Online Appendix: Two Economies? Stock Markets, Job Postings, and AI Exposure in Sweden

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A1. Sweden vs United States comparison

Figure A1 shows side-by-side comparisons of the stock market versus job postings divergence in the United States and Sweden. The US panel uses the S&P 500 and Indeed Hiring Lab aggregate job postings index; the Swedish panel uses OMXS30 and Platsbanken microdata. Both countries exhibit a similar qualitative pattern of rising stock markets and falling postings since mid-2022.
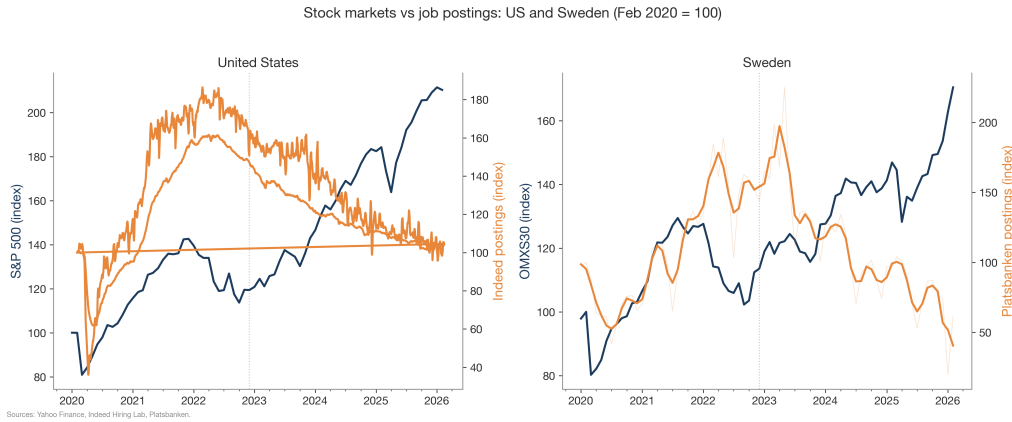

Figure A1: Stock markets vs job postings: United States (left) and Sweden (right), both indexed to 100 at February 2020.

A2. Individual quartile trends

Figure A2 shows each AI exposure quartile's posting trajectory individually. All four quartiles exhibit similar cyclical patterns, peaking in mid-2022

and declining through 2023–2024. The parallelism of these trends is consistent with a common macroeconomic driver rather than AI-specific displacement.

Figure A2: Job posting index by genAI exposure quartile (Feb 2020 = 100), individual panels.

A3. Top and bottom occupations

Table A1 lists the ten most and ten least genAI-exposed occupations according to the DAIOE index.

A4. Robustness checks

Table A2 reports results from alternative specifications: (i) using the all-apps AI exposure measure instead of genAI; (ii) using vacancy-weighted postings; (iii) excluding pandemic months (January–June 2020); (iv) using tercile classification instead of quartiles; (v) excluding IT/tech occupations

Table A1: Most and least genAI-exposed occupations (DAIOE)

SSYK	Occupation	GenAI pctl
Most exposed (top 10)		
2641	Författare m.fl.	99.9
2122	Statistiker	99.7
2121	Matematiker och aktuarier	99.4
2415	Nationalekonomer och makroanalytiker m.f	99.2
2512	Mjukvaru- och systemutvecklare m.fl.	98.9
2145	Civilingenjörsyrken inom kemi och kemite	98.7
2111	Fysiker och astronomer	98.5
2414	Traders och fondförvaltare	98.2
2513	Utvecklare inom spel och digitala media	98.0
2112	Meteorologer	97.8
Least exposed (bottom 10)		
9120	Bilrekonditionerare, fönsterputsare och	2.2
2653	Koreografer och dansare	2.0
8350	Matroser och jungmän m.fl.	1.8
7113	Betongarbetare	1.5
8341	Förare av jordbruks- och skogsmaskiner	1.3
9310	Grovarbetare inom bygg och anläggning	1.1
8342	Anläggningsmaskinförare m.fl.	0.8
8111	Gruv- och stenbrottsarbetare	0.6
7121	Takmontörer	0.3
3421	Professionella idrottsutövare	0.1

(SSYK 25xx), following Brynjolfsson et al. (2025); (vi) restricting to a balanced panel of 308 occupations observed in every month; (vii) using language-modelling task exposure from DAIOE; (viii) adding quadratic occupation-specific time trends. The ChatGPT coefficient $\hat{\beta}_2$ is insignificant in six of eight specifications but significant at the 5% level in the all-apps measure ($\hat{\beta}_2 = -0.091$, $p = 0.018$) and tercile classification ($\hat{\beta}_2 = -0.081$, $p = 0.026$). The coefficient is negative in seven of eight specifications.

