The Allocative Cost of War: A View to a Kill. . .ing of Productivity*

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November 02, 2026

Abstract

Why is war so economically costly? Our answer is that modern war lowers output not only by destroying productive factors, but also by making the surviving economy work less efficiently. Using uniquely comprehensive firm-level data collected during Russia's full-scale invasion of Ukraine in 2022, we document a dramatic collapse in the country's allocative productivity. To sharpen identification and explore key mechanisms (including the role of war intensity, internal displacement, reallocation, and macroeconomic instability), we exploit spatial heterogeneity across Ukrainian districts and comparisons with Russian aggression in 2014 and the 2008 Global Financial Crisis. Our key policy implication is that restoring allocative efficiency, and preparing institutional arrangements that facilitate rapid reallocation in times of stress, is critical for sustaining economic capacity, defense, and national security.

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

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

*We thank the LMU-ifo Economics & Business Data Centre (https://www.ifo.de/EBDC) 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 A portion of this paper was submitted as an unpublished graduate thesis by Amann at the ifo Institute, supervised by Tuuli Tähtinen.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 Centre for financial support.

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, inter-state armed conflict was seen 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 weight firms). In contrast, Ukraine's peer economies experienced no comparable decline over the same period, indicating that the shock is specific to Ukraine rather than a common regional trend; the raion-level gradient below ties it to the war itself. Using geocoded firm-level data and the war's spatial heterogeneity, we show that a one-standard-deviation increase in war intensity in a district (raion) is associated with a 12 percentage-point larger TFP decline. War intensity alone accounts for over 55 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 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, likely by 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, which suggests that allocative efficiency may be able to recover once hostilities cease. Finally, adaptation is already underway: by 2024, the economy operating under its actual composition was approximately 10 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 magni-

tude 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 a quarter. 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 direct 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 Rapid Damage and Needs Assessments (e.g., World Bank 2026*a*) 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 percent 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., Shpak

[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.

et al. 2023) to land contamination with mines (e.g., Deininger et al. 2026). In a closely related paper, Onyshchenko, Tsapin and Yaremko (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 percent, the currency depreciated by 70 percent, and half of the banks failed. The direct economic cost of the Donbas occupation alone was estimated at $21.7 billion (Havlik, Kochnev and Pindyuk 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, 2023*b*), and roughly 8 million became refugees abroad (UNHCR, 2022). As of October 2026, obituary-confirmed records identify 276,113 Russian soldiers killed (Mediazona and BBC News Russian, 2026); Kyiv has officially acknowledged 55,000 Ukrainian soldiers killed (Al Jazeera, 2026); and OHCHR (2026) has verified 17,257 Ukrainian civilian deaths, a documented total of more than 300,000 dead.[2] World Bank (2026*a*) estimates direct, war-related damages at approximately $195 billion through December 2025.

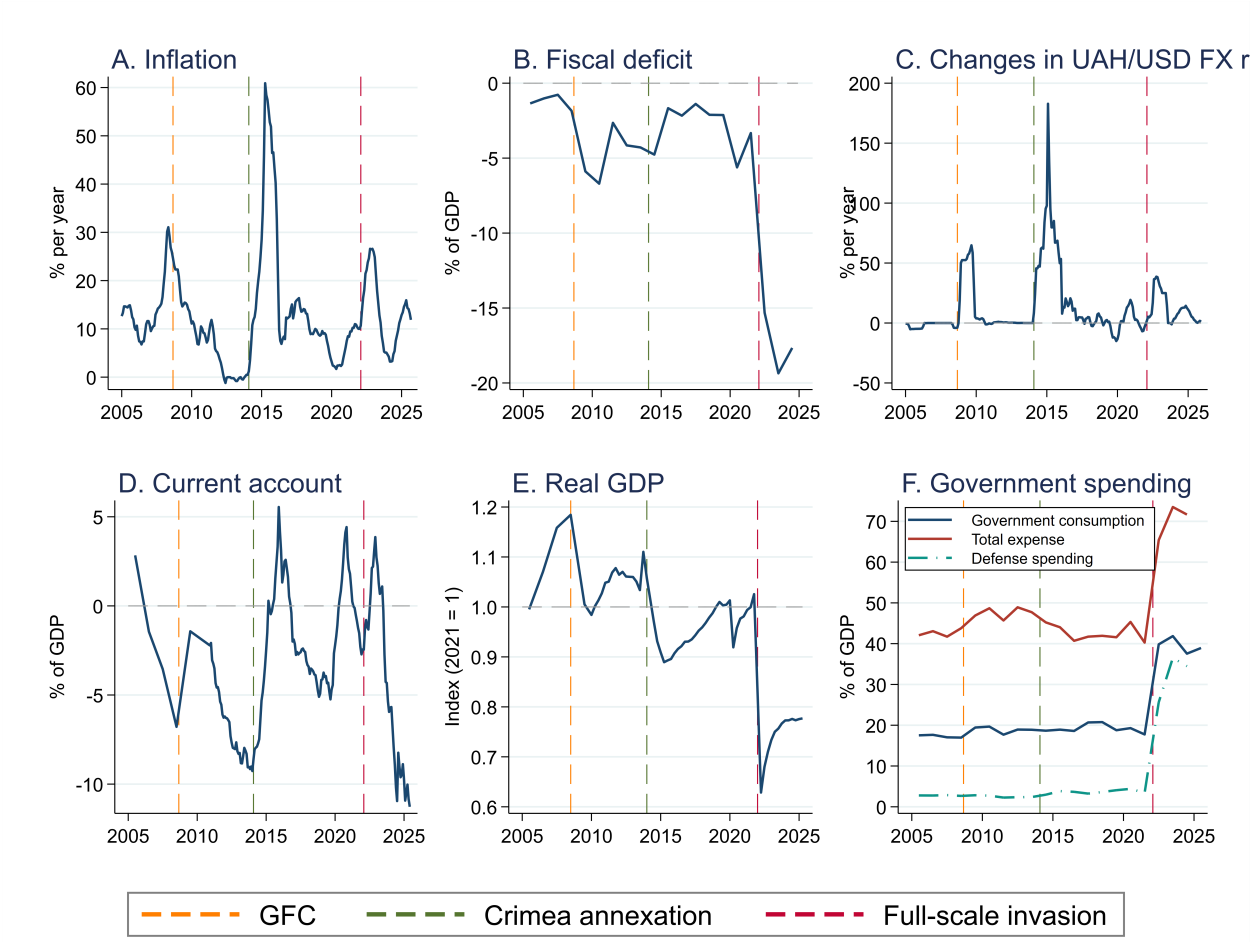
Ukraine's economy contracted sharply following Russia's full-scale invasion: real GDP fell by 28.8 percent in 2022 (Figure 1). Ukraine's government consumption as a share of GDP soared to 41.9 percent amid enormous defense spending, while consumer price inflation peaked at 26.6 percent year-on-year in 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 $436 billion in combined financial, humanitarian, and military aid as of August 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. Even the

[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, 2005–2025.



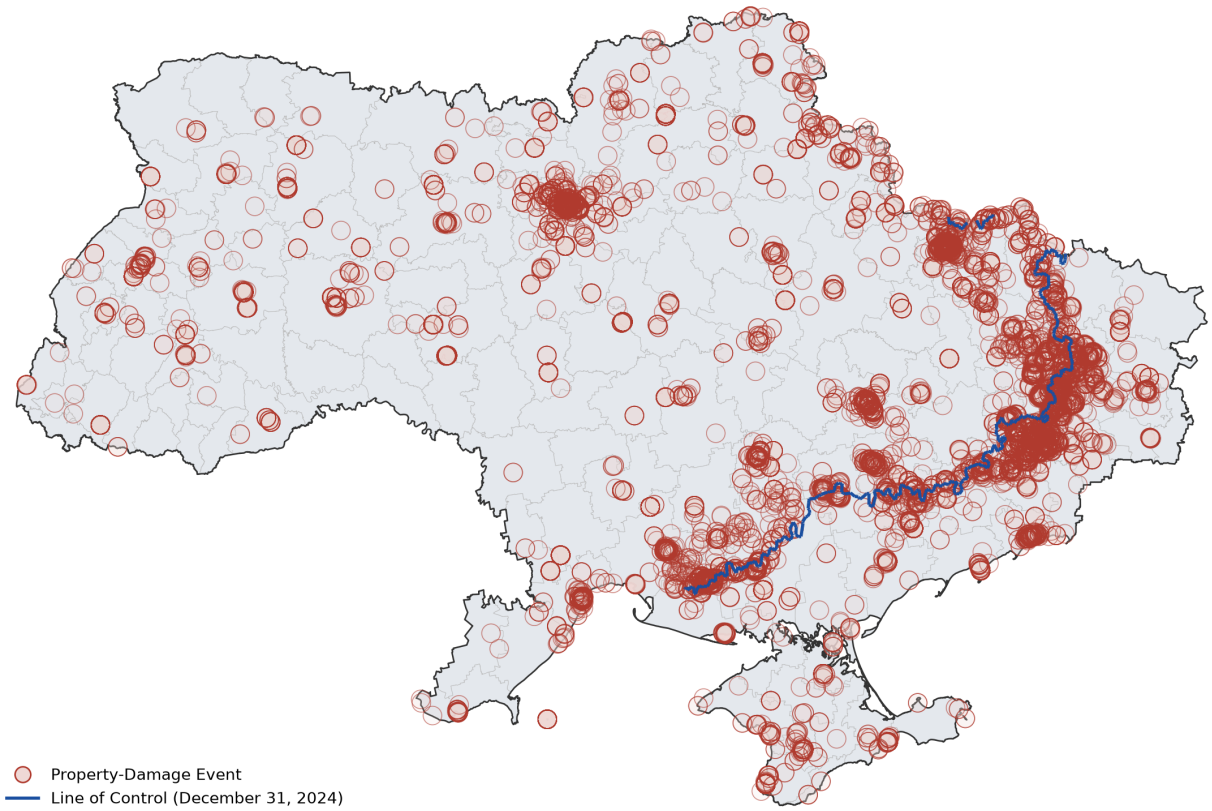
Notes: A: CPI inflation, monthly YoY (State Statistics Service of Ukraine, 2026*a*). B: fiscal balance (% GDP), annual, Ukrstat General Government Operations (State Statistics Service of Ukraine, 2026*b*). C: NBU USD exchange rate change, monthly YoY (National Bank of Ukraine, 2026*b*). D: current account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

safer regions, however, suffered severe indirect effects through supply-chain disruptions, internal displacement, and attacks on energy infrastructure. 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 (2026*a*) 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 percent of thermal generation capacity and created an electricity supply shortfall of about 5 percent (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-sectional dispersion of marginal revenue products should be zero. In practice, one should not expect perfect equalization because of, e.g., adjustment costs, measurement error, 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,

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



Notes: Data from Zhukov (2023).

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 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:

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

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

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):

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

[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.

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

Note that the measure is ex post: it records where inputs ended up over the fiscal year, not where they were placed at its start. Shocks common to an industry do not register, since no reallocation of inputs across firms could have avoided them; firm-specific distortionary forces, such as market power, regulation, trade frictions, etc., do.

War adds a large layer of such shocks that hit firms in the same industry differently: blackouts depend on a firm's position in the grid, strikes hit particular plants and transport routes, air-raid alerts interrupt production, and displacement changes the availability of workers, customers, and suppliers. The resulting misallocation is a real output loss that a peacetime economy does not incur. One can therefore 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 effectively captures 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 the two utility sectors and the public administration and defence sector, because of their heavy government ownership and regulation. For Ukraine specifically, we additionally exclude firms in unassignable raions and in raions more than 70 percent Russian-occupied as of 31 December 2024, 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. How-

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

ever, because entry and exit immediately outside the window are unobserved, a balanced panel can still leave mechanically inflated dispersion in its first and last years; 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 98.8 percent 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.[6] These filters are demanding in terms of individual firm-year observations: our final main 2018–2024 sample for Ukraine retains only 24.3 percent 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 56.6 percent 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

[6] We use 2020 rather than our 2021 base year for this comparison because the filing deadline for 2021 annual reports that Orbis data is based on was after Russia's full-scale invasion began(Verkhovna Rada of Ukraine, 2010). We therefore already see a large filing drop from war-affected areas in 2021 (see Figure 3). Recorded employment in Orbis still covers 91.8 percent in 2021 of the 6,409,664 national employees of business entities in that year(State Statistics Service of Ukraine, 2025).

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 (State Statistics Service of Ukraine, 2022): $\text{WarIntensity}_{r,t} = \ln\left(\frac{\text{PropertyDamage}_{r,t}}{\text{Population}_r/100{,}000} + 1\right)$. This fixed normalization prevents the measure from mechanically increasing in areas that experienced wartime population losses. Appendix Table B4 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, Beblavy and Thum-Thysen 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 such as 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, Boeri and Zholud (2026), Faryna et al. (2022) and Pham, Talavera and Wu (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-represent 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 (2026*e*) for Ukraine, OECD (2025*b*) for Poland, and Eurostat (2026) for Romania, Bulgaria, Croatia, Estonia, Hungary, Latvia, and Lithuania.

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 B5 (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, 2026*a*). 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, 2026*e*), workers in business-entities register (State Statistics Service of Ukraine, 2025), and Input-Output table (State Statistics Service of Ukraine, 2026*c*), with the latter also providing the sector-specific government-consumption share. We also use inflows of internally displaced persons (International Organization for Migration, 2023*b*) and a region boundary shapefile for firm-to-region geomatching and distance-to-Russia calculations (OCHA Ukraine, 2025).

5 The war effects

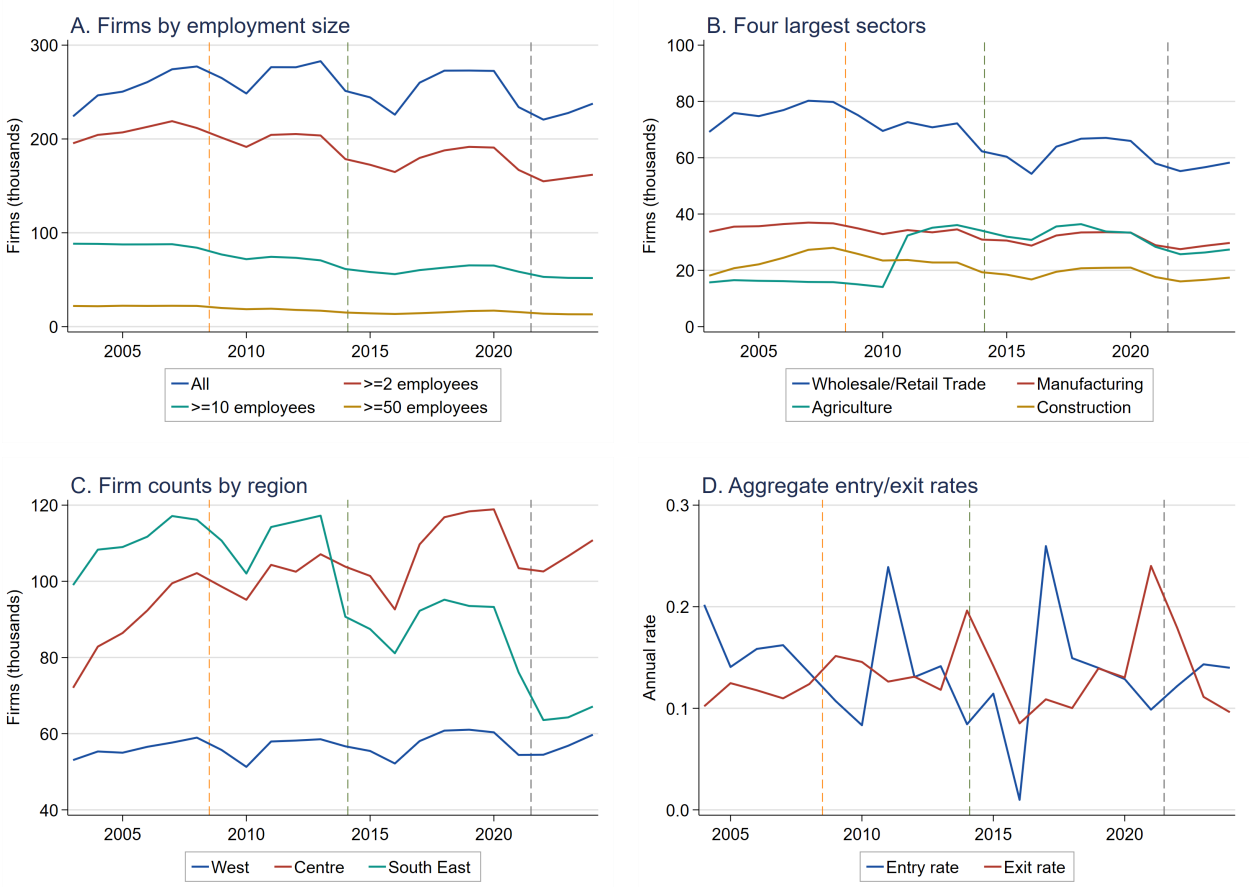
This section establishes the main national facts. We first document wartime firm destruction, then show that dispersion in marginal revenue products rose sharply among surviving firms, corroborate the labor-market component using vacancy data, and finally translate these changes into allocative TFP losses.

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.[7]

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.

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 20 percent nationally over three years, and by roughly 30 percent in the South East.

[7]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.

After stabilizing and gradually recovering around 2017, the firm count fell sharply again after the full-scale invasion: approximately 19 percent of firms disappeared between 2020 and 2022. The comparison starts in 2020 because the filing deadline for 2021 accounts fell after February 2022 (Verkhovna Rada of Ukraine, 2010), so firms in occupied and front-line areas are already absent from the 2021 count. These patterns are broadly similar by firm size (Panel A) and sector (Panel B).[8]

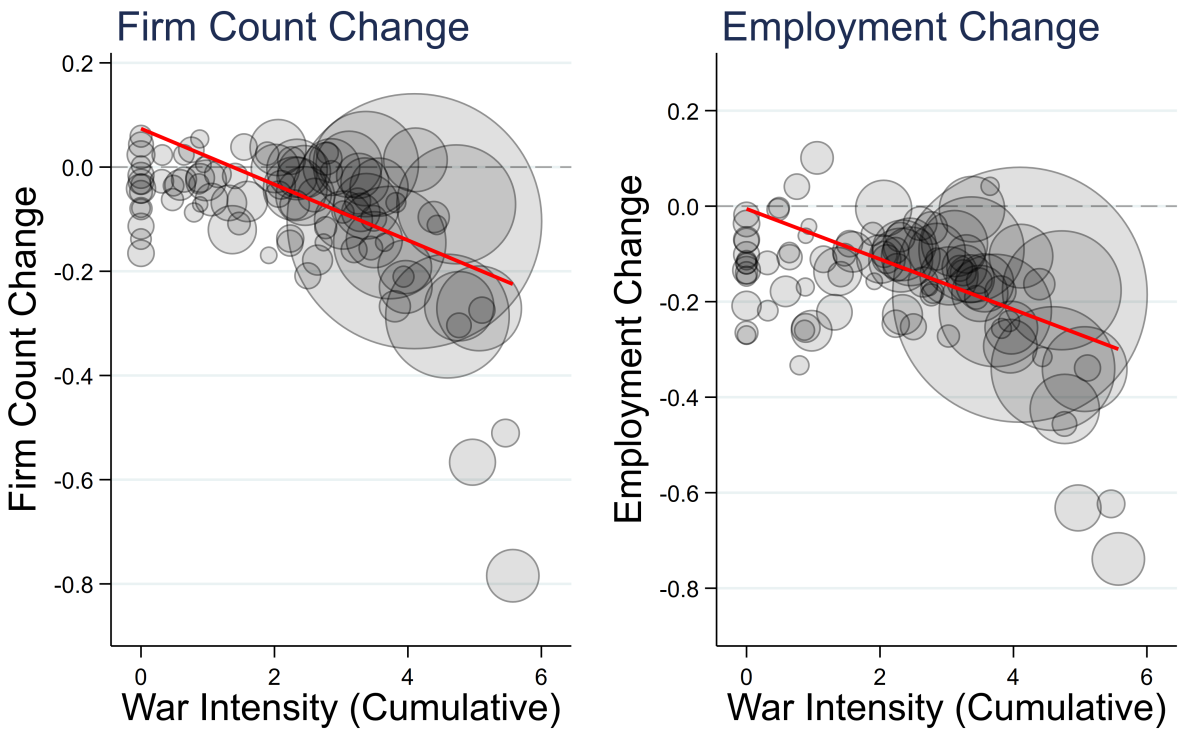
At the same time, there is a clear geographic heterogeneity (Panel C). The South East macro-region, which is closest to the front lines and most exposed to Russian attacks, lost nearly half its firms between 2014 and 2024 (with much of this loss occurring in two discrete drops: 2014–2015 and 2022–2023). The Centre 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 the front-line raions with the highest war intensity, all of them partially occupied, lost far more: Kherson lost 78 percent of its firms, Kramatorsk 57 percent and Pokrovsk 51 percent, with 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 2021, reaching approximately 20 percent and 24 percent respectively. The 2021 spike dates the full-scale invasion rather than 2021 itself, because a firm's exit is recorded in the last year it files. Thus, the war induced massive firm destruction that is *not* captured by misallocation. By 2023–2024, as the acute phase of territorial shifts subsided, exit rates fell back to their pre-war range and entry rates recovered to the pre-war level.

What kind of firms exit? If the weakest do not survive, the observed population can have

[8]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 2021 firm count. Only raions still under Ukrainian control as of 2024 with at least 100 firms in the 2020–2024 balanced panel (95 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.

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 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.

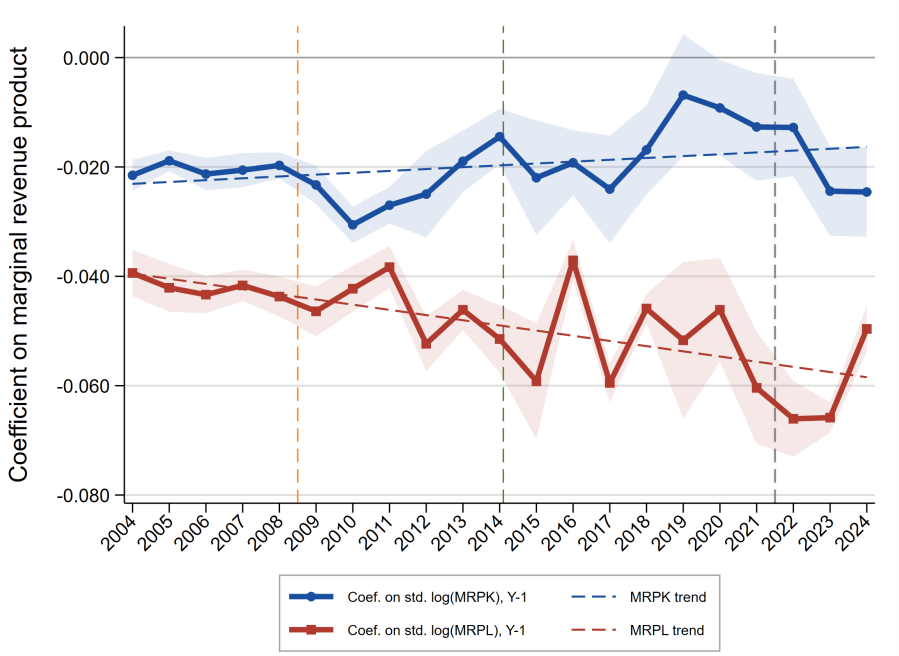
In summary, the war destroyed a large share of Ukrainian firms cumulatively, with losses concentrated in high-intensity regions. Pre-war marginal revenue products do not predict wartime exit unusually strongly predict wartime exit, suggesting that the balanced panel used for our main analysis is not 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–

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 (196 cells, imported from the balanced panel rather than re-derived on this sample) 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.

