02	0.02	0.00	-5.15
Change log earnings	0.02	0.03	0.01	69.72	0.02	0.04	0.02	72.17
Change log daily earnings	0.03	0.02	0.00	-10.12	0.03	0.04	0.00	4.15
Employment duration	342.10	342.56	0.45	0.13	335.84	340.97	5.14	1.53
Change employment duration	-2.40	1.44	3.84	-159.88	-2.88	0.37	3.24	-112.71
Unemployment duration	10.50	12.83	2.33	22.15	8.77	9.22	0.45	5.16
Unemployment duration (conditional)	74.13	75.81	1.68	2.27	83.78	79.43	-4.35	-5.19
Employment interruptions (shares)								
Employment interruption	25.30	23.69	-1.61	-6.38	25.60	21.98	-3.62	-14.13
Unemployment	14.48	17.18	2.69	18.60	10.54	11.69	1.15	10.94
Firm change	8.49	9.41	0.92	10.87	6.85	8.21	1.37	19.95
Recall	14.36	13.72	-0.64	-4.48	8.85	6.75	-2.10	-23.70
Birth	0.00	0.00	0.00	NaN	4.66	3.70	-0.96	-20.64
Parental leave	0.00	0.90	0.90	Inf	6.82	6.50	-0.31	-4.60
Sector (shares)								
Primary sector	4.02	2.94	-1.08	-26.95	1.27	1.11	-0.16	-12.73
Manufacturing	30.19	25.47	-4.72	-15.62	20.07	9.94	-10.12	-50.45
Construction	13.74	13.13	-0.61	-4.44	3.10	2.09	-1.01	-32.65
Public services	9.84	11.86	2.02	20.57	26.20	34.66	8.46	32.30
High skill services	15.91	17.98	2.08	13.05	16.68	14.94	-1.74	-10.43
Low skill services	4.07	9.36	5.30	130.11	8.95	11.41	2.46	27.51
Wholesale and retail	15.12	13.93	-1.19	-7.90	21.62	18.86	-2.75	-12.74
Age	38.71	40.42	1.70	4.40	38.49	41.46	2.96	7.70
Immigrants (share)	1.09	19.36	18.28	1,682.02	1.31	15.88	14.57	1,113.21
Number of observation	751,307.00	927,502.00	176,195.00	23.45	529,834.00	840,244.00	310,410.00	58.59

Note: The data include individuals who earned at least three times the monthly minimum security contribution basis per year in two consecutive years. Self-employed or farmers are excluded. The shares of employment interruptions (unemployment, firm change, births, parental leave) are measured over a two-year period. The unemployment share indicates the share of employees who had at least one unemployment spell in the last two years. Data on economic sectors are provided for 1990, instead of 1985, due to incomplete information prior to 1990.

Since 2015, the earnings at the bottom of the distribution have been growing stronger than at the top, for both men and women. The bottom decile increased by 10% for men and women, compressing the earnings distribution. In general, women's earnings distribution has a higher variance than men's. For example, women at the 75th percentile earned 2.25 times more than women at the 25th percentile in 2018; for men, this ratio is 1.85. This difference highlights the left-skewed earnings distribution of women, caused by a large number of women who work part-time. Compared to a similar sample from Norway (Halvorsen et al., 2022), the Austrian earnings distribution is more compressed in the lower half but is more dispersed in the upper half of the earnings distribution. It is much more compressed across the entire earnings distribution compared to the US (Guvenen et al., 2014).

The dashed line in Figure 2 shows that the evolution of the threshold, which is set annually by the social security agency, is closely tracked by the men's top earnings decile. Between 1980 and 2018, around 10% of men aged 25 to 55 earned more than the threshold, but only 2.5% of women.

3.2 Earnings volatility

To measure earnings growth volatility, we use the standard deviation of year-on-year changes in annual earnings. While the standard deviation and the variance have been used widely to measure earnings growth volatility (Haider, 2001; Gottschalk et al., 1994), others have used the differences in the 10th and 90th percentile to describe the changes (Drechsel-Grau et al., 2022). We prefer the standard deviation because it allows to decompose the variance into contributions by different groups. However, Figure 4 shows that both the p90-p10 dispersion measure and the variance indicate similar changes over time.

We exclude employees with very low and very high earnings to avoid the impact of outliers. In contrast, we do not delete observations based on their earnings gains because we want to maintain a consistent sample when we calculate the variance contributions of different groups. In Figure 3 we plot median year-on-year changes in annual earnings, these tend to be positive and small. They fluctuate around 2% between 1985 and 2000 and around 1% since then. More generally, for the large majority of employees, changes in annual earnings are modest and are within a narrow band. Throughout the period, the 25th percentile of the earnings growth distribution was almost always above -2.5% and the 75th percentile below 6.5% for men and 7.5% for women. The distance between the 25th and 75th percentile was also relatively constant at 6.5 pp for men and 7.5 pp for women. In contrast, the 10% largest gains have increased over time and the 10% largest losses have become smaller over time. The earnings losses (10th percentile) and the earnings gains (90th percentile) are about 5-10 pp greater for women than for men.

Figure 3 presents the patterns for the top and bottom deciles of the earnings growth distribution, by sex. Earnings losses, but also gains, have been greater for women than for men. The top 10% of earning gains have been increasing between 1980 and 1992 by around 10 percentage points for both men and women. While the bottom 10% of earnings losses remained stable for men, they have become smaller for women. Top earning gains for men have increased by 5 pp between 1980 and 1990 and by 10 pp for women. After 1990, the top earnings gains remained stable for men, but declined for women until 2005 and have been increasing since then. In 2018, men's and women's

10th percentile were around -10%, but women's 90th percentile at 25% is much higher than that of men's at 15%.

Figure 4 shows earnings volatility as the standard deviation of annual earnings growth (right panel) and as the p90-p10 difference in annual earnings growth, based on social security contributions and pay slip data. It shows that volatility trends are similar, irrespective of which of the two approaches we use to measure volatility or whether we use social security data alone or enrich it with pay slip data. Figure 4 reveals that volatility is substantially higher for women than for men. Drechsel-Grau et al. (2022) attribute this gap to women's labor supply changes caused by having children. Between 1980 and 1993, volatility for women increased steadily but then declined to levels just above those of the early 1980s until 2005. However, since the Global Financial Crisis (GFC), volatility for women has been increasing. For men, volatility spiked sharply in the early 1980s and again in the mid-1990s, but has generally trended downward, with a notable spike during the GFC.

Volatility levels, in contrast to volatility trends, differ depending on the data source. They are generally lower when measured using pay slip data compared to social security data. In 2010, for instance, the standard deviation of women's earnings growth was nearly 10 percentage points lower when calculated from pay slip data than from social security contributions. For men, the difference was approximately 2 percentage points. These discrepancies are partly due to the more complex structure of the social security system, which excludes certain types of earnings. As a result, earnings recorded in pay slip data tend to be higher, and year-on-year changes are more modest. Notable differences between the two data sources also emerge in the year a mother takes maternity leave, which typically spans from eight weeks before to eight weeks after the expected date of birth (Ahammer et al., 2020). In this period, the decline in earnings is less pronounced in pay slip data, as it includes earnings that are not captured in social security records. Maternity leave benefits are not included in either data source.

In contrast, for men, when we use the p90-p10 measure, volatility based on pay slip data is greater than that based on social security data. This discrepancy arises primarily from men who earn at or above the maximum social security contribution threshold. When an employee's earnings are top-coded in two consecutive years, any change in earnings is recorded as not having changed to the threshold change, masking larger fluctuations that are captured in the uncensored pay slip data. Consequently, the p90-p10 measures for social security and pay slip earnings align across much of the earnings distribution. However, volatility in social security data is notably muted within the top three earnings decile where earnings equal the maximum social security contribution threshold.

4 Analysis

4.1 Determinants of individual earnings volatility

To analyze the determinants of annual earnings volatility, we regress earnings volatility on a series of individual characteristics such as sex, age, immigration status, years since job start, economic sector, and earnings decile. We include the level and changes of the regional unemployment rate in the set of explanatory variables. The indicator of earnings volatility at the individual level is the standard deviation of log annual earnings of the past three years.[5] Note that the definition of individual earnings volatility differs from the definition of aggregate volatility used above.

The estimation results are tabulated in Table 2. The analysis shows that women's earnings volatility is, on average, 3.6 percentage points greater than that of men's. Holding all other factors constant, this amounts to a 40% greater volatility for women, given an average individual earnings volatility of 9%. Furthermore, younger employees have more volatile careers than older employees. Similarly, employees who entered the labor market within the past five years have a 5 pp greater volatility than employees who have at least 10 years of experience in the Austrian labor market. Immigrants have 15% higher volatility than natives. Employees in the bottom daily earnings decile have a 3 pp higher earnings volatility than employees in the 5th decile. The most volatile sector is the low skill service sector (+3.6 pp relative to the wholesale and retail sector) and the least volatile is the primary and manufacturing sector (-0.1 and -0.3).

In the second column of Table 2, we present results from estimations in which we control for the

[5]We use the standard deviation of the past three annual earnings instead of year-on-year changes to obtain a more structural account of an employee's earnings volatility. We use the standard deviation instead of average changes to avoid the netting out of gains and losses. The results remain qualitatively similar when using the absolute year-on-year changes in annual earnings.

frequency and the type of employment interruption (firm change, recall or parental leave). These results stress the role of employment interruptions for earnings volatility. When we include the type of interruption among the controls, the estimated volatility of the 25 to 30 age cohort drops to a quarter, compared to the results from column 1. In contrast, the coefficient on job starters shrinks only slightly. An employment interruption increases the earnings volatility by about 26 percentage points, but the effect depends on the type of employment interruption. Earnings volatility increases by 47 pp for an employee with a single interruption due to parental leave, by 31 pp for firm changes, and by 6 pp for employees who were recalled by their employer.[6] Earnings volatility is substantially greater for employees who had earnings interruptions in two out of three years than for employees who only had one interruption in three years. However, employees with interruptions in all three years have only a somewhat higher earnings volatility than those with interruptions in just one year.

Firm changes lead to greater earnings volatility than recalls. This is related to both greater volatility of employment durations and of daily earnings. For example, men who changed firms in 2018 were employed 50 days less per year than men who were recalled by their previous employer (290 days); the difference for women was 40 days. Firm changes also cause greater earnings changes than recalls. The first (9th) decile of the distribution of daily earnings changes for men and women who changed firms was -50% (+50%) as compared to -10% (+10%) for recalled employees.

Employment interruptions due to women's parental leaves increase volatility the most. The average number of days in employment over two years is the same for women who change firms and those whose employment is interrupted by parental leave, but employment durations change much more for parental leave interruptions. In 2015, the average change in women's employment duration was -50 days; women who changed firms spent about 25 days more in employment.

We estimate the same specification for earnings volatility when we use the earnings information augmented with pay slip data. The results are tabulated in Table 3. While social security data indicate that earnings volatility decreases with earnings, the pay slip data reveal a U-shaped pattern: employees in the bottom and top deciles experience higher earnings volatility compared to those in

[6] Note that these numbers are the sum of the coefficient on having one employment interruption and the coefficient on the type of the employment interruption.

the middle of the earnings distribution.