Table A2: Robustness checks

Specification	$\hat{\beta}_1$ (Riksbank)	$\hat{\beta}_2$ (ChatGPT)	N	Occ.
Baseline (genAI Q4)	-0.1271***	-0.0615	26,672	369
	(0.0388)	(0.0380)		
All-apps measure	-0.0921**	-0.0911**	26,672	369
	(0.0386)	(0.0385)		
Vacancy-weighted	-0.1038**	-0.0612	26,672	369
	(0.0443)	(0.0437)		
Excl. pandemic	-0.1159***	-0.0617	24,479	369
	(0.0356)	(0.0380)		
Terciles	-0.0936***	-0.0808**	26,672	369
	(0.0360)	(0.0362)		
Excl. IT/tech	-0.1291***	-0.0662*	26,148	362
	(0.0406)	(0.0400)		
Balanced panel	-0.1130***	-0.0325	22,176	308
	(0.0377)	(0.0345)		
Language model	-0.1154***	-0.0564	26,672	369
	(0.0386)	(0.0387)		
Quadratic trends	-0.0884***	0.0193	26,672	369
	(0.0323)	(0.0402)		

Notes: All specifications include occupation and month fixed effects. Standard errors (in parentheses) clustered at occupation level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

A4.1. Event study

Figure A3 plots monthly DiD coefficients from an event-study specification, interacting month dummies with the high-exposure indicator (omitting February 2020 as the reference period). The pre-period coefficients fluctuate around zero with no systematic trend, though a joint Wald test rejects the

null that all 26 pre-Riksbank coefficients are zero ($\chi^2_{26} = 107.1$, $p < 0.01$). Aggregating to quarterly frequency (Figure A4) reduces the number of pre-period coefficients to 9 but the test still rejects ($\chi^2_8 = 52.8$, $p < 0.01$), indicating genuine differential macro sensitivity across AI exposure groups rather than monthly noise. This motivates specification (4) in the main table, which conditions on occupation group $\times$ month fixed effects. The post-ChatGPT coefficients show no additional structural break beyond the Riksbanken hiking cycle in either specification.
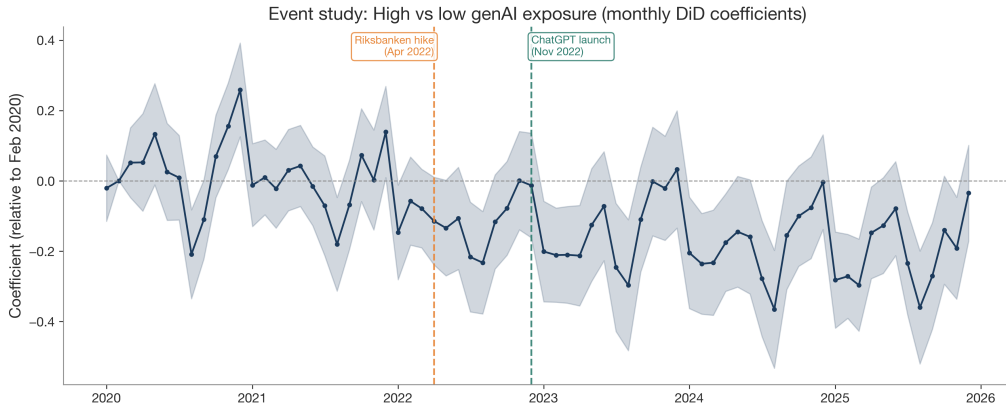

Figure A3: Event study: monthly DiD coefficients for high vs low genAI exposure occupations (reference: February 2020). Shaded area shows 95% confidence interval. Dashed lines mark the Riksbanken first rate hike (April 2022) and ChatGPT launch (December 2022).

A4.2. Quarterly event study

Figure A4 aggregates the monthly event study to quarterly frequency, reducing noise but preserving the key patterns.

