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THE ALLOCATIVE COST OF WAR: A VIEW TO A KILL…ING OF PRODUCTIVITY

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We thank the LMU-ifo Economics & Business Data Center for making the ORBIS data available. A portion of this paper was submitted as an unpublished graduate thesis by Amann at the ifo Institute, supervised by Tuuli Tähtinen. Gorodnichenko thanks the Clausen Center for financial support.

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ABSTRACT

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JEL CLASSIFICATION: F51, F52, D24, H56, D61, O47, O52, R12

KEYWORDS: geoeconomics, defense, misallocation, productivity, war, Ukraine

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Abstract

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1 Introduction

For a dismal science, modern economics has paid little attention to wars or national security. Indeed, after the end of the Cold War, an inter-state armed conflict was perceived as a remote possibility for nearly all advanced and emerging economies. But Russia's barbaric, unprovoked full-scale invasion of Ukraine in 2022 unleashed a new geopolitical era where security is the dominant factor for many economic decisions. Key questions in this context are how wars affect the economy, what forces amplify vulnerabilities, and what can be done to raise preparedness and mitigate adverse effects. To shed more light on these vitally important issues, we study the wartime allocation of resources in Ukraine. Our central finding is that modern war imposes a massive economic cost by disrupting the allocation of labor and capital, not just by destroying them.

Ukraine provides an exceptionally rare setting for studying the effects of a large-scale inter-state war. In most conflict settings, the statistical infrastructure collapses, leaving researchers to rely on retrospective surveys, satellite imagery, or fragmentary records reconstructed years after the fact. Despite the enormous scale of Russian aggression, Ukrainian state institutions have continued to function throughout the war and firms have continued to file financial statements with the State Statistics Service and the Unified State Register. As a result, we have a data environment with few, if any, parallels in the study of major armed conflicts. The combination of *i*) a massive, exogenous, and spatially heterogeneous shock, *ii*) near-universal firm-level microdata available in almost real time with consistent reporting standards before and during the war, *iii*) a large, diversified economy, and *iv*) granular conflict intensity data makes Ukraine uniquely suited for quantifying how war distorts the allocation of resources and depresses aggregate productivity. Furthermore, because Ukraine's accounting standards, legal framework, and business environment are broadly comparable to those of neighboring Eastern European states, we can construct cross-country counterfactuals to isolate war-specific effects from common regional shocks such as the European energy crisis or post-pandemic supply chain disruptions.

Our core finding is stark: allocative total factor productivity (TFP), that is, the component of aggregate TFP determined by how efficiently labor and capital are currently distributed across firms, fell by approximately 20 to 40 percent (depending on how we weigh firms). In contrast, Ukraine's peer economies experienced no comparable decline over the same period, confirming that the collapse is war-driven rather than reflecting common regional trends. Using geocoded firm-level data and the war's spatial heterogeneity, we show that a one-standard-deviation increase in war intensity for a district (raion) is associated with an 11 percentage-point larger TFP decline. War intensity alone explains over 60 percent of the cross-raion variation in productivity losses. Basic growth accounting suggests that roughly half of the total wartime output loss is attributable to misallocation rather than to the physical destruction of productive capacity. To our knowledge, this first-order macroeconomic fact about modern war and productivity has, to our knowledge, not been documented before.

In addition to reporting and validating aggregate trends, we exploit time series, sectoral, and subnational variation to inspect mechanisms. We document that actual attack intensity drives allocative losses (e.g., distance-based proxies lose explanatory power once war intensity is controlled for). We find that internal displacement of labor modestly improves allocative efficiency in receiving areas by likely alleviating war- and mobilization-induced labor shortages (however, displaced workers remain severely underemployed, which implies large unrealized gains from better integration). Our results also suggest that liberated areas show no permanent productivity "scar" from occupation once ongoing attacks are accounted for. This finding indicates that allocative efficiency can recover rapidly after hostilities cease. Finally, adaptation is already underway: by 2024, the economy operating under its actual composition was approximately 8 percentage points more efficient than it would have been under fixed pre-war weights.

Two comparison episodes sharpen our interpretations. First, Russia's 2014 illegal seizure of Crimea and parts of the Donbas caused an allocative TFP decline of similar magnitude but operated primarily through macroeconomic and financial instability (a banking crisis, currency collapse, and inflation spike) rather than direct physical destruction. The geographic gradient of TFP losses in 2014 was far shallower than in 2022, consistent with country-level financial turmoil rather than spatially concentrated violence being the dominant channel. Second, after the Global Financial Crisis of 2008–2009, which hit Ukraine severely but involved no armed conflict, allocative TFP cumulatively declined by roughly 20 percent. However, this decline had a very different signature: a "slow burn" reaching its trough only in 2011, with no similar geographic gradient, and disproportionately affecting large firms. These comparisons isolate direct violence and displacement as the distinctive channels of the 2022 allocative collapse and highlight that macroeconomic instability during conflict can compound the damage.

Our paper contributes to several literatures. First, virtually all of the huge literature on the macroeconomic implications of resource misallocation pioneered by Hsieh and Klenow (2009) (see Restuccia and Rogerson (2017) and Ghatak and Mookherjee (2025) for surveys) examines peacetime economies. Our contribution is to study misallocation under an active, large-scale inter-state war. In this setting, destruction of capital, mass displacement of workers, disruption of supply chains, energy shortages, and mobilization create powerful distortionary wedges. By doing so, we provide the first micro-level evidence on how war reshapes the allocative efficiency of an economy and quantify the resulting productivity losses.

Second, our paper contributes to the rapidly growing "geoeconomics" literature that sits at the intersection of economics, political science, and national security (see Mohr and Trebesch (2025) for a survey). A key question in this literature is how costly wars are and through which channels they affect economic outcomes. The closest work is Federle et al. (2026), who use historical data to estimate the macroeconomic effects of wars. Apart from showing that proximity to conflict is associated with substantial output losses, Federle et al. document that wars dramatically reduce productivity. In a similar spirit, Field (2022) shows that even belligerents who do not have fighting on their soil can have lower productivity. Even short of any actual conflict, the mere *risk* of war can depress economic development (e.g., Schlepper and Wochner 2026).

While this literature establishes that inter-state wars are enormously destructive in the *aggregate*, the specific channels through which conflict depresses economic performance in general and productivity specifically remain less well understood. Indeed, wars disrupt data collection to such an extent that the "fog of war" often provides only rather primitive snapshots of economic activity. Strikingly, Ukraine continues to collect high-quality micro-level data and therefore we have a unique opportunity to examine the misallocation channel under extreme conditions. Relative to the pioneering analysis in Amodio and Di Maio (2018), who study Palestinian firm performance and distortions during the Second Intifada (approximately 5,000 casualties; ∼1,500 firms in the sample), we study a much larger war shock in a much more technologically advanced economy. There is also a conceptual difference to measuring misallocation: Amodio and Di Maio (2018) focus on input access constraints and *within-firm* misallocation,[1] while we study *between-firm* misallocation. By linking firm-level measures of allocative efficiency to granular data on the geographic intensity of Russian attacks, we provide additional evidence that war distorts the allocation of capital and labor.

Finally, our work contributes to the emerging body of research specifically quantifying the economic impact of Russia's aggression against Ukraine. The World Bank's series of Rapid Damage and Needs Assessments (e.g., World Bank 2026a) provide some of the most comprehensive estimates of damages and losses. Gorodnichenko and Vasudevan (2026) use macroeconomic forecasts to estimate that, as of April 2022, professional forecasters projected a cumulative loss of 193% of Ukraine's 2021 GDP over six years and a total regional cost of $2.44 trillion. At the micro level, analyses range from psychological costs (e.g., Nüß et al. 2026) to brain drain (e.g., Ganguli and Waldinger 2024) to firms' collateral damages (e.g.,

[1] That is, firms cannot obtain intermediate inputs due to Israeli-imposed movement restrictions and hence firms must substitute toward less efficient input combinations ("making do with what you have"). Because firms are forced to use suboptimal input combinations, there is a misallocation.

Shpak et al. 2023) to land contamination with mines (e.g., Deininger et al. 2026). In a closely related paper, Onyshchenko et al. (2026) document that Russian occupation dramatically reduced firms' performance. Our paper contributes to this literature by providing a structural, bottom-up assessment of the allocative inefficiency that amplifies the war's toll on aggregate economic output.

The remainder of the paper proceeds as follows. Section 2 provides background on the war. Section 3 lays out our measurement framework. Section 4 describes our data sources and construction of key variables. Section 5 presents the aggregate results on TFP and misallocation. Section 6 exploits subnational variation to inspect mechanisms and sharpen identification. Section 7 compares the 2022 invasion to the 2014 conflict and the Global Financial Crisis. Section 8 concludes.

2 The war shock and background

Russia's repeated aggression against Ukraine has deep historical roots stretching back to the earliest days of Ukrainian independence re-gained in 1991. Moscow persistently challenged Ukraine's sovereignty through various provocations, e.g., supporting Crimean separatists in 1993–1994, threatening border renegotiation, and engineering the 2003 Tuzla Island crisis. Following the Revolution of Dignity and President Yanukovych's flight to Russia in February 2014, the Kremlin illegally annexed Crimea using unmarked military forces and a sham referendum to change a European border by force for the first time since World War II. Russia subsequently supported proxy forces in the Donbas, directly attacked the Ukrainian military, and forced Ukraine to sign the Minsk accords, effectively freezing the conflict. The direct economic cost of this first round of naked aggression was high: between 2014 and 2016, Ukraine's GDP contracted by nearly 20%, the currency depreciated by 70%, and half of the banks went bankrupt. The direct economic cost of the Donbas occupation alone was estimated at $21.7 billion (Havlik et al. 2020). Despite an ambitious IMF-supported reform program that placed Ukraine on a recovery course, the threat of future Russian aggression continued to suppress foreign direct investment and weigh on the economy.

Beginning in March 2021, Russia amassed troops on Ukraine's border; in July 2021, Putin published an essay effectively denying Ukraine's right to exist as an independent state. Russia launched a full-scale attack on February 24, 2022, intending to overthrow the Ukrainian government within three days. The scale of the resulting shock has been enormous. Approximately 4 million Ukrainians were internally displaced (International Organization for Migration, 2023b), and roughly 8 million became refugees abroad (UNHCR, 2022). As of August 2026, obituary-confirmed data account for 239,354 killed Russian soldiers (Mediazona and BBC News Russian, 2026), 55,000 killed Ukrainian soldiers were officially acknowledged by Kyiv (Al Jazeera, 2026), and (OHCHR, 2026) verified 16,431 Ukrainian civilian deaths, thus giving a documented total of more than 300,000 dead.[2] World Bank (2026a) estimates direct, war-related damages at approximately $195 billion through December 2025.

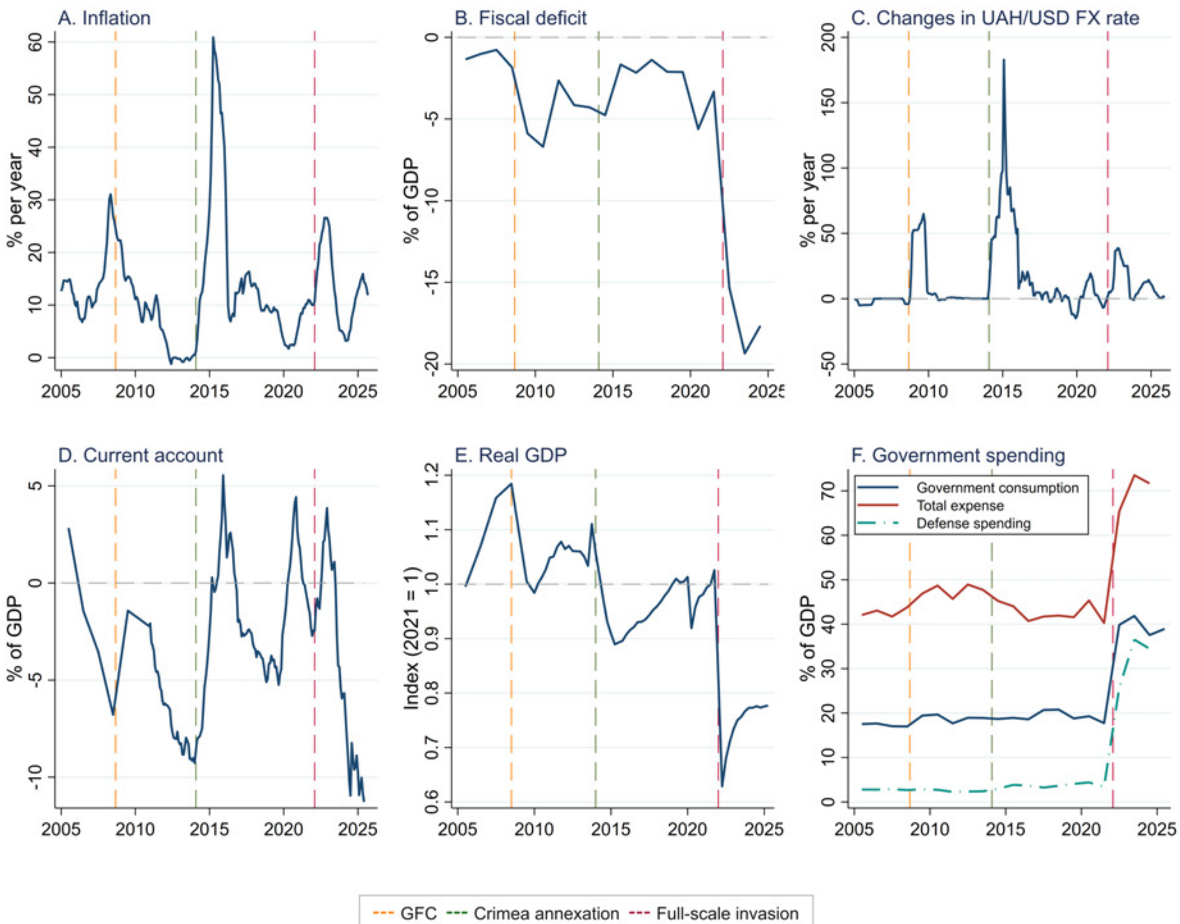
Ukraine's economy contracted sharply following Russia's full-scale invasion: real GDP fell by 28.8% in 2022 (Figure 1). Ukraine's government consumption as a share of GDP soared to 41.9% amid enormous defense spending, while consumer price inflation peaked at 26.6 percent year-on-year in December 2022. At the same time, Ukraine became an EU candidate country (June 2022) and, according to the Kiel Ukraine Support Tracker (Trebesch et al. 2023), has received approximately $408 billion in combined financial, humanitarian, and military aid as of April 2026.[3]

The invasion struck the Ukrainian economy in a highly uneven manner, with enormous regional and sectoral heterogeneity in the distribution of destruction and economic disruption. Geographically, the violence was concentrated in eastern and southern oblasts while western and central regions experienced comparatively less physical destruction (but even safer regions suffered severe indirect effects through supply chain disruptions, internal displacement,

[2]The actual death toll is almost certainly much higher. For example, estimates in Jones and McCabe (2026) are close to 600,000 military deaths alone.

[3]More details on the macroeconomic aspects of the shock and foreign aid can be found in Becker et al. (2022), Trebesch et al. (2023), Gorodnichenko and Vasudevan (2026), Gorodnichenko and Obstfeld (2026).

Figure 1: Ukraine's macroeconomic context, 2005–2024.



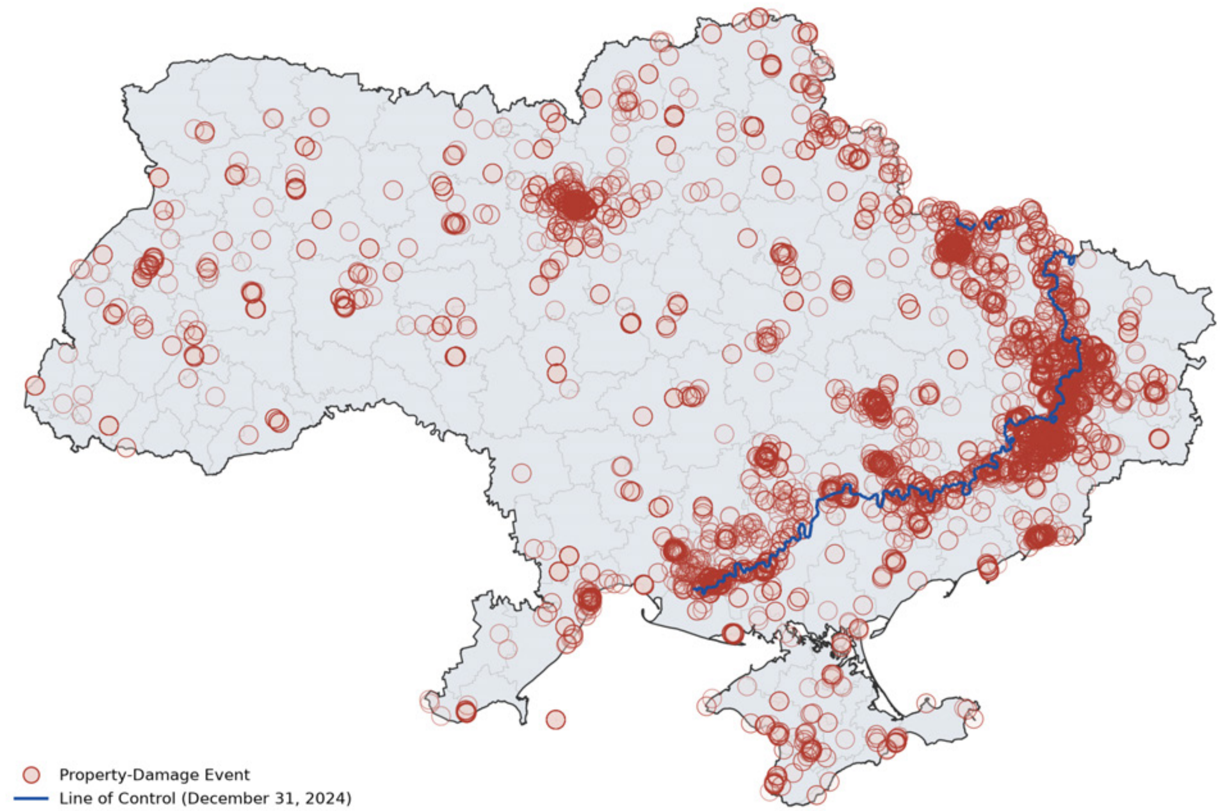
Notes: A: CPI inflation, monthly YoY (State Statistics Service of Ukraine, 2026a). B: fiscal balance (% GDP), annual, Ukrstat General Government Operations (State Statistics Service of Ukraine, 2026b). C: NBU USD exchange rate change, monthly YoY (National Bank of Ukraine, 2026b). D: current account (% GDP), annual 2005–2009 spliced onto trailing-12-month monthly 2010–2025 (National Bank of Ukraine, 2026a). E: real GDP index (2021 = 1), annual 2005–2009 spliced onto seasonally-adjusted quarterly 2010–2025 (World Bank, 2026b; State Statistics Service of Ukraine, 2026d). F: government spending (% GDP) – Government consumption and Defense spending, annual (World Bank, 2026b); Total expense, annual, same Ukrstat source as Panel B (State Statistics Service of Ukraine, 2026b). Vertical markers: GFC, Crimea annexation, full-scale invasion (Sep 2008, Feb 2014, Feb 2022).

and energy infrastructure attacks). Figure 2 shows that war intensity varied dramatically across regions and over time, with the highest concentration of violent incidents along the front lines, in areas subject to Russian occupation, and in large urban centers in the rear (e.g., Kyiv, Odesa). Oblasts further from the contact line experienced intermittent but devastating missile and drone strikes targeting critical infrastructure. World Bank (2026a) documents that the housing, transport, energy, and agricultural sectors bore disproportionate shares of physical damage. For instance, agriculture was disrupted by the mining of farmland, destruction of storage facilities, and the blockade of Black Sea ports. The energy sector suffered repeated targeted attacks that destroyed approximately 80% of thermal generation capacity and created a 5% supply shortfall of electricity (National Bank of Ukraine 2025). On the other hand, the IT sector, agribusinesses, and firms in western Ukraine proved comparatively more resilient, in some cases relocating operations domestically or abroad. In short, aggregate macroeconomic statistics mask profound distributional consequences.

3 Basic theory

In a seminal contribution, Hsieh and Klenow (2009) develop a framework for quantifying aggregate implications from misallocation of resources. In a nutshell, freely mobile capital and labor should earn the same return across firms. Departures from this textbook benchmark suggest that one can increase aggregate productivity, output and welfare by reallocating resources until the returns are equalized. In other words, the ideal allocation of resources implies that the cross-section dispersion of marginal revenue products should be zero. In practice, one should not expect perfect equalization due to e.g., adjustment costs, measurement errors, and quality differences. But one can still benchmark the dispersion against a yardstick that is known to represent a more efficient allocation of resources. For example, Hsieh and Klenow compare China and India (presumably countries with a worse allocation) to the U.S. (arguably the country with a better allocation). Furthermore, one can relate

Figure 2: Distribution of war-related property damage events, 2022–2024.



Notes: Data from Zhukov (2023).

cross-sectional dispersion to distortionary "wedges" and, under some assumptions, translate this dispersion into productivity losses.

Specifically, suppose that the revenue function of firm i at time t is given by $Y_{it} = Z_{it}K_{it}^{\alpha}L_{it}^{\beta}M_{it}^{1-\alpha-\beta}$ where Y is revenue, Z is productivity, K is capital, L is labor, and M is materials. If economic profits are small (as argued by Basu and Fernald (1997)), one can approximate elasticities with cost shares, that is, $\alpha = s^K$ and $\beta = s^L$. Hence, one can compute marginal revenue products of capital and labor as follows:

$$\log \mathrm{MRPK}_{ist} = \log\left(s_{st}^{K} \cdot \frac{\mathrm{Revenue}_{ist}}{\mathrm{Assets}_{ist}}\right), \tag{1}$$

$$\log \mathrm{MRPL}_{ist} = \log\left(s_{st}^{L} \cdot \frac{\mathrm{Revenue}_{ist}}{\mathrm{Employees}_{ist}}\right), \tag{2}$$

where cost shares may be different across sectors s.[4]

As discussed in Hsieh and Klenow (2009), the mapping from cross-sectional dispersion to aggregate productivity requires an identifying assumption. Specifically, one has to assume that one of the inputs does not have a "wedge", that is, there is no distortion in one of the input markets. Hsieh and Klenow posit no distortion in the labor market, which should be interpreted as a relative rather than literal statement. Then one can show the following relationship (see Gorodnichenko et al. (2026) for derivations):

$$\begin{aligned}\log(TFP\ loss) = &- \frac{\alpha(1-\alpha)+\alpha(1+\alpha)\sigma}{2}\,\mathrm{var}(\log(MRPK_{it}) - \log(MRPL_{it}))\\ &- \frac{\sigma(1+\alpha)}{2}\,\mathrm{var}(\log(MRPL_{it}))\\ &+ \frac{\sigma\alpha}{2}\,\mathrm{var}(\log(MRPK_{it})).\end{aligned} \tag{3}$$

As we discussed earlier, some cross-sectional dispersion in marginal revenue products stems from factors unrelated to distortions. However, some variation comes from distor-

[4] ORBIS has limited information on the cost of materials for Ukrainian firms. As a result, we cannot measure misallocation for materials. As discussed in Gorodnichenko et al. (2026), this means that our measure of TFP losses due to misallocation should be interpreted as a lower bound.

tionary forces such as market power, regulation, trade frictions, etc. In Ukraine's current context, distortions can also originate from Russian direct attacks (including stoppage due to air raids), indirect effects (e.g., access to electricity when Russia destroys Ukraine's energy infrastructure), mobilization of men (e.g., some men can choose occupations that offer deferment rather than ones that fully utilize their market potential), and shortage of qualified workforce (e.g., due to emigration, internal displacement, or mobilization). To the extent these wartime factors dominate the allocation of resources, one can expect large dispersion of marginal revenue products in Ukraine relative to peer non-belligerent countries or relative to a peacetime Ukraine.

4 Data

Our empirical design combines four ingredients: firm-level balance sheet data to measure MRPK/MRPL, official national accounts to obtain cost shares, online vacancy data to corroborate labor-market distortions, and geocoded subnational data to exploit within-country variation in war exposure.

4.1 ORBIS

A key input to our analysis is firm-level data from Bureau van Dijk's ORBIS, which provides detailed balance sheet and income statement information, ownership structures, and industry classifications for firms worldwide. Bureau van Dijk sources Ukrainian firm data primarily from official business registries and financial reporting databases, including the State Statistics Service of Ukraine and the Unified State Register. Although ORBIS coverage is not necessarily representative across countries (Kalemli-Özcan et al. 2024), it captures effectively the universe of Ukrainian firms, subject to a few caveats we verify directly against national statistics below. First, as in many countries, micro firms and sole proprietorships may be underrepresented, as reporting requirements vary by firm size and legal form. Second, financial reporting standards in Ukraine have evolved over time, so early years (e.g., early 2000s) may be less comparable to recent ones.[5] Third, ORBIS records only a firm's last known address, not an address history, so relocated firms are geocoded to their final location, which can misattribute their activity geographically for earlier years.

Following recommendations in Kalemli-Özcan et al. (2024), we apply a sequence of data cleaning filters to all countries in our analysis: restricting to firms registered in-country with a valid industry code and a December fiscal year end; deduplicating consolidated and unconsolidated reports in favor of the consolidated statement; requiring positive revenue, employment, and assets; ruling out implausible year-on-year jumps in capital or sales per worker; and excluding firms lacking active status or recent financial filings in the observation period. We also exclude three sectors, utilities, public administration, and defense, due to their heavy government ownership and regulation. For Ukraine specifically, we additionally exclude firms in occupied or otherwise unassignable raions, since firms under occupation may be compelled to re-register and report under Russian jurisdiction, in a different registry and currency, making their records not comparable to those of firms operating under Ukrainian law.

Because assets and employment are reported as annual snapshots while revenue accumulates only over the months a firm actually operated, a firm entering or exiting mid-year reports a full year of assets and employment against a partial year of revenue, which mechanically affects its measured MRPK and MRPL. A balanced panel avoids this by construction, and more broadly lets us compare the same firms' outcomes before and after the invasion rather than a shifting set of survivors. We therefore use it as our main specification. However, because firms may enter or exit mid-year, using a balanced panel can still introduce distortions for the first and last years of the panel; to address this issue we apply an edge correction described in Appendix A.2.

Immediately after deduplication, and before any sample selection filter, ORBIS covers

[5] Appendix Tables B1 and B2 report industry composition and firm counts/size by year, respectively.

98.8% of the State Statistics Service of Ukraine's national employees of business entities for 2020 (State Statistics Service of Ukraine, 2025), confirming that ORBIS approximates a census of Ukrainian firms rather than a selected subsample.These filters are demanding in terms of individual firm-year observations: our final main 2018–2024 sample for Ukraine retains only 24.2% of raw firm-year rows. They are far less demanding economically, however, since the removed rows are concentrated among small, thinly reported firms. The surviving sample still accounts for 55.8% of Ukraine's 2021 workers in business entities (State Statistics Service of Ukraine, 2025). Appendix Table B3 reports each filter's precise definition and the number of firms, firm-year rows, and employment remaining after it.

4.2 War intensity

The Violent Incident Information from News Articles (VIINA) database, constructed by Zhukov (2023), provides a comprehensive, geo-located, and near-real-time record of war events during Russia's invasion of Ukraine. The dataset is built by applying natural language processing and machine learning algorithms to news reports from a wide range of international and local media sources, extracting information on the type, location, and timing of each violent incident. Events are classified into categories including air strikes, artillery shelling, missile attacks, ground battles, and property-damaging strikes, with each event geolocated to precise coordinates across Ukrainian territory. The database covers the period from the start of the full-scale invasion on February 24, 2022 onward and is updated on a continuous basis, providing daily-frequency data that can be aggregated to any desired temporal or geographic unit. The VIINA data closely track patterns observed in official Ukrainian and international sources, while offering substantially greater geographic granularity and temporal frequency than alternative conflict datasets such as the Armed Conflict Location and Event Data Project (ACLED; see Raleigh et al. 2010) or the Uppsala Conflict Data Program (UCDP; see Sundberg and Melander 2013). For our purposes, we focus on VIINA incidents involving property damage (i.e., damage to private property or infrastructure), as these events are most likely to directly affect firms' physical capital and operating environment. We aggregate these incidents to the raion-year level and use them to construct a War Intensity Score capturing the local severity of Russian attacks faced by firms in each raion. The War Intensity Score is calculated from the property-damage incidents recorded from 2022 onward and normalized by the 2021 pre-war raion population (Brinkhoff, 2024): $\text{WarIntensity}_{r,t} = \ln\left(\frac{\text{PropertyDamage}_{r,t}}{\text{Population}_r/100{,}000} + 1\right)$. This normalization prevents the measure from mechanically increasing in areas that experienced wartime population losses. Appendix Table B6 reports summary statistics for this score.

4.3 Job vacancies

To complement ORBIS firm-level data, we scrape online job vacancy postings from Jooble.org, a job-search aggregator headquartered in Ukraine that collects listings from company websites, recruitment agencies, and job boards across the country. This approach follows an increasingly common practice in labor economics to use online job postings to study labor market dynamics at high frequency and granular geographic detail (see Faberman and Kudlyak 2016, Tsvetkova et al. 2024, Kurekova et al. 2015, Kuhn 2014 for early contributions and methodological reviews). Jooble is one of the largest job aggregators operating in the Ukrainian market, alongside Work.ua and Robota.ua. Unlike single-platform job boards like Work.ua and Robota.ua, Jooble aggregates listings from multiple sources (including company career pages, staffing agencies, and other job boards) and hence arguably provides broader coverage of the vacancy universe. As discussed in Anastasia et al. (2026), Faryna et al. (2022) and Pham et al. (2023), online job search has become the dominant channel for matching workers and firms in Ukraine.

The raw data contain over 3 million vacancy records spanning 2021–2024, each carrying a job identifier, free-text title, location, posted minimum salary, currency, salary rate, and creation date. In the pre-war year of 2021, the dataset contains approximately 2.3 million vacancy observations concentrated in major urban centers: Kyiv accounts for over one million postings, followed by Kharkiv, Dnipro, Lviv, and Odesa. Wages are reported for approximately 46 percent of postings, predominantly in Ukrainian hryvnia, though a subset of vacancies (primarily in the IT sector and remote work) are denominated in US dollars or euros. We process these records through a multi-stage pipeline that classifies free-text job titles into standardized occupations using the European Skills, Competences, Qualifications and Occupations (ESCO) taxonomy via a combination of generative AI and semantic matching, standardizes locations to Ukrainian oblasts (excluding occupied Crimea), converts salaries to a common currency using National Bank of Ukraine exchange rates, and removes duplicates following a conservative deduplication protocol. Appendix F provides the details. The resulting dataset provides a high-frequency, independent measure of labor demand and offered compensation across regions for approximately 2,000 standardized occupation categories. Consistent with the methodological literature on online vacancy data, our data over-represents technology, professional services, white-collar occupations, and urban areas relative to the full economy, and under-represents public-sector and informal employment.