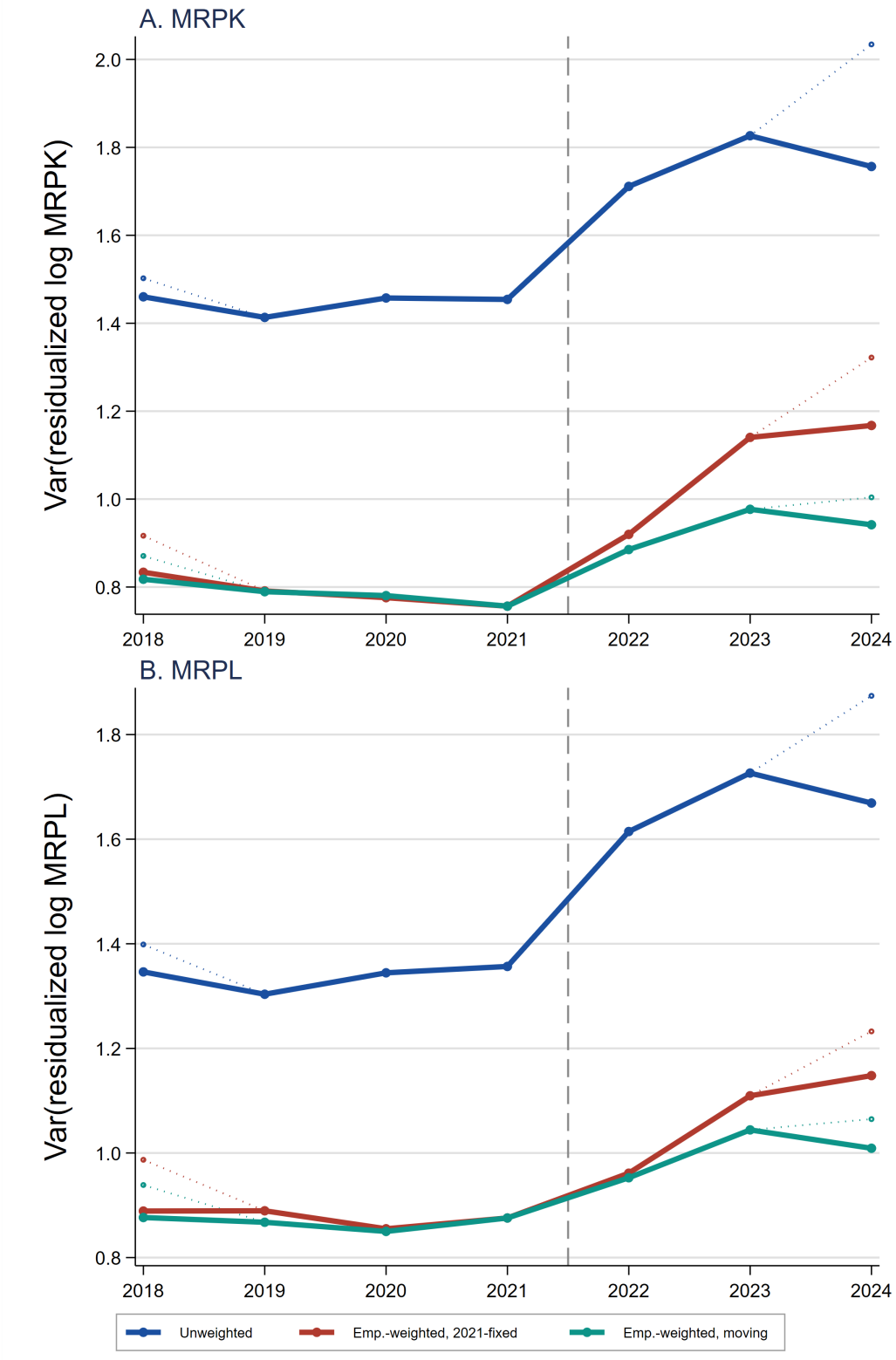
2024.[9] Our baseline measure uses the balanced sample and residualized marginal revenue products, where we remove industry-cell×year fixed effects so that the reported dispersion captures within-industry variation. The increase in dispersion is driven by dispersion within industry cells, as the dispersion between industry cells, which the residualization removes, remains roughly flat (Appendix Figure C2). The war thus widened the gaps between firms in the same industry rather than the gaps between industries: the loss is an inefficiency in how inputs are allocated among competing firms, not a shift in relative returns across sectors. 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 are lower in level for both MRPK and MRPL, but the qualitative pattern is 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-sectional 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 C3) suggests that the war-time distribution is visibly wider and has fatter 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. Splitting each variance into its revenue, input (capital or labor) and covariance terms shows that the increase comes primarily from a wider spread of revenue (Appendix Figure C4). Firms also

[9] 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: 90,984 firms, 196 industry cells, balanced 2018–2024 panel.

changed places more often in 2022: the average year-on-year move in a firm's percentile rank within its industry cell rose from about 11 to 14 points for MRPK and from 10 to 13 for MRPL, and returned to pre-war levels by 2024 (Appendix Figure C5). The reshuffling was a one-off, while the wider dispersion persisted.

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 C7). 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 C8). Third, the pattern holds whether we use total assets or fixed assets as the capital measure (Appendix Figure C9), 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 C10). Fifth, dispersion is higher in level among small firms, but the sharp increase after 2022 is uniform across firm-size quartiles (Appendix Figure C11). 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 Centre, with the West showing the smallest (though still substantial) increase (Appendix Figure C12). This geographic gradient indicates that the increase in dispersion is linked to the conflict rather than reflecting some nationwide institutional or policy change.

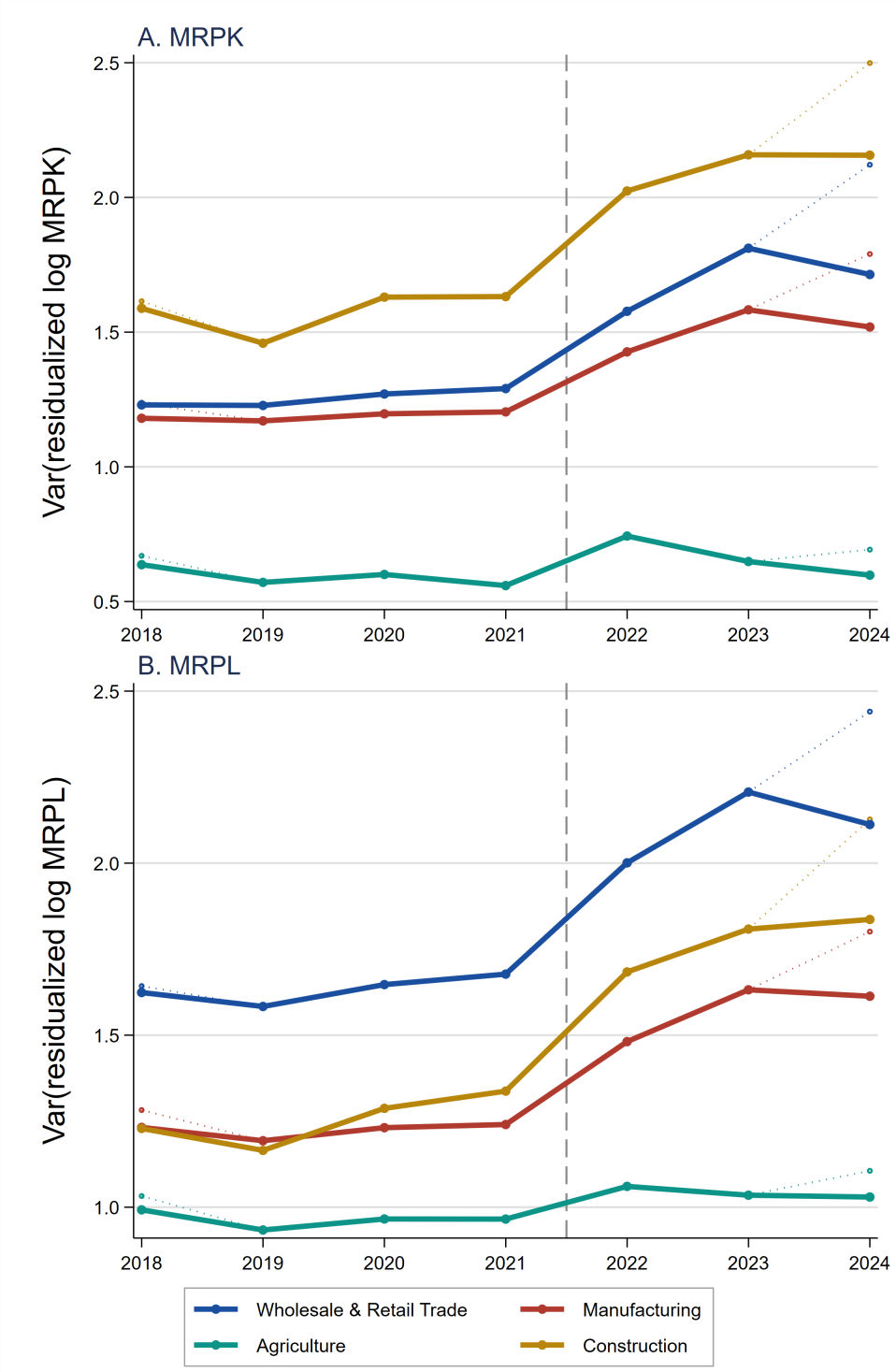
Importantly, our results are unlikely to be driven by deteriorating data quality in wartime. Using the approach in Gorodnichenko et al. (2026), we implement a time-averaging exercise designed to attenuate measurement error. Specifically, we compute each firm's average MRPK and MRPL over the pre-war years 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 C13) that the time-averaged variances for MRPK and MRPL rise by approximately 26 percent, which is similar to single-year estimates.

Figure 7 plots the dispersion time series for four major 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 (2025*a*)) 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 find that sectors exhibiting larger increases in dispersion also tend to be those that suffered larger contractions in output (Appendix Figure D1).

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), Estonia (EE), Hungary (HU), Latvia (LV), and Lithuania (LT)), 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 C14). Hence, the increase in dispersion observed in Ukraine is specific to Ukraine rather than a regional phenomenon.

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



Notes: 1% winsorized, edge-corrected dispersion measures for four major sectors. Each sector uses its own industry_cell hierarchy. Sample composition: Table B1.

5.3 Job vacancy data

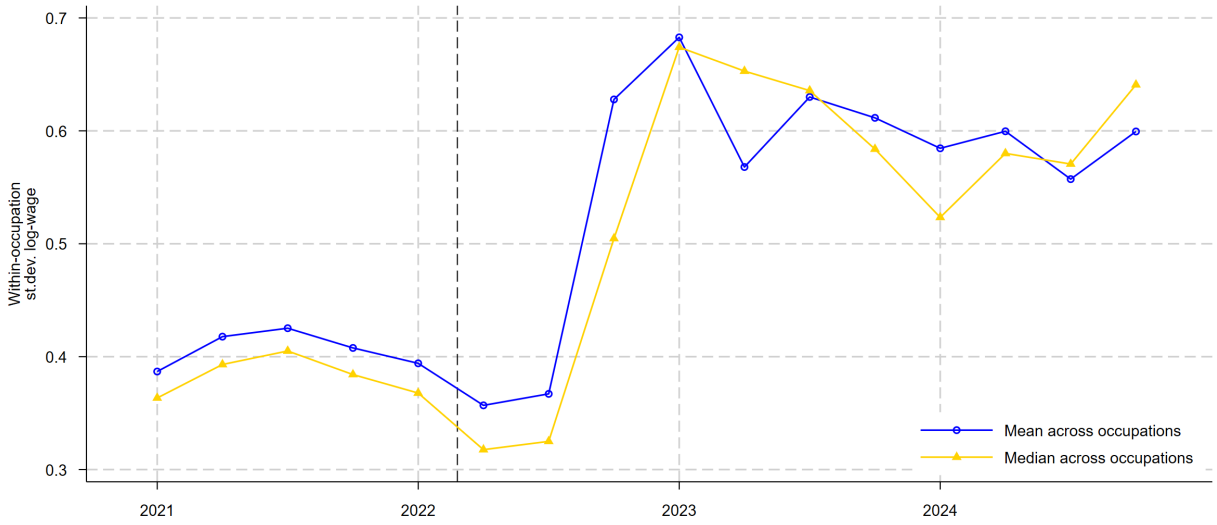
To validate our firm-level findings with an independent data source, we turn to the online job vacancy postings described in Section 4.3. Under competitive labor markets, posted wages should be equal to the marginal revenue product of labor, that is, $W = MRPL$. In practice, various wedges (non-wage 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, mobiliza-

tion 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 percent 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 three variants: unweighted, weighted by fixed 2021 employment, and weighted by contemporaneous ("moving") employment. We normalize TFP to unity in 2021 (the last pre-war year) so that all subsequent values can be read directly as a fraction of the economy's 2021 allocative efficiency.

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, though of markedly different magnitude.

The unweighted estimate treats every firm equally regardless of size; it shows the largest loss, with TFP falling to $\approx$0.64 in 2022, reaching a trough of $\approx$0.54 in 2023 and recovering only to $\approx$0.59 by 2024, a 41 percent loss. Weighting firms by their 2021, pre-war size instead

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



Notes: 1% winsorized and edge-corrected. Poland reported from 2020, Lithuania from 2021, as earlier years lack sufficient data (shortened windows). *Benchmark* = firm-count-weighted average of the benchmark countries present in each year. Donor weights and sample composition: Appendix, Table B5.

asks how much this misallocation cost the economy as it actually looked before the war, giving a smaller loss (≈0.68, 32 percent, in 2024).

The moving-weight variant, which allows the composition to shift with wartime employment changes, gives the smallest loss of the three, 21 percent in 2023 and 22 percent by 2024. The war thus destroyed between one-fifth and two-fifths of allocative efficiency, depending on weighting; none of the benchmark countries experienced anything comparable.[10]

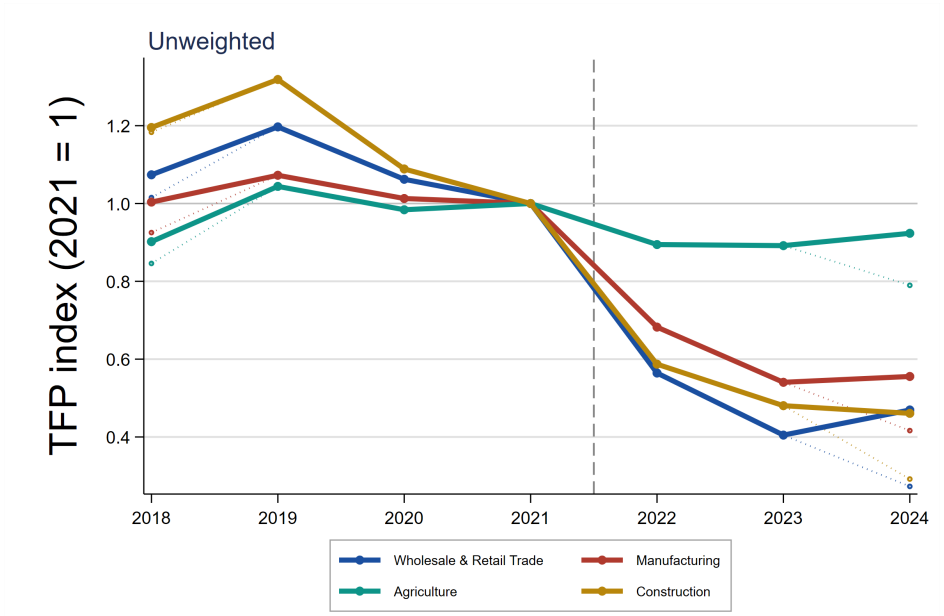
The magnitude of the estimated TFP decline depends on assumptions. For example, higher values of σ amplify the TFP consequences of any given dispersion. We find (Panel A of Appendix Figure D3) that the estimated 2024 loss (equal weights) ranges from $\approx$ 23 percent ($\sigma = 1.5$) to $\approx$ 58 percent ($\sigma = 5$). Moving to 5-percent winsorization reduces the estimated loss (equal weights) modestly (to approximately 30 percent in 2024; see Panel B of Appendix Figure D3), while removing winsorization entirely increases it (to $\approx$ 43 percent). When we instead assume no distortion in the capital market ($\tau_K = 1$), the TFP losses are somewhat larger in magnitude (because var(log MRPK) receives a larger weight under the $\tau_K = 1$ assumption) but qualitatively identical in their time-series pattern (Appendix Figure D4). Dropping the balanced-panel requirement and instead using a moving window of firms shows a very similar TFP drop in 2022, but a slightly faster recovery, showcasing the positive allocative effect of newly entered firms (Appendix Figure D5).

All quartiles by firm size experience substantial TFP declines after the invasion, but the magnitude differs by quartile (Appendix Figure D6). 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-

[10] Appendix Figure D2 plots the longer time series based on the 2006–2024 panel.

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: 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.

Figure 10 reports the unweighted TFP index for the same four sectors. Wholesale and retail trade and construction experienced the most severe TFP declines, with the index falling to ≈0.47 and ≈0.46 respectively by 2024 (losses of ≈53 and ≈54 percent relative to 2021). Manufacturing also shows a large TFP decline (≈45 percent loss) and little recovery after the initial shock. Agriculture shows the most moderate TFP decline (≈8 percent) and exhibits some recovery by 2024. These TFP declines track contraction of real value added (VA) per worker (as shown in Appendix Table B6): VA net of government consumption per worker fell ≈39 percent in construction, ≈15 percent in manufacturing, ≈14 percent in wholesale and retail trade, and ≈8 percent 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 is close to construction's, 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.[11] 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 D7).[12] 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 percent, a large loss given how important the sector is for Ukraine's export earnings and food security.[13]

The geographic gradient in TFP decline is pronounced (Appendix Figure D8). The South East experienced the most severe TFP decline, with the index (equal weights) falling to approximately 0.47 by 2024. The Centre (including Kyiv) had a significantly smaller decline to approximately 0.62. The West shows the smallest decline to 0.68, though even

[11] 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.

[12] 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.

[13] Appendix Figure D1 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.

here TFP fell substantially relative to pre-war levels. The gradient also holds within sectors (Appendix Figure D9): by 2024 the South East has the lowest index in retail, manufacturing and construction (≈0.29, 0.37 and 0.39), while agriculture falls least in every region, and barely at all in the West (≈0.96).

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, Inklaar and Timmer 2015) pre-war data for Ukraine, we set $\alpha = 0.446$.[14] As described in Section 2, total GDP contracted by $\Delta \log(Y) = \log(1 - 0.288) \approx$-0.34 in 2022.[15]

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 percent (2.4 million jobs) in 2022, relative to a pre-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).[16] This decline reflects both externally displaced refugees and internally displaced

[14] To be clear, $\alpha = 0.446$ here is a value-added capital share, appropriate for the standard growth-accounting identity, whereas the $\alpha = s_K = 0.226$ used in equation (3) is a gross-output share.

[15] Total GDP includes government consumption, which rose sharply in 2022 due to wartime military spending. GDP net of government consumption fell by almost 50 percent 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.

[16] We use a business register-based source in the next section for per-sector changes in workers. It counts

persons withdrawing from the labor force (UNHCR, 2022). Applying the labor share yields $(1-\alpha)\cdot\Delta\log(L) \approx 0.554\times\log(1-0.155)$ ≈-0.09. That is, roughly 9 log points of lost output can be attributed to the reduction in labor input.

World Bank (2026*a*) 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 percent of the pre-war capital stock in 2022. Applying the capital share yields $\alpha\cdot\Delta\log(K) \approx 0.446\times\log(1-0.16)$ ≈-0.08.

These estimates imply that "TFP" accounted for $34-9-8 \approx 17$ log points. Our estimate of the TFP decline due to misallocation, with $\sigma = 3$ and $\tau_L = 1$ (Figure 9), is a moving-weight TFP loss of 9 percentage points in 2022, which grew to 21 percentage points in 2023. Thus, misallocation induced by war-related factors can largely rationalize the observed decline in productivity.

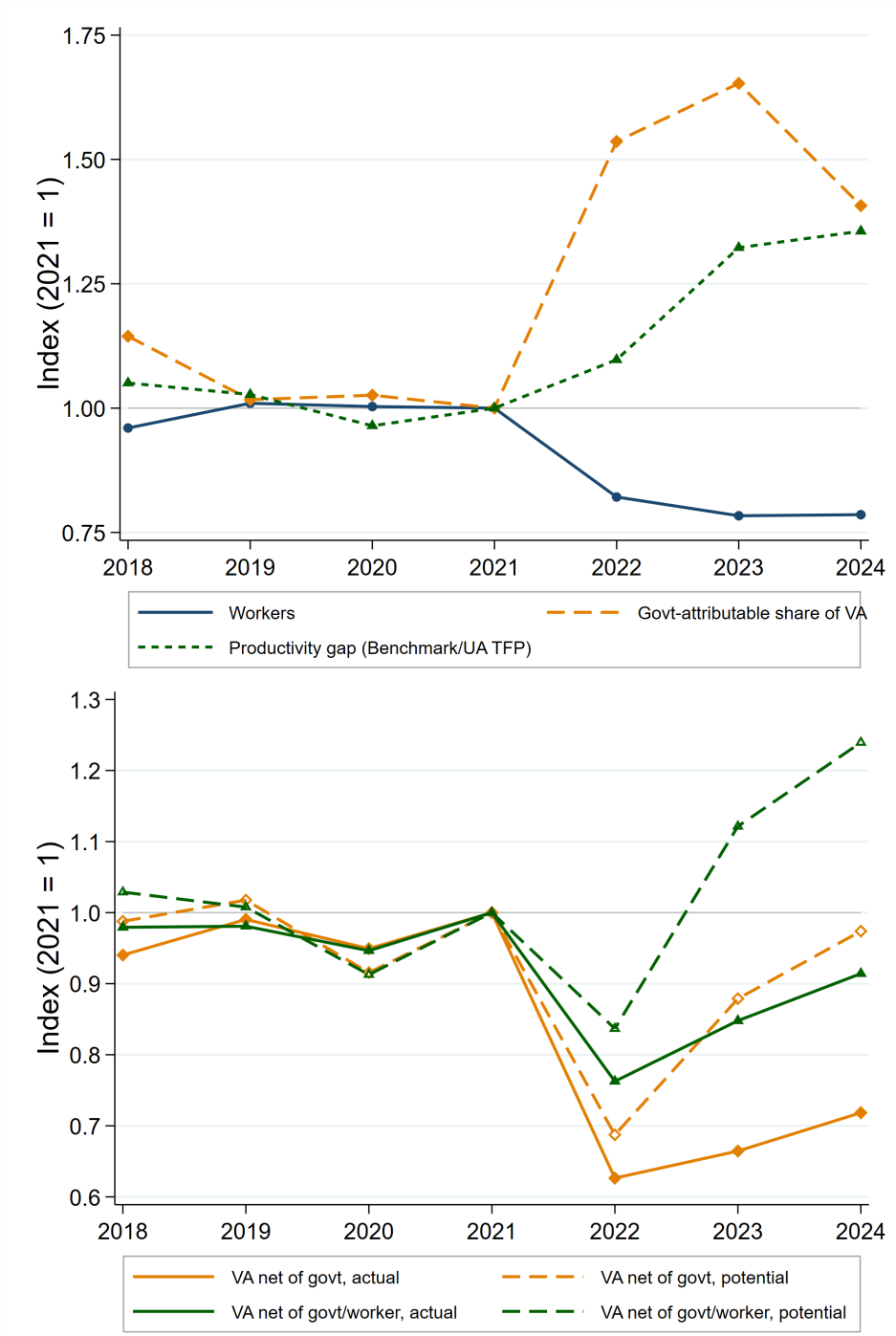
This decomposition, while imprecise, underscores that the allocative channel is quantitatively comparable to direct destruction. It also has profound policy implications: physical capital must be rebuilt (requiring time and investment), whereas allocative efficiency can, in principle, be restored by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

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.

employees of business entities excluding sole proprietors and so does not capture the wartime increase in government employment. It records employment falling from 6.4 million in 2021 to 5.4 million in 2022 (−15.1 percent), close to the ILO estimate for that year, and to 5.0 million by 2024 (−21.3 percent) (State Statistics Service of Ukraine, 2025).