In columns 2 and 3 of Table 3, we present estimation results separately for men and women. Employment interruptions lead to more earnings volatility for women than for men. Strong gender differences in earnings volatility are evident at the tails of the earnings distribution. The additional effect for employees in the bottom and top decile is more than twice as high for men than for women. Furthermore, earnings volatility is greater for men in the 7th to 9th earnings deciles than for men in the 5th decile. For women, in contrast, there is no statistical difference in earnings volatility across deciles 5 to 9.

For the years, 2002 to 2012, a full-time part-time indicator is available. The estimates for theses years suggest that employees in full-time jobs have more stable earnings. This effect is almost three times as high for men (4.2 pp) than for women (1.5 pp). Pora and Wilner (2020) or Arellano et al. (2021) highlight the significant role of changes in the employment duration for explaining earnings volatility. And, although we have no information on hours worked, for the years 2002 to 2012, the data provide an indicator for full-time or part-time employment. The estimates suggest that employees in full-time jobs have more stable earnings than part-time employees. This effect is twice as high for men (4 pp) than for women (1.8 pp).

Notes:

In addition to employment interruptions which lead to volatility in employment durations, changes in the daily wage rate may also cause earnings volatility.[7] Table 2 highlights that employment interruptions cause large earnings volatility. This is also reflected in Figure 5 which shows that volatility of employment durations closely matches the volatility of annual earnings. We infer from this that it is volatility in employment duration rather than volatility in daily earnings that lead to overall earnings volatility.

However, the degree to which changes in employment durations predict changes in annual earnings depends on the position in the earnings distribution. Figure **??** shows that for employees in the lowest deciles, changes in annual earnings are much more correlated with changes in employment durations than for employees in the top deciles. Similarly, the correlation of changes in daily earnings with changes in annual earnings is more pronounced for higher than for lower deciles. The correlation coefficients for employment durations and daily earnings are of the same size for median earnings. The lower frequency of employment interruptions for employees with higher earnings and greater fluctuation in high wages contribute to this finding.

[7] Since we do not observe hourly earnings, we approximate the wage rate using daily earnings. This is likely to be a good approximation for men who work almost exclusively full-time, but less so for women where every other women is employed part-time. Thus, changes in daily earnings could also reflect changes in hours of work.

Table 2: Determinants of individual earnings volatility

	1985-2015				1997-2012
	full sample (ssc)		men (ssc)	women (ssc)	full sample (pay slip)
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
woman	0.036*** (0.002)	0.017*** (0.001)			0.005*** (0.0006)
age_grp = 25t30	0.051*** (0.005)	0.011*** (0.001)	0.013*** (0.001)	0.005*** (0.002)	0.002** (0.0006)
age_grp = 31t35	0.033*** (0.002)	0.006*** (0.0008)	0.007*** (0.0009)	0.004*** (0.0006)	0.002*** (0.0006)
age_grp = 46t50	-0.016*** (0.001)	-0.005*** (0.0004)	-0.003*** (0.0006)	-0.008*** (0.0005)	-0.004*** (0.0005)
age_grp = 51t55	-0.020*** (0.002)	-0.008*** (0.0006)	-0.004*** (0.0008)	-0.013*** (0.0010)	-0.004** (0.001)
immigrant	0.015*** (0.002)	0.0007 (0.0009)	0.003** (0.001)	-0.001* (0.0007)	-0.002* (0.0008)
jobstart < 5 years	0.051*** (0.003)	0.043*** (0.004)	0.062*** (0.004)	0.029*** (0.003)	0.050*** (0.004)
jobstart 6-10 years	0.013*** (0.001)	0.007*** (0.0005)	0.010*** (0.0009)	0.005*** (0.0006)	0.007*** (0.001)
decile = 1	0.033*** (0.001)	0.014*** (0.0006)	0.021*** (0.001)	0.007*** (0.001)	0.016*** (0.0001)
decile = 2	0.014*** (0.001)	0.004*** (0.0003)	0.001 (0.0008)	0.009*** (0.001)	0.003*** (0.0002)
decile = 3	0.008*** (0.0006)	0.002*** (0.0003)	-0.002*** (0.0005)	0.007*** (0.0008)	0.0009** (0.0003)
decile = 4	0.004*** (0.0002)	8.9×10^{-5} (0.0002)	-0.002*** (0.0003)	0.003*** (0.0004)	0.0001 (0.0001)
decile = 6	-0.003*** (0.0002)	9.39×10^{-5} (0.0002)	0.002*** (0.0004)	-0.002*** (0.0004)	0.002*** (0.0002)
decile = 7	-0.006*** (0.0004)	0.0003 (0.0003)	0.001* (0.0007)	-0.002*** (0.0007)	0.005*** (0.0007)
decile = 8	-0.013*** (0.0010)	-0.002** (0.0008)	-0.004** (0.002)	-0.003** (0.0009)	0.008*** (0.0010)
decile = 9	-0.025*** (0.001)	-0.009*** (0.001)	-0.014*** (0.002)	-0.005*** (0.0010)	0.012*** (0.001)
decile = 10	-0.024*** (0.002)	-0.026*** (0.002)	-0.032*** (0.002)	-0.019*** (0.001)	0.032*** (0.003)
sector = construction	0.021*** (0.001)	-0.017*** (0.0006)	-0.015*** (0.0005)	0.001 (0.001)	-0.016*** (0.0004)
sector = manufacturing	-0.003** (0.001)	-0.003*** (0.0007)	-0.0004 (0.0008)	-0.007*** (0.0007)	-0.005*** (0.001)
sector = primary	-0.001 (0.001)	-0.012*** (0.0007)	-0.009*** (0.0008)	-0.018*** (0.0008)	-0.008* (0.003)
sector = public_services	0.009*** (0.002)	0.003** (0.001)	0.004** (0.001)	0.002 (0.001)	-0.002 (0.001)
sector = services_highskill	0.009*** (0.001)	0.003*** (0.0005)	0.005*** (0.0004)	0.001* (0.0008)	0.003*** (0.0005)
sector = services_lowskill	0.036*** (0.0008)	-0.008*** (0.001)	0.006*** (0.001)	-0.019*** (0.001)	-0.003* (0.001)
1 interruption		0.259*** (0.007)	0.239*** (0.007)	0.275*** (0.006)	0.186*** (0.005)
2 interruptions		0.420*** (0.009)	0.363*** (0.007)	0.480*** (0.009)	0.336*** (0.007)
3 interruptions		0.302*** (0.002)	0.279*** (0.004)	0.315*** (0.002)	0.237*** (0.002)
firm change		0.048*** (0.004)	0.058*** (0.003)	0.040*** (0.005)	0.074*** (0.004)
recall		-0.195*** (0.004)	-0.177*** (0.004)	-0.199*** (0.003)	-0.152*** (0.002)
parental leave		0.210*** (0.015)	0.039* (0.019)	0.213*** (0.009)	0.084*** (0.019)
Fixed-effects					
year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Dependent variable mean	0.09111	0.09002	0.07500	0.10924	0.08697
Observations	10,452,399	10,268,907	5,763,953	4,504,954	5,583,649
Adjusted R^2	0.04931	0.46137	0.37207	0.52345	0.34236

Notes: Standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1, The dependent variable is the standard deviation of individual annual earnings between t and $t-2$. The variables are measured every 3 years starting in 1985 until 2015. Ssc indicates that the earnings measures is based on social security contributions in contrast to pay slips. Earnings deciles are calculated based on the average daily earnings of the past three years. The dummy variable recall, firm change and parental leave equal to one if any such employment interruption occured between t and $t-2$. Sector and age are identified in year t. The base group is the wholesale and retail sector.

4.2 Earnings volatility and employment interruptions

Employment interruptions are strong predictors of annual earnings volatility. To analyze this in more detail, we decompose the total variance of annual earnings growth — as opposed to individuals' variance which we examined above — into the variance arising from employees with continuous employment and those with interruptions in year t and $t-1$. Figure 7 shows that women (men) with employment interruptions account for 91% (85%) of annual earnings volatility, despite only 21% (22%) of all female (male) employees experienced employment interruptions in 2018.

Figure 8 shows that in 2018 recalls were the most common type of employment in our sample. Around 14% of all men and 7% of women were recalled by their employer. Firm changes accounted for interruptions for 7.5% of men and 6% of women. However, these numbers do not include firm-to-firm changes without employment interruptions, which were about 20% of all firm changes. Additionally, 4% of women took parental leave, compared to less than 0.5% of men.[8]

In Figure 9 we plot the contributions of different interruption types of overall annual earnings volatility. For men, firm changes are the largest contributor, accounting for about 40% of earnings volatility while they only 7.5% of male employees changed firms. Recalled employees contribute 20%, and men on parental leave contribute 2%. For women, 40% of annual earnings volatility arises from the 4% of women who are taking maternity leave, 22% from the 6% who changed firms, and 8% from recalled employees.

Earnings from pay slip data, as opposed to social security records, include maternity leave payments for the 8 weeks before and after birth. Using this additional information results in lower volatility levels for women in the year of giving birth. When pay slip data are used, the relative contribution of maternity leave to volatility drops to 30%, while firm changes and recalls contribute 30% and 10%. Figure 10 shows that firm changes and parental leaves are associated with greater changes in daily wages and fewer days of employment — and both are likely to increase volatility. While these results do not provide causal evidence that firm changes directly lead to more volatility, they highlight the significant role of employment interruptions for earnings volatility.

4.3 Groups with high earnings volatility

Having documented the sizeable role of employment interruptions for earnings volatility, we now identify groups who are characterized by volatile employment and who increase overall volatility. Table **??** highlights the following characteristics as predictors of high volatility: young ages (25 to 30 year of age), persons who have little or high formal educational attainment, immigrants with little formal education, and persons in the low-skill service sector. Men (women) with at least one of these characteristics accounted for 40% (37%) of the sample and contributed 70% (50%) of overall volatility in 2018.

[8] Note that women who gave birth are included in the sample only if their earnings exceed the minimum threshold in two consecutive years. This creates a selection bias toward mothers with stronger labor market attachment.

Figure 11 shows that employees aged 25 to 30 contributed the most to overall volatility in 2018, accounting for 30% of men's and 25% of women's earnings volatility. Men (women) in the bottom earnings decile contributed 26% (14%) of men's (women's) volatility. Volatility based on social security contributions is about 5 percentage points lower than volatility based on pay slips. For both men and women, the low-skill service sector accounted for a significant share of overall volatility (22%), and low-educated immigrant employees contributed the fourth-largest share (20%). Employees can belong to multiple groups. For example, an employee aged 25 to 30 may also be in the bottom earnings decile. Figure 12 shows that overlaps among groups are more common for men than for women. Overall, at least 55% of each group consists of employees who do not belong to any other group. For instance, 57% of men in the bottom decile are not aged 25 to 30, low-educated immigrants or employed in the low-skill service sector.

