A Wartime Labor Market: The Case of Ukraine

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Motivation

- How does a labor market function under active and prolonged conflict? To what extent it differs from peacetime?
- This paper: focus on wartime labor market in Ukraine (2022-now)
- We know little about how the *granular* functioning of economies *during* wars
  - Most research is macro, labor research has focused on post-war
  - Lack of data, for historical or institutional reasons
  - Every war is different (this one: interstate, large, protracted, on home soil)
- Ukraine is exceptional: first modern, large-scale & protracted war with available data
- Relevant for the reconstruction and to understand large negative labor supply shocks

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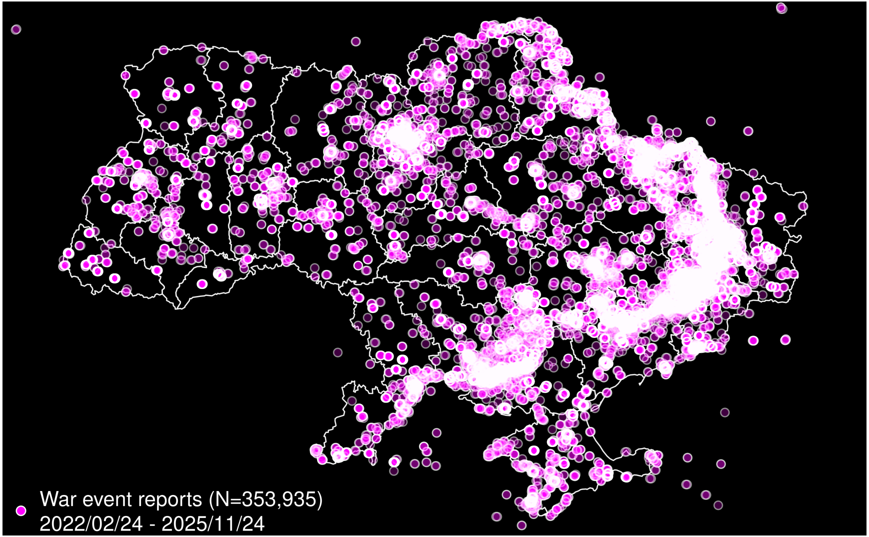
Geographic Scope of the War



Source: VIINA (Violent Incident Information from News Articles).

Literature on Wars and the Economy

- Effects of conflicts on output (Benmelech and Monteiro, 2025; Chupilkin and Koczan, 2022; Federle et al., 2024)
- Displacement and labor market outcomes (Kondylis, 2010; Torosyan et al., 2018)
- Human capital losses (Eder, 2014; Swee, 2015)
- Long-term physical and mental health deterioration (Bratti et al., 2015)
- Firm performance, informal sector, local development (Petracco and Schweiger, 2012)

Our Contribution

First descriptive evidence on how a labor market adapts to a full-scale war:

- Quantify shocks and reallocation across regions/sectors
- Assess effects of war on matching efficiency
- Document heterogeneity by region, sectors, and time-varying exposure to conflict
- Investigate firm-level adjustment channels
- Implications for policies (including army mobilization)

What Are We Talking About

3 important qualifications:

1. We cover **civilian** employment/unemployment only (military mobilization is a contraction of the labor force)
2. We cover only the **formal** sector (no data on informal sector)
3. We focus on **government-controlled territory** by Ukraine
   No Crimea, and in matching estimation no partially occupied regions of Donetsk, Luhansk, Kherson, and Zaporizhzhia

Wartime Data

Sources:

- Quarterly household survey (CATI) carried by research agency Info Sapiens, used by NBU since 2021
- Administrative data from the State Statistical Service and National Bank
- Data from Work.ua, the argest online job search platform reporting weekly stocks and inflows of vacancies and resumes, as well as posted (from vacancies) and expected (from candidates) average wages. Aggregates at region $\times$ job category. In 2024: used by 125,000 firms and 4.5 million workers
- Survey of recruitment policies for 55,000 firms in January 2025
- Other (UNHCR, IDPs surveys, etc.)

Quantifying Aggregate Shocks

Labor supply shock

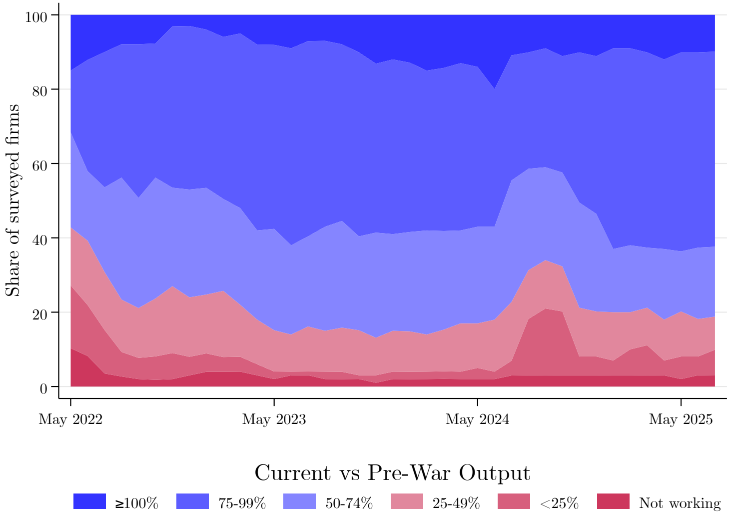
	Baseline (mln)	High	Low
Refugees	6.62	6.90	5.40
of which in the labor force (A)	2.81	2.95	2.27
Increase in military&defense	0.80	0.90	0.70
of which in the labor force (B)	0.54	0.61	0.48
Civilian casualties (deaths + injured, children excluded)	0.05	0.05	0.05
of which in the labor force (C)	0.03	0.03	0.03
Reduction in LF participation among stayers (D)		0.66	
Total LF loss in controlled territory -(A+B+C+D)	-3.38	-3.59	-2.77
Labor force drop in government-controlled territory[1]	-22%	-28%	-17%