A4.3. Alternative stock market index

Figure A5 replicates the "scary chart" using the OMXSPI (OMX Stockholm All-Share Price Index), which covers all companies listed on Nasdaq Stockholm rather than only the 30 largest. The OMXS30 is dominated by banks, industrials, and a few technology firms, raising the concern that the stock market–postings divergence reflects the performance of a narrow set of large caps. The OMXSPI comparison shows that the pattern is virtually
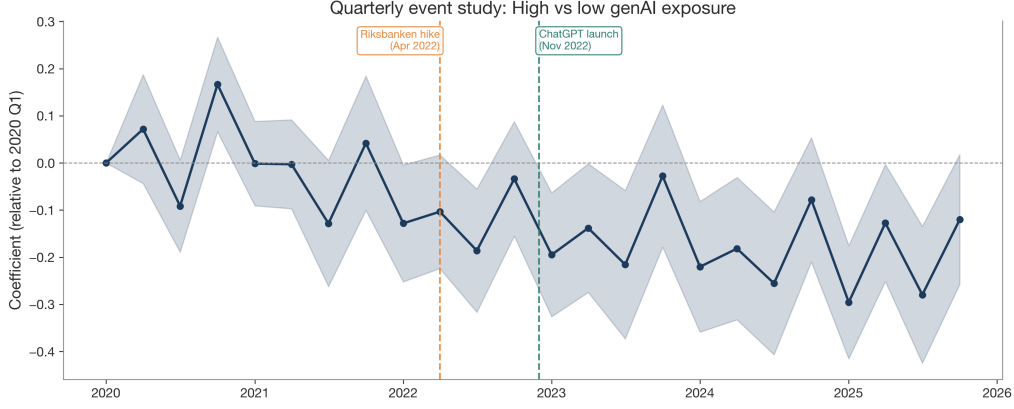
Figure A4: Quarterly event study: DiD coefficients for high vs low genAI exposure occupations (reference: 2020 Q1). Shaded area shows 95% confidence interval. Aggregating to quarters reduces monthly noise but pre-period differentials remain jointly significant ($\chi^2_8 = 52.8$, $p < 0.01$), reflecting differential macro sensitivity.

identical, confirming that the divergence is not an artefact of index composition.

A4.4. Quadratic occupation-specific trends

Adding quadratic time trends interacted with the high-exposure indicator tests whether non-linear differential dynamics — such as accelerating AI adoption over time — drive the results beyond what linear trends capture. The quadratic term is insignificant ($\hat{\delta}_2 = -0.00002$, $p = 0.56$), indicating that the linear trend specification (column 3 in the main table) is sufficient. The ChatGPT coefficient remains insignificant ($\hat{\beta}_2 = 0.019$, $p = 0.63$).