Figure 13 plots the share of employees with employment interruptions for each group. Employees in the low-skill service sector were most likely to experience interrupted employment spells: 50% of men and 45% of women had at least one employment break between 2017 and 2018. This is twice the rate for the average employee. Men in the bottom earnings decile and low-educated male migrants were 1.8 times more likely to have employment breaks. Young men aged 25 to 30 were 1.4 times more likely to experience interruptions.

For women, the likelihood of interruptions was more similar across different high-volatility groups. Women in the bottom earnings decile, persons aged 25 to 30 or low-educated immigrants were about 50% more likely to have interruptions than the average woman.

4.3.1 Age

Younger employees are more likely to change firms than older employees. Between 2017 and 2018, approximately 8% of men aged 25 to 30 changed firms, compared to about 6% of men aged 31 to 35. For women, the corresponding rates were 6.5% for those aged 25 to 30, and 4.5% for those aged 31 to 35. The variation across age groups was less pronounced for recalls. Among men, 12% of those aged 25 to 30 were recalled by their employer, compared to 11% of those aged 31 to 35. For women, recall rates were consistent across these age groups, with 8% of women aged 25 to 30 and 8% of women aged 31 to 35 being recalled.

In 1990, men (women) aged 25 to 30 accounted for 50% (60%) of earnings volatility. By 2000, this share had declined to 40% (35%). This reduction can be partly attributed to a decrease in the proportion of employees aged 25 to 30, which fell from 25% in the 1990s to 20% in 2000. For women, an additional factor contributing to this decline was the trend towards later childbirth, which further reduced the earnings volatility associated with this age group.

4.3.2 Low educated migrants

In 2015, 8% of women and 12% of men in our sample were low-educated immigrants, an increase from 4% and 8% in 1992. Although only 12% of men in our sample are immigrants, they contributed 22% to overall earnings volatility in 2018. In contrast, about 50% of all male employees are low-educated native men, but they contributed 40% to men's earnings volatility in 2015. The difference between female immigrants and female natives is less pronounced than for men: low-educated immigrant women (natives) contributed around 10% (30%) to women's overall earnings volatility and formed 10% (30%) of the female sample in 2015.

Low-educated immigrants are more likely to experience employment interruptions than low-educated natives. During the first five years of entering the labor market, 65% of immigrant men experienced an employment interruption, compared to only 40% of native men. For women, the rates are similar, 60% for immigrants versus 40% for natives. However, immigrants enter the (Austrian) labor market on average almost 10 years later than natives. For men, this employment interruption gap does not narrow over time and even after a decade in the Austrian labor market, around 40% of immigrant men still experience interruptions in employment, compared to about 20% of native men. For women, however, the gap becomes smaller over time and after 10 years experience in the Austrian labor market the interruption rates are 25% for immigrant women and 20% for native women.

The largest differences are observed for job recalls, where the gap between immigrants and natives has widened over time. This may be attributed to changes in the workforce composition in certain sectors, particularly in low-skill service jobs, following the EU enlargement which allowed easier access to the Austrian labor market (Breuss, 2016). This contrasts with earlier periods. During the 1980s and early 1990s, immigrants who arrived in Austria were primarily refugees or migrants from the collapsing Soviet Union and Yugoslavia. Male immigrants from that period predominantly worked in manufacturing and construction, while women were more often employed in public services and manufacturing — sectors with relatively more stable jobs than today's prevalent low-skill service sector jobs.

4.3.3 Bottom earnings deciles

Table 2 shows that annual earnings volatility is greatest for employees in the bottom and top earnings deciles. Other studies have highlighted similar patterns of high earnings volatility of the top percentiles, e.g., Drechsel-Grau et al. (2022) for Germany, Arellano et al. (2021) for Spain, Pora and Wilner (2020) for France, and McKinney et al. (2022) for the US.

However, volatility varies more for men than for women across the earnings deciles. This is largely due to exceptionally high volatility among men in the bottom two deciles, which accounted for approximately 45% of men's total volatility. In other words, a small group of low-earning men has significantly less stable employment compared to the majority of male employees. For women, volatility in the bottom two deciles is also notably high, accounting for 30% of women's total earnings volatility. Similarly, Ahn et al. (2023) document a segmented US labor market where 14% of workers are more than ten times as likely to be unemployed as a group representing 55% of the population with stable employment.

Figure 14 shows that the volatility across deciles correlates strongly with employment interruptions. Overall, job changes and recalls are less frequent for employees with higher daily earnings, except in the top decile, where they are relatively common. About 7.5% of employees in the top decile change jobs at least once per year, compared to 3.5% in the ninth decile and 8% in the bottom decile.

4.3.4 Low skill service sector

The manufacturing sector is the most stable sector, with 25% of men and 10% of women who account for just 10% and 7% of overall volatility. In contrast, the low-skill service sector is by far the most volatile sector for women. Women in this sector are more than twice as likely to change firms and nearly four times as likely to be recalled compared to the average female employee. The sector employs 12% of all women and contributes around 20% to overall volatility. Our definition of the low-skill service sector includes diverse sub-sectors such as food and accommodation services, services to buildings and landscapes, and other business support services. Along with construction and the primary sector, the low-skill service sector is characterized by seasonal employment patterns. The sector employs 10% of men but accounts for 30% of men's overall volatility. In contrast, the construction sector employs 12.5% of men but contributes only 12% of their overall volatility. The difference in volatility between these two sectors can be explained by employment interruption patterns. The construction sector has the highest recall rate of all sectors (around 35%), and about 7.5% of employees change firms each year. In the low-skill service sector, only 25% of employees are recalled, and about 15% change firms. Since recalls lead to lower volatility than firm changes, employees in the low-skill service sector have much more volatile careers.

Of the sub-sectors which are in the low skill service sector, employment activities stands out due to its high volatility. This sub-sector, which includes temporary and seasonal work, employs around 2.5% of all men but accounts for 12.5% of male volatility—nearly half of the low-skill service sector's earnings volatility. This sub-sector is less relevant for women, as it employs only 1% of women and accounts for 2.5% of their earnings volatility. However, employment is slightly more stable for women than for men: women in this sub-sector were employed for an average of 625 days over two years, compared to 600 days for men.

4.4 Earnings volatility and demographic trends

4.4.1 Cohorts

Figure 15 plots the role of birth cohorts for the dynamics of earnings volatility. It highlights that every cohort contributes significantly to overall volatility levels when the cohort is young, and that the contribution gradually declines as the cohort grows older. To compare cohorts consistently across time, we abstract from the role of immigrants in this section and focus exclusively on natives. We discuss the role of immigrants separately below.[9]

In the early 1980s, the careers of women who were born before WWII were already relatively stable. At the same time, women who were born between 1946 and 1955 were in their 20s and 30s and experienced high volatility due to childbirth, child care, and early career dynamics. Moreover, the baby boomer generation (i.e., those born between 1956 and 1965) entered the sample during this period. Due to the large size of this cohort, the sample

[9]Employment records are only available from 1960. Thus, we cannot identify immigrants who arrived before 1960 because cohorts in our sample that entered the Austrian labor market before 1960 include both natives and immigrants. However, in 1980 only 4% of the active labor force were immigrants (Statistik Austria, 2024f), so this is unlikely to bias our descriptive analysis.

increases for observations from between 1981 and 1989 by 15%, and the share of employees who were younger than 31 increases from 21% to 25%. The increase of the sample size was much stronger for women (+15%) than for men (+5%). Figure 15 shows that the substantial increase in women's volatility between 1980 and 1990 is largely driven by women born between 1956 and 1965. A similar pattern can be observed for men, although the relative effect of the boomer cohort was smaller because men from earlier cohorts already had much higher employment rates than women.

The early 1980s were also characterized by an overall increase in unemployment, which affected all cohorts. Unemployment was very low at the end of the 1970s and the unemployment rate increased from 1.5% in 1980 to 4% in 1983 and remained at that level until 1998 (Statistik Austria, 2024*d*). An increase in employment breaks can be observed for all age groups, but the increase was particularly strong for young employees. The increase in volatility levels by more than 50% between 1981 and 1989 was driven by both deteriorating labor market conditions and a large influx of young employees.

The decline in earnings volatility since the mid-1990s is also correlated with cohort dynamics. During that time, the careers of people born between 1956 and 1965 became more stable, while younger cohorts were smaller. Consequently, the average age increased from 38.5 in 1997 to 41.2 in 2010. Note that while the overall decline in men's earnings volatility between 1993 and 2007 appears modest, the decline for male natives was much stronger as immigrants worked in more volatile jobs. (See Figure 16.)

4.4.2 Immigration

The Austrian labor market has been characterized by large migration and refugee inflows since the 1980s. During the Yugoslav war and its aftermath, the share of foreign employees increased from 4% in 1985 to 10% in 1990 (Statistik Austria, 2024*d*). This share continued to rise, reaching 12% by 2011, when labor market access restrictions were lifted for the new member states that joined the EU in 2008 (Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia, and Slovenia). Between 2011 and 2015, the share of foreign employees increased to 15% (Statistik Austria, 2024*d*). In consequence, as immigrants' earnings are substantially more volatile than those of natives, we find increases in earnings volatility when the share of foreign employees increases.

The contribution of male immigrants to earnings volatility increased from 6% in 1989 to over 12% in 1992. It rose to 24% by 2012 and to 26% in 2013, reflecting a large influx of immigrants after labor market access restrictions were lifted. The contribution of female immigrants evolved more gradually and was much lower in magnitude, though still above than that of native women. This difference partly reflects sectoral allocation, as immigrant women are overrepresented in more volatile sectors. However, within the same sectors, volatility differences between native and immigrant women are much smaller than those observed between native and immigrant men. This finding contrasts with Hofer et al. (2017) who found that the earnings gap between natives and immigrants was larger among women than men.

Figure 16 shows that while volatility for native men has been declining since 1992, it has remained stable or slightly increased for immigrant men. Thus, the relative increase in immigrants' contribution to volatility reflects both their growing numbers and the more stable careers of native men.

The sectoral composition of employment for immigrants and natives explains some of these dynamics. In the 1990s, male immigrants' first five years of employment were predominantly in construction and manufacturing, and in each sector about 30% of employees were immigrants. By 2015, this share had declined to 20%, while low-skill services became the largest receiving sector, employing 27% of male immigrants (up from 15%). Since manufacturing jobs are the least volatile and low-skill services are the most volatile, this sectoral shift has increased earnings volatility for immigrants. Low-educated immigrants, in particular, are more likely to work in jobs with frequent recalls and seasonal patterns. Only 50% of male immigrants were continuously employed during their first five years, compared to over 30% with recalls. In contrast, volatility for low-educated natives in their first five years has been continuously decreasing.

For immigrant women, the share employed in low-skill services during their first five years increased from 30% in 1990 to over 50% in 2015. Meanwhile, the share in manufacturing declined from 20% in 1990 to 7% in 2015.