4.4 Additional data

We construct sector-level capital cost shares from national income and product accounts: State Statistics Service of Ukraine (2026e) for Ukraine, OECD (2025b) for Poland, and Eurostat (2026) for Romania, Bulgaria, Croatia, and Estonia. Appendix Section A.1 details the construction of these cost shares; the resulting values, alongside sample composition, are reported in Appendix Tables B1 (Ukraine, by sector) and B4 (benchmark countries). Appendix Table B2 reports the corresponding firm-level summary statistics by year.

We draw on several further sources for auxiliary calculations throughout the paper: the wartime employment decline, including government and military employment (International Labour Organization, 2022); the pre-war capital stock (IMF, 2021); and physical damage to capital (World Bank, 2026a). Wherever we instead need value added or employment at the sector level specifically, we use Ukrstat's production and income accounts (State Statistics

Service of Ukraine, 2026e), workers in business-entities register (State Statistics Service of Ukraine, 2025), and Input-Output table (State Statistics Service of Ukraine, 2026c), with the latter also providing the sector-specific government-consumption share. We also use inflows of internally displaced persons (International Organization for Migration, 2023b) and a region boundary shapefile for firm-to-region geomatching and distance-to-Russia calculations (OCHA Ukraine, 2025).

5 The war effects

This section establishes the main national facts. We first document wartime firm destruction, then show that dispersion in marginal revenue products rose sharply among surviving firms, corroborate the labor-market component using vacancy data, and finally translate these changes into allocative TFP losses.

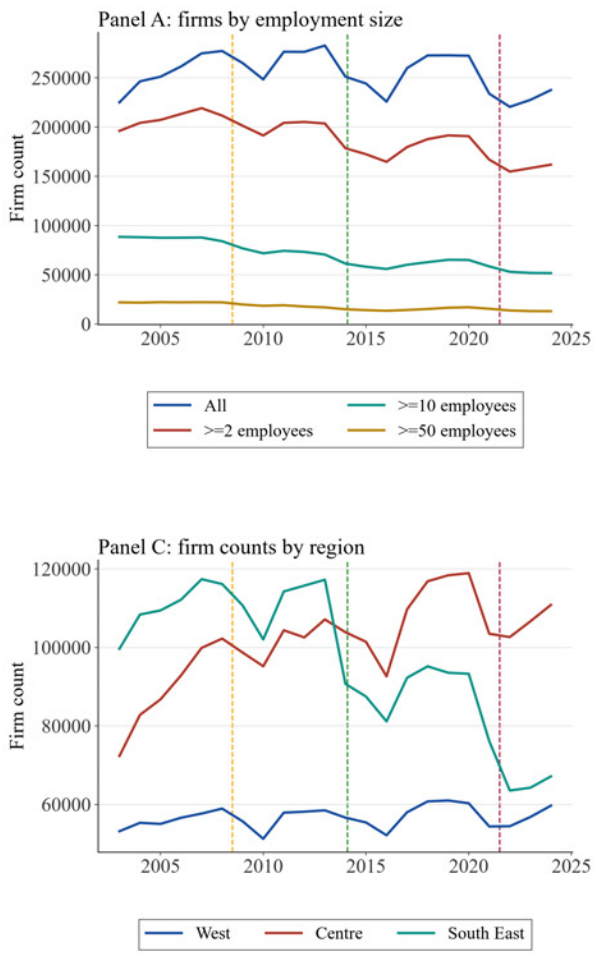
5.1 Firm counts and entry/exit

Before examining how the war distorted the *allocation* of resources across firms, we first document its effect on the *extensive* margin. This is important for interpreting our misallocation results because firm destruction is itself a first-order cost of war, and because entry/exit determines the composition of the sample over which we measure dispersion.[6]

Figure 3 presents long time series of the total number of firms with any positive employment from the ORBIS database for Ukraine over 2003–2024. The decline in the firm count after the Global Financial Crisis was dwarfed by the contraction after Russia's 2014 illegal annexation of Crimea and occupation of parts of the Donbas, when firm counts fell by roughly 30 percent over three years. After stabilizing and gradually recovering around 2017, the firm count fell sharply again after the full-scale invasion: approximately 20 percent of

[6]To be clear, the firm counts and entry/exit rates reported in this subsection draw on the full, unbalanced universe of ORBIS firms satisfying our baseline quality filters, whereas the dispersion and TFP results in subsequent sections use a balanced panel.

Figure 3: Firm counts and entry/exit rates from the ORBIS database, Ukraine, 2003–2024



Notes: Panel B's Agriculture series has a 2010–2012 level break from Ukraine's KVED-2005 → KVED-2010 (NACE Rev. 2) reclassification (State Committee of Ukraine for Technical Regulation and Consumer Policy, 2010), which folded related industries (e.g. fishing/aquaculture, previously a separate section) into agriculture.

firms disappeared cumulatively between 2021 and 2024. These patterns are broadly similar by firm size (Panel A) and sector (Panel B).[7]

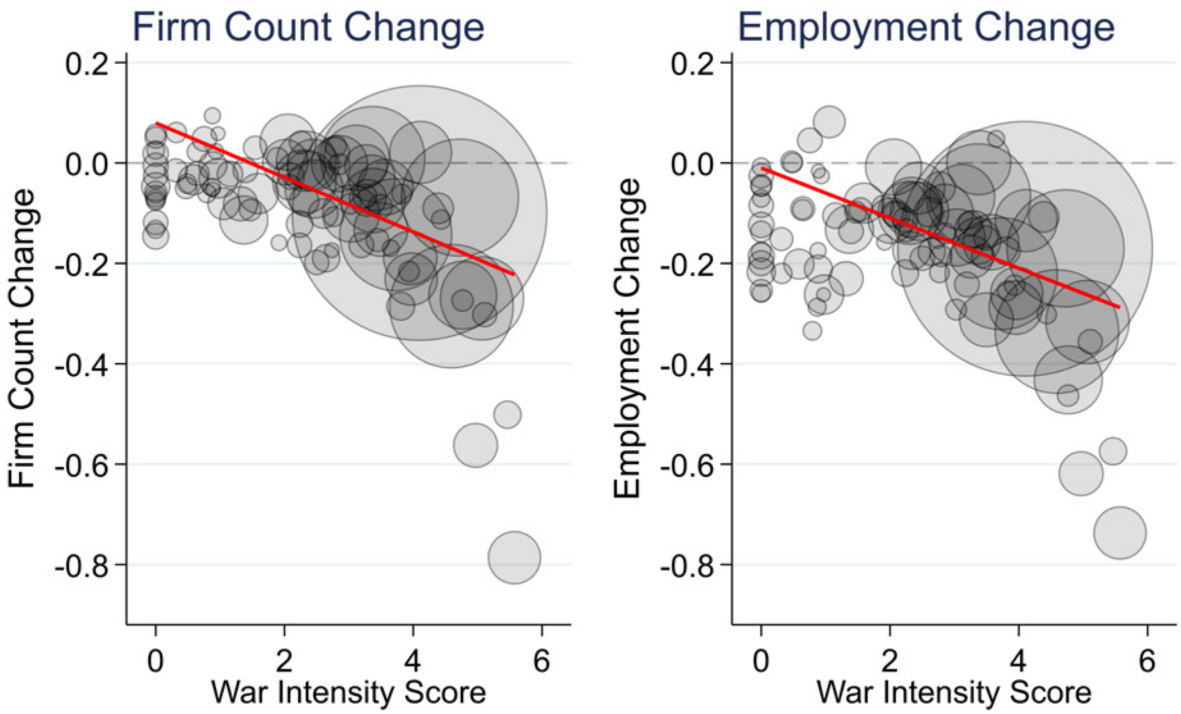
At the same time, there is a clear geographic heterogeneity (Panel C). The South-East macro-region, which is closest to the front lines and most exposed to Russian attacks, lost nearly half its firms between 2014 and 2024 (with much of this loss occurring in two discrete drops: 2014–2015 and 2022–2023). The Center and West macro-regions show much more modest declines, and in some years exhibit slight recovery, consistent with firms relocating toward safer areas. To support this point, Figure 4 relates raion-level firm counts directly to local war intensity. Raions with low war intensity (scores near zero, located predominantly in western Ukraine) experienced modest declines or even slight increases in firm counts, while raions with the highest war intensity lost 40-80 percent of their firms and a comparable share of employment.

Entry/exit rates suggest significant churn (Panel D of Figure 3). Consistent with the dynamics of firm counts, annual exit rates spiked in 2014 and again in 2022, each time reaching approximately 20 percent. Thus, the war induced massive firm destruction that is *not* captured by misallocation. By 2023–2024 when the acute phase of territorial shifts subsided, exit rates declined somewhat and entry rates recovered to the prewar level.

What kind of firms exit? If the weakest do not survive, the observed population can have a survivorship bias. On the other hand, if war destroys firms in a manner uncorrelated with pre-war productivity (a Russian missile does not discriminate based on a firm's marginal revenue product), then the surviving sample is not systematically selected on productivity and concerns about survivorship bias are attenuated. To investigate this directly, we examine whether pre-war MRPK and MRPL predict subsequent firm exit (Figure 5). Before the full-scale invasion, both measures exhibit negative relationships with exit: firms with lower marginal revenue products (i.e., those utilizing resources less efficiently) are more likely

[7] Agriculture exhibits a level break around 2010–2012 that reflects Ukraine's reclassification from KVED-2005 to KVED-2010 (which among other things folded fishing and aquaculture into agriculture) rather than a true structural change.

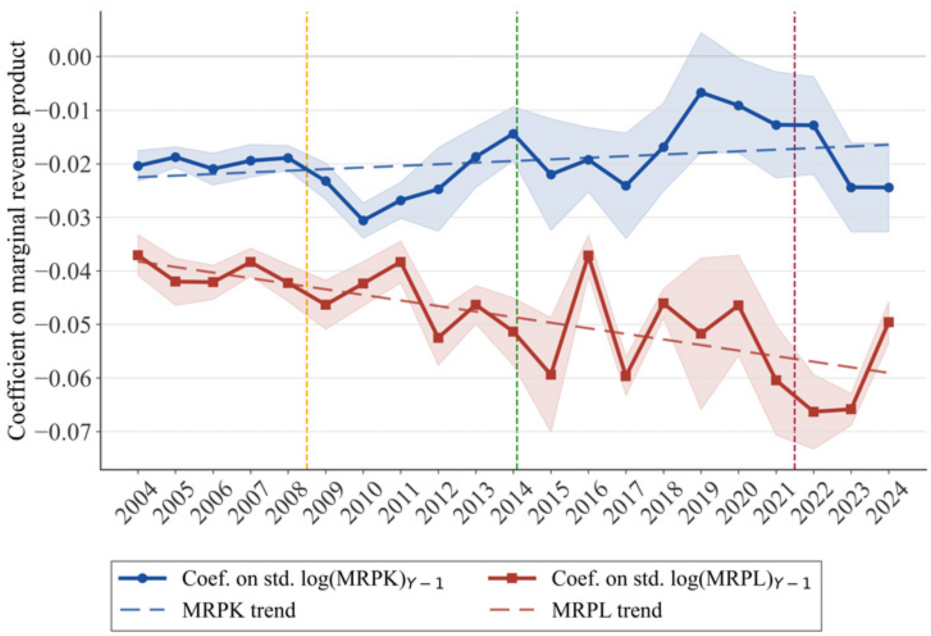
Figure 4: War intensity vs. raion-level firm and employment attrition.



Notes: Bubble size = each raion's / sector's 2021 firm count. Only raions still under Ukrainian control as of 2024 with at least 80 firms in the 2020–2024 balanced panel (96 raions), pre-balance firm/employment change 2021–2024. Same filters as the main 2018–2024 estimation sample (country, fiscal period, NACE parse, consolidation dedup, positivity, government-dominated-sector exclusion, jump filter), except the raion, balanced-panel, and status/recent-financials filters are not applied, since each would remove the entry/exit events studied here.

to exit, consistent with Schumpeterian creative destruction. The estimated selection on marginal revenue products was similar for 2021 and 2022. In later years, selection was somewhat stronger for MRPK and somewhat weaker for MRPL. This evidence suggests that wartime exit does not dramatically amplify Schumpeterian forces that cull the least efficient. Therefore, changes in dispersion of marginal revenue products among surviving firms likely reflect genuine misallocation rather than compositional shifts.

Figure 5: Lagged MRPK and MRPL vs. subsequent firm exit, Ukraine, 2004–2024.



Notes: Each point is estimated slope in separate regressions of firm absence in year Y on that firm's own standardized log(MRPK) or log(MRPL) in year $Y-1$, with industry-cell fixed effects (195 cells, identical to the main estimation pipeline) and standard errors clustered by industry-cell; shaded band is the 95% confidence interval. Dashed lines are fitted time trends. Same filters as the main 2018–2024 estimation sample (country, fiscal period, NACE parse, consolidation dedup, positivity, government-dominated-sector exclusion, jump filter), except the raion, balanced-panel, and status/recent-financials filters are not applied, since each would remove the entry/exit events studied here.

In summary, the war destroyed a large share of Ukrainian firms cumulatively, with losses concentrated in high-intensity regions. Among surviving firms, pre-war productivity does not unusually strongly predict wartime exit, suggesting that the balanced panel used for our main analysis is not severely distorted by differential selection on allocative efficiency.

5.2 Dispersion of marginal revenue products

We now turn to the central object of our analysis: the cross-sectional dispersion of marginal revenue products of capital and labor. At this stage, we do not impose any assumptions on the elasticity of demand (σ) or the source of distortions (whether $\tau_L = 1$ or $\tau_K = 1$) and therefore this section is reduced-form.

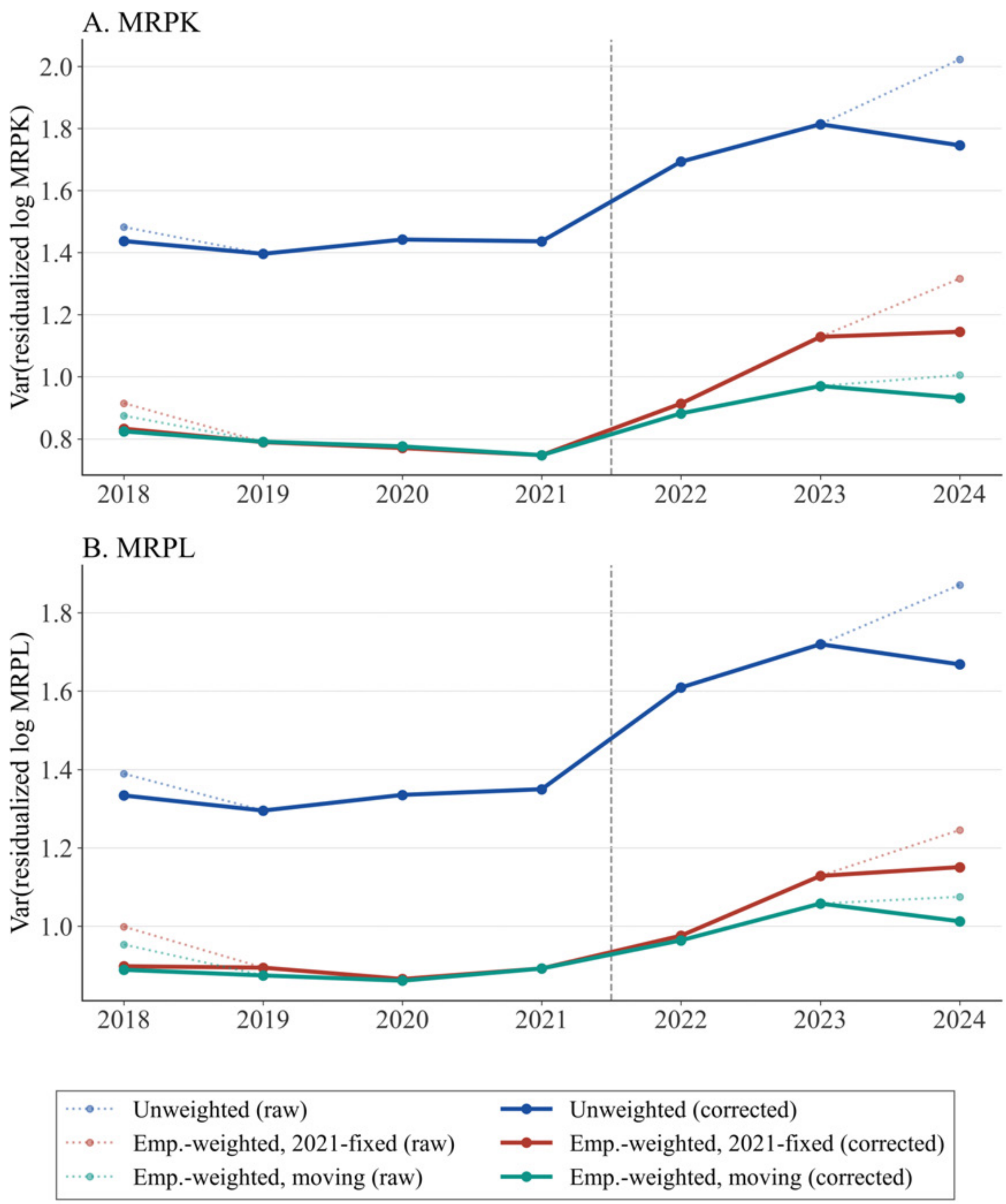
As a first pass at the data, Figure 6 presents the time series of the cross-sectional variance of residualized log MRPK (Panel A) and log MRPL (Panel B) at the national level over 2018–2024.[8] Our baseline measure uses the balanced sample and residualized marginal revenue products, where we remove industry-cell×year fixed effects so that the reported dispersion captures within-industry variation. For each panel, we report several variants: unweighted vs. employment-weighted, using either fixed 2021 employment weights or moving weights, which update each firm's weight to reflect its employment share in that year, as well as raw vs. edge-corrected series.

Ukraine's pre-war level of cross-sectional dispersion was generally higher than that in peer countries in the region (Gorodnichenko et al. 2026), which likely reflects the legacy of prior calamities (the 2014 war, the banking crises, etc.), lower financial development, weaker property rights, and less developed institutions. The employment-weighted series show somewhat different levels (higher for MRPK and lower for MRPL) but qualitatively results are the same. The COVID-19 pandemic produced, if anything, only a modest and temporary blip in dispersion.

Irrespective of what variant of the series we use, we observe a clear increase in the cross-section dispersion after the Russian full-scale invasion. Dispersion does not revert toward pre-war levels in 2023 or 2024 despite the partial stabilization of the front line and partial economic recovery. An inspection of kernel densities for the MRPK and MRPL distributions (Appendix Figure C2) suggests that the war-time distribution is visibly wider and has fatter

[8] Longer time series for 2006–2024 are reported in Appendix Figure C1. These series use a smaller balanced sample of firms.

Figure 6: Residualized MRPK/MRPL dispersion, 2018–2024



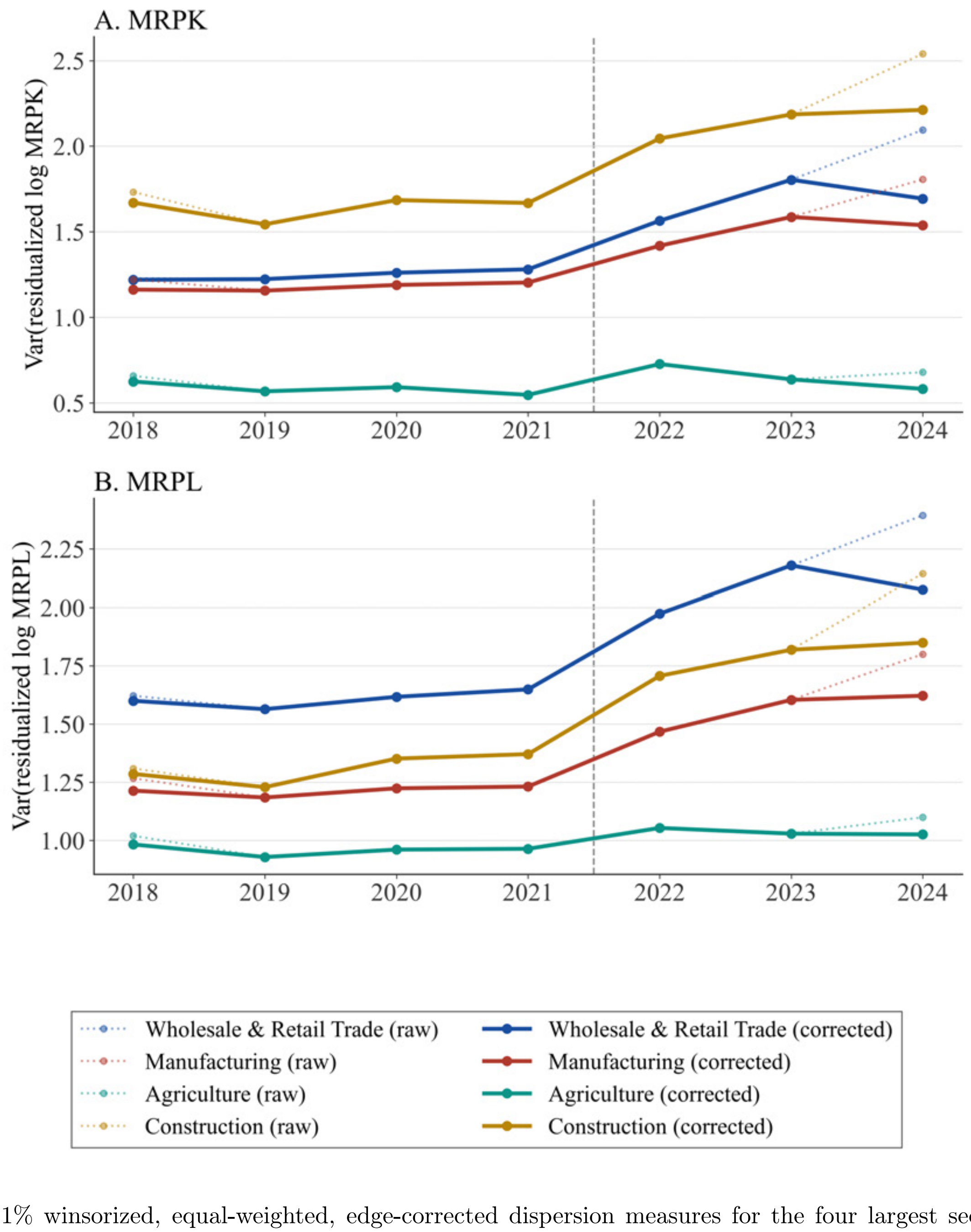
Notes: Ukraine: 90,257 firms, 195 industry cells, balanced 2018–2024 panel.

tails than the pre-war distribution. The entire distribution has spread out indicating that the war creates distortions in both directions: some firms are pushed to use far too much capital (or labor) relative to their revenue, while others are starved of inputs.

We do a number of checks to establish robustness. First, moving from 1 percent to 5 percent winsorization reduces the level of dispersion but does not alter the timing, magnitude, or persistence of the post-invasion increase (Appendix Figure C3). Even with no winsorization, the break in 2022 is clearly visible, though the levels are higher due to outliers. Second, when we restrict the sample to firms with at least 3, 5 or 10 employees to exclude the "noisiest" micro-firms, the results are similar (Appendix Figure C4). Third, the pattern holds whether we use total assets or fixed assets as the capital measure (Appendix Figure C5), confirming that the trend does not depend on a particular definition of the capital stock. Fourth, the interquartile range (IQR) and the 90–10 gap, which are less sensitive to outliers than the variance, show the same pattern (Appendix Figure C6). Fifth, while the levels differ, the dynamics of dispersion are similar across firm-size quartiles (Appendix Figure C7). Sixth, although we defer the detailed raion-level analysis to Section 6.1 (where we relate dispersion and TFP directly to war intensity), the South-East macroregion exhibits the largest increase in both MRPK and MRPL dispersion after February 2022, followed by the Center, with the West showing the smallest (though still substantial) increase (Appendix Figure C8). This geographic gradient indicates that the increase in dispersion is linked to the conflict rather than reflecting some nationwide institutional or policy change.

Importantly, our results are unlikely to be driven by deteriorating data quality in wartime. Using the approach in Gorodnichenko et al. (2026), we implement a time-averaging exercise designed to attenuate measurement error. Specifically, we compute each firm's average MRPK and MRPL over the pre-war years 2019–2021 and separately over the wartime years 2022–2024, and then compare the cross-sectional variance of these time-averaged measures. We find (Appendix Figure C9) that the time-averaged variances for MRPK and MRPL rise by approximately 30%, which is similar to single-year estimates.

Figure 7: Dispersion levels by sector, Ukraine, 2018–2024.



Notes: 1% winsorized, equal-weighted, edge-corrected dispersion measures for the four largest sectors by 2021 firm count. Each sector uses its own industry_cell hierarchy. Sample composition: Table B1.

Figure 7 plots the dispersion time series by the four largest sectors: wholesale and retail trade, manufacturing, agriculture, and construction. All four sectors experience increases in both MRPK and MRPL dispersion after the invasion, and so the aggregate result is not driven by a single industry. The sectoral patterns are informative about the mechanisms driving misallocation. The fact that construction (where mobilization of working-age men is especially binding; see OECD (2025a)) shows some of the largest increases is consistent with mobilization and displacement being key drivers of increased dispersion. On the other hand, agriculture's relatively modest increase in dispersion is consistent with its decentralized production and consequently lower vulnerability to Russian attacks. Using independent sectoral data on output dynamics from the National Bank of Ukraine and the State Statistics Service, we note that sectors exhibiting larger increases in dispersion also tend to be those that suffered larger contractions in output.

A key identification concern is whether the increase in dispersion reflects common shocks that affected all countries in the region (e.g., the 2022 energy crisis, post-pandemic supply chain disruptions, or the global inflation surge) rather than war-specific effects. To address this, we compute dispersion for a set of Eastern European peer countries (Romania (RO), Poland (PL), Croatia (HR), Bulgaria (BG), and Estonia (EE)), which have near-universal firm coverage in ORBIS. In short, peer countries show essentially flat dispersion with small fluctuations (with a small, common 2020 COVID-related spike) well within normal variation (Appendix Figure C10). Hence, the increase in dispersion observed in Ukraine must be driven by the war.

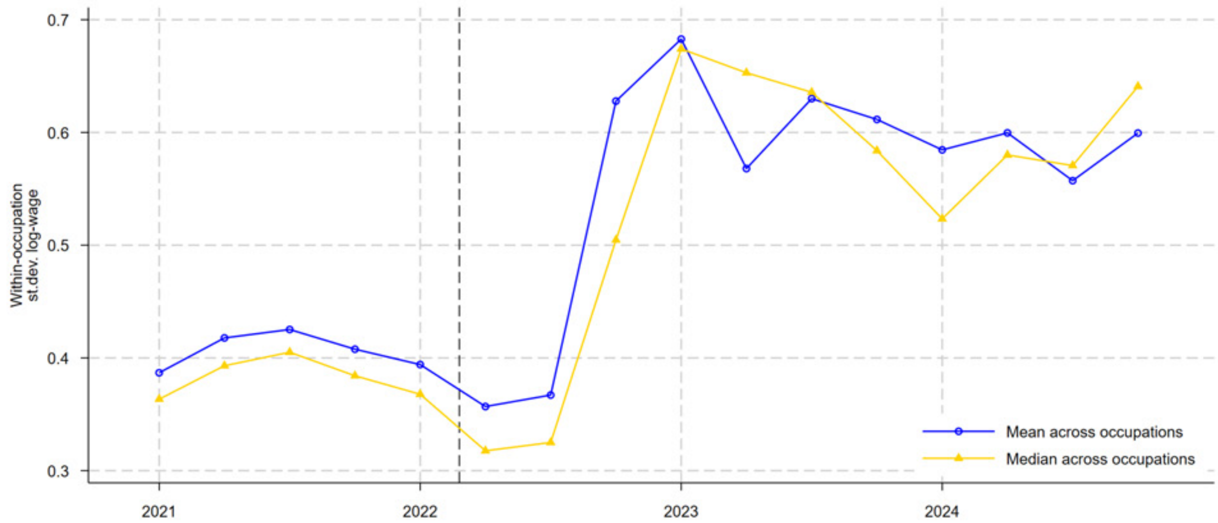
5.3 Job vacancy data

To validate our firm-level findings with an independent data source, we turn to the online job vacancy postings described in Section 4.3. Under competitive labor markets, posted wages should be equal to the marginal revenue product of labor, that is, $W = MRPL$. In practice, various wedges (non-wage benefits, search frictions, monopsony power, regulatory constraints) drive a gap between wages and marginal products. Assuming these wedges are approximately constant across firms and do not change differentially over time, one may expect that the cross-sectional dispersion of log posted wages should mirror the dispersion of log $MRPL$: $\text{var}(\log W_{it}) \propto \text{var}(\log MRPL_{it})$. In other words, we can normalize both the ORBIS-based and vacancy-based dispersion series to their pre-war baselines and compare proportional changes. Note that while ORBIS data are at the annual frequency, the job posting data are available at much higher frequency and thus can provide a more granular description of the economic response.

For each quarter, we compute the standard deviation of log wages within every occupation cell that contains at least 10 postings, and then summarize the cross-section of these within-occupation dispersions by their mean and median. All wages are converted to a common currency (USD) at the posting-month exchange rate, restricted to monthly-paid postings with a plausible salary floor, and winsorized at the 1st and 99th percentiles.

Figure 8 shows the time series of within-occupation wage dispersion. The within-occupation log-wage standard deviation was approximately 0.41 during the pre-war period. Following the full-scale invasion, dispersion initially compressed to approximately 0.36 during the acute shock in early 2022. This compression does not indicate improved allocation; it reflects the collapse of the vacancy market itself. During the most intense phase of the war, high-paying vacancies largely disappeared. The surviving vacancies clustered toward lower-wage, essential-service positions, thus mechanically reducing measured spread. Once the first shock passed, posting volume stabilized at this much lower level through 2023–2024, with the composition of surviving vacancies still severely distorted (mass displacement, mobilization of working-age men, destruction of productive capacity, acute labor shortages). Over this period, within-occupation wage dispersion widened substantially, reaching a level that is roughly 50% above the pre-war level.

