SECTORAL ANALYSIS OF FIRM PRODUCTIVITY IN UKRAINE UNDER COVID-19 AND THE FULL – SCALE WAR

By

Hulko Pavlo

A thesis submitted in partial fulfilment of
the requirements for the degree of
BA in Business Economics, Social Sciences Department

Kyiv School of Economics

2026

Thesis Supervisor: Dmytro Krukovets, PhD

Approved by: ____

Head of the KSE Defense Committee, Professor _________

Date:_______________

TABLE OF CONTENTS

Kyiv School of Economics

Abstract

SECTORAL ANALYSIS OF FIRM PRODUCTIVITY IN UKRAINE UNDER COVID-19 AND THE FULL – SCALE WAR

by
Hulko Pavlo
Thesis Supervisor: Dmytro Krukovets

The aim of this study is to investigate how COVID-19 and the Full-Scale Russian invasion affected the productivity of Ukrainian enterprises. The focus is on inter-industry, inter-regional, and inter-firm heterogeneity. The study is based on a rich dataset with financial reports of Ukrainian enterprises for 2000-2024, which contains information on financial indicators, number of employees, industry affiliation (KVED), and region of the firm's location.

The main indicator of efficiency is labor productivity, calculated as the ratio of enterprise revenue to the number of employees. To assess the effects, panel regression models with fixed effects for years and firms are used, allowing for control of enterprise characteristics and general macroeconomic shocks.

The results show that both the pandemic and the war have a statistically significant and heterogeneous impact on enterprise productivity. COVID-19 affected mainly contact sectors, while the war caused deeper inter-industry and regional asymmetry. Furthermore, the results indicate an increase in productivity dispersion, or heterogeneity in economic outcomes across firms.

The economic findings highlight the value of targeted policies that consider sectoral, regional, and structural characteristics of firms during periods of large-scale shocks.

Chapter 1. Introduction

The existing literature shows that economic shocks have a significantly heterogeneous impact on industries. Studies of the COVID–19 pandemic demonstrate that the consequences vary greatly depending on the sector, firm size, and initial level of productivity (Fernández-Cerezo et al.; European Investment Bank). Contact sectors such as trade, transport and hospitality were most negatively affected by the restrictions on social interaction. Some studies suggest that in some cases productivity may have increased due to structural selection and the exit of less efficient firms from the market (European Central Bank).

Unlike pandemics, war shocks are more complex and accompanied by significant regional asymmetries. Studies on Ukraine show that the impact of war depends largely on the geographical location of enterprises, access to infrastructure and the degree of integration into production chains (World Bank et al.), which creates the prerequisites for greater heterogeneity of economic indicators compared to pandemics.

Despite the large number of studies analyzing individual shocks, comparative analysis of the impact of pandemics and wars at the enterprise level remains limited. This is especially true for countries with transition economies, where structural features can significantly change the mechanisms of business adaptation to crisis.

The aim of this thesis is to assess the impact of the COVID–19 pandemic and the full–scale war on the productivity of Ukrainian enterprises, with an emphasis on intersectoral, interregional and interfirm heterogeneity. To achieve this goal, a large panel dataset of for 2000-2024 is used and fixed-effects models are applied that allow control for constant firm characteristics and general economic trends.

The main contribution of this study is to combine the analysis of two different types of shocks – pandemic and war in a single empirical framework. This allows not only to assess their individual impacts, but also to compare the degree of heterogeneity and structural changes they caused. The structure of the work is as follows. The second section formulates the main research hypotheses. The third section contains a literature review. The fourth section describes the data and research methodology. The fifth section is devoted to the empirical results, and the sixth section is devoted to discussion. The final section contains the main conclusion of the study.

Chapter 2. Hypotheses

Based on theoretical premises and results of previous research, this paper formulates hypotheses regarding the impact of the COVID-19 pandemic and Full-Scale War on the productivity of Ukrainian enterprises. Particular attention is paid to the cross-sectoral, cross-regional, and structural heterogeneity of these effects.

H1 (Sectoral heterogeneity):

The effects of COVID-19 and the full-scale war on labor productivity differ significantly across sectors of the economy, with sector G serving as the baseline category.

H2 (Frontline):

During the full-scale war period, firms located in frontline regions had lower labor productivity than firms located in non-frontline regions, with the magnitude of this productivity gap varying across KVED sectors.

H3 (Regional asymmetry):

The impact of The War on enterprise productivity is more regionally asymmetric compared to the impact of the pandemic.

H4 (Productivity dispersion):

Periods of economic shocks are accompanied by an increase in productivity dispersion across firms.

Chapter 3. Literature Review

Studies of the impact of large economic shocks on business performance show that their consequences are significantly heterogeneous and depend on the characteristics of firms, the sectoral structure of the economy, and the institutional environment. Particular attention in the current literature has been paid to the analysis of the heterogeneity of the effects of the COVID-19 pandemic, as well as, in more recent works, the consequences of military conflicts.

3.1. HETEROGENEITY OF THE EFFECTS OF THE COVID-19 PANDEMIC.

The COVID-19 pandemic has been one of the most studied global economic shocks of the last decade. A large body of empirical literature demonstrates that its impact on firms varied significantly depending on the sector, firm size, and its initial level of productivity.

Fernández-Cerezo et al. show, based on microdata, that less productive and financially vulnerable firms were – more negatively affected during the pandemic. Importantly, the authors find significant variation in the effects even within the same sector and region, highlighting the role of internal heterogeneity within firms.

Similar findings are found in research by the European Investment Bank, which shows that the response of firms to the pandemic depended largely on their productivity, financial resilience, and ability to adapt to changes in demand.

The sectoral dimension is particularly important for understanding the impact of COVID-19. Research shows that contact sectors such as trade, transport and hospitality have been most negatively affected by restrictions on mobility and social interaction. This is because businesses in these sectors are directly dependent on the physical presence of consumers.

At the same time, some work suggests that productivity gains may be possible in some sectors. The European Central Bank notes that the pandemic may have had a “cleansing” effect, with less efficient businesses leaving the market, temporarily increasing average productivity.

Thus, the literature is consistent in concluding that COVID-19 has had a significantly heterogeneous impact, with sectoral structure and business characteristics playing a key role.

3.2. IMPACT OF WAR SHOCKS ON THE ECONOMY AND ENTERPRISES.

Unlike pandemics, war shocks are more complex and combine economic, institutional, and physical channels of impact. They are accompanied by the destruction of infrastructure, disruption of production and logistics chains, displacement of enterprises and labor, as well as a sharp change in demand.