4.4.3 Births and parental leave

Births, and maternal leaves in general, explain approximately 40% of women's earnings volatility. Births increased from 20,000 to 30,000 between 1980 and 1990. This increase reflects demographic change as younger cohorts are having their children later and our sample is restricted to 25 to 55 year old employees. For example, in 1980, about 50% of births occurred to mothers younger than 25, compared to just 11% in 2020 (Statistik Austria, 2024*c*). The number of births in our sample declined from 30,000 in 1990 to 23,000 in 2005 and increased to 32,000 in 2018 (Figure 17). While the number of births recorded by mothers in our sample amount only to around one third of all births in Austria, the fertility trends in our sample match those of official birth statistics.

Figure 18 shows the contributions to earnings volatility from women who gave birth and those on maternity leave, by year. Importantly, women on maternity leave are a subset of all mothers, as all women in the sample are eligible for maternity leave. Differences between these groups can largely be attributed to parental leave reforms. For an overview of reforms since 1980, see Kleven et al. (2024) who analysed the impact of the reform on mothers' child penalty.

The reform of 1990, which extended parental leave from 12 to 24 months, resulted in more mothers delaying their return to the labor market. This reduced the number of women meeting the dataset's inclusion criteria, causing earnings volatility to drop in 1991 due to compositional changes. In 1996, parental leave was reduced to 18 months. Although this increased the number of women in the sample, volatility rose only marginally. Later reforms in 2008 and 2010 introduced incentives for shorter parental leaves (Rille-Pfeiffer and Kapella, 2022), increasing the number of mothers on leave in the sample. Combined with higher birth rates, these reforms resulted in more volatility during this period.

In summary, while spikes and drops in volatility are directly linked to parental leave reforms, long-term trends are primarily driven by fluctuations in birth rates.

4.5 Earnings volatility across cohorts

4.5.1 Age

Figure 19 presents annual earnings volatility over career stages for cohorts of native employees. It shows that volatility tends to be greater at younger ages and declines as people age and careers become more stable.

For men, there are two noticeable differences across birth cohorts. First, younger cohorts have higher earnings volatility below the age of 30 than older cohorts. This is largely due to more men who continue to tertiary education and who either have student jobs or volatile early careers. This can be seen in the share of native employees who enter the labor market between ages 20 and 25: the proportion increased for men from 27% in the oldest cohort (1956–1960) to 41% in the youngest cohort (1981–1985). For women, the share increased from 15% to 35%. Although daily earnings for younger cohorts are more volatile than for older cohorts, their employment is relatively more stable.

Second, earnings volatility has been declining across all cohorts after age 35. This reduction is due to fewer employment interruptions, recalls, or job changes and is evident in all earnings quartiles. For instance, at age 30, approximately 6% of men in the 1981 cohort changed jobs, compared to 7% in the cohort born 20 years earlier. Similarly, the share of recalled employees decreased from 11.5% in older cohorts to 9.5% in younger cohorts. Thus, recalls and job changes after age 35 have become less frequent in younger cohorts than in older cohorts.

One contributing factor to the decreased volatility in younger cohorts is the changing sectoral composition of employment. Older cohorts were more likely to work in the construction sector, which is typically more volatile compared to most other sectors. Furthermore, volatility in the construction sector itself has been declining, particularly for older employees. More broadly, employment has become less volatile for natives in most sectors, with exceptions in the primary sector, public services, and low-skill services.[10]

For women aged 25 to 35, volatility trends differ from those of men. As the average age at first birth has increased, the volatile post-birth period for women has shifted to older ages. Consequently, careers of women aged 25 and 30 have become more stable for younger cohorts, whereas employment after age 30 has become more unstable compared to older cohorts. This change is most pronounced among women in the top earnings quartile, who in younger cohorts are more likely to have formal education, start families later, and delay their labor market entry due to their longer education.

Panel A in Figure 20 plots the annual earnings volatility from the second to the 10th year after the first birth

[10] Note that civil servants are excluded from our data. Over time, institutions have gradually reduced the number of civil servant positions, leading to a much smaller share of civil servants in younger cohorts. However, the public sector has increased its overall number of employees, growing from 27% in 1990 to 39% in 2018 for women and from 10% to 14% for men. New hires in the public sector are no longer granted civil servant status but are employed under private-sector contracts. As a result, employees in younger cohorts with relatively stable careers who might have previously become civil servants are now included in our sample. This shift contributes to the lower volatility observed in younger cohorts compared to older ones.

for different cohorts of mothers and shows a gradual decline in earnings volatility after first birth. [11]

The standard deviation of annual earnings growth does not differ much across cohorts, but it is slightly lower for younger cohorts by the eighth year after the first birth. In contrast, the volatility in daily earnings growth and the volatility in annual employment durations reveal substantial differences across cohorts. Notably, volatility in daily earnings during the first few years after birth has been higher for younger cohorts. It is likely that increased part-time employment rates among mothers have contributed to this changing pattern. Furthermore, volatility in changes in employment durations has been decreasing, particularly after the fifth year after having had the first child.

The labor market attachment of mothers after their first child has increased, resulting in a changed sample composition. The left panel of Figure 21 shows that 82% of mothers born in 1972 returned to the labor market within 10 years after the first birth as compared to 70% of mothers born in 1955. The center panel highlights that this increase in return rates is mainly driven by mothers with one or two children. While the rate of returns remained unchanged for mothers with 3 or more children, mothers with one or two children born in 1972 returned at least 10 percentage points more frequently than those born in 1960. The right panel indicates that the increase in the return rate was similar across pre-first birth earnings quartiles. This is in line with research by Frühwirth-Schnatter et al. (2014) who show that late returns are less likely, the higher the education of mothers (and educational attainment levels increased over time).

In contrast to the return rate of mothers, the cumulative employment duration conditional on return within 10 years after first birth has changed little across cohorts. The left panel of Figure 22 shows that the employment duration declined from 5.3 years for the 1955 cohort to 4.6 years for the 1965 cohort but has increased for younger cohorts.

The greatest heterogeneity in the number of years in employment is linked to the number of children. See the central panel of Figure 22. Mothers of an only child are employed 6 out of 10 years, mothers with two children 4.5 years, and mothers with 3 or 4 children are employed for 3.5 and 3 years. This pattern has remained relatively constant across cohorts with the exceptions of mothers with two children: Mothers born in 1972 are employed 4.6 years compared to 4.2 year for mothers born in 1960. The right panel suggests that the recent increase is driven by mothers with higher earnings.

The decline in the cumulative employment duration is likely to be linked to extensions of maternity leave in 1990 and 2000. Figure 23 shows that changed fertility pattern would predict the opposite as the number of births per mother declined slightly for the cohorts 1960 to 1967 and increased for the cohorts 1969 to 1972.

[11] We focus on the years after women's first child, recognizing that volatility during this period is notably higher than in the years preceding childbirth. A consistent comparison across cohorts requires observing the entire fertility cycle and an additional 10 years post-birth. The youngest cohort of mothers for whom we have sufficient data are of 1972. These mothers were 37 years old in 2009 and we can follow them for 10 years post-birth. Since births are recorded only from 1972 onward, the oldest cohort included in our analysis was born in 1956 (i.e., aged 16 in 1972). To improve the comparability across cohorts, we exclude immigrant mothers. Additionally, as the age at first birth has been increasing, we include observations starting at age 18 (instead of 25) and remove earnings restrictions to capture mothers with lower labor market attachment.

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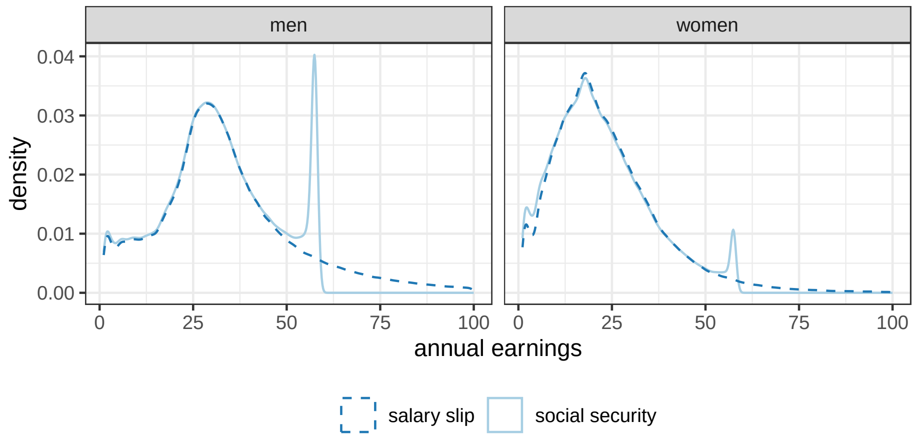
A Appendix

Figure 1: Annual earning density, by data source



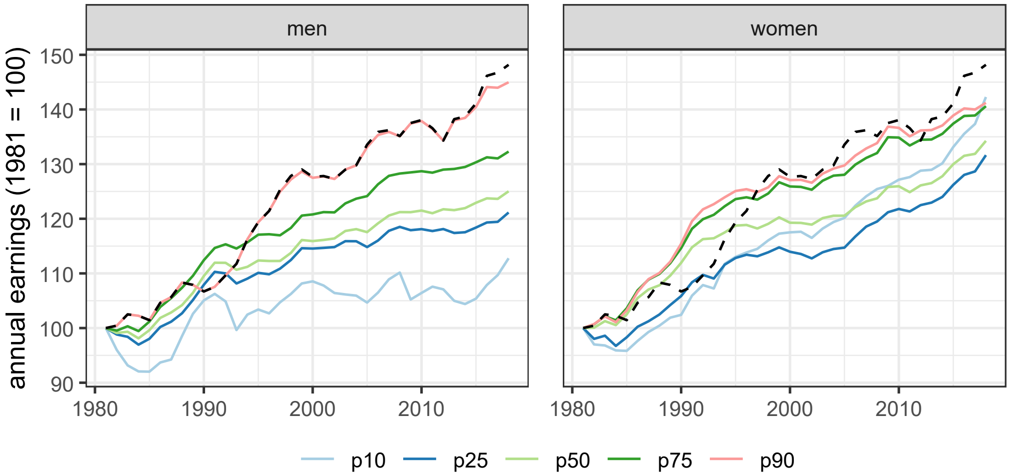
Notes: The graph illustrates the earnings density based on two data sources: salary slips and social security contributions. Social security data are top-coded, while salary slips include earnings during maternity leave (8 weeks prior to and after childbirth), which are excluded from social security contributions. The sample consists of employees aged 25 to 55 in the year 2010.