Figure 8: Within-occupation wage dispersion over time



Notes: Within-occupation standard deviation of log posted wages. For each quarter, the standard deviation is computed within every occupation cell with at least 10 postings; the series plot the mean and the median of those cell-level standard deviations across occupations, for quarters with at least 5 qualifying occupations. Wages are monthly, converted to USD at the posting-month official NBU rate, and winsorized at the 1st and 99th percentiles of the pooled distribution. Dashed line: 24 February 2022.

The vacancy-based wage dispersion dynamics mirror what we observe in the ORBIS firm-level data. Both sources show: *i*) a sharp disruption at the onset of the full-scale invasion, followed by *ii*) a persistent increase in the dispersion of labor's marginal compensation that exceeds pre-war levels during 2023–2024. The magnitudes are broadly comparable: the 50–65 percent increase in within-occupation posted-wage dispersion is of a similar order of magnitude to the increase in the cross-sectional variance of $\log MRPL$ documented in Section 5.2.

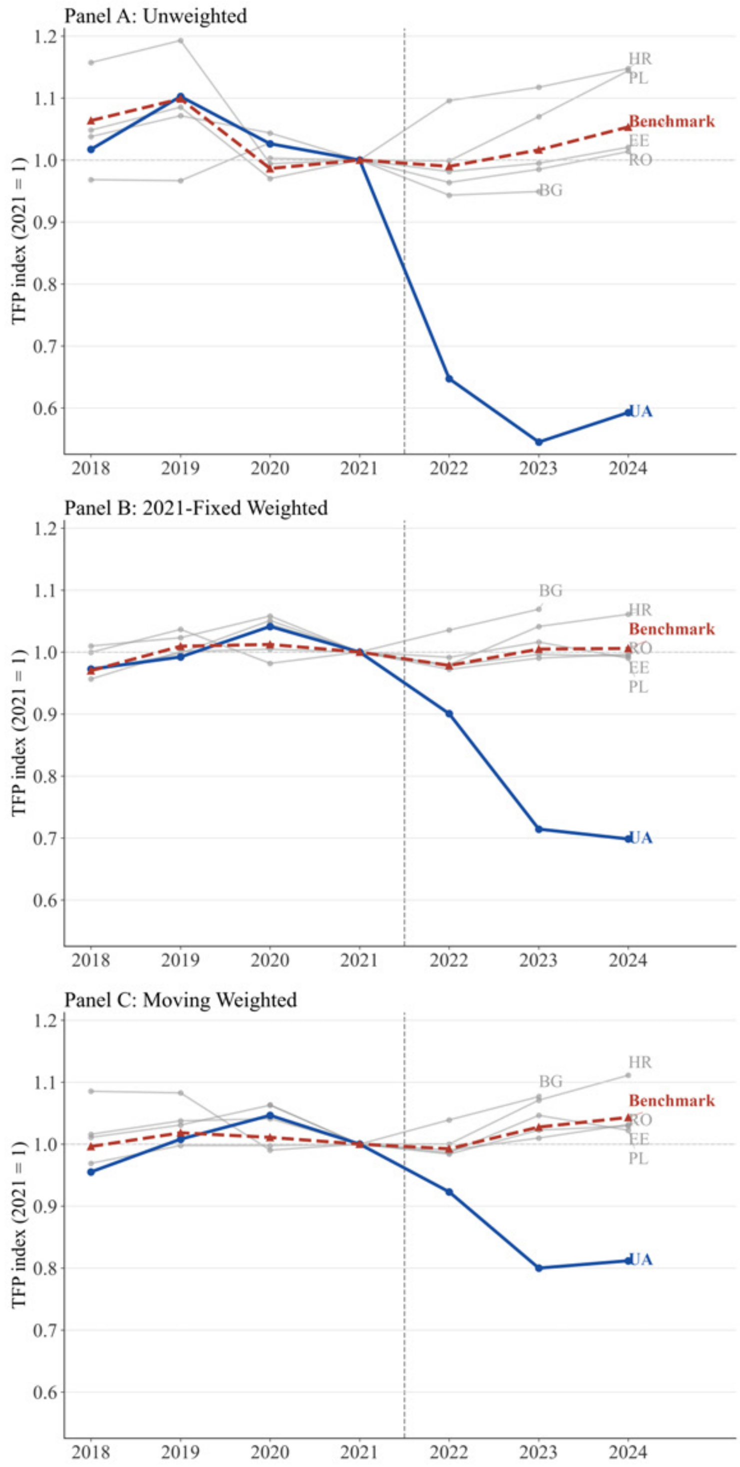
These results are subject to two caveats. First, the post-invasion vacancy sample is orders of magnitude smaller than the pre-war sample, reflecting conditions among firms that are actively hiring according to Jooble. These firms constitute an arguably more resilient subset. If anything, this selection implies that the true extent of labor misallocation in the broader economy (including firms that cannot hire at all) is understated by the vacancy evidence. Second, posted wages may differ from transacted wages. However, we are not aware of changes in labor market practices that would change the gap differentially across firms within an occupation precisely at the time of the invasion. So the within-occupation trends should indicate changes in the underlying dispersion of labor's value to firms.

5.4 Allocative productivity

We now translate the dispersion measures documented in the previous section into aggregate productivity losses using the Hsieh and Klenow (2009) framework described in Section 3. Following the literature, our baseline uses $\sigma = 3$, assumes no distortion in the labor market ($\tau_L = 1$), winsorizes at the 1st and 99th percentiles within each industry cell, and applies the edge correction for the first and last years of the balanced sample. Equation 3 maps the three variance terms $var(\log(MRPK) - \log(MRPL))$, $var(\log(MRPL))$, and $var(\log(MRPK))$ into a single log TFP loss measure. We report both unweighted and employment-weighted variants. We normalize TFP to unity in 2021 (the last pre-war year) so that all subsequent values can be read directly as the fraction of potential allocative efficiency that the economy retains.

Figure 9 shows TFP roughly stable or modestly improving over 2018–2021, consistent with Ukraine's gradual post-2014 recovery, before the full-scale invasion produced a catastrophic decline under all three weighting schemes, of markedly different magnitude. The unweighted estimate treats every firm equally regardless of size; it shows the largest loss, with TFP falling to ≈0.62 in 2022 and recovering only to ≈0.64 by 2024, a 36 percent loss. Weighting firms by their 2021, pre-war size instead asks how much this misallocation cost the economy as it actually looked before the war, giving a smaller loss (≈0.72, 28 percent, in 2024). The moving-weight variant, which allows the composition to shift with wartime employment changes, gives the smallest loss of the three, 20 percent in 2023, easing slightly

Figure 9: National TFP index by country, 2018–2024, 2021 = 1.



Notes: 1% winsorized, equal-weighted, edge-corrected. Poland: shortened 2020–2024 window. Bulgaria: through 2023 only. *Benchmark* = firm-count-weighted average of other countries. Donor weights and sample composition: Appendix, Table B4.

to 19 percent by 2024. The war thus destroyed between one-fifth and one-third of allocative efficiency, depending on weighting; none of the benchmark countries experienced anything comparable.[9]

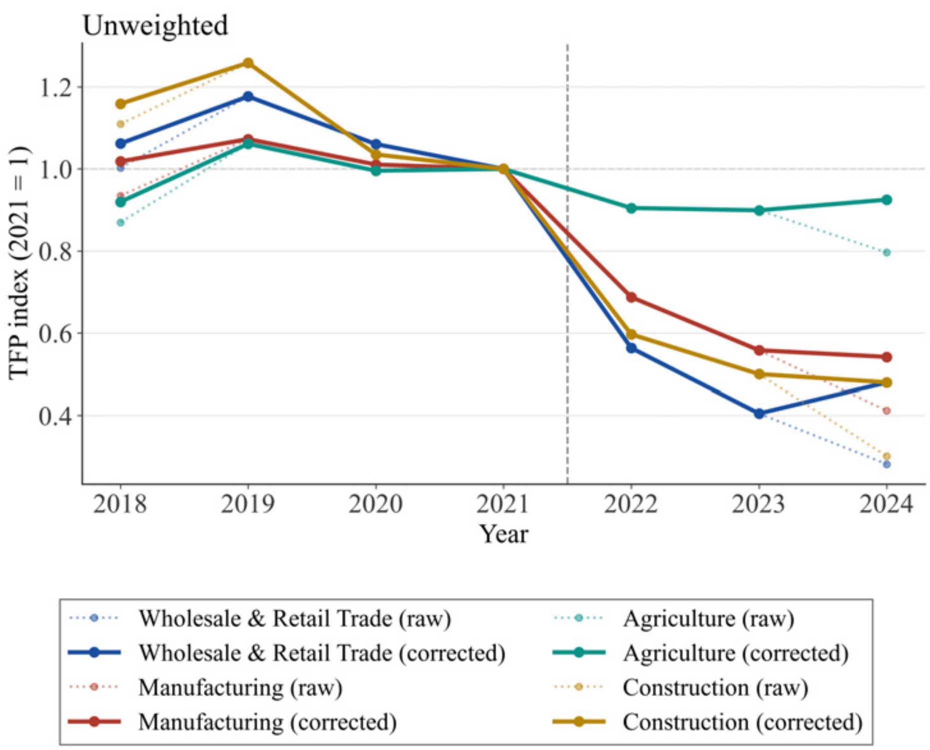
The magnitude of the estimated TFP decline depends on assumptions. For example, higher values of σ amplify the TFP consequences of any given dispersion. We find (Panel A of Appendix Figure D2) that the estimated 2024 loss (equal weights) ranges from $\approx 20\%$ ($\sigma = 1.5$) to $\approx 55\%$ ($\sigma = 5$). Moving to 5-percent winsorization reduces the estimated loss (equal weights) modestly (to approximately 30% in 2024; see Panel B of Appendix Figure D2), while removing winsorization entirely increases it (to $\approx 42\%$). When we instead assume no distortion in the capital market ($\tau_K = 1$), the TFP losses are somewhat larger in magnitude (because the variance of log MRPK which receives a larger weight under the $\tau_K = 1$ assumption) but qualitatively identical in their time-series pattern (Appendix Figure D3).

All quartiles by firm size experience substantial TFP declines after the invasion, but the magnitude differs by quartile (Appendix Figure D4). The smallest firms (Q1) show the largest decline, consistent with small firms having fewer resources to adapt (e.g., they cannot easily relocate, diversify suppliers, or install backup generators). The largest firms (Q4) show a smaller decline, suggesting that scale provides some buffer against allocative shocks. We conjecture that this may operate through internal markets that facilitate reallocation across divisions, greater access to credit, or political connections that provide priority access to scarce resources such as electricity. The gap between the unweighted and employment-weighted aggregate TFP series (as seen in Figure 9) is therefore driven primarily by the differential impact on small versus large firms: small firms suffer more, but because they account for less employment, their effect on the weighted aggregate is attenuated.

Figure 10 reports the unweighted TFP index for the four largest sectors. Wholesale and retail trade and construction experienced the most severe TFP declines, with the index

[9] Appendix Figure D1 plots the longer time series based on the 2006–2024 panel.

Figure 10: National TFP index by four major sectors, Ukraine, 2018–2024.



Notes: 1% winsorized, equal-weighted, edge-corrected. Each sector uses its own industry_cell hierarchy and its own capital cost share s_K^{rev}. Sample composition: Table B1.

falling to ≈0.48 in both by 2024 (a ≈52% loss relative to 2021). Manufacturing also shows a large TFP decline (≈46% loss) and little recovery after the initial shock. Agriculture shows the most moderate TFP decline (≈7–8%) and exhibits some recovery by 2024. These TFP declines track contraction of real value added (VA) per worker (as shown in Appendix Table B7): VA net of government consumption per worker fell ≈39% in construction, ≈15% in manufacturing, ≈14% in wholesale and retail trade, and ≈8% in agriculture. Construction, manufacturing, and agriculture rank the same way on both measures, while wholesale and retail trade is a clear outlier: its VA-per-worker decline is the second-mildest of the four, yet its TFP decline ties construction for the largest. This divergence likely reflects differences in firm-size composition as wholesale and retail trade is one of the most extreme cases of firm-size concentration.[10] Consistent with this explanation, the severe unweighted TFP decline in retail is far milder under firm weighting, while construction (less firm-size concentrated) and manufacturing (comparably concentrated, but usually single-site) show similar-magnitude declines under both weighting schemes (see Appendix Figure D5).[11] Several features of agriculture help explain its relative resilience: production is geographically dispersed (reducing vulnerability to localized strikes), the sector is less dependent on urban infrastructure, and the gradual reopening of grain export corridors (first through the Black Sea Grain Initiative and then through alternative routes) eased shipping constraints. Nevertheless, even with the mildest per-worker decline of the four sectors, total VA in agriculture still fell by ≈22%, a

[10]For wholesale and retail trade, a handful of national chains account for a large share of employment. In our data, ATB Market, the largest retailer, has more employees than the smallest half of retail firms combined. ATB and other large national chains benefit from the same buffers as large firms elsewhere in the economy: internal markets that facilitate reallocation across divisions, greater access to credit, and priority access to scarce resources such as electricity. Retail chains have a further advantage specific to their business model: because ORBIS records financials at the firm level rather than the store level, the revenue, assets, and employment of a chain are pooled across its entire national store network, so disruption to outlets in front-line regions is averaged against continued operation elsewhere. A single-location shop has no such buffer: its entire financial profile sits in one place, so local war shocks such as blackouts, displacement of employees and customers, or direct attacks pass straight through to its measured MRPK and MRPL. This geographic pooling is largely unavailable to large manufacturing firms, which are typically concentrated in a single plant or site.

[11]We generally prefer unweighted TFP as our headline sector-level measure: weighted estimates are more exposed to thin-cell noise, are stable only in the largest sectors or the national economy (even for benchmark countries), and mask real dispersion trends among small firms.

large loss given how important the sector is for Ukraine's export earnings and food security.[12]

The geographic gradient in TFP decline is pronounced (Appendix Figure D7). The South-East experienced the most severe TFP decline, with the index (equal weights) falling to approximately 0.46 by 2024. The Center (including Kyiv) had a significantly smaller decline to approximately 0.62. The West shows the smallest decline of 0.68, though even here TFP fell substantially relative to pre-war levels.

5.5 Growth accounting

To gauge the importance of misallocation for the decline in output, we use standard growth accounting. We first perform a back-of-the-envelope calculation and then use additional assumptions and data to refine our estimates.

5.5.1 Back of the envelope calculations

Recall that changes in output can be decomposed as follows: $\Delta \log(Y) \approx \Delta \log(TFP) + \alpha \Delta \log(K) + (1-\alpha)\Delta \log(L)$. Based on Penn World Table (Feenstra et al. 2015) pre-war data for Ukraine, we set $\alpha = 0.446$.[13] As described in Section 2, total GDP contracted by $\Delta \log(Y) = \log(1 - 0.288) \approx -0.34$ in 2022.[14]

Ukraine's State Statistics Service (Ukrstat) conducted a detailed pre-war labor force survey, but has not published a comparable total employment series since the 2022 invasion (Matuszak, 2026), so we rely on an alternative source. The International Labour Organization estimates that employment fell 15.5% (2.4 million jobs) in 2022, relative to a pre-

[12] Appendix Figure D6 illustrates that this connection between TFP and effective output decline generally holds across the other sectors as well. However, both VA and TFP are volatile in small sectors even during peacetime, including in the benchmark countries. This is especially the case for financial and insurance; arts and entertainment; and mining and quarrying, each of which has fewer than 600 firms. Restricting to the 13 larger sectors in Panel B sharpens the TFP/VA correlation considerably.

[13] To be clear, $\alpha = 0.446$ here is a value-added capital share, appropriate for the standard growth-accounting identity, whereas the $\alpha = s_K = 0.195$ used in equation 3 is a gross-output share.

[14] Total GDP includes government consumption, which rose sharply in 2022 due to wartime military spending. GDP net of government consumption fell by almost 50% in 2022. Our use of total GDP together with the headcount employment decline below therefore likely understates the true contraction of the private economy, so residual TFP estimates below could be read as conservative.

war (2021) level of approximately 15.5 million, the broadest available measure as it covers the whole economy, including the wartime increase in military and other government employment not covered by business register-based data (International Labour Organization, 2022).[15] This decline reflects both externally displaced refugees and internally displaced persons withdrawing from the labor force (UNHCR, 2022). Applying the labor share yields $(1-\alpha)\cdot\Delta\log(L) \approx 0.554 \times \log(1-0.155) \approx -0.09$. That is, roughly 9 log points of lost output can be attributed to the reduction in labor input.

World Bank (2026a) estimated direct damage to physical assets at approximately \$80 billion (net of housing) through 2022. According to IMF (2021), Ukraine's aggregate capital stock in 2019 was approximately \$490 billion. These figures imply destruction of approximately 16% of the pre-war capital stock in 2022. Applying the capital share yields $\alpha \cdot \Delta\log(K) \approx 0.446 \times \log(1-0.16) \approx -0.08$.[16]

These estimates imply that "TFP" accounted for $34-9-8 \approx 17$ log points. We have a range of estimates for the TFP decline due to misallocation: with $\sigma = 3$ and $\tau_L = 1$ (Figure 9), equally-weighted TFP loss was approximately 35 percentage points in 2022 while moving-weight TFP loss was 8 percentage points (and it grew to 20 percentage points in 2023). Thus, misallocation induced by war-related factors can largely rationalize the observed decline in productivity.

This decomposition, while imprecise, underscores that the allocative channel is quantitatively at least as important as direct destruction. It also has profound policy implications: physical capital must be rebuilt (requiring time and investment), whereas allocative efficiency can, in principle, be restored by removing the frictions that prevent factors from reaching their highest-value uses.

[15] We use a business register-based source in the next section for per-sector changes in workers. This source does not capture the wartime increase in government employment and so clearly overstates the true employment decline: it records employment at business entities falling from 7.4 million in 2021 to 6.1 million in 2022 (-17.4%) and to 5.8 million by 2024 (-21.2%) (State Statistics Service of Ukraine, 2025).

[16] Among firms that survive in our data (Appendix Table B2), total assets fall by only 7.2% in 2022 against a 17% employment decline, consistent with rising capital intensity among survivors; this comparison is a lower bound on aggregate capital destruction, as it excludes firms that exited entirely.

Figure 11: Actual vs. TFP-benchmark potential value added

Notes: Worker counts (State Statistics Service of Ukraine, 2025); government-consumption share (State Statistics Service of Ukraine, 2026c); value added (VA) (State Statistics Service of Ukraine, 2026e). The TFP ratio is moving-weighted and edge-corrected.

5.5.2 TFP counterfactual

What would Ukraine's value added have looked like if Ukraine's TFP had tracked the benchmark countries' TFP during the war? Figure 11 reports this exercise for the 16 sectors studied throughout the paper. Panel A reports three drivers of value added, each indexed to 2021 = 1: total workers, the government-consumption share of value added, and the productivity gap.

The number of workers in business entities (State Statistics Service of Ukraine, 2025) fell sharply in 2022 and has stayed roughly flat since, a roughly 21 pp decline by 2024, reflecting both displacement and the mobilization of Ukrainian men into the armed forces, which had grown to close to 1 million personnel by early 2025 (Kyiv Independent, 2025). The government-consumption share of value added (State Statistics Service of Ukraine, 2026e,c) rose from ≈12% in 2021 to 17–20% during 2022–2024, a far smaller swing than in the whole economy (Figure 1), since our 16 sectors already exclude utilities, public administration, and defense, the sectors that absorbed most of the wartime increase in government spending. We net out government consumption throughout Panel B because our worker denominator excludes government employees: in sectors such as education, where VA includes teachers' salaries but our worker series does not count teachers, "raw" VA per worker would be mechanically inflated.

By 2024, Ukraine's own TFP in this series (moving-weighted, as shown in Panel C, Figure 9) had fallen ≈19 pp from 2021, while the benchmark countries' TFP had risen ≈5 pp, consistent with continued post-COVID recovery; the resulting gap, the ratio of the two levels, left the benchmark countries' TFP about 30% above Ukraine's.

Panel B compares actual VA to this "potential" path, actual VA multiplied by the productivity gap: the output Ukraine's realized workers and capital would have produced had TFP tracked the benchmark rather than falling behind. By 2024, the actual VA net of government consumption index stood at ≈0.72 against a potential of ≈0.93; per worker, actual was ≈0.91 against a potential of ≈1.18. Cumulated over 2022–2024, the productivity shortfall alone cost close to $59 billion in private-sector value added net of government consumption (constant 2021 prices), about 44% of these sectors' entire 2021 net output ($\approx$\$134 billion).

If Ukrainian TFP had instead stayed flat at its 2021 level rather than following the benchmark countries' steady increase, potential VA per worker would fall to $\approx$1.13 in 2024, itself still substantially above pre-war levels. This remaining excess partly reflects three further factors held at their realized paths. First, while we net out government consumption, we ignore any government spending multipliers. Second, capital per worker likely rose: among surviving firms in our balanced ORBIS panel, total assets fell by less than employment (Appendix Table B2), though this reflects the composition of survivors rather than an economy-wide capital-stock measure. Third, the remaining workforce may have shifted toward higher-wage workers, since mobilization exempts employees of critical enterprises and workers above a salary threshold (OSW Centre for Eastern Studies, 2024).

6 Inspecting the mechanism

The previous sections documented that after the full-scale invasion, dispersion of marginal revenue products increased sharply, allocative TFP collapsed, and firm exit spiked. We now seek to better understand the channels through which the war generated these losses. While some potentially important mechanisms are difficult to measure directly (e.g., the duration of electricity blackouts at the firm level or the number of men drafted from each region are not publicly available), we exploit open subnational information on attack intensity, displacement, and occupation to shed light on these channels and on how the economy has adapted to war.

6.1 Subnational data

The analysis so far has relied primarily on time-series variation and the break before and after February 2022. While informative, this approach does not fully exploit the spatial heterogeneity of the war. As described in Section 2, the invasion struck the Ukrainian economy in a highly uneven manner: some areas experienced intense and sustained bombardment, temporary or prolonged occupation, and massive population outflows, while others suffered mostly indirect effects through supply chain disruptions, energy shortages, etc. This variation can sharpen identification because one can hold constant all nationwide factors (monetary policy, fiscal policy, martial law, global commodity prices, etc.) and hence isolate the incremental war effects and channels.

In this analysis, we restrict the sample to 96 raions, out of 139 Ukrainian raions[17], after excluding 32 raions under Russian occupation as of 2024 and 11 raions with fewer than 80 firm observations in our balanced 2020–2024 panel (Appendix Table B8). All other filters are identical to the national sample (Appendix Table B3).

Figure 12 maps the resulting 96-raion sample's unweighted TFP changes and yearly war intensity across Ukrainian territory for 2022, 2023, and 2024. In each row, the left-hand map indicates the local War Intensity Score, while the right-hand map represents TFP change relative to 2021. The visual correspondence is striking: raions in the east and south (which are closest to the front line and subject to the most intense Russian attacks) exhibit the largest TFP declines (deep red). Western raions (which experienced minimal direct attacks, many recording none at all) show only comparatively modest declines.

Figure 13 plots raion-level TFP change (relative to 2021) against our War Intensity Score for each of the three wartime years (2022, 2023, 2024). Each bubble represents a raion, with bubble size proportional to the raion's 2021 firm count. Raions with higher war intensity experienced larger TFP declines. The relationship steepens between 2022 and 2023, consistent with cumulative damage and the persistence of attacks, and remains steep

[17]Raion borders as defined in the 2020 administrative reform Verkhovna Rada of Ukraine (2020)

Figure 12: TFP change and war intensity by raion, 2022–2024 (unweighted)

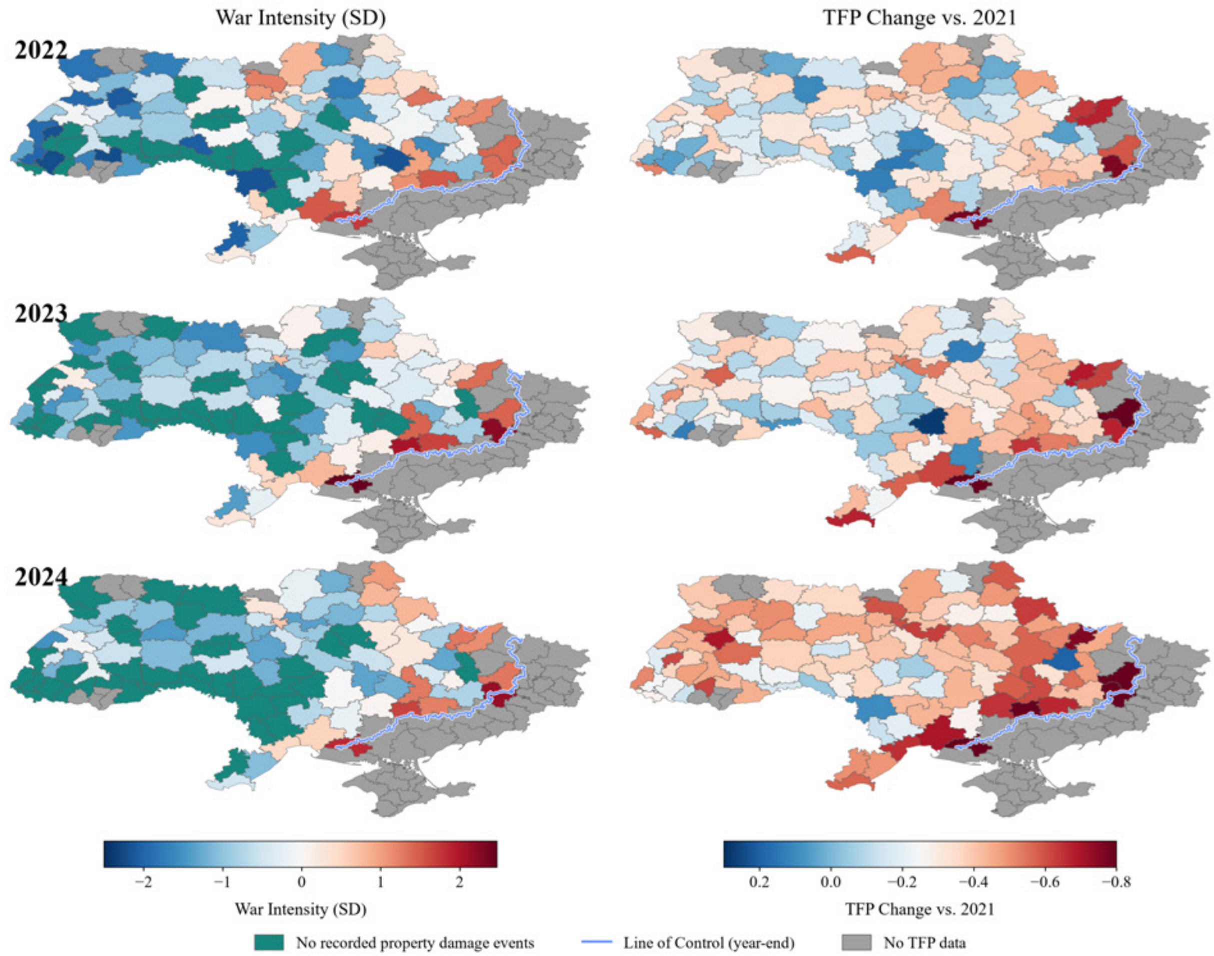
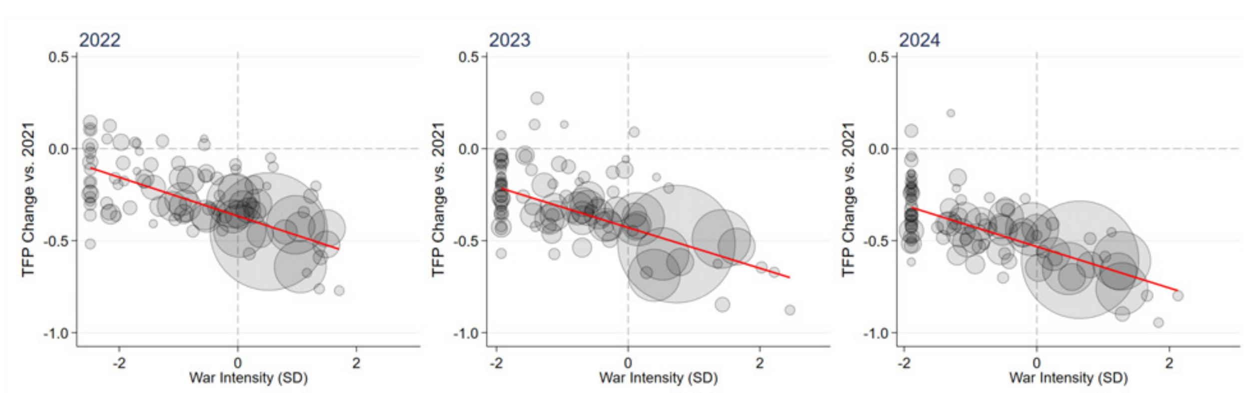


Figure 13: Raion TFP change vs. war intensity score



in 2024. Kyiv City (the largest bubble) is particularly informative. Despite being located relatively far from the Russian border and the front line, Kyiv experienced heavy missile and drone strikes throughout the war, and accordingly suffered a substantial TFP decline. In other words, geographic proximity to Russia or to the line of contact is an imperfect proxy for actual war exposure, because Russian aerial attacks with ballistic and cruise missiles as well as drones can reach deep into Ukrainian territory.[18]

Table 1 formalizes the relationship between war intensity and TFP decline. The dependent variable is the raion-level TFP drop relative to 2021 (in percentage points) and regressors are standardized to have unit variance. We organize the discussion around four main findings.

First, war intensity is the dominant predictor of local TFP losses. Column (1) shows that a one-standard-deviation increase in the War Intensity Score is associated with an 11 percentage-point larger TFP decline. The R^2 of 0.632 indicates that war intensity single-handedly accounts for over 60 percent of the cross-raion variation in productivity losses. Column (2) demonstrates that the result is robust to using 2021-fixed firm-weighted TFP rather than the equal-weighted version. The coefficient is somewhat smaller (8.8 pp per SD), as expected: larger firms, which receive greater weight in this specification, tend to have more resources to absorb shocks and are less likely to be located in the most dangerous areas.[19]

Second, distance-based proxies are informative but have little predictive power given actual attack data. Columns (3) and (4) examine distance to the Russian border and distance

[18] Since ORBIS records a year-end snapshot, firms adjusting employment or assets mid-year could show a temporary wedge with revenue that looks like elevated dispersion, and hence a larger TFP drop. If this adjustment noise were driving the relationship between war intensity and TFP decline in Figure 13, it should fade once year-on-year changes in capital and labor stabilize (and they do in the data; see Appendix Figure E1). Instead, MRPK and MRPL dispersion (Figure 6) remains far above its pre-war level and the relationship between TFP losses and war intensity if anything intensifies in 2024.