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, 2026*c*); value added (VA) (State Statistics Service of Ukraine, 2026*e*). The TFP ratio is moving-weighted and edge-corrected.

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, 2026*e*,*c*) rose from ≈12 percent in 2021 to 17–20 percent 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 ≈22 pp from 2021, while the benchmark countries' TFP had risen ≈6 pp, consistent with continued post-COVID recovery; the resulting gap, the ratio of the two levels, left the benchmark countries' TFP about 36 percent 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 ≈0.97; per worker, actual was ≈0.91 against a potential of ≈1.24. Cumulated over 2022–2024, the productivity shortfall alone cost close to $71 billion in private-sector value added net of government consumption (constant 2021 prices), about 53 percent of these sectors' entire 2021 net output (≈$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 ≈1.17 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 95 raions, out of 139 Ukrainian raions[17], after excluding 32 raions under Russian occupation as of 2024 and 12 raions with fewer than 100 firm observations in our balanced 2020–2024 panel (Appendix Table B7). The 100-firm floor is the one we impose on industry cells, and it is cheap: the raions it drops hold 0.6 percent of the firms and 0.6 percent of the employment in the sample. Appendix Table E1 re-estimates column (1) of Table 1 at floors from 20 to 200 firms, and the coefficient on war intensity stays between -11.6 and -12.1. All other filters are identical to the national sample (Appendix Table B3). Because this panel is balanced, firms that disappeared during the war are absent from it by construction, so the gradient we estimate is a within-survivor effect.

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 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

[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)

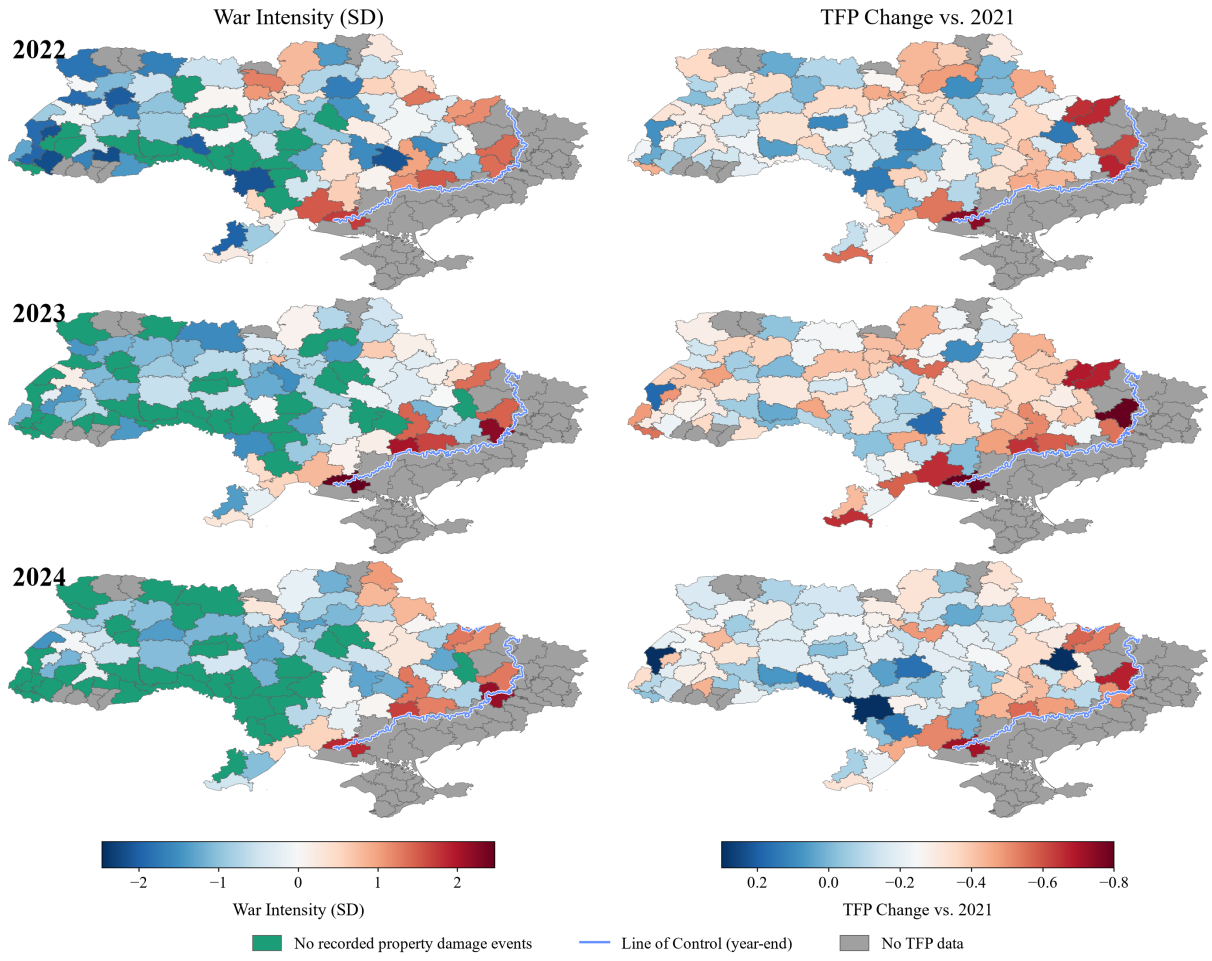
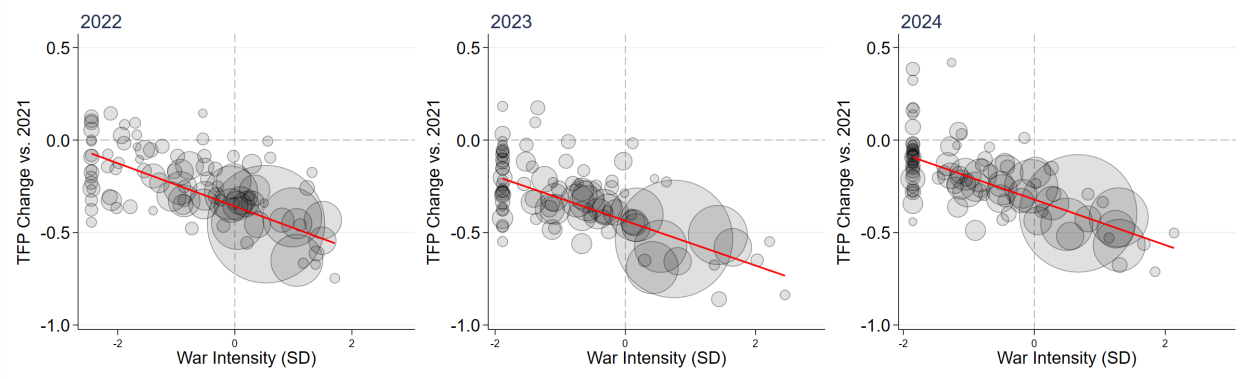


Figure 13: Raion TFP change vs. war intensity score



Notes: Equal-weighted, 1% winsorized. Each bubble is a raion, sized by its firm count; fit lines are firm-count weighted. War intensity is that year's own property-damage events per 100,000 pre-war population, logged and standardized within each year. Balanced 2020–2024 panel, 95 raions, minimum 100 firms per raion. No raion is corrected on its own dispersion; the final year carries the national edge correction of the same balanced panel, applied as one common level shift to every raion. Regression estimates in Table 1, Colum 1.

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 a 12 percentage-point larger TFP decline. The within R^2 of 0.592 indicates that war intensity on its own accounts for roughly 59 percent of the cross-raion variation in productivity losses.

[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 E2). 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.

Column (2) demonstrates that the result is robust to using 2021-fixed firm-weighted TFP rather than the equal-weighted version. [19]

Second, distance-based proxies are informative but add little predictive power once actual attack data are included. Columns (3) and (4) examine distance to the Russian border and distance 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 a third 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 ($R^2 = 0.063$). 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, Rowe and Pietrostefani 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

[19] This relationship is specific to the 2022 invasion. Appendix Figures E3 and E4 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.

[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.

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								
Percentage-point change in raion TFP per 1 SD increase in the regressor										
War Intensity	-12.0^{***}	-8.5^{***}					-11.8^{***}	-11.8^{***}	-12.2^{***}	-11.2^{***}
	(1.12)	(3.11)					(1.19)	(1.04)	(1.13)	(1.11)
Russia Border			6.0^{***}				0.4			
			(2.30)				(1.66)			
Line of Control				5.7^{***}				0.5		
				(1.75)				(1.42)		
IDP Inflow					-1.0				1.6^{*}	
					(1.70)				(0.89)	
Liberation Share						-6.7^{***}				-1.8
						(1.78)				(1.14)
R^2	0.628	0.118	0.224	0.210	0.063	0.258	0.628	0.629	0.602	0.637
Within R^2	0.592	0.086	0.150	0.135	0.004	0.187	0.593	0.593	0.577	0.603
Mean of dep. var. (pp)	-24.9	-7.3	-24.9	-24.9	-27.0	-24.9	-24.9	-24.9	-27.0	-24.9
Raion-years	285	285	285	285	189	285	285	285	189	285

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Year FE included; SEs clustered by raion. Raions weighted by firm count. Dep. var.: raion-level TFP relative to 2021, in pp. Every column uses the same sample, 107,316 firms in 95 raions; column (2) weights by 2021 employment, 4,204,972 in total. Firms per raion range from 114 for Nadvirna Raion to 27,692 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) December survey round each year(International Organization for Migration, 2023*b*); IDP Inflow (registered IDPs per 100,000 pre-war population,logged) is only available for 2022 and 2023, and for 189 rather than 190 raion-years, as Khersonskyi Raion was under Russian occupation and unsurveyed in the 2022 round. Registered IDPs within the sample: 3,490,825 in 2022; 3,441,996 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).

war intensity (column 9), the coefficient flips sign and becomes marginally significant (1.6 pp per SD), suggesting that, holding local war exposure constant, the arrival of displaced workers modestly improves allocative efficiency, likely by alleviating labor shortages created by mobilization and emigration. Yet these gains appear far from fully realized: survey evidence in International Organization for Migration (2023*a*) indicates that IDPs remained grossly underemployed throughout 2022–2023, constrained by housing shortages, credential recognition barriers, 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, Tsapin and Yaremko (2026). Raions with a higher cumulative liberation share suffered significantly larger TFP declines (-6.7 pp per 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.

Bohodukhiv's own war intensity is only around 20 percent of Kharkiv's, yet still more than 50 percent above the median raion.

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: Industry × 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	0.915	0.897	+1.8			
2023	0.796	0.717	+7.9	33.1%	24.7%	42.2%
2024	0.784	0.683	+10.1	34.5%	19.8%	45.8%

TFP index (2021=1). Difference is moving minus fixed weight, in percentage points: the part 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 (industry x raion shift-share), exact and additive by construction; 2022 omitted, gap too small for a stable split. The sample differs from the main panel: firms that cannot be geolocated to a raion are dropped, as are raions with fewer than 100 firms, and the industry hierarchy is coarser (196 cells against 196 nationally) because we require each industry to be present in at least two-thirds of eligible raions, so that the industry classification does not become a raion fixed effect. 90,256 firms, 94 raions. See Appendix Table B8 for sample composition.

In 2022, the difference between the two indices was still small (+1.8 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 (+7.9 pp), and it widened further to +10.1 pp by 2024. That is, by 2024, the economy operating under its actual (i.e., moving) composition was about 10 percentage points more efficient than it would have been had the pre-war composition been frozen in place—evidence of significant but incomplete adaptation.

[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 100 firms. See Appendix Table B8 for the sample summary statistics.

Employment weights enter the national index through three nested margins. With $e_{i,t}$ firm i's employment, $E_{j,t}$ that of industry cell j, and $E_{jr,t}$ that of cell j in raion r,

$$\omega_{i,t} = \underbrace{E_{j,t}}_{\text{between industry}} \times \underbrace{\frac{E_{jr,t}}{E_{j,t}}}_{\text{between raion}} \times \underbrace{\frac{e_{i,t}}{E_{jr,t}}}_{\text{within raion}} \tag{4}$$

Table 2 splits the gap between fixed and moving weights into these three margins by Shapley value, exact and additive; see Appendix A.4 for a detailed explanation.

Between-raion reallocation is the largest channel, accounting for 42–46 percent of the gap and rising between 2023 and 2024, which reflects the physical movement of economic activity toward safer areas. A further 20–25 percent occurred within raions, that is, firms and workers found workarounds locally, shifting across industries or reallocating resources across firms within the same geographic area, a share that falls as relocation grows. The remaining roughly one-third occurred through between-industry shifts, as the sectoral composition of the economy adjusted toward less war-vulnerable activities. Construction and transportation and storage were among the sectors losing the most employment, consistent with employment falling most in the sectors that suffered the largest TFP declines (Appendix Figure D10).

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 geographic relocation toward safer areas, within-raion reallocation, 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

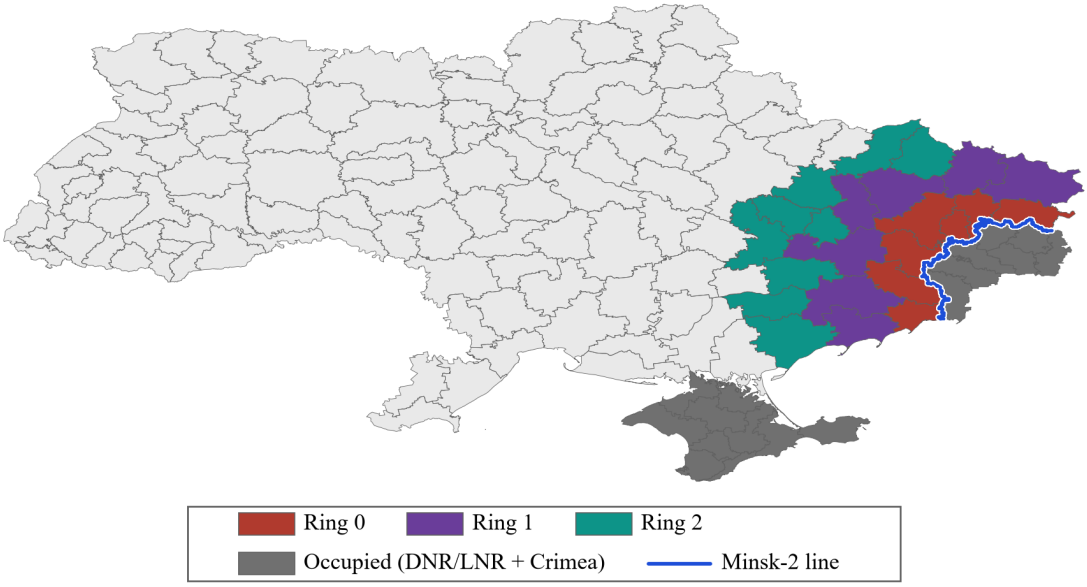
To further disentangle the channels driving our results, we compare the 2022 invasion with two earlier crises that isolate its two main components. Russia's 2014 seizure of Crimea and the Donbas combined limited military action with a severe macroeconomic crisis; the 2008–2009 Global Financial Crisis 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 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

Figure 14: War-exposure ring classification

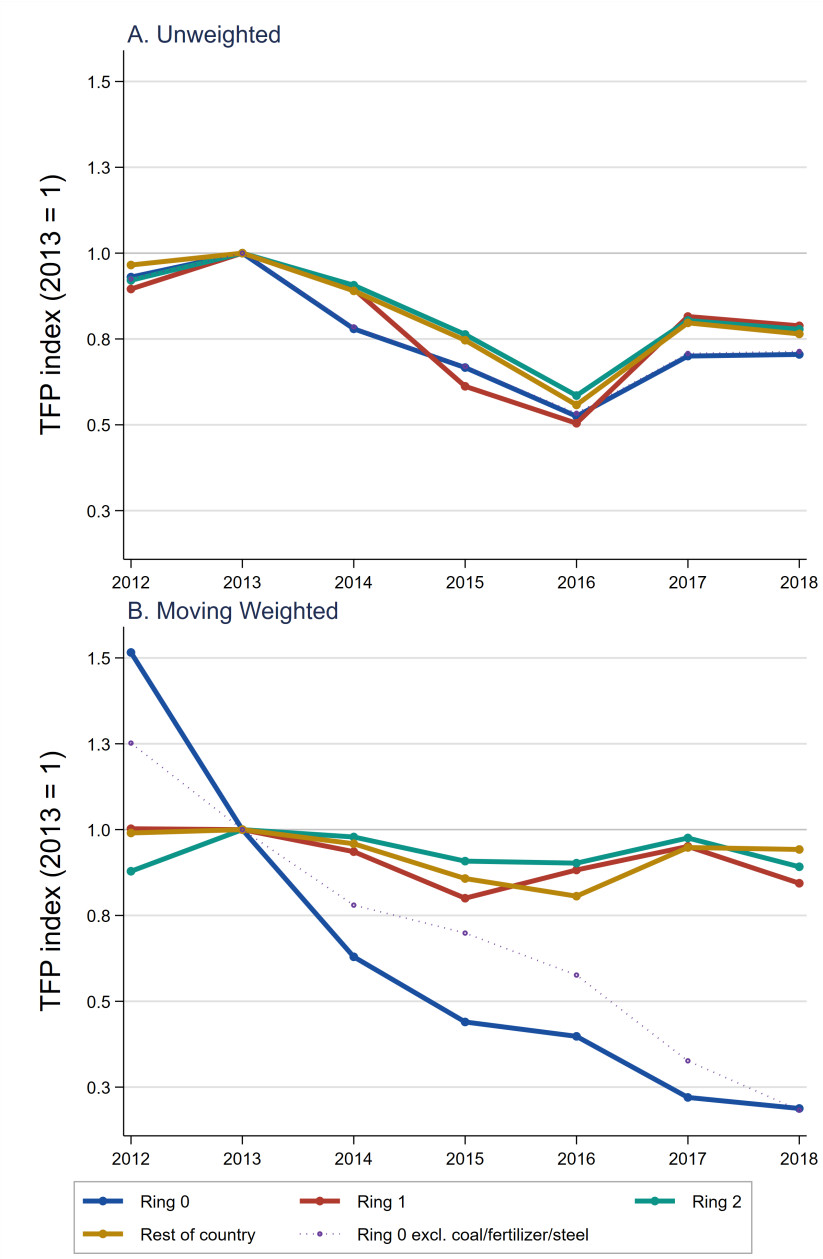


physical violence than Ring 0). Ring 2 covers raions that are further from the contact line (and hence even less direct violence) but still had some exposure to the conflict's economic spillovers.

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: Ring 0 experienced much 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

[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, Kirchberger and Parkhomenko 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 3,309 firms; Ring 1 2,221; Ring 2 10,918; and the rest of the country 92,486.

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 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

[23] Appendix Figure D11 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 overran 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.

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

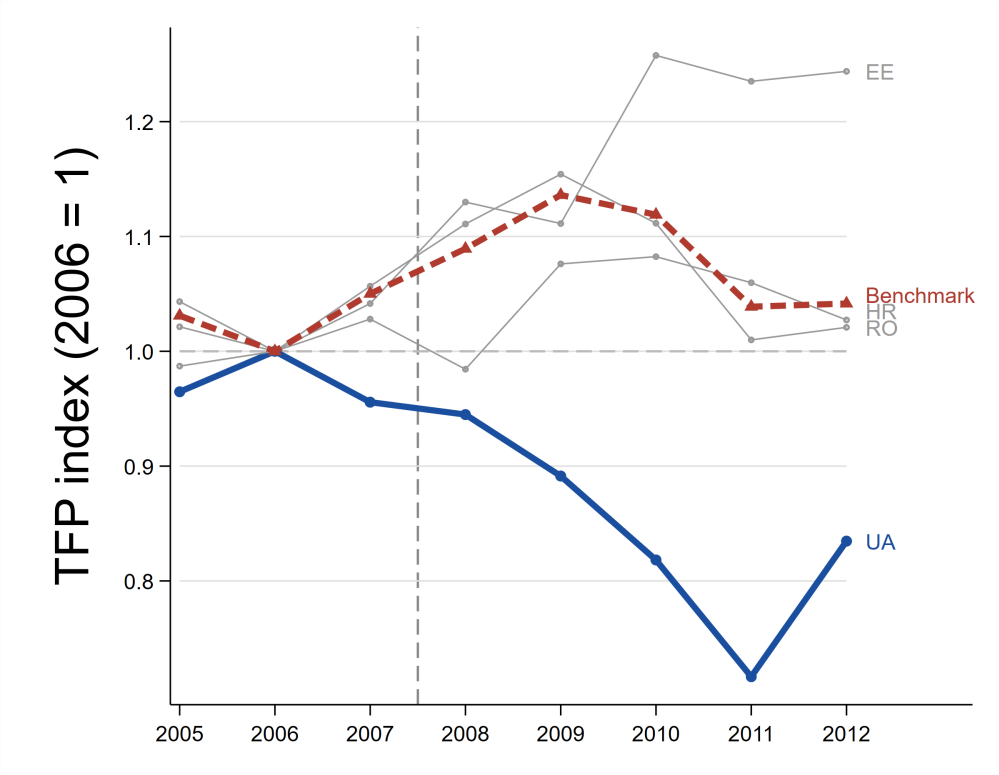
7.2 Global Financial Crisis 2008–2009

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 (real GDP fell about 20 percent year-on-year 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 a quarter 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.

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 B9.

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, although it recovered part of the loss after the 2011 trough. This persistent underperformance 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 D12). 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 quartile that declines the most (Appendix Figure D6). The 2014 episode runs in the same direction as the GFC, with the largest firm quartile affected most, but the gradient is considerably weaker (Appendix Figure D13).

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 D14).[25] Fourth, the sectoral incidence differs substantially across episodes. Of these four sectors, agriculture was the worst affected during the GFC (Appendix Figure D15), the reverse of its position after 2022, when it was the most resilient of the four. One likely reason is policy: Ukraine restricted agricultural exports through quotas and export taxes between 2006 and 2012 (Nivievskyi, Martyshev and Kvasha 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 D16).

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 relative macroeconomic stability after February 2022, supported by the NBU's capital controls and

[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".

liquidity provision and by international assistance, likely prevented the allocative damage from being even worse than what we document.

8 Conclusion

Modern war reduces output not only by killing and displacing workers and destroying 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. 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 implications for military cost-benefit analysis. 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, our

results imply that Ukrainian strikes deep into Russia may worsen the allocation of resources there 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 B5, B10, B9) is computed once per reference year as an employment-weighted average of industry-level revenue-based capital cost shares,

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

where $s_{K,i}^{rev}$ 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 D4) is constructed identically, using each industry's labor cost share in place of s_K^{rev}.

Source data by country:

- **Poland**: OECD STAN, per NACE 2-digit division, 2021 only (OECD, 2025*b*).
- **Romania, Bulgaria, Croatia, Estonia, Hungary, Latvia, Lithuania**: (Eurostat, 2026), per NACE 2-digit division.
- **Ukraine**: State Statistics Service of Ukraine (2026*e*). Unlike the other countries, the source data are 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 Figure 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. An auxiliary panel shifted one year later makes that year interior. Because the two panels are balanced on different sets of firms and sit at different levels, we take the shifted panel's own change over the final step and add it to the main panel's value for the preceding year.

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 estimate this correction raion by raion, since it is only stable in large samples. Instead we estimate it once on the national aggregate

of the same balanced panel and add it to every raion's final-year index as a common level shift, rather than a rescaling, which would assume the edge bias grows with a raion's own dispersion. Because the shift is common to all raions within the year, the year fixed effects of Table 1 absorb it: it moves the levels plotted in Figures 12 and 13, but not the estimated coefficients.

A.3 Industry cell hierarchy

We use industry-by-year fixed effects, with four-digit NACE Rev. 2.1 codes as the baseline classification, aggregating a code to the three-digit, two-digit, or full sector level whenever it falls below 100 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 five sectors for Bulgaria (arts, other services, education, finance, and mining) and one sector each for Croatia and Estonia (mining); Romania, Poland, Hungary, Latvia, and Lithuania 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 196 industry cells covering 90,984 firms: 99 at the four digit level, 50 at the three digit level, 40 at the two digit division level, and 7 collapsed to the full sector. Cell size ranges from 100 firms in the smallest cell, NACE 28.25, "Manufacture of Non-Domestic Cooling and Ventilation Equipment," to 10,848 firms in the largest, NACE 01.11, "Growing of Cereals (Except Rice), Leguminous Crops and Oil Seeds."