Table 3: Determinants of individual earnings volatility

	1997-2012			2005-2012	
	full sample (pay slip)	men (pay slip)	women (pay slip)	men (pay slip)	women (pay slip)
Model:	(1)	(2)	(3)	(4)	(5)
woman	0.005*** (0.0006)				
age_grp = 25t30	0.002** (0.0006)	0.007*** (0.001)	-0.005* (0.002)	0.009*** (0.0007)	-0.004* (0.0009)
age_grp = 31t35	0.002*** (0.0006)	0.004** (0.001)	0.0007 (0.0005)	0.006*** (0.0004)	0.002** (0.0003)
age_grp = 46t50	-0.004*** (0.0005)	-0.0006 (0.0006)	-0.007*** (0.0005)	-0.002** (0.0003)	-0.007*** (0.0004)
age_grp = 51t55	-0.004** (0.001)	0.0004 (0.001)	-0.009*** (0.001)	-0.002 (0.0008)	-0.010*** (0.0006)
immigrant	-0.002* (0.0008)	0.001 (0.001)	-0.003** (0.0010)	0.003* (0.0008)	-0.0007* (0.0002)
jobstart < 5 years	0.050*** (0.004)	0.062*** (0.006)	0.037*** (0.002)	0.050*** (0.001)	0.031*** (0.002)
jobstart 6-10 years	0.007*** (0.001)	0.007*** (0.001)	0.006*** (0.001)	0.009*** (0.0003)	0.008*** (0.0005)
decile = 1	0.016*** (0.0001)	0.022*** (0.001)	0.009*** (0.0008)	0.015*** (0.0010)	0.001 (0.001)
decile = 2	0.003*** (0.0002)	-0.003** (0.0007)	0.011*** (0.001)	-0.002 (0.0010)	0.004** (0.0006)
decile = 3	0.0009** (0.0003)	-0.004*** (0.0005)	0.008*** (0.0006)	-0.004* (0.001)	0.003* (0.0008)
decile = 4	0.0001 (0.0001)	-0.003*** (8.68×10^{-5})	0.004*** (0.0002)	-0.003*** (6.82×10^{-5})	0.002** (0.0003)
decile = 6	0.002*** (0.0002)	0.004*** (0.0002)	-0.001* (0.0004)	0.005*** (0.0001)	-0.0002 (0.0004)
decile = 7	0.005*** (0.0007)	0.009*** (0.0004)	-0.001 (0.001)	0.009*** (0.0004)	-0.0003 (0.001)
decile = 8	0.008*** (0.0010)	0.015*** (0.0005)	-0.001 (0.001)	0.014*** (0.0004)	-0.0001 (0.001)
decile = 9	0.012*** (0.001)	0.022*** (0.001)	-0.0009 (0.002)	0.020*** (0.0009)	0.001 (0.001)
decile = 10	0.032*** (0.003)	0.046*** (0.003)	0.015*** (0.003)	0.043*** (0.0004)	0.015** (0.002)
sector = construction	-0.016*** (0.0004)	-0.014*** (0.0002)	0.002* (0.001)	-0.014*** (0.0001)	0.0006 (0.0006)
sector = manufacturing	-0.005*** (0.001)	-0.004** (0.001)	-0.007*** (0.001)	-0.002* (0.0004)	-0.003* (0.0009)
sector = primary	-0.008* (0.003)	-0.008* (0.004)	-0.008** (0.003)	-0.009* (0.002)	-0.011*** (0.0006)
sector = public_services	-0.002 (0.001)	0.0004 (0.002)	-0.002 (0.001)	0.0007 (0.001)	-0.0008 (0.0003)
sector = services_highskill	0.003*** (0.0005)	0.003*** (0.0005)	0.005*** (0.0006)	0.002 (0.0009)	0.005** (0.0009)
sector = services_lowskill	-0.003* (0.001)	0.008*** (0.001)	-0.014*** (0.001)	0.009*** (0.0004)	-0.009** (0.001)
1 interruption	0.186*** (0.005)	0.183*** (0.009)	0.187*** (0.004)	0.200*** (0.004)	0.189*** (0.004)
2 interruptions	0.336*** (0.007)	0.302*** (0.010)	0.379*** (0.004)	0.317*** (0.007)	0.384*** (0.006)
3 interruptions	0.237*** (0.002)	0.227*** (0.004)	0.243*** (0.004)	0.230*** (0.006)	0.239*** (0.007)
firm change	0.074*** (0.004)	0.076*** (0.004)	0.070*** (0.003)	0.070*** (0.005)	0.068*** (0.002)
recall	-0.152*** (0.002)	-0.143*** (0.004)	-0.152*** (0.002)	-0.150*** (0.005)	-0.150*** (0.004)
parental leave	0.084*** (0.019)	0.056* (0.022)	0.081*** (0.016)	0.030 (0.020)	0.060*** (0.004)
full time				-0.042*** (0.002)	-0.015** (0.002)
Fixed-effects					
year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Dependent variable mean	0.08697	0.08215	0.09295	0.07958	0.09026
Observations	5,583,649	3,090,504	2,493,145	1,571,248	1,342,108
Adjusted R^2	0.34236	0.30676	0.38483	0.32208	0.38992

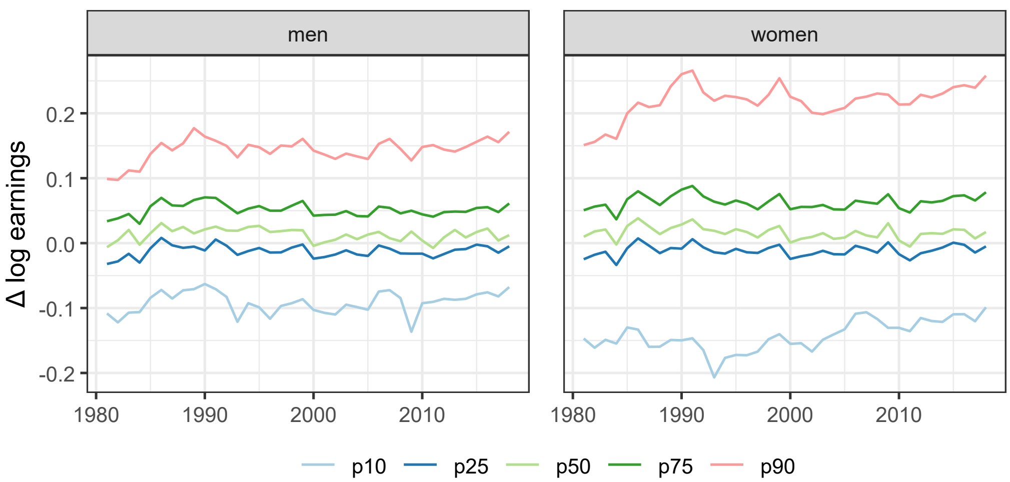
Standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1, The dependent variable is the standard deviation of individual annual earnings between t and $t-2$. The variables are measured every 3 years starting in 1985 until 2015. Ssc indicates that the earnings measures is based on social security contributions in contrast to pay slips. Earnings deciles are calculated based on the average daily earnings of the past three years. The dummy variable recall, firm change and parental leave equal to one if any such employment interruption occured between t and $t-2$. Sector and age are identified in year t. The base group is the wholesale and retail sector.

Figure 2: Growth in annual earnings and maximum social security contribution basis (100 = 1981)



Notes: The figure displays the growth of annual earnings for specific percentiles of the earnings distribution. The dashed line indicates the growth of the maximum social security contribution basis. Since more than 10% of men aged 25 to 55 have been earning at least the maximum social security contribution basis in most years, growth in men's top earnings decile is determined by changes in the maximum social security contribution basis.

Figure 3: Distribution of year-on-year changes in annual earnings

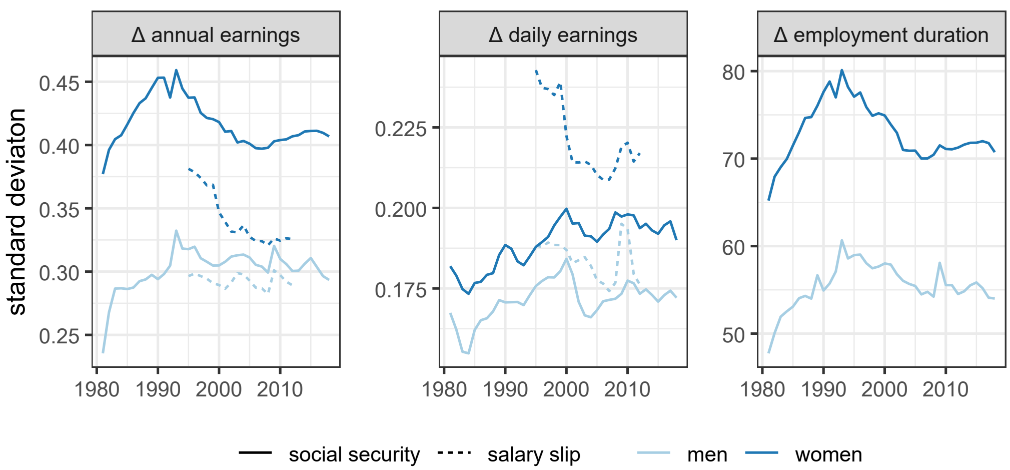


Notes: The figure illustrates specific percentiles of the year-on-year log annual earnings growth distribution. Earnings are defined based on social security contributions. The sample consists of employees aged 25 to 55.

Figure 4: Earnings volatility, by data source and volatility measure

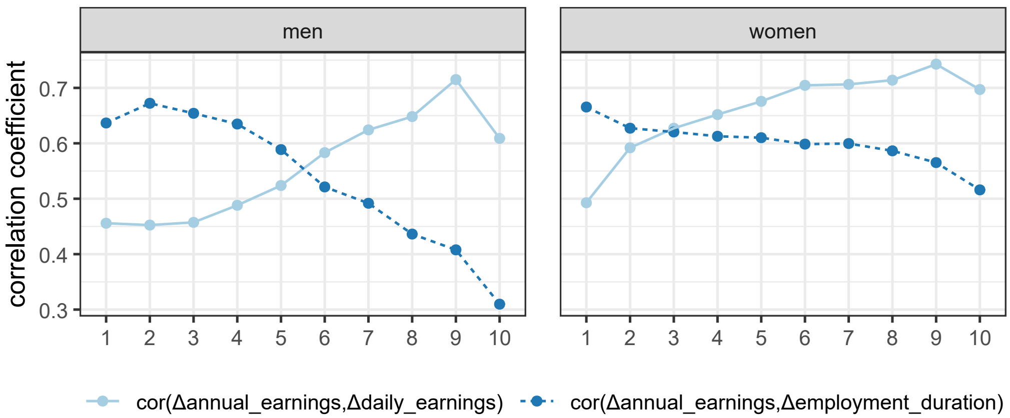
Notes: The figure illustrates two dispersion measures of year-on-year log annual earnings growth: the p90-p10 gap (90th percentile minus 10th percentile) and the standard deviation. The solid line represents earnings based on social security data, while the dashed line represents earnings based on salary slips. The sample consists of employees aged 25 to 55.