[1] Between 7 and 11% of the pre-war labor force is currently under Russian occupation.

Labor Demand Shock

	Total (mln)	% of pre-war
Overmanning assuming constant productivity (adm data)		
Year 2022	-2.95	-17%
Year 2023	-2.46	-14%
Year 2024	-1.83	-11%
Employment in firms with excess capacity (survey of firms)		
Year 2022		-18%
Year 2023		-14%
Year 2024		-14%
Hiring freeze: drop in the stock of online vacancies		
One month window	-0.04	-37%
One year window	-0.05	-55%

Firms output compared to pre-invasion levels over time



Historical Precedents

- **Labour Supply Shock:** Serbia-Montenegro during WWI (-30%), USSR displacement under Nazi invasion, Rwanda genocide (-40 to -50%)

- **Labor Demand Shock:** vacancies during the Great Financial Recession in the US (all registered -23%, online vacancies -35%) and in UK (all registered -30%)

Aggregate Labor Market Dynamics

Aggregate Statistics

One might expect these shocks to have produced dramatic effects on the aggregate labor market, given their magnitude plus wartime frictions. Mismatch unemployment, human capital losses reducing wages, etc.

Facts:

1. Number of people officially employed: -16% in 2022, then relatively stable
2. Unemployment rate: 9% pre-war, spike in 2022, 13% in 2024 (forecast 2025: 11.3%)
3. Real wages: initial drop, then in 2024 above pre-war levels
4. Higher dispersion of employment growth across sectors and regions ▸ Lilien Index

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Including prewar

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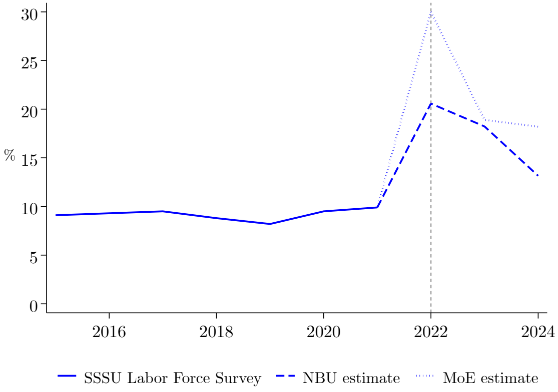
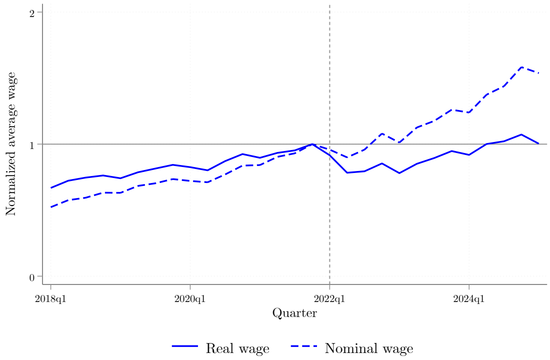


