War and Corporate Investment

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Abstract

Armed conflicts represent an extreme form of geopolitical risk that goes beyond uncertainty by directly destroying facilities, displacing workers, and shutting operations. Using Russia's 2022 invasion of Ukraine as a natural experiment, we examine how multinational firms respond to operational exposure to conflict. We construct a novel firm-level conflict exposure index that combines regional vulnerability to conflict with real-time military activity, weighted by each firm's pre-invasion workforce distribution across Ukrainian regions. Firms with higher conflict exposure lost significant market value and reduced capital expenditures following the invasion, yet simultaneously increased R&D spending. This compositional shift contradicts standard models predicting uniform investment cuts under extreme uncertainty. U.S. firms cut capital spending more sharply but increased R&D more aggressively than non-U.S. counterparts facing identical conflict exposure. Our findings reveal that extreme geopolitical shocks trigger strategic reallocations from physical capital toward innovation rather than uniformly depressing investment, with effects propagating through firms' operational networks.

Keywords: Geopolitical Risk, Corporate Investment, R&D Spending, Firm Valuation

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"The Russian invasion of Ukraine has put an end to the globalization we have experienced over the last three decades."

— Larry Fink, CEO, BlackRock, March 24, 2022.

"The war could severely destabilize the global economy, causing both short-term and long-term disruptions...a sudden escalation could severely destabilize the global economy, cause a stock market crash, and accelerate deglobalization."

— Kenneth Rogoff, Professor of Economics, Harvard University, January 31, 2023.

I Introduction

Geopolitical risk has become a defining economic challenge in the twenty-first century, with armed conflicts representing its most severe manifestation. The ongoing wars in Ukraine and the Middle East demonstrate how military confrontations pose unique threats to international commerce that far exceed the disruptions caused by trade tensions or policy disputes. While firms can often manage conventional geopolitical challenges such as the U.S.-China trade war through hedging and strategic adaptation, armed conflicts directly imperil physical infrastructure, displace workers, and disrupt business operations. The resulting fractures to global supply chains, spikes in commodity prices, and collapse of cross-border investment flows extend well beyond conflict zones through the network of multinational firms that account for over two-thirds of world trade (WTO, 2024). For these firms, investment decisions become especially consequential during armed conflicts because such commitments involve substantial capital allocation and long-term planning horizons, making them acutely sensitive to the extreme uncertainty and physical risks that warfare creates. Understanding how firms navigate investment under these conditions is therefore essential for policymakers seeking to maintain economic stability and for business leaders managing operations in an increasingly volatile world.

A substantial body of research demonstrates that policy uncertainty (Baker, Bloom, and Davis, 2016; Gulen and Ion, 2016), election cycles (Julio and Yook, 2012), and geopolitical risk (Caldara and Iacoviello, 2022; Hassan et al., 2019) reduce corporate investment. These studies developed innovative measures of geopolitical risk from news articles and earnings call transcripts, capturing perceived threats through media coverage and managerial discussions. Country-level news-based indices provide valuable aggregate measures of geopolitical uncertainty, while firm-level text-based measures from earnings calls reveal how managers perceive and communicate risks to investors. Building on these insights, we examine whether armed conflicts require additional considerations given their distinctive characteristics. Unlike the diffuse uncertainties created by policy disputes or trade tensions examined in prior work, armed conflicts generate localized operational disruptions with clear geographic boundaries, allowing us to identify which firms face direct exposure and measure the intensity of that exposure. This geographic specificity enables us to connect localized operational disruptions to firm-wide investment decisions. Firms with subsidiaries in conflict zones may adjust their global capital allocation in response to these exposures, reducing overall investment even in unaffected regions as they reassess risk across their entire portfolio. By directly measuring operational exposure to armed conflicts, we can isolate how these extreme events shape corporate investment behavior in ways that complement the perception-based measures developed in earlier research.

We develop a granular measure of firm-level operational exposure to armed conflict by combining data on subsidiary locations with spatially precise information on conflict intensity. This approach allows us to examine three central questions about corporate responses to extreme geopolitical shocks. First, how do firms adjust their capital allocation when subsidiaries face operational disruptions from warfare? Second, do armed conflicts produce uniform investment reductions consistent with standard uncertainty models, or do they trigger compositional shifts in how firms allocate resources between physical capital and innovation? Third, do these investment responses vary systematically based on the home country of the parent firm? We find that armed conflict exposure generates distinct patterns of corporate behavior. Rather than uniformly cutting all investment, firms strategically reallocate capital across investment types. Moreover, these responses exhibit substantial heterogeneity across parent countries, with firms from different nations responding differently to identical levels of conflict exposure.

We investigate these questions using the Russian invasion of Ukraine in February 2022 as a natural experiment. Prior to the invasion, multinational firms had established operations across Ukrainian regions based on conventional business considerations, with location decisions made years before the conflict began. Two features of the invasion support our identification strategy. First, the timing of the invasion was unexpected by financial markets, as evidenced by sharp global equity declines when Russia attacked. This surprise element mitigates concerns that firms with Ukrainian operations had already adjusted their investment strategies in anticipation of conflict. Second, the geographic progression of military operations reflected Russian and Ukrainian strategic objectives that were orthogonal to the distribution of multinational firm activity in Ukraine. This spatial variation allows us to compare firms with similar ex ante characteristics but differential exposure to combat intensity based on where their Ukrainian subsidiaries happened to be located. Together, these features enable us to isolate the causal effect of conflict exposure on corporate investment decisions.

To measure firm-level exposure to the Ukraine invasion, we construct a time-varying index combining three components. First, we measure regional conflict vulnerability using the ethnic Russian population share across Ukrainian regions (*oblasts*) from the 2001 census. Regions with larger ethnic Russian populations have stronger historical ties to Russia, making them more susceptible to military targeting and occupation.[1] Second, we measure regional conflict intensity using geocoded data from local news reports on military incidents and territorial control. While vulnerability captures which regions are prone to conflict, intensity measures when and how severely fighting actually occurs. The interaction between these dimensions matters because regions with similar vulnerability may experience different conflict trajectories due to strategic military priorities, defensive capabilities, or geography, while similar levels of fighting may produce different disruptions depending on underlying regional vulnerabilities.[2] This combined measure captures temporal variation, remaining near zero before the invasion and then fluctuating as military operations intensify or subside across regions. Third, we translate these regional measures into firm-level exposure by weighting each region's vulnerability-intensity combination by the firm's workforce share in that region during the 36 months preceding the invasion. The weighted sum yields a firm-level conflict exposure measure that varies over time with evolving combat intensity but depends entirely on each firm's pre-invasion operational footprint in Ukraine.

Our sample comprises 5,684 publicly traded multinational firms headquartered across 44 countries, with quarterly observations spanning February 2019 to February 2025. U.S. firms constitute nearly half of this sample (2,757 firms). Among the 1,647 firms with Ukrainian operations prior to the invasion, 889 are U.S.-headquartered. The largest non-U.S. representation among firms active in Ukraine comes from the United Kingdom (93 firms), France (69), Japan (64), and Germany (53). For firms that operated in Ukraine before the invasion, their mean workforce share in Ukraine was 1.6% of their global workforce.[3] The

[1]Prior research shows that such ethnic linkages predict both the geographic pattern of conflict and its spillovers to economic activity and firm behavior (Korovkin and Makarin, 2023; Korovkin, Makarin, and Miyauchi, 2025).

[2]For instance, Kharkiv Oblast (25.6% ethnic Russian) faced intense urban combat, while Zaporizhzhia Oblast with similar vulnerability (24.7% ethnic Russian) saw more localized fighting mainly around key infrastructure like the Zaporizhzhia Nuclear Power Plant. Conversely, similar conflict intensity may cause varying damage depending on variations in regional vulnerability. For example, fighting in low-vulnerability Chernihiv Oblast (5.0% ethnic Russian) resulted in successful Ukrainian defense by late March 2022, whereas high-vulnerability Donetsk Oblast (38.2% ethnic Russian) fell to sustained occupation despite both oblasts facing significant Russian offensives in the initial weeks of the invasion.

[3]For each firm, we calculate the Ukrainian workforce as a share of its total global workforce. The Ukrainian workforce is the sum of employees across all oblasts in which the firm operated, averaged over the pre-invasion period. The resulting conditional mean of 1.6% for firms with Ukrainian operations differs from the unconditional mean of 0.46% reported in Table 3, which includes all the sample firms regardless of

observed Ukrainian workforce shares in our sample are consistent with typical multinational employment patterns in markets of comparable size and development level.[4]

A key feature of our conflict exposure index is that it exhibits substantial variation among firms with Ukrainian operations. During the invasion period, quarterly conflict exposure has a mean of 2.65 and standard deviation (SD) of 12.71 index units (scaled by 10,000) for the full sample, with U.S. firms having higher average exposure (3.15) compared to non-U.S. firms (2.19). This variation reflects how firms' operational footprints across Ukrainian oblasts translated into markedly different degrees of exposure to military activity.[5]

We validate our conflict exposure measure using two complementary approaches. First, we analyze quarterly earnings call transcripts to assess whether managerial perceptions align with our conflict exposure measure. Following Hassan et al. (2019) and Hassan et al. (2024), who developed textual metrics to measure firm-level political risk and Brexit-related exposure, we construct analogous war-specific measures from the question-and-answer portions of earnings calls, where executives provide unscripted responses to analyst queries. We measure war exposure (the frequency of Ukraine-related discussions), war risk (co-occurrence of war terms with risk-related words), and war sentiment (net positive versus negative tone in war-related discussions). All three measures are near zero before the invasion but surge immediately following February 2022, with war exposure rising 53% above pre-war levels during the first two quarters and war sentiment dropping sharply to -40%. When weighted by firms' conflict exposure, high-exposure firms discussed the war more frequently and expressed greater concern about conflict-related risks, demonstrating that our measure aligns with managerial assessments of operational disruptions resulting from the invasion.

Second, we conduct an event study analyzing stock market reactions during the first three trading days following the invasion. We find that firms with higher conflict exposure experienced significantly larger stock price declines. A one standard deviation increase in conflict exposure corresponds to a 3.3% decline in cumulative stock returns, controlling for firm characteristics, market risk exposures, and firms' operational ties to Ukraine prior to the conflict. The effects are substantially more pronounced for non-U.S. firms (3.7% decline) compared to U.S. firms (2.6% decline).[6] These differential responses in stock returns

whether they were present in Ukraine.

[4]Multinational corporations distribute their operations across dozens of countries, with individual host countries typically accounting for only a small share of total employment. Foreign affiliates of U.S. multinationals, for example, often represent localized production and service operations rather than primary centers of activity (Desai, Foley, and Hines, 2009). Emerging and secondary markets like Ukraine frequently serve as regional offices or production sites, where workforce allocations typically range between 1 to 3% of global headcount (Bureau of Economic Analysis, 2024).

[5]For our regression analysis, we standardize conflict exposure within each quarter to have a mean of zero and standard deviation of one, facilitating interpretation of effect sizes across different time periods.

[6]This differential sensitivity reflects several documented factors. European firms, which constitute a signifi-

demonstrate that our conflict exposure measure captures economically meaningful variation, as investors immediately priced firms based on their operational ties to conflict-affected regions.

We next examine how conflict exposure affects corporate investment decisions by relating firms' quarterly capital expenditures and R&D spending to their contemporaneous exposure level, controlling for firm characteristics and various sources of heterogeneity across countries, industries, and time periods. The results reveal a striking compositional shift in investment behavior. Firms with higher conflict exposure reduce their capital expenditures by approximately 2% for each SD increase in exposure, consistent with their reluctance to commit to physical investments during periods of heightened geopolitical uncertainty. In sharp contrast, these same firms increase their R&D spending by approximately 5%, reflecting strategic reallocation toward innovation investments that offer greater flexibility and adaptation opportunities. These opposing effects demonstrate that geopolitical shocks do not uniformly depress corporate investment but instead trigger reallocation from physical to knowledge-intensive assets.

These investment effects vary substantially across headquarter countries. U.S. firms exhibit capital expenditure declines of 3% and R&D increases of 7% per SD of exposure, compared to 2% capital expenditure declines and no significant R&D response among non-U.S. firms. These cross-country differences reveal how institutional environments may shape corporate responses to geopolitical disruptions. While Hassan et al. (2019) document that political risk uniformly reduces both capital expenditures and R&D, our findings show that armed conflict triggers divergent investment responses that vary systematically by institutional context. Several factors may explain why U.S. firms exhibit stronger R&D responses. U.S. firms' access to deeper equity markets may facilitate innovation financing (Brown, Fazzari, and Petersen, 2009; Hsu, Tian, and Xu, 2014), enabling them to increase R&D even while cutting capital expenditures. In contrast, firms in non-U.S. countries where bank financing dominates (Porta et al., 1998; Rajan and Zingales, 1995) and equity market financing of innovation is less developed show no significant R&D response despite comparable conflict exposure. This interpretation aligns with the stock market evidence: U.S. firms experienced smaller price declines than non-U.S. firms, suggesting investors viewed them as better positioned to navigate the operational disruptions.

cant portion of the non-U.S. sample, are geographically closer to Ukraine and more reliant on regional supply chains for energy, metals, and other commodities (Aizenman et al., 2024; Auer et al., 2025). The non-U.S. sample also includes substantial representation from Asian countries, particularly Japan and China, whose firms had notable operations in Ukrainian manufacturing and trade networks before the invasion, especially in machinery and electronics sectors (Silva, Wilhelm, and Tabak, 2023). More broadly, the patterns are consistent with differences in financial market development affecting firms' ability to fund long-term investments during periods of heightened uncertainty (Brown, Fazzari, and Petersen, 2009).

Related Literature. Our study contributes to the literature on geopolitical uncertainty, corporate investment, and international economics. While prior work shows that policy and political uncertainty typically reduce capital expenditures and hiring (Baker, Bloom, and Davis, 2016; Gulen and Ion, 2016; Hassan et al., 2019; Jens, 2017; Julio and Yook, 2012; Nguyen and Sila, 2025), and in some cases R&D spending (Czarnitzki and Toole, 2011; Xu, 2020), we find that firms with direct operational exposure to armed conflict cut capital expenditures but increase R&D spending. While policy uncertainty typically leading to precautionary reductions in capital expenditures (Gulen and Ion, 2016; Julio and Yook, 2012), armed conflict shapes firms' investment responses differently because war imposes direct and persistent operational disruptions and revenue losses that heighten risks for physical capital and force strategic reallocation under liquidity constraints. R&D investments, on the other hand, offer greater flexibility and enable firms to develop innovations that mitigate supply disruptions, adapt to market changes, and support post-conflict recovery, with U.S. firms showing stronger such responses than non U.S. counterparts.

Our findings build on real options models predicting asymmetric effects of uncertainty across investment types (Bernanke, 1983; Dixit and Pindyck, 1994). Empirically, our results align with Stein and Stone (2013), who show that uncertainty depresses tangible investment while encouraging intangible investments including R&D, and with Bloom, Bond, and Van Reenen (2007), whose model shows that uncertainty can increase R&D when firms operate below optimal innovation levels. More recently, Atanassov, Julio, and Liu (2024) identify conditions under which political uncertainty encourages R&D as firms pursue growth opportunities. We extend this literature by demonstrating that armed conflict generates distinct investment dynamics than policy uncertainty, with capital expenditures declining but R&D increasing. This pattern distinguishes active warfare from other geopolitical shocks such as trade disputes that uniformly suppress corporate investment (Caldara and Iacoviello, 2022), terrorism that triggers R&D cutbacks through heightened deferral options (Li et al., 2022), and foreign political risk that motivates greater domestic innovation to substitute away from vulnerable foreign dependencies (Fajgelbaum et al., 2025).

Second, we contribute to the literature on cross-border shock transmission and spillover effects. Prior studies document global propagation of uncertainty shocks through financial channels (Colacito et al., 2018; Forbes and Warnock, 2012; Maggiori, 2017; Rey, 2015) and the operational networks of multinational firms (Biermann and Huber, 2024; Boehm, Flaaen, and Pandalai-Nayar, 2019; Carvalho et al., 2021; Cravino and Levchenko, 2017). A key challenge in this literature is measuring firm-specific exposure to localized geopolitical shocks. Hassan et al. (2019) and Hassan et al. (2024) address this by deriving firm-specific risk measures from earnings call transcripts, capturing managerial concerns about geopolitical events.[7] Our method offers a complementary, more direct, and exogenous measure of firm-level operational exposure by integrating regional vulnerability (ethnic Russian population shares), real-time conflict intensity, and firms' pre-invasion workforce distribution across Ukrainian oblasts. Leveraging this granular operational footprint data, we provide the first comprehensive firm-level analysis of geopolitical shock transmission, documenting how conflict exposure simultaneously affects multinational firms' investment decisions and market valuations across countries.

Third, we document substantial cross-country heterogeneity in corporate responses to geopolitical shocks, implying that institutional environments critically mediate uncertainty transmission. These patterns align with U.S. firms' greater access to equity markets for financing innovation amid uncertainty (Brown, Fazzari, and Petersen, 2009; Hsu, Tian, and Xu, 2014), and with evidence that financial frictions amplify uncertainty shocks (Alfaro, Bloom, and Lin, 2023).

Finally, our study contributes to the recent literature on how the Ukraine conflict affects firm behavior and economic activity. Korovkin and Makarin (2023) show that the 2014 Russian annexation of Crimea and eastern oblasts reduced trade between Ukrainian and Russian firms due to inter-ethnic trust breakdown, with deeper declines in districts with fewer ethnic Russians. Building on this framework, Korovkin and Makarin (2022) document how the conflict's effects propagated through production networks, disrupting trade even for firms outside conflict zones. Korovkin, Makarin, and Miyauchi (2025) extend this by examining endogenous supply chain reorganization away from conflict-exposed partners. These studies rely on static vulnerability measures based on regional ethnic Russian shares to identify exposure to the 2014 conflict. We advance this literature by analyzing the larger, more globally disruptive 2022 invasion and developing a dynamic firm-level measure that augments static conflict vulnerability with real-time conflict intensity and pre-invasion workforce distributions of multinational firms across oblasts, better capturing the spatial and temporal transmission of shocks to corporate investment decisions.

II Sample Construction

Our primary sample consists of 5,778 publicly traded firms headquartered in 82 countries, covering the period from February 2019 to February 2025. To ensure sufficient representation, we restrict the analysis to countries with at least 10 firms each, yielding a final sample of 5,684 firms across 44 countries. Table 1 summarizes the geographic distribution of these

[7] A contemporaneous paper by Caldara et al. (2025) examines the investment effects of the 2022 invasion using a text-based measure of firm-level exposure derived from earnings call transcripts, documenting aggregate declines in capital expenditures.

sample firms. U.S. firms represent 49% of the sample (2,757 firms). Among the 1,647 firms with Ukrainian operations before the invasion, 889 (54%) are U.S.-headquartered. Among non-U.S. firms, those from the U.K. (93 firms), France (69), Japan (64), and Germany (53) show the most substantial Ukrainian presence before the invasion.

We construct a firm-level measure of conflict exposure by integrating three granular components: regional vulnerability to the conflict at the oblast level, time-varying conflict intensity, and firms' pre-invasion workforce distribution across Ukrainian oblasts. Regional vulnerability is measured using the ethnic Russian population share at the oblast level from the 2001 All-Ukrainian Population Census (Ukraine, 2001). This pre-invasion baseline is exogenous to firm decisions and unaffected by territorial changes from the 2014 annexation of Crimea or the 2022 invasion.

Conflict intensity is measured using three complementary sources to ensure comprehensive spatial and temporal coverage of the conflict throughout the sample period. The first data source we use is the Global Database of Events, Language, and Tone (GDELT), which provides daily geocoded news reports classified by Conflict and Mediation Event Observations (CAMEO) codes for military activities (Leetaru and Schrodt, 2013). GDELT offers consistent coverage of the Ukrainian war from 2019 onward. Second, we use the Violent Incident Information from News Articles (VIINA) database, which delivers high-frequency geocoded data on specific conflict events (such as airstrikes, shelling, drone attacks, casualties) from February 24, 2022 onwards (Zhukov and Ayers, 2023), providing event-specific details such as weapon types and casualty counts not captured in GDELT. Our third source of conflict-related information is VIINA's Territorial Control dataset, which tracks daily occupation status (Ukrainian control, Russian control, or contested) for individual populated places. We aggregate this data to the oblast level by calculating the share of territorial area under each control status using geospatial boundaries from GeoNames and official administrative datasets from the Ukrainian statistical office (Ukrstat).

Firm-level workforce data come from Revelio Labs, which aggregates employment information from professional network profiles (e.g., LinkedIn), job postings, and public records to generate monthly headcount estimates by firm, geography, occupation, and job seniority.[8] The platform collects self-reported data from individual employee profiles, including employer, job title, work location, and employment dates. Revelio employs proprietary algorithms to standardize company names, geographic locations, and job classifications across millions of profiles, which are then aggregated to produce firm-level workforce counts by geographic location, occupation, and seniority. Crucially, the work locations reported by individuals indicate their actual office sites rather than headquarters, enabling precise geo-

[8] A detailed description of Revelio's data collection process is provided in Appendix **??**.

graphic attribution of workforce allocations. This methodology yields two features essential for our analysis. First, the Revelio data provide granular, location-specific workforce counts at the Ukrainian oblast level, updated monthly as employees update their profiles. Second, because the data rely primarily on direct observations rather than broad imputations, we can construct reliable monthly measures of each firm's workforce allocation across all Ukrainan oblasts. This geographic granularity is uncommon in studies of multinational firm operations and allows us to track how firms dynamically adjusted their labor allocations in response to evolving local conflict conditions.

To examine how conflict exposure affects firm-level outcomes, we combine each firm's time-varying conflict exposure with financial statement and stock market information. Financial statement data on the firms come from Compustat Global and North America databases, providing quarterly measures of capital expenditures, R&D spending, assets, sales, debt, profitability, and total headcount. Daily stock prices and market index returns from the Center for Research in Security Prices (CRSP) and Refinitiv enable us to compute firm-level stock returns and betas with respect to both headquarters country equity market indices and major global indices. We convert all financial variables to U.S. dollars using prevailing exchange rates from Refinitiv and merge firms across datasets using standardized identifiers (GVKEY, ISIN). To mitigate the influence of outliers, we winsorize continuous variables at the st and 99^{th} percentiles. Because financial statement data are reported quarterly while our conflict exposure measure varies monthly, we aggregate the latter to the quarterly level by averaging monthly values per firm-quarter.

Lastly, to complement our firm-level conflict exposure measure with managerial perceptions of the war's impact on their operations, we obtain quarterly earnings call transcripts from Refinitiv StreetEvents. We focus exclusively on the question-and-answer portions of these calls, where executives provide unscripted, forward-looking responses to analyst queries that might reveal managerial concerns and strategic priorities regarding the conflict. Transcript coverage is limited to firms headquartered in the U.S., U.K., European Union, Australia, and Canada.

III Measuring Firm-level Conflict Exposure

To quantify firm-level exposure to the 2022 Russian invasion of Ukraine, we construct a conflict exposure index integrating three components at the oblast level: ethnic Russian population shares measuring regional vulnerability, geocoded military incident data tracking conflict intensity over time, and each firm's pre-invasion workforce distribution across Ukrainian oblasts. Our approach builds on established methodologies in the geopolitical risk literature. Hassan et al. (2019) develop firm-specific measures of political risk from earnings call transcripts, demonstrating that firm-level exposure better predicts corporate responses than country-level aggregates. Korovkin and Makarin (2023) show that ethnic Russian population shares predict the severity of trade disruptions during the 2014 Russia-Ukraine conflict, validating ethnic composition as an exogenous proxy for conflict vulnerability. We extend these approaches by integrating regional vulnerability measures with real-time conflict intensity data and firms' pre-invasion workforce allocations to identify how localized military shocks affected multinational corporations through their specific operational exposure to Ukraine's conflict zones.