A.4 Shift-share decomposition of the reallocation gain

Index the three margins of equation (4) in order by A (industry), B (raion) and C (within raion). Setting each to its year-t value ($s_\bullet = 1$) or its 2021 value ($s_\bullet = 0$) gives eight weighting schemes indexed by $s = (s_A, s_B, s_C) \in \{0,1\}^3$, from all fixed ($\omega_{i,t} = e_{i,2021}$) to all

moving ($\omega_{i,t} = e_{i,t}$):

$$\omega_{i,t}^{(s)} = E_{j,\tau_A} \frac{E_{jr,\tau_B}}{E_{j,\tau_B}} \frac{e_{i,\tau_C}}{E_{jr,\tau_C}}, \qquad \tau_\bullet = \begin{cases} t & \text{if } s_\bullet = 1, \\ 2021 & \text{if } s_\bullet = 0. \end{cases} \tag{5}$$

Each scheme passes through the same industry-cell $\times$ year fixed-effects regressions as the baseline, giving a log TFP loss $\ell_t^{(s)}$. The reallocation gain is $G_t = \ell_t^{(111)} - \ell_t^{(000)}$, and margin A contributes its Shapley value

$$\phi_t^A = \tfrac{1}{3}\big(\ell^{100} - \ell^{000}\big) + \tfrac{1}{6}\big(\ell^{110} - \ell^{010}\big) + \tfrac{1}{6}\big(\ell^{101} - \ell^{001}\big) + \tfrac{1}{3}\big(\ell^{111} - \ell^{011}\big), \tag{6}$$

with ϕ_t^B and ϕ_t^C symmetric. The weights average each margin's marginal contribution over the six orders in which the margins can be switched on, so $\phi_t^A + \phi_t^B + \phi_t^C = G_t$ exactly. Table 2 reports the three shares $\phi_t^\bullet / G_t$; the 2022 gap is too small relative to later years for a stable split, so shares begin in 2023.

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)	2018–2024	2006–2024
Wholesale and retail trade; repair of motor vehicles and motorcycles	0.282	14.7%	43	46,287	22,603	7,148
Manufacturing	0.087	27.4%	70	24,207	14,695	6,545
Agriculture, forestry and fishing	0.324	13.6%	12	22,598	12,779	3,820
Real estate activities	0.653	4.1%	5	19,080	8,338	4,003
Construction	0.088	7.8%	11	13,609	6,540	2,304
Professional, scientific and technical activities	0.265	3.1%	10	13,523	6,124	1,917
Transporting and storage	0.175	6.5%	4	9,724	4,967	1,673
Information and communication	0.371	4.7%	11	8,339	4,050	1,348
Administrative and support service activities	0.177	1.3%	11	8,783	3,961	1,022
Human health and social work activities	0.004	2.6%	1	4,342	2,017	478
Provision of other types of services	0.390	0.7%	5	2,917	1,515	676
Accommodation and food service activities	0.374	0.9%	3	3,083	1,345	515
Education	0.084	3.2%	4	1,342	619	196
Financial and insurance activities	0.378	2.4%	2	1,222	570	132
Mining and quarrying	0.389	6.7%	2	777	462	235
Arts, entertainment and recreation	0.093	0.5%	2	893	399	126

Notes: Sectors defined as in State Statistics Service of Ukraine (2026*e*). Sector weight is the sector's share of gross output among the sectors covered in the 2021 production account (Section A.1); the national capital cost share is the ratio of the covered sectors' gross operating surplus to their output, i.e. the output-weighted average of the sector shares. "2021 (pre-balance)" = distinct firms in that sector at year 2021, before any multi-year balance requirement (the filter chain of Table B3 through the status step, before the window-specific balance requirement); "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				Total Assets (USD)			Revenue (USD)		
		Mean	Median	Min	Max	Mean	Min	Max	Mean	Min	Max
2018	90,984	40	7	1	260,253	2,922,502	4	24,694,227,967	2,761,512	22	9,104,655,427
2019	90,984	41	7	1	251,014	2,810,791	4	21,051,108,289	2,739,055	8	7,343,803,685
2020	90,984	40	7	1	244,103	2,909,995	4	16,388,039,574	2,689,150	16	4,964,830,225
2021	90,984	40	7	1	232,837	3,114,165	4	16,619,917,289	3,222,375	7	6,246,693,405
2022	90,984	37	6	1	210,742	2,822,417	3	15,828,628,643	2,294,110	3	5,180,944,230
2023	90,984	34	6	1	187,620	2,783,018	3	14,083,129,557	2,493,024	3	4,892,588,941
2024	90,984	33	5	1	178,616	2,877,529	3	14,352,811,943	2,708,240	3	5,299,614,833

Notes: Total assets and revenue in constant 2021 USD (CPI-deflated, World Bank (2026*b*); fixed 2021 NBU rate, National Bank of Ukraine (2026*b*)). 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	ORBIS records in the Ukrainian extract with a 2018–2024 fiscal year, before any filter	2,619,474	616,062	6,419,822	100.0%
Country filter	`bvdid` carries Ukraine's own registry prefix, which 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.	2,389,291	565,855	6,000,577	91.2%
Fiscal period	Closing month is December and the filing period spans a full 12 months	2,389,290	565,855	6,000,577	91.2%
NACE parse	Industry code parses to a valid 4-digit NACE class	2,388,532	565,362	6,000,558	91.2%
Consolidation deduplication	Consolidated statement kept when both consolidated and unconsolidated reports exist	2,386,999	565,362	5,886,254	91.1%
Raion exclusion	Drops firms in raions more than 70% under Russian occupation as of 31 December 2024 and all firms registered in Crimea or Sevastopol; a firm whose address does not resolve to a raion is kept	2,319,260	541,513	5,677,674	88.5%
Positivity	Revenue, employment, and total assets variables are reported and strictly positive	1,526,478	366,610	5,577,461	58.3%
Government-dominated sectors	Drops utilities, public administration, and defense sectors	1,494,614	359,589	5,169,319	57.1%
Jump filter	No implausible year-on-year jump in capital- or sales-per-worker exceeding 500x between consecutive years inside the window, the first pair being the year before the window and its first year; a firm is dropped entirely if any such year-pair triggers this	1,476,066	355,326	5,131,271	56.3%
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	1,287,105	266,932	4,793,642	49.1%
Balance filter	Present in every year of the estimation window (2018–2024)	692,958	98,994	3,635,692	26.5%
Single-employee filter	Drops firms reporting exactly 1 employee in every year	636,888	90,984	3,627,682	24.3%

Notes: Raion exclusion filter only applied for Ukraine, otherwise, all filters are identically applied to all countries. The pre-balance column of Table B1 ends the filter series after the status step, before the balance requirement; the pre-balance raion sample of Figure 4 ends after the jump filter.

Table B4: War intensity score summary statistics

	N (raions)	Mean	Median	Min	Max
Cumulative (2022–2024)	95	2.25	2.31	0.00	5.57
Flow 2022	95	1.86	1.80	0.00	4.73
Flow 2023	95	1.09	0.81	0.00	4.43
Flow 2024	95	1.15	0.84	0.00	4.54

Raion TFP sample (Table B7, balanced 2020–2024, 95 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 B5: 2018–2024 balanced panel: benchmark country sample composition and weights

Country	Capital Cost Share	Firms	Industry Cells	Employment (2021)	Benchmark Weight
Ukraine	0.226	90,984	196	3,627,682	–
Romania	0.287	177,446	252	2,808,969	0.353
Hungary	0.222	117,492	243	1,853,628	0.234
Lithuania	0.221	48,842	146	858,178	0.097
Croatia	0.222	46,253	134	761,291	0.092
Poland	0.230	43,031	144	3,559,823	0.086
Latvia	0.201	35,012	120	423,137	0.070
Estonia	0.193	24,602	93	264,042	0.049
Bulgaria	0.216	10,381	46	909,565	0.021

Notes: Poland's panel begins in 2019, once its 2018 digital-filing mandate (Parlament Rzeczypospolitej Polskiej, 2018) was fully in effect; Lithuania's in 2020, with its helper window from 2019, as Orbis holds about a third as many Lithuanian accounts for 2018 as for 2019. Edge correction consumes the first year, so TFP figures using these samples report Poland from 2020 and Lithuania from 2021. 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 B6: 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, 2026*e*), 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, 2026*b*). VA net of govt. uses a government-consumption share built from Ukrstat's Input-Output table (State Statistics Service of Ukraine, 2026*c*) (open Leontief demand-driven model, domestic-flows variant). Figure D1 plots this table's VA/Worker-net-% column against each sector's TFP change for the 16 study sectors; the TFP change is not reported here.

Table B7: Raion TFP sample summary statistics

	N (raions)	Mean	Median	Min	Max
Firms per raion (2021)	95	1,130	372	114	27,692
Employees per raion (2021)	95	44,263	13,268	3,114	1,317,272

Balanced 2020–2024 panel (Section 6.1), min 100 firms/raion; 107,316 firms, 212 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 B8: Shift-share sample summary statistics

	N (raions)	Mean	Median	Min	Max
Firms per raion (2021)	94	960	329	105	22,495
Employees per raion (2021)	94	38,389	11,792	1,584	1,194,398

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 100 firms; 90,256 firms, 196 industry cells. Not the same sample as Table B7, which uses the shorter 2020–2024 panel above.

Table B9: GFC 2005–2012 balanced panel: benchmark country sample composition and weights

Country	Capital Cost Share	Firms	Industry Cells	Employment (2006)	Benchmark Weight
Ukraine	0.192	96,214	198	5,695,447	–
Romania	0.276	82,412	175	1,586,971	0.729
Croatia	0.213	20,786	74	435,462	0.184
Estonia	0.222	9,917	47	160,945	0.088

Notes: Benchmark Weight = donor's share of total non-Ukraine firms. Bulgaria, Poland, Hungary, Latvia, and Lithuania 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, 2026*e*)).

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

Country	Capital Cost Share	Firms	Industry Cells	Employment (2013)	Benchmark Weight
Ukraine	0.188	109,067	210	4,104,646	–
Romania	0.286	136,037	230	2,402,656	0.456
Bulgaria	0.230	109,773	206	1,670,371	0.368
Croatia	0.232	32,633	112	546,384	0.109
Estonia	0.207	20,131	77	216,242	0.067

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

Table B11: 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	23,144	1,587,553	5	11,938,655,079	1,942,362	29	6,214,499,314
Poland	83	1	37,002	13,099,532	257	27,457,187,458	16,315,046	257	33,780,977,368
Croatia	16	1	9,653	2,739,016	24	12,201,606,269	2,101,885	47	3,520,836,508
Bulgaria	88	1	17,077	10,620,129	1,209	3,905,703,060	12,633,637	1,814	4,303,370,095
Estonia	11	1	4,864	1,675,776	108	1,875,661,671	1,887,567	35	971,763,090
Hungary	16	1	55,318	2,741,173	3	36,208,709,210	2,301,116	10	9,139,789,255
Lithuania	18	1	12,353	1,663,115	2	2,676,527,879	2,134,976	14	2,296,228,341
Latvia	12	1	3,762	1,247,160	1	828,364,263	1,576,936	21	2,190,489,314

Notes: Same panel as Table B5. Firm-level mean/min/max, constant 2021 USD at the ECB's 2021 average rate (European Central Bank, 2021).

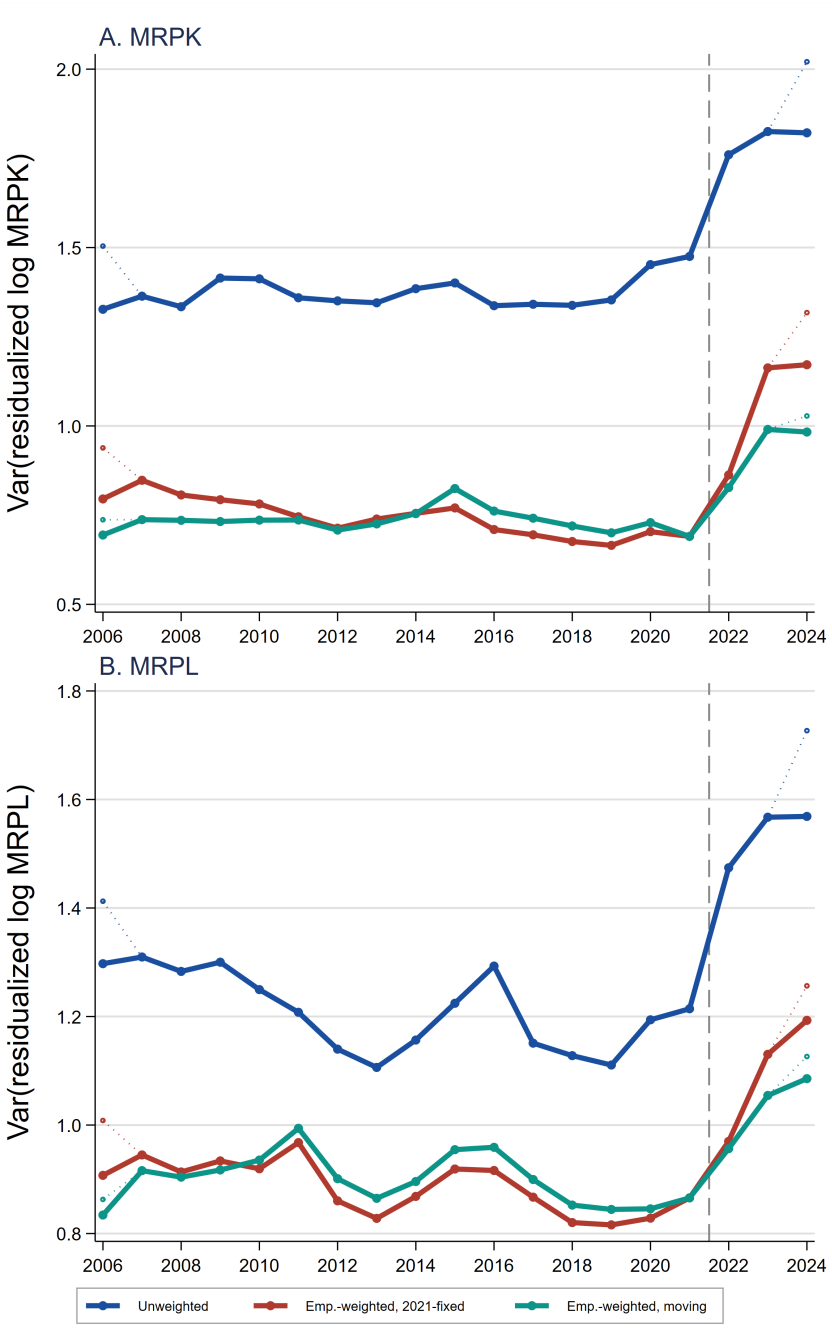
Table B12: 2006–2024 balanced panel: benchmark country sample composition and weights

Country	Capital Cost Share	Firms	Industry Cells	Employment (2021)	Benchmark Weight
Ukraine	0.226	32,138	110	1,808,459	–
Romania	0.287	47,765	126	1,137,259	0.679
Croatia	0.222	14,692	62	367,300	0.209
Estonia	0.193	7,859	36	119,336	0.112

Notes: Benchmark Weight = donor's share of total non-Ukraine firms. Bulgaria, Poland, Hungary, Latvia, and Lithuania are excluded due to insufficient data. Capital Cost Share as in Table B5.

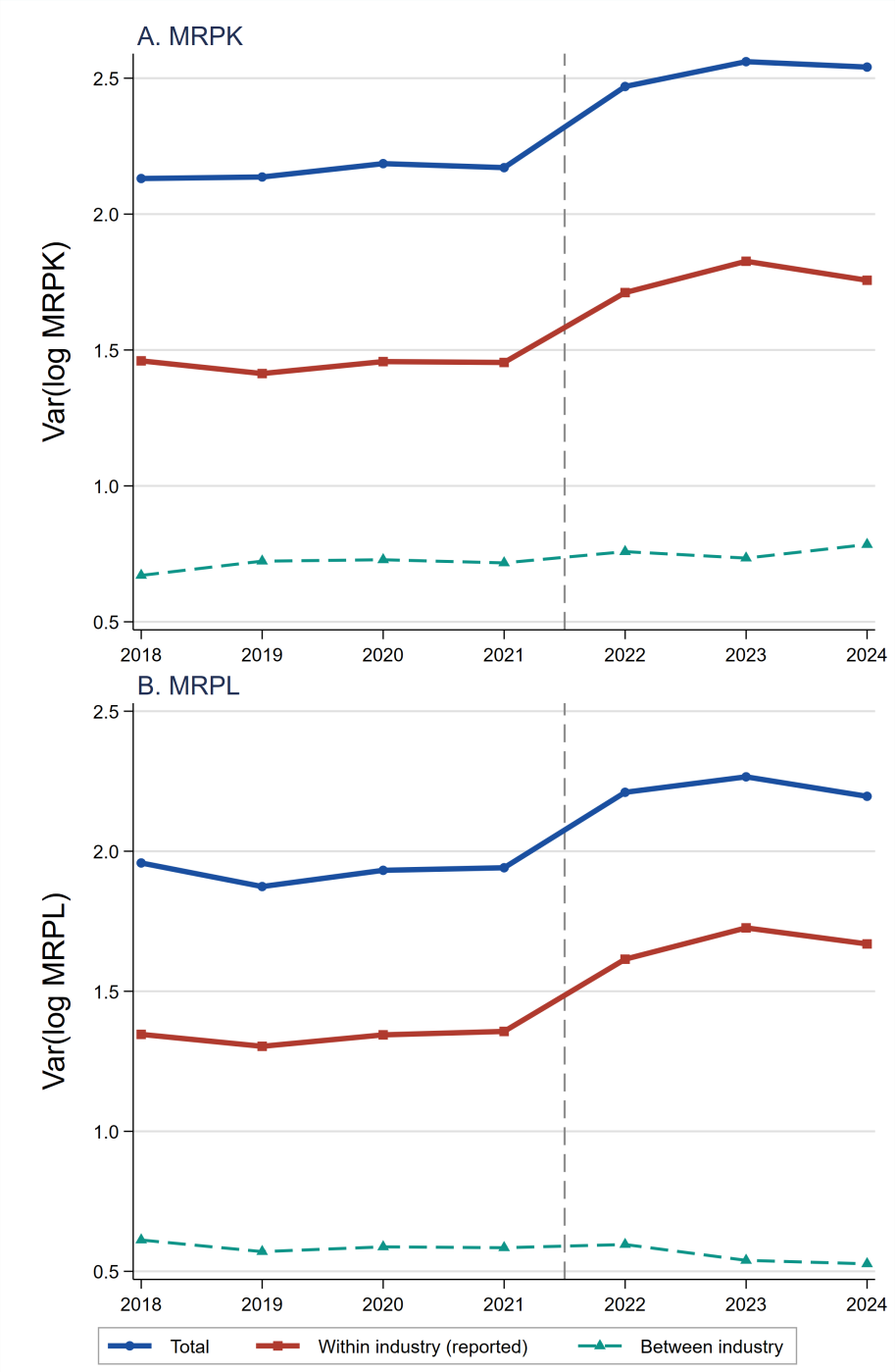
C Appendix C: Additional Measures of Dispersion

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



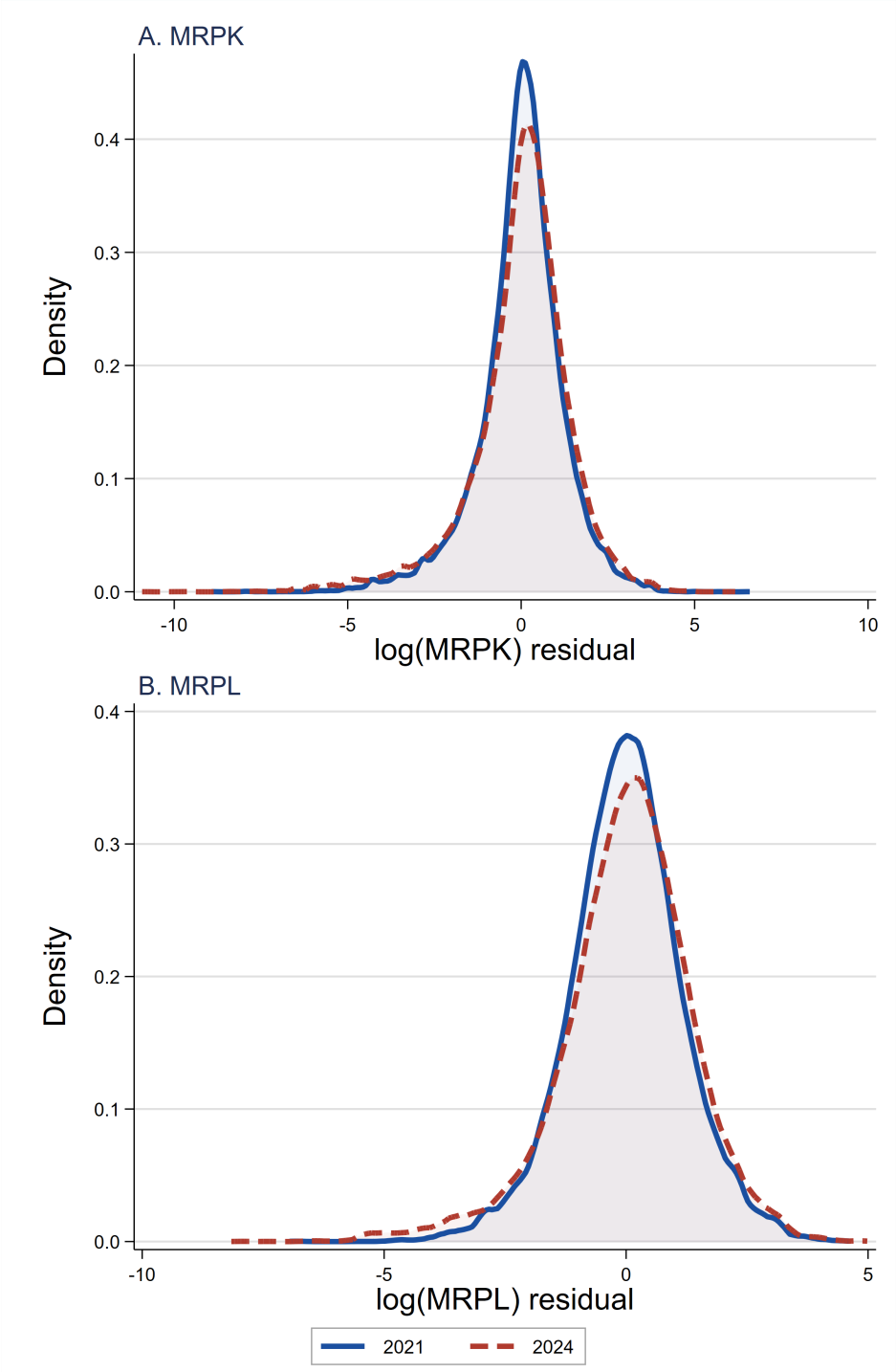
Notes: Var(residualized log MRPK) and Var(residualized log MRPL), industry_cell × year FE, edge-corrected. Ukraine: 32,138 firms, 110 industry cells (2006–2024 balanced panel).

Figure C2: MRPK and MRPL dispersion, within and between industry cells, Ukraine, 2018–2024.