[19] This relationship is specific to the 2022 invasion. Appendix Figures E2 and E3 show the relationship between the 2022–2024 War Intensity Score and raion-level TFP changes during two other historic shocks, the Global Financial Crisis and the Donbas war. No slope is statistically significantly distinguishable from zero in any year. The Donbas war placebo shows a consistently negative, though insignificant, slope, which is expected given that the fighting then, though far smaller in scale, took place in some of the same raions later hit hardest during the post-2022 full-scale invasion.

to the line of control as alternative predictors of war exposure. Both are statistically significant when entered alone: closer proximity to the enemy is associated with larger TFP declines, consistent with the intuition that geography structures conflict exposure. However, these distance-based measures have substantially less predictive power than the War Intensity Score, with R^2 values roughly half as large because distance is a crude proxy (Kyiv City illustrates the point). Columns (7) and (8) support this interpretation through horse-race specifications. When entered jointly with the War Intensity Score, both distance measures become statistically insignificant, while the War Intensity Score continues to be significant. That is, conditional on knowing the actual intensity of Russian attacks in a raion, knowing how far that raion is from Russia or the front line provides no additional explanatory power. This result underscores that Russia's long-range aerial bombardment can decouple economic damage from simple geographic proximity.

Third, internal displacement modestly improves allocative efficiency in receiving areas, but large potential gains remain unrealized. Column (5) shows that the unconditional coefficient on IDP inflows is negative but statistically insignificant ($R^2 = 0.046$). This near-zero relationship captures the net effect of opposing forces: *i*) IDPs tend to move locally (from the most dangerous areas to somewhat less dangerous neighboring raions; see Iradukunda et al. 2025) and so IDP-receiving areas are themselves exposed to substantial war intensity;[20] *ii*) labor flows to areas where jobs are abundant. When we control for war intensity (column 9), the coefficient flips sign and becomes marginally significant (1.5 pp per SD), suggesting that, holding local war exposure constant, the arrival of displaced workers modestly improves allocative efficiency by likely alleviating labor shortages created by mobilization and emigration. Yet these gains appear far from fully realized: survey evidence in International Organization for Migration (2023a) indicates that IDPs remained grossly underemployed throughout 2022–2023, constrained by housing shortages, credential recognition barriers,

[20] For example, Bohodukhiv Raion received the highest IDP share relative to pre-war population of any raion in our sample and sits directly next to Kharkiv Raion, one of the most war-affected raions in our data. Bohodukhiv's own war intensity is only around 20% of Kharkiv's, yet still more than 50% above the median raion.

skills mismatch, and the psychological toll of displacement. Reducing frictions that prevent IDPs from accessing employment commensurate with their skills could unlock substantial additional productivity gains without requiring new physical investment.

Fourth, for liberated areas, we do not find evidence of a permanent productivity "scar" from Russian occupation once ongoing attacks are accounted for. Column (6) examines liberation status, which proxies the disruptive effects of Russian occupation studied by Onyshchenko et al. (2026). Raions with a higher cumulative liberation share suffered significantly larger TFP declines (-6.2 pp per one standard deviation). This is intuitive: occupation severs firms from Ukrainian markets, exposes assets to confiscation and looting, and forces a costly restart upon liberation. However, when entered jointly with the War Intensity Score (column 10), the liberation coefficient shrinks by roughly three-quarters and becomes statistically insignificant. Hence, the persistence of TFP losses in liberated areas appears driven not by some permanent "scar" of occupation itself but rather by the ongoing Russian attacks to which these areas remain subject after liberation. This interpretation carries a cautiously optimistic implication for post-war recovery. If the allocative damage associated with occupation dissipates once attacks cease, then the binding constraint on productivity in liberated areas is ongoing conflict rather than irreversible institutional or organizational destruction.

Table 1: War intensity, distance to Russia / the frontline, IDP inflow, liberation share, and horse-race regressions on raion-level TFP decline

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Equal-Weighted TFP	X		X	X	X	X	X	X	X	X
Firm-Weighted TFP (2021)		X								
War Intensity (per 1 SD, pp)	-11.0^{***}	-8.8^{***}					-10.6^{***}	-10.5^{***}	-11.1^{***}	-10.2^{***}
	(1.12)	(2.89)					(1.22)	(1.06)	(1.13)	(1.12)
Russia Border (per 1 SD, pp)			5.8^{***}				0.7			
			(2.20)				(1.76)			
Line of Control (per 1 SD, pp)				5.7^{***}				1.0		
				(1.63)				(1.48)		
IDP Inflow (per 1 SD, pp)					-0.9				1.5^{*}	
					(1.56)				(0.91)	
Liberation Share (per 1 SD, pp)						-6.2^{***}				-1.7
						(1.72)				(1.20)
R^2	0.632	0.146	0.307	0.303	0.046	0.327	0.633	0.635	0.545	0.641
Mean of dep. var. (pp)	-32.2	-9.4	-32.2	-32.2	-27.2	-32.2	-32.2	-32.2	-27.2	-32.2
Firms	102,373	102,373	102,373	102,373	102,373	102,373	102,373	102,373	102,373	102,373
Employment (2021)		4,034,535								
Raions	96	96	96	96	96	96	96	96	96	96
Raion-years	288	288	288	288	191	288	288	288	191	288

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Year FE included; SEs clustered by raion. Raions weighted by firm count. Dep. var.: raion-level TFP relative to 2021, in pp. Firms per raion range from 96 for Tyachiv Raion to 27,348 for Kyiv City. Columns (1)-(6) are single-regressor specifications (war intensity, distance to the Russia border, distance to the line of control, IDP inflow, liberation share); columns (7)-(10) are horse-race regressions entering war intensity jointly with the Russia border, line of control, IDP inflow, and liberation share respectively. Russia Border and Line of Control measure the geodesic distance from each raion's centroid to the nearest point on Ukraine's border with Russia and on that year's own end-of-year line of control, respectively. War Intensity, Line of Control, and Liberation Share are all constructed with data from the VIINA project (Zhukov, 2023); Distance to Russian Border is computed from Ukraine's own administrative boundary geometry as defined in (OCHA Ukraine, 2025). Columns (5) and (9) use IOM (UN Migration)'s December survey round each year(International Organization for Migration, 2023b); IDP Inflow (registered IDPs per 100,000 pre-war population,logged) is only available for 2022 and 2023, and for 191 rather than 192 raion-years, as Khersonskyi Raion was under Russian occupation and unsurveyed in the 2022 round. Registered IDPs within the sample: 3,499,874 in 2022; 3,453,181 in 2023. Liberation Share is the standardized cumulative net liberation of a raion's territory as of that year's end (historical peak Russian-occupied-territory share minus the share on that year's own last date).

6.2 Adaptation

In the next step, we examine the channels through which the economy has adapted. To this end, Table 2 provides a complementary perspective by decomposing the gap between moving-weight and 2021-fixed-weight TFP indices, shown in Panels C and B of Figure 9 respectively, into its constituent channels.[21] Recall that the moving-weight index allows each firm's employment share to evolve with wartime changes, while the 2021-fixed-weight index freezes the pre-war composition. The difference between the two captures the extent to which the economy has adapted through reallocation of workers.

Table 2: Sector × raion shift-share decomposition of the war-driven TFP gap

Year	Moving Weight	2021 Fixed Weight	Difference (pp)	Between Industry	Within Raion	Between Raion
2022	0.921	0.912	+0.9			
2023	0.797	0.732	+6.5	20.2%	57.7%	22.1%
2024	0.792	0.712	+8.1	19.9%	54.7%	25.4%

TFP index (2021=1). Difference is moving minus fixed weight, in percentage points: the share of the fixed-weight loss recovered by allowing employment weights to move, i.e. the reallocation/adaptation gain. Channels are Shapley-Owen decomposition shares of that year's gap (sector x raion shift-share), exact and additive by construction; 2022 omitted, gap too small for a stable split. See Appendix Table B9 for sample composition.

In 2022, the difference between the two indices was still small (+0.9 percentage points), indicating that little reallocation had occurred in the first year of the full-scale war. This is consistent with a sudden, overwhelming shock to which firms had neither the time nor the resources to adapt in the immediate aftermath of the invasion. By 2023, however, a meaningful gap had opened (+6.5 pp), and it widened further to +8.1 pp by 2024. That is, by 2024, the economy operating under its actual (i.e., moving) composition was over 8 percentage points more efficient than it would have been had the pre-war composition been frozen in place—evidence of significant but incomplete adaptation.

The shift-share decomposition reveals the channels through which this adaptation oper-

[21] This sample differs slightly from the national 2018–2024 sample used in Figure 9: it additionally excludes firms that cannot be assigned to a raion and firms in raions with fewer than 80 firms, and uses the same raion-aware industry hierarchy construction as Section 6 (Appendix A.3), applied to this panel's own 2018–2024 window; see Appendix Table B9.

ates. In 2023–2024, approximately 55–58 percent of the reallocation gain occurred within raions, that is, firms and workers found workarounds locally, shifting across industries or reallocating resources across firms within the same geographic area. Between-raion reallocation accounted for 22–25 percent of the gap, reflecting the physical movement of economic activity toward safer areas. The remaining roughly 20 percent occurred through between-industry shifts, as the sectoral composition of the economy adjusted toward less war-vulnerable activities, construction and transportation and storage among the sectors losing the most employment, consistent with employment falling more in sectors that suffered larger TFP declines (Appendix Figure D8).

In summary, the war had a large negative effect on allocative efficiency. In the immediate aftermath of the invasion, firms were largely "frozen" in place; over 2023–2024, gradual adaptation occurred through within-raion reallocation, geographic relocation toward safer areas, and sectoral shifts. Internal displacement contributed modestly to this adaptation by partially alleviating labor shortages; however, as we show above, IDPs tend to move only locally, to neighboring raions still well above average war intensity, rather than to much safer areas further from home, and large unrealized gains remain due to IDP underemployment. Finally, the experience of liberated regions suggests that allocative efficiency can recover once active hostilities cease, which has important implications for post-war reconstruction planning.

7 Comparison episodes: 2014 and the GFC

To further disentangle the channels driving our results, we compare the 2022 invasion with two earlier crises that isolate its two main components. Russia's 2014 seizure of Crimea and the Donbas combined limited military action with a severe macroeconomic crisis; the 2008–2009 Global Financial Crisis was a comparable macroeconomic shock with no military component at all. Comparing across these three episodes helps separate the role of direct violence from that of macroeconomic instability, and shows how the relative stability maintained during 2022 may have limited the damage.

7.1 Crimea and the Donbas 2014

Russia's attack on Ukraine in 2014 provides another natural experiment for understanding how conflict destroys allocative efficiency. In contrast to the full-scale invasion, Russia illegally annexed Crimea in a matter of weeks using unmarked forces and subsequently occupied parts of the Donetsk and Luhansk oblasts. Although the human cost was substantial (approximately 14,000 deaths over 2014–2021), the conflict was geographically circumscribed (central and western Ukraine experienced virtually no direct violence) and frozen relatively quickly under the Minsk Accords. Strikingly, Ukraine continued to trade with the occupied territories in the Donbas for several years, and economic links with Crimea were severed gradually.

Figure 14: War-exposure ring classification

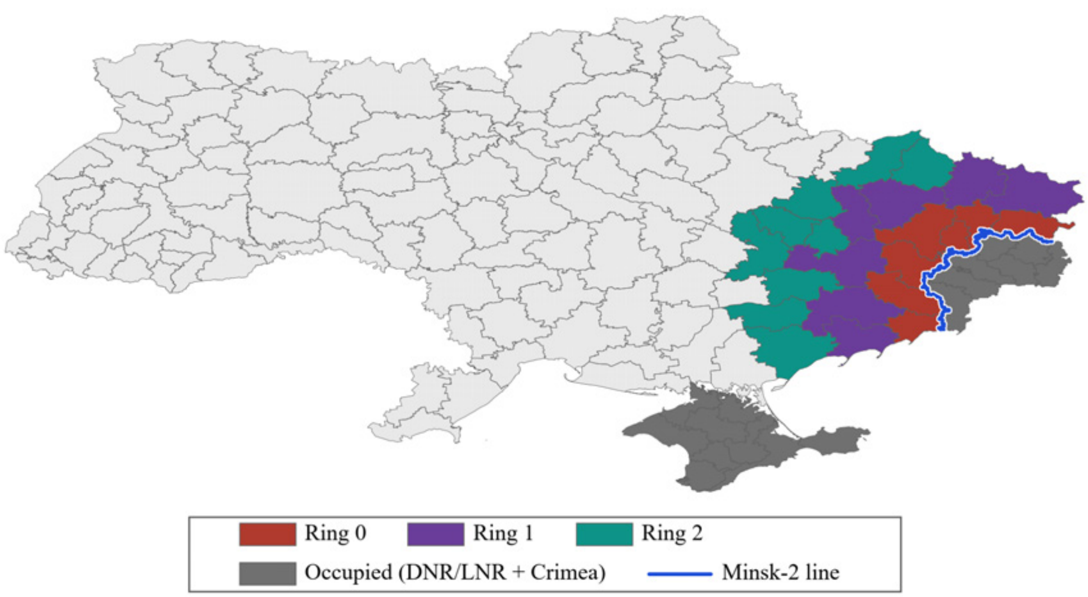
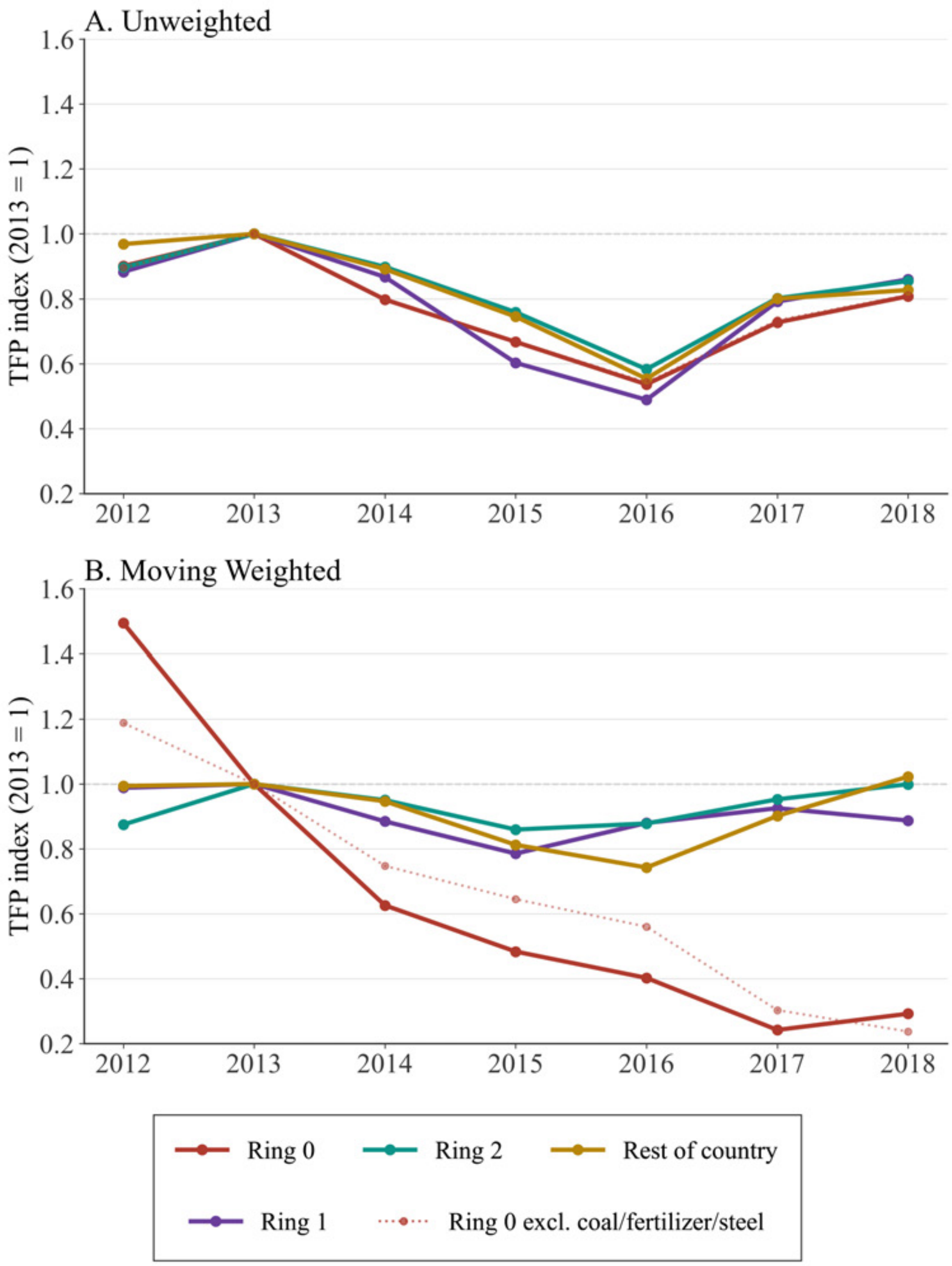


Figure 14 presents concentric exposure "rings" of conflict in 2014. We use Ukraine's post-2020 reform raion borders, which in Donetsk and Luhansk oblasts follow the Minsk-2 line exactly, since raions on occupied territory were left unreformed pending de-occupation (Verkhovna Rada of Ukraine, 2020). Ring 0 is the raions bordering this line. Armed hostilities were concentrated overwhelmingly in Ring 0 (shelling, sniper fire, and infrastructure damage along the contact line) and Ring 1 (occasional security incidents, large IDP inflows, and significant pre-war economic linkages with the occupied territories, but less direct physical violence than Ring 0). Ring 2 covers raions that are further from the contact line (and hence even less direct violence) but still had some exposure to the conflict's economic spillovers.

Figure 15 plots our TFP index by war-exposure ring for 2012–2018 (normalized to 2013 = 1). Several patterns are notable.[22] First, TFP declined substantially in all rings after 2014. Second, the decline was somewhat larger in Rings 0 and 1 than in Ring 2 or the rest of Ukraine, but the differential was modest in the unweighted specification. The geographic gradient is far less steep than what we observe for the 2022 war. Third, the moving-weighted TFP index (Panel B of Figure 15) shows a larger divergence in TFP: Rings 0 and 1 experienced larger TFP declines under moving weights than under equal weights. This pattern indicates that the largest firms in the frontline regions suffered disproportionately large productivity losses. This is consistent with the fact that these Soviet-legacy firms were deeply integrated with the occupied Donbas through input-output linkages. For example, giant steel mills in Mariupol (Azovstal and Ilyich Steel) relied on coking coal and semi-finished inputs from mines and coke plants in the occupied Donetsk oblast. The Azot nitrogen fertilizer complex in Sievierodonetsk faced persistent supply chain disruptions as conflict in the surrounding region affected access to inputs and markets. In addition, many of these same plants became easy targets for Russian shelling. For example, Avdiivka Coke and Chemical Plant (which employed approximately 4,000 people) was hit by mortars and artillery shells

[22] These patterns should be interpreted against a longer-run structural trend. Even before 2014, Ukraine's economic center of gravity had been gradually shifting from east to west, as the legacy Soviet industrial base in the Donbas declined relative to the more dynamic service and manufacturing economies of Kyiv, Lviv, and Dnipro (Green et al. 2022, Glaeser et al. 2025). The 2014 shock accelerated this reorientation.

Figure 15: TFP by war-exposure ring, Ukraine 2012–2018 (2013 = 1), by firm-weighting scheme.



Notes: Panel A unweighted, Panel B moving-weighted. Ring 0 has approximately 3,000; Ring 1 has approximately 2,000 firms; Ring 2 has approximately 10,000 firms; the Rest of country has approximately 90,000 firms.

over 165 times by early 2015 alone (BBC 2015). As a result, large firms experienced far greater disruption than smaller, more diversified/flexible enterprises. Moving-weighted TFP in Ring 0 did not recover to its 2013 level even as the rest of the country (including Ring 1) gradually stabilized, which is consistent with a permanent reallocation of economic activity away from the conflict zone.[23] Consistent with evidence in Schlepper and Wochner (2026), Ring 0's persistent non-recovery may also partly reflect anticipated risks of future conflicts, a channel complementary to the destruction and linkage effects.[24]

The fact that allocative efficiency collapsed across the entire country suggests that misallocation of resources during the 2014 crisis operated primarily through country-level forces. Indeed, Ukraine experienced a full-blown banking crisis, a run on the currency (the hryvnia lost approximately 70 percent of its value against the dollar), and inflation peaked at 61 percent year-on-year in April 2015. The fiscal position deteriorated sharply, and an emergency IMF program was required to stabilize the economy. By contrast, the 2022 full-scale invasion, which was an order of magnitude more destructive militarily, was not accompanied by a banking panic. The National Bank of Ukraine maintained financial stability through capital controls and liquidity support, the exchange rate depreciated by a comparatively moderate 25 percent under a managed peg, and inflation, while elevated, peaked at 26.6 percent year-on-year in December 2022, well under half the earlier crisis's peak.

The 2014 episode thus leads to two broader conclusions. First, conflict can destroy allocative efficiency through multiple channels: direct violence and physical destruction (which dominated in 2022), macroeconomic and financial instability (which dominated in 2014), and the severance of supply-chain linkages (which operated in both episodes but was particularly salient for the integrated heavy-industry firms near the Donbas). Second, the 2022 war is far

[23]Appendix Figure D9 reports allocative TFP series for peer countries. The divergence between Ukraine and its peers confirms that the 2014 TFP decline was driven by Ukraine-specific factors (the war and the associated financial crisis) rather than common regional trends.

[24]Since 2014, Ukraine fortified towns at and just behind the contact line into the Donbas "fortress belt" (Helsinki Commission, 2026), so that areas in and in front of the belt could expect renewed fighting in any escalation, while areas just behind it enjoyed relatively greater security, which is roughly what happened after 2022: Russia destroyed or overrun much of the exposed area (e.g., Avdiivka, Toretsk), while the belt's rear anchors (e.g., Kramatorsk, Sloviansk) still hold at the time of writing.

more damaging to allocative efficiency precisely because it combines many of these channels simultaneously and at a much larger scale while the 2014 shock, though severe, operated primarily through one channel (financial/macroeconomic turmoil) and was geographically contained.

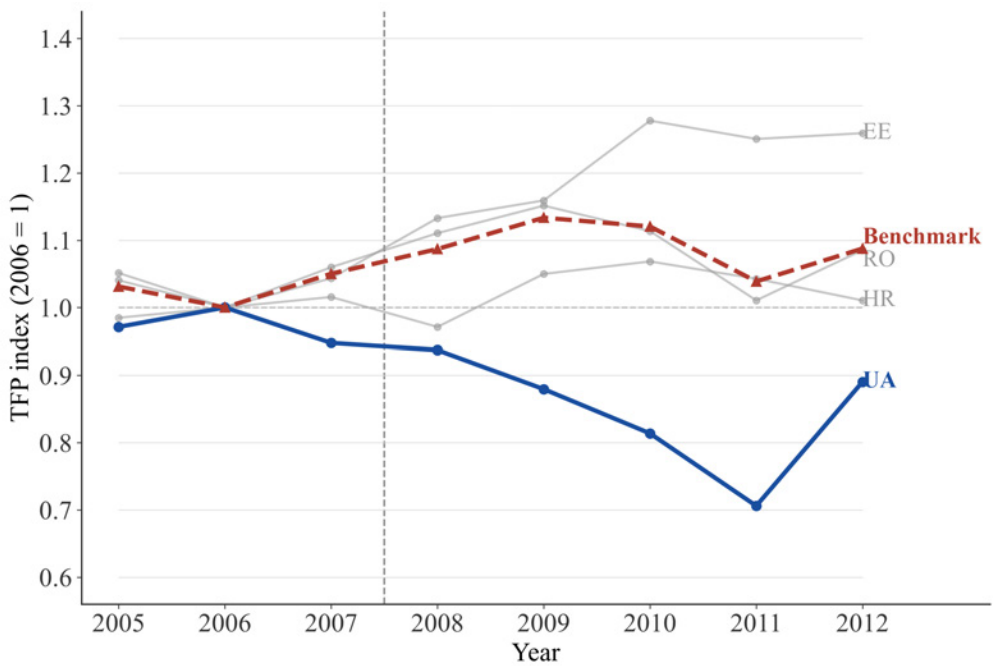
7.2 Global Financial Crisis 2008–2009

The previous section suggests that macroeconomic and financial instability can be a powerful channel through which conflict destroys allocative efficiency. To test whether purely economic crises can generate similar patterns of misallocation in the absence of armed conflict, we turn to the Global Financial Crisis (GFC) of 2008–2009. The GFC provides a clean comparison case: Ukraine went through a deep contraction (GDP declined by 20% in 2009Q1), a severe banking crisis, a currency crisis, a collapse in export demand for steel and other commodities, and a sharp fiscal contraction, but no military conflict on its territory.

Figure 16 plots our allocative TFP index for Ukraine alongside the benchmark peer countries (Romania, Croatia, and Estonia) over 2005–2012 (normalized to 2006 = 1). Ukraine experienced a large decline in allocative TFP beginning in 2008 with a cumulative loss of roughly 20 percent relative to the pre-crisis level. The decline was larger than for the peer countries, which also suffered from the GFC but recovered more quickly. Ukraine's trajectory reflected a variety of factors, including its heavy dependence on commodity exports, weak pre-crisis policy frameworks that left the banking sector fragile and over-leveraged, and the absence of EU membership or a credible external anchor that might have facilitated faster stabilization.

Four features of the GFC-era TFP dynamics contrast with the war episodes. First, the temporal profile is one of gradual deterioration, that is, a "slow burn" that unfolded over several years rather than the sudden, catastrophic drop observed in 2014 and especially in 2022 (Figure 9). Unlike the peer countries, which recovered relatively quickly, Ukraine's allocative efficiency remained depressed through the end of the panel. This persistent under-

Figure 16: National TFP index by country, Global Financial Crisis, 2005–2012



Notes: 1% winsorized, moving-weighted, edge-corrected. *Benchmark* = firm-count-weighted average of Romania (RO), Croatia (HR), and Estonia (EE). Other Eastern European countries reported in the main 2018–2024 panel have insufficient data for this panel. Sample composition: Table B11.

performance is consistent with the well-documented dysfunction of Ukraine's banking sector during this period. A large share of bank lending had been directed to insiders, generating massive non-performing loan portfolios that were addressed by sweeping reforms only in 2014–2015 (Carletti et al. 2024).

Second, the losses are strongly graded by firm size (Appendix Figure D10). The largest quartile of firms suffered the deepest and most persistent decline and the third quartile a considerably smaller one, while firms below the median size of eleven employees dipped only briefly in 2009 before recovering. This is what one would expect of a shock arriving through the banking system, since firms' exposure to it scaled with their integration into the formal financial sector. After the 2022 Russian invasion, it is instead the smallest firm quantile that declines the most (Appendix Figure D4). The 2014 episode runs in the same direction as the GFC, with the largest firm quantile affected most, but the gradient is considerably weaker (Appendix Figure D11).

Third, the geographic gradient was much smaller, with the highest losses in the Centre and lower losses in the West and South East (Appendix Figure D12).[25] Fourth, the sectoral incidence differs substantially across episodes. Of the four largest sectors, agriculture was the worst affected during the GFC (Appendix Figure D13), the reverse of its position after 2022, when it is the most resilient of the four. Ukraine restricted agricultural exports through quotas and export taxes between 2006 and 2012 (Nivievskyi et al. 2022), with quota volumes assigned to individual companies by a government commission.[26] The 2014 war shows no comparable sectoral pattern: sectors fall together to a common trough and diverge only in the recovery (Appendix Figure D14).

These features point to a broader message for wartime economic management: maintaining macroeconomic and financial stability during a conflict is not merely desirable for its own sake but essential for preventing allocative damage from compounding. Ukraine's

[25] Over half of all firms in the Centre are located in Kyiv city, and the region has the highest concentration of financial firms.

[26] von Cramon-Taubadel and Raiser (2006) find the quota system's administration "highly non-transparent".

relative macroeconomic stability after February 2022, supported by this policy response and international assistance, likely prevented the allocative damage from being even worse than what we document.

8 Conclusion

Modern war reduces output not only by destroying workers, capital, and infrastructure, but also by impairing the economy's ability to allocate surviving resources to their highest-value uses. Using comprehensive firm-level data from Ukraine, we show that the 2022 full-scale Russian invasion triggered a collapse in allocative productivity, with effects comparable in magnitude to those of physical capital destruction and wartime losses in the workforce.

On the bright side, the allocative component of TFP loss represents output that can in principle be recovered through better matching of resources to uses, even without requiring massive investment. For example, housing support for displaced workers, remote-work facilitation, subsidies for re-training workers, and transparent information on regional labor demand are examples of policies that can grease the wheels of the labor market and hence yield substantial efficiency gains. In a similar spirit, policies that restore financial intermediation (e.g., credit guarantees for firms in war-affected areas, war insurance), encourage reallocation to safer regions, and reduce regulatory barriers (e.g., expediting permits, simplifying firm entry and exit) can help release capital trapped in low-return uses. More broadly, the policy objective should be to remove barriers that prevent market forces from equalizing marginal products.

Our analysis also has ramifications for "military" calculus. For example, conventional cost-benefit accounting for air defense assesses relative costs against operational benefits (see, e.g., Lostumbo et al. 2016), typically counting averted casualties and infrastructure damage. Our raion-level results suggest a further benefit: more effective air defense can help minimize the productivity losses for the wider regional economy. Relatedly, one may expect that Ukrainian strikes deep into Russia can worsen the allocation of resources in Russia and thus reduce the Kremlin's capacity to wage war.

Although not directly studied in the paper, a recurring theme in business and policy discussions is consistent with our results: centralized, single-point-of-failure systems in energy generation, administrative authority, or resource allocation amplify the allocative TFP damage of war. For instance, when a single thermal plant powers an entire region, one missile strike simultaneously disrupts thousands of firms. Decentralization of decision-making, distributed energy architecture, and related measures can address such vulnerabilities.

Our findings carry vitally important lessons for countries that face security threats. The magnitude of allocative losses we document suggests that economic preparedness should encompass not only defense spending and strategic reserves but also institutional arrangements that facilitate rapid reallocation in times of stress. Countries with more flexible labor markets, deeper financial systems, better digital infrastructure, and diversified geographic distribution of economic activity are likely to suffer smaller allocative losses conditional on a given level of physical destruction. Pre-conflict investments in flexible allocation of resources and resilience thus offer potentially very high returns.