A4.5. Sensitivity to violations of parallel trends

Figure A6 reports a sensitivity analysis following the relative magnitudes framework of Rambachan and Roth (2023). The average post-ChatGPT event-study coefficient for high-exposure occupations is $\hat{\theta} = -0.169$ (SE = 0.059), significantly negative under exact parallel trends ($\bar{M} = 0$). However, the "breakdown value" is $\bar{M} = 0.25$: if post-period violations of parallel trends are as little as 25% of the maximum pre-period violation, the honest confidence interval includes zero. This confirms that while there is suggestive evidence of a negative AI effect on postings, the finding is fragile — consistent with the imprecision documented in the main regression table.
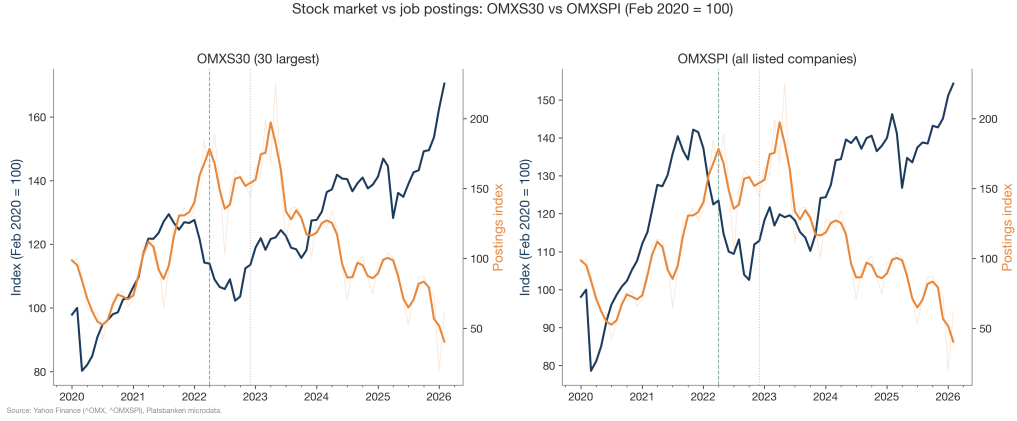
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Figure A5: Stock market vs job postings using OMXS30 (left) and OMXSPI All-Share (right). Both panels show the same divergence pattern, confirming it is not driven by the composition of the OMXS30.
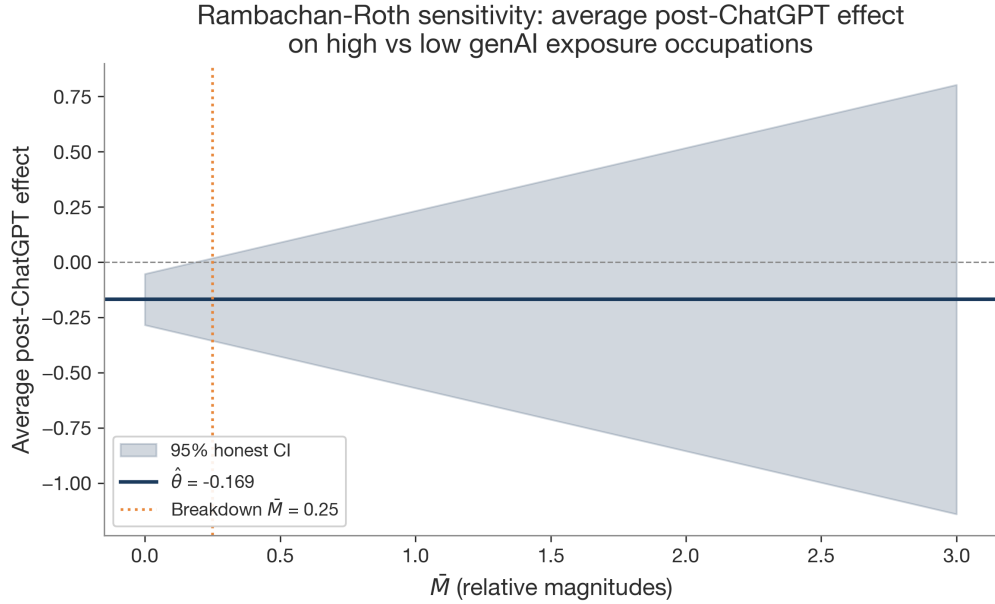

Figure A6: Rambachan-Roth sensitivity analysis for the average post-ChatGPT effect on high vs low genAI exposure occupations. The solid line shows the point estimate ($\hat{\theta} = -0.169$); the shaded area shows the 95% honest confidence interval as a function of $\bar{M}$ (the maximum ratio of post- to pre-period trend violations). The dotted line marks the breakdown value $\bar{M} = 0.25$.

A5. Employment by age group and AI exposure

Brynjolfsson et al. (2025) find that young US workers in AI-exposed occupations experienced disproportionate employment declines — "canaries in the coal mine." Our posting-based analysis cannot test this age-specific hypothesis. As a supplementary check, we use publicly available register data from SCB (Yrkesregistret, table YREG54BAS) providing annual employment counts by SSYK 4-digit occupation and age group for 2020–2024.

Figure A7 shows employment indexed to 2020, for four groups defined by age (16–24 vs 25+) and AI exposure (top quartile vs rest). All groups recover strongly from the 2020 pandemic trough, with youth employment growing fastest. There is no visible divergence between young workers in high- vs low-AI-exposure occupations after ChatGPT. A triple-difference regression (occupation-age entity and year fixed effects, clustered at entity level) yields an insignificant interaction: $\hat{\beta}_{\text{Post}\times\text{Young}\times\text{High}} = 0.038$ ($p > 0.10$), providing no evidence of a canaries effect.