In the context of Ukraine, an important source is the Rapid Damage and Needs Assessment (RDNA) reports. In particular, the latest RDNA5 shows that the impact of war is significantly heterogeneous both regionally and sectorally (World Bank et al.).

According to this report, the greatest economic losses are concentrated in front-line regions, as well as in sectors related to infrastructure, energy, and transport. This leads to significant disparities in enterprise productivity and economic activity.

In addition, war significantly disrupts logistics chains and access to resources, which particularly negatively affects capital-intensive and transport-dependent industries. As a result, the effects of war are not only stronger but also more uneven compared to a pandemic.

3.3. PRODUCTIVITY DISPERSION AND STRUCTURAL CHANGE.

A separate strand of literature focuses on the analysis of changes in the distribution of productivity across enterprises during crises. Studies show that economic shocks are often accompanied by an increase in productivity dispersion, reflecting the uneven adaptation of enterprises to new conditions.

The European Central Bank and the European Investment Bank note that the gap between high- and low-productivity firms increased during the pandemic. This may be due to both processes of “creative destruction” and unequal adaptation capabilities of enterprises.

In wartime, these processes may be even more pronounced due to physical constraints, loss of assets, and regional fragmentation of the economy. The increase in productivity dispersion has important implications for long-term economic development, as it can reflect both efficient reorganization of the economy and inefficient allocation of resources.

3.4. STRUCTURAL ISSUES OF PRODUCTIVITY AND RESOURCE ALLOCATION.

In addition to the short-term effects of economic shocks, it is important to analyze the long-term structural characteristics of the economy. In particular, the efficiency of resource allocation and the level of competition determine the ability of the economy to adapt to crises.

The study by Akcigit et al. shows that even before the start of the full-scale war, the Ukrainian economy was characterized by a low level of business dynamism and limited "creative destruction". The authors find an increase in market concentration and dominance of existing enterprises, which limits competition and inhibits productivity growth.

One of the key findings is the presence of inefficient resource allocation, when less productive enterprises continue to occupy a significant market share. This creates structural imbalances that can increase the heterogeneity of the effects of economic shocks.

Importantly, the authors emphasize that post-war recovery cannot be based on investment alone. Instead, institutional reforms, the development of competition, and the promotion of efficient resource allocation play a key role.

These findings are consistent with the results of this study, which demonstrate significant cross-sectoral and inter-firm heterogeneity in productivity.

3.5. RESEARCH GAP AND CONTRIBUTION OF THE PAPER.

Despite the significant number of studies, there are several important gaps in the literature.

First, most studies focus exclusively on the COVID-19 pandemic, while the analysis of war shocks remains limited. Second, comparative analysis of different types of shocks within a single empirical framework is practically absent. Third, for Ukraine, there is a lack of studies that use large panel data at the enterprise level to analyze productivity.

This paper fills these gaps by combining the analysis of the COVID-19 pandemic and full-scale war in a single empirical model. The use of a detailed panel dataset allows us to assess the heterogeneity of effects across sectors, regions, and enterprise groups, as well as analyze changes in the distribution of productivity.

Chapter 4. Methodology

4.1. DATA SOURCE AND SAMPLE

The study uses a large panel dataset of Ukrainian firms covering the period from 2000 to 2024. The dataset includes firm-level information on financial performance, employment, sector classification (based on KVED-2010), and regional location.

To construct the analytical sample, several filtering steps were applied. Specifically, only observations with non-missing firm identifiers, year, revenue, and employment were retained. Observations with zero or negative revenue were excluded to allow for logarithmic transformations. As a result, the initial dataset consists of the following number of 7.9mn observations and 1.16mn unique firm id, and after cleaning 5.4 mn observations and 0.83 mn unique firm id.

The final dataset covers a period of 25 years and provides sufficient variation to estimate both sectoral and regional heterogeneity with high statistical precision.

4.2 KEY VARIABLES

Key variables were constructed as follows: labor productivity is measured as revenue per employee, and logarithmic transformations (e.g., log revenue, log employment, log productivity) are applied to reduce skewness and allow for interpretation of coefficients in percentage terms.

$\text{Labor Productivity}_{it} = \text{Revenue}_{it} / \text{Staff}_{it}$, where:

- Revenue_{it} – revenue of enterprise (proxied by net income)
- Staff_{it} – the number of staff,

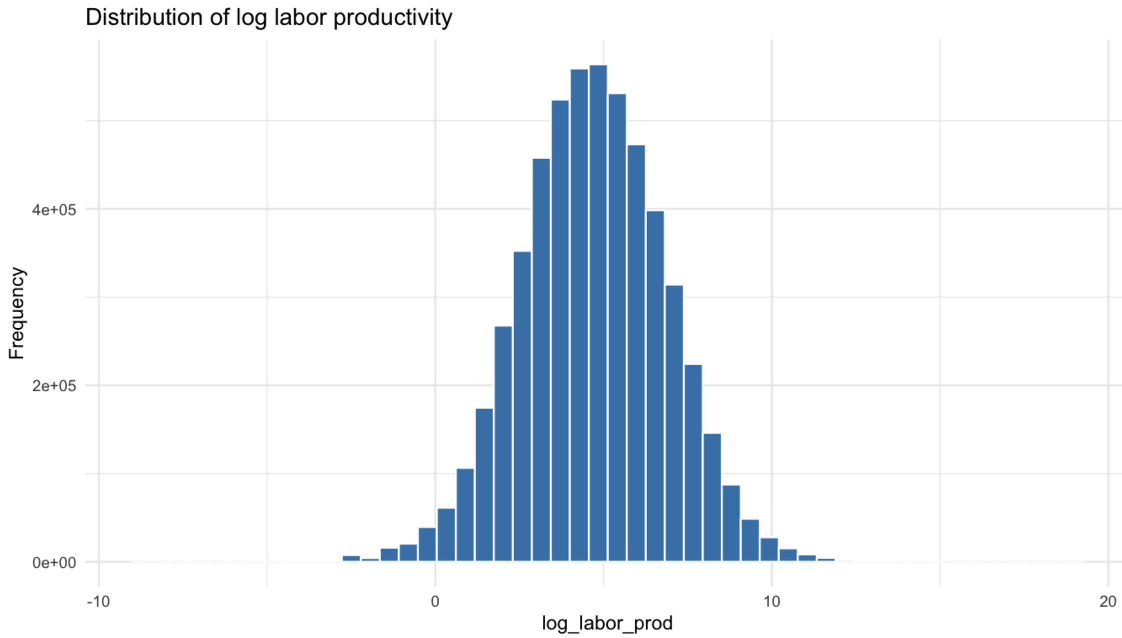

Figure 1. Distribution of log labor productivity:

Source: Own calculation based on data

To reduce the asymmetry of the distribution and stabilize the dispersion, the logarithmic form is used: Log (Labor Productivity $_{it}$) = Log (Revenue $_{it}$ / Staff $_{it}$)

4.3 IDENTIFICATION:

4.3.1 SHOCKS:

To analyze the impact of macroeconomic shocks, two main variables are introduced:

COVID-19 shock:

- $COVID_t = \{\ 1,\ if\ t \in \{2020,\ 2021\}\ 0,\ if\ else$

War shock:

- $WAR_t = \{\ 1,\ if\ t \geq 2022\ 0,\ if\ else$

4.3.2 REGIONS:

- North: Sumy, Chernihiv
- South: Odesa, Mykolaiv, Kherson, Autonomous Republic of Crimea, Sevastopol City

- East: Dnipropetrovsk, Zaporizhzhia, Donetsk, Luhansk, Kharkiv
- West: Volyn, Zakarpattia, Ivano-Frankivsk, Lviv, Ternopil, Rivne, Khmelnytskyi, Chernivtsi
- Center: Vinnytsia, Zhytomyr, Kyiv Oblast, Kyiv City, Kirovohrad, Poltava, Cherkasy

In addition, for the analysis it is necessary to identify regions that have a frontline and those that do not have frontline:

- Frontline regions: Dnipropetrovsk, Zaporizhzhia, Donetsk, Luhansk, Kharkiv, Kherson, Mykolaiv, Odesa, Sumy, Chernihiv
- Non-frontline regions: Volyn, Zakarpattia, Ivano-Frankivsk, Lviv, Rivne, Ternopil, Khmelnytskyi, Chernivtsi, Vinnytsia, Zhytomyr, Kyiv Oblast, Kyiv City, Kirovohrad, Poltava, Cherkasy

4.4 BASIC EMPIRIC MODEL:

$$log\ LP_{it} = \beta_1\left(COVID_t \times Z_i\right) + \beta_2\left(WAR_t \times Z_i\right) + \alpha_i + \delta_t + \varepsilon_{it}$$

where:

- Z_i – company characteristics (sector, region, or group)
- α_i – fixed effect of firm
- δ_t – fixed effect of year

The use of fixed effects allows us to control for immutable characteristics of enterprises and general economic shocks.

4.5 KVED

KVED	Sector Name
A	Agriculture, forestry, fishing
B	Mining and quarrying
C	Manufacturing
D	Electricity, gas, steam, and air conditioning supply
E	Water supply; sewerage, waste management and remediation activities

F	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycles
H	Transportation and storage; Logistics
I	Accommodation and food service activities
J	Information and communication
K	Financial and insurance
L	Real estate
M	Professional, scientific, and technical activities
N	Administrative and support service activities
O	Public administration and defense; compulsory social security
P	Education
Q	Human health and social work activities
R	Arts, entertainment, and recreation
S	Other service activities
T	Activities of household as employers
U	Activities of extraterritorial organization and bodies

Table 1. reports the KVED-2010 sector letters and their corresponding economic activity categories.
Source: based on the official classification of the State Statistics Service of Ukraine.

4.6 HETEROGENEOUS TEST (H1)

To test the hypothesis of intersectoral heterogeneity, the following model is used:

$$logLP_{it} = \sum_{S} \beta_s \left(COVID_t \times Sector_{is}\right) + \sum_{S} \theta_s \left(WAR_t \times Sector_{is}\right) + \alpha_i + \delta_t + \varepsilon_{it}$$

where $Sector_{it}$ –sector indicators (KVED 2010 letter).

The hypothesis is tested using the Wald test for joint significance of the coefficients:

$$H_0: \beta_s = 0 \forall s$$

4.7 FRONTLINE (H2)

To test hypotheses, the sample is restricted to the war period (2022–2024), and the productivity gap between frontline and non-frontline firms is estimated separately for each KVED sector. The model takes the following form:

$$log\ LP_{it} = \sum_{s} \gamma_s \left(Sector_{is} \times Frontline_i \right) + \delta_t + \mu_s + \varepsilon_{it}$$

Where:

$Frontline_i$ is a binary indicator equal to one if $firm_i$ is in a frontline region and zero otherwise,

- δ_t are year fixed effects,
- μ_s are sector (KVED) fixed effects,
- γ_s captures the within-sector, within-year difference in log labor productivity between frontline and non-frontline firms during the war period.

The model is estimated on observations from 2022–2024 only. Firm fixed effects are not included, as the cross-sectional nature of the war-period sample does not permit within-firm identification. The estimates therefore reflect the productivity gap between frontline and non-frontline firms in each sector, encompassing both direct war impact and any pre-existing differences in firm composition across regions. Standard errors are clustered at the firm level.

4.8 REGIONAL ASYMMETRY (H3)

To analyze regional heterogeneous asymmetry, the model is used:

$$logLP_{it} = \sum_{r} \beta_r (COVID_t \times Region_{ir}) + \sum_{r} \theta_r (WAR_t \times Region_{ir}) + \alpha_i + \delta_t + \varepsilon_{it}$$

4.9 DISPERSION ANALYSIS (H4)

To assess changes in the distribution of productivity, an aggregate level is used:

- standard deviation
- interquartile range
- difference between the 90th and 10th percentiles

$$Dispersion_{st} = \beta_1 COVID_t + \beta_2 WAR_t + \alpha_s + \varepsilon_{st}$$

To check heterogeneity, it is necessary to turn to a certain sector that will be tested. For this, sector G (wholesale and retail trade) is used to interpret the coefficients. The choice of this sector is justified for several reasons:

- Firstly, this sector is the largest and most represented in the sample, which ensures the stability of the estimates and reduces the influence of the choice of choice.
- Secondly, the sector is representative of the economy, because of this it has the characteristics of both manufacturing and services and is not too specialized.
- Thirdly, the sector has suffered from both the pandemic and the war, which makes it a natural point of reference for comparing other sectors.

Chapter 5. Results

5.1. SECTORAL HETEROGENEITY (H1)

To test the hypothesis of sectoral heterogeneity in the effects of COVID-19 and the full-scale war on firm-level labor productivity, a two-way fixed-effects model was estimated with interactions between sector dummies (KVED-2010 letter codes) and the respective shock indicators. Sector G (wholesale and retail trade) serves as the baseline category. All reported coefficients therefore reflect the differential effect of a given sector relative to sector G during the shock period. The model is estimated on 5,300,092 firm-year observations covering 692,818 unique firms and 25 years, with standard errors clustered at the firm level. The overall fit of the model is strong, with an adjusted R^2 of 0.73.