III.A Conflict Vulnerability

Our first step is to construct a measure of regional conflict vulnerability to capture the pre-invasion susceptibility of Ukrainian oblasts to disruptions from the 2022 invasion. Following Korovkin and Makarin (2023), we use ethnic Russian population shares based on the 2001 census as a proxy for vulnerability.[9] Korovkin and Makarin (2023) demonstrate that Ukrainian sub-regions (*raions*) with larger ethnic Russian populations experienced greater inter-ethnic tensions and more severe trade disruptions with Russian firms during the 2014 conflict.[10] This historical pattern suggests that oblasts with higher ethnic Russian shares faced greater vulnerability during the 2022 invasion for several reasons. First, Russia's stated justification for the invasion centered on protecting ethnic Russian populations in Ukraine, making regions with larger Russian-speaking communities more likely military targets. Second, these regions have stronger historical, cultural, and economic ties to Russia, which Russian military strategists may have perceived as facilitating territorial control and reducing local resistance. Third, ethnic composition likely correlates with pre-existing pro-Russian sentiment and political alignment, potentially making these oblasts strategically valuable for establishing territorial footholds. These mechanisms imply that ethnic Russian population shares serve as a pre-determined measure of regional exposure to Russian military aggression.

For each oblast l in the set of Ukrainian oblasts ℓ, we define the vulnerability measure V_l as the share of residents who self-identified as ethnic Russian in the 2001 census:

$$V_l = \frac{\sum_{i \in \mathscr{P}_o} \mathbb{I}\{\text{Ethnicity}_i = \text{Russian}\}}{\mathscr{P}_l}$$

[9] The 2001 All Ukrainian Population Census is the most recent comprehensive census conducted before the 2014 annexation of Crimea and the outbreak of conflict in eastern Ukraine. As Korovkin and Makarin (2023) note, using the 2001 census ensures that our vulnerability measure is exogenous to post-2014 geopolitical developments, territorial changes, and conflict-induced migration patterns that could be endogenous to firm operational decisions.

[10] Ukraine's administrative structure consists of 24 oblasts (plus Crimea), each subdivided into *raions* (districts). While Korovkin and Makarin (2023) measure ethnic composition at the raion level, we aggregate to the oblast level because Revelio Labs workforce data are only available at this geographic resolution.

where $\mathscr{P}_l$ denotes all individuals recorded in the 2001 census as residing in oblast l, and $\mathbb{I}\{\cdot\}$ is an indicator equal to one if individual i self-identified as ethnically Russian. V_l exhibits substantial geographic variation, ranging from near-zero in western oblasts (Ternopil: 1.2%, Lviv: 4%) to substantially higher shares in the east (Zaporizhzhya: 25%, Kharkiv: 26%, Donetsk: 38%, Crimea: 58%).[11] These demographic patterns reflect historical legacies of Soviet-era Russification policies implemented primarily in eastern and southern Ukraine, where industrialization programs in the 19th and 20th centuries attracted Russian-speaking workers to mining and manufacturing centers (Magocsi, 2010; Subtelny, 2009). This created a persistent east-west gradient in ethnic composition: western oblasts retained predominantly Ukrainian ethnic majorities due to their later incorporation into the Soviet Union (1939-45) and weaker industrial development (Snyder, 2003; Wilson, 2015), while eastern oblasts became heavily Russified through decades of planned migration and linguistic assimilation policies (Krawchenko, 1985; Kulyk, 2011). This geographic variation, which persisted through the 2001 census, provides cross-sectional variation in vulnerability that is orthogonal to contemporary economic conditions or firm location choices.

Conflict vulnerability among firms before invasion. To assess the distribution of conflict vulnerability among foreign firms operating in Ukraine, we examine their geographic footprint across oblasts during the 36 months preceding the invasion. Because V_l captures ethnic composition as of 2001, well before these shares became predictive of invasion risk, firms' location patterns reflect economic considerations (market access, infrastructure quality, industrial agglomeration, labor availability) rather than strategic positioning relative to potential conflict zones. This ensures that firms' pre-invasion operational footprints are orthogonal to the conflict vulnerability those oblasts would subsequently experience.

Figure 1 documents the geographic distribution of multinational firms across Ukrainian oblasts and their exposure to regional vulnerability before the invasion. Panel 1(a) maps the number of these firms operating in each oblast before February 2022, with shading indicating ethnic Russian population shares, revealing that these firms operated across oblasts with widely varying vulnerability levels. Firms' operations span oblasts with widely varying vulnerability levels: western oblasts like Kyiv and Lviv (with low ethnic Russian shares below 13%) host substantial foreign firm presence, as do high-vulnerability eastern oblasts such as Kharkiv, Dnipropetrovsk, and Odessa (with substantial ethnic Russian shares of 14-26% or more). We exclude the easternmost oblasts Donetsk, Luhansk, and Crimea (with ethnic

[11] Figure A1 in the appendix presents an alternative specification of the vulnerability measure using the share of Russian speakers (rather than ethnic Russians) in each oblast from the 2001 All-Ukrainian National Census. The resulting pattern of regional vulnerability remains qualitatively similar, supporting V_l as our primary measure.

Russian shares exceeding 28%) from our analysis because these regions were already under Russian occupation following the 2014 annexation and consequently exhibit no foreign firm presence in our data.

Panel 1(b) shows that the majority of firms operated in multiple oblasts before the invasion: approximately 33% were active in just one oblast, while the remaining operated across two or more oblasts, meaning most firms had operations spanning multiple Ukrainian regions with varying vulnerability levels. Because firms operated in different combinations of oblasts, their aggregate vulnerability varies substantially based on their specific geographic footprints.

Panel 1(c) plots the cumulative distribution of average conflict vulnerability across firms, showing that the median firm faced an average vulnerability of 13%, while the most exposed firms operated in oblasts averaging 25.6% ethnic Russian populations. To quantify this heterogeneity in firm-level vulnerability, $\overline{V_{i,l}}$, Panel 1(c) plots the distribution of average vulnerability across all firms with Ukrainian operations. The median firm operated in oblasts with an average ethnic Russian share of 13%, while the most vulnerable firms averaged over 25%. Critically, this heterogeneity stems from economic location decisions made by firms independently of conflict risk, yet directly determined their operational vulnerability when the invasion materialized. Comparing U.S. and non-U.S. firms, the CDF for U.S. firms lies consistently below that for non-U.S. firms across all quantiles, indicating that U.S. firms operated in slightly less vulnerable oblasts on average, though both groups exhibit similar distributional patterns.

In sum, these patterns reveal substantial heterogeneity in firm-level vulnerability to the conflict, with operations spanning a mix of low- and high-risk oblasts driven by economic considerations rather than geopolitical foresight. This variation allows us to identify how operational exposure to specific Ukrainian regions shaped firms' responses to the invasion.

Conflict vulnerability and labor market adjustments during invasion. Before constructing our firm-level conflict exposure measure, we validate that regional vulnerability predicts firms' labor market responses to the conflict. We estimate how the invasion differentially affected firms' local employment, wages, and hiring across oblasts with varying vulnerability levels V_l using the following specification:

$$Y_{i,l,t} = \beta \left(V_l \times Post_t\right) + \alpha_i + \alpha_l + \alpha_t + \delta_{i,t} + \theta_{i,l} + \phi_{c,t} + \varepsilon_{i,l,t} \tag{1}$$

where $Y_{i,l,t}$ represents labor market outcomes (local salaries, workforce shares, hiring and separation rates, market exits) for firm i in oblast l during month t. $Post_t$ equals one for months after February 2022 and zero otherwise. The coefficient β estimates how the invasion differentially affected firm i's operations within each local oblast based on that oblast's vulnerability V_l: it captures whether firms' local employment, wages, and hiring varied more sharply in high-vulnerability oblasts than in low-vulnerability oblasts. The specification also includes firm, oblast, month, firm-by-month, firm-by-oblast, and country-by-month fixed effects to control for time-invariant firm and location characteristics, common time shocks, and firm-specific trends, respectively.

Panel A of Table 2 reports results at the firm-oblast-month level. The coefficient β indicates significant post-invasion contractions in firms' local operations within higher-vulnerability oblasts. A one standard deviation (SD) increase in oblast vulnerability (7.4 percentage points in ethnic Russian share) is associated with a 7.8% decline in average local salaries, a 13.6% reduction in the firm's local workforce share (as a percentage of the firm's total Ukrainian headcount in the preceding month), an 8.8% drop in local hiring rates, and a 3.8% decrease in local separation rates (models 1–4). These effects are economically meaningful. The 7.8% differential wage decline in higher-vulnerability oblasts is substantial given that Ukraine's nationwide real wage contraction was only 11% during the first ten months of 2022 (Djankov and Blinov, 2022), indicating that pre-existing vulnerabilities amplified war-induced labor market disruptions at the local level. The simultaneous reduction in both hiring and separations suggests firms curtailed new hires while retaining existing employees to preserve operational continuity, resulting in gradual workforce attrition rather than abrupt downsizing. Model 5 shows that the probability of complete market exit increased by 26.2% in higher-vulnerability oblasts following the invasion. This indicates that while some firms fully withdrew from vulnerable oblasts, most adapted through workforce reductions while maintaining local presence.[12]

III.B Conflict Intensity

While V_l captures cross-sectional differences in vulnerability across Ukrainian oblasts as measured before the invasion, this static measure alone cannot identify the causal impact of conflict because it lacks the temporal and spatial variation introduced by the unfolding war. To exploit local dynamic shocks resulting from the conflict, which are plausibly exogenous

[12]Figure A4 presents event study estimates corresponding to the pooled difference-in-differences results in Panel A of Table 2 at the firm-oblast-month level, showing how conflict vulnerability affected the local labor market outcomes of multinational firms within Ukraine. Each panel plots month-by-month coefficients from specifications interacting V_l with monthly indicators relative to the February 2022 invasion, with January 2022 serving as the reference period. Post-invasion, coefficients for average salaries, headcount, hiring, and separations turn negative immediately and remain persistently so, indicating sustained contractions in firm operations within high vulnerability oblasts. The negative coefficient on separations alongside reduced hiring suggests firms simultaneously curtailed new hires and retained existing employees to preserve operational continuity. For local market exits, the coefficient turns positive post-invasion and remains significant with wide confidence intervals, consistent with our finding that most firms remained in Ukraine overall but selectively reduced their presence in the most vulnerable oblasts.

to individual firm decisions, we introduce a time-varying measure of *conflict intensity*, $S_{l,t}$, which quantifies the severity of active hostilities in oblast l during month t. Whereas V_l reflects predetermined regional characteristics (share of ethnic Russians) that made certain oblasts more susceptible to conflict-related disruption, $S_{l,t}$ captures the realized intensity of military operations in each oblast as the conflict evolved. This distinction allows us to separately identify how baseline vulnerabilities and actual combat intensity combined to shape firms' operational exposure to the war.

To construct $S_{l,t}$, we combine data from three complementary sources to achieve comprehensive temporal and spatial coverage of conflict intensity throughout our sample period, including months before the February 2022 invasion.

First, we draw on the Global Database of Events, Language, and Tone (GDELT), which monitors worldwide news media in near real-time and provides geocoded daily reports of global events. From GDELT, we extract news reports geocoded to individual Ukrainian oblasts and classify those related to military activity using Conflict and Mediation Event Observations (CAMEO) codes associated with conflict, coercion, and assault. GDELT provides consistent coverage of local events from 2019 onward, allowing us to measure any local tensions that may have occurred even before the invasion. Second, we incorporate high frequency geocoded conflict data from the Violent Incident Information from News Articles (VIINA) database. Since February 2022, this database has systematically compiled daily reports of armed engagements from a wide range of Ukrainian and Russian news sources, classifying events into categories such as airstrikes, artillery shelling, drone attacks, territorial control changes, and military casualties. These records provide detailed, near real-time documentation of specific military actions, including their timing, type, location, and source.[13] Third, we track the daily percentage of each oblast under Russian occupation using VIINA's territorial control dataset. Unlike event counts that measure discrete military actions, territorial control data captures sustained military dominance by revealing which forces (Russian or Ukrainian) control populated areas on each day. This dimension is critical because foreign occupation directly disrupts firm operations through displacement of workers, destruction of infrastructure, and suspension of normal economic activity.

Using these multiple data sources is essential because each captures distinct dimensions of military conflict: GDELT provides consistent longitudinal coverage starting well before military hostilities began, VIINA offers granular incident-level data on specific combat actions during active warfare, and territorial control data reveals the geographic extent and duration

[13] Government briefings and traditional news outlets frequently consolidate multiple military incidents into summary reports or overarching narratives. In contrast, VIINA documents each individual military engagement separately, recording its source, exact timestamp, geographic coordinates, and event type. This granular detail enables precise tracking of variations in hostilities within specific oblasts.

of military occupation. Together, these sources enable us to measure conflict intensity more completely than any single dataset could provide.[14]

For each day d and oblast l, we compute three daily measures of conflict intensity that correspond to our three data sources. First, the GDELT based measure, $M^G_{l,d}$, calculates the share of all news reports geocoded to oblast l on day d that GDELT classifies as military activity:

$$M^G_{l,d} = \frac{\Sigma \text{ military-related GDELT reports in } l \text{ on } d}{\Sigma \text{ total GDELT reports in } l \text{ on } d}$$

Second, the event based measure from VIINA, $M^V_{l,d}$, calculates the share of incident reports geocoded to oblast l on day d that document military activity:

$$M^V_{l,d} = \frac{\Sigma \text{ military-related VIINA reports in } l \text{ on } d}{\Sigma \text{ total VIINA reports in } l \text{ on } d}$$

Third, the territorial occupation measure, $O^V_{l,d}$, calculates the percentage of oblast l's total area under Russian control on day d, derived from VIINA's Territorial Control repository. This database assigns each populated place within an oblast a daily control status: UA for areas under Ukrainian control, RU for areas under Russian control, or $CONTESTED$ for areas where control is actively disputed.[15] We aggregate the geographic areas of all places classified as Russian controlled and divide by the total oblast area, using place geometries from GeoNames and KATOTTH datasets. The territorial occupation measure is formally defined as:

$$O^V_{l,d} = \frac{\sum_{p \in l, \text{status}_{p,d} = \text{RU}} \text{Area}_p}{\sum_{p \in l} \text{Area}_p}$$

These three measures are combined into a composite daily conflict intensity metric by

[14]Figure A2 in the appendix examines media coverage patterns before and after the invasion across multiple dimensions, comparing oblasts with above-median versus below-median conflict vulnerabilities. The figure tracks the share of news articles covering military activity (from both global media via GDELT and regional sources via VIINA), migration events, and labor market disruptions, as well as overall media tone and Goldstein (1992) scale scores (which measure the adversarial versus cooperative nature of reported news events, ranging from -10 for hostile military actions to +10 for cooperative diplomatic actions). Prior to the invasion, coverage patterns were similar across both groups of oblasts. Following February 2022, however, sharp divergences emerged: high vulnerability regions experienced substantially elevated coverage of military actions, and population displacement, while exhibiting more negative media sentiment and more adversarial Goldstein scores. These systematic differences demonstrate that media-based measures from GDELT and VIINA serve as effective proxies for regional conflict intensity, and confirm that conflict intensity is also systematically correlated with pre-existing regional vulnerabilities.

[15]VIINA's Territorial Control database determines the control status of place p on day d through majority vote across four sources: crowdsourced Wikipedia maps, VIINA event reports, DeepStateMap, and the Institute for the Study of War (ISW).

taking their arithmetic mean:

$$S_{l,d} = \frac{M^G_{l,d} + M^V_{l,d} + O^V_{l,d}}{3}$$

We aggregate $S_{l,d}$ to the oblast-month level to align with the temporal frequency of our workforce dynamics data:

$$S_{l,t} = \frac{1}{D_t} \sum_{d \in D_t} S_{l,d}, \tag{2}$$

where D_t denotes the set of days in month t. This aggregation identifies periods and locations of heightened military activity. To illustrate the measure's variation, VIINA documented over 500 military incidents in Kharkiv Oblast during March 2022 alone, while western oblasts such as Lviv experienced fewer than 50 incidents during the same period. Our measure captures temporal and spatial variations in local military activity that are plausibly exogenous to firm operations because the timing and geography of hostilities reflect strategic political and military objectives rather than the operational decisions of individual firms.

Conflict intensity and local labor market dynamics. Having constructed the conflict intensity measure $S_{l,t}$, we now examine how it affects local labor markets. This measure complements the static vulnerability proxy V_l by tracking the realized severity of military hostilities, which varies substantially across oblasts even among those with similar ethnic Russian population shares.

We begin by examining the spatial and temporal patterns of the conflict across Ukraine. Figure 2(a) maps the geographic distribution of military incidents across Ukrainian districts from February 2022 to February 2025, with circle sizes representing the total number of attacks in each district. The map reveals substantial variation in the scale of military actions across Ukraine. While eastern and southern regions experienced the highest concentration of attacks, particularly in areas with larger ethnic Russian populations (indicated by darker shading), intense military activity extended even to western oblasts, demonstrating that conflict intensity was shaped by strategic military objectives beyond mere geographic proximity to Russia or regional ethnic composition. Turning to the temporal dimension, Figure 2(b) plots the nationwide number of military attacks per month. The plot reveals a sharp initial surge to approximately 15,879 events in March 2022, followed by a steep decline through mid 2022. The conflict subsequently entered a phase of stalemate characterized by limited territorial gains on both sides.[16]

[16]By January 2025, monthly military incidents fell below 3,700, reflecting the conflict's transition into a protracted war of attrition characterized by defensive stalemates, mutual resource exhaustion including manpower and ammunition shortages, and stalled large scale offensives amid persistent drone warfare and

Figure 2(c) reveals substantial spatial heterogeneity in conflict intensity. We plot the share of monthly military attacks occurring in each oblast against its ethnic Russian population share from the 2001 census (V_l). Oblasts with higher V_l experienced disproportionately intense military hostilities, with some receiving up to 30% of all nationwide attacks. This spatial variation in conflict intensity, combined with heterogeneous firm presence across oblasts, generated substantial differences in aggregate firm exposure to the war. Firms with significant operations in heavily attacked oblasts faced greater operational risks and disruptions, while firms concentrated in oblasts with lower attack intensity remained more insulated from direct conflict effects.

To assess how firms responded to ongoing hostilities, we examine exits from oblasts experiencing military actions after the invasion began. Figure A3(a) in the appendix plots the average monthly share of military actions occurring in each oblast against the overall firm exit rate from that oblast. Oblasts experiencing more intense hostilities saw greater firm exits, though the mean exit rate across all oblasts remains modest at 8.2%. These patterns indicate selective firm withdrawals from heavily contested areas rather than widespread exodus. Most firms adapted their operations to continue functioning amid ongoing hostilities, consistent with the results in column (5) of Table 2. Figure A3(b) shows a similar relationship for territorial occupation: oblasts with higher average Russian occupation levels experienced greater firm exits.

Panel B of Table 2 augments equation (1) by interacting V_l with $S_{l,t}$. This refinement captures how baseline vulnerability is amplified or attenuated by realized hostilities, yielding a more granular measure of local conflict exposure that exploits both temporal and spatial variation during the invasion. To facilitate interpretation and account for month to month shifts in nationwide attack levels, we standardize $V_l \times S_{l,t}$ within each month across all oblasts. The estimates are consistent with Panel A, revealing that local labor outcomes respond dynamically to real time attack intensities. A one SD increase in $V_l \times S_{l,t}$ is associated with a 3% decline in local salaries, a 9% reduction in local workforce share, a 3% drop in hiring rates, a 1% decrease in separation rates, and a 13% rise in firm exits from the oblast.[17] These

economic pressures (Army University Press, 2025; Carnegie Endowment for International Peace, 2025; Center for Strategic and International Studies, 2025).

[17]Figure A5 in the appendix presents event study estimates corresponding to Panel B of Table 2, disaggregating the pooled coefficients into month-by-month effects of the interaction between conflict vulnerability (V_l) and realized conflict intensity ($S_{l,t}$) on local labor market outcomes at the firm-oblast-month level. Each panel plots coefficients from specifications where the treatment variable is the standardized product $V_l \times S_{l,t}$, capturing how pre-invasion vulnerability translates into actual labor market disruptions when interacted with active military hostilities at the regional level. January 2022 serves as the reference month for this analysis. The pre-invasion coefficients cluster largely around zero, supporting parallel trends. Post-invasion, the coefficients exhibit greater temporal variation compared to Figure A4, reflecting the fluctuating nature of conflict intensity across oblasts and over time. Average salaries and headcount show

magnitudes are smaller than those in Panel A because $V_l \times S_{l,t}$ identifies effects only during periods when vulnerability coincides with active hostilities.[18]

III.C Local Workforce Shares

While V_l and $S_{l,t}$ are strongly associated with local labor market dynamics (as shown in Table 2), they do not fully capture firm-level exposure to the conflict. This is because both these measures take identical values for all firms operating within an oblast in a given month, ignoring heterogeneity in the scale of each firm's operations there. For example, consider two firms operating in Kharkiv: one with 1,000 employees in Kharkiv out of 2,000 total employees worldwide (50% of its workforce), and another with 10 employees in Kharkiv out of 10,000 total employees (0.1% of its workforce). The first firm faces substantially greater exposure because Kharkiv operations constitute a much larger share of its global workforce, yet V_l and $S_{l,t}$ alone assign both firms identical conflict exposure levels.

To construct a precise firm specific measure of conflict exposure, we calculate the monthly share of each firm's global workforce located in each oblast:[19]

$$W_{i,l,t} = \frac{\sum_{k \in K_{i,l,t}} 1}{\sum_{l' \in \mathcal{L}} \sum_{k \in K_{i,l',t}} 1} = \frac{H_{i,l,t}}{\sum_{l' \in \mathcal{L}} H_{i,l',t}},$$

where $K_{i,l,t}$ is the set of employees of firm i in oblast l during month t, $H_{i,l,t}$ is the total local headcount, and $\mathcal{L}$ is the set of all worldwide locations where the firm operates. The monthly share $W_{i,l,t}$ captures immediate workforce adjustments as the conflict evolves in given oblast l, including relocating staff to safer regions or experiencing attrition in active combat zones.

To avoid endogeneity from invasion induced changes in workforce allocation, we construct our conflict exposure measure using a baseline that reflects firm operations before the war began. Specifically, we compute the average workforce share for each firm-oblast pair over

persistent negative effects that vary in magnitude with attack intensity, while hiring and separation patterns display more month-to-month volatility as firms responded dynamically to changing local conditions. The exit coefficient remains positive but less stable than in the static vulnerability specification, underscoring that firms adjust their local presence based on realized rather than anticipated conflict exposure. These patterns demonstrate that incorporating time-varying conflict intensity refines our understanding of how firms respond to actual hostilities beyond baseline regional vulnerabilities.

[18] For example, northeastern oblasts such as Kharkiv and Sumy have higher ethnic Russian shares but experienced intense fighting only during the initial months of the invasion. After Russian forces withdrew from these oblasts in spring 2022, conflict intensity there declined substantially. Panel A of Table 2, which uses only the static vulnerability measure V_l, implicitly treats these oblasts as equally exposed throughout the entire period after February 2022. In contrast, Panel B accounts for the actual temporal variation in hostilities through $S_{l,t}$, thereby producing smaller average effect estimates that reflect periods of both high and low combat intensity.