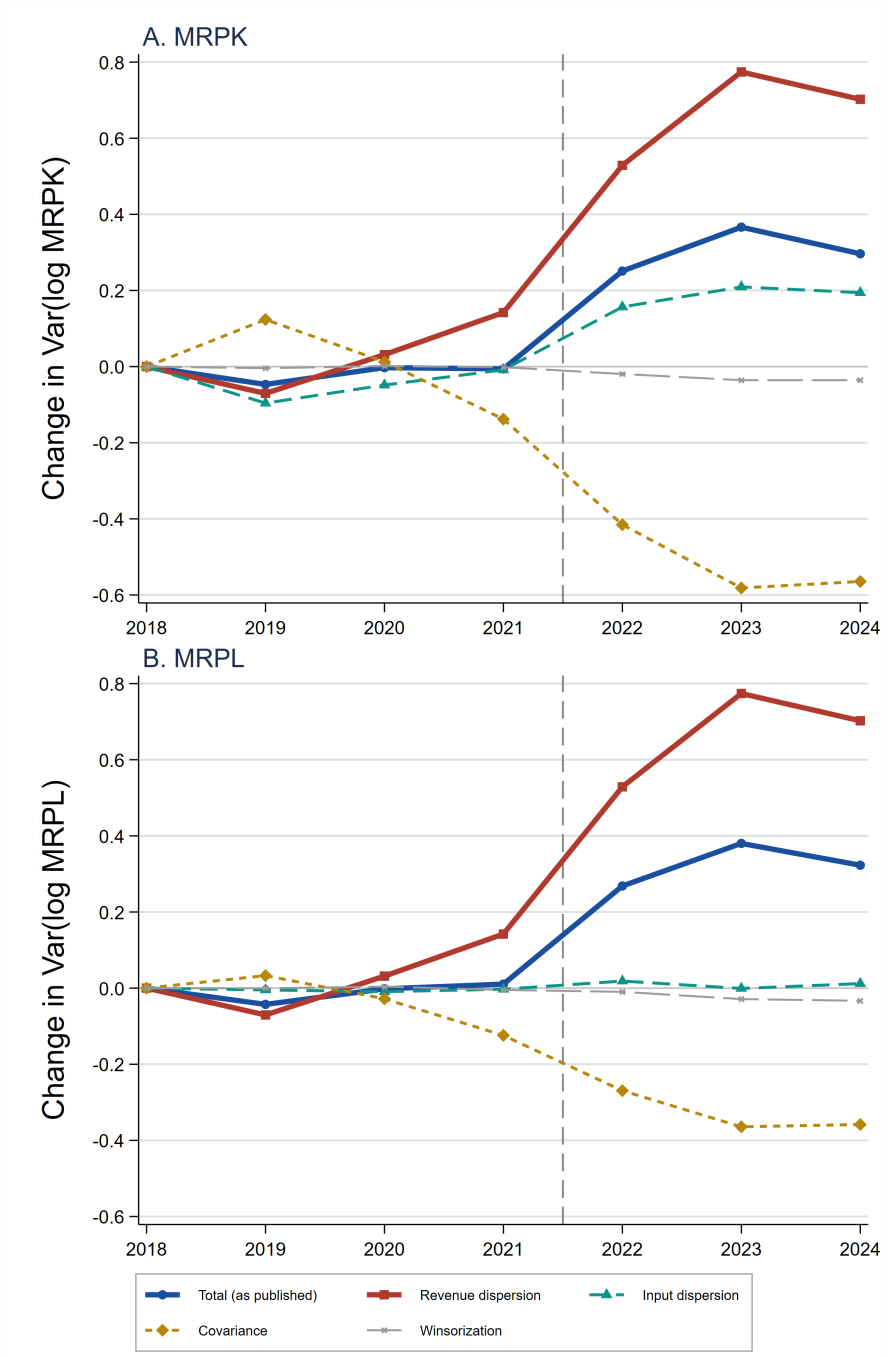
Notes: Equal-weighted, 1% winsorized, edge-corrected. The split is exact: within a year the total variance is the variance of the industry-cell means plus the variance of the residuals, and the within part is what the paper reports everywhere else. Sample sizes: Appendix Table B2.

Figure C3: Kernel density of log(MRPK) and log(MRPL) residuals, Ukraine, 2021 vs. 2024.



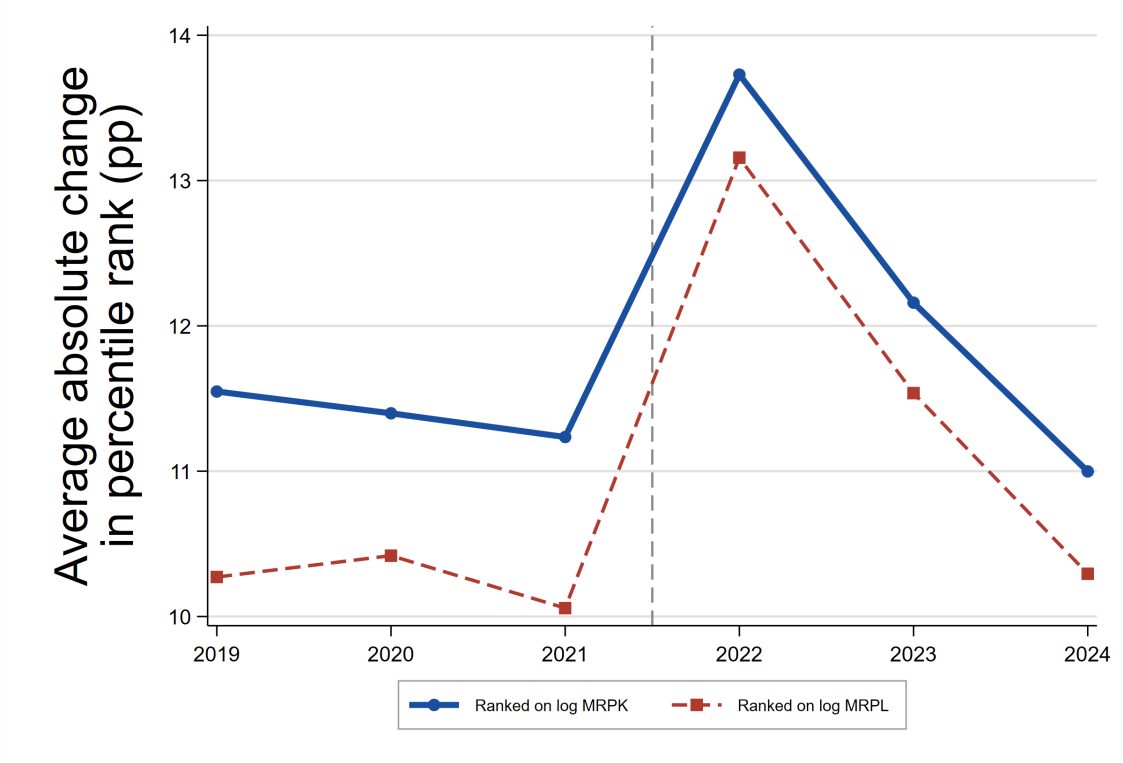
Notes: Industry_cell × year FE residuals of log(MRPK)/log(MRPL), 1% winsorized, unweighted. The same residuals as in Figure 6.

Figure C4: MRPK and MRPL dispersion split into revenue, input and covariance, Ukraine, 2018–2024.



Notes: Cumulative change since 2018 of each term of $\mathrm{Var}(e_{mrpk}) = \mathrm{Var}(e_y) + \mathrm{Var}(e_k) - 2\,\mathrm{Cov}(e_y, e_k)$, and the same for MRPL, on the residuals of the industry cell by year projection. The total is the published series of Figure 6; the winsorization term is the gap left by winsorizing the ratio rather than its parts, which is not linear. Sample sizes: Appendix Table B2.

Figure C5: Reordering of firms within their industry cell, Ukraine, 2019–2024.



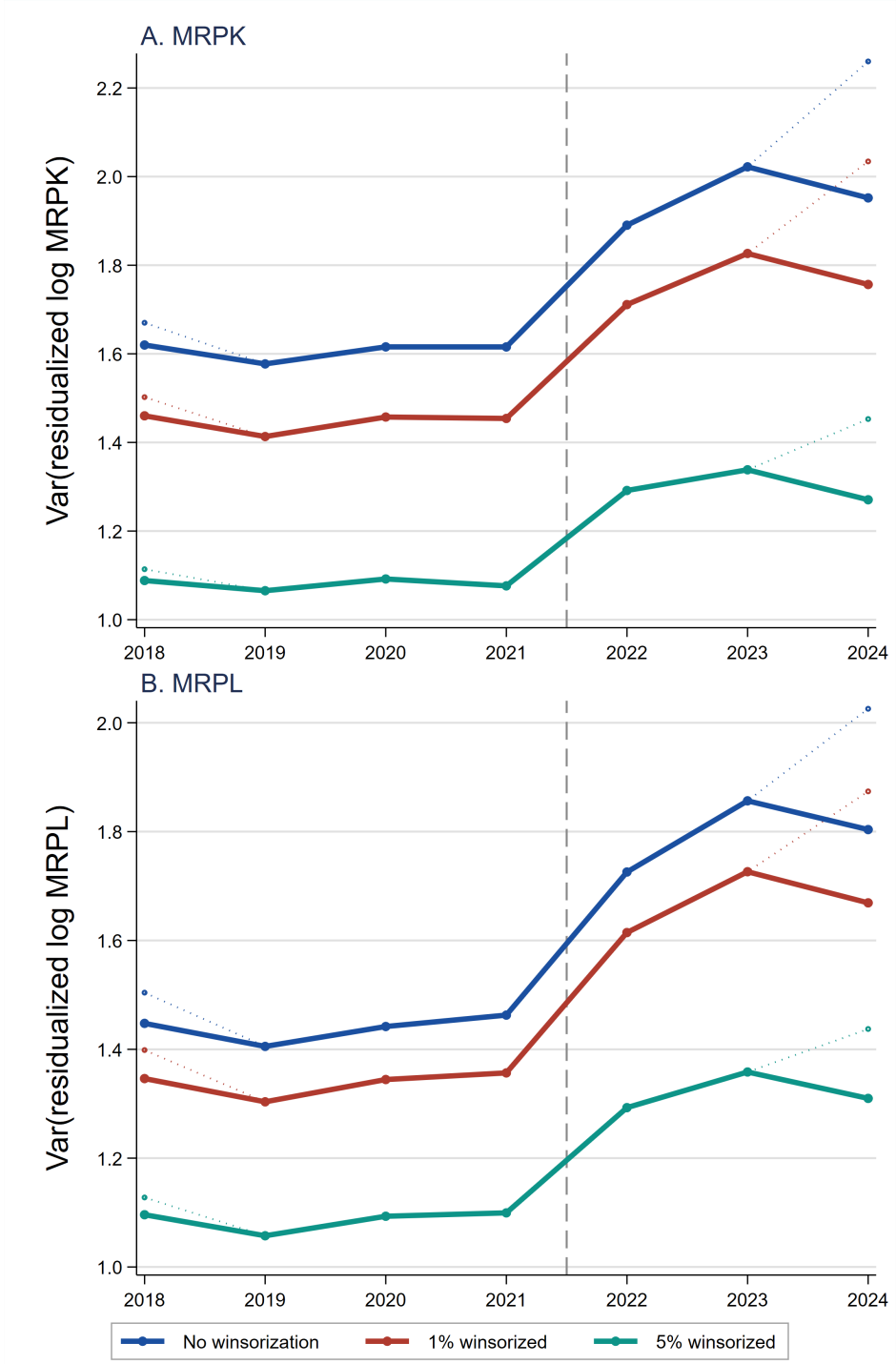
Notes: Average absolute year-on-year change in a firm's percentile rank, in percentage points. Ranks are formed inside each industry cell and year over the national sample, are unwinsorized, and are built separately on each marginal revenue product; both series use the same firms of the balanced panel, a firm entering only when both ratios are present. Where Figure 6 asks how far apart the firms are, this asks how much they change places. The same reordering as a transition matrix: Appendix Table C6. Sample sizes: Appendix Table B2.

Table C6: Year-on-year quartile transitions, by marginal revenue product

	Ranked on log MRPK				Ranked on log MRPL			
Quartile in the earlier year	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Panel A. 2020 to 2021, before the invasion								
Q1 (lowest)	**75.5**	17.5	4.6	2.4	**76.5**	18.0	4.1	1.4
Q2	16.9	**57.2**	21.3	4.6	18.4	**58.9**	19.5	3.3
Q3	5.0	20.8	**55.6**	18.6	3.7	20.1	**59.3**	17.0
Q4 (highest)	2.5	4.6	18.4	**74.5**	1.4	3.2	17.1	**78.4**
Panel B. 2021 to 2022, across the invasion								
Q1 (lowest)	**68.9**	22.9	5.7	2.6	**69.3**	23.5	5.1	2.1
Q2	19.8	**48.4**	26.2	5.6	20.8	**49.2**	25.2	4.9
Q3	7.5	21.8	**48.1**	22.5	7.2	21.8	**49.6**	21.5
Q4 (highest)	3.6	7.1	20.0	**69.4**	2.7	5.7	20.0	**71.6**

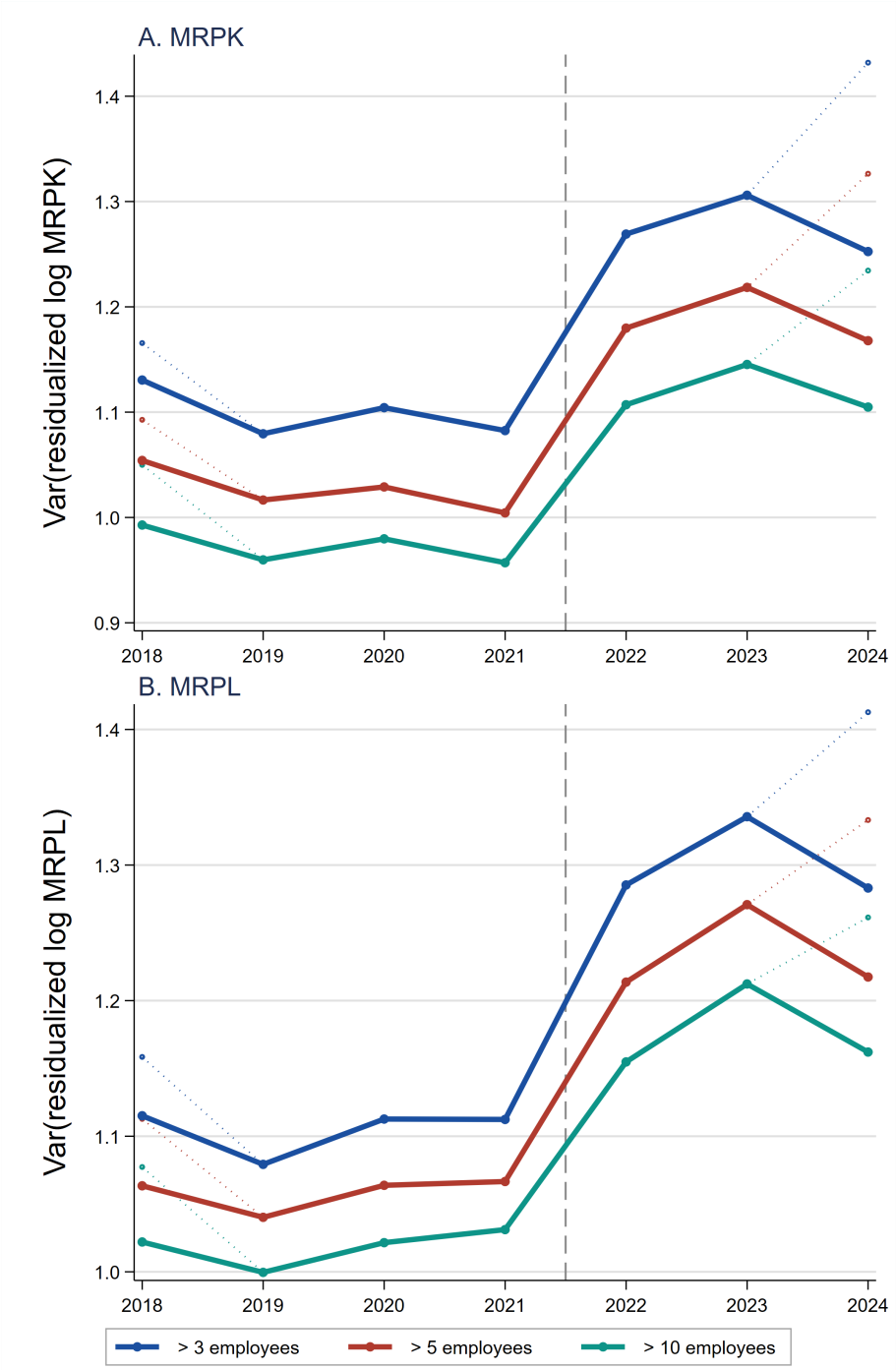
Row percentages; rows sum to 100. Quartiles are formed inside each industry cell and year, over the national sample summarized in Table B2, so each year's marginal distribution is flat and 25.0 is the no-persistence benchmark in every cell. Ranks are unwinsorized and formed separately on each marginal revenue product; all four matrices rest on the same 90,984 firms, a firm entering only when both ratios are present. Diagonal entries in bold.

Figure C7: National dispersion levels by winsorization level, Ukraine, 2018–2024.



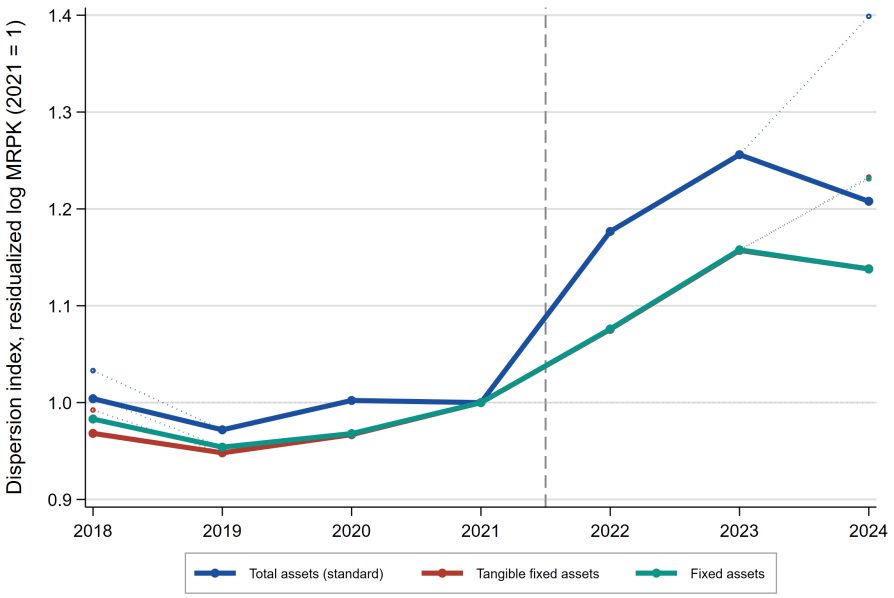
Notes: Var(residualized log MRPK/MRPL), industry_cell × year FE, equal-weighted. Compares no winsorization, 1% (this project's standard), and 5%. Solid = edge-corrected; dotted = raw (uncorrected). Ukraine: 90,984 firms, 196 industry cells.

Figure C8: National dispersion levels by minimum employee-count floor, Ukraine, 2018–2024.



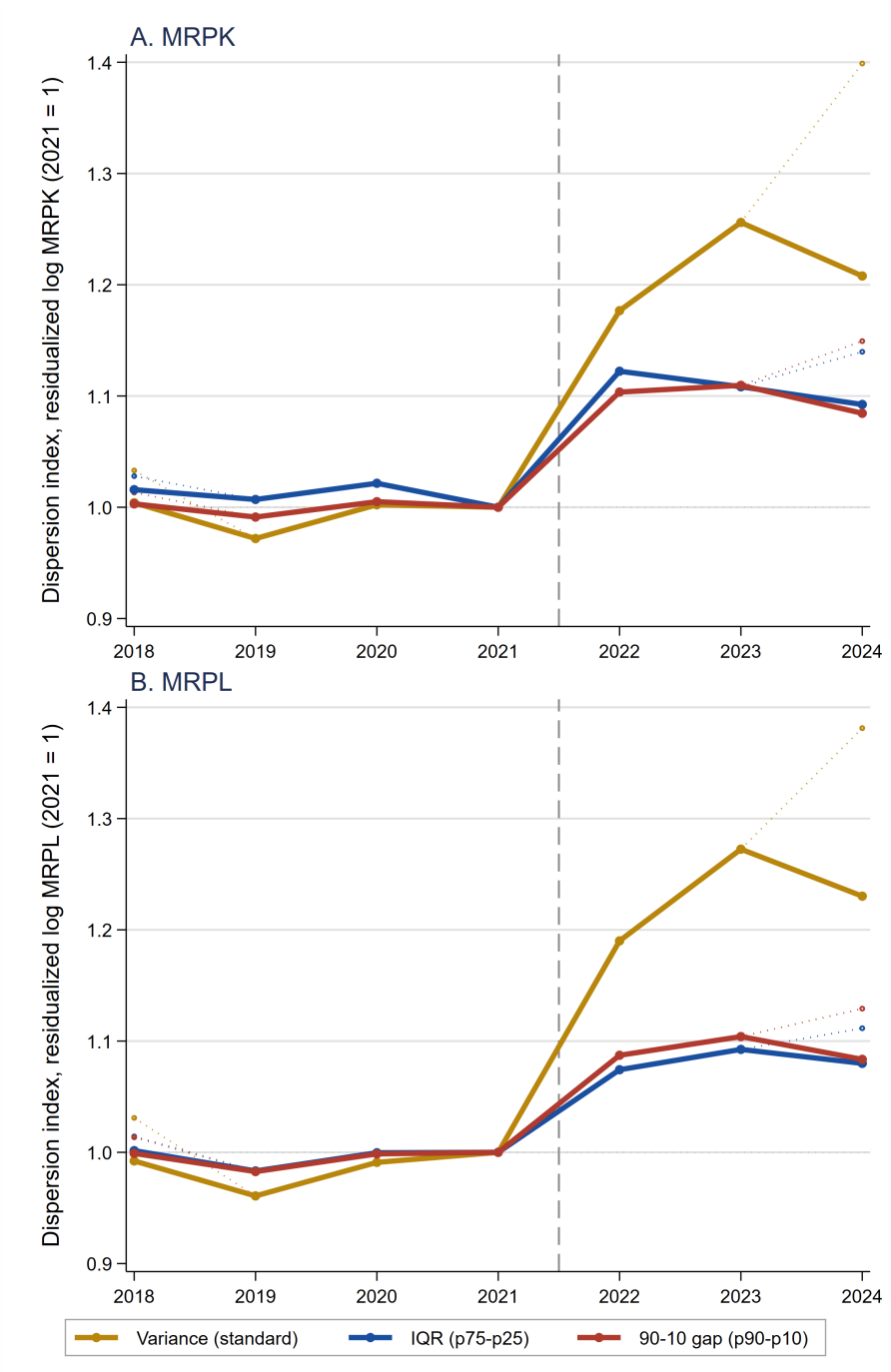
Notes: Equal-weighted, 1% winsorized, edge-corrected. Same national dispersion methodology as Figure 6, restricted to firms with more than a fixed employee-count floor. Of the 90,984-firm base panel (main window UA_hier_2018_2024): >3 employees keeps 49,295 firms; >5 employees keeps 36,712 firms; >10 employees keeps 23,706 firms.

Figure C9: National MRPK dispersion by capital measure, Ukraine, 2018–2024 (2021 = 1).