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A Appendix A: Supplemental Methodology

A.1 Capital cost share computation

Each country's national capital cost share (α, reported in Tables B4, B10, B11) is computed once per reference year as an employment-weighted average of industry-level revenue-based capital cost shares,

$$\alpha = \frac{\sum_i \text{employees}_i \cdot s^{rev}_{K,i}}{\sum_i \text{employees}_i}, \qquad s^{rev}_K = 1 - \frac{D_1}{P_1} - \frac{P_2}{P_1},$$

where $s^{rev}_{K,i}$ is industry i's own capital cost share (output net of compensation of employees and intermediate consumption, over output) and the sum runs over the finest industry grain available for that country. Because employment weights are taken from each panel's own reference year, the resulting national α differs slightly across panels. Only the 16 sectors as listed in Table B1 are considered. Employment weights are each industry's share of total national employment, pre-balance (defined as in B3) in the reference year. The labor cost share β used in the $\tau_K = 1$ robustness specification (Appendix Figure D3) is constructed identically, using each industry's labor cost share in place of s^{rev}_K.

Source data by country:

- **Poland**: OECD STAN, per NACE 2-digit division, 2021 only (OECD, 2025b).
- **Romania, Bulgaria, Croatia, Estonia**: (Eurostat, 2026) , per NACE 2-digit division.
- **Ukraine**: State Statistics Service of Ukraine (2026e). Unlike the other countries, the source data is reported only at the sector level, not by finer NACE 2-digit division. The employment-weighting step is otherwise unchanged. Cost shares for Ukraine are only available starting in 2010, so for the 2006 base year used in Table 16, we use the 2010 cost share.

A.2 Edge correction

Although the balanced panel excludes firms that enter or exit within the window, confirming that a given calendar year reflects a full year of operation, rather than a partial year adjoining entry or exit just outside the window, requires checking it against an adjacent year. The panel's first and last years have only one adjacent year within the window instead of two, so measured dispersion in those years is mechanically inflated relative to every interior year, independent of any real change in misallocation. We correct this using auxiliary panels, each shifted by one year relative to the main panel, so that the year in question becomes interior there and is measured on equal footing with the rest of the window.

First year of the window. An auxiliary panel starting one year earlier makes the main window's first year interior within it, and we substitute that value directly for the main panel's edge estimate.

Last year of the window, when later data exist. Symmetric to the first case: an auxiliary panel shifted one year later makes that year interior, and we substitute its value directly.

Last year of the window, when no later data exist (2024 in our sample). No later auxiliary panel can be built. Instead, we build one ending a year earlier than the main window and compare its own last-year value, which suffers the same edge problem, against the main panel's value for that identical calendar year, where it is interior. The gap between the two measurements isolates the edge distortion, which we then apply to the main window's true final year. Unlike the other two cases, this is an inferred correction rather than a direct substitution, since the terminal year can never be observed as interior in any panel, and it rests on the untestable assumption that the spurious edge dispersion was equally large in 2023 and 2024. All 2024 edge-corrected values should therefore be treated as estimates rather than direct measurements. We do not apply edge correction to subnational (raion level) results, as this adjustment is only stable in large samples.

A.3 Industry cell hierarchy

We use industry by year fixed effects, with four digit NACE Rev. 2 codes as the baseline classification, aggregating a code to the three digit, two digit, or full sector level whenever it falls below one hundred firms nationally, so that each firm is assigned to the finest cell meeting this minimum. Aggregation never crosses sector boundaries; a sector failing the threshold at its coarsest level is dropped from the panel rather than merged into another. This provision does not bind for Ukraine's 2018–2024 panel, all sixteen of whose sectors clear the threshold. Among the benchmark countries it drops four sectors for Bulgaria (other services, education, finance, and mining) and one sector each for Croatia and Estonia (mining); Romania and Poland retain all sixteen.

The one hundred firm minimum is required for winsorization. Our main specification winsorizes at the first and ninety ninth percentile, which requires at least one hundred firms per cell for the trim to remove a whole observation at each tail rather than none; below this threshold winsorization is degenerate. We also report results under other winsorization thresholds in the appendix.

Applied to Ukraine's 2018 to 2024 panel, this yields 195 industry cells covering 90,257 firms: 96 at the four digit level, 52 at the three digit level, 40 at the two digit division level, and 7 collapsed to the full sector. Cell size ranges from 101 firms in the smallest cell, NACE 96.02, "Hairdressing and Other Beauty Treatment," to 10,825 firms in the largest, NACE 01.11, "Growing of Cereals (Except Rice), Leguminous Crops and Oil Seeds."

Our raion-level analyses (Section 6 and the shift-share decomposition) impose an additional condition: a cell must have firms present in at least two-thirds of raions, or it rolls up further. An industry can clear the national firm-count floor while sitting almost entirely in one or two raions, e.g., concentrated in Kyiv; such a cell has nothing to compare across raions and cannot support a between-raion or within-raion channel. We apply this rule separately within each panel window used below.

B Appendix B: Summary Statistics

Table B1: Sample composition by sector, Ukraine

Sector	Capital Cost Share	Sector Weight	Industry cells (2018–2024)	Firms: 2021 (pre-balance)	Firms: 2018–2024	Firms: 2006–2024
Wholesale and retail trade; repair of motor vehicles and motorcycles	0.282	21.1%	47	52,695	23,454	7,482
Manufacturing	0.087	26.5%	68	25,199	14,322	6,459
Agriculture, forestry and fishing	0.324	9.4%	12	24,300	12,731	3,810
Real estate activities	0.653	1.9%	4	19,109	7,806	3,944
Construction	0.088	5.0%	11	16,020	6,834	2,380
Professional, scientific and technical activities	0.265	3.4%	10	14,860	6,140	1,914
Transporting and storage	0.175	15.7%	3	10,350	4,865	1,664
Information and communication	0.371	2.4%	11	9,079	4,008	1,347
Administrative and support service activities	0.177	3.7%	11	9,734	4,006	1,030
Human health and social work activities	0.004	4.2%	1	4,568	2,016	479
Accommodation and food service activities	0.374	1.1%	3	3,447	1,336	505
Provision of other types of services	0.390	0.2%	4	1,463	700	404
Education	0.084	0.3%	4	1,488	619	193
Financial and insurance activities	0.378	0.6%	2	1,345	573	141
Mining and quarrying	0.389	4.0%	2	803	449	231
Arts, entertainment and recreation	0.093	0.5%	2	975	398	127

Notes: Sectors defined as in State Statistics Service of Ukraine (2026e). Sector weight is each sector's 2021 employment share, used (together with each sector's own capital cost share) to compute the single national capital cost share. "2021 (pre-balance)" = distinct firms in that sector at year 2021, before any multi-year balance requirement (same filter chain as every other Ukraine model through the jump filter, cut short before the window-specific balance step); "2018–2024"/"2006–2024" = distinct firms surviving that window's own full-panel balance. Excluded from the panel entirely due to high government involvement creating distortions: Electricity, gas, steam and air conditioning supply; Public administration and defence; compulsory social security; Water supply; sewerage; waste management and remediation activities.

Table B2: Ukraine balanced panel profile by year, 2018–2024

Year	Firms	Employees: Mean	Employees: Median	Employees: Min	Employees: Max	Total Assets (USD): Mean	Total Assets (USD): Min	Total Assets (USD): Max	Revenue (USD): Mean	Revenue (USD): Min	Revenue (USD): Max
2018	90,257	40	7	1	260,253	2,864,731	4	24,694,227,967	2,734,352	22	9,104,655,427
2019	90,257	41	7	1	251,014	2,756,588	4	21,051,108,289	2,717,696	8	7,343,803,685
2020	90,257	40	7	1	244,103	2,854,952	4	16,388,039,574	2,674,537	16	4,964,830,225
2021	90,257	40	7	1	232,837	3,052,624	4	16,619,917,289	3,205,251	7	6,246,693,405
2022	90,257	36	6	1	210,742	2,772,283	3	15,828,628,643	2,267,805	3	5,180,944,230
2023	90,257	34	6	1	187,620	2,735,643	3	14,083,129,557	2,471,981	3	4,892,588,941
2024	90,257	33	5	1	178,616	2,833,902	3	14,352,811,943	2,687,129	3	5,299,614,833

Notes: Total assets and revenue in constant 2021 USD (CPI-deflated, (World Bank, 2026b); fixed 2021 NBU rate, (National Bank of Ukraine, 2026b)). Maximum total assets and maximum revenue are Naftogaz in every year; maximum employees is Ukrzaliznytsia (Ukrainian Railways).

Table B3: Sample construction: firms, rows, and employment remaining after each filter. Example: Ukraine 2018–2024 balanced panel

		Remaining after filter			
Step	Definition	Firm-years	Firms	Employment (2021)	% of raw firm-years
Raw ORBIS data	Ukraine-registered ORBIS records with a 2018–2024 fiscal year, before any filter	2,615,994	615,515	6,420,406	100.0%
Country filter	`bvdid` carries Ukraine's own registry prefix – removes firms that are physically located in Ukraine but not registered there. Removed firms are predominantly Russian firms located in internationally recognized Ukrainian territory, especially Crimea.	2,388,042	565,283	6,001,778	91.3%
Fiscal period	Closing month is December and the filing period spans a full 12 months	2,388,041	565,283	6,001,778	91.3%
NACE parse	Industry code parses to a valid 4-digit NACE class	2,387,328	564,826	6,001,254	91.3%
Consolidation deduplication	Consolidated statement kept when both consolidated and unconsolidated reports exist	2,385,801	564,826	5,888,131	91.2%
Raion exclusion	Raion identifiable and not under more than 70% Russian occupation as of 31 December 2024	2,323,912	543,048	5,685,115	88.8%
Positivity	Revenue, employment, and total assets variables are reported and strictly positive	1,530,718	368,115	5,584,966	58.5%
Government-dominated sectors	Drops utilities, public administration, and defense sectors	1,499,092	361,075	5,179,563	57.3%
Jump filter	No implausible year-on-year jump in capital- or sales-per-worker exceeding 500x, checked across the firm's full ORBIS history, not only 2018–2024; a firm is dropped entirely if any single year-pair triggers this	1,468,023	353,963	5,091,133	56.1%
Status & recent financials	Active status (firm is not registered as bankrupt or inactive), and financials were filed for the most recent recorded year rather than carried forward unchanged from the previous year	1,337,939	286,403	4,891,639	51.1%
Balance filter	Present in every year of the estimation window (2018–2024)	687,400	98,200	3,585,974	26.3%
Single-employee filter	Drops firms reporting exactly 1 employee in every year	631,799	90,257	3,578,031	24.2%

Notes: Raion exclusion filter only applied for Ukraine, otherwise, all filters are identically applied to all countries. Pre-balance (used for cost shares calculation defined as in A.1, Figure 3 and Figure 4 ends the filter series before the status/recent financials step, and does not apply the raion filter for Ukraine.

Table B4: 2018–2024 balanced panel: benchmark country sample composition and weights

Country	Capital Cost Share	Firms	Industry Cells	Employment (2021)	Benchmark Weight
Ukraine	0.195	90,257	195	3,578,031	–
Romania	0.258	176,733	248	2,742,560	0.594
Croatia	0.185	47,056	136	761,972	0.158
Poland	0.244	37,894	133	3,368,009	0.127
Estonia	0.158	25,473	91	282,005	0.086
Bulgaria	0.198	10,127	46	913,228	0.034

Notes: Bulgaria's panel ends in 2023, as 2024 data was not yet available at time of writing. Poland's panel begins in 2019, once its 2018 digital-filing mandate (Parlament Rzeczypospolitej Polskiej, 2018) was fully in effect; edge correction consumes this first year, so TFP figures using this sample report Poland only from 2020. Benchmark Weight = donor's share of total non-Ukraine firms. Capital Cost Share computation formula and data can be found in Section A.1.

Table B5: 2006–2024 balanced panel: benchmark country sample composition and weights

Country	Capital Cost Share	Firms	Industry Cells	Employment (2021)	Benchmark Weight
Ukraine	0.195	32,110	107	1,801,491	–
Romania	0.258	47,755	127	1,102,549	0.674
Croatia	0.185	14,920	63	376,152	0.211
Estonia	0.158	8,202	39	127,607	0.116

Notes: Benchmark Weight = donor's share of total non-Ukraine firms. Bulgaria and Poland are excluded due to insufficient data. Capital Cost Share as in Table B4.

Table B6: War intensity score summary statistics

	N (raions)	Mean	Median	Min	Max
Cumulative (2022–2024)	96	2.24	2.31	0.00	5.57
Flow 2022	96	1.84	1.80	0.00	4.73
Flow 2023	96	1.09	0.82	0.00	4.43
Flow 2024	96	1.14	0.83	0.00	4.54

Raion TFP sample (Table B8, balanced 2020–2024, 96 raions) only. War Intensity Score is log property-damage events per 100k pre-war population. Cumulative: 2022–2024 total. Flow Y: that year's own events only, standardized separately by year in the figures that use it (raw, unstandardized values shown here).

Table B7: Sector value added and workers, Ukraine, 2021 and 2024 (constant 2021 USD)

Sector	VA 2021 (mln USD)	Workers 2021	Net of govt. VA 2021 (mln USD)	Net of govt. VA % chg. 2024 vs. 2021	Net of govt. VA per worker % chg. 2024 vs. 2021
Agriculture, forestry and fishing	21,746	520,262	21,514	-22.1%	-8.0%
Mining and quarrying	12,869	214,192	12,378	-37.6%	-2.7%
Manufacturing	20,543	1,439,486	19,814	-36.8%	-15.1%
Construction	5,509	318,199	5,260	-60.4%	-39.4%
Wholesale and retail trade	27,198	1,634,707	25,850	-30.6%	-13.8%
Transporting and storage	10,822	773,379	10,020	-31.6%	-11.4%
Accommodation and food services	1,802	186,355	1,752	-38.5%	-22.5%
Information and communication	9,369	165,560	8,866	-9.0%	+1.5%
Financial and insurance	5,935	197,931	5,338	+7.7%	+42.1%
Real estate	11,536	160,573	11,150	-28.4%	-12.4%
Professional, scientific and technical	5,775	216,214	4,946	-46.6%	-30.5%
Administrative and support services	2,487	262,367	2,317	-33.4%	-12.8%
Education	8,614	26,922	1,243	-6.0%	-5.1%
Human health and social work	4,943	745,031	1,241	+72.6%	+99.3%
Arts, entertainment and recreation	1,169	36,581	425	+44.9%	+65.3%
Provision of other types of services	1,709	40,121	1,679	-26.8%	-8.5%
All sectors (16)	152,025	6,937,880	133,793	-28.2%	-8.6%

Notes: VA from the Production and Income Generation Account (State Statistics Service of Ukraine, 2026e), worker counts from Ukrstat's business-entity release (State Statistics Service of Ukraine, 2025), covering only workers hired by registered business entities; not including proprietors (self-employed individuals) or government workers, for whom no comparable series is published. Currency: Ukrstat's own constant-2021-UAH-price series, converted once to USD at the fixed 2021 NBU annual-average rate (National Bank of Ukraine, 2026b). VA net of govt. uses a government-consumption share built from Ukrstat's Input-Output table (State Statistics Service of Ukraine, 2026c) (open Leontief demand-driven model, domestic-flows variant). Figure D6 plots this table's TFP-% and VA/Worker-net-% columns against each other for the 16 study sectors.

Table B8: Raion TFP sample summary statistics

	N (raions)	Mean	Median	Min	Max
Firms per raion (2021)	96	1,066	315	96	27,348
Employees per raion (2021)	96	42,026	11,942	2,000	1,220,579

Balanced 2020–2024 panel (Section 6.1), min 80 firms/raion; 102,373 firms, 62 industry cells. A shorter panel than the national 2018–2024 sample, giving more observations since pre-war trends are not of interest here. Sample underlying Figure 12, Figure 13, and Table 1.

Table B9: Shift-share sample summary statistics

	N (raions)	Mean	Median	Min	Max
Firms per raion (2021)	95	904	279	83	22,188
Employees per raion (2021)	95	36,390	10,426	1,487	1,096,303

A raion-restricted version of the national 2018–2024 panel (Section 5), excluding firms that cannot be geolocated to a raion and firms in raions with fewer than 80 firms; 85,925 firms, 64 industry cells. Not the same sample as Table B8, which uses the shorter 2020–2024 panel above.

Table B10: 2012–2018 balanced panel: benchmark country sample composition and weights

Country	Capital Cost Share	Firms	Industry Cells	Employment (2013)	Benchmark Weight
Ukraine	0.194	108,520	114	4,080,964	–
Romania	0.237	135,394	227	2,385,142	0.447
Bulgaria	0.216	113,189	207	1,686,717	0.374
Croatia	0.174	33,319	115	558,768	0.110
Estonia	0.187	21,097	79	234,593	0.070

Notes: Benchmark Weight = donor's share of total non-Ukraine firms. Poland is excluded due to insufficient data. Capital Cost Share computation formula and data can be found in Section A.1.

Table B11: GFC 2005–2013 balanced panel: benchmark country sample composition and weights

Country	Capital Cost Share	Firms	Industry Cells	Employment (2006)	Benchmark Weight
Ukraine	0.216	81,902	190	5,047,568	–
Romania	0.265	77,451	169	1,517,265	0.720
Croatia	0.177	19,929	71	415,859	0.185
Estonia	0.224	10,157	47	175,922	0.094

Notes: Benchmark Weight = donor's share of total non-Ukraine firms. Bulgaria and Poland excluded (insufficient data). Capital Cost Share computation formula and data can be found in Section A.1. For Ukraine, 2010 capital cost shares are used (the first year reported in (State Statistics Service of Ukraine, 2026e)).

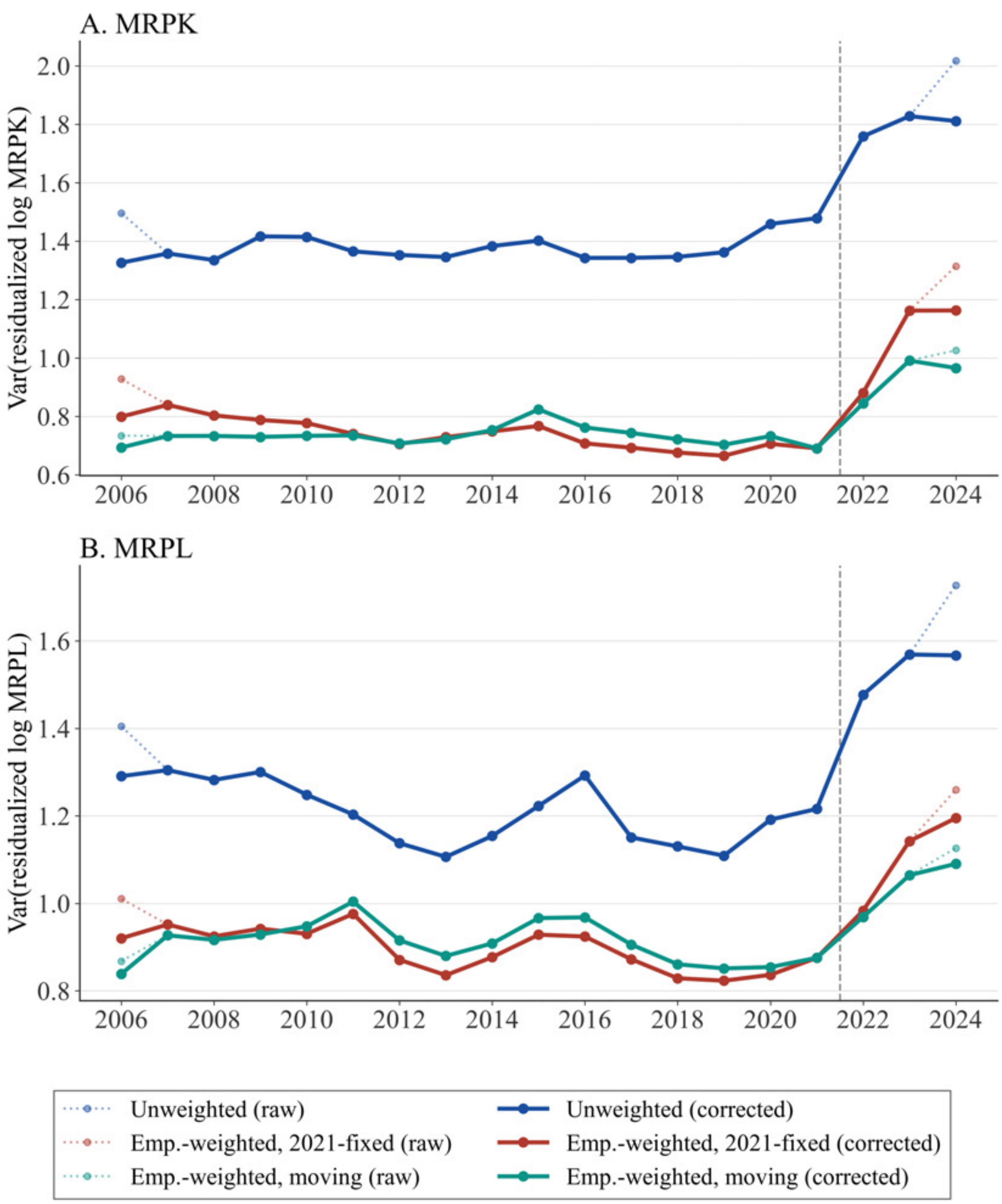
Table B12: 2018–2024 balanced panel: benchmark country firm-level profile, 2021 cross-section

	Employees			Total Assets (USD)			Revenue (USD)		
Country	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Romania	16	1	15,980	1,562,568	5	11,938,655,079	1,942,220	40	6,214,499,314
Poland	88	1	37,002	14,100,785	257	27,457,187,458	17,572,903	257	33,780,977,368
Croatia	16	1	9,589	2,537,908	24	12,201,606,269	1,950,697	47	3,230,659,772
Bulgaria	90	1	17,077	10,869,826	1,814	3,905,703,060	12,914,281	1,814	4,303,370,095
Estonia	11	1	4,864	1,744,843	18	1,875,661,670	1,984,041	35	971,763,090

Notes: Same panel as Table B4. Firm-level mean/min/max, constant 2021 USD at the ECB's 2021 average rate ((European Central Bank, 2021)).

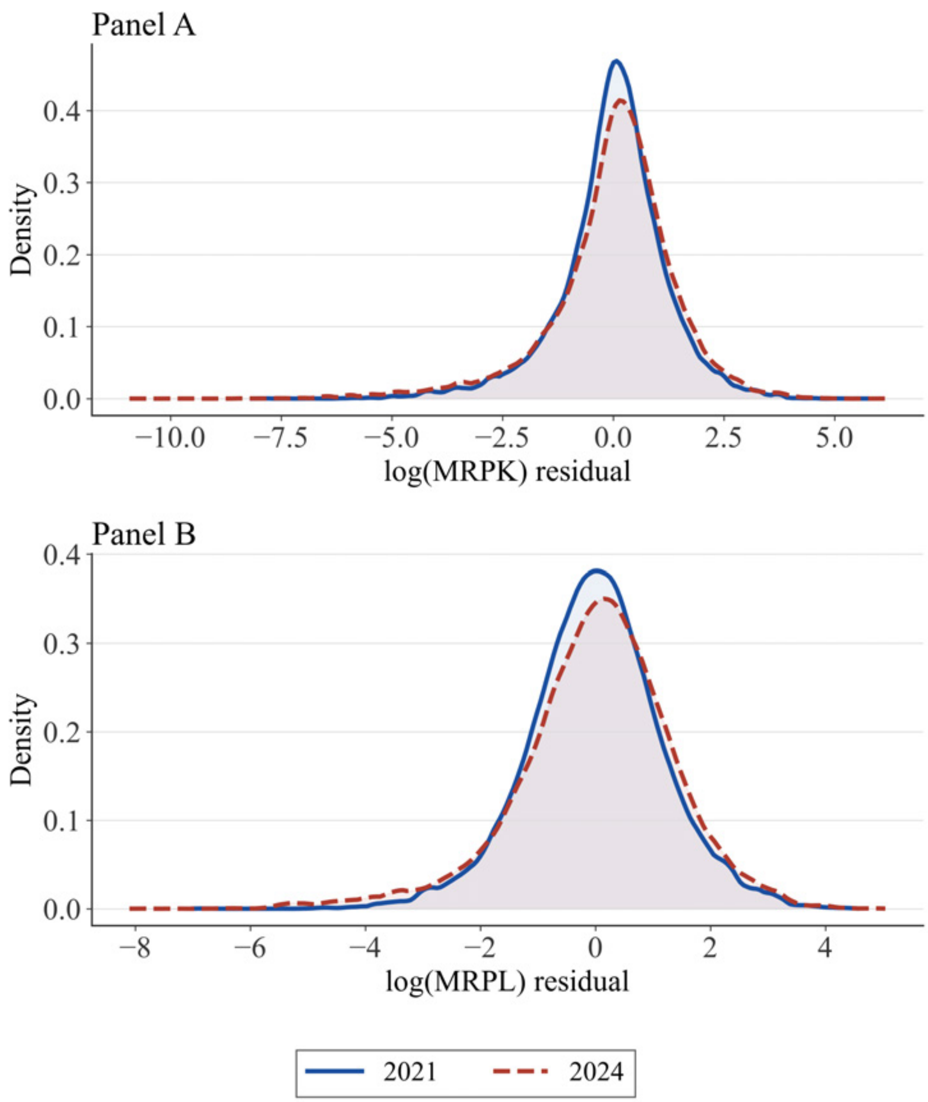
C Appendix C: Additional Measures of Dispersion

Figure C1: National dispersion levels, Ukraine, 2006–2024.



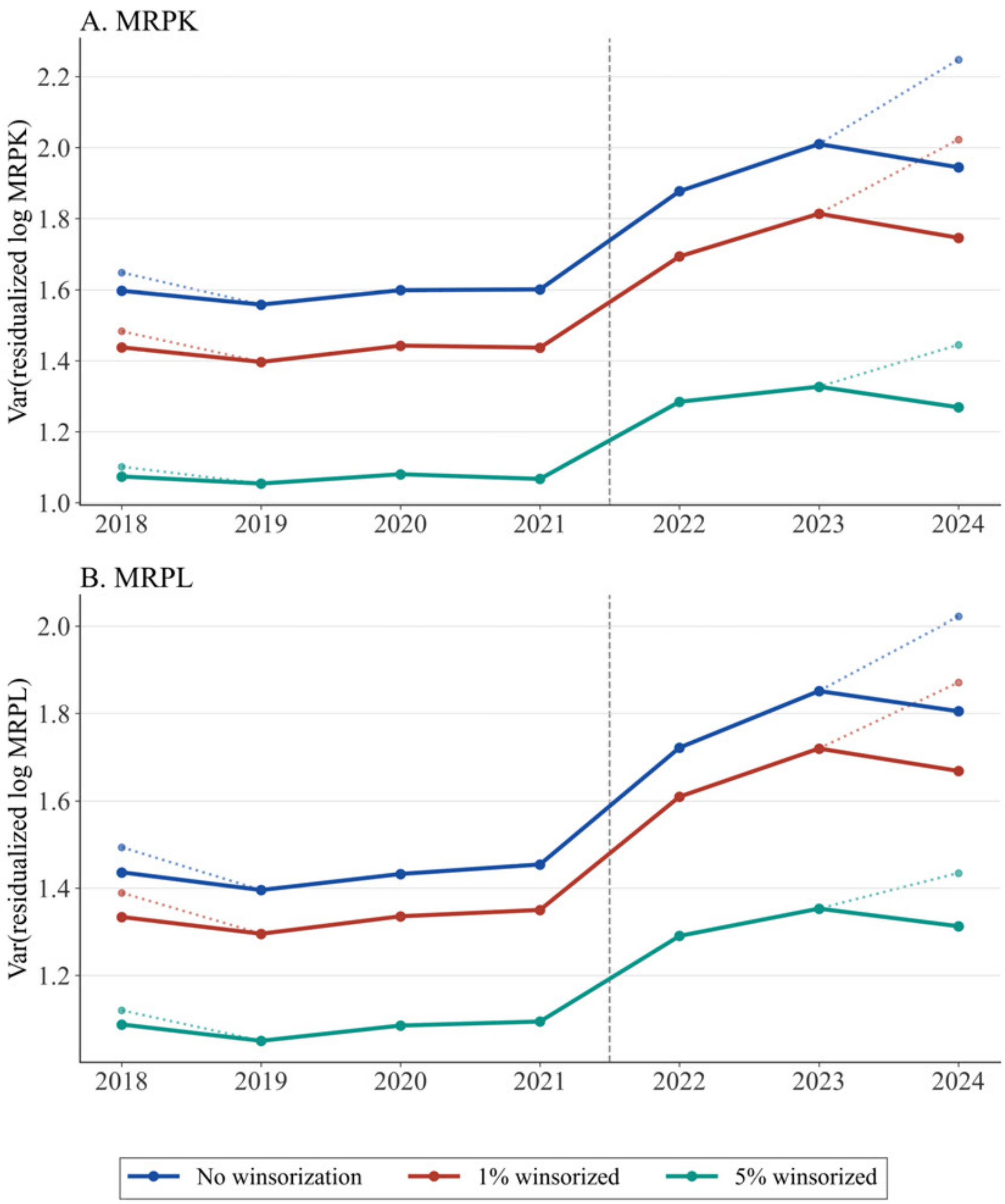
Notes: Var(residualized log MRPK) and Var(residualized log MRPL), industry_cell × year FE, edge-corrected. Ukraine: 32,110 firms, 107 industry cells (2006–2024 balanced panel).

Figure C2: Kernel density of log(MRPK) and log(MRPL) residuals, Ukraine, 2021 vs. 2024.