(a) Unemployment rate



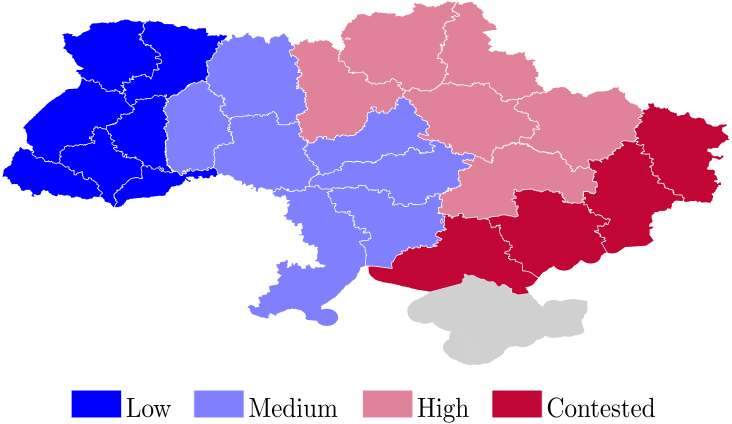
(b) Wages

Reallocation: Geographical & Sectoral

Measuring Exposure to War

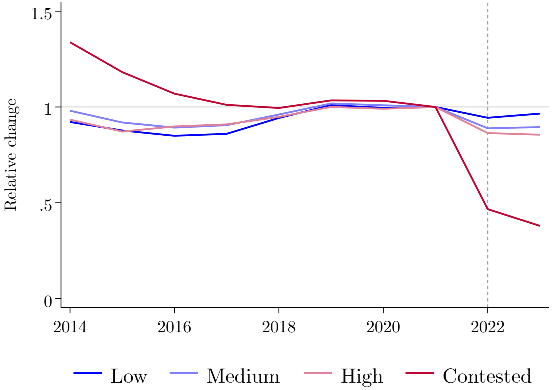
- Exposure to air raid alarm data (online repository: `https://github.com/Vadimkin/ukrainian-air-raid-sirens-dataset`)
  Only alerts from official sources
- Sirens sound when missile or drone attacks are detected, remain active for the duration of the event
- 3 alternative exposure metrics at the oblast level:
  1. Total duration of alarms measured in hours
  2. Number of alarm events per 10,000 residents
  3. Number of days with at least one active alarm
- Contested regions (Donetsk, Luhansk, Kherson, Zaporizhzhia) are hand-coded
  Remaining regions are classified in terciles based on exposure: low, medium, high

The Geography of Exposure

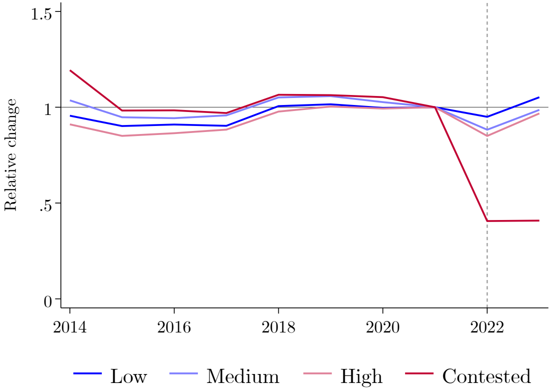


Ukrainian oblasts by exposure (duration of alarms)

Employment by Exposure



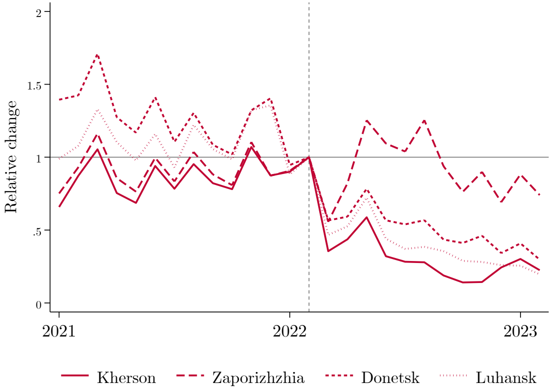
(a) Total employed



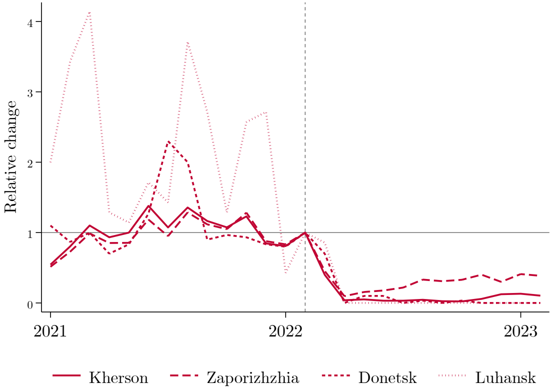
(b) Individual entrepreneurs

Employment by exposure (duration of alarms), normalized to 2021

When Labor Markets Shut Down



(a) New resumes



(b) New vacancies

Monthly inflows in contested regions, normalized to invasion week

Sectoral Reallocation

Three main facts:

1. Correlation between pre- and post-war employment growth by sector is close to zero
   - ↦ Marked change in the structure of labor demand
2. Most sectors grew before the invasion, most sectors decline after the invasion
   - ↦ Aggregate contraction
3. Military-related activities cluster disproportionately among highest-growing sectors
   - ↦ Surge in defense-related demand