During the COVID-19 period (2020–2021), the Wald test for joint significance of all sectoral interaction terms yields a test statistic of 190.8, confirming that the null hypothesis of uniform sectoral effects can be firmly rejected. The direction and magnitude of individual coefficients reveal a clearly differentiated pattern. Agriculture (sector A) exhibits the largest positive differential relative to sector G during the pandemic, with an estimated coefficient of 0.639, suggesting that agricultural firms were substantially more productive than trade firms during this period. Similarly, sector D (electricity supply) and sector Q (human health and social work activities) recorded large positive differentials of 0.519 and 0.441 respectively, both statistically significant at the 0.1% level. These sectors, characterized by inelastic demand and continued essential operation during lockdowns, plausibly maintained or increased measured productivity as less productive firms exited or reduced activity.

By contrast, the accommodation and food services sector (I) recorded a marginally negative and statistically insignificant coefficient of −0.021 during the pandemic, while the recreation and entertainment sector (R) recorded −0.005 ($p = 0.918$). The transport sector (H) also showed no statistically significant differential (0.024, $p = 0.163$). These findings are consistent with the established literature on COVID-19 impacts: contact-intensive and mobility-dependent sectors did not outperform the trade baseline, while essential and non-contact sectors gained relatively. The construction sector (F) recorded a positive differential of 0.186, and information and communication (J) recorded 0.192, consistent with the digital acceleration observed in many transition economies during the pandemic.

The war shock (2022–2024) exhibits even stronger evidence of sectoral heterogeneity. The Wald test for joint nullity of all war interaction terms yields a test statistic of 10,444.8, an order of magnitude larger than the analogous COVID-19 statistic, suggesting that the war induced far greater cross-sectoral divergence in labor productivity outcomes.

Among economically significant sectors, agriculture (A) again records the largest positive differential during war (0.713, $p < 0.001$), followed by sector Q (health) at 0.738, sector D (energy) at 0.647, sector P (education) at 0.414, and real estate activities (L) at 0.409. Sectors that plausibly benefit from wartime demand pressures, government contracts, or reduced competition from exiting firms show the strongest relative productivity gains versus sector G. The logistics and transport sector (H) also records a significant positive differential during war (0.189, $p < 0.001$), in contrast to its near-zero and insignificant estimate during COVID-19, which is consistent with the heightened importance of supply chain management and military logistics under wartime conditions.

Notably, the construction sector (F) exhibits an asymmetric pattern: a positive and significant differential during COVID (0.186) but a considerably smaller one during war (0.103), consistent with the large-scale physical destruction of infrastructure and the resulting disruption to the construction industry in conflict-affected regions. Professional, scientific, and technical activities (M) showed a near-zero and statistically insignificant differential in both periods (0.039 during COVID, 0.017 during war), suggesting relatively uniform performance relative to the trade sector baseline. These findings collectively support the hypothesis H1 that sectoral effects of both shocks are significantly heterogeneous, with the war generating substantially greater cross-sectoral divergence than the pandemic.

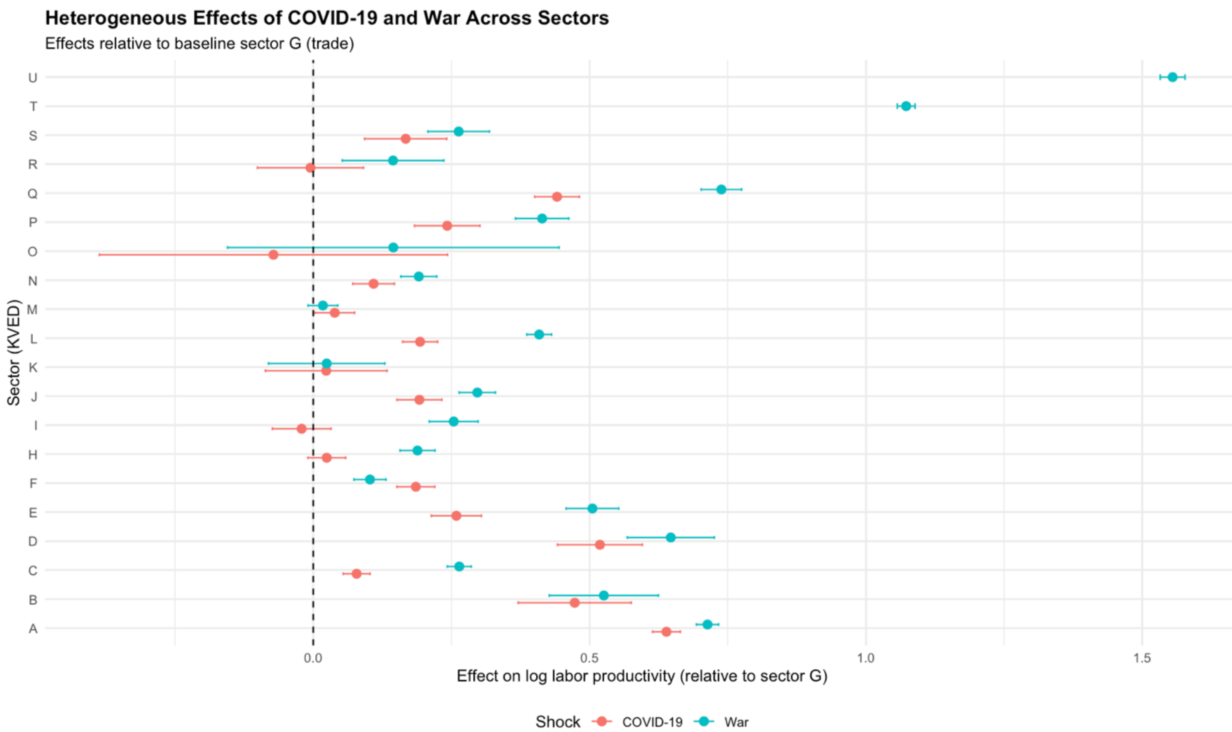

Figure 2. Heterogeneous effects of COVID-19 and War across Sectors.

Source: based on own calculation on data

5.2. FRONTLINE REGIONAL EFFECTS (H2)

The model is estimated on the basis of 669933 observations for the period 2022-2024 and includes year and sector effects of the KVED. The results are presented in the figure. The estimated result is negative in all the sectors indicated, although its magnitude and statistical significance are different. The estimates range from -0.008 in sector E (water supply) to -1.023 in sector O (public administration). The within R^2 is low, as expected, after the model is sold, not explaining the productivity of the overall difference, but also estimating sector-specific differences between frontline regions during the war period.