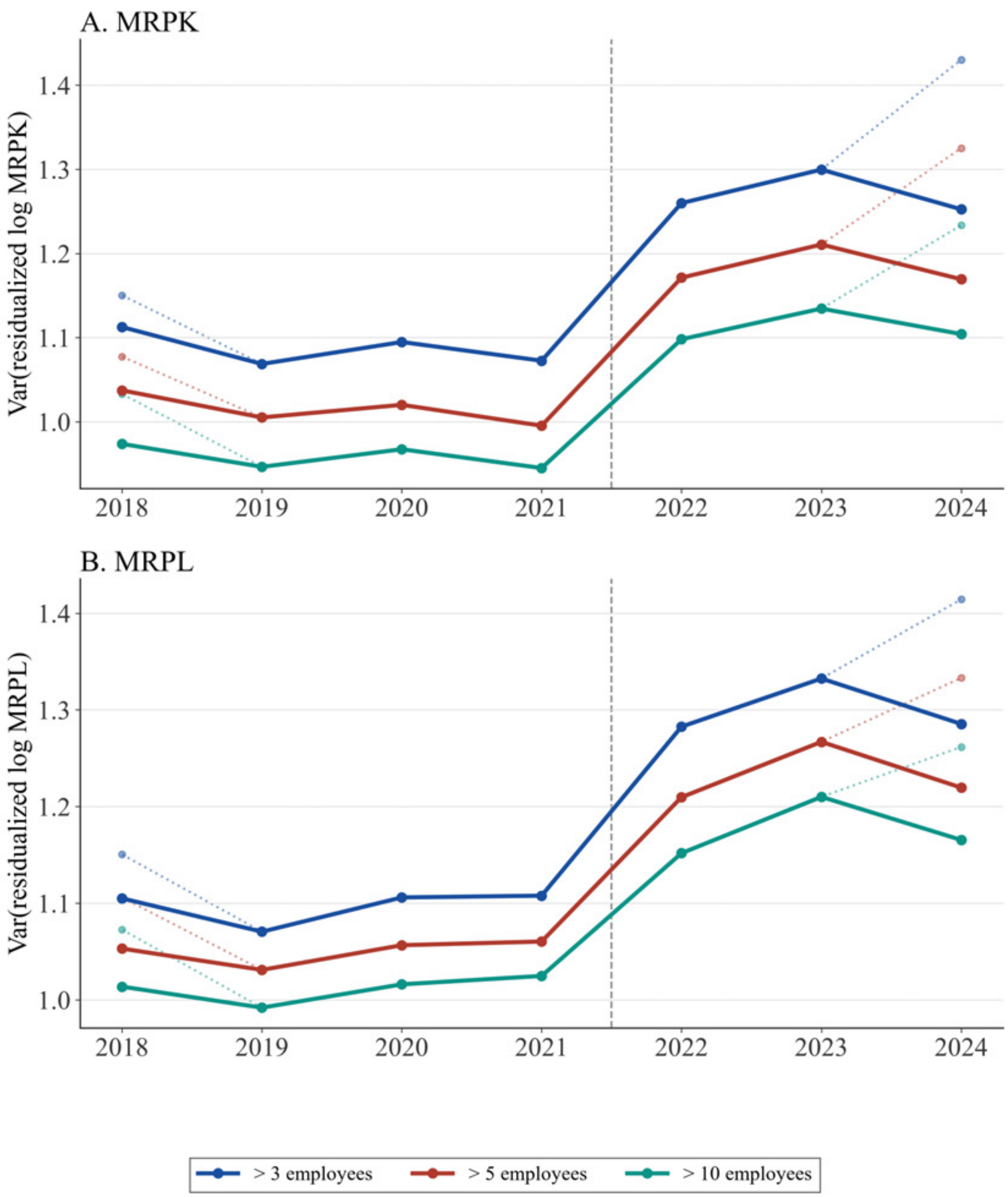
Notes: Industry_cell × year FE residuals of log(MRPK)/log(MRPL), 1% winsorized, unweighted. The same residuals as in Figure 6.

Figure C3: National dispersion levels by winsorization level, Ukraine, 2018–2024.



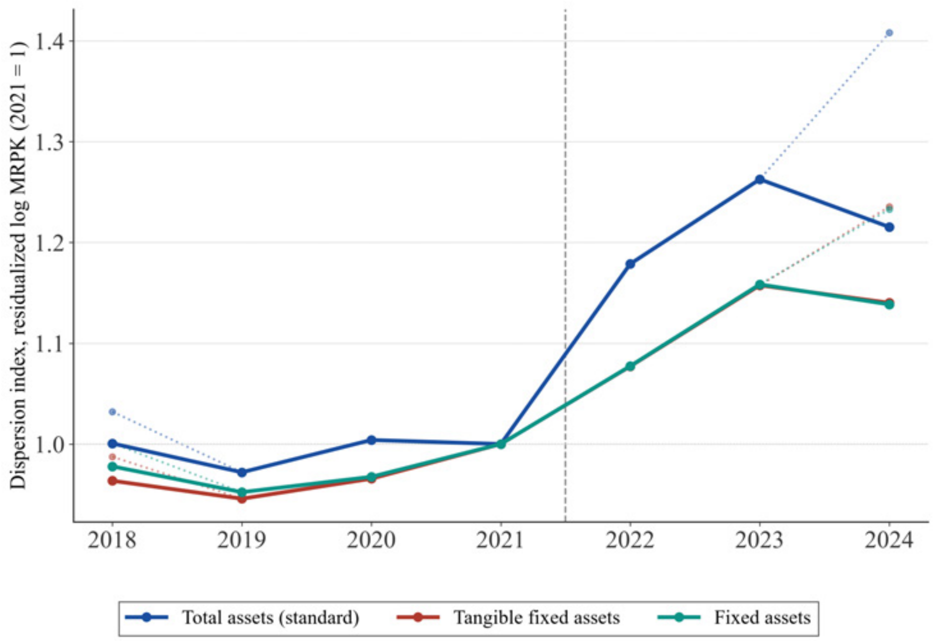
Notes: Var(residualized log MRPK/MRPL), industry_cell × year FE, equal-weighted. Compares no winsorization, 1% (this project's standard), and 5%. Solid = edge-corrected; dotted = raw (uncorrected). Ukraine: 90,257 firms, 195 industry cells.

Figure C4: National dispersion levels by minimum employee-count floor, Ukraine, 2018–2024.



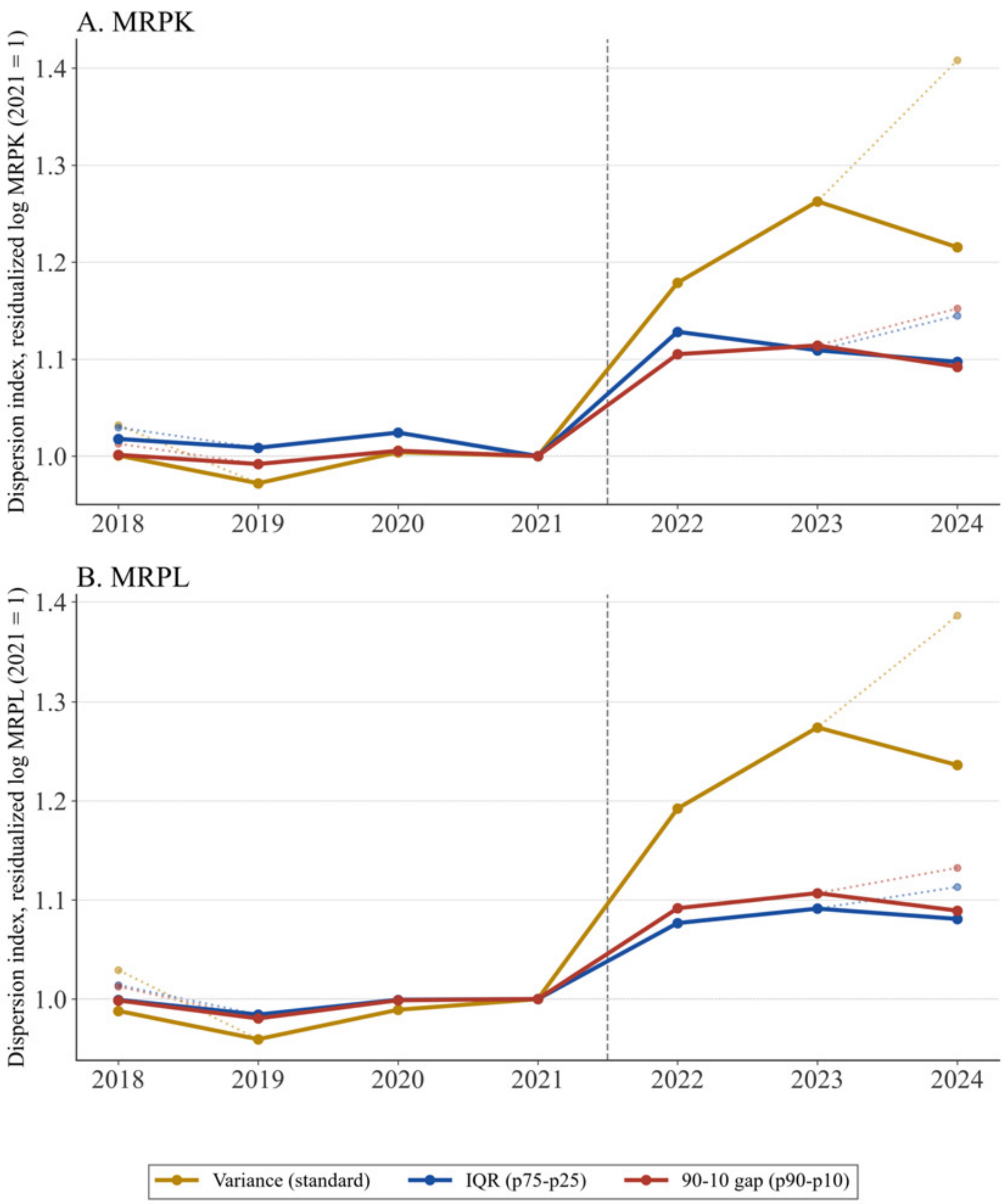
Notes: Equal-weighted, 1% winsorized, edge-corrected. Same national dispersion methodology as Figure 6, restricted to firms with more than a fixed employee-count floor. Of the 90,257-firm base panel (main window UA_hier_2018_2024): >3 employees keeps 48,913 firms; >5 employees keeps 36,441 firms; >10 employees keeps 23,542 firms.

Figure C5: National MRPK dispersion by capital measure, Ukraine, 2018–2024 (2021 = 1).



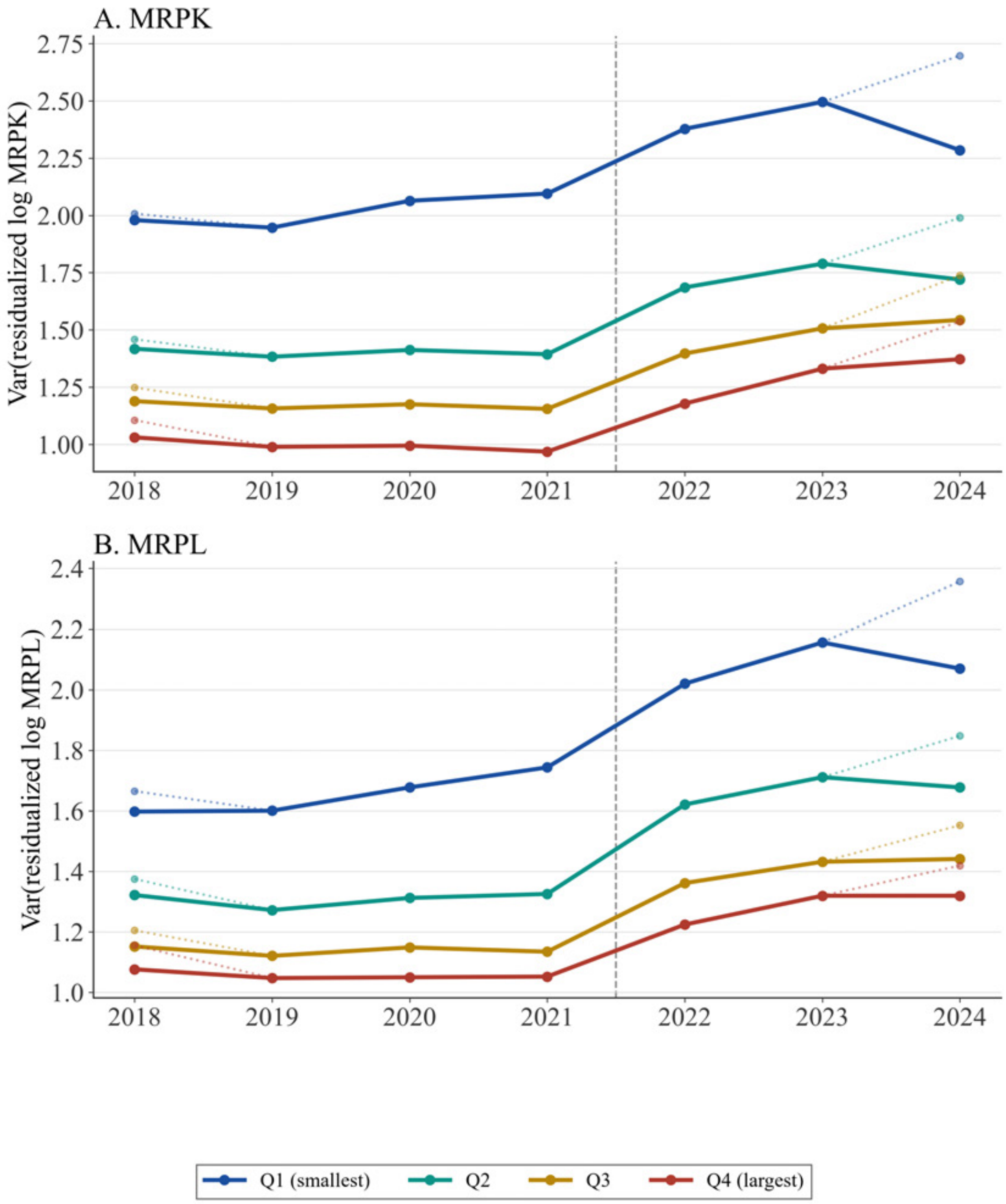
Notes: Equal-weighted, 1% winsorized, raw (dotted) and edge-corrected (solid). Compares total assets (standard) against tangible fixed assets and fixed assets as MRPK's denominator, each normalized to its own 2021 value. Total assets has 90,257-firm observations. Only a subset of 69,995 firms for tangible fixed assets and 72,382 for fixed assets report the alternative capital measures; these firms are on average larger than the standard sample mean.

Figure C6: National dispersion, Ukraine, 2018–2024 (2021 = 1): variance vs. interquartile range vs. 90–10 percentile gap.



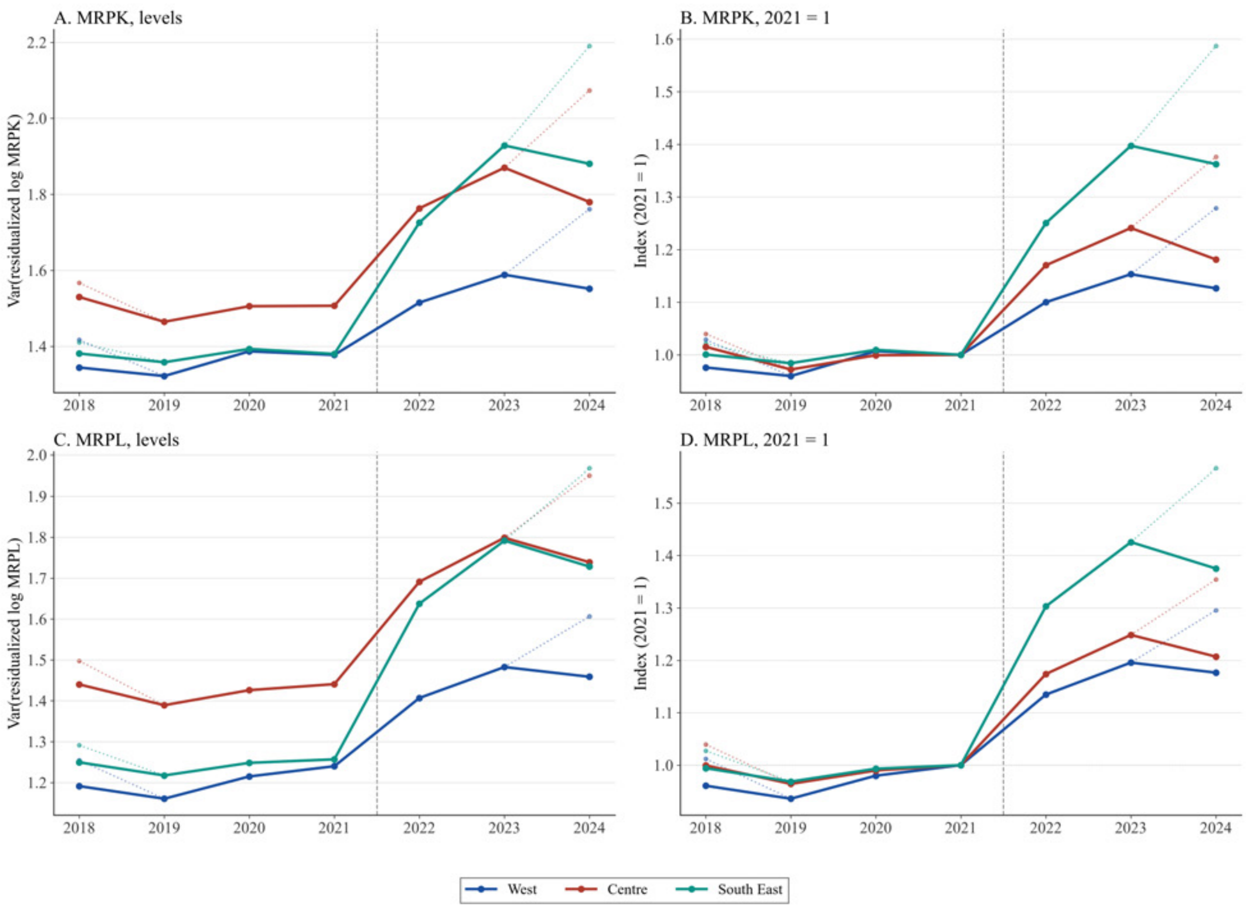
Notes: Equal-weighted, 1% winsorized, edge-corrected. Same national sample as Figure 6 (90,257 firms, 195 industry cells, balanced 2018–2024 panel. The standard variance measure from Figure 6 is plotted alongside two alternative statistics, the interquartile range (p75−p25) and the 90–10 percentile gap; all three are normalized to their own 2021 value.

Figure C7: National dispersion levels by firm-size quartile, Ukraine, 2018–2024.



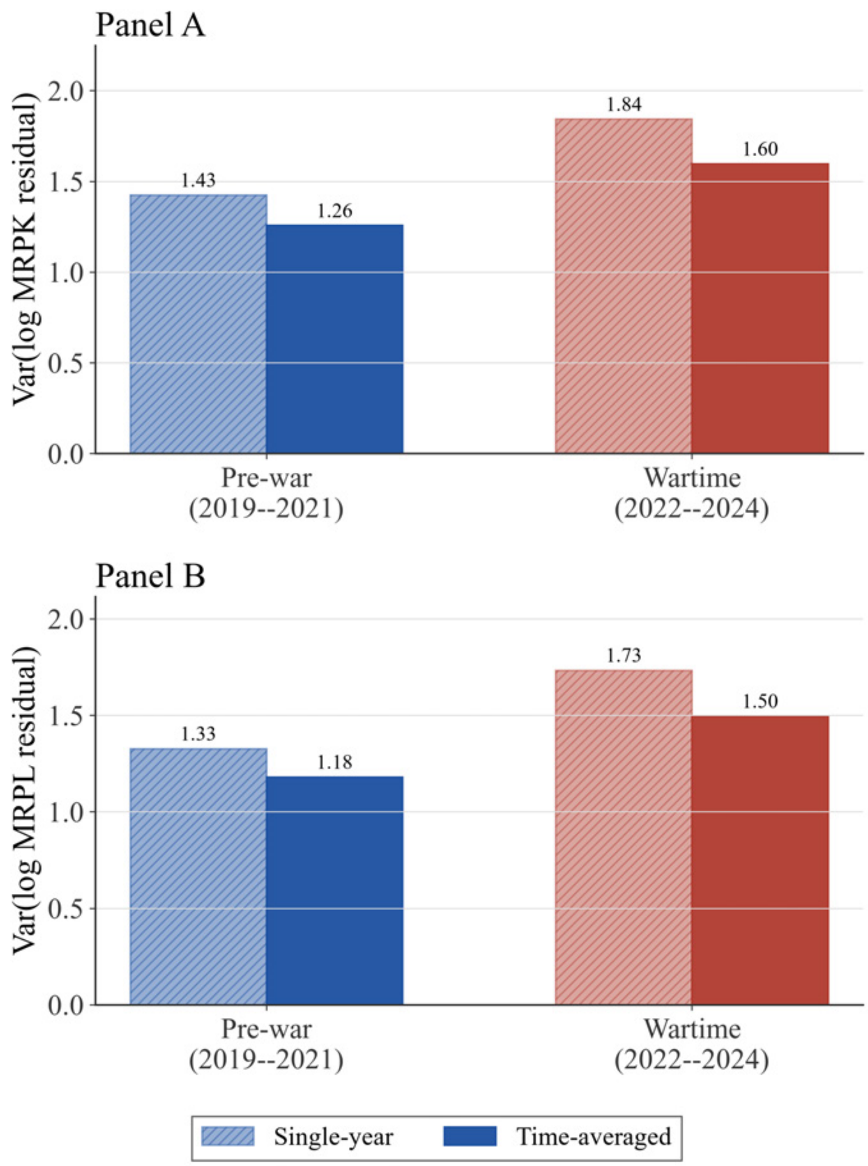
Notes: Firm-size quartile assigned once per firm from its own 2021 employees (Q1 = smallest 25%, Q4 = largest 25%); industry_cell × year fixed effects, edge-corrected. 90,257 firms, 195 industry cells. Quartile is fixed at 2021.

Figure C8: National dispersion levels by macro region, Ukraine, 2018–2024



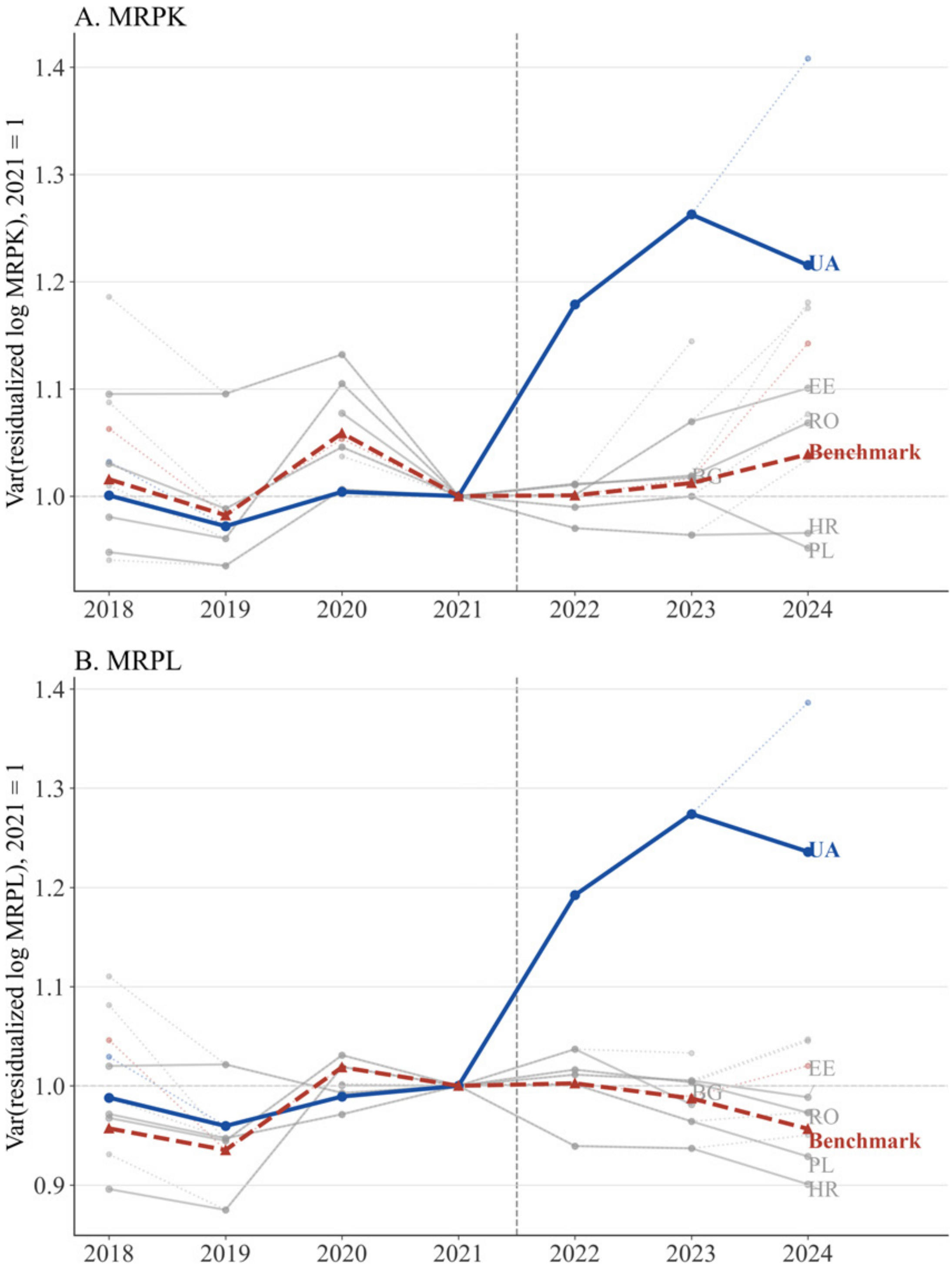
Notes: Equal-weighted, 1% winsorized, edge-corrected. Same national dispersion methodology as Figure 6, split by macro region (West/Centre/South East). Panels B and D normalize each region's series to its own 2021 value. Of the 90,257-firm base panel: West 24,682 firms; Centre 40,522 firms, of which 22,196 are in Kyiv city; South East 25,052 firms.

Figure C9: Pre-war vs. wartime dispersion, single-year vs. time-averaged.



Notes: Industry_cell × year FE residuals of log(MRPK)/log(MRPL), 1% winsorized, unweighted, 2018–2024, 90,257-firm balanced panel. Pre-war: 2019–2021. Wartime: 2022–2024."Single-year" = mean of that period's own 3 within-year variances; "Time-averaged" = variance of each firm's own 3-year average residual (attenuates potential firm-year measurement error). Not edge-corrected.

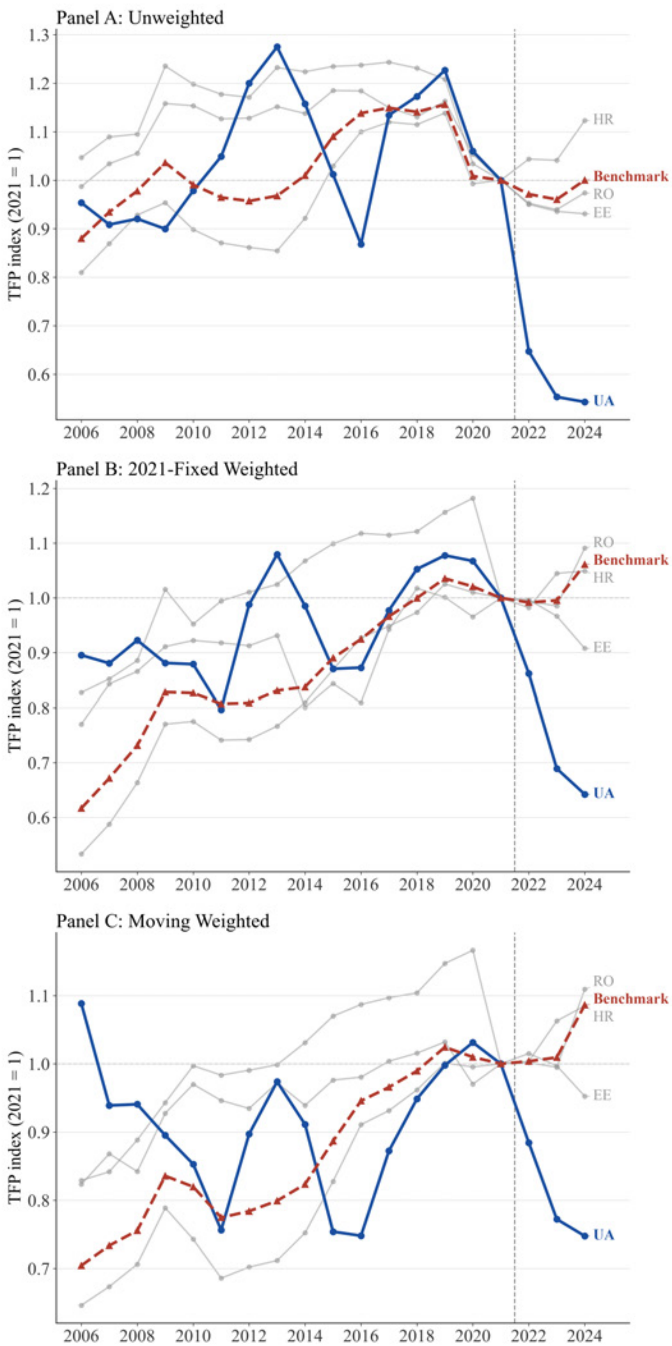
Figure C10: National dispersion index by country, 2018–2024 (2021 = 1).



Notes: Equal-weighted, 1% winsorized, raw (dotted) and edge-corrected (solid); each country's series normalized to its own 2021 value. Observation counts and summary statistics: Appendix Table B12. At the point of writing, 2024 data for Bulgaria is only partially available, and is therefore excluded. Bulgaria's panel ends in 2023; its partial 2024 data are used only for the 2023 edge correction.