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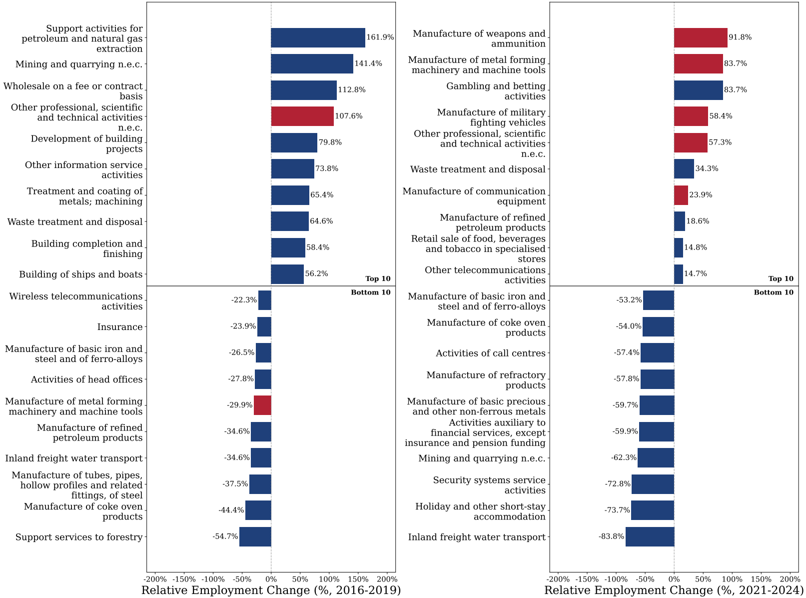
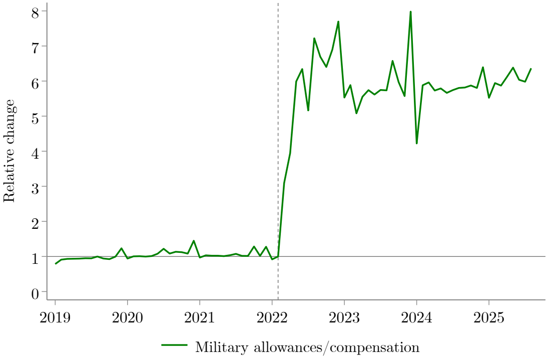
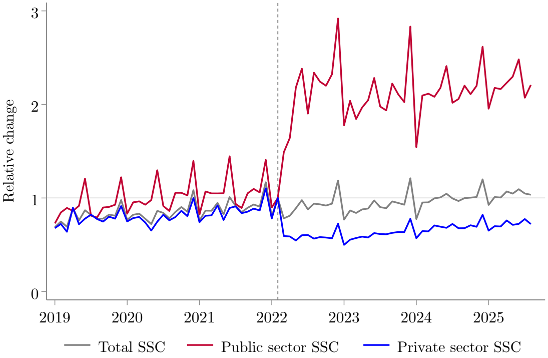


Top & Bottom 10 sectors by relative employment change, 2016-2019 vs 2021-2024

Civilian vs Military, Public vs Private



(a) Military wage bill



(b) Social security contributions

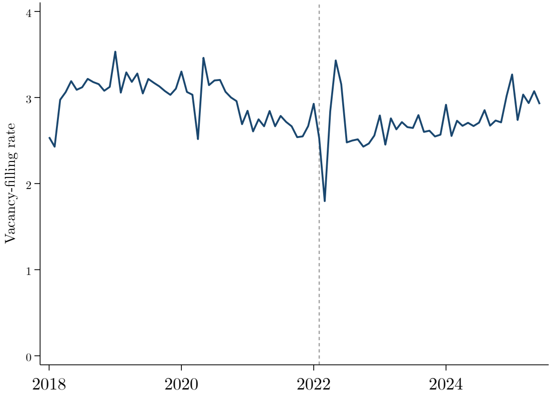
Evolution of military compensation and civilian social security contributions

Recap

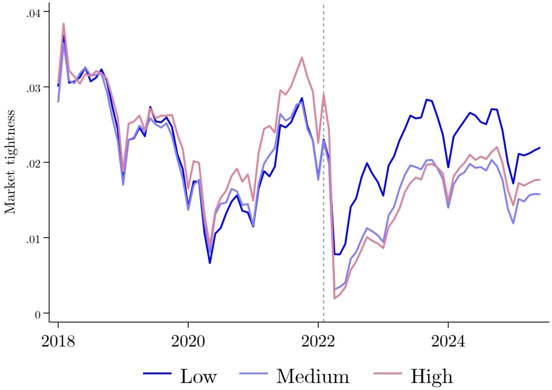
- Huge labor supply shock and large labor demand shock
- Major reallocation across regions, sectors, public/private
- Moderate aggregate impacts on the labor market
- How efficient has the labor market been? Resiliency? Frictions?

Matching Efficiency in Wartime

Vacancy Filling and Market Tightness



(a) Vacancy-filling rate (aggregate)



(b) Market tightness by war exposure

Vacancy-filling rate and market tightness (by exposure)

Measuring Matches

- We are interested in measuring matching efficiency and heterogeneity by exposure
- We observe stocks and flows of resumes from job-seekers (U_{rct}) and vacancies posted by firms (V_{rct}) on the largest online job platform in Ukraine
- Unit is region $r \times$ category $c \times$ month t
- Recover matches via vacancy stock-flow identity:

$$M_{rct} \equiv V_{rct} + \text{inflow}V_{rct} - V_{rc,t+1}$$

- Assumption: all exits are matches, i.e. filled vacancies (no costs in keeping vacancies online; subscriptions based on inflow of vacancies)

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Matching Estimation

- We model the matches as a Cobb–Douglas function of job-seekers and vacancies:

$$\begin{aligned} M_{rct} &= A_{rct}\, U_{rct}^{\alpha} V_{rct}^{\beta} \\ \log M_{rct} &= \log A_{rct} + \alpha \log U_{rct} + \beta \log V_{rct} \end{aligned}$$

  A_{rct} is the matching efficiency and α, β are elasticities wrt resumes and vacancies