[19] We use workforce shares rather than absolute headcount to normalize for firm size. Absolute headcount would create upward bias in the exposure measure for larger firms, even when Ukrainian operations constitute a small portion of their total workforce. On the other hand, workforce shares ensure comparability across firms of different sizes.

the 36 months preceding the invasion:

$$\overline{W}_{i,l}^{pre} = \frac{1}{T_{pre}} \sum_{t \in T_{pre}} W_{i,l,t}$$

where $T_{\text{pre}} = 36$ denotes the 36 months from February 2019 to January 2022. Averaging over this period achieves two objectives. First, it establishes a stable baseline that reflects each firm's typical operational presence in each oblast before the conflict began, smoothing out temporary fluctuations from seasonal hiring patterns or other short term adjustments. Second, because $\overline{W}_{i,l}^{\text{pre}}$ uses only data from before the invasion, it remains unaffected by any workforce adjustments that firms undertook in response to the war, thereby preserving the exogeneity required for causal identification.

III.D Firm-Level Conflict Exposure

Finally, we construct a time-varying, firm-level conflict exposure index by integrating regional vulnerability (V_l), conflict intensity ($S_{l,t}$), and firms' workforce shares in each oblast before the invasion ($\overline{W}_{i,l}^{\text{pre}}$). This index measures how localized conflict shocks propagate through firms' Ukrainian operations based on where their employees were located before the invasion began, allowing us to identify differential impacts on investment, innovation, and other outcomes. We first calculate the exposure index at the firm-oblast-month level as follows:

$$E_{i,l,t} = V_l \cdot S_{l,t} \cdot \overline{W}_{i,l}^{pre}. \tag{3}$$

Equation 3 measures the impact of the invasion on firm i's operations in oblast l during month t, weighted by the average share of the firm's global workforce that was located in that oblast before the war began. We then aggregate across all oblasts where firm i operated to obtain total conflict exposure for firm i in month t as:

$$E_{i,t} = \sum_{l \in \mathcal{L}_i} E_{i,l,t}, \tag{4}$$

where $\mathcal{L}_i$ is the set of oblasts with positive workforce shares for firm i in month t. To aid interpretation and control for monthly shifts in overall conflict activity, we standardize $E_{i,t}$ within each month across all firms.

III.E Identifying Assumptions

Balancedness. Our identification relies on the assumption that firms' workforce distributions across Ukrainian regions before February 2022 were driven by standard business considerations, rather than anticipation of future conflict or characteristics correlated with responses after the invasion. If firms' observable characteristics such as size, profitability, or leverage were systematically correlated with their location choices in oblasts with larger ethnic Russian populations, this could introduce selection bias and confound our estimates of conflict exposure effects.

To test for such potential self-selection, we use a time-invariant potential exposure measure: $\overline{\text{Potential Exposure}}_i = \sum_l (\bar{W}_{i,l,\text{pre}} \times V_l)$, where $\bar{W}_{i,l}$ is firm i's average workforce share in oblast l over the pre-invasion period (Q1'2019–Q1'2022) and V_l is the ethnic Russian population share in oblast l from the 2001 census. By construction, potential exposure identifies the same treatment variation as our main conflict exposure measure but is defined using only information available before the invasion, making it suitable for testing balance on firm characteristics.

Table A1 presents results from regressing ten firm characteristics averaged over the pre-invasion period on potential exposure, controlling for headquarters country and industry fixed effects. The coefficient β captures whether potential exposure systematically predicts pre-invasion firm characteristics. Under our identifying assumption that workforce location decisions were driven by economic considerations orthogonal to subsequent responses to the invasion, we expect $\beta \approx 0$ for all characteristics. Across all specifications, we find no evidence that potential exposure predicts firm size, operational performance, financial structure, market risk, or workforce dynamics. The two investment-related variables warrant closer examination: capital expenditure intensity shows a marginally insignificant relationship (p = 0.100), while R&D intensity exhibits a marginally significant association at the 10% level (p-val = 0.097).[20] Importantly, both relationships are absorbed by our inclusion of lagged dependent variables in Tables 5 and 6, which control for any differences in investment intensity prior to the invasion.

These largely null results reflect the economic nature of firms' location decisions. Workforce allocations across Ukrainian oblasts were driven by standard economic determinants–proximity to markets, labor costs, supplier networks, and historical business relationships–rather than strategic positioning related to geopolitical risk. The ethnic Russian population share in each oblast was determined by the 2001 census and represents a demographic characteristic that, while correlated with subsequent conflict intensity, was not a salient factor in firms' location decisions made years or decades before the conflict. The resulting orthogonality between potential exposure and firm characteristics supports the exogeneity of our treatment variation.

Pre-Invasion Firm Locations and Conflict Patterns. Another potential concern for

[20] A Wald test of joint significance for all ten coefficients yields $\chi^2 = 15.256$ (df = 10, p-val = 0.123), indicating that we cannot reject the null that potential exposure is unrelated to the full set of firm characteristics.

our identification strategy is that multinational firms may have anticipated the February 2022 invasion and strategically adjusted their workforce locations beforehand, concentrating operations in oblasts they expected would remain safer during subsequent hostilities. Such anticipatory behavior would violate our key identifying assumption that the spatial distribution of firms' Ukrainian workforce before invasion is orthogonal to subsequent conflict patterns. If firms systematically avoided high vulnerability regions before the war, our estimates would conflate anticipatory selection with the causal effect of conflict exposure on firm outcomes.

To test this possibility, we estimate monthly panel regressions relating post-invasion conflict intensity in each oblast to the pre-invasion distribution of firms and employment across those oblasts, interacted with conflict vulnerability. Specifically, we regress oblast-level conflict intensity on each oblast's share of total firms and employment share averaged over the 12 months before February 2022, controlling for ethnic Russian population shares and month fixed effects. Under the null hypothesis of no anticipatory selection, the pre-invasion distribution of firms and employment should not predict where conflict subsequently materialized, implying coefficients near zero. Table A2 presents the results. Across all specifications, neither pre-invasion firm shares nor employment shares significantly predict post-invasion conflict intensity, with coefficients remaining economically small and statistically insignificant. The interaction terms with conflict vulnerability (ethnic Russian shares) are similarly insignificant. These findings suggest that firms did not systematically avoid high-vulnerability oblasts before the invasion, supporting our identifying assumption that workforce locations were orthogonal to firms' subsequent responses during the invasion.

IV Validation

In this section, we verify whether the conflict exposure measure $E_{i,t}$ captures meaningful operational impacts of the February 2022 invasion on multinational firms. This is done through several checks. First, we examine aggregate temporal patterns to confirm that $E_{i,t}$ tracks the onset and evolution of the war. Second, we examine cross-country and cross-industry variation in conflict exposure to verify that the invasion produced systematic variation in exposure rather than random noise. Third, we examine whether conflict exposure aligns with managerial perceptions by analyzing war-related discussions in quarterly earnings calls of the sample firms.

IV.A General Trends in Conflict Exposure

Figure 3 plots the median firm-level conflict exposure $E_{i,t}$ for each month in our sample, showing patterns for all firms as well as separately for U.S. and non-U.S. firms. Before February 2022, median conflict exposure hovers around zero across all groups, reflecting the absence of active military hostilities despite underlying regional vulnerabilities within Ukraine. Following the invasion, median $E_{i,t}$ spikes sharply, rising during the initial months of intense combat from March through May 2022, and then fluctuating with time as the war evolved.[21] These temporal patterns confirm that our measure reflects realized conflict exposure rather than pre-existing differences in Ukrainian operations among firms. Both U.S. and non-U.S. firms experienced substantial increases in conflict exposure after the invasion. However, U.S. firms exhibit slightly lower median exposure throughout this period, consistent with their greater concentration in less vulnerable oblasts before the invasion (as seen in Figure 1(c)).

Figure 4 shows mean conflict exposure by firm headquarters country, calculated as the average $E_{i,t}$ for firms in each country over all months, separately for the periods before and after the invasion. Before the invasion, mean $E_{i,t}$ remains consistently near zero across countries, capturing only latent vulnerabilities in the absence of active hostilities. After the invasion, mean $E_{i,t}$ rises substantially for most countries, demonstrating that the measure captures both the geographic distribution of actual military operations and the subsequent reallocation of workers by affected firms.

Furthermore, countries with substantial firm representation in the sample, such as the U.S., U.K., Japan, France, and Germany (see Table 1), exhibit modest increases post-invasion ranging from approximately 0.22 (U.S.) to 0.41 (Japan).[22] In contrast, firms from Mexico, Austria, New Zealand, Taiwan, and Canada, which had limited operations in Ukraine, experienced dramatic surges in exposure, rising from near zero to as high as 0.95 after the invasion. This pattern likely reflects the presence of firms from these countries in eastern and southern oblasts, which experienced intense military activity during the invasion.[23] These cross-country patterns demonstrate substantial variation in average conflict exposure across headquarters countries. The uniformly low exposure across all countries before February 2022, followed by systematic divergence with firms from different countries experiencing differential post-invasion exposure, confirms that our measure captures realized conflict ex-

[21] Elevated median $E_{i,t}$ levels align with major conflict periods including the Battle of Bakhmut (Dec'22–May'23), the Ukrainian counteroffensive in Zaporizhzhia and Donetsk oblasts (Jun'23–Nov'23), the Russian capture of Avdiivka (Oct'23–Feb'24), and the Ukrainian incursions into Russia's Kursk oblast (Aug'24 onward) (Center for Preventive Action, 2025). Conversely, median $E_{i,t}$ exhibits relative dips during periods of stalemate with limited changes in territorial control in late 2023 and mid 2024 (Center for Preventive Action, 2025).

[22] For instance, U.S. firms like EPAM Systems, with extensive IT operations across Ukraine, relocated thousands of employees to safer locations within the country and abroad, including Poland, while adapting local operations to maintain business continuity (Olechnicka and Kniazevych, 2025).

[23] For example, Austria-based Raiffeisen Bank operated a large subsidiary with branches across Ukraine, including in heavily contested onlasts, and faced substantial operational disruptions during the war S&P Global Ratings, 2022.

posure rather than pre-existing operational characteristics.

Figure 5 presents similar analysis at the industry level, plotting mean conflict exposure before and after the invasion. Consistent with the documented country-level patterns, mean exposure remains negligible across industries before the invasion. During the invasion, however, exposure rises unevenly across industries, with sectors dependent on physical infrastructure, local supply chains, or concentrated workforces experiencing the largest increases. For instance, professional services exhibit the highest rise in mean exposure (0.74), reflecting their concentration of employees in major urban centers like Kyiv that experienced attacks and workforce evacuations. Defense, automotive, and electronics industries also show substantial increases in exposure, consistent with their reliance on manufacturing facilities in industrial hubs such as Kharkiv and Donetsk that experienced intense combat, occupation, and supply chain disruptions. In contrast, sectors less dependent on fixed physical assets, such as finance and software services, exhibit more modest increases.These industry-level patterns demonstrate that conflict exposure varies systematically not only across headquarters countries but also across industries, with both dimensions showing uniform pre-invasion levels followed by post-invasion divergence.

IV.B War-related Discussions in Earnings Calls

Having established our conflict exposure measure $E_{i,t}$ as a strong predictor of localized labor disruptions within Ukraine during the invasion, we now examine whether it aligns with managerial perceptions of the conflict. Specifically, we measure the frequency and tone of war-related discussions in quarterly earnings calls and test whether firms with higher $E_{i,t}$ mention the Ukrainian war more frequently and express more negative sentiment about its impact. This analysis provides additional validation to our measure by comparing objective firm-specific exposures against subjective managerial assessments about the conflict.

Following Hassan et al. (2024), who developed novel textual metrics to measure Brexit-related exposure, risks, and sentiment among firms, we construct analogous war-specific metrics from the earnings calls of our sample firms.[24] We derive these measures exclusively from the question and answer portions of the calls, where executives provide unscripted responses to analyst queries. We construct three textual measures from earnings call transcripts to capture different dimensions of how firms discussed the war.

The first measure, *WarExposure*, quantifies the frequency of war related discussions in earnings calls, analogous to the Brexit exposure measure in Hassan et al. (2024). Specifically, *WarExposure* captures the proportion of total bigrams (two-word sequences) in the question and answer portion that relate to the Ukraine war, Russia, or associated conflict terms.

[24]This analysis covers only firms headquartered in the U.S., U.K., European Union, Australia, and Canada, reflecting the geographic coverage of our earnings call transcript provider.

Figure 6(a) plots average *WarExposure* across all the firms for each quarter. The plot shows that war-related discussions were virtually absent from earnings calls before the invasion, with *WarExposure* near zero. The February 2022 invasion triggered an immediate surge, with mean *WarExposure* rising approximately 53% above baseline levels during the first two quarters before gradually declining, though remaining elevated throughout our sample period. These patterns remain consistent when we weight each firm's quarterly war exposure by either the share of its global workforce located in Ukraine or by its mean $E_{i,t}$ value during the corresponding quarter. Notably, the weighted *WarExposure* values remain consistently below the unweighted ones after the invasion, indicating that firms without Ukrainian operations also engaged in substantial war-related discussions. This broader pattern of concern likely reflects several channels through which the conflict affected firms globally, including disruptions to energy markets, volatility in commodity prices for wheat and metals, increased macroeconomic uncertainty, and concerns about broader geopolitical instability affecting international trade and investment.

While *WarExposure* measures the frequency of war related discussions, it does not distinguish whether executives express concern, identify opportunities, or provide neutral updates. To capture the perceived uncertainty and tone of these discussions, we construct two complementary measures following Hassan et al. (2024). First, *WarRisk* identifies sentences where war terms appear alongside risk related words such as "risk," "threat," or "uncertain." Second, *WarSentiment* measures net sentiment by subtracting the share of negative words from positive words in sentences containing war references in close proximity to these words.

Figure 6(b) shows that *WarRisk* follows a similar temporal pattern to *WarExposure*, rising sharply after the invasion with pronounced fluctuations throughout the period. These fluctuations suggest that managerial risk perceptions responded sensitively to evolving developments in the Ukrainian conflict, reflecting ongoing uncertainty about the war's trajectory and economic implications. Lastly, Figure 6(c) shows the most striking pattern. *WarSentiment* remained near zero before the invasion but dropped sharply to approximately 40% below baseline levels immediately after the invasion, reflecting predominantly negative managerial assessments of the conflict.

Notably, all three war-related textual measures gradually converged toward their baseline levels by 2024, suggesting that executives discussed the war less frequently and with less concern as the conflict persisted. This pattern indicates that the war transitioned from an acute crisis requiring immediate managerial attention to an ongoing geopolitical situation incorporated into firms' routine strategic planning.

V Market Reactions to the Ukraine Invasion

The 2022 Russian invasion of Ukraine provides a unique setting to examine how geopolitical shocks affect the market valuations of multinational firms with varying exposure to conflict zones. Despite months of military buildup by Russia along Ukraine's borders, the invasion beginning on February 24, 2022, caught global markets largely unprepared (Neely, 2022). Intelligence assessments had underestimated Russia's willingness to launch a comprehensive military operation, with many Western officials and analysts dismissing the possibility of a major European war as implausible. Global equity indices declined sharply on the day of the invasion, with Asian markets down as much as 3.2%, European indices losing up to 4%, and Eastern European markets experiencing particularly steep declines. U.S. markets opened sharply lower but recovered by the day end (Boungou and Yatié, 2022).[25]

The widespread stock market response on the day of the invasion provide an ideal setting for event study analysis. The sharp declines across global equity markets on February 24, 2022 indicate that investors immediately reassessed firm valuations upon learning of the invasion. Research on geopolitical shocks demonstrates that such events significantly alter market expectations and investor sentiment (Caldara and Iacoviello, 2022; Dräger, Gründler, and Potrafke, 2025), implying that the observed price movements reflect genuine information processing rather than random volatility. If stock prices incorporated information about the invasion, then firms with greater operational exposure to Ukraine should experience larger stock price declines during the event window.

V.A Event Study Results

We examine firm-level stock returns over a short event window surrounding February 24, 2022 to assess how investors priced the invasion. We estimate the following cross-sectional regression:

$$r_{i,[0,\tau]} = \alpha + \beta \overline{E}_{i,Post} + \gamma' \mathbf{X}_i + \delta_c + \theta_j + \mu_t + \epsilon_i \tag{5}$$

where $\text{CumRet}_{i,[0,\tau]}$ is the cumulative stock return for firm i over the τ-day window starting from day $t = 0$ (February 24, 2022, the onset of the invasion). $\overline{E}_{i,\text{Post}}$ is the average conflict exposure for firm i in the period following invasion, constructed by averaging the

[25] On February 24, 2022, major global equity indices declined in response to the invasion: Asian markets closed lower, with Japan's Nikkei 225 down 1.8%, Hong Kong's Hang Seng 3.2%, and China's Shanghai Composite 1.7%; European indices fell, with the STOXX Europe 600 declining 3.2%, London's FTSE 100 dropping 3.9%, Germany's DAX 4%, and France's CAC 40 3.8%; Eastern European markets experienced larger losses, with the Warsaw WIG20 index declining 10.9% and the Moscow MOEX suspended after falling as much as 45%; U.S. indices, which opened sharply lower, recovered by the day's close, with the S&P 500 rising 1.5%, the Dow Jones Industrial Average up 0.3%, and the Nasdaq Composite rising 3.3%.

firm's monthly conflict exposure, $E_{i,t}$ over the entire post-invasion period. $\mathbf{X}_i$ is a vector of firm level controls included to isolate the effect of conflict exposure on stock returns. We control for firm size measured by total assets, asset growth, and the cash to assets ratio. Firm size controls for the possibility that larger firms can better absorb geopolitical shocks. Asset growth and cash holdings capture growth opportunities and financial flexibility that may affect resilience to disruptions. We include the firm's beta with respect to its headquarters country equity market index to control for systematic domestic market risk. We also include betas with respect to major global equity market indices (U.S., U.K., China, Japan, and Russia) to account for differential sensitivities to international equity markets that may correlate with geopolitical exposure. Finally, we control for the firm's average conflict exposure before the invasion to isolate the incremental effect of the invasion itself rather than preexisting operational ties to Ukraine.

We also include three sets of fixed effects to control for unobserved heterogeneity. Headquarters country fixed effects (δ_c) absorb time invariant differences across countries, including institutional quality, regulatory environments, and baseline market conditions. Industry fixed effects (θ_j) absorb sector level characteristics that may correlate with conflict exposure. For example, manufacturing industries may have greater operational presence in Ukraine due to lower labor costs, while financial services firms may have smaller footprints concentrated in major cities. Similarly, energy intensive sectors may face indirect exposure through commodity price shocks even without direct Ukrainian operations. Day fixed effects (μ_t) absorb market wide shocks common to all firms on each day of the event window.

Table 4 presents the results for our primary event window covering the first three trading days following the invasion ($\tau = 3$). Panel A reports estimates for the full sample. The coefficient on $\overline{E}_{i,Post}$ is negative and statistically significant across all specifications. In the baseline model (column 1), a one SD increase in $\overline{E}_{i,Post}$ corresponds to a 2.2% decline in cumulative stock returns over the three day event window, indicating that firms with higher conflict exposure experienced larger valuation losses following the invasion. Columns (2) through (5) progressively add controls for firm characteristics, domestic and global market betas, and average conflict exposure of the firm before the invasion. The coefficient on $\overline{E}_{i,Post}$ remains stable in both magnitude and statistical significance, indicating that the negative stock price response is not driven by firm size, financial characteristics, systematic market risk exposures, or operational ties to Ukraine that existed before the invasion. The fully specified model (column 6) shows an estimated decline of 3.3% per SD of conflict exposure.

Panel B focuses on U.S. headquartered firms, which constitute a large share of the sample and had substantial operations in Ukraine before the invasion. For these firms, the baseline specification in column (1) shows a 1.1% stock price decline per SD increase in conflict exposure. This smaller coefficient reflects U.S. firms' greater concentration in less vulnerable oblasts before the invasion, as shown in Figure 1(c). U.S. firms therefore experienced smaller stock price declines during the event window than the average firm in the full sample.

Lastly, Panel C examines the stock price response for non-U.S. firms. The coefficient estimates for $\overline{E}_{i,Post}$ range from -0.015 to -0.037 across specifications. In the fully specified model (column 6), a one SD increase in conflict exposure corresponds to a 3.7% stock price decline, larger than the estimate for U.S. firms. This heightened sensitivity likely reflects distinct vulnerabilities among non-U.S. firms. European firms, which constitute a significant portion of the non-U.S. sample, are geographically closer to Ukraine and more reliant on regional supply chains for energy, metals, and other commodities (Aizenman et al., 2024; Auer et al., 2025), potentially making them more exposed to disruptions from the conflict. The non-U.S. sample also includes substantial representation from Asian countries, particularly Japan and China. Firms from these countries experienced notable stock price declines, consistent with their substantial operations in Ukrainian manufacturing and trade networks before the invasion, especially in machinery and electronics sectors (Silva, Wilhelm, and Tabak, 2023). The larger stock price declines for non-U.S. firms are consistent with their higher average conflict exposure and more concentrated operations in vulnerable Ukrainian oblasts, as documented in Figures 4 and **??**. |redFig A2 to be revised

These results demonstrate that the invasion affected firm valuations differentially based on operational exposure to Ukraine, with effects persisting after controlling for firm characteristics, market risk exposures, and pre-existing operations in Ukraine. The cross-sectional variation in stock price responses indicates that equity markets priced the economic costs of the conflict based on firms' specific operational footprints rather than uniform country or industry exposures.

To examine the timing and persistence of the market reaction, Figure 7 plots coefficient estimates and 95% confidence intervals for $\overline{E}_{i,Post}$ using a consistent three day event window but varying the starting date from eight days before to eight days after the actual invasion (day 0 is on February 24, 2022). We estimate equation (5) separately for each placebo and actual event date, progressively adding the control variables shown in Table 4. The figure reveals several important patterns. First, coefficients remain close to zero and statistically insignificant for event windows starting before the invasion, indicating no anticipatory market reaction and confirming that stock prices did not reflect conflict exposure prior to the actual invasion. Second, coefficients turn sharply negative and statistically significant for event windows beginning on or immediately after February 24, 2022, demonstrating that investors immediately repriced firms based on their Ukrainian exposure once the invasion occurred. Third, the negative effect remains significant and relatively stable for event windows starting in the days following the invasion, indicating persistent valuation effects rather than a temporary market overreaction that quickly reversed. Fourth, the pattern remains consistent across specifications with different sets of controls, indicating the results are not driven by firm size, financial characteristics, market risk exposures, or preexisting operational ties to Ukraine. These patterns confirm that the negative valuation effects documented in Table 4 reflect genuine market responses to the invasion that emerged precisely at the time of the event and persisted in the subsequent days.

VI Firm-level Effects of the Ukraine Invasion

The preceding analysis establishes several key findings regarding how the February 2022 Russian invasion of Ukraine affected multinational firms. First, although most firms operating in Ukraine maintained their presence, many substantially reduced their local workforce, with particularly sharp contractions in oblasts experiencing more intense military activity. Second, the conflict commanded immediate managerial attention, as evidenced by a sharp increase in war-related discussions during earnings calls in the quarters following the invasion. Third, equity markets rapidly incorporated the invasion into stock valuations, with firms experiencing differential stock price declines proportional to their exposure to the conflict.