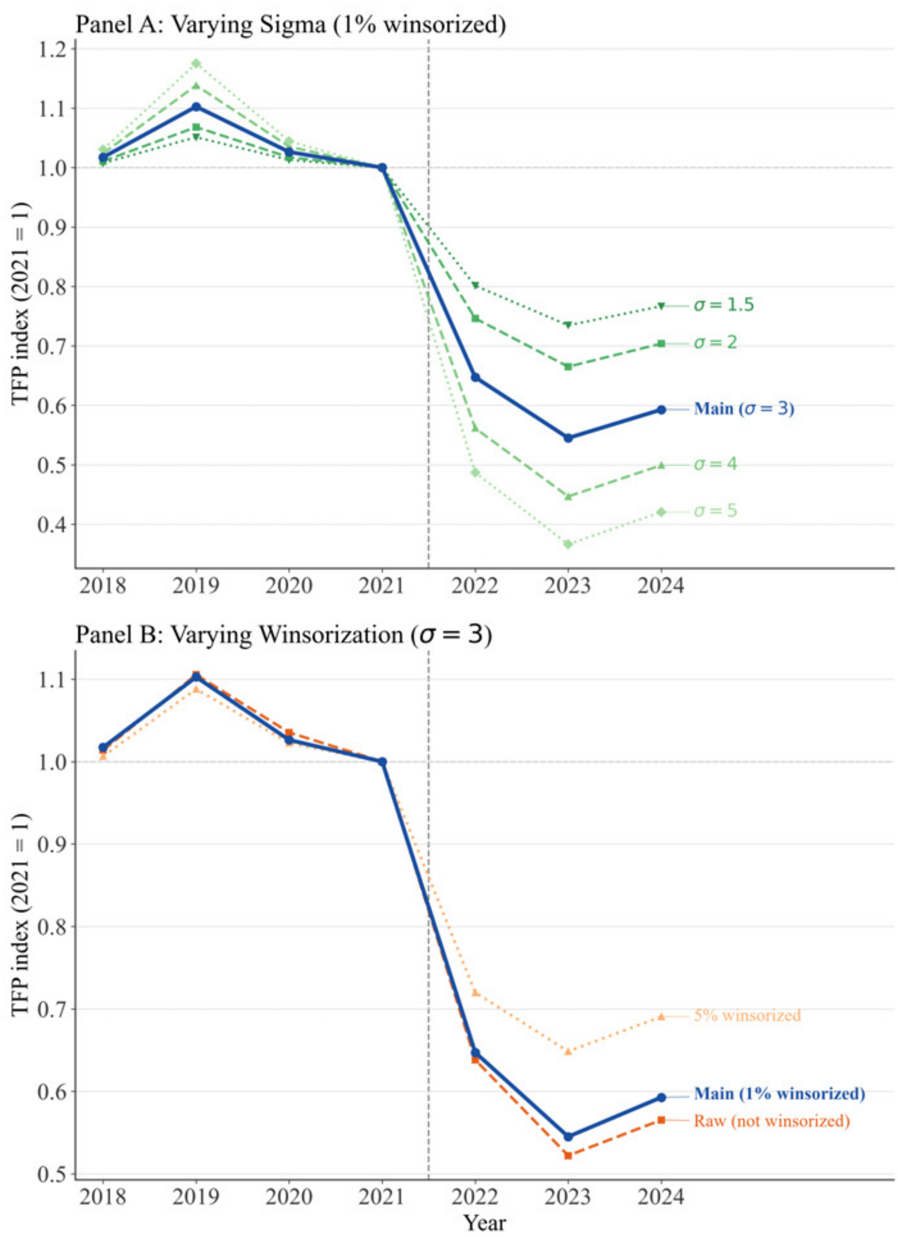
D Appendix D: Additional Figures for TFP

Figure D1: National TFP index by country, 2006–2024, 2021 = 1



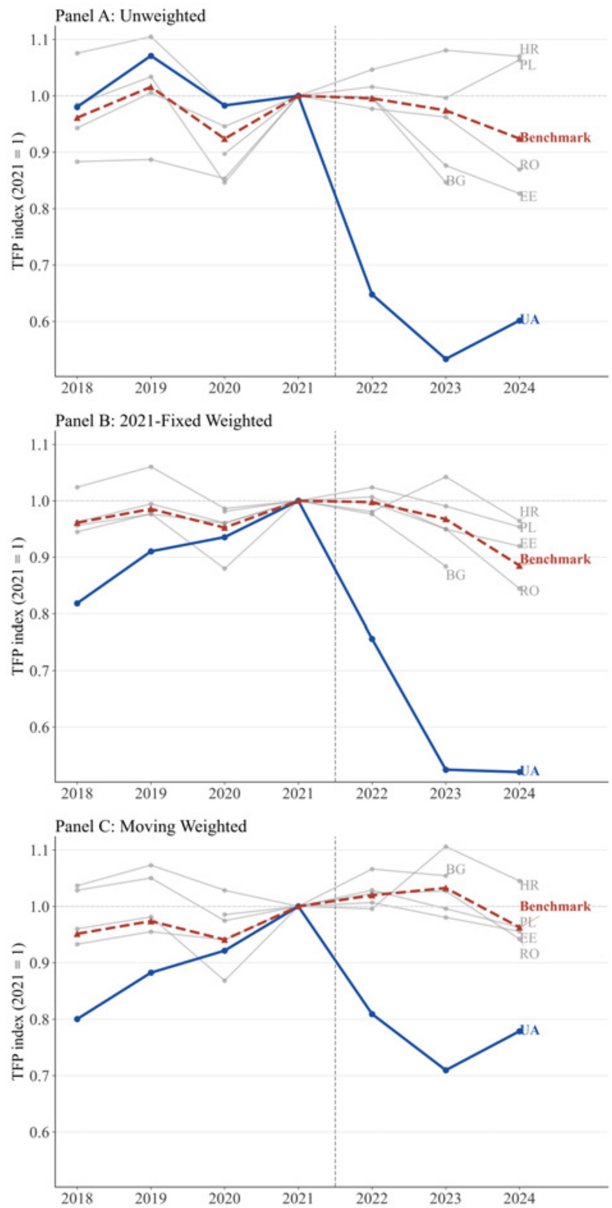
Notes: 1% winsorized, edge-corrected. *Benchmark* as in Figure 9; donor weights in Table B5.

Figure D2: Ukraine national TFP index, sensitivity to σ and winsorization, 2018–2024.



Notes: Unweighted, edge-corrected, base year 2021. Main 2018–2024 panel, Ukraine. Main series uses an elasticity of demand $\sigma = 3$, and is 1% winsorized, as used throughout the paper. Panel A varies $\sigma \in \{1.5, 2, 4, 5\}$, holding winsorization fixed. Panel B varies the winsorization threshold (raw/1%/5%), holding $\sigma = 3$ fixed.

Figure D3: National TFP index by country under the $\tau_K = 1$ alternative assumption, 2018–2024

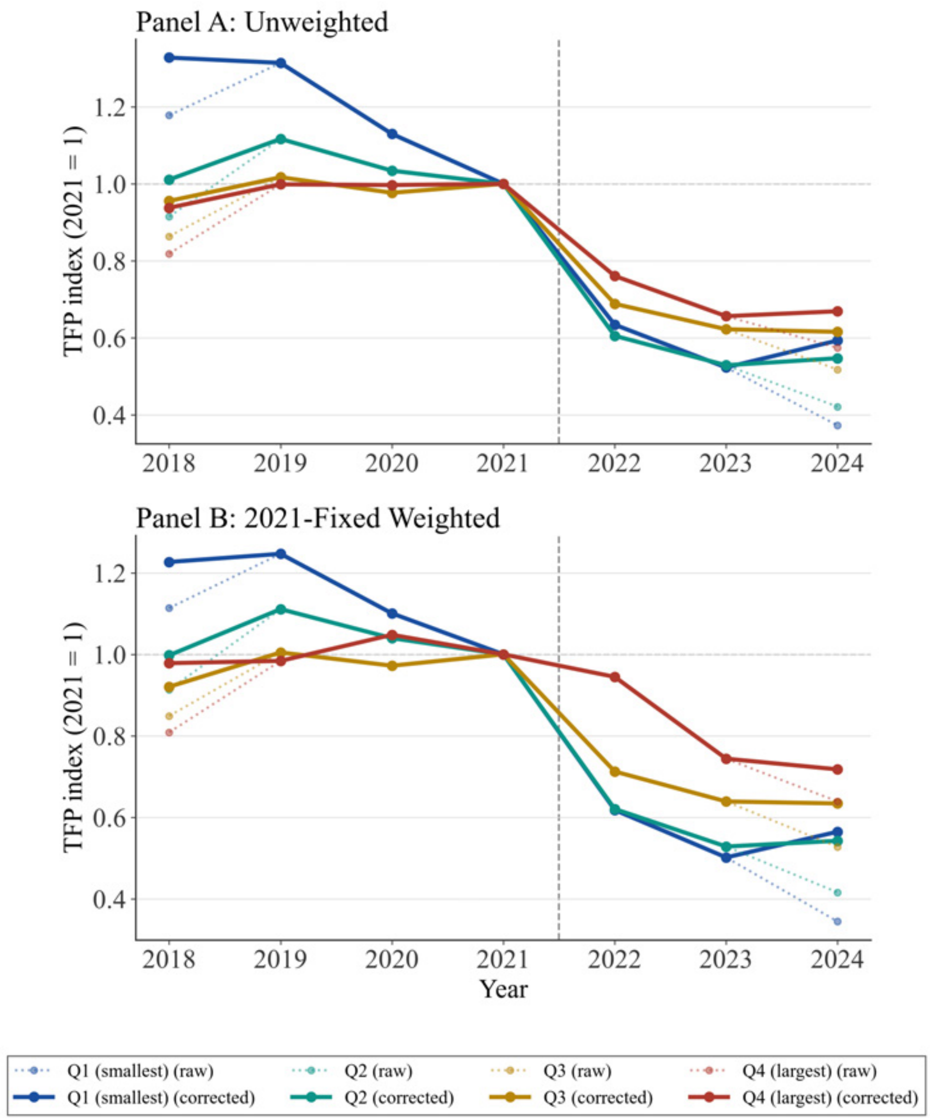


Notes: 1% winsorized, edge-corrected. Assumes no distortion in the capital market ($\tau_K = 1$) instead of the main specification's no-distortion-in-labor assumption:

$$\log(TFP\ loss) = -\frac{\beta(1-\beta) + \beta(1+\beta)\sigma}{2}\,\mathrm{var}(\log(MRPK_{it}) - \log(MRPL_{it})) - \frac{\sigma(1+\beta)}{2}\,\mathrm{var}(\log(MRPK_{it})) + \frac{\sigma\beta}{2}\,\mathrm{var}(\log(MRPL_{it})).$$

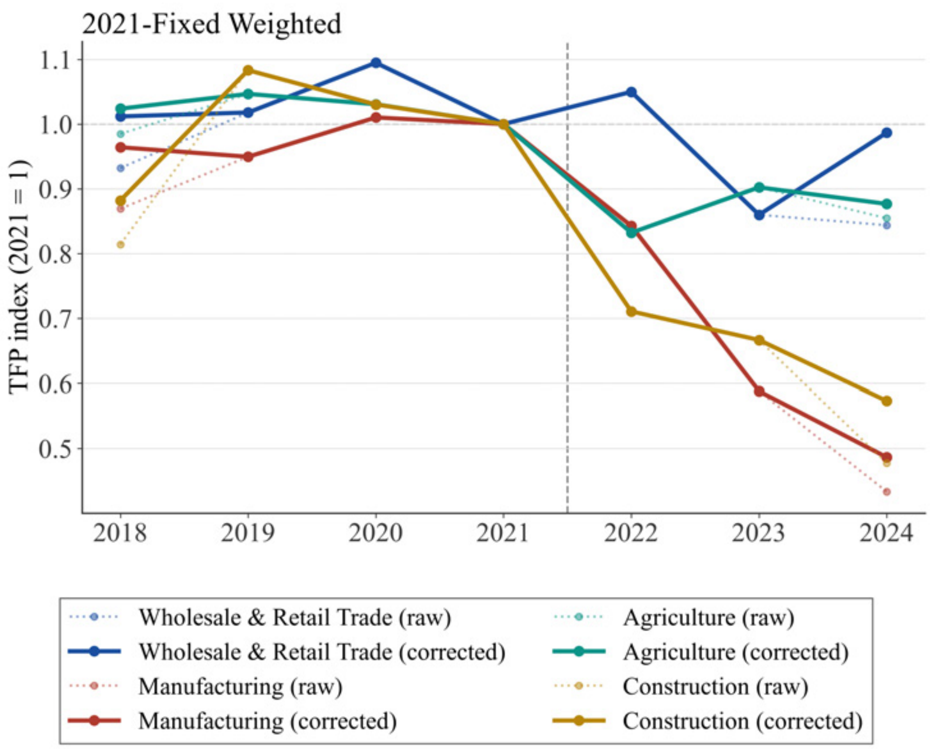
where β is national labor cost share. Poland: shortened 2020–2024 window. Bulgaria: through 2023 only. *Benchmark* = firm-count-weighted average of other countries. Donor weights and sample composition: Appendix, Table B4.

Figure D4: TFP index by firm-size quartile, Ukraine, 2018–2024



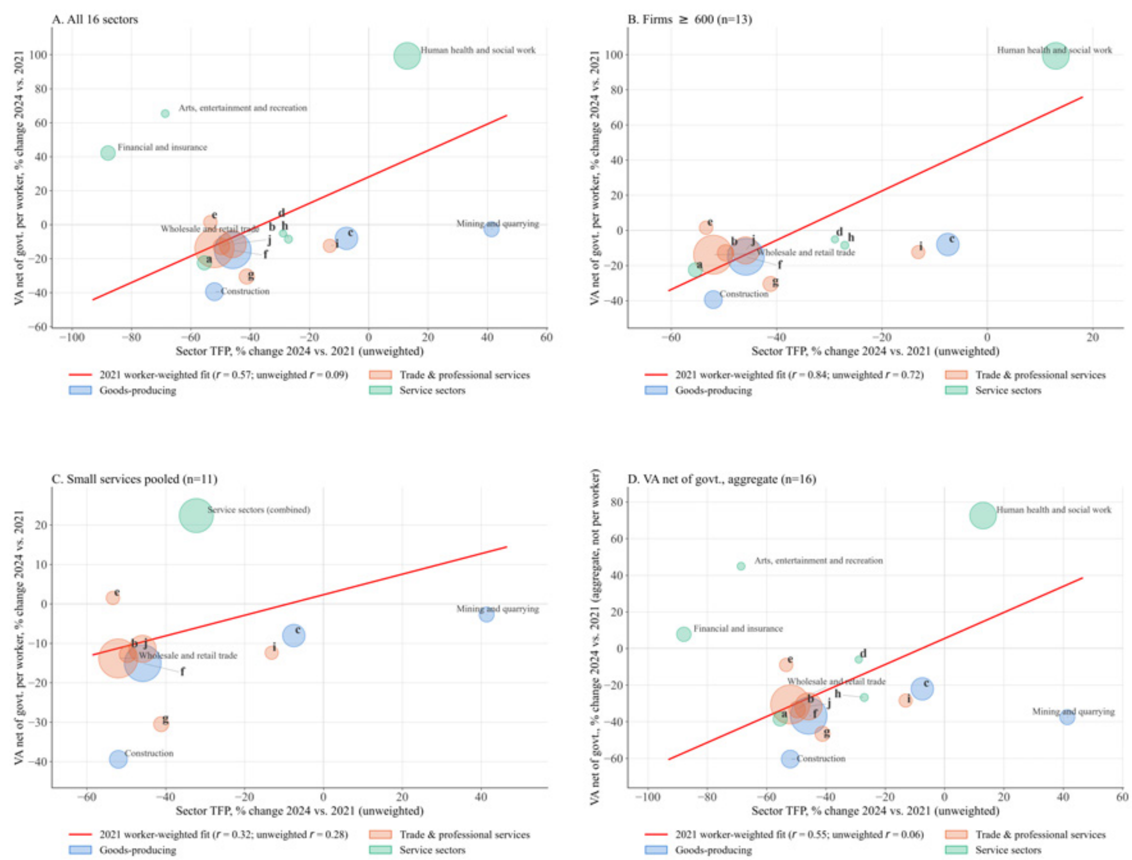
Notes: Normalized to 2021=1. Firm-size quartile assigned once per firm from its own 2021 employees (Q1 = smallest 25%, Q4 = largest 25%); industry_cell × year fixed effects, edge-corrected. 90,257 firms, 195 industry cells. Quartile is fixed at 2021.

Figure D5: National TFP index by sector, Ukraine, 2018–2024, 2021-fixed weighted.



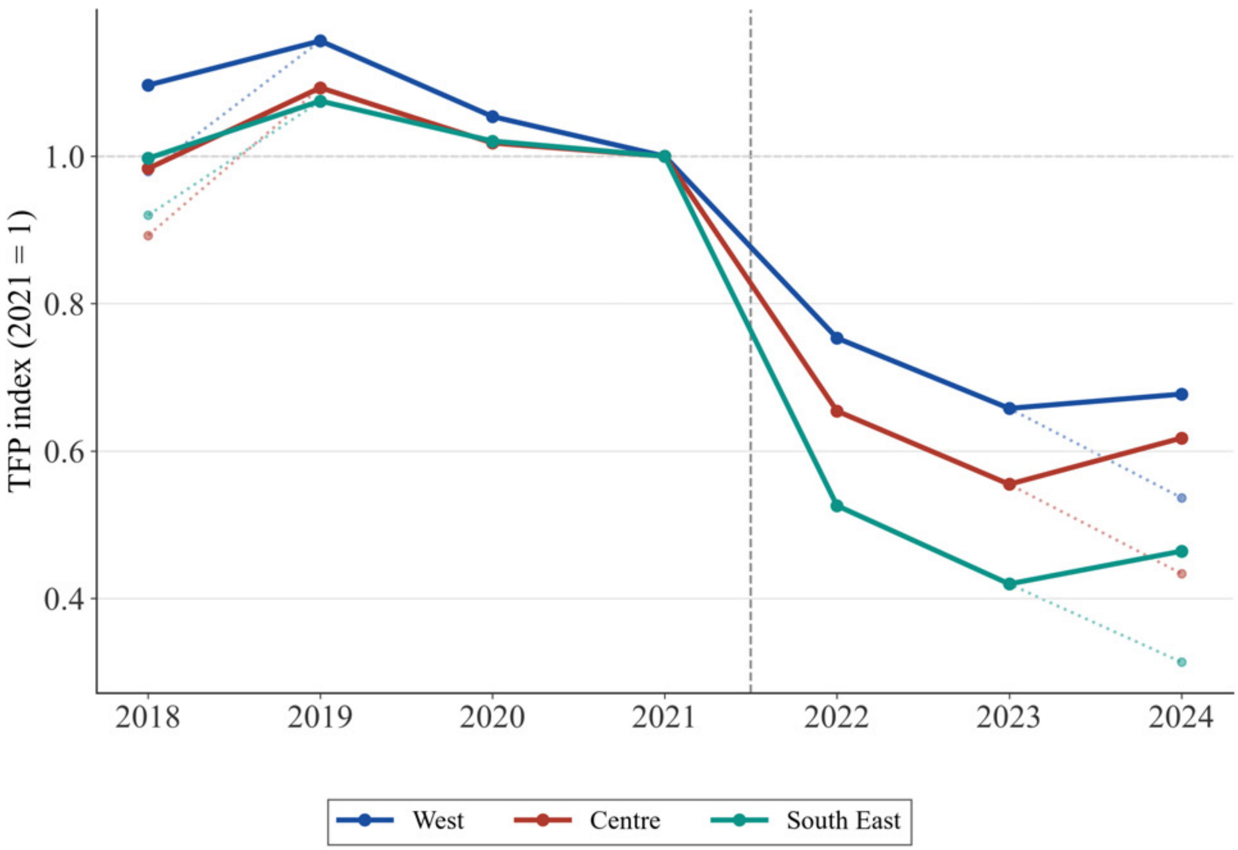
Notes: 1% winsorized, 2021-fixed firm weighted, edge-corrected. Same 4 sectors, same sector-specific industry_cell hierarchy and capital cost share s_K^{rev} as the equal-weighted Figure 10; only the weighting scheme differs.

Figure D6: Sector TFP vs. VA/worker, Ukraine, 2024 vs. 2021, robustness variants



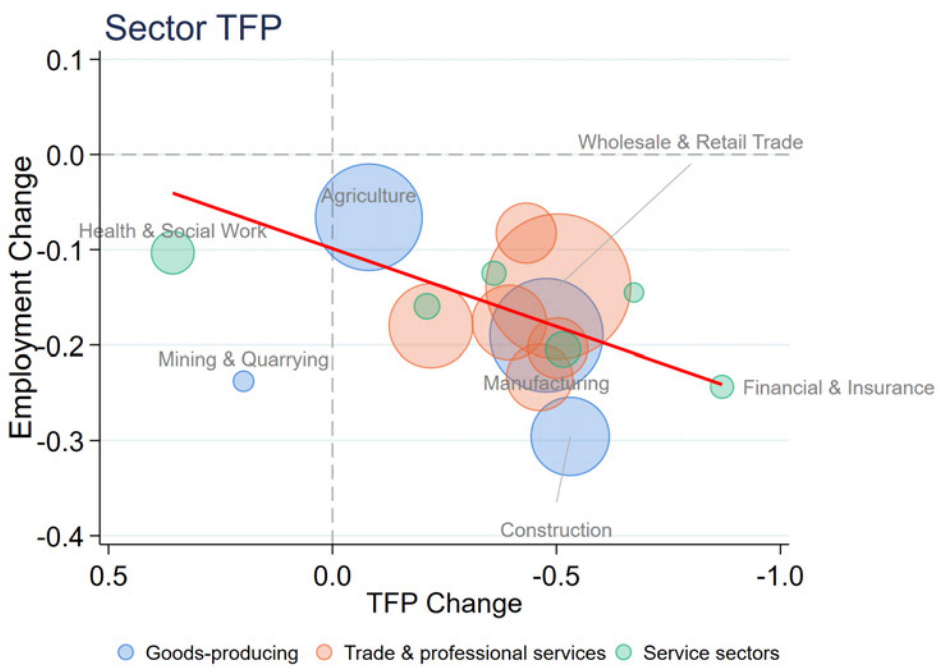
Notes: x = sector TFP % change 2024 vs. 2021 (unweighted, edge-corrected); y = VA net of govt. per worker % change (Panels A–C) or aggregate VA net of govt., (Panel D), from Ukrstat national accounts (State Statistics Service of Ukraine, 2026e, 2025); see Table B7 for the full source/currency/coverage notes. Bubble area and fit line/r are 2021-worker-weighted. Panel B: firms ≥ 600 (n=13). Panel C: the 6 thinnest service sectors (green in Panels A/B/D) pooled into one re-estimated point (n=11). Lettered points: c = Agriculture, forestry and fishing; f = Manufacturing; j = Transporting and storage; a = Accommodation and food services; e = Information and communication; i = Real estate; g = Professional, scientific and technical; b = Administrative and support services; d = Education; h = Provision of other types of services.

Figure D7: TFP by macro region, Ukraine, 2018–2024



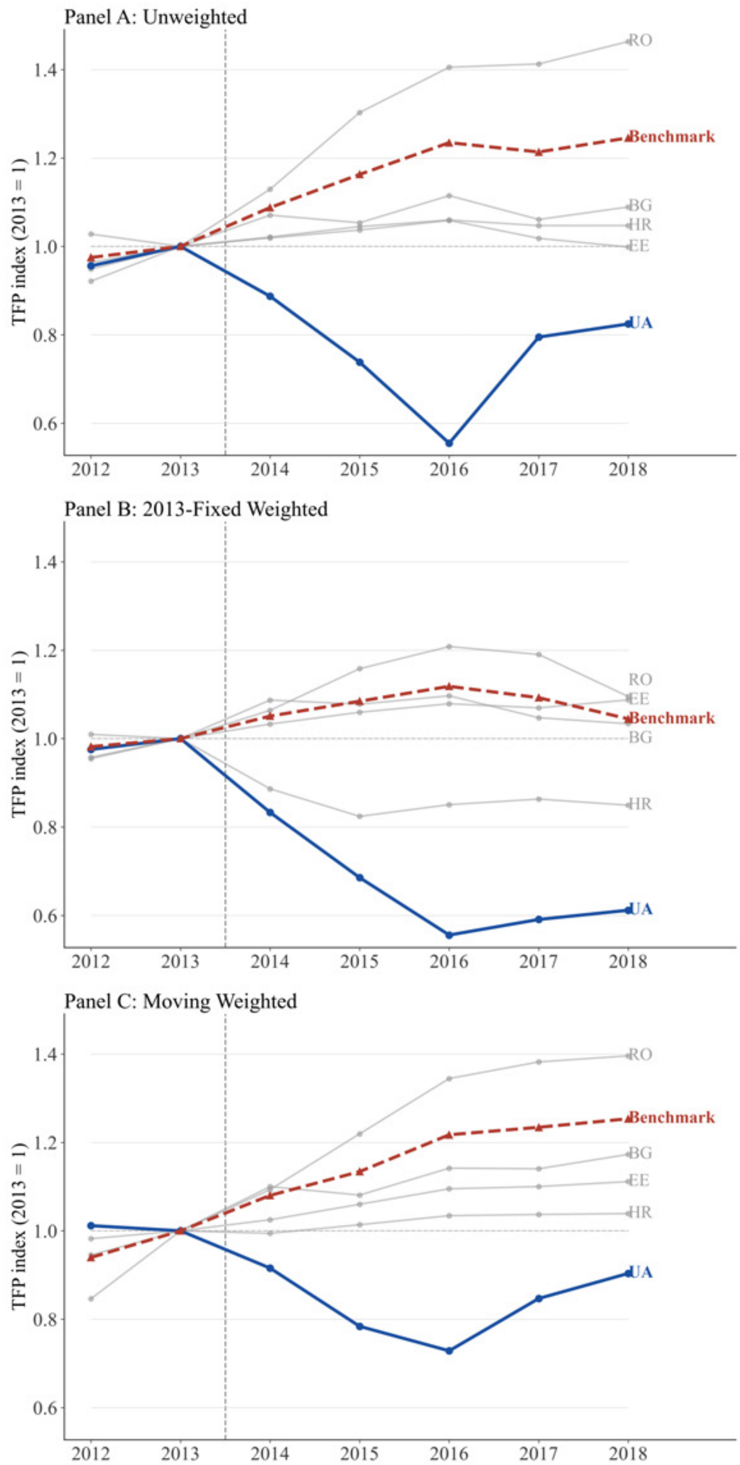
Notes: Equal-weighted, 1% winsorized, edge-corrected. Same national TFP methodology as Figure 9, split by macro region (West/Centre/South East). Each region's series is normalised to its own 2021 value. Of the 90,257-firm base panel: West 24,682 firms; Centre 40,522 firms, of which 22,196 are in Kyiv city; South East 25,052 firms.

Figure D8: Sector TFP change vs. employment change, 2024 vs. 2021.



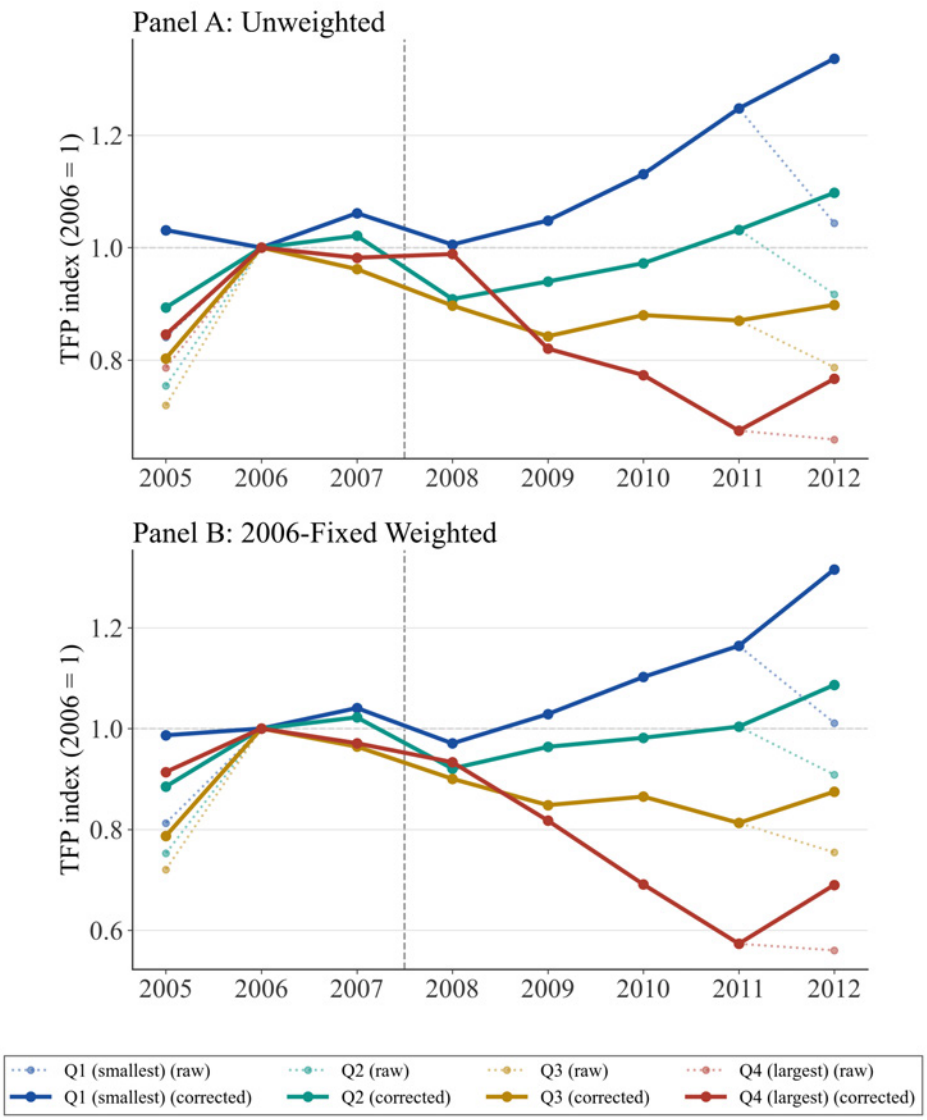
Notes: One bubble per sector (16 sectors), national 2018–2024 balanced panel. Bubble size = each sector's own 2021 firm count.