Three caveats apply: (i) SCB changed the underlying register from RAMS to BAS from reference year 2022, introducing a methodological break at our treatment timing; (ii) the 2020 pandemic trough as base year inflates all growth rates; (iii) with only five annual observations, statistical power is limited. Monthly employer declaration (AGI) data, available in Sweden's secure research environment (MONA), would permit a more granular test of this hypothesis.

A6. DAIOE exposure distribution

The DAIOE genAI percentile ranking provides a continuous measure of occupational exposure to generative AI capabilities. The distribution across Swedish SSYK 4-digit occupations is approximately uniform by construction (it is a percentile ranking), with quartile boundaries at approximately the 25th, 50th, and 75th percentiles of the occupation distribution.

A7. Data documentation

A7.1. Platsbanken

Historical job advertisement data from the Swedish Public Employment Service (Arbetsförmedlingen), published under CC0 licence. Each record contains: ad identifier, publication date, SSYK 2012 four-digit occupation
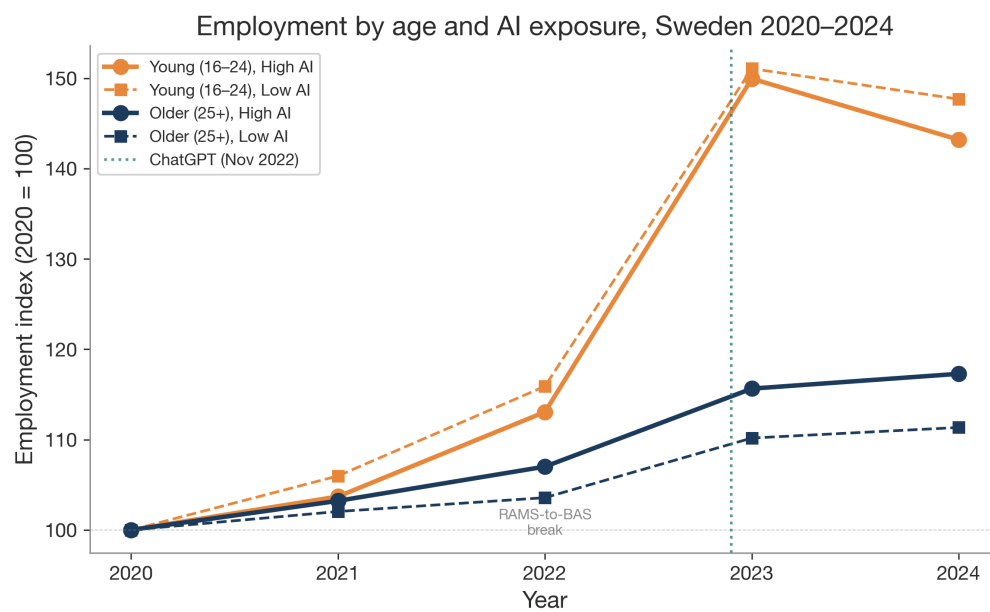
Figure A7: Employment by age group and AI exposure, Sweden 2020–2024 (2020 = 100). Data: SCB Yrkesregistret (YREG54BAS). Young = 16–24 years; High AI = top quartile of DAIOE genAI exposure. The dotted line marks ChatGPT launch (November 2022). Note: methodological break (RAMS to BAS) at 2022.

code, number of vacancies, municipality code, employer name, and source type. Available at `https://data.jobtechdev.se/annonser/historiska/`.

A7.2. DAIOE

The Dynamic AI Occupational Exposure index maps AI benchmark performance to occupational task content. The genAI variant focuses on capabilities relevant to large language models and image generation. Publicly available; see Lodefalk and Engberg (2024).

A7.3. OMXS30

Stockholm OMX 30 daily closing prices from Yahoo Finance (ticker: `^OMX`).

A7.4. Riksbanken policy rate

Manually compiled from Riksbanken press releases. Key dates verified against `https://riksbank.se`.

References

Brynjolfsson, E., Chandar, B., Chen, J., 2025. Generative AI at work: Canaries in the coal mine Working paper.

Lodefalk, M., Engberg, E., 2024. Dynamic AI occupational exposure: Measuring the impact of AI on the labour market Örebro University / RATIO. Publicly available dataset.

Rambachan, A., Roth, J., 2023. A more credible approach to parallel trends. Review of Economic Studies 90, 2555–2591.