- Decompose:

$$\log A_{rct} = \kappa + \gamma \cdot \text{Post}_t + \delta_r + \theta_c$$

- Estimate:

$$\log M_{rct} = \kappa + \alpha \log U_{rct} + \beta \log V_{rct} + \gamma \cdot \text{Post}_t + \delta_r + \theta_c + \varepsilon_{rct}$$

  γ measures the change in efficiency after February 2022

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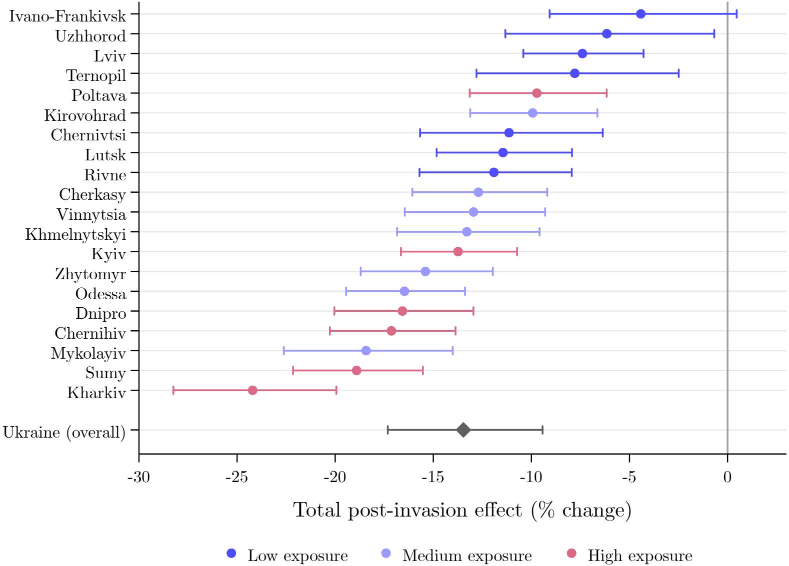
Matching Efficiency: Results

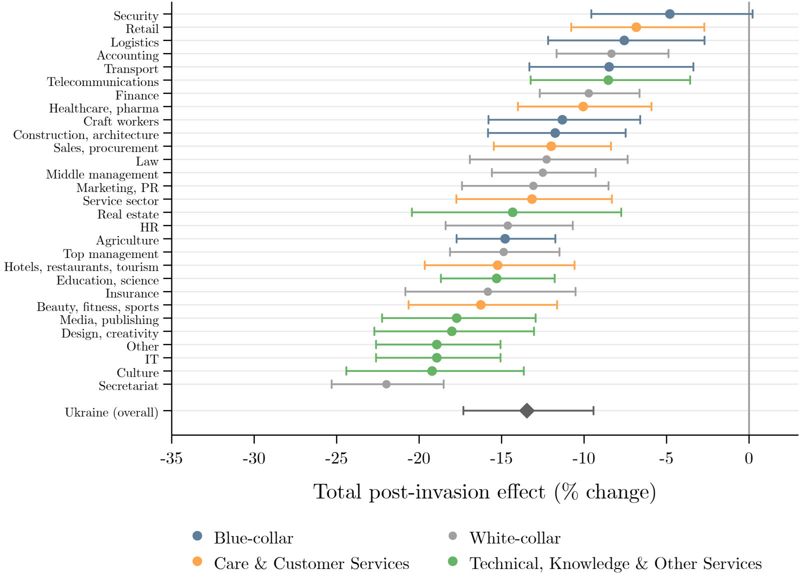
	(1)	(2)	(3)	(4)
Elasticity wrt resumes (log U)	0.032	0.058*	0.117***	0.071**
	(0.028)	(0.030)	(0.015)	(0.027)
Elasticity wrt vacancies (log V)	0.979***	0.960***	0.907***	0.897***
	(0.021)	(0.022)	(0.013)	(0.013)
Post-invasion ($\geq$ Feb 2022)		-0.147***	-0.168***	-0.145***
		(0.016)	(0.016)	(0.023)
Constant	0.807***	0.739***	0.483***	0.870***
	(0.176)	(0.183)	(0.078)	(0.204)
Observations	49950	49950	49950	49950
R^2	0.965	0.967	0.977	0.977
Category FE	No	No	Yes	Yes
Region FE	No	No	No	Yes
CRS test p-value	0.554	0.347	0.008	0.214

Notes. Dependent variable: $\log M_{rct}$. CRS test $H_0 : \alpha + \beta = 1$. Two-way clustered standard errors (region $\times$ category) in parentheses. Sample: January 2018 to June 2025, excluding contested oblasts.