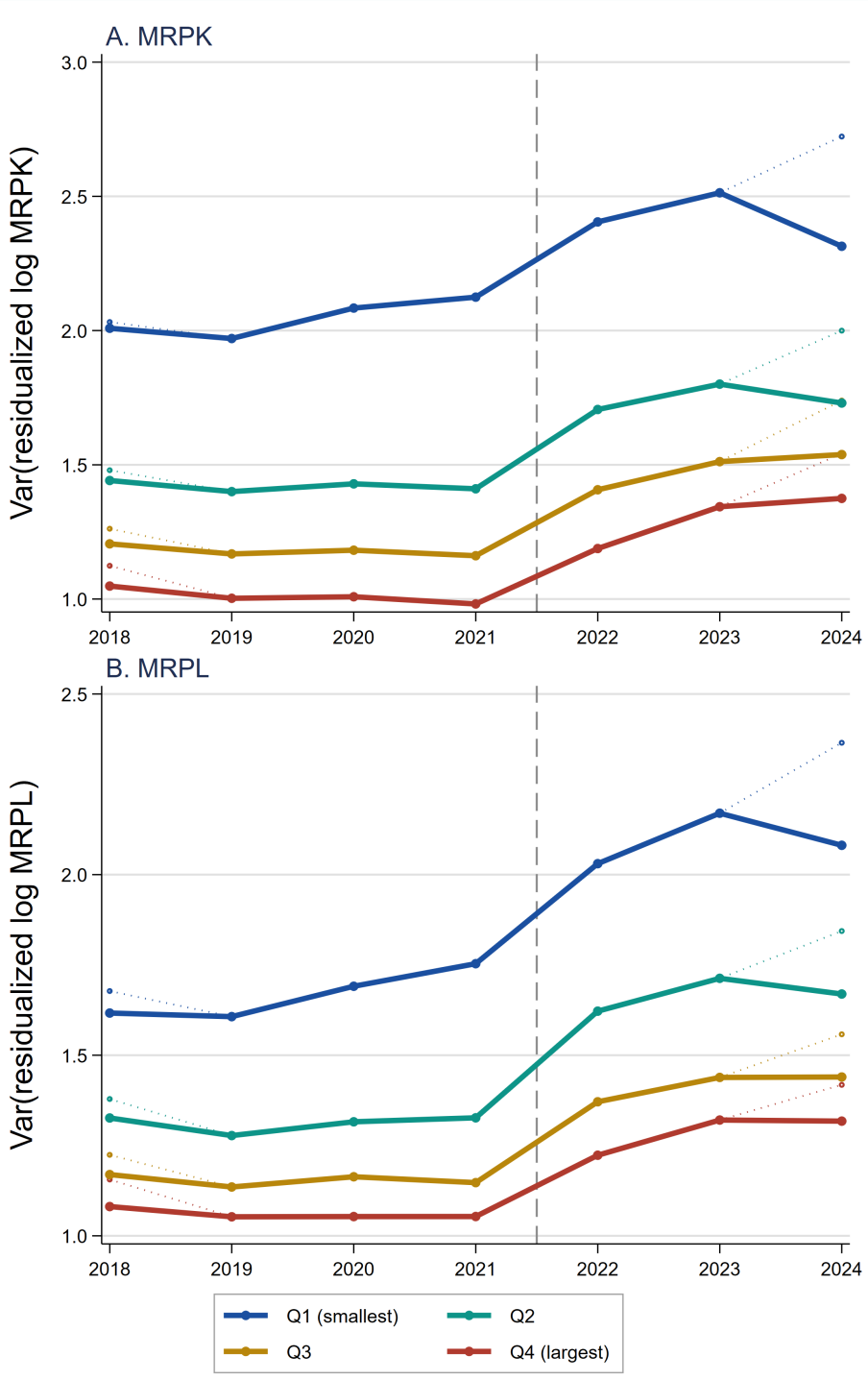
Notes: Equal-weighted, 1% winsorized, raw (dotted) and edge-corrected (solid). Compares total assets (standard) against tangible fixed assets and fixed assets as MRPK's denominator, each normalized to its own 2021 value. Total assets has 90,984-firm observations. Only a subset of 70,726 firms for tangible fixed assets and 73,176 for fixed assets report the alternative capital measures; these firms are on average larger than the standard sample mean.

Figure C10: National dispersion, Ukraine, 2018–2024 (2021 = 1): variance vs. interquartile range vs. 90–10 percentile gap.



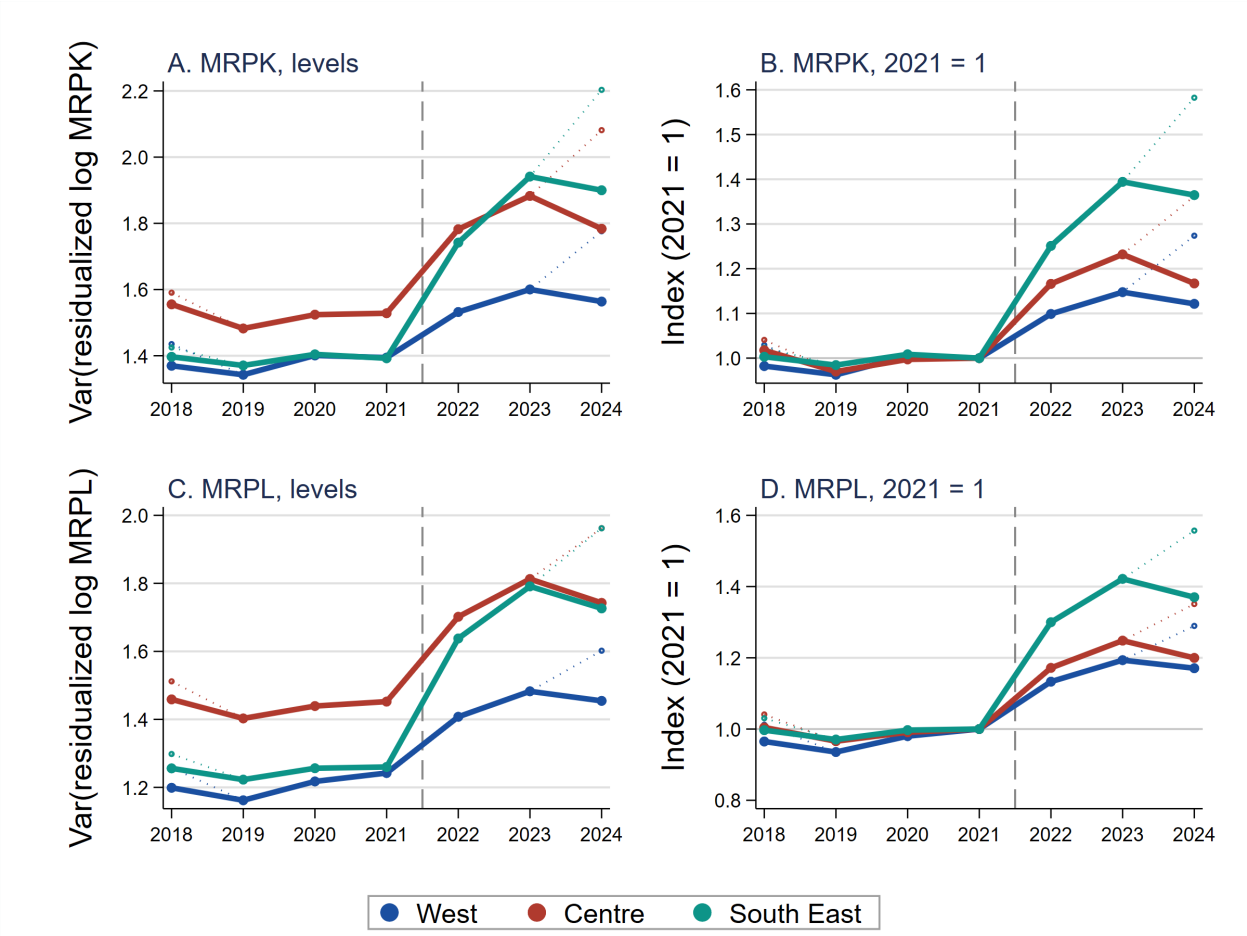
Notes: Equal-weighted, 1% winsorized, edge-corrected. Same national sample as Figure 6 (90,984 firms, 196 industry cells, balanced 2018–2024 panel. The standard variance measure from Figure 6 is plotted alongside two alternative statistics, the interquartile range (p75−p25) and the 90–10 percentile gap; all three are normalized to their own 2021 value.

Figure C11: National dispersion levels by firm-size quartile, Ukraine, 2018–2024.



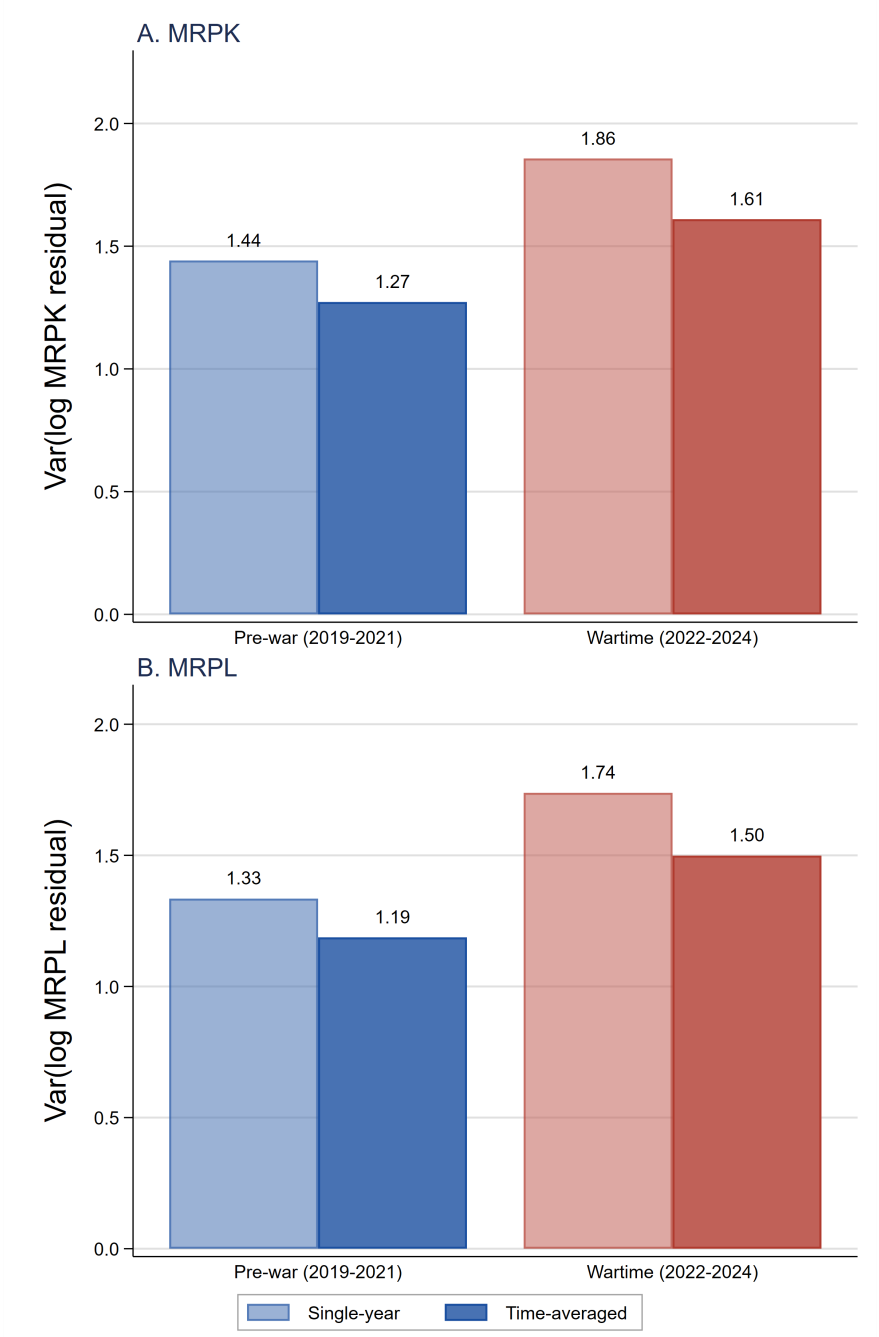
Notes: Firm-size quartile assigned once per firm from its own 2021 employees (Q1 = smallest 25%, Q4 = largest 25%); industry_cell × year fixed effects, edge-corrected. 90,984 firms, 196 industry cells. Quartile is fixed at 2021.

Figure C12: National dispersion levels by macro region, Ukraine, 2018–2024



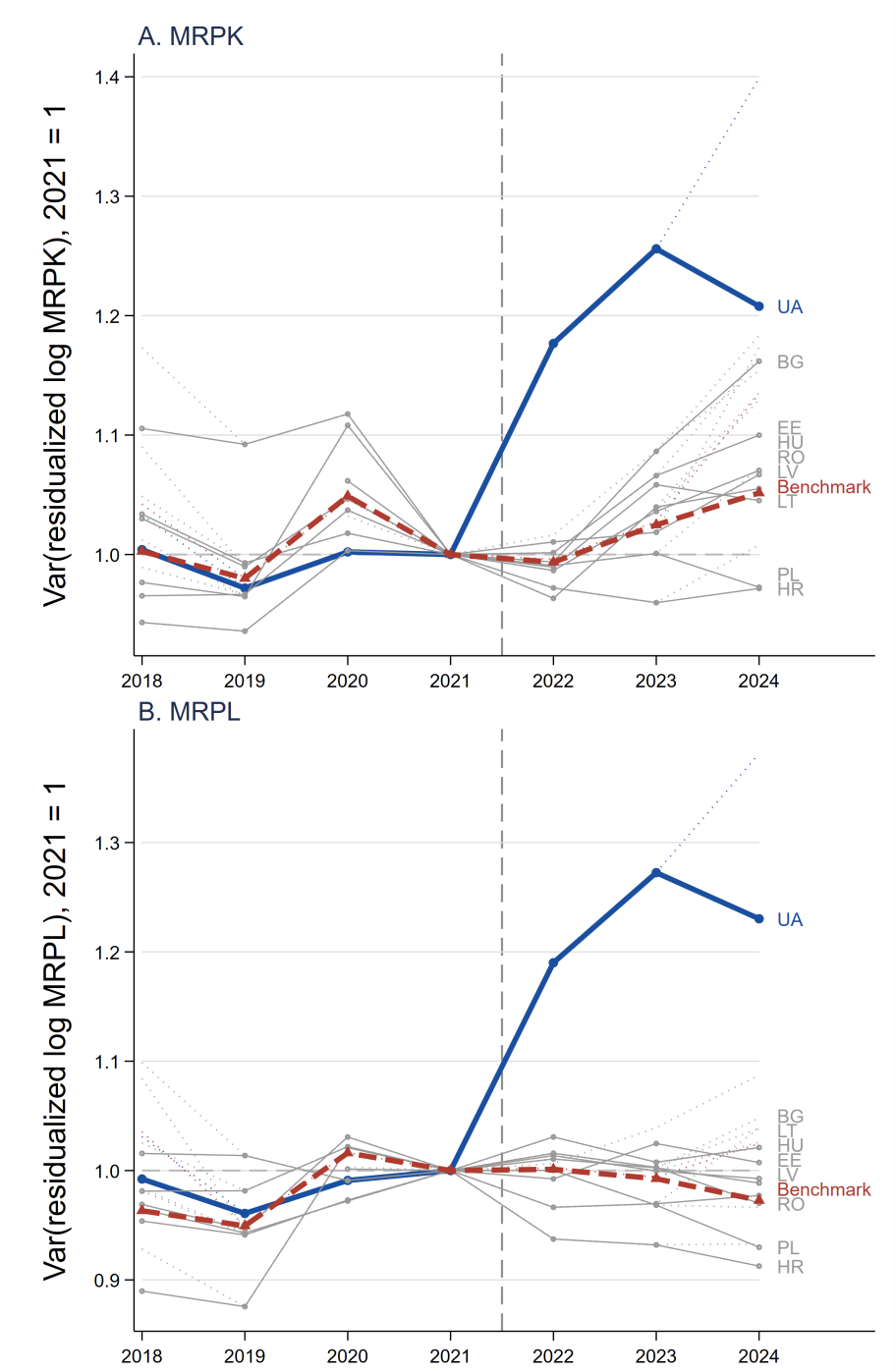
Notes: Equal-weighted, 1% winsorized, edge-corrected. Same national dispersion methodology as Figure 6, split by macro region (West/Centre/South East). Panels B and D normalize each region's series to its own 2021 value. Of the 90,984-firm base panel: West 24,811 firms; Centre 40,934 firms, of which 22,491 are in Kyiv city; South East 25,238 firms.

Figure C13: 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, 90,984-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 C14: 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. Poland reported from 2020, Lithuania from 2021, as earlier years lack sufficient data (shortened windows). Observation counts and summary statistics: Appendix Table B11.

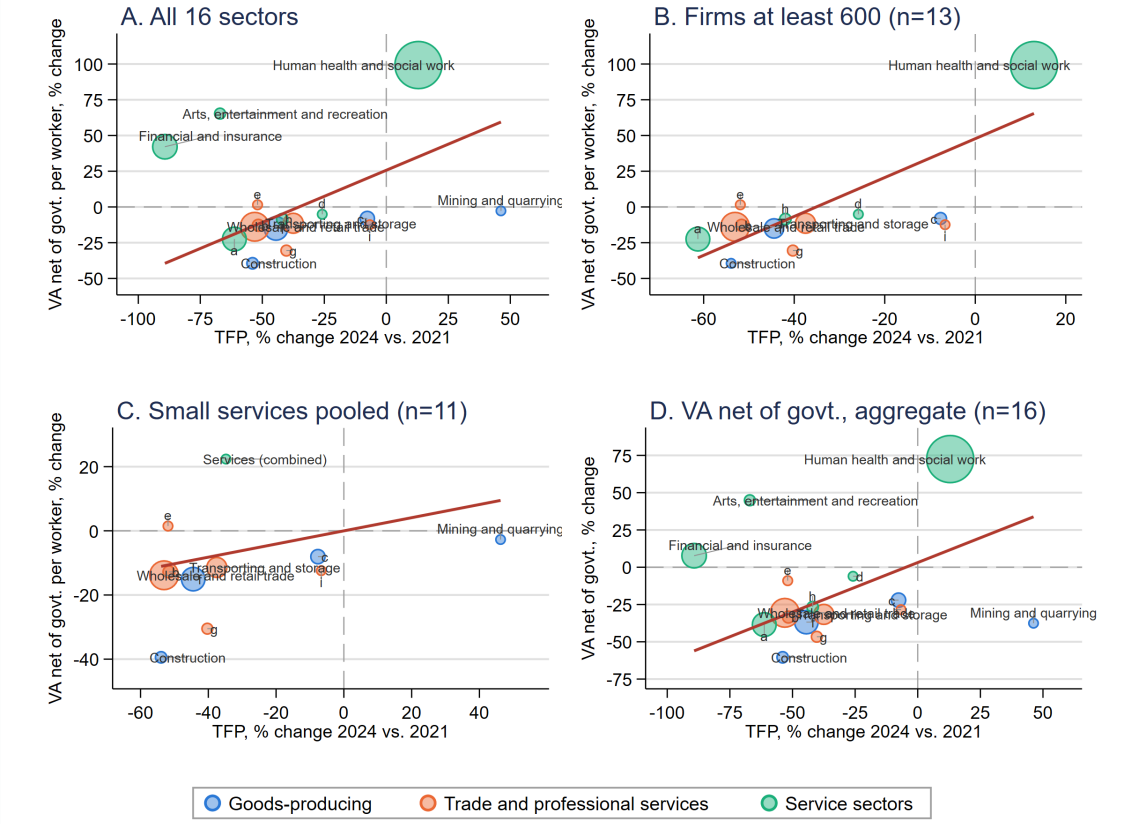
Figure C15: National dispersion levels on the moving-window panel, Ukraine, 2018–2024.



Notes: Equal-weighted, 1% winsorized, edge-corrected. The balanced series is the one Figure 6 plots. The moving series keeps a firm-year whenever the firm also reports in the year before and the year after, so the firm set is the only difference between the two; the industry cells are the balanced window's in both. Sample sizes for the balanced panel: Appendix Table B2. The companion for the index rather than its components is Appendix Figure D5.

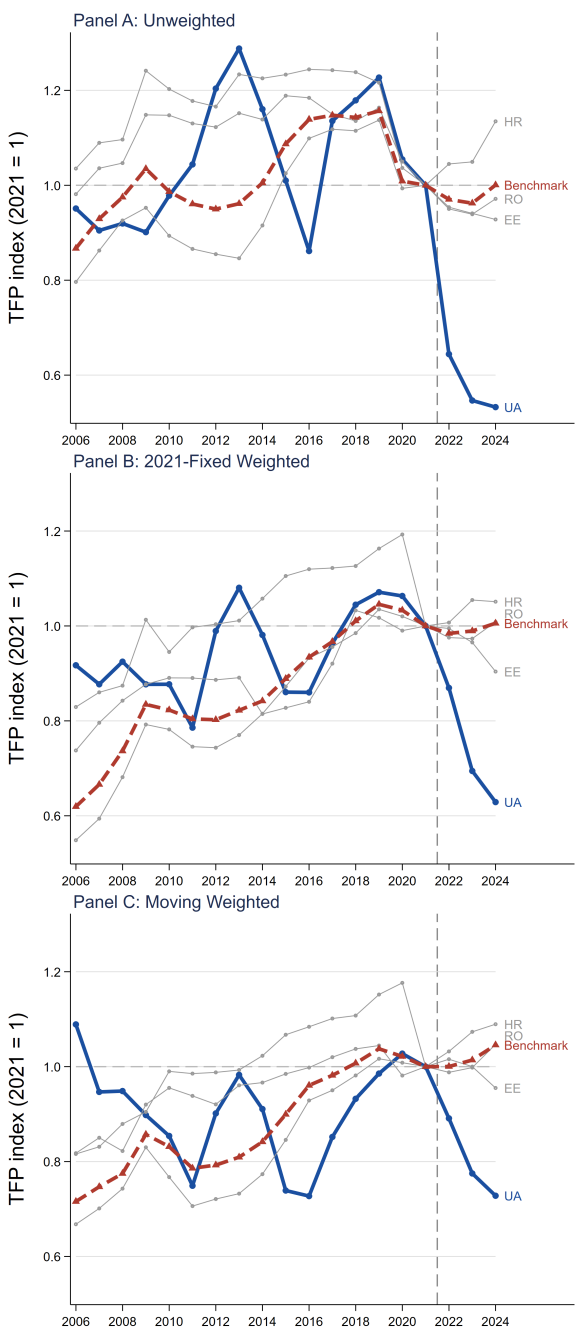
D Appendix D: Additional Figures for TFP