The largest statistically significant negative gaps are observed in sectors that are likely to be strongly affected by local demand conditions, physical disruptions, or immobility of assets and workers. Accommodation and food services (I) records a gap of −0.363, while recreation and entertainment (R) shows an even larger gap of −0.735. These results are consistent with the interpretation that discretionary consumption and civilian mobility were severely disrupted in frontline areas. Professional, scientific and technical activities (M) also shows a large negative gap of −0.345, which may reflect the displacement of skilled labor and business activity from high-risk regions. Energy (D) records a gap of −0.353, consistent with the vulnerability of infrastructure-intensive sectors to military disruptions. Information and communication (J) records a negative and statistically significant gap of −0.321. Although this sector is often viewed as more geographically flexible due to the possibilities of teleworking, the result suggests that firms located in frontline areas were not completely insulated from the productivity effects of the conflict. Education (P) and health (Q) also show significant negative gaps of −0.281 and −0.278 respectively, indicating that basic social services in frontline regions experienced lower measured labor productivity compared to the same sectors in non-frontline regions.

Other large sectors also show statistically significant negative differences. Trade (G) records a gap of -0.229, transport and logistics (H) -0.201, real estate (L) -0.221, manufacturing (C) -0.108, agriculture (A) -0.136, and construction (F) -0.148. These estimates indicate that the productivity gap on the frontline was not limited to a narrow group of service sectors, but was present across a wide range of economic activities.

The two sectors do not show statistically significant gaps in frontline performance. Sector E, water and waste management, has an estimate close to zero, while sector B, mining, has a negative but statistically insignificant coefficient of −0.157. These results should not necessarily be interpreted as evidence of the absence of military disruption; rather, they may reflect smaller subsample sizes, sector-specific operational characteristics, or higher uncertainty in the estimates

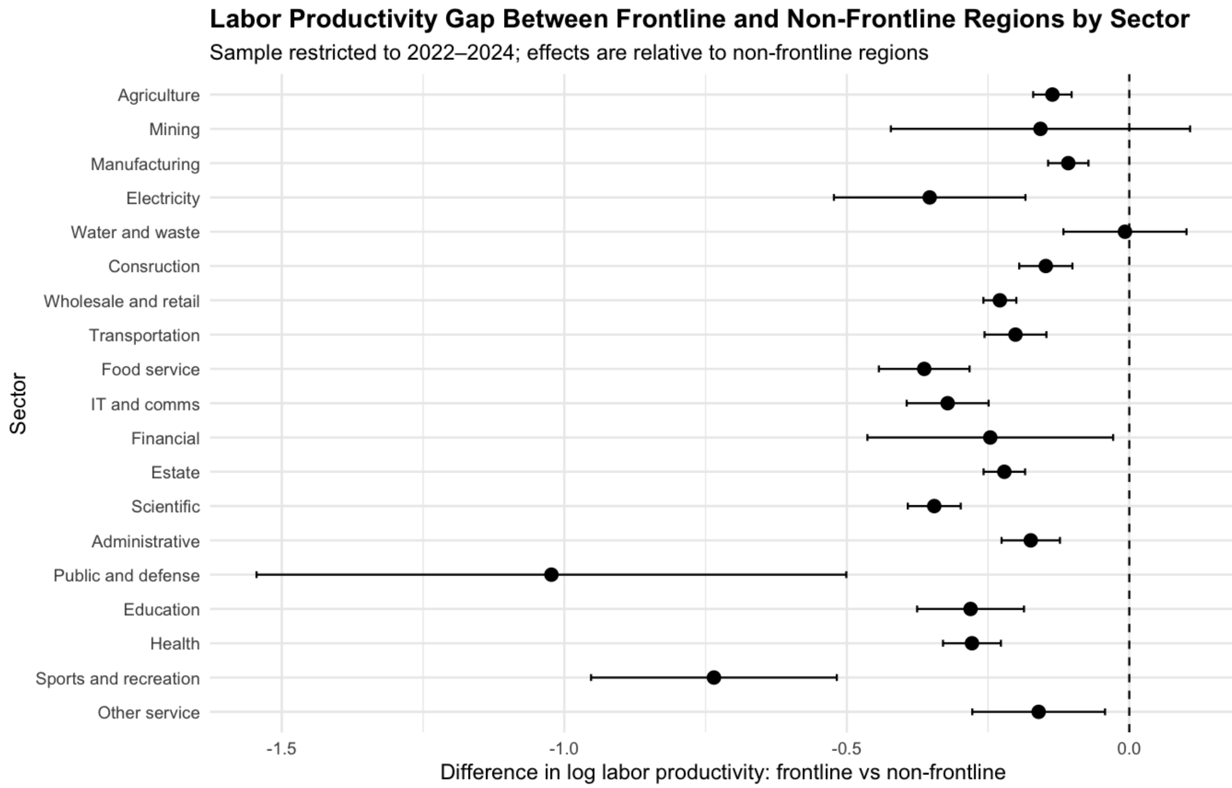

Figure 3. Labor Productivity Gap Between Frontilne and Non-Frontline Regions by Sector

Source: based on own calculation on data

5.3. REGIONAL ASYMMETRY (H3)

To assess whether the war generated greater regional asymmetry in productivity outcomes than the COVID-19 pandemic, a model was estimated with interactions between the shock indicators and five regional groupings: west (baseline), center, north, south, and east. The model is estimated on the full sample of 5,300,092 firm-year observations. Results from the Wald tests confirm that both the pandemic and the war induced statistically significant regional heterogeneity, but the patterns and magnitudes differ substantially.

During the COVID-19 period, regional differentials relative to the western baseline are statistically significant but of moderate magnitude. The center region records a negative differential of −0.074, while the eastern region records −0.089, suggesting that more industrialized and densely populated regions experienced somewhat greater pandemic-related productivity losses relative to the western regions. The north region, by contrast, shows a positive differential of 0.116, a finding that warrants further investigation. The southern region exhibits no statistically significant differential from the west. The relatively modest magnitudes and mixed signs of COVID-era regional differentials are consistent with a shock that, while economically severe, operated primarily through demand-side and behavioral channels rather than through geographically concentrated physical destruction.

The war period presents a strikingly different picture. All regional differentials relative to the western baseline are negative and highly statistically significant, consistent with the expectation that the war's negative productivity impact was most severe in regions geographically closer to the conflict zone. The eastern region records the largest negative differential at −0.421, followed by the south at −0.31, and the center at −0.304. The northern region, which includes Sumy and Chernihiv oblasts directly bordering Russia, records a war-period differential of −0.09. These results confirm hypothesis H3: the war induced a far more pronounced and spatially structured pattern of regional productivity losses compared to the pandemic. The gradient from east to west in the magnitude of war-period differentials reflects the geography of active conflict, infrastructure destruction, and population displacement.