In this section, we examine how these initial responses to the conflict translated into longer-term strategic adjustments in corporate investment and innovation. Beyond these immediate responses, the critical question is whether and how firms adjusted their capital allocation decisions given the heightened operational uncertainty and disruption the conflict generated. The substantial cross-sectional variation in conflict exposure implies that firms faced markedly different degrees of operational disruption in Ukraine. This variation in disruption severity could potentially influence firms' overall capital allocation as managers reassess investment priorities and resource deployment across their global operations.

Two distinct responses are theoretically plausible. First, precautionary motives may induce firms to reduce all forms of investment uniformly in response to elevated geopolitical uncertainty. This response accords with standard real options theory, whereby firms delay irreversible commitments until uncertainty resolves. Alternatively, firms may respond through compositional shifts in capital allocation, curtailing physical capital investments vulnerable to geopolitical disruption while increasing adaptive innovation spending that enhances operational flexibility and supply chain resilience. Distinguishing between these responses is essential for understanding how geopolitical shocks propagate through corporate decision making. If firms reduce investment uniformly, geopolitical conflicts primarily depress aggregate capital allocation due to dominant precautionary motives. If instead firms engage in compositional reallocation, conflicts may accelerate physical capital investment as firms relocate operations, or may accelerate innovation spending as firms develop adaptive or new technologies, even as the other investment category declines. Moreover, because capital expenditures and R&D involve multi-year commitments with substantial irreversibility, these decisions provide sharper identification of persistent strategic adjustments rather than transitory operational responses. Distinguishing between these responses reveals how geopolitical shocks propagate through corporate capital allocation and ultimately shape long-run productivity and competitive positioning.

To distinguish between these competing mechanisms, we examine how conflict exposure affected firms' capital expenditures, R&D spending, and related corporate outcomes including employment and profitability. We exploit cross-sectional variation in firms' exposure to the conflict and implement the following difference-in-differences (DiD) specification:

$$Y_{i,q+1} = \beta \overline{\mathrm{E}}_{i,q} + \gamma' \mathbf{X}_{i,q} + \mu_q + \delta_c + \theta_j + \phi_{c,j} + \eta_{c,q} + \lambda_{j,q} + \epsilon_{i,q} \tag{6}$$

where $Y_{i,q+1}$ denotes the firm-level outcome of interest for firm i in quarter $q+1$, such as capital expenditures, R&D expenditures,and other firm outcomes. $\overline{E}_{i,q}$ denotes firm i's quarterly conflict exposure, computed by averaging monthly values $E_{i,t}$ within quarter q and standardizing across all firms.[26] The coefficient of interest, β, captures the differential effect of conflict exposure on firm outcomes. Because firms' pre-invasion workforce allocations across Ukrainian oblasts were determined by economic considerations unrelated to which regions Russia would subsequently target, and because the invasion's timing and intensity of military operations across these oblasts were beyond individual firms' control, this variation provides plausibly exogenous identification of the conflict's impact.

The vector $\mathbf{X}_{i,q}$ includes firm-level controls similar to those in Equation 5, but at the quarterly frequency. To isolate the effects of conflict exposure on firm outcomes, our specification includes a rich set of fixed effects. Quarter (time) fixed effects (μ_q) absorb aggregate shocks common to all firms in each period, global financial market volatility and commodity price fluctuations triggered by the invasion. Headquarter country fixed effects (δ_c) control for time-invariant institutional differences across countries that may affect firm resilience to geopolitical shocks, including proximity to the conflict zone or historical trade ties with Ukraine and Russia. Industry fixed effects (θ_j) account for sector-specific exposures to geopolitical risks, such as heightened vulnerabilities in industries reliant on Ukrainian commodities like wheat, sunflower oil, and iron ore. More importantly, equation 6 includes three sets of interaction fixed effects that absorb potentially confounding time-varying heterogeneity.

[26] Since financial outcomes at the firm level are reported only quarterly in Compustat, we aggregate the monthly exposure measure $E_{i,t}$ to the quarterly level by averaging it within each quarter.

Country × quarter fixed effects ($\phi_{c,j}$) control for time-varying factors in each country, including domestic policy responses to the invasion, macroeconomic conditions, and refugee inflows that could systematically affect firms within each country. Country × industry fixed effects ($\phi_{c,j}$) control for persistent structural differences across country-industry pairs, including sector-specific trade linkages with Ukraine, differential regulatory exposure to Eastern European operations, and industry-specific agglomeration patterns that vary systematically across headquarter countries. Lastly, industry × quarter fixed effects ($\lambda_{j,q}$) absorb time-varying sectoral trends, such as energy price shocks affecting manufacturing or agricultural disruptions impacting food processing companies.

VI.A Impact on Capital Expenditures

We first examine the effects of conflict exposure on corporate capital expenditures. Capital expenditures represent physical investments in property, plant, and equipment – commitments that are largely irreversible and vulnerable to geopolitical disruption. Following the theoretical framework in Section **??**, which predicts that heightened geopolitical uncertainty induces firms to delay irreversible capital investments until conditions stabilize, we estimate equation 6 to test this mechanism.

Table 5 presents the results. The dependent variable is capital expenditures in the next quarter q+1 scaled by total assets in current quarter q. The key independent variable is $E_{i,q}$, the firm's standardized conflict exposure in quarter q. Panel A reports estimates for the full sample.

The coefficient on conflict exposure is negative and statistically significant at the 1% level across all specifications. Column (1) presents the baseline result, which includes the lagged dependent variable as a control. A one SD increase in conflict exposure corresponds to a 1.9% decline in capital expenditures relative to the sample mean of 2.1%.[27] This effect is robust to including additional controls for firm size, asset growth, and realized volatility in columns (2) through (4). Across these specifications, a one SD increase in conflict exposure corresponds to a 2.0% to 2.1% decline in capital expenditures relative to the sample mean.

To further investigate the dynamics of this relationship over time, we employ a rolling window estimation approach separately for the pre- and post-invasion periods. Specifically, we estimate the following specification using rolling windows of five quarters each.[28] We

[27]Since the dependent variable is bounded between zero and one, we estimate equation 6 using fractional logit regressions following Papke and Wooldridge (2008). The coefficient β does not directly represent the marginal effect in this nonlinear model. We therefore compute the average marginal effect as AME $= \frac{1}{N}\sum_{i=1}^{N}\beta \cdot \hat{p}_i \cdot (1-\hat{p}_i)$, where $\hat{p}_i$ are fitted values and N is the number of observations. We report the relative marginal effect as $\left(\frac{\text{AME}}{\overline{y}}\right) \times 100\%$, where $\overline{y}$ is the sample mean.

[28]Standard event study designs with lead and lag indicators assume binary or time-invariant treatment status, which is unsuitable here since $\overline{\text{E}}_{i,q}$ is a continuous, firm-specific measure that varies substantially

estimate the following specification using rolling windows of five quarters each:

$$Y_{i,q+1} = \beta_q \cdot \overline{\mathrm{E}}_{i,q} + \gamma Y_{i,q} + \delta \log(\mathrm{Assets}_{i,q}) + \alpha_q + \mu_j + \nu_c + \eta_{c,q} + \theta_{c,j} + \epsilon_{i,q} \tag{7}$$

where $Y_{i,q+1}$ is capital expenditures in the next quarter scaled by current total assets, β_q is the time-varying coefficient estimated for each central quarter q, and the fixed effects are as defined in equation 6.[29] Each rolling window is centered on a focal quarter, extending two quarters before and after.

Figure 8 plots the coefficients from these rolling window estimations, illustrating how the impact of conflict exposure on capital expenditures evolves around the invasion. For the full sample (Panel 8(a)), pre-invasion coefficients are close to zero and statistically insignificant. This pattern is expected given that conflict exposure itself, on average, was minimal before February 2022 (see Figure 3). Critically, it validates the parallel trends assumption by confirming that firms followed similar investment trajectories before the invasion, regardless of how exposed they would become once hostilities began. Following the invasion, the coefficients become negative and statistically significant, and remain so throughout the post-invasion period. This persistent negative effect is consistent with the capital expenditure reductions documented in Table 5. The shift from insignificant coefficients before the invasion to consistently negative coefficients afterward confirms a causal effect of conflict exposure on capital expenditures. This pattern is also consistent with firms deferring capital investments in response to workforce contractions and facility exits in conflict-affected oblasts (Table 2).

across both firms and time based on each firm's evolving conflict exposure. Moreover, estimating effects quarter-by-quarter using raw exposure values may produce unstable coefficients that obscure systematic patterns, as quarterly fluctuations in firm-level exposure reflect not only meaningful changes in conflict intensity but also measurement noise, temporary operational adjustments, and idiosyncratic firm decisions. To address these challenges, we employ a rolling window approach that smooths short-term fluctuations and reveals the underlying evolution of exposure effects over time. Following Inoue, Jin, and Rossi (2017), the optimal window size for such analysis grows with $T^{2/3}$, where T is the sample period length. With 12 pre-invasion quarters (Q1'2019 to Q4'2021) and 13 post-invasion quarters (Q1'2022 to Q1'2025), this yields an optimal window size of 5 quarters. Each estimate in the plots uses data from two quarters before and two quarters after the focal quarter, to capture the invasion's impact clearly while keeping the estimates stable. We exclude quarters whose windows would span the invasion boundary. However, we adopt a slightly more flexible approach at the sample period boundaries within the pre period: for instance, Q2'2019 and Q3'2021 are included despite having only one quarter prior and after within their respective windows. This approach prioritizes avoiding contamination across the invasion boundary while maximizing data use within each period. This approach ensures that all estimates use data exclusively from either the pre-invasion or post-invasion period, preventing contamination from the structural break at the invasion onset. The analysis thus tracks exposure effects from Q2'2019 through Q3'2021 pre-invasion, and from Q3'2022 through Q3'2024 post-invasion.

[29] We include the lagged outcome variable and log assets as controls, as in model (2) of Table 5. The model is estimated using a fractional logit model with quasi-binomial family and logit link, with standard errors clustered at the firm level.

We next examine heterogeneity in capital expenditure responses based on firm headquarters location. Panel B of Table 5 reports results for U.S. firms, which constitute nearly half the sample and had substantial pre-invasion presence in Ukraine (32.3% of them operated there before the conflict, as seen in Table 1). A one SD increase in conflict exposure corresponds to a 2.2% reduction in capital expenditures relative to the U.S. firm sample mean of 1.75%. Figure 8(b) plots coefficients from rolling window regressions for U.S. firms, showing how this effect evolved over time. The pre-invasion coefficients remain close to zero and statistically insignificant, indicating no relationship between conflict exposure and capital expenditures before February 2022. Following the invasion, coefficients turn sharply negative and remain so through Q1 2024, demonstrating that conflict exposure induced persistent capital expenditure reductions among U.S. firms, with more exposed firms cutting investment relative to their less exposed peers.

Panel C of Table 5 presents results for non-U.S. firms, where a one SD increase in conflict exposure corresponds to a 1.85% reduction in capital expenditures relative to their sample mean of 2.45%. Figure 8(c) displays the corresponding rolling window estimates for non-U.S. firms. While the post-invasion coefficients are consistently negative, most do not achieve statistical significance at conventional levels. This pattern contrasts with the significant negative effect documented in Panel C of Table 5. The difference reflects the distinct objectives of these specifications. The rolling window approach is designed to trace temporal evolution in the relationship between conflict exposure and investment, revealing whether effects strengthen, weaken, or remain stable over time. For the non-U.S. sample spanning multiple countries with diverse institutional environments, this temporal flexibility comes at a cost: if investment responses vary substantially across countries or evolve differently over time, the rolling window estimates may fail to achieve significance even when an average effect exists. In contrast, the pooled specification in Panel C, Table 5 imposes a constant average effect across all post-invasion quarters and leverages country-by-quarter and industry-by-quarter fixed effects to absorb institutional heterogeneity, yielding a precise estimate of the average investment response among non-U.S. firms. The significant pooled estimate thus indicates that on average, non-U.S. firms reduced capital expenditures in response to conflict exposure, even though this response may have varied in timing or magnitude across different headquarters countries.

The larger proportional reduction in capital expenditures among U.S. firms exposed to the Ukraine invasion merits further consideration. This heterogeneity cannot be attributed solely to differences in conflict exposure, as both U.S. and non-U.S. firms maintained substantial presence in Ukraine before the invasion. Instead, the differential response likely reflects institutional differences across headquarters countries that shape how firms adjust investment in response to geopolitical disruptions.

Several mechanisms may contribute to the stronger U.S. response. First, U.S. firms' extensive global supply chains and deep integration into international production networks may amplify their exposure to geopolitical shocks. When conflicts disrupt key nodes in these networks, U.S. firms may face greater operational uncertainties that prompt stronger precautionary cutbacks in capital investments (Hassan et al., 2019). Second, differences in financial market structure may intensify uncertainty transmission in the United States. Deeper and more liquid U.S. capital markets enable investors to rapidly incorporate geopolitical developments into asset prices, potentially leading to sharper increases in firms' cost of capital and equity risk premiums following adverse shocks (Alfaro, Bloom, and Lin, 2023). This rapid price adjustment may reinforce managerial incentives to curtail capital expenditures. Third, institutional differences in labor market flexibility, corporate governance structures, and regulatory environments across countries may affect both the operational disruptions firms experience and their capacity to adjust strategically (Julio and Yook, 2012).

VI.B Impact on R&D Spending

Having established that conflict exposure reduced capital expenditures, we now examine whether firms also curtailed R&D spending or instead reallocated capital toward innovation. This distinction is critical for understanding the nature of firm responses to geopolitical shocks. If precautionary motives dominate, firms should reduce both physical and innovation investments uniformly. Alternatively, if firms engage in compositional reallocation, they may increase R&D spending to develop adaptive technologies, alternative supply chains, or products less vulnerable to geopolitical disruption, even as they curtail capital expenditures.

Table 6 reports estimates from equation 6 where the dependent variable is R&D expenditures in quarter $q+1$ scaled by total assets in quarter q. Panel A presents results for the full sample. The coefficient on conflict exposure is positive across all specifications, ranging from 0.033 (SE = 0.020) in column (1) to 0.044 (SE = 0.021) in column (4). These estimates suggest that a one SD increase in conflict exposure is associated with a 0.04 percentage point rise in subsequent R&D spending (based on column (4) estimates) relative to an unexposed firm. This effect corresponds to a 4.9% increase in subsequent R&D investments relative to the sample mean. Figure 9(a) plots coefficients from rolling window regressions for the full sample, revealing the temporal evolution of this effect. Pre-invasion coefficients fluctuate around zero and are statistically insignificant, consistent with firms exhibiting similar R&D patterns before the invasion regardless of their subsequent conflict exposure levels. The coefficients turn positive and remain significant throughout most of the post-invasion period, implying that conflict exposure induced persistent increases in innovation spending. This temporal pattern confirms that the positive R&D response emerged specifically after the invasion and persisted as firms adapted to the operational challenges created by the conflict.

Panel B of Table 6 reports results for U.S. firms, where the positive effect on R&D is more pronounced. The coefficient on conflict exposure ranges from 0.053 (SE = 0.024) in column (1) to 0.066 (SE = 0.023) in column (4). A one SD increase in conflict exposure corresponds to a 6.7% increase in R&D intensity relative to the sample mean for U.S. firms. Figure 9(b) plots the rolling window estimates for these firms, showing near-zero coefficients before the invasion followed by consistently positive coefficients afterward, confirming a persistent increase in R&D spending among more U.S. firms with greater conflict exposure. Panel C reports results for non-U.S. firms, where coefficients are close to zero and statistically insignificant across all specifications, indicating no discernible R&D response to conflict exposure among these firms. Figure 9(c) plots the rolling window estimates for non-U.S. firms, showing that coefficients remain near zero throughout the sample period with no discernible shift in R&D spending after the invasion. This pattern stands in contrast to the persistent positive response in R&D investment among U.S. firms post-invasion.

The cross-country heterogeneity in R&D responses to conflict merits consideration. U.S. firms increased innovation spending substantially while non-U.S. firms showed no systematic R&D response, despite both groups experiencing workforce contractions in Ukraine (Table 2). This heterogeneity likely reflects institutional differences in financial market depth and operational flexibility. U.S. firms' access to deep equity markets for financing innovation (Brown, Fazzari, and Petersen, 2009; Hsu, Tian, and Xu, 2014) may have enabled them to increase R&D spending even while managing operational disruptions due to the conflict. In contrast, non-U.S. firms, particularly those in Europe and Japan where bank financing dominates equity financing (Porta et al., 1998; Rajan and Zingales, 1995) and where equity market financing of innovation is less developed (Brown, Fazzari, and Petersen, 2009; Hsu, Tian, and Xu, 2014), maintained stable rather than increased R&D spending despite comparable conflict exposure.

The effects of conflict exposure on capital expenditures and R&D spending diverged sharply, revealing reallocation across investment categories rather than uniform reductions. While capital expenditures declined by approximately 2% for the full sample (Table 5), R&D spending increased by 4.9% (Table 6). This divergence was driven primarily by U.S. firms, which reduced capital expenditures while simultaneously increasing R&D spending. In contrast, non-U.S. firms reduced capital expenditures but exhibited no systematic R&D response. Overall, these patterns are inconsistent with standard precautionary models predicting uniform investment reductions or deferrals under uncertainty. Instead, U.S. firms appear to have strategically reallocated capital away from irreversible physical investments toward innovation spending. The results demonstrate that geopolitical shocks do not uniformly depress corporate investment but instead trigger compositional shifts in capital allocation. The direction and magnitude of these shifts depend critically on firms' institutional environment, with U.S. firms exhibiting greater flexibility to reallocate toward innovation during periods of heightened geopolitical risk.

VI.C Robustness Checks

Permutation Tests. Previously, our balance tests reported in Table A1 verify that potential conflict exposure, our measure of firms' latent vulnerability based on their pre-invasion workforce distribution across Ukrainian oblasts, did not predict observable firm characteristics leading into the invasion. To further validate that our results on investment outcomes are driven by the actual geographic pattern of firms' Ukrainian operations rather than spurious correlations, we conduct permutation tests. While balance tests address selection on observable characteristics, permutation tests examine whether the actual match between specific firms and their conflict-affected locations is essential to our findings. If unobserved factors correlated with both location choices and investment responses were driving our findings, randomly reassigning exposure across firms should produce similar coefficients, as these underlying confounders would persist despite reshuffled exposure. Conversely, if our results genuinely reflect the geographic pattern of operational exposure, random permutation should yield null results.

We implement the test by randomly shuffling conflict exposure values across firms within each quarter. This procedure breaks the link between each firm's actual Ukrainian operations and its conflict exposure, while preserving the distribution of exposure levels within quarters and the temporal evolution of overall conflict intensity. We re-estimate Equation 6 with these placebo exposures 1,000 times to generate an empirical distribution of coefficients under random assignment.

Figure A6 displays the permutation distributions for capital expenditures (Panel A6(a)) and R&D spending (Panel A6(b)). The red vertical lines mark our baseline coefficients from Model (2) of Panel A in Tables 5 and 6, respectively. The permuted coefficients center around zero, with our baseline estimate of -0.020 for capital expenditures exceeding 98.6% of placebo coefficients, and our baseline estimate of 0.044 for R&D spending exceeding 99.98% of placebo coefficients. These results confirm that our findings are driven by the geographic distribution of conflict across firms' actual operational locations, rather than by selection on unobservables or other confounding factors.

Placebo tests for conflict timing. To test whether our results depend on the actual timing of the conflict, we conduct placebo tests that shift the timing of conflict exposure backward in time. Specifically, we assign firms their realized conflict exposure from k quarters in the future ($k = 1$ to 12 quarters) and re-estimate equation (9) using only observations from the pre-invasion period. This procedure tests whether firms' investment patterns during the period before the invasion were systematically related to the conflict exposure they would experience k quarters later. If our results were driven by factors other than actual conflict exposure during the invasion, we would observe similar coefficients even when conflict timing is artificially shifted backward.

Figure A7 presents the results. For capital expenditures (Panel A7(a)), placebo coefficients are centered around zero and statistically insignificant across nearly all timing shifts, with the actual coefficient of -0.020 falling outside the placebo distribution. For R&D spending (Panel A7(b)), placebo coefficients similarly cluster near zero, while the actual coefficient of 0.044 lies in the upper tail of the distribution. These findings confirm that our results are driven by the actual timing of the conflict, as artificially shifting exposure backward eliminates the observed investment effects.

VII Conclusion

We examine how geopolitical risk affects multinational firms through their operational exposure to conflict zones. Exploiting the February 2022 invasion of Ukraine by Russia as a quasi-natural experiment, we construct a novel time-varying, firm-level conflict exposure measure that integrates regional vulnerability based on ethnic Russian population shares from the 2001 census, local conflict intensity from geocoded military incident data, and firms' pre-invasion workforce allocation across Ukrainian oblasts.

We document three main findings. First, conflict exposure generates substantial valuation losses: a one standard deviation increase in exposure produces a 3.3% stock price decline. Second, firms reallocate capital across investment types rather than uniformly cutting spending. Capital expenditures decline by 2% while R&D spending increases by 4.9% among firms with active operations in Ukraine before the war. Third, these investment responses vary systematically by headquarters country: U.S. firms exhibit larger capital expenditure reductions but stronger R&D increases compared to non U.S. counterparts.

These results contribute to the literature on geopolitical uncertainty and firm behavior in three ways. First, our granular firm-level measure documents heterogeneity in responses to localized geopolitical shocks, extending aggregate analyses (Baker, Bloom, and Davis, 2016; Caldara and Iacoviello, 2022). Second, we show that active conflict generates asymmetric investment responses, reducing capital expenditures while stimulating R&D , rather than lead to uniform reductions in investment allocation under policy uncertainty. Third, cross-country heterogeneity highlights how institutional factors, such as financial market development, shape corporate resilience to geopolitical uncertainties (Brown, Fazzari, and Petersen, 2009).

Several considerations warrant attention when interpreting our results. While our identification strategy exploits plausibly exogenous variation in conflict exposure arising from the interaction of predetermined workforce allocations and unanticipated conflict intensity, the 2022 invasion coincided with other major geopolitical events that may potentially confound our estimates: Western governments imposed extensive sanctions on Russia, disrupting trade and financial flows. Commodity markets experienced sharp volatility, with Brent crude oil prices rising from \$78 to \$130 per barrel (Troderman, 2023), and wheat futures increased over 50% between mid-February and early March 2022 (Patel, 2024). The conflict also initiated supply chain adjustments as firms recalibrated their regional dependencies on Ukraine and Russia (Srai et al., 2023). These contemporaneous shocks make it challenging to isolate the pure effect of operational conflict exposure from related macroeconomic disruptions.

Our empirical strategy addresses these concerns through extensive fixed effects that absorb country, industry, and firm specific heterogeneity across time, alongside controls for observable firm characteristics. Nevertheless, we cannot definitively rule out that broader macroeconomic disruptions may potentially contribute to our documented effects. Three patterns, in particular, support a causal interpretation. First, the results remain stable across specifications with different types of controls, indicating robustness to alternative explanations. Second, we document substantial cross-sectional heterogeneity in firm responses to the invasion: firms with greater Ukrainian exposure experience systematically larger valuation declines and investment reallocations than firms with lower exposure. This granular variation is inconsistent with aggregate shock explanations that would affect all firms uniformly. Third, the compositional shift from capital expenditures to R&D spending suggests targeted strategic adaptation to operational disruption rather than the uniform retrenchment characteristic of financial distress or broad based uncertainty shocks.