Figure D1: Sector TFP vs. VA/worker, Ukraine, 2024 vs. 2021, robustness variants



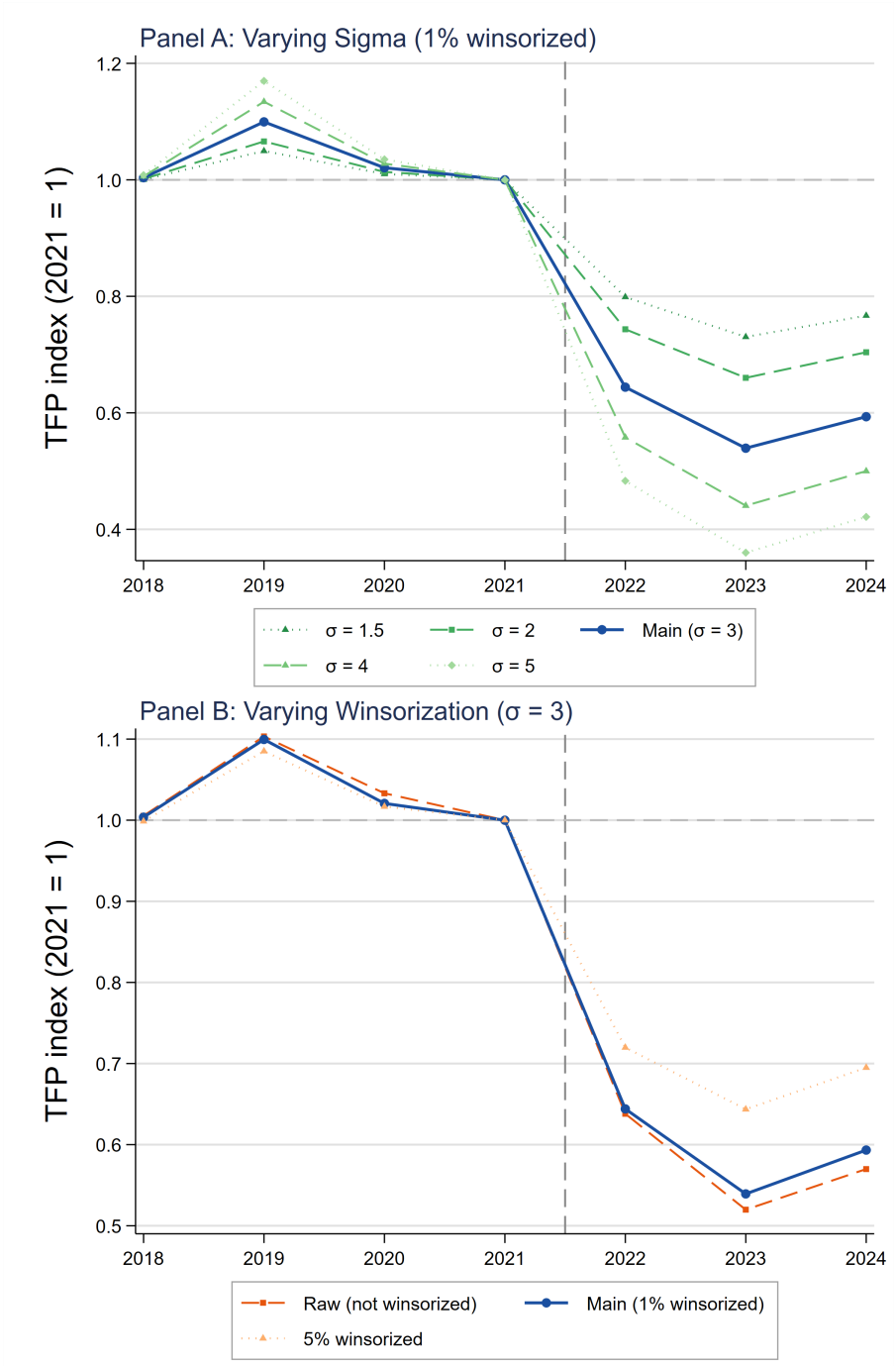
Notes: x = sector TFP % change 2024 vs. 2021 (unweighted, edge-corrected); y = VA net of govt. per worker % change (Panels A–C) or aggregate VA net of govt., (Panel D), from Ukrstat national accounts (State Statistics Service of Ukraine, 2026*e*, 2025); see Table B6 for the full source/currency/coverage notes. Bubble area and fit line/r are 2021-worker-weighted. Panel B: firms $\geq$ 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 D2: National TFP index by country, 2006–2024, 2021 = 1



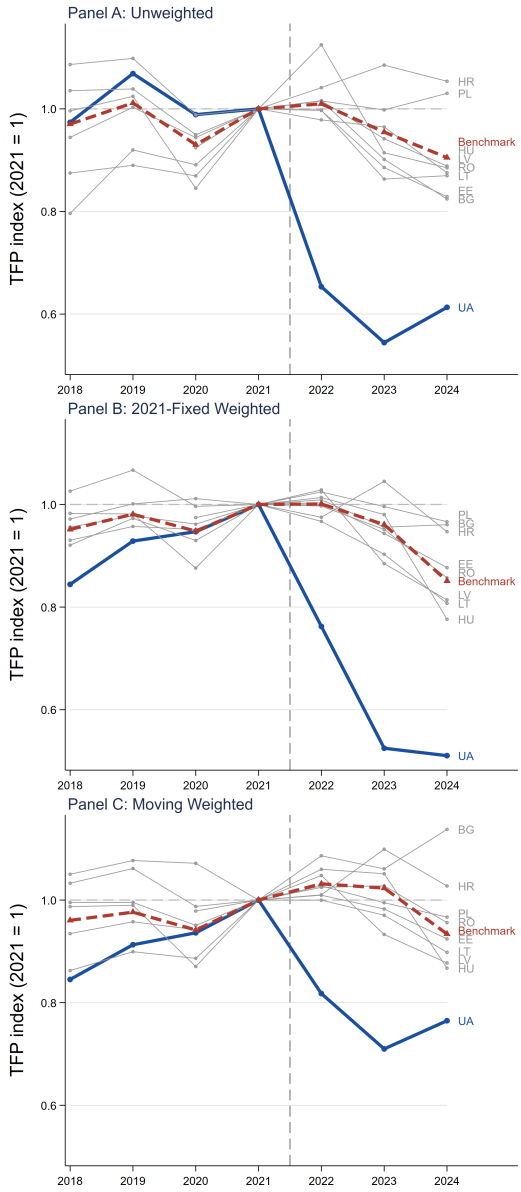
Notes: 1% winsorized, edge-corrected. *Benchmark* = firm-count-weighted average of Romania (RO), Croatia (HR), and Estonia (EE); donor weights in Table B12.

Figure D3: 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 D4: National TFP index by country under the $\tau_K = 1$ alternative assumption, 2018–2024

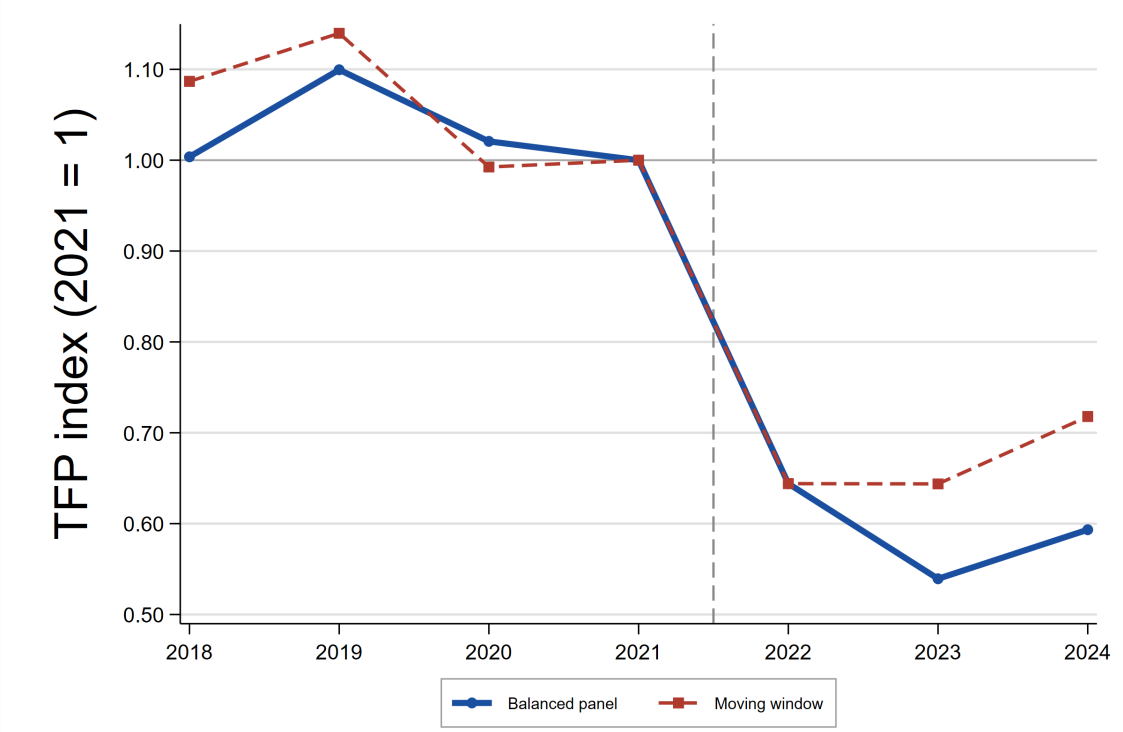


Notes: 1% winsorized, edge-corrected. Assumes no distortion in the capital market ($\tau_K = 1$) instead of the main specification's no-distortion-in-labor assumption:

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

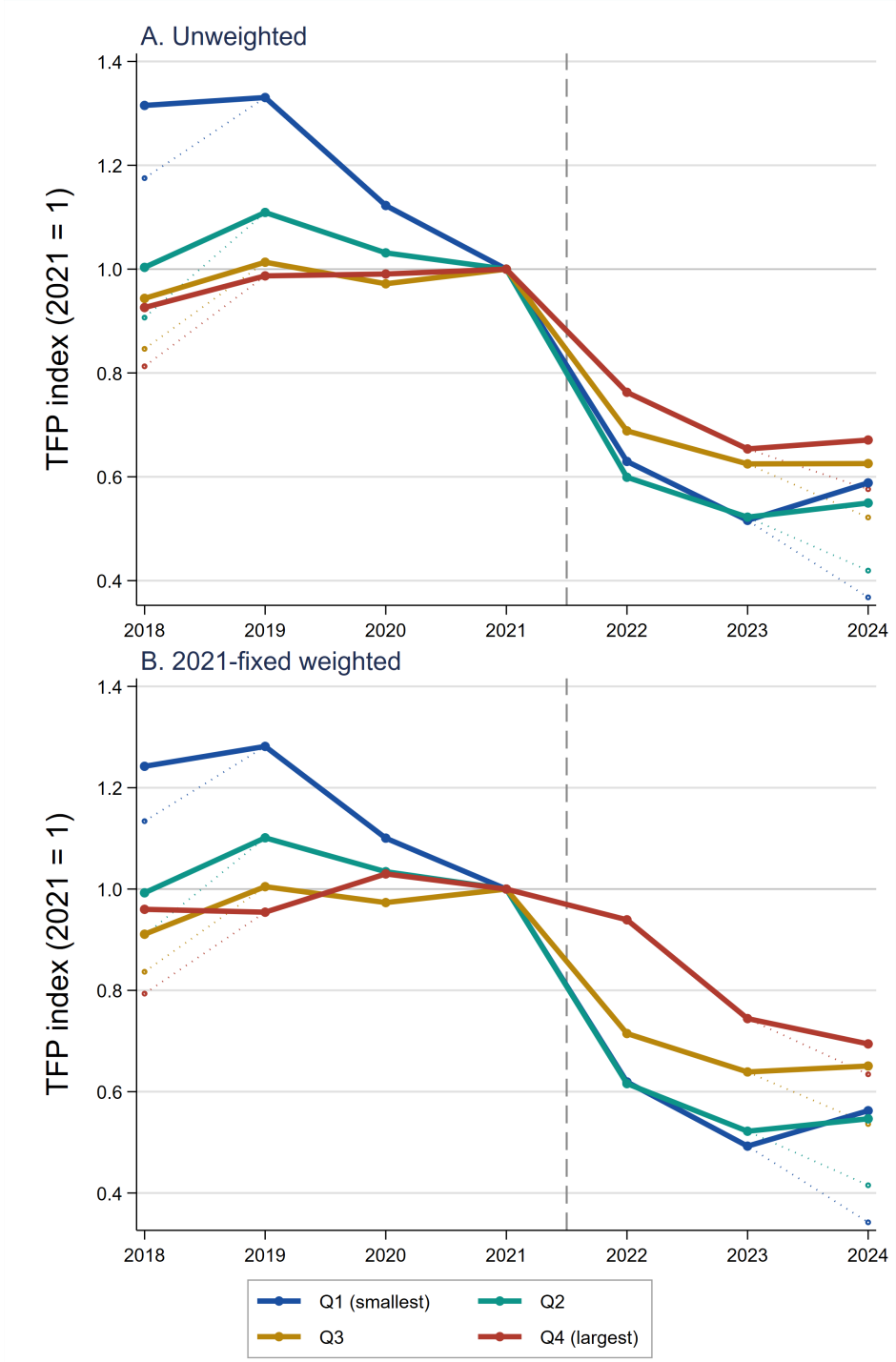
where β is national labor cost share. Poland reported from 2020, Lithuania from 2021, as earlier years lack sufficient data (shortened windows). *Benchmark* = firm-count-weighted average of the benchmark countries present in each year. Donor weights and sample composition: Appendix, Table B5.

Figure D5: National TFP index on the moving-window panel, Ukraine, 2018–2024 (2021 = 1).



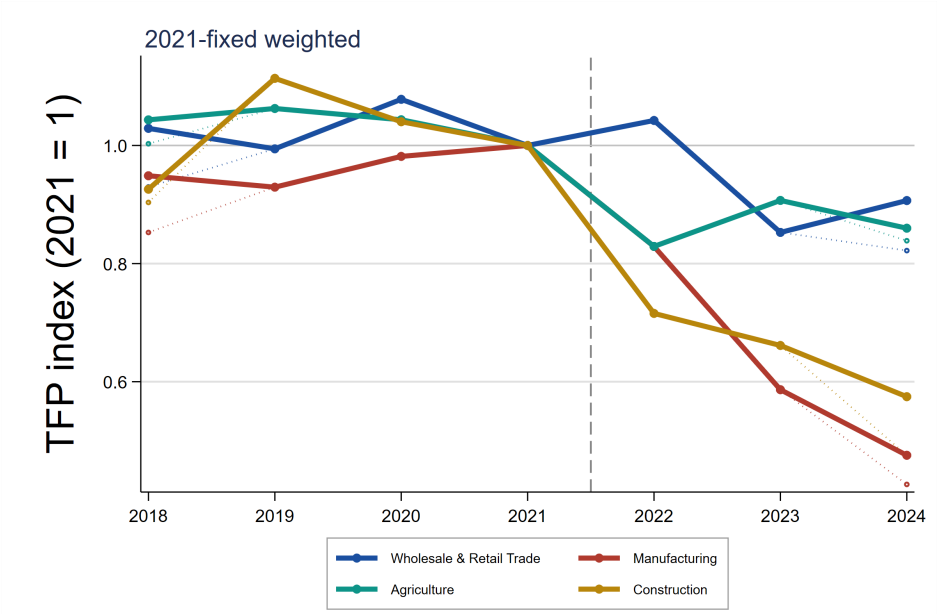
Notes: Equal-weighted, 1% winsorized, edge-corrected. The balanced line is the Ukrainian series of Figure 9 under the unweighted scheme. The moving line keeps a firm-year whenever the firm also reports in the year before and the year after; the firm sets differ and nothing else does. The companion for the dispersion rather than the index is Appendix Figure C15. Sample sizes for the balanced panel: Appendix Table B2.

Figure D6: TFP index by firm-size quartile, Ukraine, 2018–2024



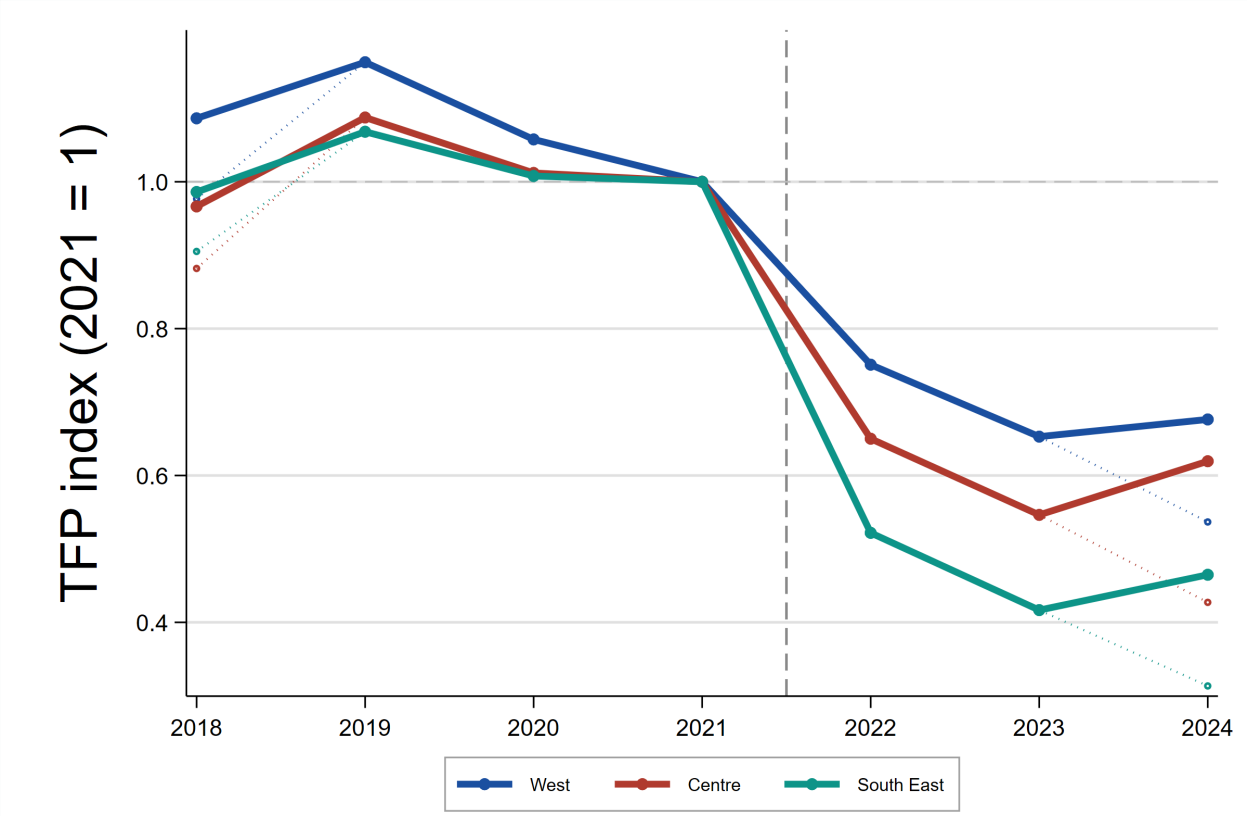
Notes: Normalized to 2021=1. Firm-size quartile assigned once per firm from its own 2021 employees (Q1 = smallest 25%, Q4 = largest 25%); industry_cell × year fixed effects, edge-corrected. 90,984 firms, 196 industry cells. Quartile is fixed at 2021.

Figure D7: National TFP index by sector, Ukraine, 2018–2024, 2021-fixed weighted.



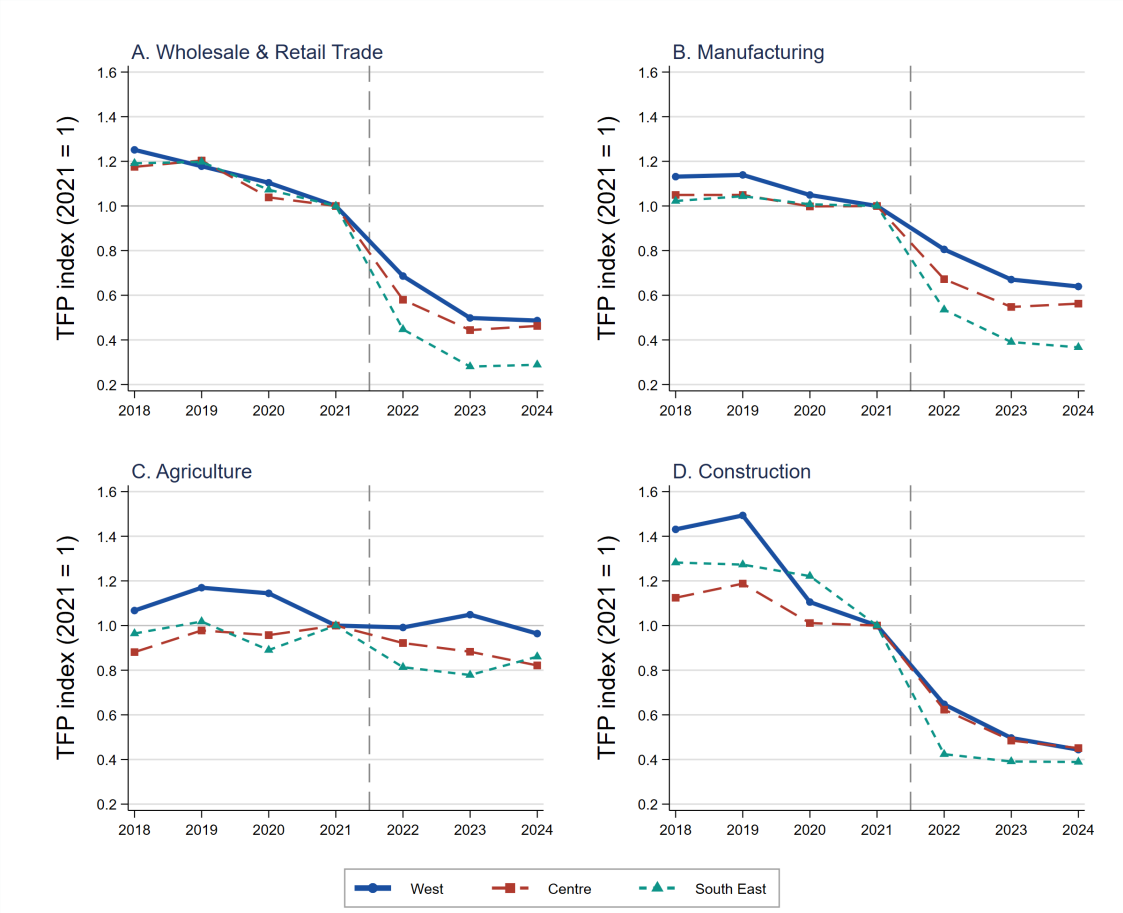
Notes: 1% winsorized, 2021-fixed firm weighted, edge-corrected. Same 4 sectors, same sector-specific industry_cell hierarchy and capital cost share s_K^{rev} as the equal-weighted Figure 10; only the weighting scheme differs.

Figure D8: TFP by macro region, Ukraine, 2018–2024



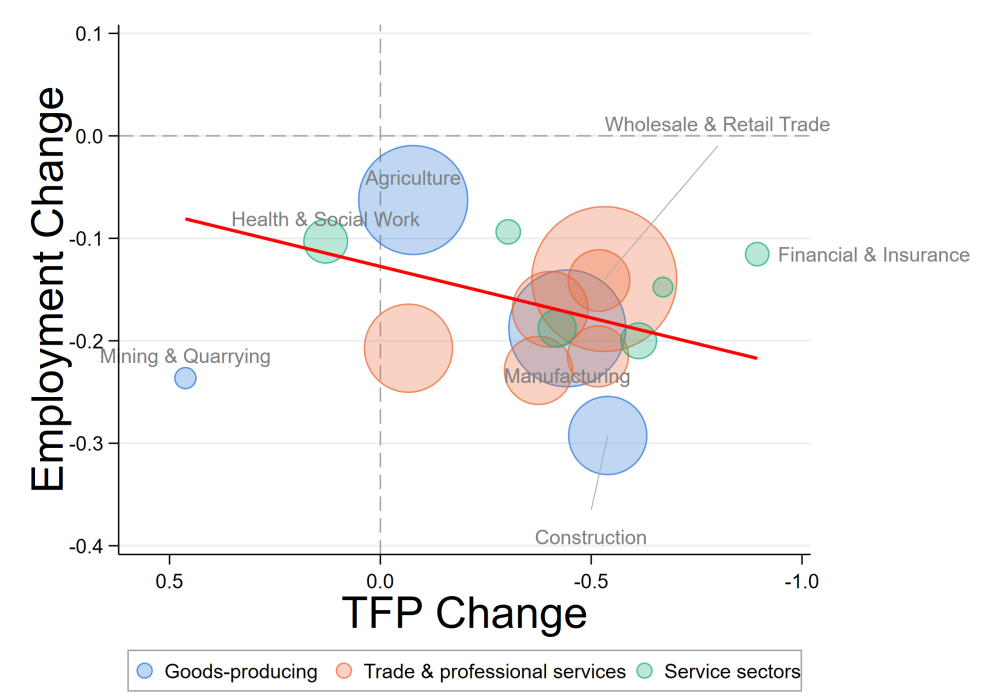
Notes: Equal-weighted, 1% winsorized, edge-corrected. Same national TFP methodology as Figure 9, split by macro region (West/Centre/South East). Each region's series is normalised to its own 2021 value. Of the 90,984-firm base panel: West 24,811 firms; Centre 40,934 firms, of which 22,491 are in Kyiv city; South East 25,238 firms.

Figure D9: TFP by sector and macro region, Ukraine, 2018–2024.