Heterogeneity by Region



Heterogeneity by Sector



Impact of air raid alarms

	Alarms per Capita		Days with Alarms		Total Duration	
	(1)	(2)	(3)	(4)	(5)	(6)
Elasticity wrt resumes (log U)	0.047	0.146***	0.062*	0.144***	0.042	0.144***
	(0.030)	(0.027)	(0.031)	(0.027)	(0.030)	(0.027)
Elasticity wrt vacancies (log V)	0.965***	0.895***	0.956***	0.893***	0.972***	0.896***
	(0.023)	(0.016)	(0.023)	(0.015)	(0.022)	(0.016)
Exposure (alarms per 10k)	-0.110***	-0.031**				
	(0.028)	(0.014)				
Exposure (days with alarms)			-0.006***	-0.003**		
			(0.001)	(0.001)		
Exposure (duration, 100 hours)					-0.032**	-0.013**
					(0.012)	(0.005)
Constant	0.759***	0.220	0.709***	0.273	0.764***	0.234
	(0.182)	(0.196)	(0.188)	(0.203)	(0.187)	(0.198)
Observations	49950	49950	49950	49950	49950	49950
R^2	0.966	0.983	0.967	0.983	0.966	0.983
Category FE	No	Yes	No	Yes	No	Yes
Region FE	No	Yes	No	Yes	No	Yes
Month FE	No	Yes	No	Yes	No	Yes
CRS p-value	0.500	0.079	0.347	0.126	0.453	0.090

Details

Comments

Takeaways:

- Post-invasion matching efficiency drops on aggregate by around 13.5%
  - ↦ We interpret as moderate decline given reallocation, mismatch, shocks, loss of networks
  - ↦ Benchmark: US during Great Financial Crisis (-25 to -30 %)
- Strong heterogeneity by regions post-war
- Strong heterogeneity by sectors post-war
- Time-varying exposure associated to declines in matching efficiency
- Approximately constant returns to scale $(\alpha + \beta \approx 1)$, consistent with the literature

Caveats:

- May not capture the full universe of the labor market
- Measurement error

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Evidence on Firm-level Adjustment to Shocks

Interpretation

Possible mechanisms mitigating decline in matching efficiency:

1. Mobilization of underrepresented groups: women, elderly and disabled people
   - Women employed in positions traditionally held by men (miners, truck drivers, etc.)
   - In 2025, on average 13% of employees are aged more than retirement age (60 years old)
   - Employees with disability/special needs: 10% (Oct 2024), relatively large in OECD
2. Remote work
   - Relevant also for refugees: among those abroad and employed, 14% work remotely for Ukrainian companies and have higher intention to return
3. Wage flexibility
   - Minimum wage kept unchanged in 2022 and 2023, inflation made it less binding
   - Wage dispersion widened
4. Declining gap between offered and asked wages

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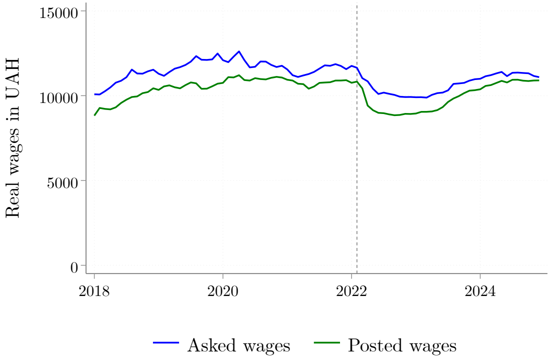
Recruitment of Under-Represented Groups, WFH and Exposure

Firm-level adjustments to exposure: Hiring and remote work

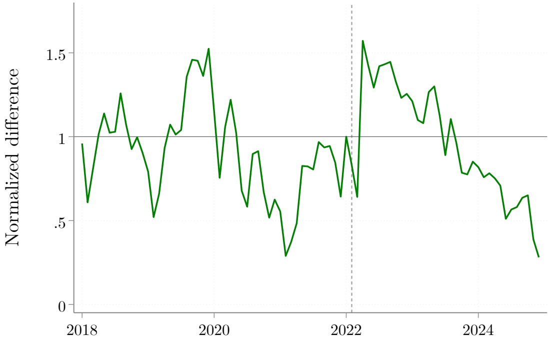
	Hiring IDPs		Hiring people aged 60+		Hiring people with disabilities		Remote work allowed	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Days with Alarms: Medium	0.096***		0.064***		0.033**		0.028*	
	(0.023)		(0.015)		(0.012)		(0.015)	
Days with Alarms: High	0.075***		0.035*		-0.026**		0.066***	
	(0.018)		(0.017)		(0.010)		(0.023)	
Duration: Medium		0.081***		0.070***		0.035**		0.013
		(0.018)		(0.017)		(0.015)		(0.016)
Duration: High		0.092***		0.040**		-0.011		0.059***
		(0.024)		(0.019)		(0.015)		(0.014)
Constant	0.528***	0.529***	0.261***	0.261***	0.444***	0.444***	-0.003	-0.003
	(0.022)	(0.023)	(0.020)	(0.020)	(0.013)	(0.014)	(0.023)	(0.023)
Observations	16,553	16,553	16,552	16,552	16,553	16,553	51,221	51,221
R^2	0.082	0.082	0.084	0.084	0.065	0.064	0.077	0.078
Sector FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. OLS with sectors FEs and log of firm size in 2025. Sample: survey of firms in Jan 2025. With controls.