The comparison between the COVID and war panels is particularly informative. Under COVID-19, only two regional differentials are statistically significant (center and east), both below 0.09 in absolute value. Under the war, all four regional differentials are significant and range from 0.090 to 0.421 in absolute value –a fivefold increase in the maximum regional disparity. This asymmetry strongly supports the theoretical argument that war shocks, unlike pandemic shocks, operate through geographically concentrated physical and institutional channels that generate deep regional fragmentation of economic activity.

5.4. PRODUCTIVITY DISPERSION (H4)

To assess whether both shocks were accompanied by an increase in within-sector productivity dispersion – as predicted by hypothesis H4 – two aggregate-level models were estimated using sector-year panel data. The dependent variables are, respectively, the within-sector standard deviation of log labor productivity (sd_log_lp) and the 90th–10th percentile gap (p90_p10_gap). Both models include sector fixed effects and are estimated on 470–473 sector-year observations covering 21 sectors.

The results provide partial support for hypothesis H4. For the standard deviation specification, the war dummy is estimated at 0.164 (SE = 0.057, $p = 0.009$), indicating that the war is associated with a statistically significant increase in within-sector productivity dispersion of approximately 0.164 log points relative to the pre-shock baseline, controlling for sector fixed effects. This finding is consistent with the hypothesis that the war, through its asymmetric impact on firms within the same sector depending on their location, capital exposure, and supply chain integration, leads to a widening of the productivity distribution.

The COVID-19 coefficient in the standard deviation model is positive (0.078) but does not achieve statistical significance at conventional levels ($p = 0.210$). While the point estimate is directionally consistent with hypothesis H4, the lack of significance suggests that the pandemic did not systematically widen within-sector productivity distributions to a statistically detectable degree in this sample. This may reflect the shorter duration of the most severe COVID restrictions, or partial offsetting effects from government support measures that prevented firm exits and compressed the lower tail of the productivity distribution.

For the 90th–10th percentile gap specification, neither the COVID (0.130, $p = 0.365$) nor the war (0.276, $p = 0.123$) coefficients achieve statistical significance, though both point estimates are positive and quantitatively non-trivial. The lack of significance in this specification is likely attributable to the smaller number of observations and the higher within-sector heterogeneity in the percentile gap measure, which reduces statistical power when clustering at the sector level with only 20–21 clusters. Taken together, the dispersion results suggest that the war –but not the pandemic –induced a statistically robust widening of within-sector productivity distributions, providing partial empirical support for hypothesis H4.

Chapter 6. Discussion

The empirical results presented in the preceding chapter allow for a systematic comparative evaluation of the mechanisms through which the COVID-19 pandemic and the full-scale Russian war against Ukraine affected the labor productivity of Ukrainian firms. The analysis reveals that both shocks generated statistically significant and heterogeneous effects on labor productivity, across almost all sectors, but differed substantially in the channels, magnitude, and geographic distribution of those effects.

The finding of strong sectoral heterogeneity under both shocks (H1) is broadly consistent with the existing literature. The results for the COVID-19 period mirror the patterns documented for other European economies: contact-intensive service sectors such as accommodation and food services (I) and entertainment (R) did not outperform the trade baseline, while essential and non-contact sectors – particularly agriculture (A), energy (D), and health (Q) – exhibited significant positive productivity differentials. These patterns are consistent with the demand-side disruptions associated with mobility restrictions and social distancing (Fernández-Cerezo et al.), and with the “cleansing” hypothesis proposed by the European Central Bank, whereby market exits of less productive firms in high-contact sectors temporarily raise average measured productivity within those sectors.

The magnitude of the war's sectoral Wald statistic (10,444.8) compared to that of COVID-19 (190.8) deserves particular attention. This difference of two orders of magnitude reflects not merely a larger average effect of the war, but a fundamentally more dispersed impact across sectors. Under the war, sectors that are dependent on physical infrastructure (construction, logistics), geographically exposed to conflict zones, or reliant on normal supply chain functioning are severely disrupted, while sectors that benefit from wartime demand –defense-adjacent industries, energy, healthcare, agriculture –record large positive productivity differentials. The transport and logistics sector (H) provides a clear illustration of this dynamic: it shows no significant differential during COVID but a large positive differential (0.189) during war, reflecting the critical and expanding role of logistics in supplying both civilian and military needs under wartime conditions.

The frontline results (H2) reveal that the full-scale war imposed a significant and pervasive productivity penalty on firms located in conflict-proximate regions, with all but one sector recording a negative and statistically significant productivity gap relative to non-frontline counterparts during 2022–2024. The near-universality of the negative gap across sectors underscores that frontline exposure constitutes a broad-based economic shock rather than a sector-specific disruption: regardless of industry, firms operating in frontline regions faced systematically lower productivity than comparable firms in non-frontline regions.

The magnitude of the gap varies substantially across sectors, revealing the differential channels through which frontline exposure operates. Sectors dependent on physical consumer presence –accommodation (I, −0.363), entertainment (R, −0.735), education (P, −0.281) –suffered the largest losses, consistent with the collapse of local civilian demand and population displacement. Sectors reliant on skilled, mobile human capital –professional services (M, −0.345), IT (J, −0.321) –were severely affected by the evacuation of qualified workers from frontline cities, a channel distinct from physical destruction but equally damaging to productive capacity. Energy (D, −0.353) reflects infrastructure targeting, while manufacturing (C,

−0.108) and logistics (H, −0.201) reflect supply chain disruption and physical damage to production and transport assets.

The exception of water supply (E) is a policy-relevant positive finding: it demonstrates that regulatory obligations combined with targeted state support can effectively maintain the measured productivity of essential infrastructure providers even under active conflict conditions. This finding suggests that the design of wartime economic policy –and by extension reconstruction policy –must differentiate between sectors where state intervention can neutralize the productivity impact of conflict exposure and sectors where market mechanisms and physical constraints make such insulation infeasible. The substantial frontline penalty in IT (J) also challenges the narrative of the sector's geographic resilience and warrants careful

These findings are consistent with the World Bank RDNA5 report (World Bank), which documents that economic losses are disproportionately concentrated in front-line and heavily contested regions, and with the broader literature on the economic consequences of war, which consistently finds that geographic proximity to conflict is one of the strongest predictors of economic disruption (see, e.g., the discussion of regional heterogeneity in Akcigit et al., and the RDNA series more broadly). The magnitude of the estimated effect –14 log points –is substantial and suggests that regional targeting of reconstruction and productivity support policies will be essential in the post-war recovery period.