Figure D9: National TFP index by country, 2012–2018



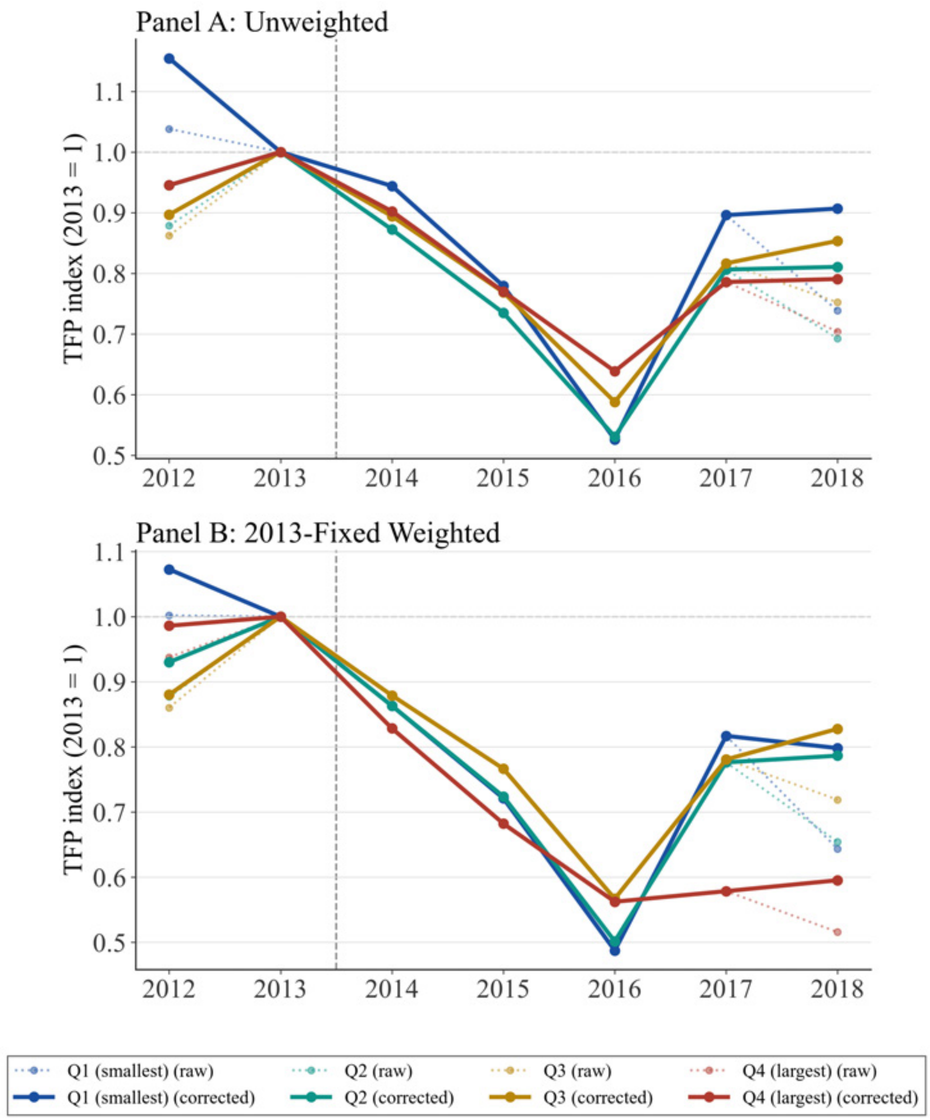
Notes: 1% winsorized, edge-corrected, base year 2013. First and last years edge-corrected via direct substitution from backward/forward helper windows, since Orbis data exists on both sides of this window. *Benchmark* = firm-count-weighted average of the other four countries. Donor weights and sample composition: Appendix, Table B10.

Figure D10: TFP index by firm-size quartile, Ukraine, Global Financial Crisis, 2005–2012



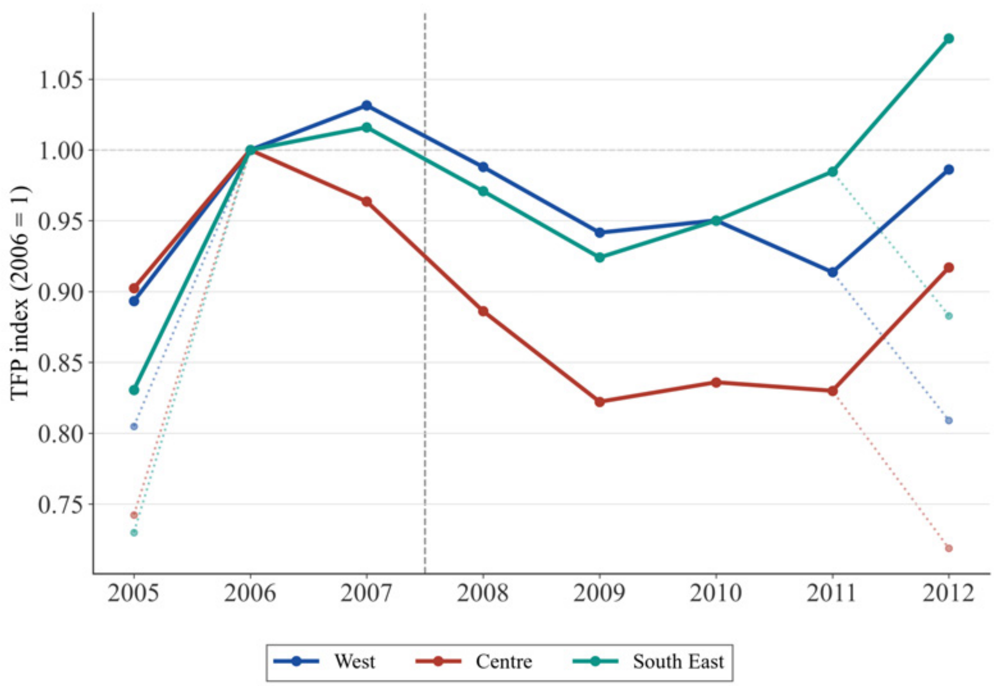
Notes: Normalized to 2006=1. Firm-size quartile assigned once per firm from its own 2006 employees (Q1 = smallest 25%, Q4 = largest 25%); industry_cell × year fixed effects, edge-corrected. 96,144 firms, 201 industry cells. Quartile is fixed at 2006.

Figure D11: TFP index by firm-size quartile, Ukraine, Crimea and the Donbas, 2012–2018



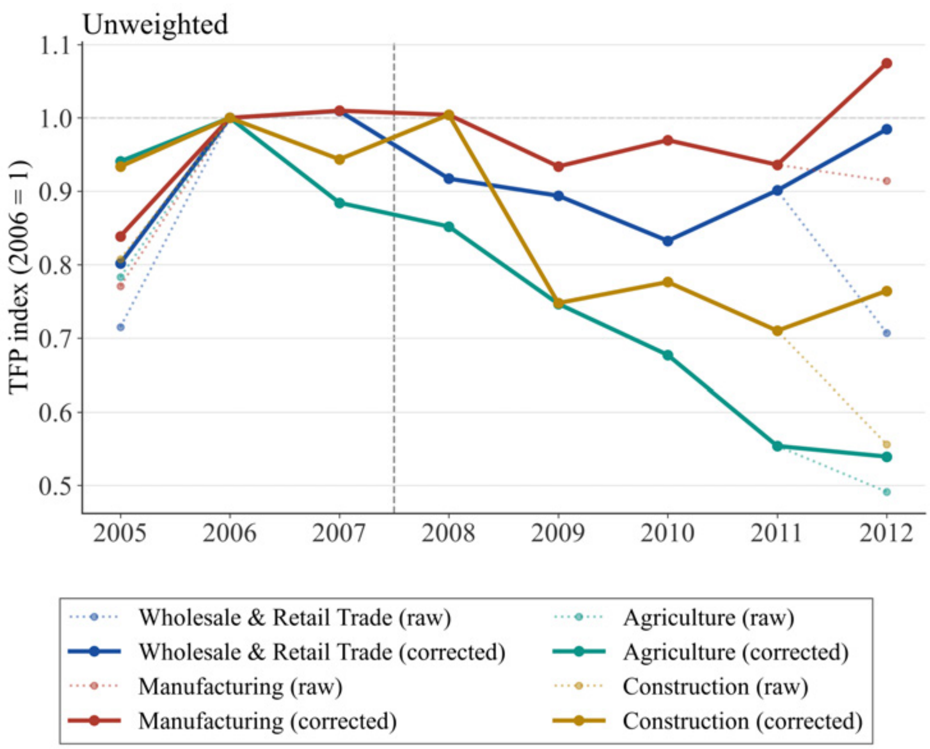
Notes: Normalized to 2013=1. Firm-size quartile assigned once per firm from its own 2013 employees (Q1 = smallest 25%, Q4 = largest 25%); industry_cell × year fixed effects, edge-corrected. 108,426 firms, 114 industry cells. Quartile is fixed at 2013. Firms in raions annexed or occupied in 2014 are excluded.

Figure D12: TFP by macro region, Ukraine, Global Financial Crisis, 2005–2012



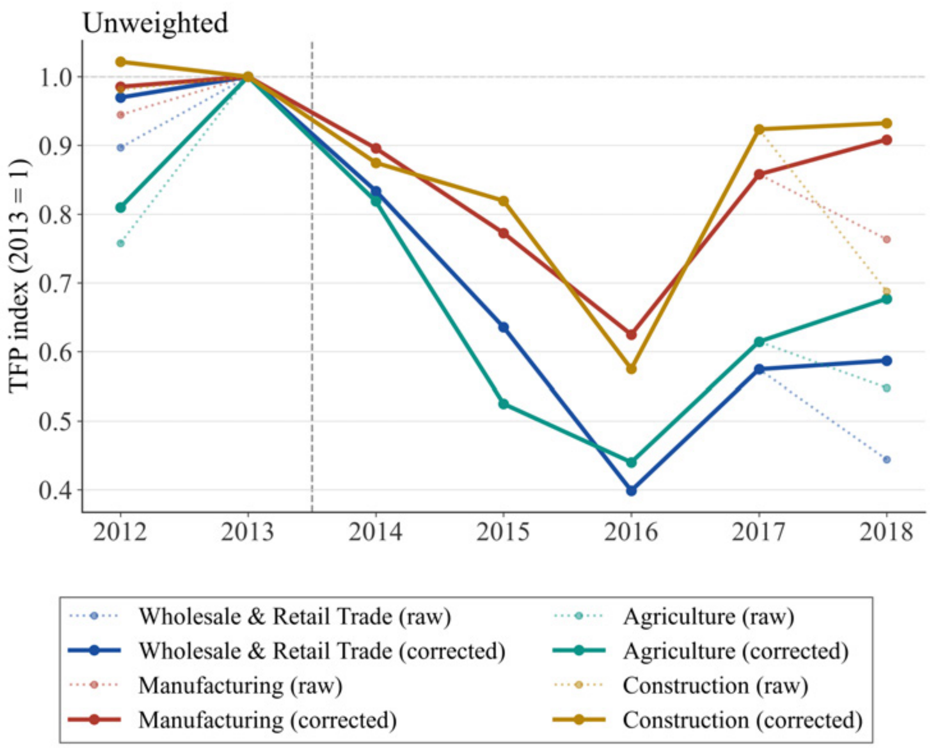
Notes: Equal-weighted, 1% winsorized, edge-corrected. Same national TFP methodology as Figure 16, split by macro region (West/Centre/South East). Each region's series is normalised to its own 2006 value. Of the 96,144-firm panel: West 24,383 firms; Centre 32,139 firms, of which 16,928 are in Kyiv city; South East 39,622 firms.

Figure D13: National TFP index by four major sectors, Ukraine, Global Financial Crisis, 2005–2012.



Notes: 1% winsorized, equal-weighted, edge-corrected. Normalized to 2006=1. Each sector uses the national industry_cell hierarchy and its own 2006 capital cost share s_K^{rev}.

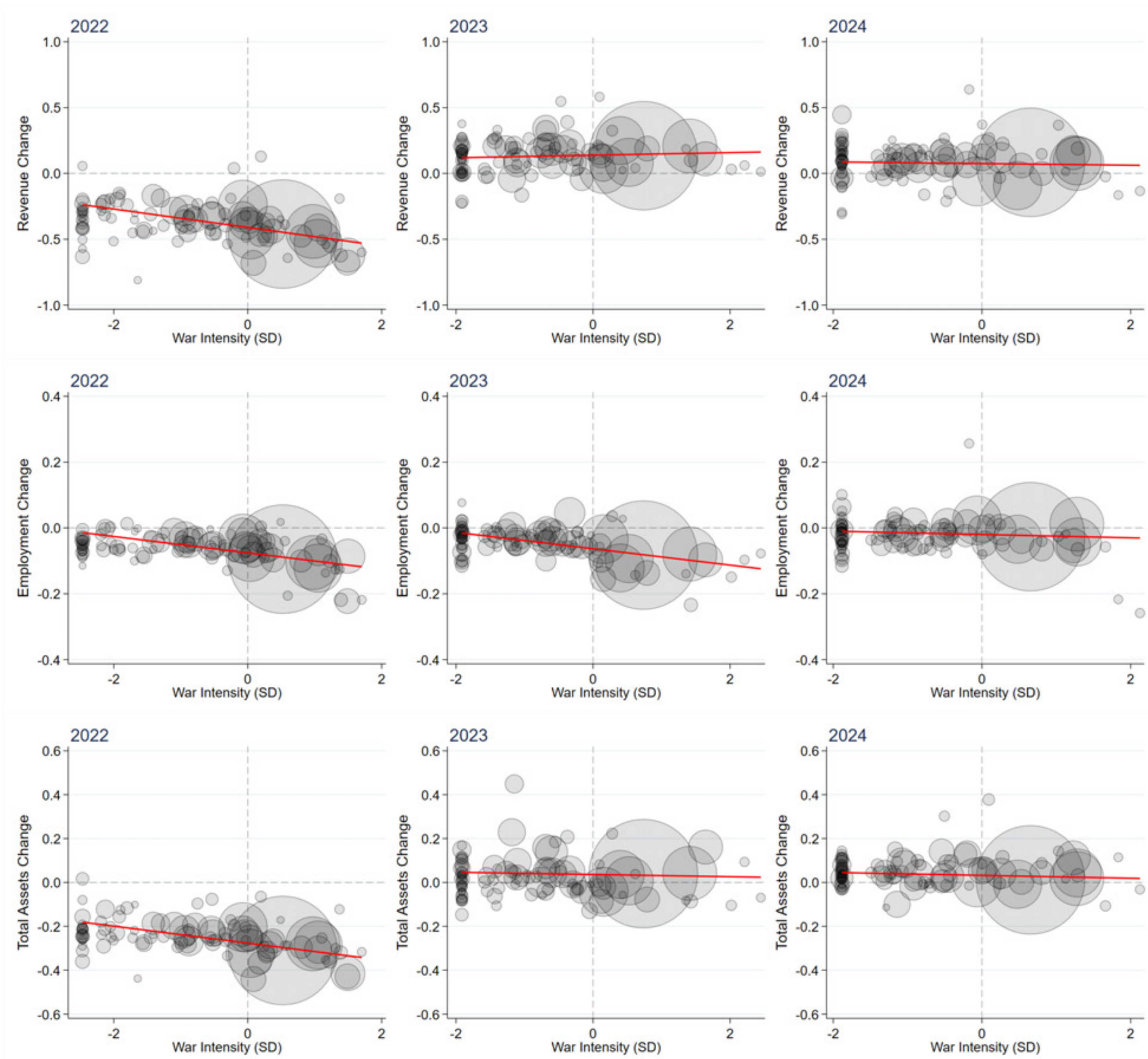
Figure D14: National TFP index by four major sectors, Ukraine, Crimea and the Donbas, 2012–2018.



Notes: 1% winsorized, equal-weighted, edge-corrected. Normalized to 2013=1. Each sector uses the national industry_cell hierarchy and its own 2013 capital cost share s_K^{rev}. Firms in raions annexed or occupied in 2014 are excluded.

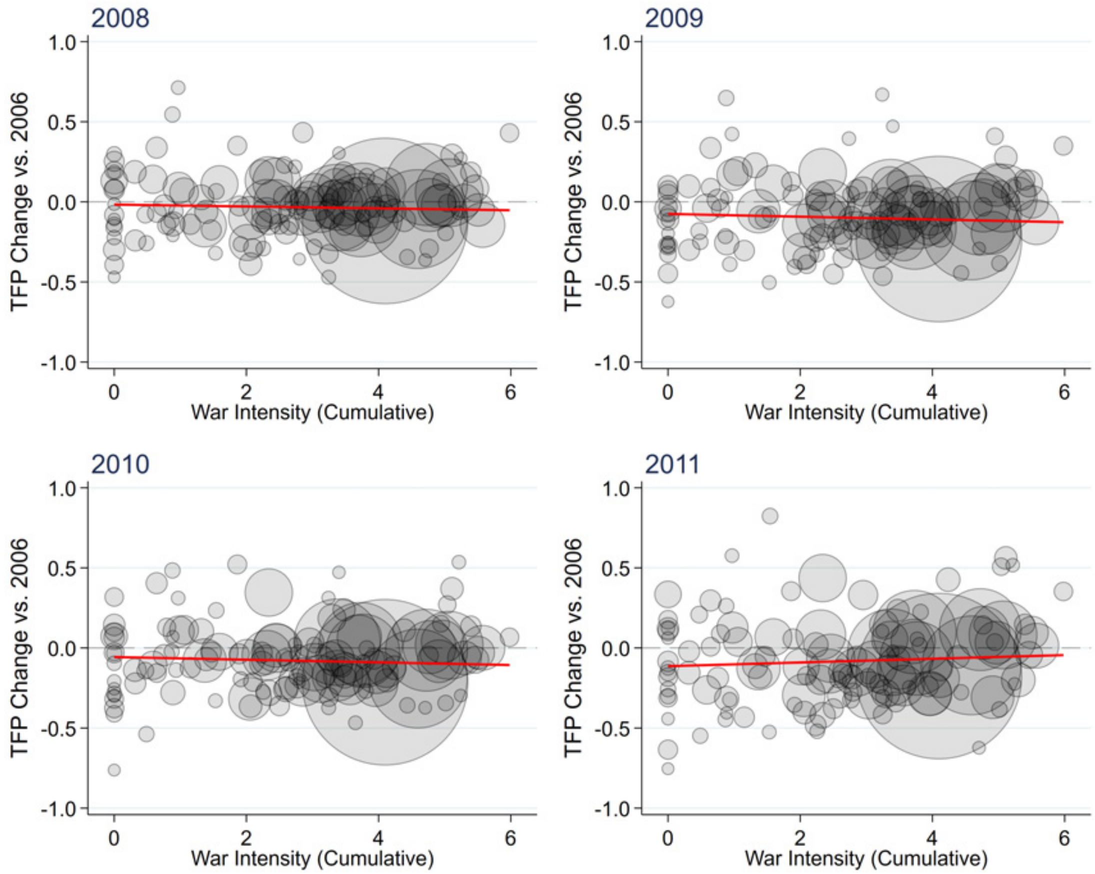
E Appendix E: Additional Subnational Figures

Figure E1: War intensity vs. raion-level year-over-year change: revenue, employment, and total assets



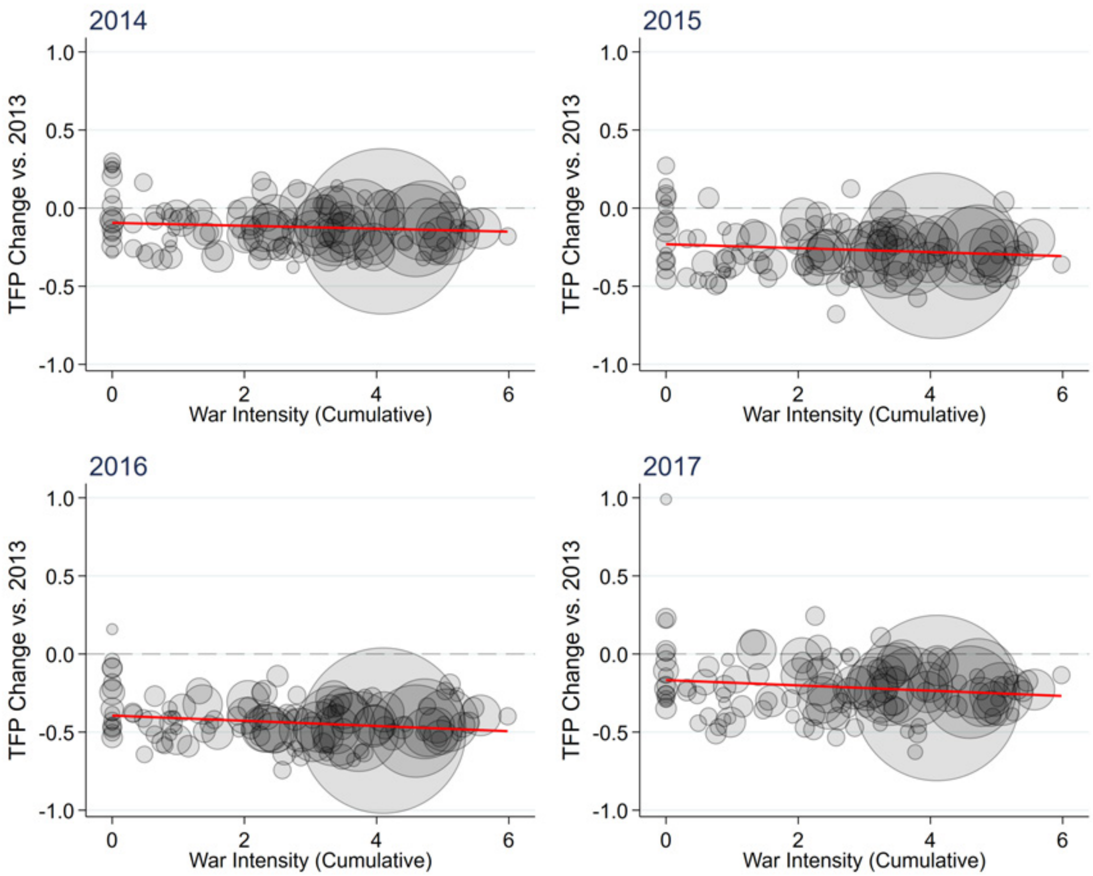
Notes: Same 96-raion balanced-panel sample and war-intensity construction as Figure 13 (that year's flow of property-damage events, standardized within each year). Y-axis: year-on-year % change. Bubble size = each raion's 2021 firm count. Rows 1 and 3 (Revenue, Total Assets) are in constant 2021 prices, CPI-adjusted (National Bank of Ukraine, 2025).

Figure E2: Placebo: post-2022 war intensity and raion-level TFP during the Global Financial Crisis



Notes: Each bubble is a raion; bubble size = the raion's 2006 firm count; fit lines are firm-count weighted. The x-axis is the cumulative 2022–2024 War Intensity Score. The y-axis is raion-level TFP change relative to 2006. Balanced 2005–2012 panel, 124 raions, minimum 80 firms per raion, equal firm weighting within raion, industry-cell × year fixed effects estimated once nationally.

Figure E3: Placebo: post-2022 war intensity and raion-level TFP during the Donbas war



Notes: As Figure E2, for the 2014 episode: balanced 2012–2018 panel, 114 raions, TFP change relative to 2013, bubble size = the raion's 2013 firm count. The x-axis is the cumulative 2022–2024 War Intensity Score.

F Appendix F: Processing of Jooble Vacancy Data

This appendix documents the data-processing pipeline that turns the raw job-board records supplied by Jooble.org into the cleaned Stata files used for analysis. It follows the approach in Pham et al. (2023) and Faryna et al. (2022).

F.1 Overview

The data are provided by Jooble.org, a global job-search aggregator headquartered in Ukraine that collects listings from company websites, recruitment agencies and job boards. Each raw record describes one vacancy and carries a job identifier, title, description, location, minimum/maximum salary, currency, salary rate, number of clicks, and a created date. The pipeline converts these unstructured records into a rectangular dataset with ten standardized variables — `id`, `min_salary`, `curr_id`, `sal_rate`, `date_created`, `loc`, `loc_en`, `esco_title`, `cleaned_title`, `code` — and writes them to `.dta`.

F.2 Stage 1 — title classification with GenAI

Job titles are free text, so they must be mapped to a standard occupational taxonomy. The chapter uses ESCO (the European Skills, Competences, Qualifications and Occupations classification, an EU extension of the ILO's ISCO). Rather than train a bespoke classifier, which needs a labeled sample, the pipeline uses a Generative-AI model (OpenAI `GPT-4o-mini`) via the **Batch API**. A carefully crafted prompt specifies the *role*, the *task*, and the required JSON *output* (translated title and closest ESCO occupation); seniority words are ignored, and ambiguous or non-title inputs return `NA`.

Listing 1: Classification prompt.

```
categorize\_prompt = '''
You are a data expert working for the European Commission's
```

```
Directorate-General for Employment, Social Affairs and
Inclusion, specialized in analyzing job postings. Each
input is a job title from an online job board, in English
or another language. Map the input (or its English
translation) to the closest ESCO occupation. Ignore
seniority (trainee/junior/middle/senior). Only return a
match you are sure about; otherwise return "NA".
If an input is not a single job title, return "NA".
Output a JSON object:
{ translated: string, ESCO\_title: string }'''
```

Requests are written to a `.jsonl` batch file — one request per unique title, each with a `custom_id` so outputs can be re-joined, and `temperature = 0` for deterministic results. Up to 50,000 requests are allowed per batch; large datasets are split into shards subject to the API rate limits.

Listing 2: Building a Batch API request file.

```
task = {
    "custom_id": f"task-{i}",
    "method": "POST", "url": "/v1/chat/completions",
    "body": {
        "model": "gpt-4o-mini", "temperature": 0,
        "response_format": {"type": "json_object"},
        "messages": [
            {"role": "system", "content": categorize_prompt},
            {"role": "user",   "content": title},
        ],
    },
```

```
}
```

The file is uploaded and processed asynchronously; once complete, the output `.jsonl` is retrieved and parsed back into `(custom_id, translated, ESCO_title)`.

Listing 3: Submitting and retrieving a batch job.

```
client = OpenAI(api_key=...)
batch_file = client.files.create(file=open("titles.jsonl","rb"),
purpose="batch")
batch_job  = client.batches.create(input_file_id=batch_file.id,
                        endpoint="/v1/chat/completions",
                        completion_window="24h")
# when finished:
out = client.files.content(
    client.batches.retrieve(batch_job.id).output_file_id)
```

F.3 Stage 2 — normalizing to the ESCO taxonomy

GPT often returns a reasonable occupation that is not the *preferred* ESCO label (e.g. "DevSecOps Engineer" → "Information technology security specialist"). A normalization step snaps each GPT title to an official ESCO title using semantic similarity: both the GPT titles and every ESCO label (preferred and alternative) are embedded with **JobBERT-v2**, an LLM fine-tuned for job-title representation; the ESCO title with the highest cosine similarity is kept, and matches below a **0.7** similarity threshold are discarded as noise. This yields the `esco_title` and its occupation `code`, and permits analysis at different aggregation levels (e.g. 4-digit vs 3-digit ISCO). JobBERT can be swapped for OpenAI `text-embedding-3-large` embeddings if preferred.

Listing 4: Title normalization via JobBERT cosine similarity.

```
model = SentenceTransformer('jensjorisdecorte/JobBERT-v2')
```

```
esco_embeddings     = model.encode(esco_titles, batch_size=1000)
vacancy_embeddings = model.encode(gpt_titles,  batch_size=1000)
cosine_scores       = util.cos_sim(vacancy_embeddings, esco_embeddings)
max_sim, max_idx    = torch.max(cosine_scores, dim=1)
# keep best; drop < 0.70
```

F.4 Stage 3 — location standardization

Raw location strings are mapped to clean Ukrainian regions through a lookup dictionary, producing the Cyrillic `loc` and English `loc_en`. Only locations in Ukraine are retained, *except* Crimea and Sevastopol.

F.5 Stage 4 — salary coding, cleaning and deduplication

Currency and rate strings are mapped to the numeric codes stored (with value labels) in the `.dta`: currency `1=EUR, 2=RUB, 3=UAH, 4=USD` and rate `1=day, 2=hour, 3=month, 4=week, 5=year`. The cleaning rules are then applied:

1. for each *id–region–date*, keep the minimum posted `min_salary`;
2. deduplicate by *id–region–date–min_ salary–curr_ id–sal_ rate*;
3. where several records remain for an *id–region–date–min_ salary* group, keep the UAH-denominated one.

F.6 Variables

Below we provide variable definitions and descriptive statistics.

Table F1: Jooble vacancy data: variable description

Variable	Type	Description
`id`	string	Vacancy identifier (2,475,315 unique values; the same id can recur across regions and dates).
`min_salary`	numeric	Minimum posted wage, in the posting's original currency.
`curr_id`	numeric	Currency code (labelled): `1` = EUR, `2` = RUB, `3` = UAH (dominant), `4` = USD.
`sal_rate`	numeric	Pay-period code (labelled): `1` = day, `2` = hour, `3` = month, `4` = week, `5` = year.
`date_created`	date	Date the vacancy was posted (Stata `%td`).
`loc`	string	Region name (Cyrillic).
`loc_en`	string	Region name (English).
`esco_title`	string	ESCO occupation title returned by the matching step (14,590 distinct strings). Not a clean preferred-label field: most occupation codes map to several title variants, so `code` rather than `esco_title` is the occupation identifier used throughout the analysis.
`cleaned_title`	string	Cleaned job title (5,545 unique).
`code`	string	ESCO / ISCO occupation code (2,016 unique).

Table F2: Jooble vacancy postings by year

Year	Observations
2021	2,259,574
2022	713,198
2023	73,120
2024	33,804
Total	3,079,696

Notes: All Jooble vacancy postings for Ukraine, January 2021–December 2024.

F.7 Wages and currency

Table F3: Median posted wage by original currency of the posting

Original currency	Median, nominal USD	Median, constant 2021 USD	Obs.
USD	1,500	1,486	61,295
EUR	2,032	1,980	6,613
UAH	306	303	967,387

Notes: Data include Jooble vacancy postings for Ukraine with a monthly pay period, a posted wage in EUR, UAH or USD, and an ESCO occupation code. Sample coverage is from January 2021 to December 2024. Wages are converted to UAH at the posting-month official NBU rate (EUR at the annual average ECB rate), deflated by the Ukrainian CPI (2021 = 100) and expressed in constant 2021 USD.

F.8 Geography and occupations

Postings are concentrated in major cities, dominated by Kyiv City (1,064,058 observations), followed by Kharkiv (303,455), Dnipropetrovsk (205,860), Lviv (205,790) and Odesa (177,502). Among standardized occupations, software roles dominate (software developer 273,894; software engineer 76,871; web developer 55,863; software tester 45,534), alongside common manual and service roles (cleaner, security guard, sales representative); 379,363 rows have a blank `esco_title`.

Table F4: Vacancy postings: descriptive statistics by occupation group

			Median wage			SD of log wage	
ISCO-08 major group	N	Share (%)	Pre	Post	Δ (%)	Pre	Post
Technicians and associate professionals	170,062	16.4	293	254	-13.2	0.50	0.51
Service and sales workers	163,020	15.7	297	240	-19.1	0.46	0.83
Craft and related trades workers	160,984	15.5	365	269	-26.3	0.47	0.37
Professionals	158,418	15.3	438	528	20.4	0.96	0.99
Plant and machine operators	132,315	12.8	366	255	-30.3	0.56	0.46
Elementary occupations	109,518	10.6	279	207	-25.8	0.47	0.35
Managers	76,688	7.4	424	359	-15.4	0.66	0.89
Clerical support workers	34,206	3.3	341	207	-39.3	0.60	0.85
Unclassified	21,315	2.1	244	207	-15.2	0.52	0.45
Skilled agricultural workers	8,769	0.8	227	207	-8.6	0.30	0.26
All postings	1,035,295	100.0	336	248	-26.2	0.64	0.73

Notes: Data include Jooble vacancy postings for Ukraine with a monthly pay period, a posted wage in EUR, UAH or USD, and an ESCO occupation code. Sample coverage is from January 2021 to December 2024. Wages are converted to UAH at the posting-month official NBU rate (EUR at the annual average ECB rate), deflated by the Ukrainian CPI (2021 = 100) and expressed in constant 2021 USD. “Pre” and “Post” split the sample at February 24, 2022.