Gap between Asked and Posted Wages



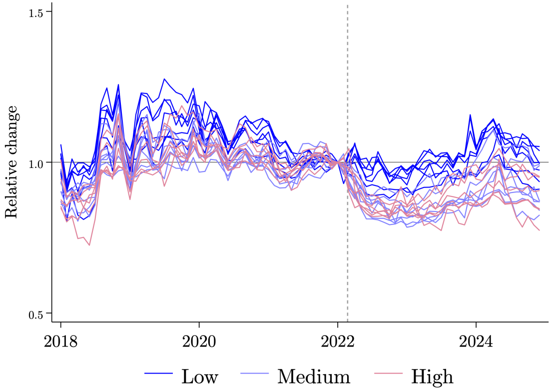
(a) Evolution



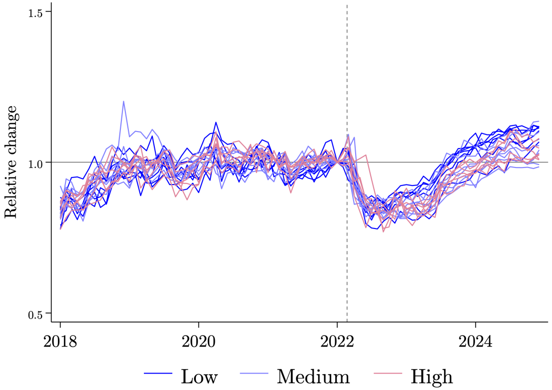
(b) Difference (normalized to Jan 2022)

Asked vs posted, average real wages

Asked and Posted Wages by Exposure



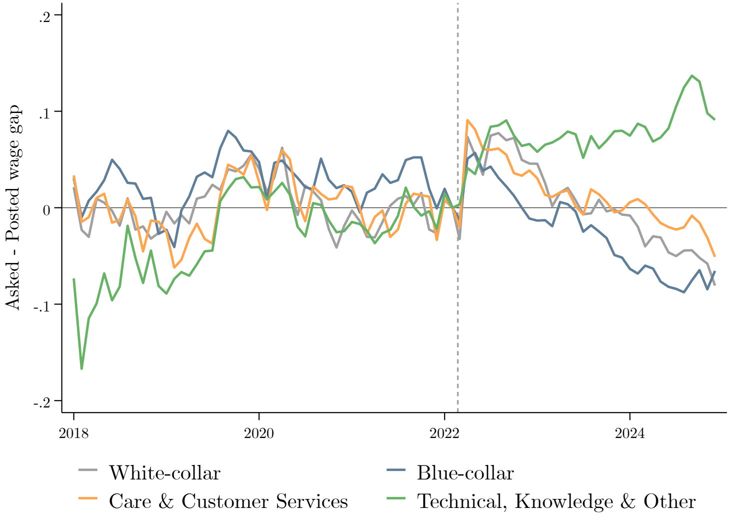
(a) Asked wages (from resumes)



(b) Posted wages (from vacancies)

Asked vs offered, average real wages (by region and war exposure)

Out-migration Pressures for Technical&Knowledge Service Workers?



Conclusion

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- The full-scale invasion of 2022 generated one of the largest combined labor supply and reallocation shocks in recent history
- Despite the magnitude of the shock, Ukraine's labor market has proven resilient
- Adjustment occurred through profound regional and sectoral reallocation
- Uneven impact: shielded regions reabsorbed displaced workers, frontline and occupied territories saw near-total collapse of labor market activity
- Major structural challenges ahead (lasting human capital losses, reintegration of veterans, additional worker outflows, etc.)

Policies for Wartime and (hopefully soon) Beyond

- Long wars are won in factories rather than battlefields
- Five priorities:
  1. Rebuilding human capital before infrastructure (avoid further brain drain investing now more resources in education)
  2. Inclusion policies (reintegration of veterans, female labor force, vulnerable groups)
  3. ALMP (facilitate reallocation across regions and sectors)
  4. Migration (incentive schemes for returnees, remote work, prepare to manage significant immigration in reconstruction)
  5. Tailor military mobilization taking into account on labor market needs

Thank you!

Reallocation

- The Lilien (1982) Index measures the extent of reallocation by quantifying how much individual growth rates deviate from aggregate growth:

$$LI_t = \sqrt{\sum_i s_{it} \left[\ln\left(\frac{x_{it}}{x_{i,t-1}}\right) - \ln\left(\frac{X_t}{X_{t-1}}\right) \right]^2}$$

  - $s_{it} = x_{it}/X_t$: employment (or inflows of vacancies/resumes) share of unit i
  - x_{it}: employment in unit i
  - X_t: aggregate employment

- Intuition: $LI_t = 0$ when all units grow at the same rate as the aggregate. Higher LI_t indicates faster structural change and stronger reallocation.