The regional asymmetry results (H3) further reinforce this interpretation. While COVID-19 generated relatively modest and geographically diffuse productivity differentials (maximum absolute differential of 0.089 across regions), the war produced a strong spatial gradient from west to east, with the eastern region recording a differential of −0.421 –approximately five times the maximum regional COVID effect. This gradient directly maps onto the geography of active conflict and infrastructure destruction, with the most affected regions being those closest to, or directly experiencing, military operations. The finding that even the western and central regions –far from the front –recorded significant war–period productivity losses (e.g., center: −0.304) highlights the economy–wide transmission channels of the war, including energy grid disruptions, refugee displacement, and aggregate demand compression, which extended well beyond the immediate conflict zone.

The comparison between COVID and war regional effects has important implications for the analysis of shock heterogeneity more broadly. It suggests that the assumption of spatially uniform macroeconomic shocks – which underlies many aggregate analyses of pandemic impacts – is severely violated in the case of war. Models that treat the war as a common shock to all Ukrainian firms, absent regional controls, will substantially underestimate the heterogeneity of its effects and produce biased estimates of average impacts.

The dispersion results (H4) provide additional evidence consistent with the war generating more structural and lasting disruptions to the firm productivity distribution than the pandemic. The statistically significant increase in within-sector standard deviation of log productivity during the war (0.164, $p = 0.009$) –compared to a positive but insignificant COVID effect (0.078, $p = 0.210$) –suggests that the war widened the gap between high- and low-productivity firms within sectors. This is consistent with the hypothesis that the war's asymmetric geographic impact creates sharp intra-sector divergence: firms in the same industry but different locations experience fundamentally different productivity trajectories, depending on their proximity to the front, access to infrastructure, and ability to relocate operations.

The non-significant result for the percentile gap (p90–p10) under both shocks may reflect low statistical power due to the small number of sector clusters, rather than a genuine absence of effect. The point estimates (0.130 for COVID, 0.276 for war) are quantitatively meaningful and directionally consistent with the standard deviation results. Future work with richer data could employ finer sector disaggregation to increase the number of clusters and improve the precision of these estimates.

More broadly, the findings of this study are consistent with the structural analysis of the Ukrainian economy by Akcigit et al, who document significant pre-war resource misallocation and low business dynamism. The shocks analyzed here may interact with these pre-existing structural features in important ways: in an economy with limited competitive pressure and high incumbent persistence, the "cleansing" effects of shocks may be muted, while the negative effects on incumbent firms that lack adaptive capacity may be amplified. Post-war recovery policies must therefore address not only direct war damages but also the structural barriers to productivity-enhancing reallocation identified in the pre-war literature.

Chapter 7. Conclusion

This thesis investigates the differential impact of the COVID-19 pandemic and the full-scale Russian war against Ukraine on the productivity of Ukrainian firms, using a large, unbalanced panel dataset covering approximately 5.4 million firm-year observations from 2000 to 2024. Employing two-way fixed-effects models with firm and year fixed effects and standard errors clustered at the firm level, the study estimates the heterogeneous effects of both shocks across sectors, regions, and the within-sector productivity distribution.

Four main hypotheses are tested. The evidence strongly supports H1: both the COVID-19 pandemic and the full-scale war generated statistically significant and highly heterogeneous effects on labor productivity across economic sectors. The Wald statistics for joint sectoral significance are 190.8 (COVID) and 10,444.8 (war), with the latter being approximately 55 times larger, indicating that the war produced fundamentally greater cross-sectoral divergence in productivity outcomes. Essential and non-contact sectors – particularly agriculture, energy, and healthcare –outperformed the trade baseline under both shocks, while contact-intensive and infrastructure-dependent sectors faced greater disruptions.

H2 is supported: firms located in frontline regions recorded statistically significant and economically large productivity gaps relative to non−frontline firms across virtually all KVED sectors during the war period (2022–2024). The magnitude of the gap ranges from near zero in water supply (E) to −0.735 in recreation (R) and −1.023 in public administration (O), with large gaps of 0.28–0.36 log points in accommodation, energy, professional services, and information technology. The near−universal negativity of the frontline gap across sectors, combined with substantial cross−sector variation in magnitude, establishes that frontline exposure is a broad−based but heterogeneous shock: it operates through multiple channels –demand collapse, labor displacement, infrastructure targeting, and supply chain disruption –whose relative importance differs by sector. These findings argue for reconstruction policies that are targeted at the intersection of geographic exposure and sectoral vulnerability, rather than treating either dimension in isolation.

H3 is also supported: the war generated a far more pronounced and geographically structured pattern of regional productivity losses compared to the pandemic. War-period regional differentials range from −0.090 (north) to −0.421 (east) relative to the western baseline, following the spatial gradient of active conflict, while COVID-period regional differentials are modest and do not exceed 0.089 in absolute value. This finding underscores the importance of treating war shocks as spatially heterogeneous rather than uniform macroeconomic events.

H4 receives partial support. The war is associated with a statistically significant increase in within-sector productivity dispersion (coefficient on standard deviation: 0.164, $p = 0.009$), while the COVID-19 effect is positive but statistically insignificant (0.078, $p = 0.210$). The percentile gap measure does not yield statistically significant results for either shock, likely reflecting limited statistical power due to the small number of sector clusters.

Taken together, the findings of this study contribute to the literature on firm-level responses to large economic shocks in several important ways. First, they provide one of the first systematic, enterprise-level comparative analyses of pandemic and war shocks within a single empirical framework, enabling direct comparison of the degree and nature of heterogeneity across shock types. Second, they document the significant regional fragmentation of the Ukrainian economy under wartime conditions, highlighting the critical role of geographic proximity to conflict as a determinant of firm-level productivity. Third, they establish that the war –unlike the pandemic –induced a statistically robust widening of the within-sector productivity distribution, with implications for resource allocation and competitive dynamics in the post-war economy.

The final results have clear policy implications. Reconstruction that ignores the significant differences in the impact of the war across sectors, regions, and firms risks misallocating already limited resources at a time when Ukraine can least afford them. Rebuilding physical infrastructure, targeted support for firms in the hardest-hit regions, and reallocating resources away from unviable and uncompetitive firms are essential. These steps will lead to a sustainable recovery in productivity only if they are accompanied by the institutional reforms required by Ukraine's EU accession process. The study's findings suggest that the problems existed before the war and were exacerbated by it. Addressing them is not a long-term aspiration, but a priority short-term policy objective.