Figure 5: Annual earnings volatility, daily earnings volatility and employment duration volatility



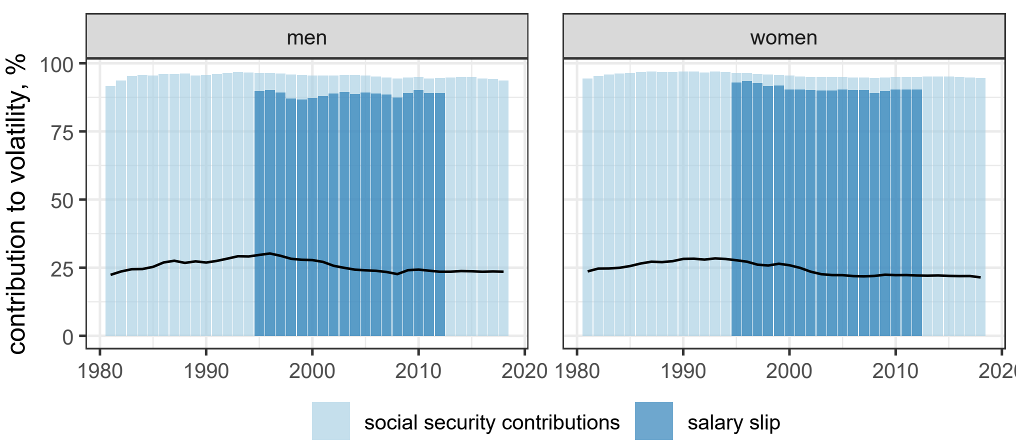
Notes: This figure illustrates volatility, measured as the standard deviation, for three variables: annual earnings, daily earnings, and employment duration. Volatility in annual earnings changes (left panel) can be attributed to volatility in wage rate changes (center panel) or volatility in employment duration changes (right panel). The solid line represents earnings derived from social security contributions, while the dashed line represents earnings based on salary slips for the years where this data is available. The sample includes employees aged 25 to 55.

Figure 6: Correlation between changes in annual earnings, changes in daily earnings and changes in employment duration, across earnings deciles



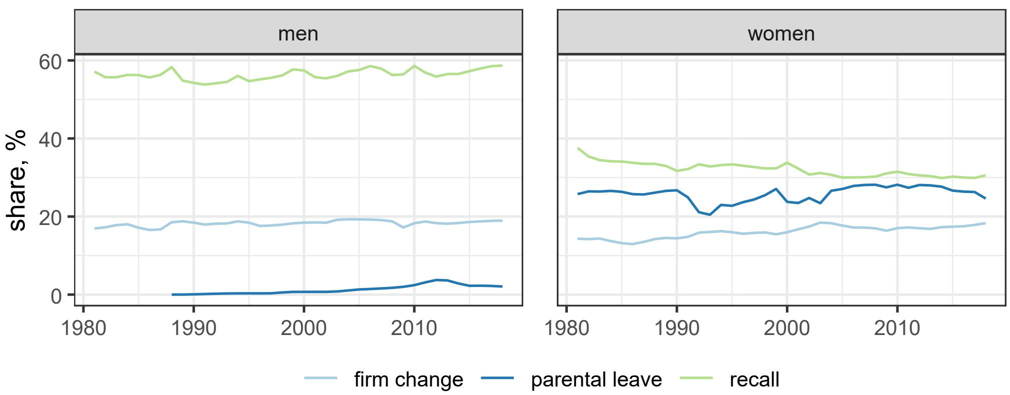
Notes: Each dot represents the correlation coefficient between two variables. The changes in annual earnings and changes in daily earnings or changes in annual earnings and changes in the employment duration within the daily earnings decile for the year 2010.

Figure 7: Volatility contribution of employees with employment interruptions



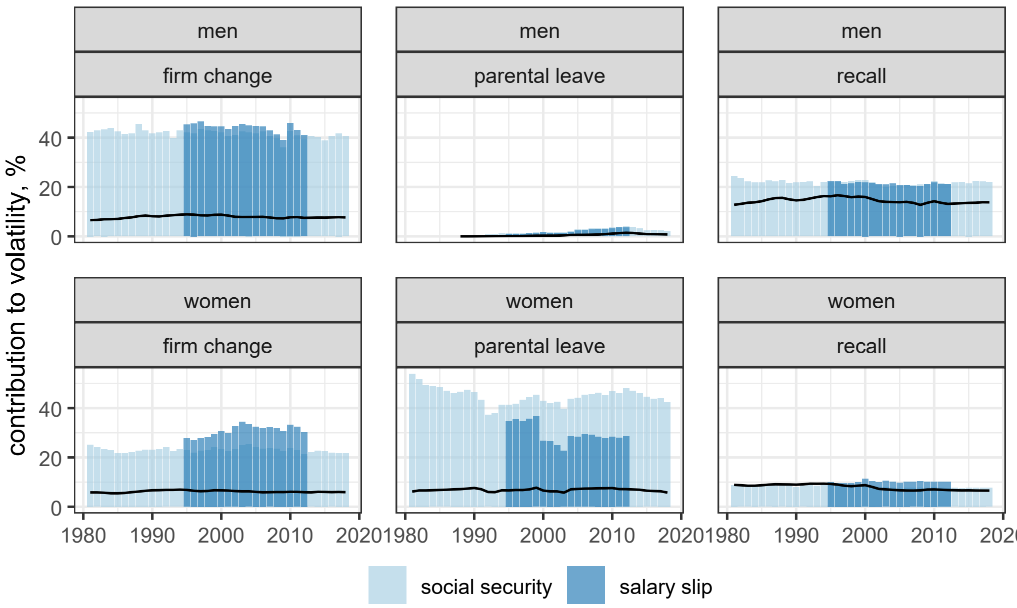
Notes: The figure illustrates the contribution to total earnings volatility (bars) by employees with at least one employment interruption during the observed two-year period. The black line represents the share of employees experiencing at least one employment interruption. Volatility contributions are calculated using variance decomposition. The light blue bars represent earnings volatility contributions based on social security data, while the dark blue bars correspond to earnings derived from salary slips.

Figure 8: Type of employment breaks as a share of total employment breaks



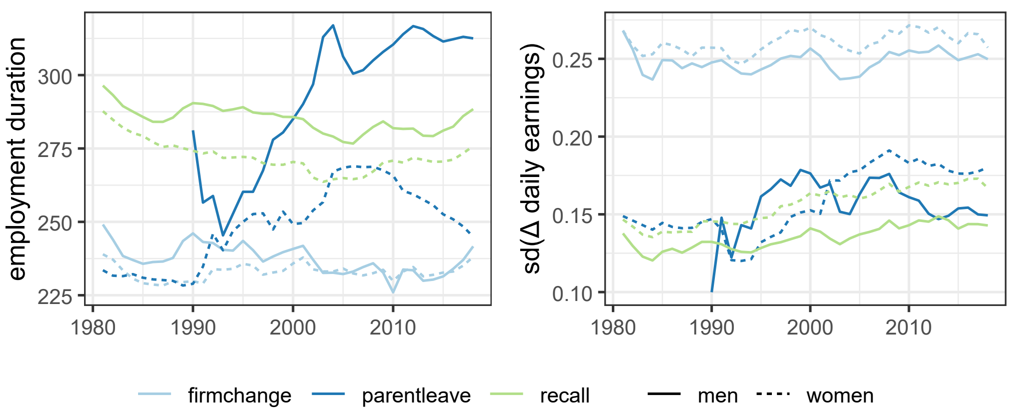
Notes: The figure shows the distribution of employment interruptions, categorized by type: parental leave, recall, and firm change. If an employee had multiple types of interruptions, they are assigned to one category based on the following hierarchy: parental leave > recall > firm change. In this hierarchy, parental leave is prioritized over the other types, and recall is prioritized over firm change.

Figure 9: Volatility contribution of different break types



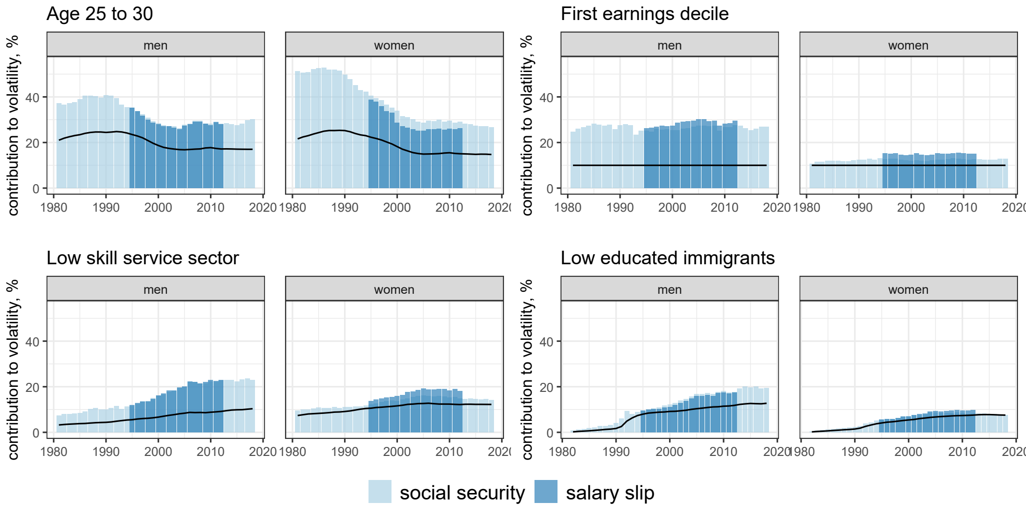
Notes: The figure illustrates the contribution to total earnings volatility (bars) by employees who changed firms in year t or $t-1$ (left panel), took parental leave (centre panel) and were recalled by their employer (right panel). The black line represents the share of employees with the respective characteristic. Volatility contributions are calculated using variance decomposition. The light blue bars represent earnings volatility contributions based on social security data, while the dark blue bars correspond to earnings derived from salary slips.

Figure 10: Annual employment duration and volatility in daily earnings by type of employment interruption



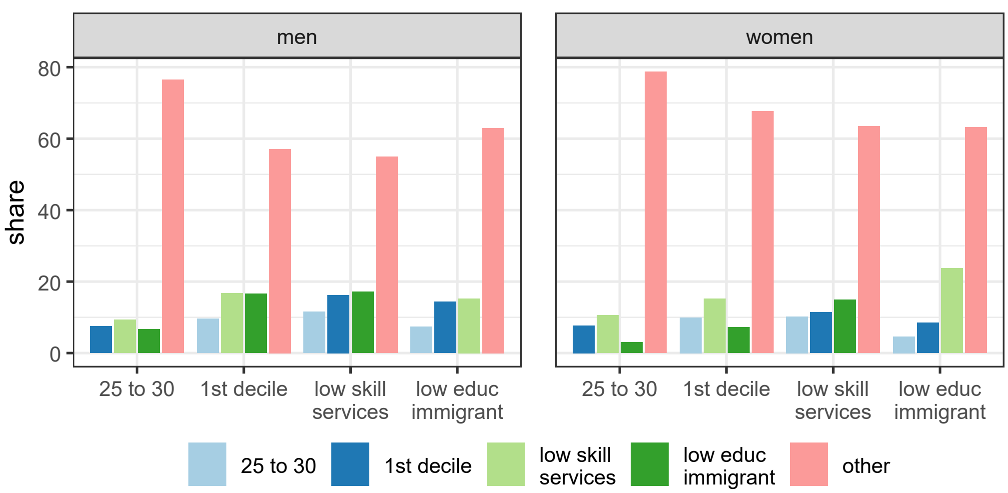
Notes: The figure illustrates two metrics: annual employment duration (left panel) and the standard deviation of year-to-year changes in daily earnings (right panel). Annual employment duration is calculated as the average number of days employed during year t and year $t-1$, categorised by three types of employment interruptions: firm change, parental leave, and recall. The standard deviation of year-to-year changes in daily earnings is also categorised by the three type of employment interruption. Earnings data are derived from social security contributions. If an individual had multiple types of employment interruptions within the two-year period, they are classified according to the following hierarchy: parental leave $>$ recall $>$ firm change. In this hierarchy, parental leave is prioritized over the other types, and recall is prioritized over firm change.