Our findings suggest several avenues for future research. First, analyzing the post-conflict period more broadly would determine whether the shift from physical to knowledge capital persists or reverses as military hostilities subside. Tracking the same firms over multiple years could distinguish temporary disruption from permanent strategic reorientation in capital allocation. Second, examining patent filings and citations would clarify whether increased R&D spending produces process innovations that reduce supply chain vulnerabilities, product innovations that substitute for disrupted inputs, or exploratory research positioning firms for new markets. Third, applying our measurement approach to other armed conflicts in different regions, would test whether our findings generalize across settings or depend on specific conflict characteristics, regional institutions, or firm nationality patterns. Fourth, comparing the investment responses across ownership structures, board independence levels, and CEO backgrounds would reveal whether concentrated ownership accelerates investment reallocation, whether experienced boards moderate overreaction to geopolitical shocks, or whether CEOs with international experience maintain R&D spending more effectively during conflicts.

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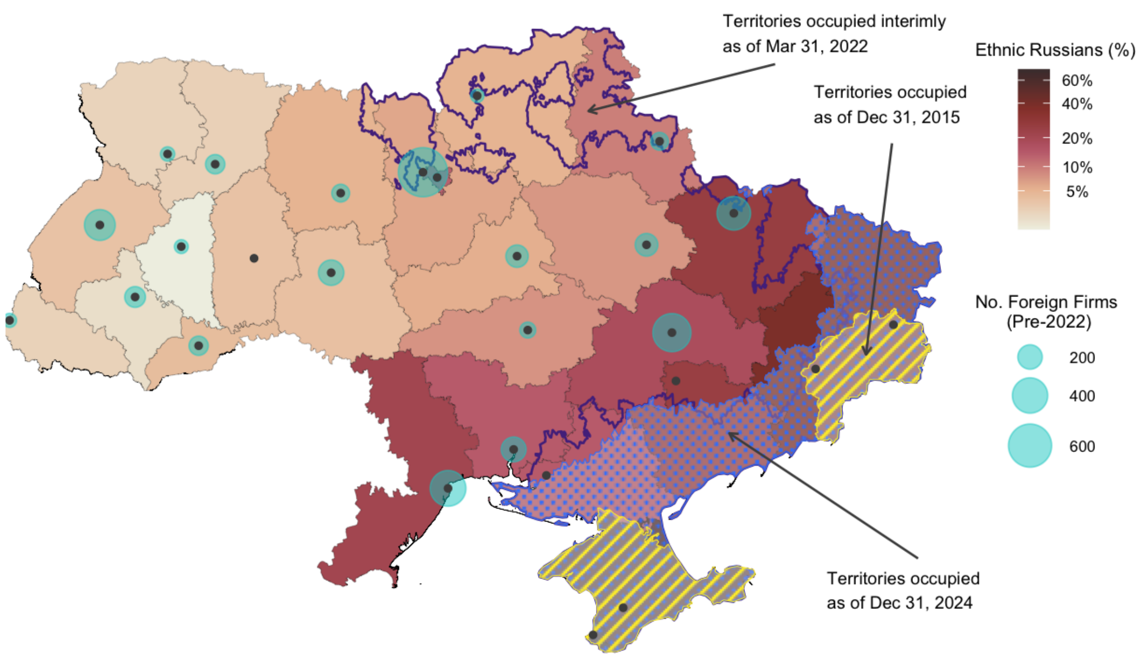
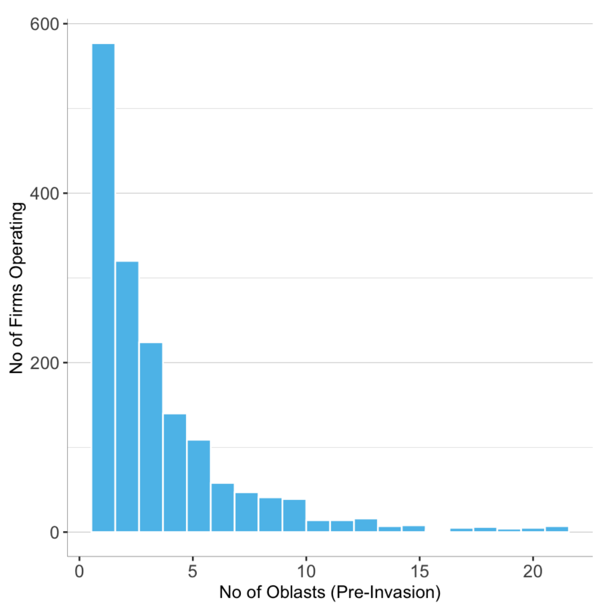
Figure 1: **Geographic distribution of multinational firm operations across Ukraine**
This figure presents the geographic distribution of multinational firm operations across Ukrainian oblasts prior to the February 2022 Russian invasion. Panel (a) reports the number of firms operating in each oblast and the corresponding share of ethnic Russians from the 2001 All-Ukrainian Population Census, which serves as our measure of regional conflict vulnerability (V_l). Panel (b) summarizes the distribution of firm presence across oblasts, showing the number of firms operating in one, two, or multiple oblasts. Panel (c) presents the cumulative distribution of firm-level conflict vulnerability, calculated as the average ethnic Russian population share across all oblasts where each firm operated, weighted by the firm's pre-invasion workforce allocation in each oblast.

(a) Geographic distribution of firms



(b) Firm presence across oblasts before invasion



(c) Conflict vulnerability among firms

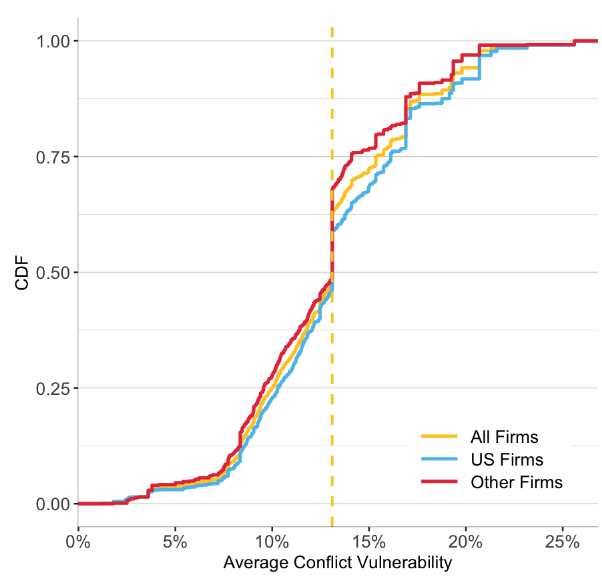
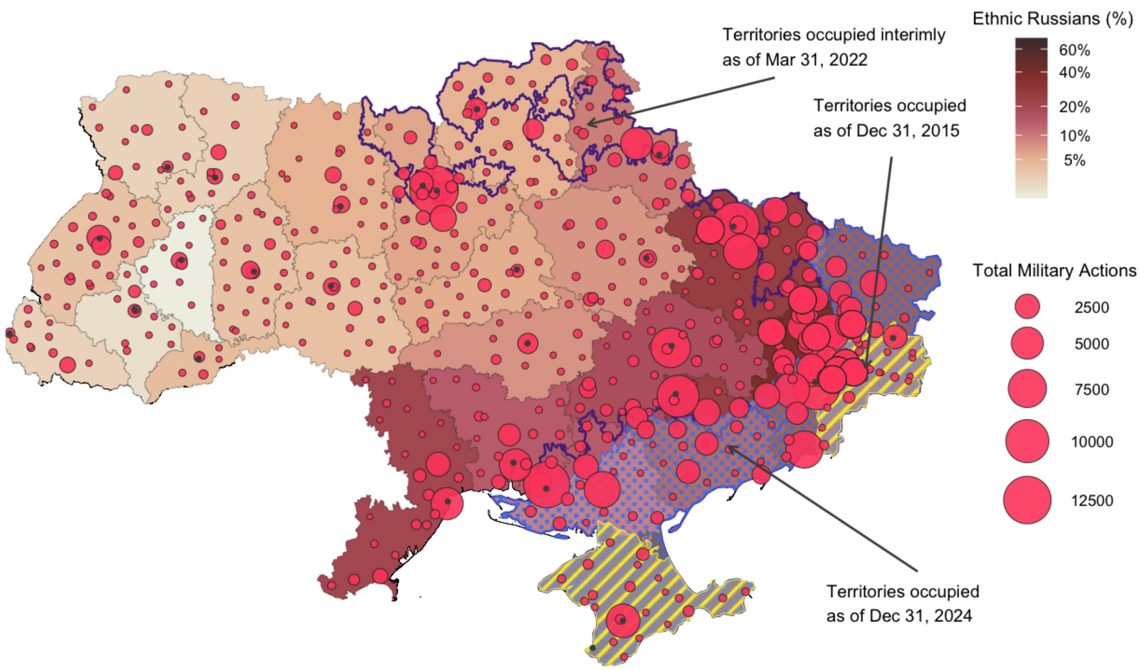
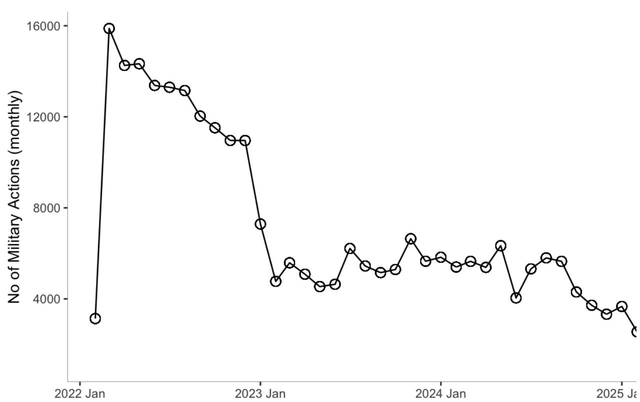


Figure 2: **Conflict intensity during the invasion**
This figure examines the relationship between conflict intensity and firm operational adjustments across Ukrainian oblasts during the February 2022 invasion. Panel (a) maps the geographic distribution of military incidents from February 2022 to February 2025, with shading indicating ethnic Russian population shares from the 2001 census and circle sizes representing the number of attacks in each *raion* (district) during this period. Panel (b) plots the monthly nationwide count of military actions, showing the temporal evolution of conflict intensity throughout the sample period. Panel (c) examines the cross-sectional relationship between oblast-level conflict vulnerability and conflict intensity (share of nationwide military attacks occurring in each oblast), with circle sizes proportional to the number of firms operating in each oblast before the invasion. Oblasts Donetsk, Luhansk, and Crimea are excluded from this analysis due to Russian occupation of these regions during the 2014 annexation.

(a) Geographic distribution of military actions (Feb'22 – Feb'25)



(b) Attacks per month nationwide



(c) Heterogentiy by oblast vulnerability

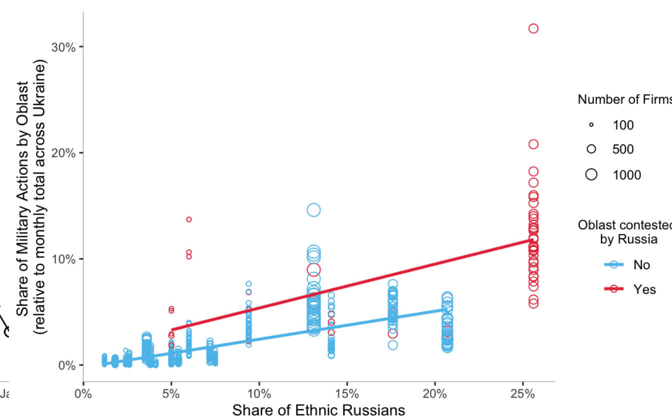


Figure 3: **Evolution of firm-level conflict exposure over time**
This figure plots the median monthly conflict exposure $E_{i,t}$ for firms in our sample from February 2019 to February 2025. Conflict exposure is calculated as the weighted average of conflict intensity across all Ukrainian oblasts where a firm operates, with weights based on the firm's pre-invasion workforce allocation across oblasts. The vertical dashed line marks February 24, 2022, the onset of the Russian invasion. Results are shown separately for all firms (red line), U.S.-headquartered firms (blue line), and non-U.S. firms (teal line).

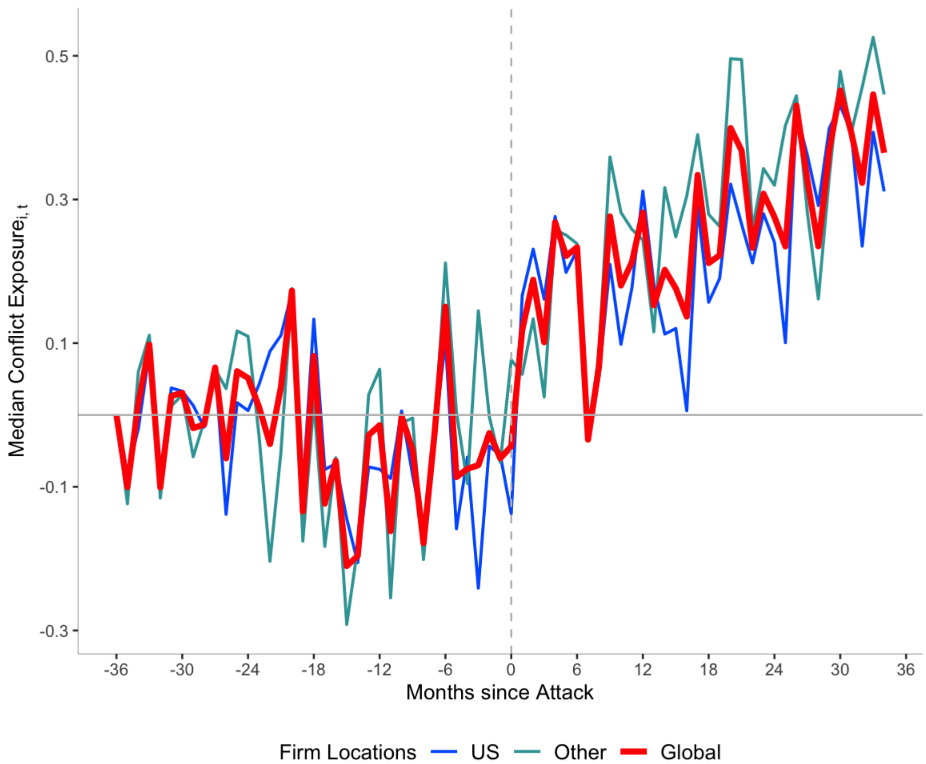


Figure 4: **Cross-country heterogeneity in firm conflict exposure**
This figure presents mean firm-level conflict exposure $E_{i,t}$ by headquarters country, calculated by averaging monthly conflict exposure across all firms and months within each country. Panel (a) shows the pre-invasion period (February 2019 to January 2022), and panel (b) shows the post-invasion period (February 2022 to February 2025).

(a) Before Feb'22 invasion (b) After Feb'22 invasion

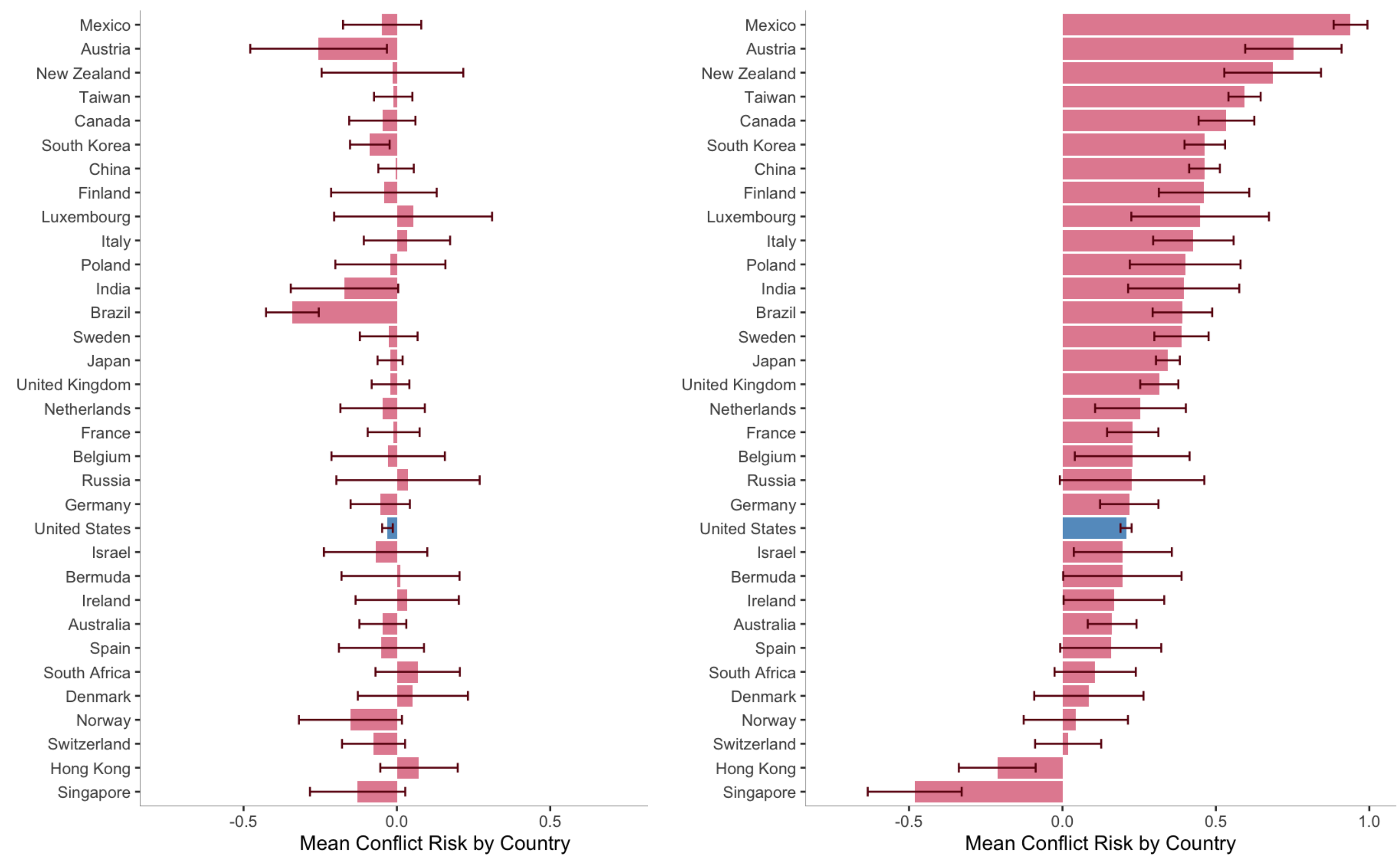


Figure 5: **Cross-industry heterogeneity in firm conflict exposure**

This figure presents mean firm-level conflict exposure $E_{i,t}$ by industry, calculated by averaging monthly conflict exposure across all firms and months within each industry. Panel (a) shows the pre-invasion period (February 2019 to January 2022), and panel (b) shows the post-invasion period (February 2022 to February 2025). Industries are classified using Revelio's *rics_k50* taxonomy, which groups firms into 50 distinct industry categories based on standardized company classifications.Error bars represent 95% confidence intervals.

(a) Before Feb'22 invasion

(b) After Feb'22 invasion

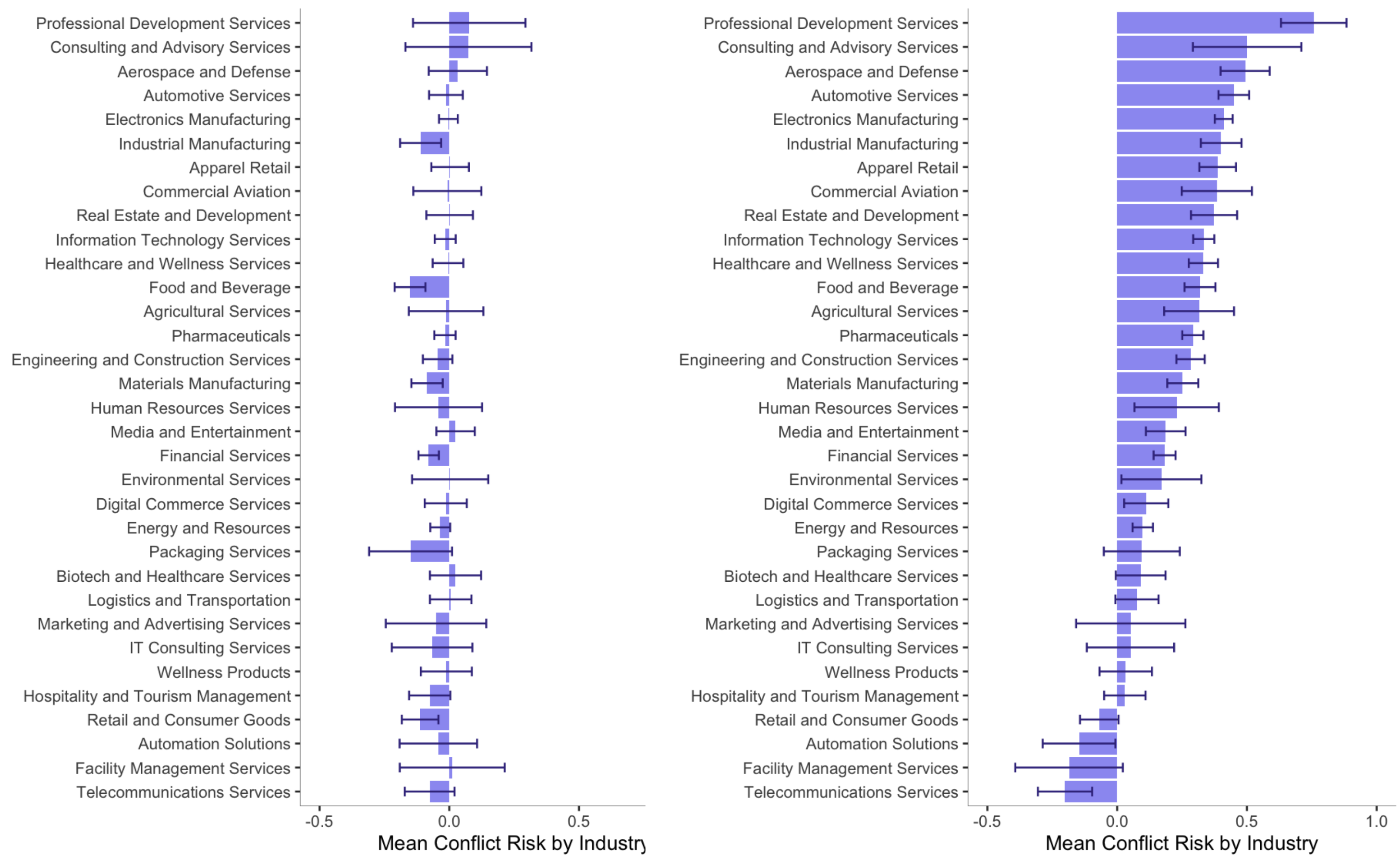
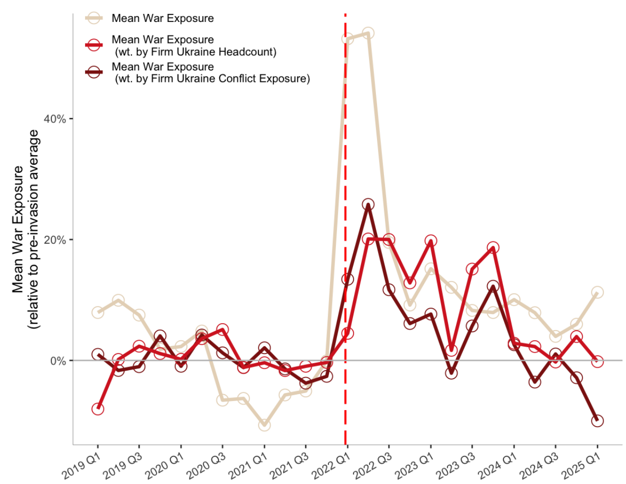
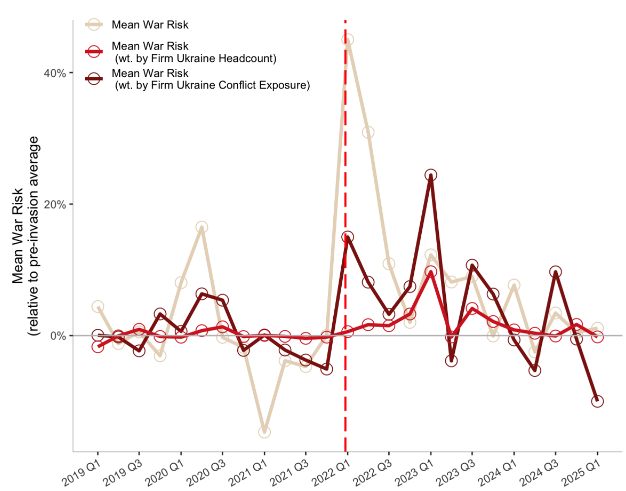


Figure 6: **Ukraine war discussions in firm earnings calls**
This figure presents three text-based measures of how firms discussed the Ukraine war in quarterly earnings call transcripts from 2019 Q1 to 2024 Q4. Panel (a) plots $WarExposure$, the proportion of total bigrams in the question-and-answer portion that relate to the Ukraine war, Russia, or associated conflict terms. Panel (b) plots $WarRisk$, which identifies sentences where war terms appear alongside risk-related words such as "risk," "threat," or "uncertainty." Panel (c) plots $WarSentiment$, which measures net sentiment by subtracting the share of negative words from positive words in sentences containing war references. Each measure is shown as a raw average across all firms (light red), weighted by the share of each firm's global workforce located in Ukraine before invasion (medium red), and weighted by the firm's mean conflict exposure $E_{i,t}$ during the corresponding quarter (dark red). The vertical dashed line marks February 24, 2022, the onset of the Russian invasion. The sample is restricted to firms headquartered in the U.S., U.K., European Union, Australia, and Canada based on available earnings call transcripts.