This study is subject to several limitations. First, labor productivity is measured as revenue per employee, using net income as a proxy for revenue due to data constraints. This approximation introduces measurement error, particularly for firms in sectors with high cost shares. Second, the fixed-effects estimator controls for time-invariant firm heterogeneity but does not address potential endogeneity arising from time-varying unobserved determinants of productivity that are correlated with shock exposure. Third, the dataset does not include information on capital stocks for all firms, limiting the analysis of capital-adjusted productivity measures. Future research could address these limitations by incorporating additional financial indicators, employing instrumental variable strategies to sharpen identification, and extending the analysis to explicitly model firm entry and exit dynamics, which are likely to be important channels through which both shocks affected the measured productivity distribution.

The policy implication is that Ukraine's post-war recovery should not be designed as a uniform national program. Since the war affected firms differently across sectors, regions, and productivity groups, reconstruction policy should be targeted. Priority should be given to firms and sectors in frontline and heavily affected regions, especially where productivity losses are linked to infrastructure damage, labor displacement, or disrupted logistics. At the same time, support should be combined with institutional reforms and better resource allocation, so that recovery increases productivity rather than only compensating losses.

Works Cited

Akcigit, Ufuk, et al. *Engineering Ukraine's Wirtschaftswunder*. World Bank, 2025, https://documents.worldbank.org/en/publication/documents-reports/documentdetail/099436507282523261.

European Central Bank. "The Impact of COVID-19 on Productivity." *ECB Economic Bulletin*, 2021, https://www.ecb.europa.eu/press/economic-bulletin/focus/2021/html/ecb.ebbox202107_04~c9050e1d70.en.html.

European Investment Bank. *Productivity and Responses to the COVID-19 Pandemic*. European Investment Bank, 2022, https://www.eib.org/files/publications/economics_working_paper_2022_09_en.pdf.

Fernández-Cerezo, Alejandro, et al. *Firm-Level Heterogeneity in the Impact of the COVID-19 Pandemic*. Banco de España, 2021, https://www.bde.es/f/webpi/SES/staff/fernandezalejandro/Files/FirmlevelheterogeneityinheimpactoftheCOVID19pandemic.pdf.

State Statistics Service of Ukraine. *Classification of Economic Activities (KVED-2010)*. State Statistics Service of Ukraine, https://kved.ukrstat.gov.ua/KVED2010/kv10_i.html. Accessed 6 June 2026.

World Bank, et al. *Ukraine Fifth Rapid Damage and Needs Assessment (RDNA5): February 2022–December 2025*. United Nations Development Programme, 2026, https://www.undp.org/ukraine/publications/ukraine-fifth-rapid-damage-and-needs-assessment-rdna5-february-2022-december-2025.

Appendix A.

Sectoral Heterogeneity in Labor Productivity During COVID-19 and the Full-Scale War

Table A1. Fixed-Effects Estimates of Sectoral Differences in Labor Productivity During COVID-19 and the Full-Scale War

Sector	COVID-19 coefficient	War coefficient
A	0.639***	0.713***
B	0.473***	0.526***
C	0.078***	0.264***
D	0.519***	0.647***
E	0.259***	0.505***
F	0.186***	0.103***
H	0.024	0.189***
I	-0.021	0.254***
J	0.192***	0.297***
K	0.023	0.024
L	0.193***	0.409***
M	0.039*	0.017
N	0.109***	0.191***

Sector	COVID-19 coefficient	War coefficient
O	-0.072	0.145
P	0.242***	0.414***
Q	0.441***	0.738***
R	-0.005	0.144**
S	0.167***	0.263***
T	—	1.073***
U	—	1.555***

Model summary:

Dependent variable: log labor productivity.

Observations: 5,300,092.

Firm fixed effects: Yes.

Year fixed effects: Yes.

Standard errors: Clustered at the firm level.

Adjusted R^2: 0.730.

Within R^2: 0.004.

RMSE: 1.031.

Wald test

Wald test, H0: joint nullity of kved_2010_letter::A:covid, kved_2010_letter::B:covid, kved_2010_letter::C:covid, kved_2010_letter::D:covid, kved_2010_letter::E:covid, kved_2010_letter::F:covid and 12 others

stat = 190.8, p-value < 2.2e-16, on 18 and 4,607,212 DoF, VCOV: Clustered (firm_id).

Wald test, H0: joint nullity of kved_2010_letter::A:war, kved_2010_letter::B:war, kved_2010_letter::C:war, kved_2010_letter::D:war, kved_2010_letter::E:war, kved_2010_letter::F:war and 14 others

stat = 10,444.8, p-value < 2.2e-16, on 20 and 4,607,212 DoF, VCOV: Clustered (firm_id).

Notes:

*The coefficients report sector-specific differences in log labor productivity relative to the baseline sector G. Statistical significance levels are indicated as follows: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are clustered at the firm level.*

Appendix B.

Labor Productivity Gap Between Frontline and Non-Frontline Regions by Sector

Table B1. Sector-Specific Frontline Gap in Labor Productivity, 2022–2024

Sector	Coefficient	Std. error	t-value	p-value
A	-0.136	0.017	-7.844	<0.001***
B	-0.157	0.135	-1.163	0.245
C	-0.108	0.018	-5.931	<0.001***
D	-0.353	0.086	-4.086	<0.001***
E	-0.008	0.056	-0.137	0.891
F	-0.148	0.024	-6.151	<0.001***
G	-0.229	0.015	-15.401	<0.001***
H	-0.201	0.028	-7.210	<0.001***
I	-0.363	0.041	-8.866	<0.001***
J	-0.321	0.037	-8.692	<0.001***

K	-0.246	0.111	-2.218	0.027*
L	-0.221	0.019	-11.795	<0.001***
M	-0.345	0.024	-14.446	<0.001***
N	-0.174	0.026	-6.614	<0.001***
O	-1.023	0.266	-3.841	<0.001***
P	-0.281	0.048	-5.823	<0.001***
Q	-0.278	0.026	-10.651	<0.001***
R	-0.735	0.111	-6.625	<0.001***
S	-0.160	0.060	-2.675	0.007**

Model summary

Dependent variable: log labor productivity.

Sample period: 2022–2024.

Observations: 669,933.

Fixed effects: year and sector.

Standard errors: clustered at the firm level.

RMSE: 1.775.

Adjusted R^2: 0.100.

Within R^2: 0.003.

Notes:

The table reports sector-specific differences in log labor productivity between firms located in frontline regions and firms located in non-frontline regions. Negative coefficients indicate lower labor productivity among firms in frontline regions within the corresponding sector. Statistical significance levels are indicated as follows: $* p < 0.05$, $** p < 0.01$, $*** p < 0.001$.