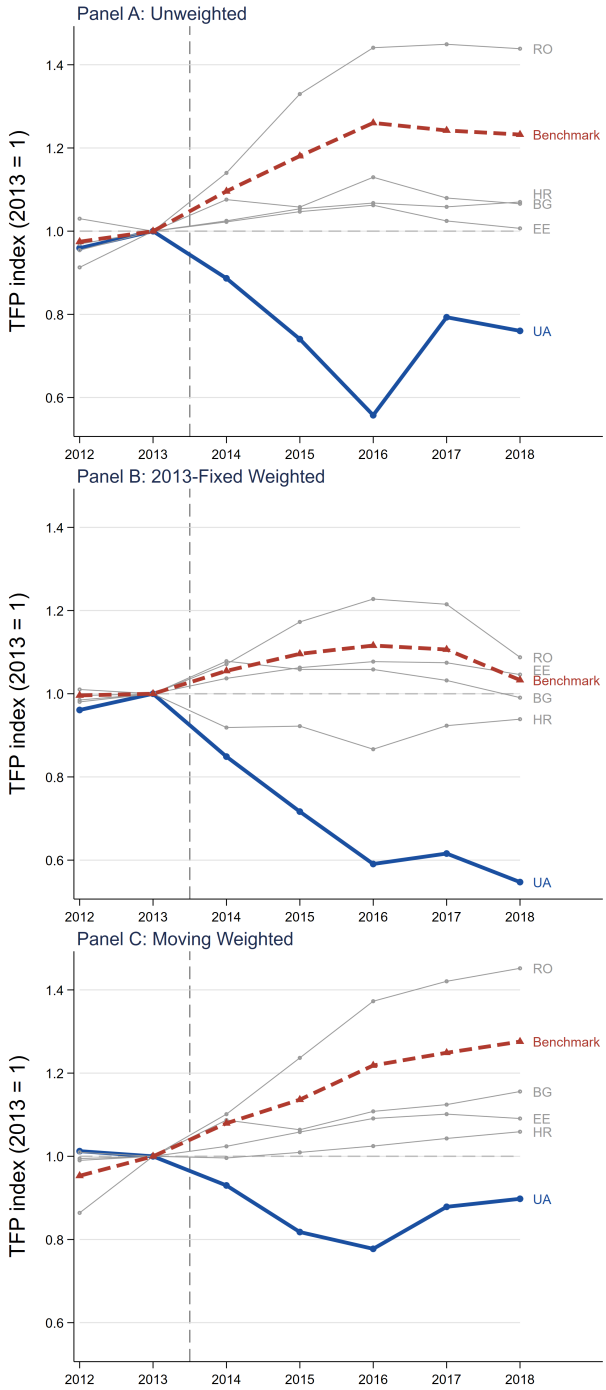
Notes: Equal-weighted, 1% winsorized, edge-corrected. The four sectors of Figure 10, each split by macro region. Each sector carries its own industry cells, its own winsorization and its own cell-by-year fixed effects, and is indexed on its own 2021 value; the four panels share a vertical axis. Firms per panel (West / Centre / South East): retail 5,506 / 10,599 / 6,498; manufacturing 4,712 / 5,701 / 4,282; agriculture 3,870 / 5,144 / 3,765; construction 2,015 / 2,847 / 1,678. Kyiv city is in the Centre. Sample sizes: Appendix Table B2.

Figure D10: Sector TFP change vs. employment change, 2024 vs. 2021.



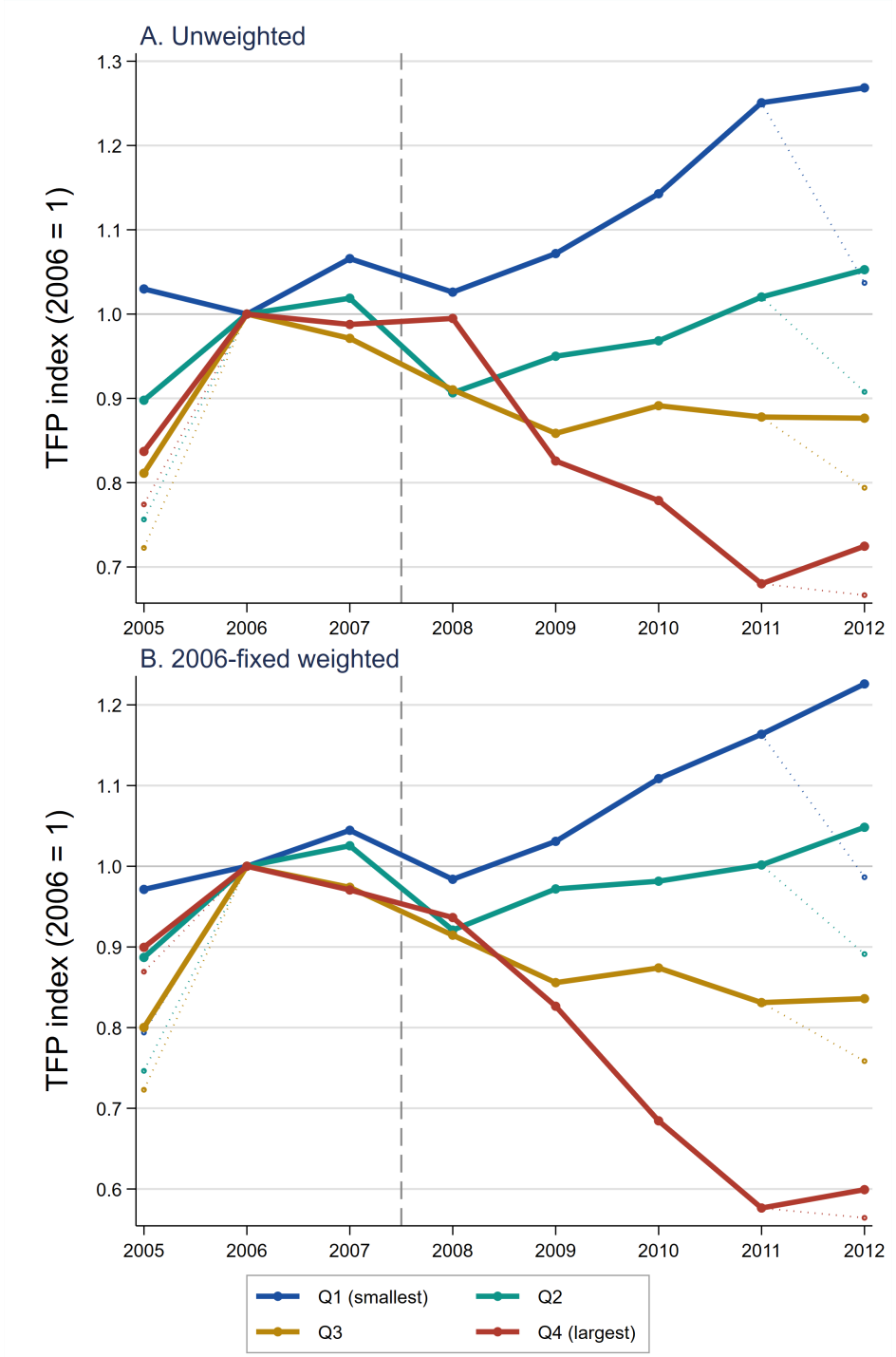
Notes: One bubble per sector (16 sectors), national 2018–2024 balanced panel. Bubble size = each sector's own 2021 firm count.

Figure D11: National TFP index by country, 2012–2018



Notes: 1% winsorized, edge-corrected, base year 2013. Orbis data exist on both sides of this window, so the first year is substituted from the backward helper window and the last year carries the forward helper's change over the final step. *Benchmark* = firm-count-weighted average of the other four countries. Donor weights and sample composition: Appendix, Table B10.

Figure D12: TFP index by firm-size quartile, Ukraine, Global Financial Crisis, 2005–2012



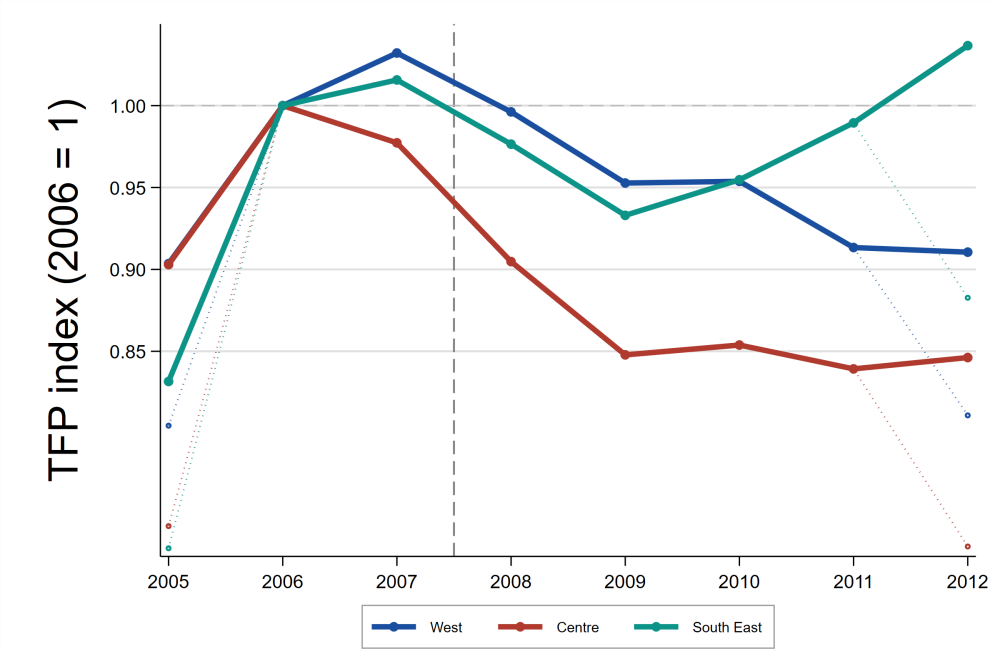
Notes: Normalized to 2006=1. Firm-size quartile assigned once per firm from its own 2006 employees (Q1 = smallest 25%, Q4 = largest 25%); industry_cell × year fixed effects, edge-corrected. 96,214 firms, 198 industry cells. Quartile is fixed at 2006.

Figure D13: TFP index by firm-size quartile, Ukraine, Crimea and the Donbas, 2012–2018



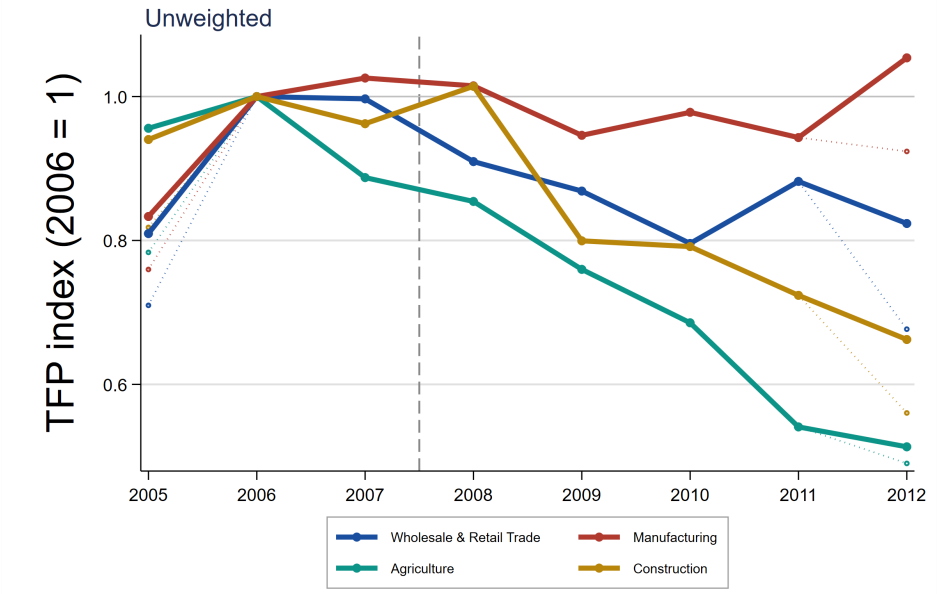
Notes: Normalized to 2013=1. Firm-size quartile assigned once per firm from its own 2013 employees (Q1 = smallest 25%, Q4 = largest 25%); industry_cell × year fixed effects, edge-corrected. 109,006 firms, 210 industry cells. Quartile is fixed at 2013. Firms in raions annexed or occupied in 2014 are excluded.

Figure D14: 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 96,214-firm panel: West 24,386 firms; Centre 32,170 firms, of which 16,924 are in Kyiv city; South East 39,658 firms.

Figure D15: 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 D16: 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.

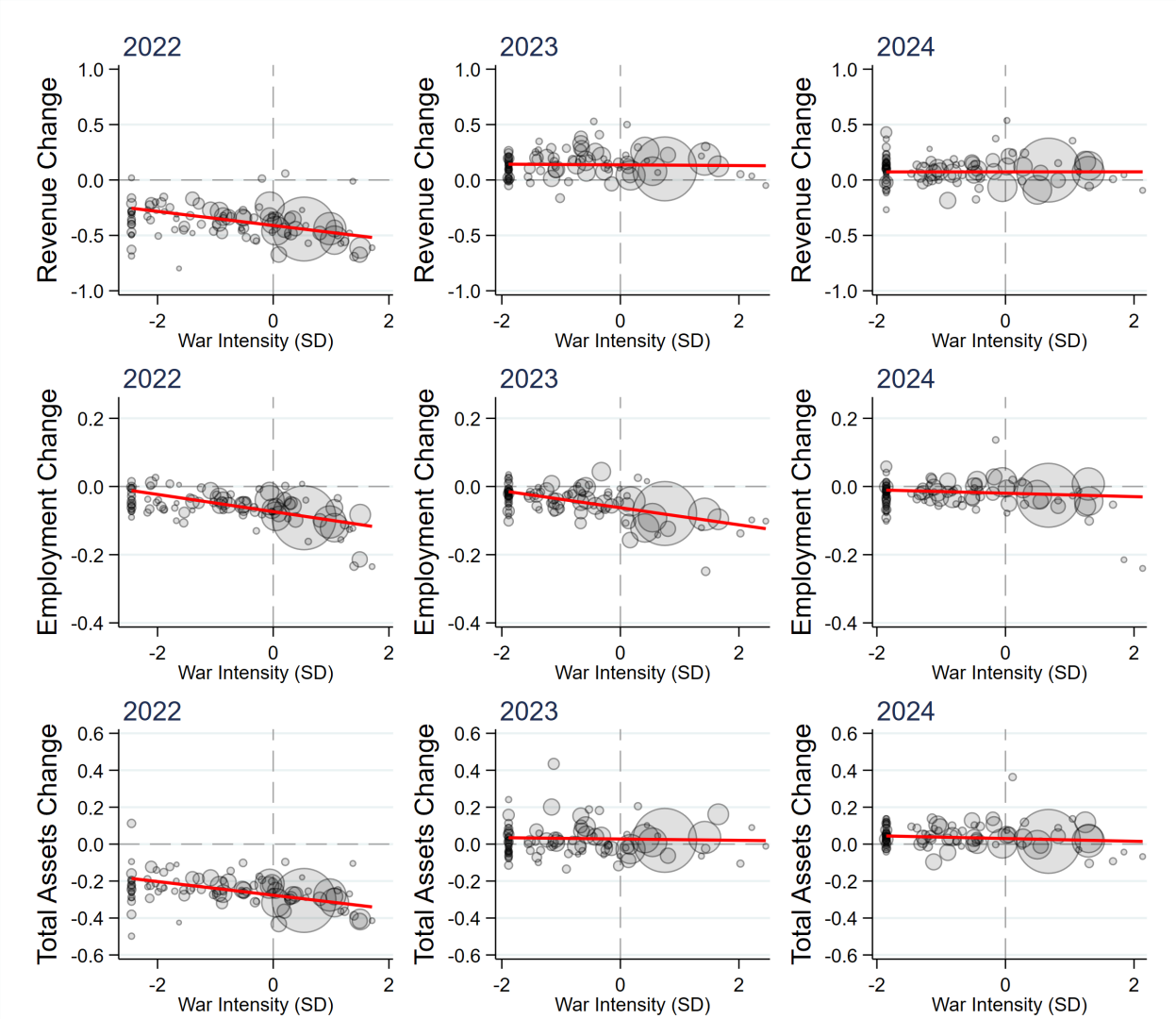
E Appendix E: Additional Subnational Figures

Table E1: Sensitivity of the raion sample to the minimum firm count

Minimum firms	20	50	75	100	150	200
Raions	106	102	100	95	90	78
Firms	108,014	107,857	107,745	107,316	106,684	104,506
Employment	4,229,976	4,224,269	4,220,706	4,204,972	4,182,140	4,079,308
War intensity	-11.992	-12.059	-12.038	-12.025	-11.971	-11.588
Within R^2	0.565	0.578	0.578	0.592	0.598	0.599

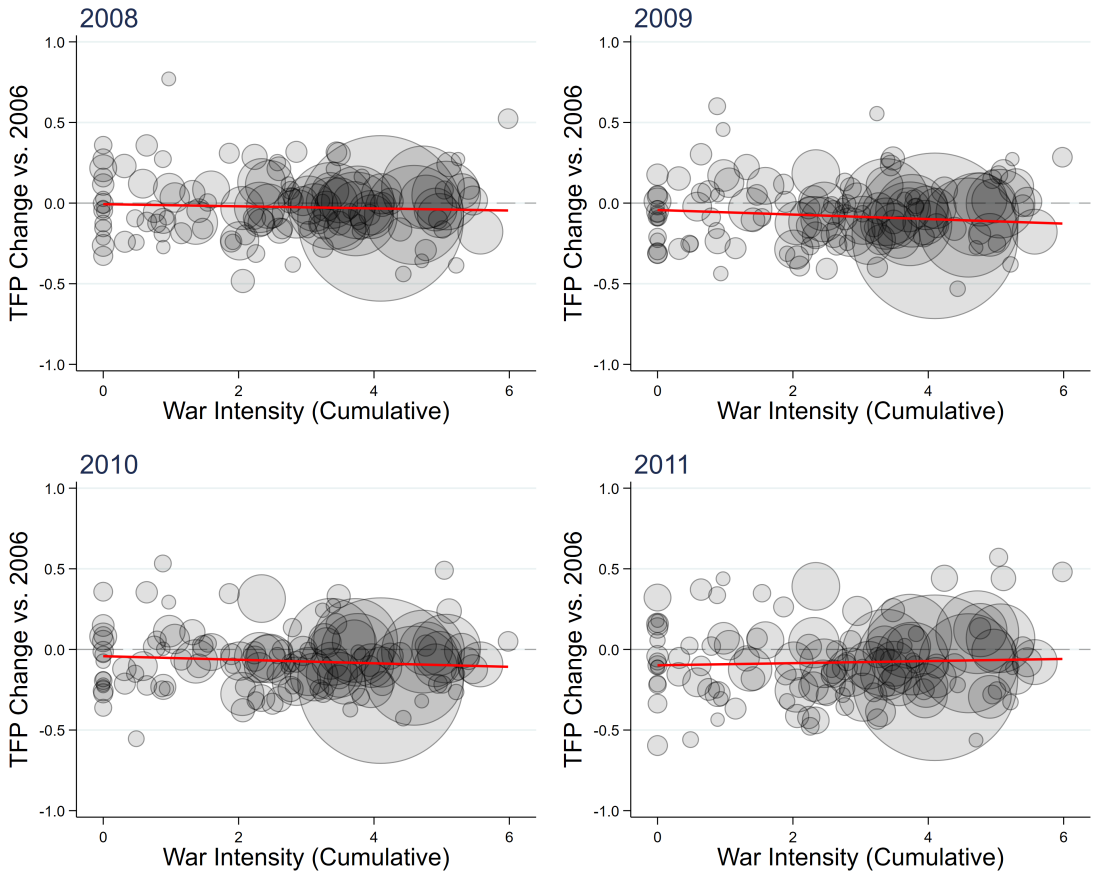
Column (1) of Table 1 re-estimated at each minimum. A raion enters when it has at least the stated number of geolocated firms in every year of the balanced 2020–2024 panel. Year fixed effects, firm-count weights, standard errors clustered by raion. The paper uses 100.

Figure E2: War intensity vs. raion-level year-over-year change: revenue, employment, and total assets



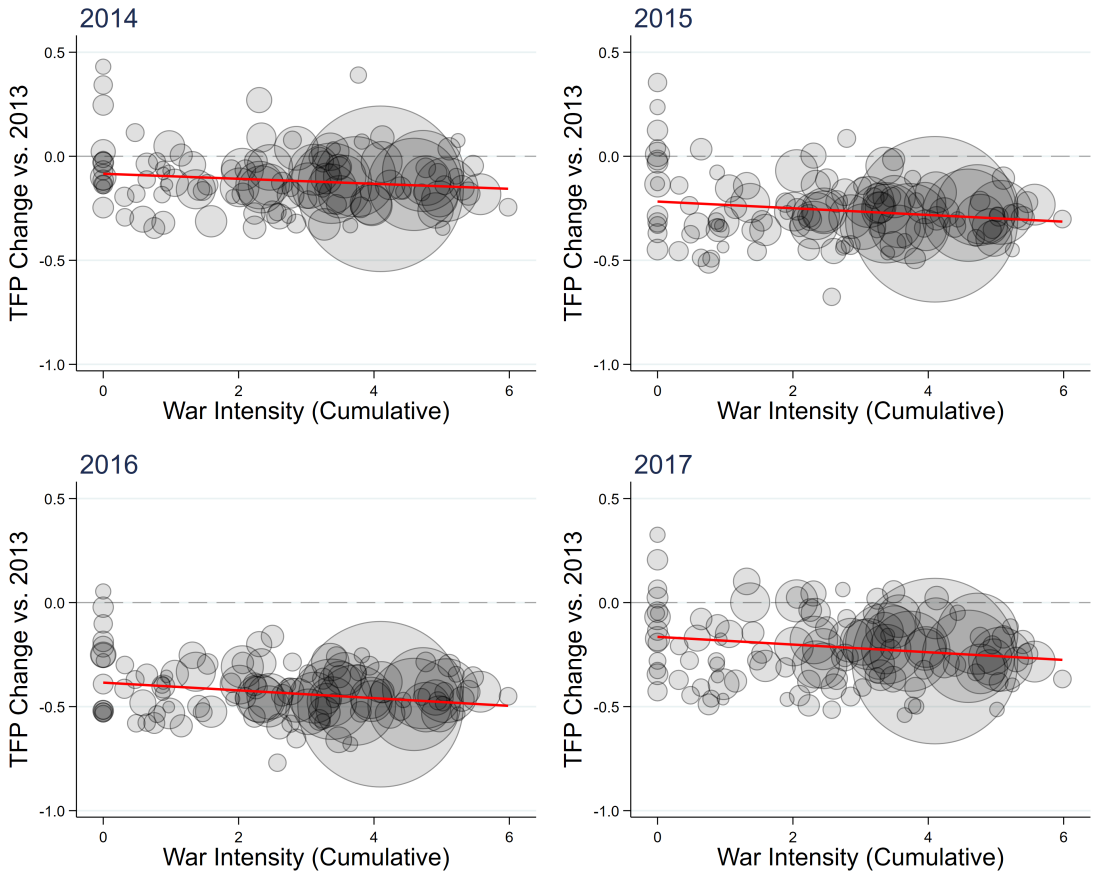
Notes: Same 96-raion balanced-panel sample and war-intensity construction as Figure 13 (that year's flow of property-damage events, standardized within each year). Y-axis: year-on-year % change. Bubble size = each raion's 2021 firm count. Rows 1 and 3 (Revenue, Total Assets) are in constant 2021 prices,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

Figure E3: 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, 120 raions, minimum 100 firms per raion, equal firm weighting within raion, industry-cell × year fixed effects estimated once nationally.

Figure E4: Placebo: post-2022 war intensity and raion-level TFP during the Donbas war



Notes: As Figure E3, for the 2014 episode: balanced 2012–2018 panel, 113 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 Faryna et al. (2022) and Pham, Talavera and Wu (2023).

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, namely `id`, `min_salary`, `curr_id`, `sal_rate`, `date_created`, `loc`, `loc_en`, `esco_title`, `cleaned_title`, `code`.

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 parts 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).

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.