Figure 11: Contributions to volatility, by group and data source



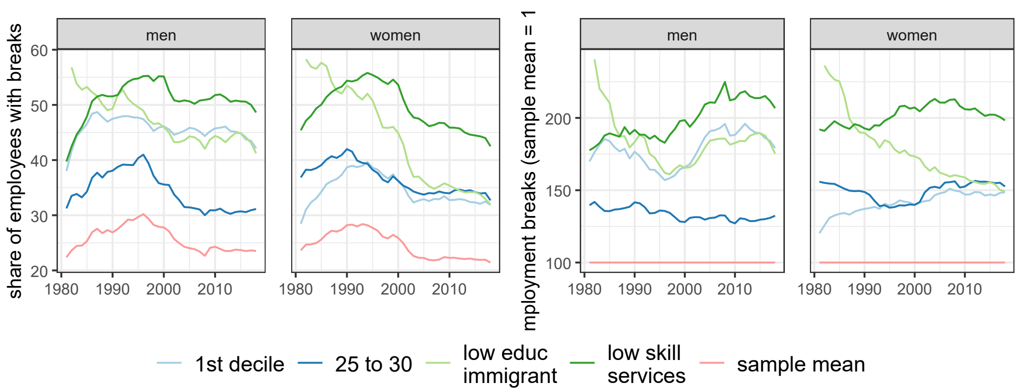
Notes: The figure illustrates the contribution to total earnings volatility (bars) by employees who are aged 25 to 30 in year t or $t-1$ (top left panel), belonged to the bottom earnings decile within the sex, birthyear cell (top right panel), received the majority of their earnings from the low skill service sector (bottom left panel) and for employees who are low skilled immigrants (bottom right panel). The black line represents the share of employees with the respective characteristic. Volatility contributions are calculated using variance decomposition. The light blue bars represent earnings volatility contributions based on social security data, while the dark blue bars correspond to earnings derived from salary slips.

Figure 12: Overlap of high volatility groups, share of employees



Notes: This figure depicts the overlap the four high volatility groups as employees can be part of multiple groups. The category "other" encompasses employees who are not categorised as 'high volatility groups'. For example, 75% of employees aged 25 to 30 are neither in the bottom earnings decile, nor low educated immigrants and do no work in the low skill sector. Around 10% of the employees aged 25 to 30 also work in the low skill service sector.

Figure 13: Share of employment breaks

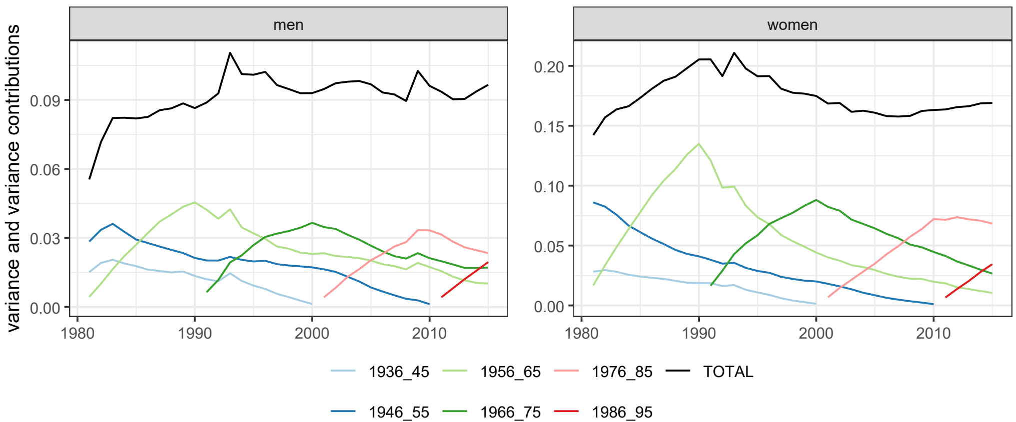


Notes: This figure illustrates the share of employees who have at least one employment interrutpion in year t or $t-1$ for each of the high volatility group (left panel). The right panel presents the same statistic, but expressed relative to the average share of employment interruptions in the full sample.

Figure 14: Share of employment breaks, job changes, recalls, by earnings decile

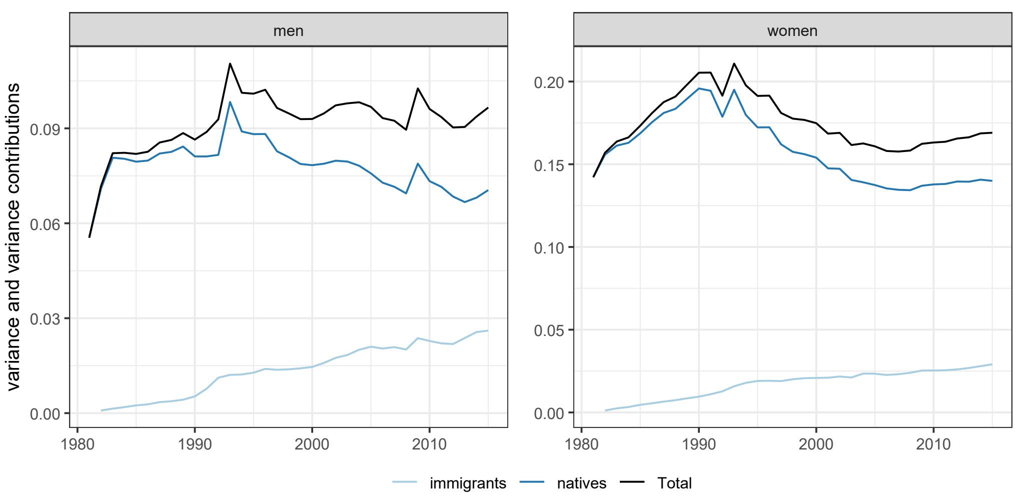
Notes: This figure illustrates the share of employees with at least one employment interruption in year t or $t-1$ (left panel), employees recalled at least once (center panel), and employees who changed firms (right panel) across daily earnings deciles in the year 2018. The daily earnings deciles are defined within the dimensions of year, age, and sex. The position in the daily earnings distribution is determined by the average daily earnings over the two-year period. Earnings are derived from social security contributions.

Figure 15: Volatility decomposition, by cohort group



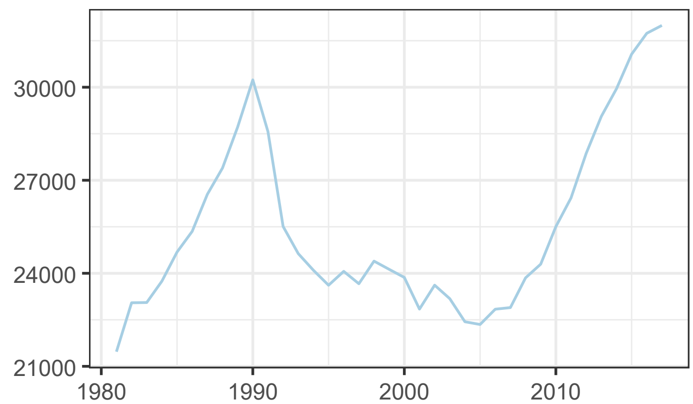
Notes: This figure illustrates annual earnings volatility for the different earnings cohorts. The sample includes 25 to 55 year olds of each cohort and earnings is based on social security contributions.

Figure 16: Volatility decomposition, by immigrant status



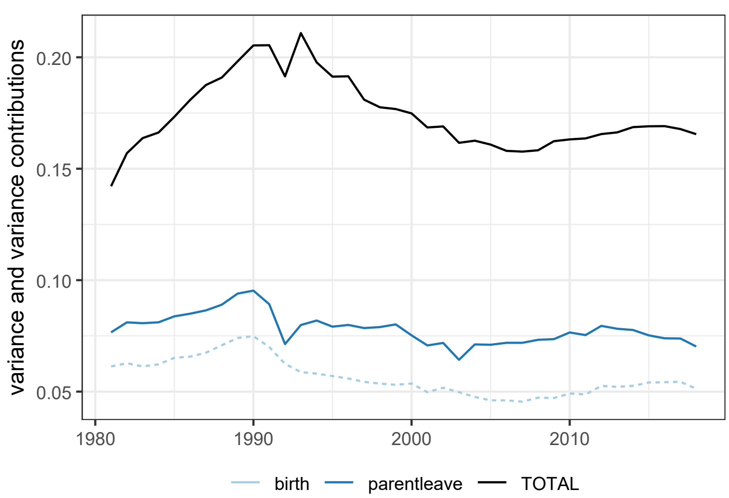
Notes: This figure illustrates annual earnings volatility for natives and immigrants. Note that the immigration status is derived indirectly as described in section 2. The initial stock of immigrants in our sample is not known and employees who had entered the labour market before 1960 are categorised as natives. The sample includes 25 to 55 year olds of each cohort and earnings is based on social security contributions.

Figure 17: Number of births



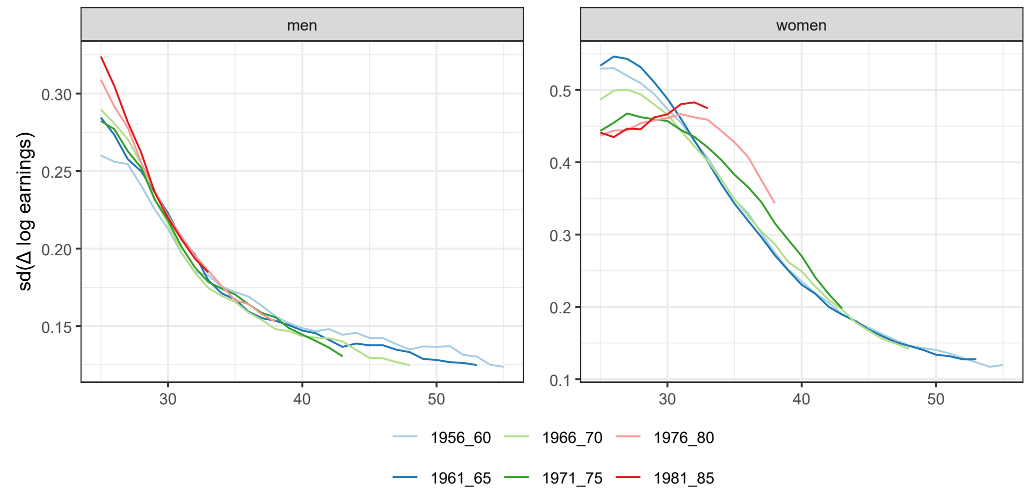
Notes: The figure depicts the total number of births recorded in our sample. Note that this number is around one third of all births recorded by Statistik Austria which is due to our data restrictions related to age and labour market attachment.