Reallocation: Lilien Index

Source	Indicator	Dimension	Period	
			2017-2019	2022-2024
Administrative data	Total employed (private sector)	Sectors	0.92	1.05
		Regions	0.81	1.11
Online job platform	Inflows of vacancies	Sectors	0.34	0.51
		Regions	0.29	0.55
	Inflows of job seekers	Sectors	0.30	0.34
		Regions	0.23	0.44

LI increases post-war in administrative and platform data, both across regions and sectors

$\Longrightarrow$ Dispersion of growth rates accelerated after the start of the full-scale invasion

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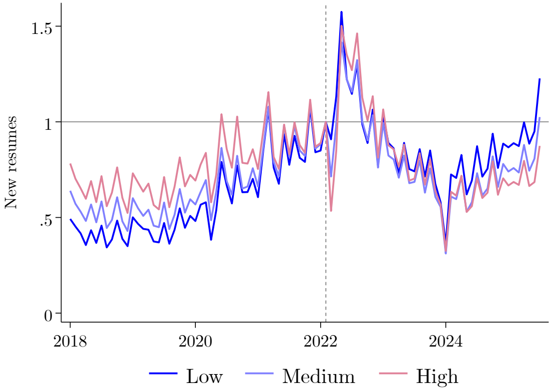
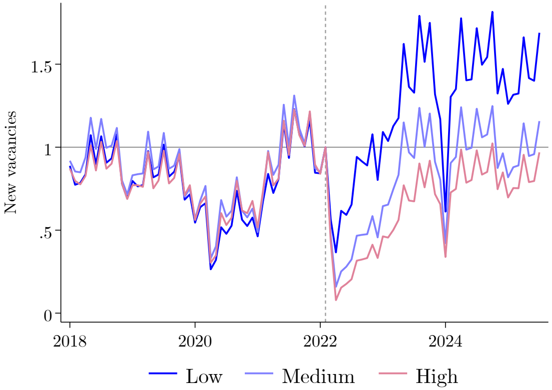
Jobseekers and Vacancies by Exposure



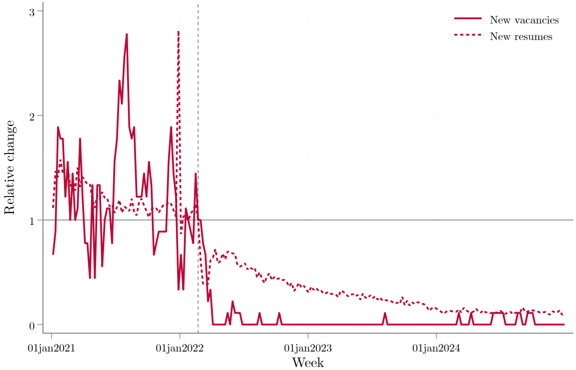
(a) New resumes



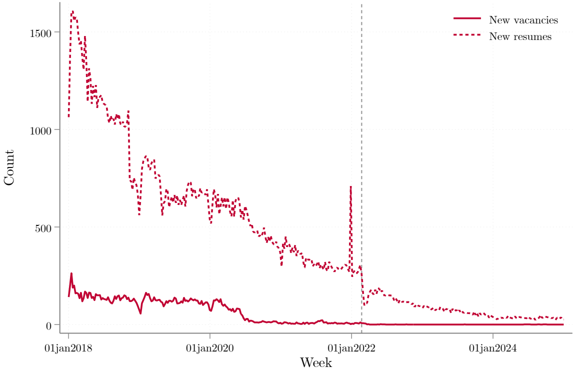
(b) New vacancies

Monthly inflows by exposure (duration of alarms), normalized to invasion month

Labor Market Shutdown in Occupied Regions



(a) Inflows normalized to invasion week



(b) Absolute inflows in Donetsk

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Matching and time-varying exposure to war

We use air raid alarm data to measure regional war exposure. Decompose:

$$\log A_{rct} = \kappa + \phi \cdot \text{Exposure}_{rt} + \delta_r + \theta_c + \lambda_t$$

λ_t are month FEs and Exposure_{rt} captures war exposure in region r during month t.

Estimating equation:

$$\log M_{rct} = \kappa + \alpha \log U_{rct} + \beta \log V_{rct} + \phi \cdot \text{Exposure}_{rt} + \delta_r + \theta_c + \lambda_t + \varepsilon_{rct}$$

where ε_{rct} is an idiosyncratic error term capturing unobserved determinants of matching efficiency at the region-category-month level.

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Recruitment and WFH with Controls

Firm-level adjustments to exposure: Hiring and remote work

	Hiring IDPs		Hiring people aged 60+		Hiring people with disabilities		Remote work allowed	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Days with Alarms: Medium	0.112***		0.121***		0.062**		0.017	
	(0.030)		(0.026)		(0.023)		(0.024)	
Days with Alarms: High	0.101***		0.095***		-0.003		0.069**	
	(0.027)		(0.019)		(0.019)		(0.026)	
Duration: Medium		0.108***		0.110***		0.034		0.034
		(0.028)		(0.023)		(0.022)		(0.021)
Duration: High		0.092***		0.070***		-0.031		0.091**
		(0.032)		(0.015)		(0.021)		(0.035)
Constant	0.241	0.284	-0.367**	-0.260**	0.168	0.358***	-0.276	-0.403**
	(0.183)	(0.177)	(0.137)	(0.108)	(0.149)	(0.115)	(0.187)	(0.184)
Observations	16,517	16,517	16,516	16,516	16,517	16,517	51,126	51,126
R^2	0.108	0.108	0.115	0.115	0.080	0.079	0.103	0.102
Sector FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. Back. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.