(a) War Exposure



(b) War Risk



(c) War Sentiment

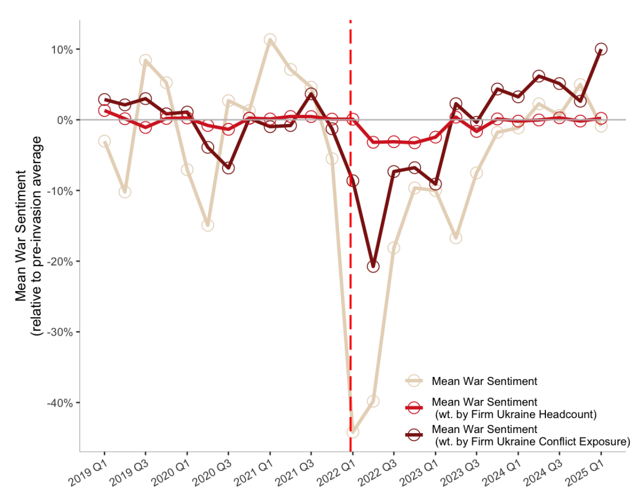


Figure 7: **Stock returns around the invasion**

This figure plots coefficient estimates and 95% confidence intervals for $\overline{E}_{i,Post}$ (mean post-invasion conflict exposure) from cross-sectional regressions of three-day cumulative stock returns on conflict exposure. The x-axis indicates the starting day of each three-day event window relative to February 24, 2022 (day 0), the onset of the Russian invasion. Each point represents a separate regression using equation (8) with a three-day window beginning on that day. Five specifications are considered, progressively adding the following controls: firm size (log assets); firm asset growth and cash-to-assets ratio; headquarters-country market beta; global market betas for U.S., U.K., China, Japan, and Russia; and pre-invasion conflict exposure. The vertical dashed line marks the actual invasion date. All specifications include headquarters-country, industry, and day fixed effects. Standard errors are double-clustered by firm headquarters country and date.

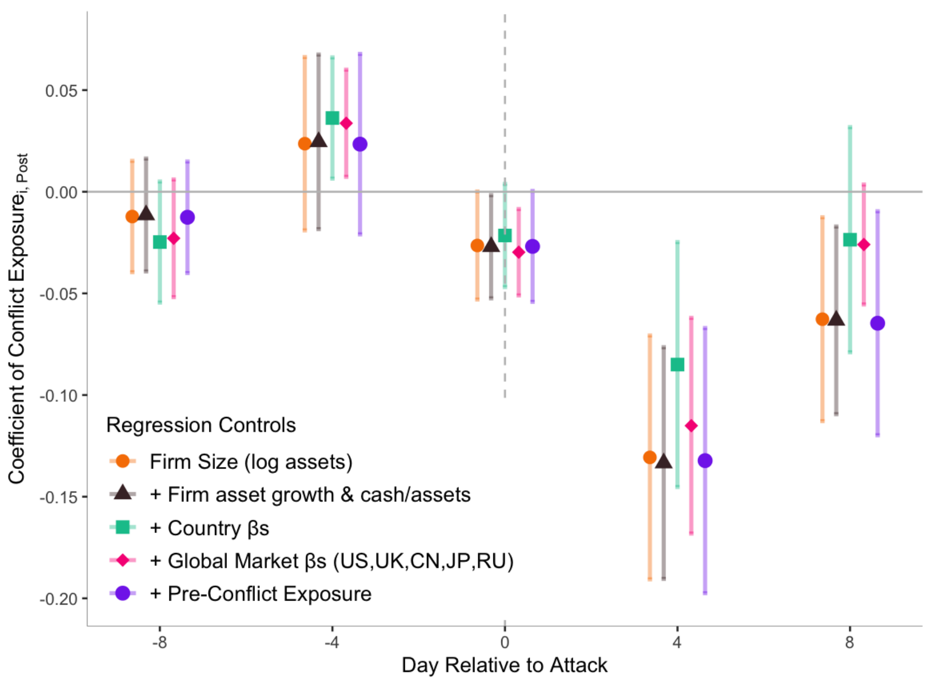
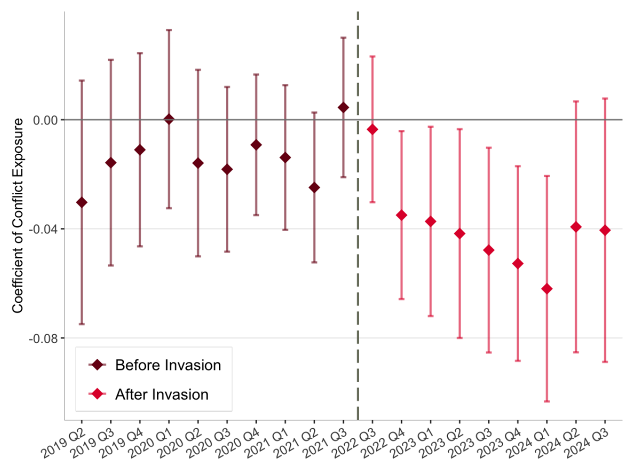
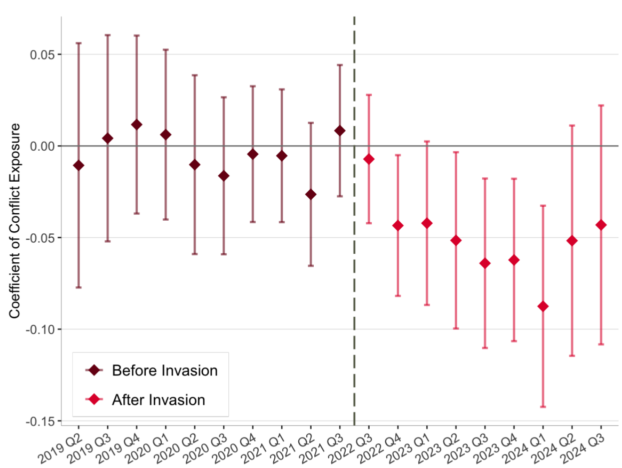


Figure 8: **Conflict exposure and firm capital expenditures around the invasion**
This figure plots coefficient estimates and 95% confidence intervals from rolling four-quarter window regressions of capital expenditures on conflict exposure, estimated separately before and after the February 2022 invasion. The dependent variable is capital expenditures in quarter $q+1$ scaled by total assets in quarter q. The key independent variable is $E_{i,q}$, the firm's average monthly conflict exposure over quarter q, standardized within each quarter. Each point represents the coefficient estimate β_q from equation 7 for a five-quarter window centered on quarter q. The rolling window approach smooths quarter-to-quarter volatility in coefficient estimates while capturing the time-varying relationship between conflict exposure and investment decisions. Panel (a) presents results for all firms, panel (b) for U.S.-headquartered firms, and panel (c) for non-U.S. firms. All specifications include the lagged dependent variable, firm size (log assets), and quarter, industry, headquarters-country, headquarters-country × industry, headquarters-country × quarter, and industry × quarter fixed effects. The model is estimated using fractional logit model with quasi-binomial family and logit link, with standard errors clustered at the firm level. The vertical dashed line marks the invasion date.

(a) All Firms



(b) U.S. Firms



(c) Non-U.S. Firms

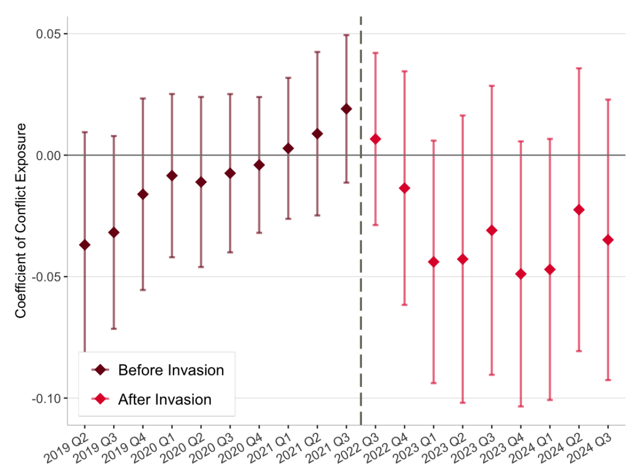
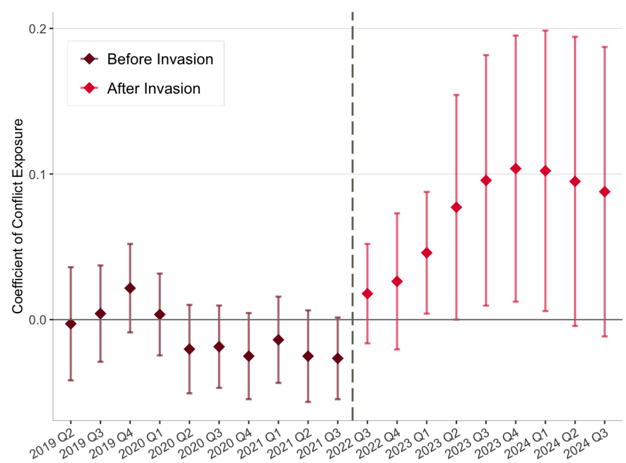


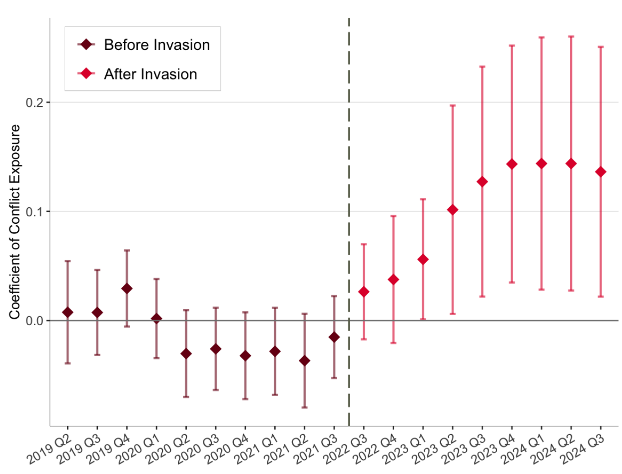
Figure 9: **Conflict exposure and R&D spending around the invasion**

This figure plots coefficient estimates and 95% confidence intervals from rolling four-quarter window regressions of R&D expenditures on conflict exposure, estimated separately before and after the February 2022 invasion. The dependent variable is R&D expenditures in quarter $q+1$ scaled by total assets in quarter q. The key independent variable is $E_{i,q}$, the firm's average monthly conflict exposure over quarter q, standardized within each quarter. Each point represents the coefficient estimate β_q from equation 7 for a five-quarter window centered on quarter q. The rolling window approach smooths quarter-to-quarter volatility in coefficient estimates while capturing the time-varying relationship between conflict exposure and innovation spending. Panel (a) presents results for all firms, panel (b) for U.S.-headquartered firms, and panel (c) for non-U.S. firms. All specifications include the lagged dependent variable, firm size (log assets), and quarter, industry, headquarters-country, headquarters-country × industry, headquarters-country × quarter, and industry × quarter fixed effects. The model is estimated using fractional logit model with quasi-binomial family and logit link, with standard errors clustered at the firm level. The vertical dashed line marks the invasion date.

(a) All Firms



(b) U.S. Firms



(c) Non-U.S. Firms

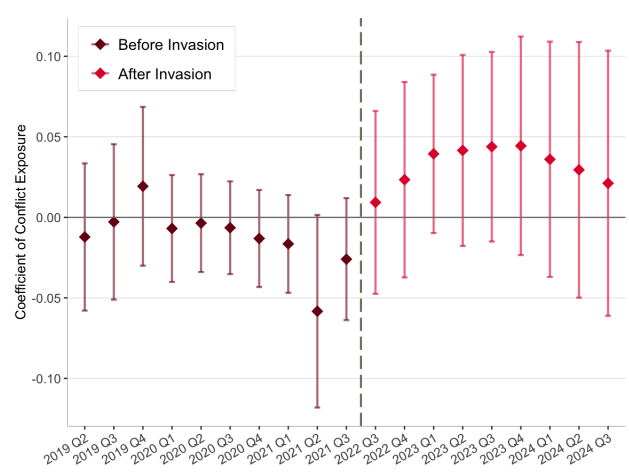


Table 1: **Multinational firm operations in Ukraine by headquarters country**
This table reports the number and percentage of firms from each headquarters country with operations in Ukrainian oblasts before and after the February 2022 invasion. The first column shows the total number of firms from each country in our sample. The second and third columns report the number and percentage of firms with Ukrainian operations before the invasion (February 2019 to January 2022). The fourth and fifth columns show the corresponding figures after the invasion (February 2022 to February 2025). The final column reports the percentage point change in the share of firms with Ukrainian operations from the pre-invasion to post-invasion period. Firm operations are measured by the presence of employees in at least one Ukrainian oblast.

		Multinational Firms Operating in Ukraine				
		Pre-Invasion		Post-Invasion		Δ
Country	Total Firms in Sample	# Firms	% Total	# Firms	% Total	Post% – Pre%
United States	2757	889	32.25	874	31.70	-0.55
Japan	521	64	12.28	63	12.09	-0.19
China	263	27	10.27	26	9.89	-0.38
United Kingdom	222	93	41.89	89	40.09	-1.80
Taiwan	219	12	5.48	10	4.57	-0.91
South Korea	151	34	22.52	32	21.19	-1.33
Australia	141	24	17.02	20	14.18	-2.84
France	124	69	55.65	68	54.84	-0.81
Germany	93	53	56.99	50	53.76	-3.23
Sweden	92	35	38.04	33	35.87	-2.17
Brazil	88	29	32.95	29	32.95	0.00
Canada	80	17	21.25	14	17.50	-3.75
Switzerland	76	34	44.74	32	42.11	-2.63
Hong Kong	58	8	13.79	8	13.79	0.00
South Africa	49	14	28.57	15	30.61	2.04
Malaysia	47	8	17.02	8	17.02	0.00
Netherlands	43	19	44.19	19	44.19	0.00
Italy	39	19	48.72	16	41.03	-7.69
Spain	36	9	25.00	7	19.44	-5.56
Singapore	35	5	14.29	5	14.29	0.00
India	32	17	53.12	16	50.00	-3.12
Israel	32	11	34.38	10	31.25	-3.13
Norway	32	10	31.25	10	31.25	0.00
Ireland	31	16	51.61	15	48.39	-3.22
Saudi Arabia	31	8	25.81	8	25.81	0.00
Finland	30	14	46.67	13	43.33	-3.34
Mexico	29	4	13.79	4	13.79	0.00
Philippines	29	3	10.34	3	10.34	0.00
Thailand	29	1	3.45	0	0.00	-3.45
Denmark	28	18	64.29	18	64.29	0.00
Indonesia	27	2	7.41	2	7.41	0.00
Belgium	26	12	46.15	12	46.15	0.00
Poland	26	15	57.69	15	57.69	0.00
Bermuda	24	8	33.33	9	37.50	4.17
Chile	22	3	13.64	2	9.09	-4.55
New Zealand	18	5	27.78	3	16.67	-11.11
Russia	17	11	64.71	8	47.06	-17.65
Turkey	17	3	17.65	3	17.65	0.00
Austria	14	7	50.00	7	50.00	0.00
Luxembourg	14	3	21.43	3	21.43	0.00
Pakistan	12	3	25.00	4	33.33	8.33
Argentina	10	3	30.00	3	30.00	0.00
Greece	10	2	20.00	2	20.00	0.00
Portugal	10	2	20.00	2	20.00	0.00

Table 2: **Impact of the 2022 Russian invasion on local labor markets**

Standard errors are double-clustered by firm and month, and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Establishment-level job flows measures are based on Davis and Haltiwanger (1992) and Burgess, Lane, and Stevens (2000): *Hiring* is defined as $\left[\frac{H_{ilt}}{0.5\times(E_{ilt}+E_{ilt-1})}\right]$, and *Separation* is defined as $\left[\frac{S_{ilt}}{0.5\times(E_{ilt}+E_{ilt-1})}\right]$. *Share of Ethnic Russians* x *Attacks* is standardized per month across all firm-states.

Dependent Variables:	$\log \overline{\text{Salary}}_{i,l,t}$	$\text{Headcount}_{i,l,t}(\%)$	$\text{Hiring}_{i,l,t}$	$\text{Separation}_{i,l,t}$	$\text{Local Market Exit}_{i,l,t}$
Model:	(1)	(2)	(3)	(4)	(5)
Panel A: Impact of Conflict Vulnerability					
Share of Ethnic Russians_l × Post Invasion_t	-1.05***	-1.83***	-1.19***	-0.509***	3.53***
	(0.056)	(0.239)	(0.067)	(0.063)	(0.605)
R^2	0.879	0.965	0.316	0.305	0.899
Panel B: Impact of Conflict Vulnerability & Attack Intensity					
Share of Ethnic Russians_l × $\text{Attacks}_{l,t}$ × Post Invasion_t	-0.030***	-0.091***	-0.031***	-0.011**	0.131***
	(0.004)	(0.018)	(0.005)	(0.005)	(0.046)
R^2	0.856	0.962	0.320	0.309	0.900
Fixed-effects					
Firm (i)	✓	✓	✓	✓	✓
State (Oblast) (l)	✓	✓	✓	✓	✓
Month (t)	✓	✓	✓	✓	✓
Firm x Month	✓	✓	✓	✓	✓
Firm x State	✓	✓	✓	✓	✓
Firm HQ Country x Month	✓	✓	✓	✓	✓
Observations	812,950	812,950	812,950	812,950	812,950
Dep. Var. Mean	5.899	25.190	0.317	0.298	63.500
Dep. Var. SD	4.033	34.531	1.980	1.812	48.143
Firms	3057	3057	3057	3057	3057
States	21	21	21	21	21

Table 3: **Descriptive statistics**

This table presents means, medians, and standard deviations of the main variables used in the subsequent analysis. Conflict vulnerability ($\overline{V}^{pre}_{i,q}$) represents the average ethnic Russian population share (V_l) across all oblasts l where firm i operated before the invasion and is shown for the pre-invasion period only, as this measure reflects predetermined regional characteristics that remained constant throughout our sample. Conflict intensity ($\overline{S}^{post}_{l,q}$) and conflict exposure ($\overline{E}^{post}_{i,q}$) are shown for the post-invasion period only, as these measures were effectively zero before February 2022 when military hostilities began in Ukraine. All conflict-related measures are scaled by 10,000 for presentation purposes. For regression analysis, these measures are standardized within each quarter across all firms. All firm-level characteristics except Total Assets$_{i,q}$, Total Sales$_{i,q}$, and Realized Volatility$_{i,q}$ are expressed in percentage terms (multipled by 100).