Figure 18: Volatility decomposition, by women's parental leave and birth status



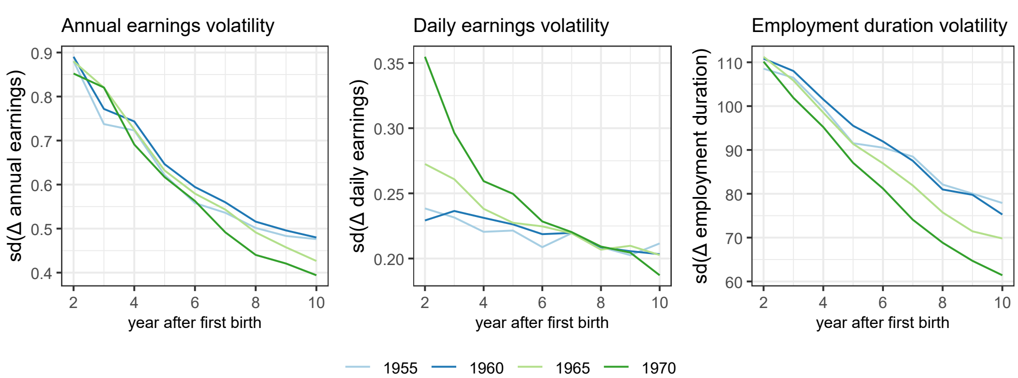
Notes: This figure illustrates annual earnings volatility for mothers who had a maternity spell in year t or $t-1$ or who had a birth in a given year. Note that the latter is a subgroup of the former. The sample includes 25 to 55 year olds of each cohort and earnings is based on social security contributions.

Figure 19: Volatility, by age and cohorts



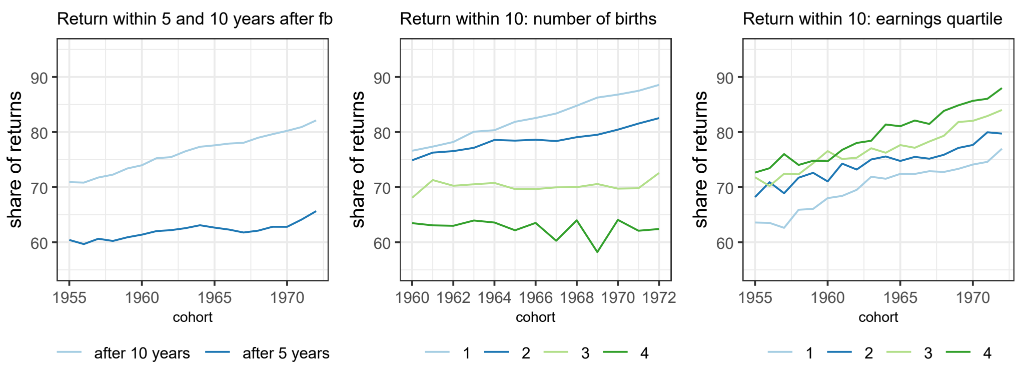
Notes: This figure illustrates annual earnings volatility for different native cohorts at different ages. Earnings are derived from social security contributions.

Figure 20: Mothers' post-birth volatility, by cohorts



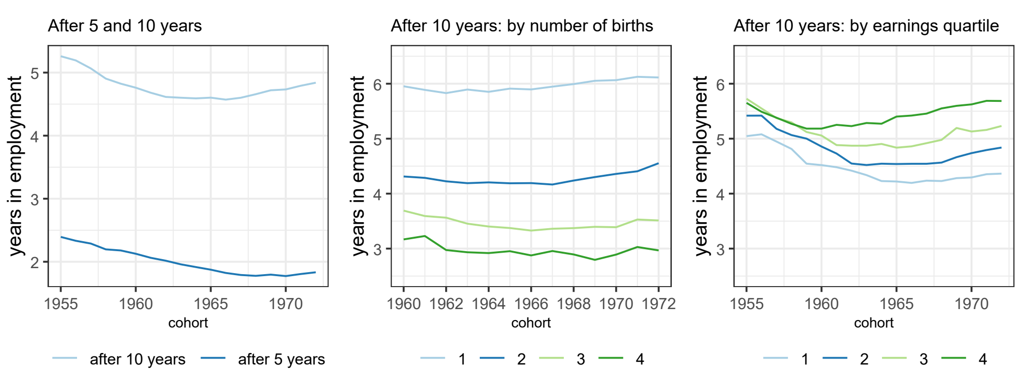
Notes: This figure illustrates annual earnings volatility for four different native mother cohorts in the years after first birth. after at different ages. The data includes mothers from age 18 and earnings are derived from social security contributions.

Figure 21: Mothers' post-birth return rate, by cohorts



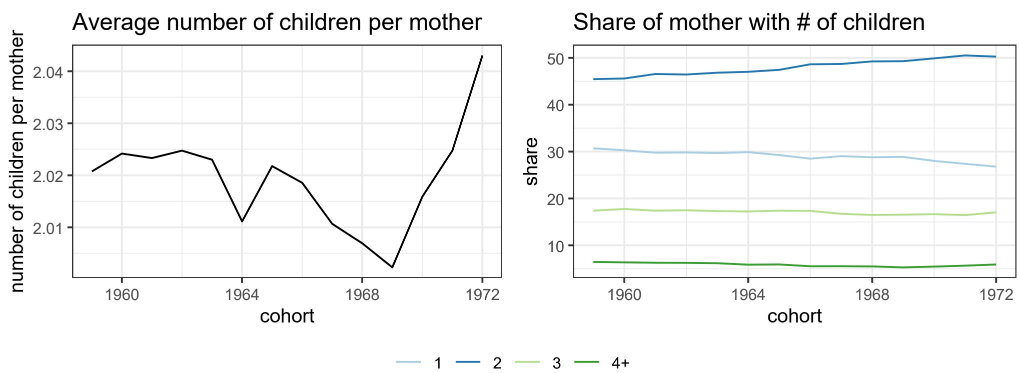
Notes: The figure illustrates the share of mothers who returned (employed at least 365 days) to the labour market within 5 and 10 years after their first birth (left panel), the share of mothers who returned to the labor market within 10 years after their first birth categorised by the mother's total number of children (centre panel), and the share categorised by the mother's pre-first-birth earnings quartile (right panel). The data includes mothers aged 18 and older, and earnings are derived from social security contributions.

Figure 22: Mothers' number of years in employment after first birth, by cohorts



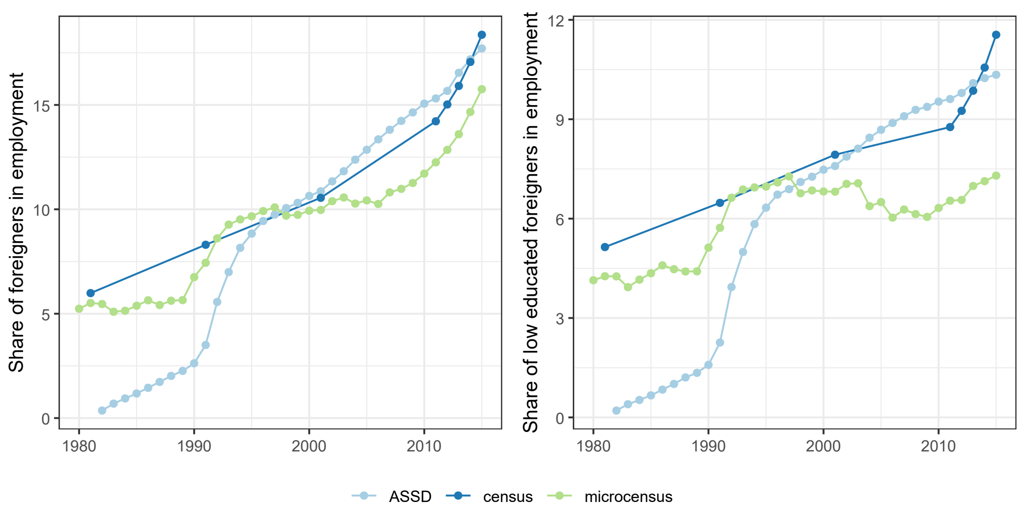
Notes: This graph illustrates mothers' number of years in employment after 10 and 5 years after first birth (left panel), the number of years in employment after 10 years by the mother's total number of births (centre panel) and by the mother's pre-first-birth earnings quartile (right panel). The data includes mothers aged 18 and older, and earnings are derived from social security contributions.

Figure 23: Number of children per mother, by cohorts



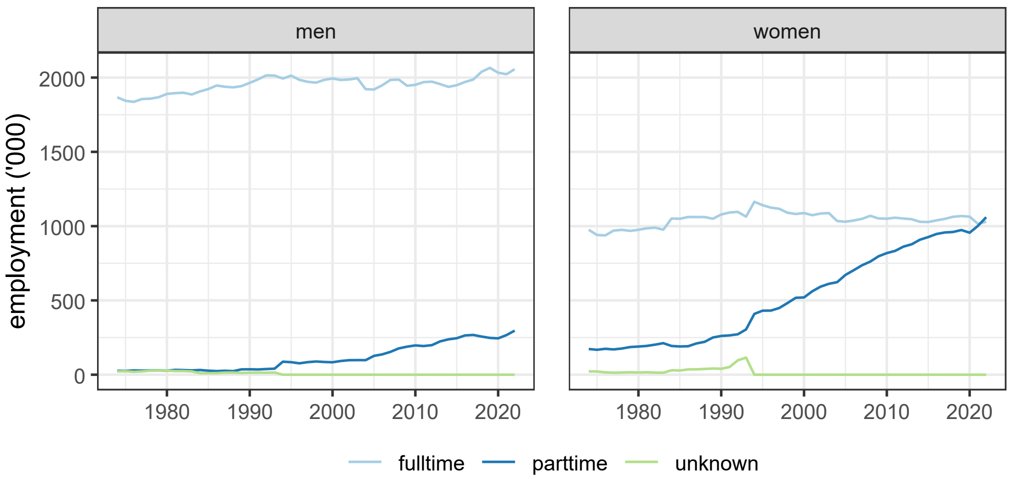
Notes: This figure depicts mothers' number of births after completing their fertility for each cohort according to our ASSD sample.

Figure 24: Share of immigrant employees by different data source (aged 25 to 55)



Notes: This figure compares the share of foreigners in the labour force from different data sources. Census and Microcensus data are from Statistik Austria (2024*b*,*d*,*f*). The Microcensus has been conducted every year, while the census in the years 1981, 1991, 2001 and 2011. Since 2011, the register based census is conducted annually. While the Microcensus and the Census classifies individuals based on their citizenship we classify employees in the ASSD as immigrants or as natives depending when they first enter the Austrian labour market.

Figure 25: Number of people in full-time and part-time employment (Microcensus)



Notes: This figure shows the number of Austrian full-time and part-time employees based on data from the Microcensus (Statistik Austria, 2024e) .