	All Firms			U.S. Firms			Non-U.S. Firms		
Variable	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Firm-level Conflict Exposure Measures									
Conflict Vulnerability ($\overline{V}^{pre}_{i,q}$)	7.27	0.46	27.50	8.76	0.65	31.30	5.89	0.32	23.35
Conflict Intensity ($\overline{S}^{post}_{l,q}$)	4.16	0.16	14.75	5.14	0.38	16.89	3.25	0.03	12.38
Conflict Exposure ($\overline{E}^{post}_{i,q}$)	2.65	0.00	12.71	3.15	0.00	14.36	2.19	0.00	10.93
Firm Characteristics									
Ukraine Workforce Share ($\overline{W}^{pre}_{i,l}$)	0.46	0.04	3.50	0.64	0.04	4.58	0.30	0.03	2.01
Total Assets$_{i,q}$ (\$, millions)	12838.61	2285.54	45424.28	11721.85	1664.37	42121.87	13950.43	2877.53	48463.97
Asset Growth$_{i,q}$	3.23	0.66	68.85	3.82	0.60	67.22	2.64	0.74	70.43
Total Sales$_{i,q}$ (\$, millions)	1447.24	302.20	3684.66	1215.72	191.81	3434.38	1704.88	445.92	3928.57
Sales Growth$_{i,q}$	517.65	165.07	3131.05	568.71	186.51	3418.84	461.33	137.01	2778.09
Realized Volatility$_{i,q}$	0.02	0.02	0.01	0.02	0.02	0.01	0.01	0.02	0.01
Capex$_{i,q+1}$/Assets$_{i,q}$	2.10	1.17	2.72	1.75	0.82	2.62	2.45	1.53	2.78
R&D$_{i,q+1}$/Assets$_{i,q}$	1.24	0.03	3.97	1.91	0.00	5.40	0.57	0.05	1.27
LT Debt$_{i,q+1}$/Assets$_{i,q}$	21.16	16.63	20.17	25.15	20.98	22.68	17.19	13.89	16.37
Gross Profit$_{i,q+1}$/Sales$_{i,q}$	24.23	36.20	123.02	15.11	40.97	163.99	36.14	32.14	30.63
Δ Emp$_{i,q+1}$/Emp$_{i,q}$	4.80	0.00	37.91	5.17	0.00	43.23	4.43	0.00	31.74

Table 4: **Impact of the 2022 Russian invasion on firms' stock returns**

This table reports the results from cross-sectional regressions of cumulative stock returns over a three-day event window on firm-level conflict exposure. Day t=0 marks February 24, 2022, the start date of the Russian invasion. The dependent variable is the cumulative stock return from days $t = 0$ to $t = 3$. The key independent variable is *Mean Conflict Exposure*$_{i,Post}$, which is the average of firm i's monthly conflict exposure values $E_{i,t}$ over the entire post-invasion period (February 2022 onwards), and standardized across all firms. Panel A presents results for all firms, Panel B for U.S.-headquartered firms, and Panel C for non-U.S. firms. Models (1)-(6) progressively add control variables: firm size (total assets), firm asset growth and cash-to-assets ratio, headquarters-country market beta, global market betas (of equity markets in the U.S., U.K., China, Japan, Russia), and the firm's average conflict exposure before the conflict. All specifications include headquarters-country, industry, and day fixed effects. Standard errors are double-clustered by firm headquarters country and date, and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Cumulative Stock Returns$_{i,t=[0,3\ days]}$					
	Panel A: All Firms					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Mean Conflict Exposure$_{i,Post}$	-0.022***	-0.024***	-0.021***	-0.030***	-0.023***	-0.033***
	(0.001)	(0.001)	(0.0003)	(0.002)	(0.001)	(0.003)
	Panel B: U.S. Firms					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Mean Conflict Exposure$_{i,Post}$	-0.011***	-0.014***	-0.012***	-0.027***	-0.008***	-0.026***
	(0.001)	(0.001)	(0.0001)	(0.002)	(0.001)	(0.002)
	Panel C: Non-U.S. Firms					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Mean Conflict Exposure$_{i,Post}$	-0.025***	-0.027***	-0.024***	-0.042***	-0.015***	-0.037***
	(0.004)	(0.002)	(0.0005)	(0.003)	(0.003)	(0.004)
Controls						
Firm size (log assets)	✓	✓	✓	✓	✓	✓
+ Firm asset growth & cash/assets		✓				✓
+ Firm HQ Country βs			✓			
+ Global market βs (US, UK, CN, JP, RU)				✓		✓
+ Pre-conflict exposure					✓	✓
Firm HQ Country	✓	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓	✓
Day	✓	✓	✓	✓	✓	✓
Observations	3,757	3,757	3,757	3,757	3,757	3,757
R^2	0.213	0.215	0.213	0.280	0.213	0.280

Table 5: **Impact of the invasion on firm capital expenditures**

This table reports the results from panel regressions of capital expenditures on firm-level conflict exposure. The dependent variable is firm i's capital expenditures in quarter $q+1$ scaled by its total assets in quarter q. The key independent variable is Conflict Exposure$_{i,q}$, which is the average of firm's monthly conflict exposure values $E_{i,t}$ over quarter q, standardized across all firms within that quarter. Panel A presents results for all firms, Panel B for U.S.-headquartered firms, and Panel C for non-U.S. firms. Models (1)-(4) progressively add control variables: lagged capital expenditures scaled by total assets in the preceding quarter, firm size (log assets), firm asset growth, and realized volatility (the standard deviation of daily stock returns over the preceding quarter. Since the dependent variable in our sample is continuous and varies between 0 and 1 (see Table 3 for descriptive statistics), we estimate all specifications using a fractional response model with quasi-maximum likelihood estimation, employing a logit link function and quasi-binomial variance structure following Papke and Wooldridge (2008). All specifications include quarter, industry, headquarters-country, headquarters-country × industry, headquarters-country × quarter, and industry × quarter fixed effects. Standard errors are clustered at the firm level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	$\text{Capex}_{i,q+1}/\text{Assets}_{i,q}$			
	Panel A: All Firms			
Model:	(1)	(2)	(3)	(4)
Conflict Exposure$_{i,q}$	-0.018***	-0.020***	-0.020***	-0.020***
	(0.005)	(0.005)	(0.005)	(0.005)
Observations	124,456	124,456	124,456	124,456
Pseudo R^2	0.618	0.619	0.621	0.619
	Panel B: U.S. Firms			
Model:	(1)	(2)	(3)	(4)
Conflict Exposure$_{i,q}$	-0.020**	-0.022***	-0.022***	-0.022***
	(0.008)	(0.008)	(0.008)	(0.008)
Observations	62,144	62,144	62,144	62,144
Pseudo R^2	0.569	0.572	0.575	0.572
	Panel C: Non-U.S. Firms			
Model:	(1)	(2)	(3)	(4)
Conflict Exposure$_{i,q}$	-0.015**	-0.015***	-0.016***	-0.015***
	(0.006)	(0.006)	(0.006)	(0.006)
Observations	62,312	62,312	62,312	62,312
Pseudo R^2	0.667	0.666	0.670	0.661
Controls				
$\text{Capex}_{i,q}/\text{Assets}_{i,q-1}$ (lagged depvar.)	✓	✓	✓	✓
+ Firm size$_{i,q}$ (log assets)		✓	✓	✓
+ Firm asset growth$_{i,q}$			✓	
+ Realized Volatility$_{i,q}$				✓

Table 6: **Impact of the invasion on firm R&D**

This table reports the results from panel regressions of R&D expenditures on firm-level conflict exposure. The dependent variable is firm i's R&D expenditures in quarter $q+1$ scaled by its total assets in quarter q. The key independent variable is Conflict Exposure$_{i,q}$, which is the average of firm's monthly conflict exposure values $E_{i,t}$ over quarter q, standardized across all firms within that quarter. Panel A presents results for all firms, Panel B for U.S.-headquartered firms, and Panel C for non-U.S. firms. Models (1)-(4) progressively add control variables: lagged R&D expenditures scaled by total assets in the preceding quarter, firm size (log assets), firm asset growth, and realized volatility (the standard deviation of daily stock returns over the preceding quarter). Since the dependent variable in our sample is continuous and varies between 0 and 1 (see Table 3 for descriptive statistics), we estimate all specifications using a fractional response model with quasi-maximum likelihood estimation, employing a logit link function and quasi-binomial variance structure following Papke and Wooldridge (2008). All specifications include quarter, industry, headquarters-country, headquarters-country × industry, headquarters-country × quarter, and industry × quarter fixed effects. Standard errors are clustered at the firm level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	R&D$_{i,q+1}$/Assets$_{i,q}$			
	Panel A: All Firms			
Model:	(1)	(2)	(3)	(4)
Conflict Exposure$_{i,q}$	0.033	0.044**	0.044**	0.044**
	(0.020)	(0.021)	(0.021)	(0.021)
Observations	124,456	124,456	124,456	124,456
Pseudo R^2	0.364	0.365	0.365	0.366
	Panel B: U.S. Firms			
Model:	(1)	(2)	(3)	(4)
Conflict Exposure$_{i,q}$	0.053**	0.066***	0.066***	0.066***
	(0.024)	(0.023)	(0.023)	(0.024)
Observations	62,144	62,144	62,144	62,144
Pseudo R^2	0.261	0.262	0.261	0.264
	Panel C: Non-U.S. Firms			
Model:	(1)	(2)	(3)	(4)
Conflict Exposure$_{i,q}$	0.001	0.003	0.004	0.004
	(0.019)	(0.020)	(0.020)	(0.020)
Observations	62,312	62,312	62,312	62,312
Pseudo R^2	0.497	0.495	0.499	0.491
Controls				
Capex$_{i,q}$/Assets$_{i,q-1}$ (lagged depvar.)	✓	✓	✓	✓
+ Firm size$_{i,q}$ (log assets)		✓	✓	✓
+ Firm asset growth$_{i,q}$			✓	
+ Realized Volatility$_{i,q}$				✓

A Additional figures and tables

Figure A1: **Distribution of multinational firms across Ukraine before invasion: Alternative vulnerability measure**
This figure presents the geographic distribution of multinational firm operations across Ukrainian oblasts prior to the February 2022 Russian invasion, using an alternative measure of regional conflict vulnerability. The map reports the number of firms operating in each oblast and the corresponding share of residents who spoke Russian as their first language from the 2001 All-Ukrainian Population Census.

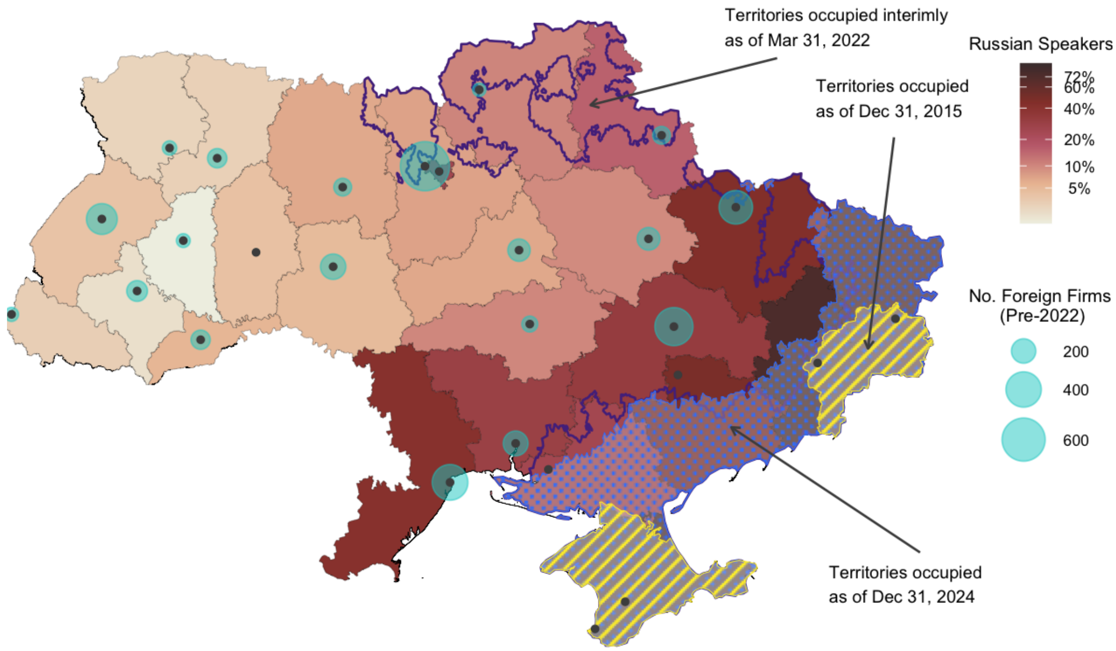
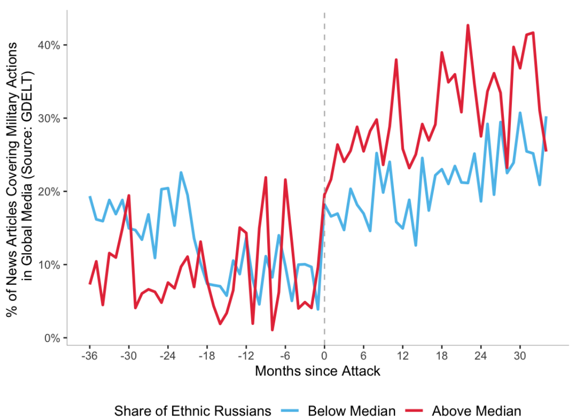
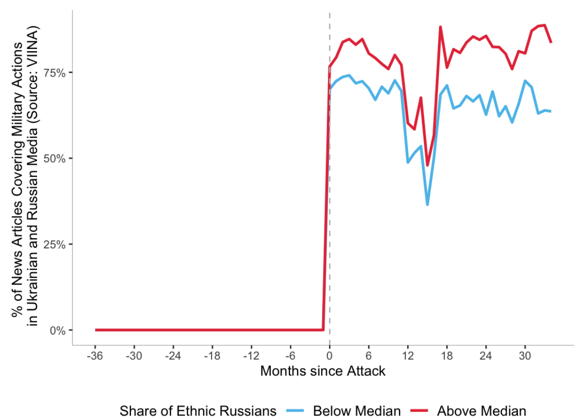


Figure A2: **Media coverage around the February 2022 invasion**
These figures examine news coverage patterns across Ukrainian oblasts before and after the February 2022 invasion, comparing oblasts with above-median (red line) versus below-median (blue line) ethnic Russian population shares from the 2001 census. Each panel plots monthly averages aggregated across oblasts in each group, with months on the x-axis measured relative to the invasion date (marked by the vertical dashed line). Panel (a) shows the share of news articles covering military actions in global media from GDELT, capturing international attention to violence across different regions. Panel (b) shows the share of articles covering military actions in Ukrainian and Russian media from VIINA, reflecting local and regional conflict coverage. Panel (c) shows the share of articles covering migration events from GDELT, tracking displacement and population movement narratives. Panel (d) shows the share of articles covering labor market events from GDELT, measuring attention to employment and workforce disruptions. Panel (e) shows the average tone of news articles covering Ukraine from GDELT, where higher values indicate more positive sentiment. Panel (f) shows the average Goldstein scale scores from GDELT. The Goldstein scale, developed by (Goldstein, 1992), assigns numerical scores to political events based on their level of conflict or cooperation, ranging from -10 (most conflictual actions such as use of conventional military force, armed attacks, and mass violence) through 0 (neutral events like statements or meetings) to +10 (most cooperative actions such as peace agreements, aid provisions, and diplomatic negotiations).

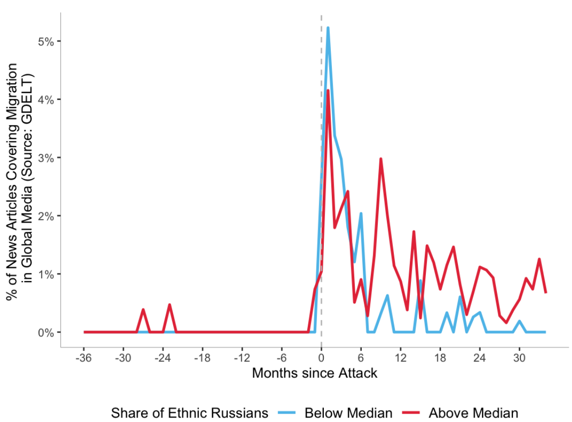
(a) Military activity



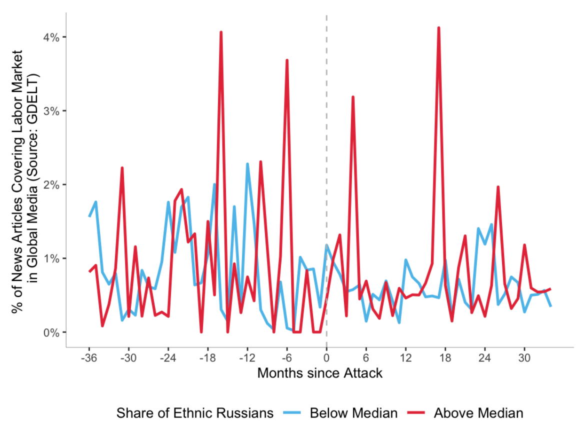
(b) Military attacks (Ukrainian & Russian media)



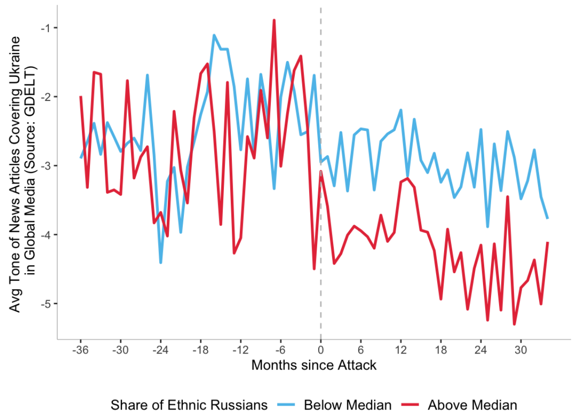
(c) Migration



(d) Labor market



(e) Media tone



(f) Media tone (Goldstein scale)

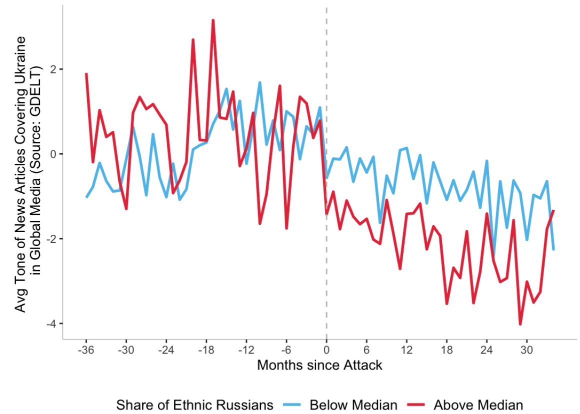
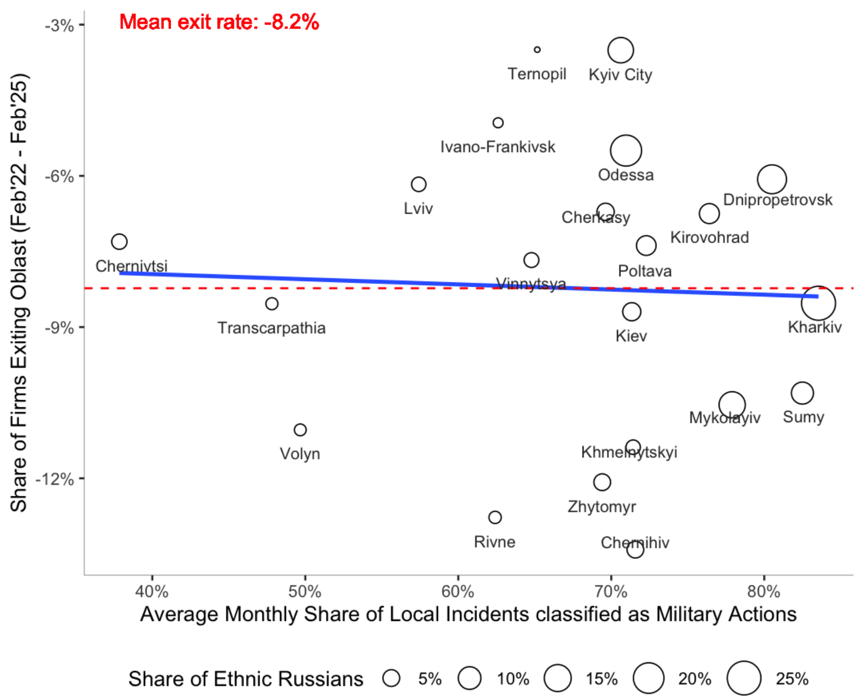


Figure A3: **Military activity and multinational firm exits during the invasion**
These figures illustrate the relationship between conflict intensity and multinational firm exits at the oblast level during the invasion period (February 2022–January 2025). Panel (a) plots the average monthly share of military actions occurring in each oblast against the overall firm exit rate from that oblast. Panel (b) plots the average share of oblast territory under Russian occupation against the overall firm exit rate from that oblast. Each point represents one Ukrainian oblast that was previously uncontested by Russia before the February 2022 invasion.

(a) Attack intensity and firm exits



(b) Territorial occupation by Russia and firm exits

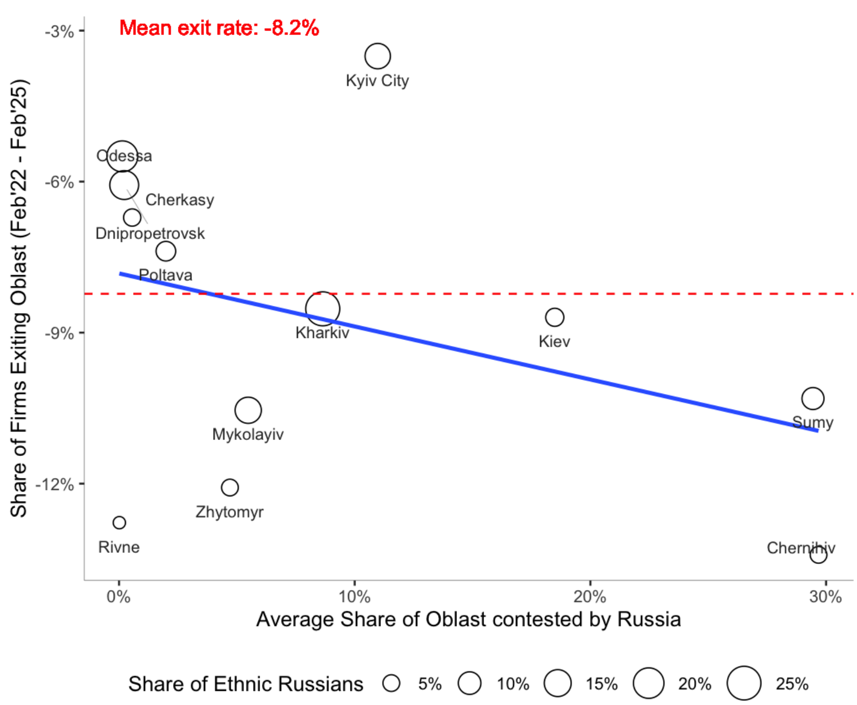
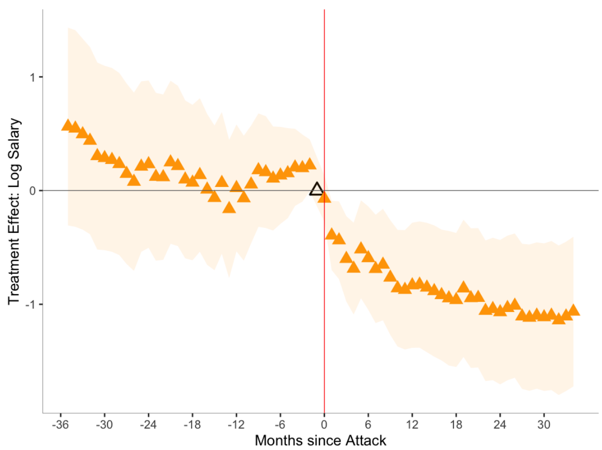


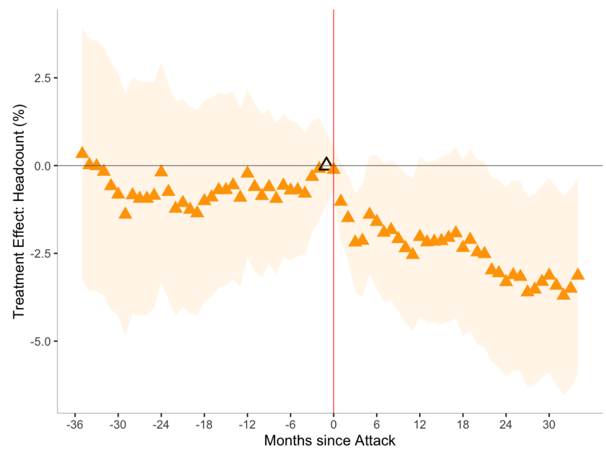
Figure A4: **Dynamic effects of conflict vulnerability on multinational firm labor market outcomes in Ukraine**

These figures present dynamic treatment effects of conflict exposure on labor market outcomes of multinational firms operating in Ukraine, showing disaggregated month-by-month estimates corresponding to the pooled results in Panel A of Table 2. Each panel plots coefficients from a difference-in-differences specification interacting conflict vulnerability (V_l) with monthly indicators relative to the February 2022 invasion, with month -1 (January 2022) serving as the reference period (marked by the hollow triangle at zero). The vertical red line marks the invasion month (February 2022). Shaded areas represent 95% confidence intervals with standard errors clustered at the firm and month levels.

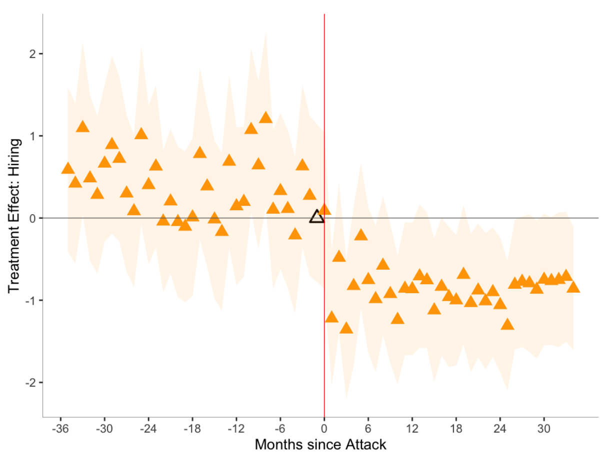
(a) $\log \overline{\text{Salary}}$



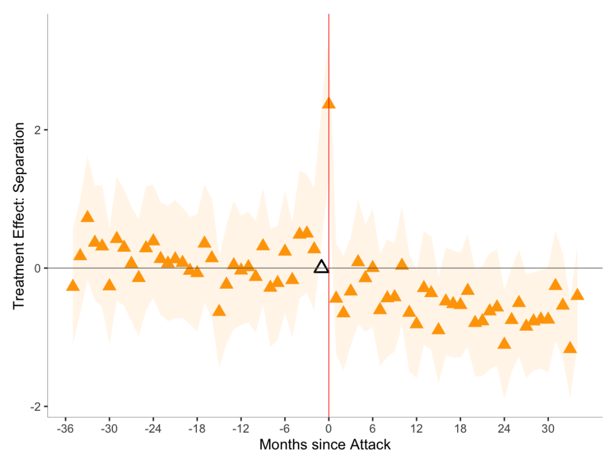
(b) Local Headcount (%)



(c) Hiring



(d) Separation



(e) Exit from Local Market

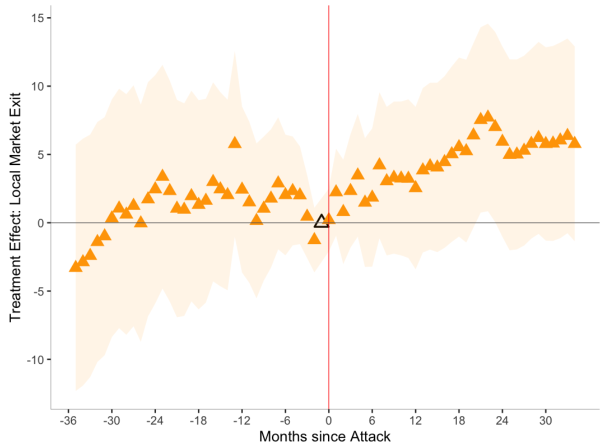
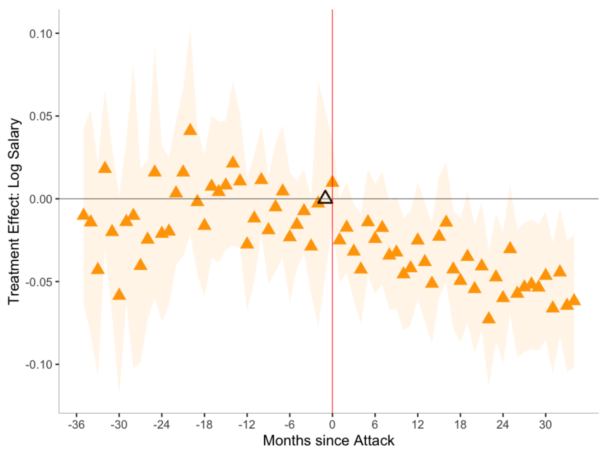


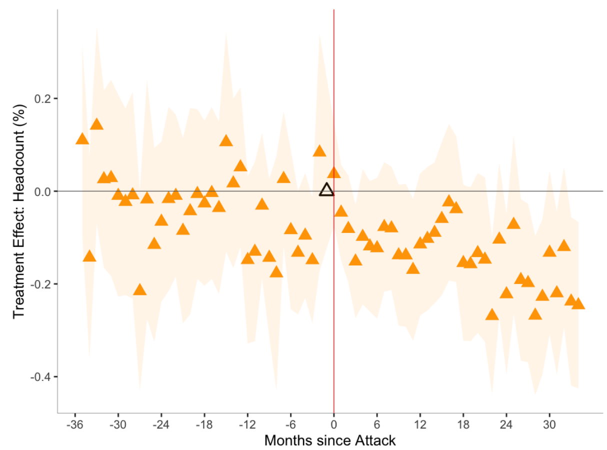
Figure A5: **Dynamic effects of conflict vulnerability and intensity on multinational firm labor market outcomes in Ukraine**

This figure presents dynamic treatment effects of conflict exposure incorporating realized attack intensity on firm labor market outcomes in Ukraine, showing disaggregated month-by-month estimates corresponding to the pooled results in Panel B of Table 2. Each panel plots coefficients from a difference-in-differences specification interacting the product of conflict vulnerability (V_l) and conflict intensity ($S_{l,t}$) with monthly indicators relative to the February 2022 invasion, with month -1 (January 2022) serving as the reference period. The vertical red line marks the invasion month (February 2022). Shaded areas represent 95% confidence intervals with standard errors clustered at the firm and month levels.

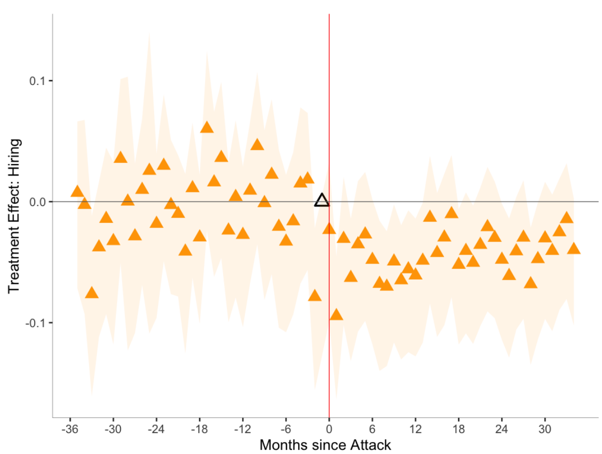
(a) $\log \overline{\text{Salary}}$



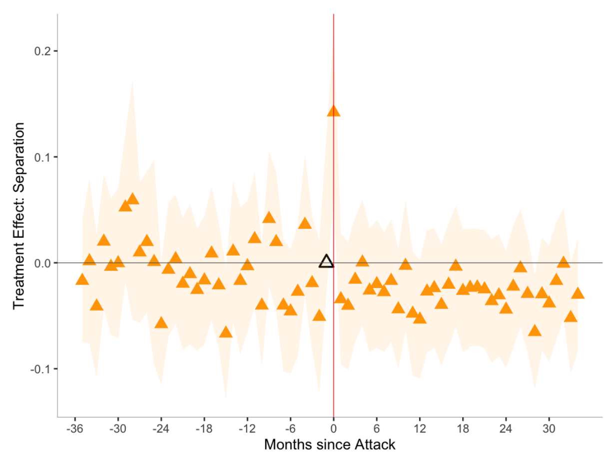
(b) Local Headcount (%)



(c) Hiring



(d) Separation



(e) Exit from Local Market

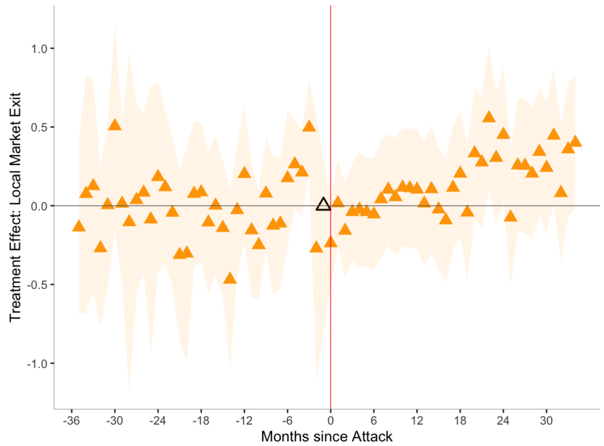
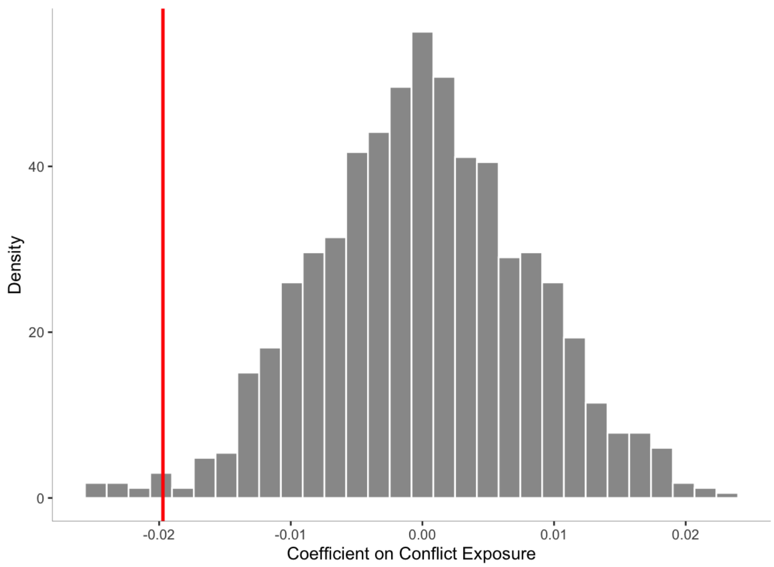


Figure A6: **Robustness for random assignment of conflict exposure**
This figure plots 1,000 estimated coefficients on conflict exposure in placebo regressions using the global sample of multinational firms, computed based on Equation 6. Firm-level conflict exposure values are randomly permuted across firms within each quarter to break any systematic relationship with actual operational locations while maintaining the quarterly distribution of exposure levels. Panel (a) examines capital expenditures, and Panel (b) examines R&D spending. The red vertical line indicates the "true" β estimate based on the same specification (as shown in model (2), panel A of Tables 5 and 6).

(a) Capital expenditures



(b) R&D

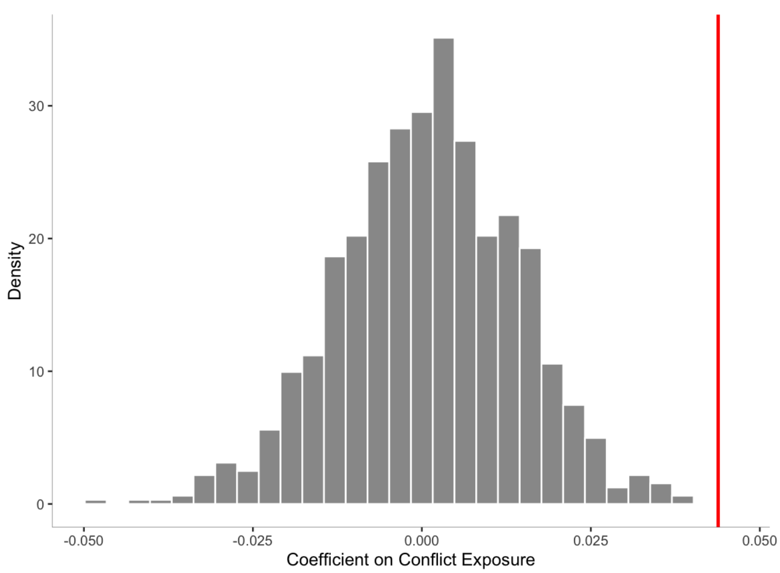
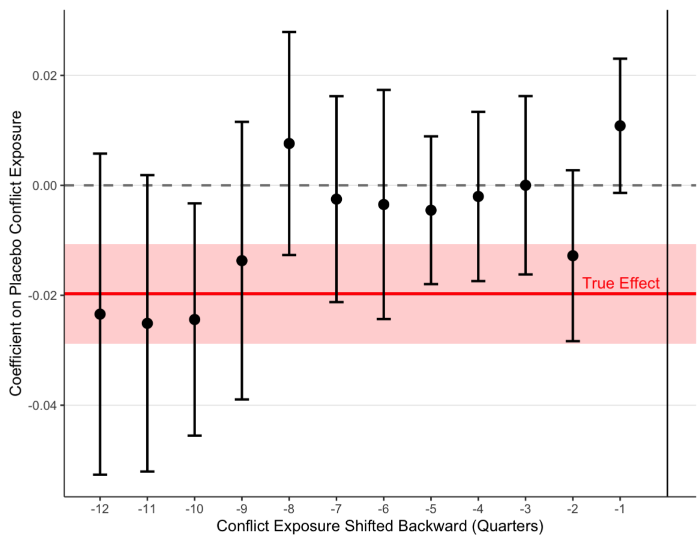


Figure A7: **Placebo tests for conflict timing**

This figure plots coefficients from timing placebo regressions that test whether pre-invasion firm investment was systematically related to future conflict exposure. For each placebo test, we assign firms their conflict exposure from k quarters in the future (where k ranges from 1 to 12 quarters), and re-estimate equation (9) using only pre-invasion data. This procedure examines whether firms that would later experience higher conflict exposure already exhibited different investment patterns before the invasion occurred. Panel (a) examines capital expenditures, and Panel (b) examines R&D spending. Each point represents the coefficient estimate from a placebo regression where conflict exposure is shifted backward by k quarters, with error bars showing 95% confidence intervals based on standard errors clustered at the firm and industry levels. The horizontal red line indicates the true post-invasion coefficient from Model 2, Panel A of Table 5 (for capital expenditures) and Table 6 (for R&D spending), with the shaded red band representing its 95% confidence interval. The vertical black line at zero marks the invasion date (Q1 2022), with negative values on the x-axis representing quarters before the invasion.

(a) Capital expenditures



(b) R&D

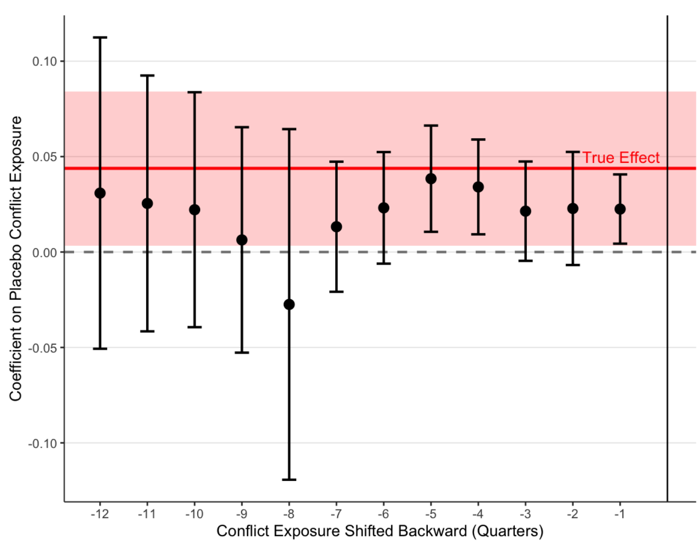


Table A1: **Balance tests: pre-invasion firm characteristics and potential conflict exposure**

This table examines whether firms' pre-invasion workforce locations in Ukraine were systematically associated with observable firm characteristics, testing the validity of our identification strategy. The main independent variable is constructed as $\textit{Potential Exposure}_{i,q} = \sum_l (W_{i,l,q} \times V_l)$, where $W_{i,l,q}$ is firm i's share of Ukrainian employees in oblast l during quarter q and V_l is the ethnic Russian population share in oblast l from the 2001 All-Ukrainian Population Census. This measure captures each firm's latent vulnerability to the conflict based on the geographic distribution of its workforce across Ukrainian oblasts that would become differentially exposed to military hostilities after the February 2022 invasion. For the balance tests, we average this measure for each firm across all pre-invasion quarters (Q1'2019–Q1'2022) to obtain a time-invariant firm-level exposure metric. For each dependent variable representing quarterly pre-invasion firm characteristics (also averaged over Q1'2019–Q1'2022), we estimate:

$$\overline{\text{Firm Characteristic}}_i = \beta \times \overline{\text{Potential Exposure}}_i + \alpha_c + \alpha_j + \varepsilon_i, \tag{8}$$

where α_c denotes headquarters country fixed effects, and α_j denotes industry fixed effects. The coefficient β captures whether potential exposure predicts pre-invasion firm characteristics. Under the identifying assumption that workforce location decisions were driven by economic considerations orthogonal to firms' subsequent responses to the 2022 invasion, we expect $\beta \approx 0$ for all characteristics. Standard errors are clustered at the headquarters country level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Firm characteristics (pre-invasion averages)	Coefficient	Std. Error	t-statistic	p-value
$\overline{\text{log(Total Assets)}}_{i,q}$	-0.027	0.035	-0.788	0.434
$\overline{\text{Asset Growth}}_{i,q}$	0.000	0.000	-0.785	0.436
$\overline{\text{log(Total Sales)}}_{i,q}$	-0.064	0.046	-1.390	0.170
$\overline{\text{Sales Growth}}_{i,q}$	0.083	0.065	1.276	0.207
$\overline{\text{Capex}}_{i,q+1}/\text{Assets}_{i,q}$	0.001	0.000	1.671	0.100
$\overline{\text{R\&D}}_{i,q+1}/\text{Assets}_{i,q}$	0.000	0.000	1.687	0.097*
$\overline{\text{LT Debt}}_{i,q+1}/\text{Assets}_{i,q}$	0.004	0.003	1.101	0.275
$\overline{\text{Gross Profit}}_{i,q+1}/\text{Sales}_{i,q}$	0.734	0.511	1.436	0.156
$\overline{\text{Employment Growth}}$ ($\Delta\text{Emp}_{i,q+1}/\text{Emp}_{i,q}$)	0.015	0.012	1.198	0.236
$\overline{\text{Realized Volatility}}_{i,q}$	0.000	0.000	-0.338	0.736

Table A2: **Pre-invasion firm distributions as predictors of post-invasion conflict intensity**

This table examines whether oblast-level shares of multinational firms and their global headcount prior to the 2022 invasion predict conflict intensity in Ukrainian oblasts following the invasion, testing for potential anticipatory selection in firms' operational locations across Ukrainian regions. The dependent variable is oblast-level conflict intensity measured monthly, $S_{l,t}$, as defined in Equation 2. Independent variables include each oblast l's share of total firms (as a percentage of the national total) and employment share (where employment shares are fractions of each firm's global headcount based in the oblast), each averaged over the 12 months before February 2022 (Q1'2021–Q1'2022), and the oblast's ethnic Russian population share from the 2001 census, which proxies for conflict vulnerability V_l. We estimate monthly panel regressions for the post-invasion period of the form:

$$\text{Conflict Intensity}_{l,t} = \beta_1 \overline{\text{Region Share}}_{l,pre-12m} + \beta_2 V_l + \beta_3(\overline{\text{Region Share}}_{l,pre-12m} \times V_l) + \alpha_t + \varepsilon_{l,t}, \quad (9)$$

where $\overline{\text{Region Share}}_{l,pre-12m}$ denotes the averaged pre-invasion firm or employment share in oblast l over the 12 months prior to the invasion, V_l is the ethnic Russian share, and α_t denotes month fixed effects. Under the identifying assumption that the spatial distribution of firms' workforce across oblasts was orthogonal to subsequent conflict patterns, we expect $\beta_1 \approx 0$ and $\beta_3 \approx 0$. Standard errors are clustered at the oblast level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Panel A: Conflict Intensity$_{l,t}$			
Model:	(1)	(2)	(3)	(4)
$\overline{ShareFirms}_{l,\,12m\ Pre\text{-}Invasion}$	0.051	0.645		
	(0.207)	(0.771)		
$\overline{ShareEmployment}_{l,\,12m\ Pre\text{-}Invasion}$			-2.40	-4.40
			(14.4)	(20.5)
Share of Ethnic Russians$_l$		1.38***		1.00**
		(0.399)		(0.374)
$\overline{ShareFirms}_{l,\,12m\ Pre\text{-}Invasion}$ × Share of Ethnic Russians$_l$		-9.62		
		(6.25)		
$\overline{ShareEmployment}_{l,\,12m\ Pre\text{-}Invasion}$ × Share of Ethnic Russians$_l$				-228.8
				(190.3)
Month FE	✓	✓	✓	✓
Observations	735	735	735	735
R^2	0.136	0.390	0.135	0.351

Table A3: **Impact of the invasion on firms' stock returns: country-level evidence**
Day t=0 marks the start of the Russian invasion of Ukraine on February 24, 2022. Standard errors are double-clustered by firm HQ country, and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Cumulative Stock Returns$_{i,t=[0,3\ days]}$			
Firm HQ Country	United States	United Kingdom	Japan	China
Model:	(1)	(2)	(3)	(4)
Mean Conflict Exposure$_{i,Post}$	-0.018***	-0.026***	-0.094*	-0.030
	(0.0007)	(0.0000)	(0.050)	(0.090)
Controls				
Firm size (log assets)	✓	✓	✓	✓
+ Firm HQ Country βs	✓	✓	✓	✓
Firm HQ Country	✓	✓	✓	✓
Industry	✓	✓	✓	✓
Date	✓	✓	✓	✓
Observations	2,203	169	401	124
R^2	0.175	0.411	0.250	0.129

Table A4: **Impact of the invasion on other firm outcomes**

All specifications include quarter, industry, firm HQ country, country x industry, country x quarter, & industry x quarter fixed effects. Models for LT Debt/Assets are GLM Logit as depvar extends beyond 0 and 1.

Panel A: All Firms						
Dependent Variables:	LT $\text{Debt}_{i,q+1}/\text{Assets}_{i,q}$		Gross $\text{Profit}_{i,q+1}/\text{Sales}_{i,q}.100$		Δ $\text{Emp}_{i,q+1}/\text{Emp}_{i,q}.100$	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Conflict $\text{Exposure}_{i,q}$	0.011**	0.12**	0.468**	0.463**	-0.007**	-0.007**
	(0.005)	(0.006)	(0.224)	(0.225)	(0.003)	(0.003)
Observations	124,456	124,456	124,456	124,456	124,456	124,456
R^2	0.701	0.672	0.370	0.372	0.378	0.382

Panel B: U.S. Firms						
Dependent Variables:	LT $\text{Debt}_{i,q+1}/\text{Assets}_{i,q}$		Gross $\text{Profit}_{i,q+1}/\text{Sales}_{i,q}.100$		Δ $\text{Emp}_{i,q+1}/\text{Emp}_{i,q}.100$	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Conflict $\text{Exposure}_{i,q}$	0.014**	0.12**	0.760**	0.752**	-0.006*	-0.006*
	(0.008)	(0.005)	(0.295)	(0.296)	(0.003)	(0.003)
Observations	62,144	62,144	62,144	62,144	62,144	62,144
R^2	0.628	0.597	0.370	0.372	0.364	0.378

Panel C: Non-U.S. Firms						
Dependent Variables:	LT $\text{Debt}_{i,q+1}/\text{Assets}_{i,q}$		Gross $\text{Profit}_{i,q+1}/\text{Sales}_{i,q}.100$		Δ $\text{Emp}_{i,q+1}/\text{Emp}_{i,q}.100$	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Conflict $\text{Exposure}_{i,q}$	0.008	0.13*	0.167	0.166	-0.008*	-0.008*
	(0.005)	(0.006)	(0.273)	(0.271)	(0.005)	(0.005)
Observations	62,312	62,312	62,312	62,312	62,312	62,312
R^2	0.776	0.748	0.509	0.516	0.426	0.426

Controls						
Lagged Depvar.	✓	✓	✓	✓	✓	✓
+ Firm $\text{size}_{i,q}$ (log assets)	✓	✓	✓	✓	✓	
+ Firm asset $\text{growth}_{i,q}$	✓		✓		✓	
+ Realized $\text{Volatility}_{i,q}$		✓		✓		✓

Appendix References

Goldstein, Joshua (1992). "A conflict-cooperation scale for WEIS events data". *Journal of Conflict Resolution* 36.2, pp. 369–385.