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**Proximity to War: The stock market
response to the Russian invasion of
Ukraine**

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Abstract

The outbreak of a war exposes countries and firms in its proximity to the risk of military escalation. Disaster risk goes up and stock markets decline accordingly. In support of this hypothesis, we identify a "proximity penalty" in the stock market response to the Russian invasion of Ukraine. The closer countries and---even within countries---firms are located to Ukraine, the more negative their equity returns in a four-week window around the start of the war. Controlling for trade-related spillovers, 1,000 kilometers of extra distance equate to 1.1 percentage points in equity returns.

JEL Classification: F50, F51, G15

Keywords: Rare Disasters, Proximity Penalty, war, Military Spillovers, International Conflicts, Russia, Ukraine, Trade, Neighbors

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May 31, 2022

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1 Introduction

The risk of rare economic disasters is reflected in asset prices. In particular, the potential for large, if rare, economic disasters has been proposed as the key driver of the equity risk premium (Rietz, 1988; Veronesi, 2004; Barro, 2006). However, precisely because they are rare, quantifying the size and probability of such disasters is challenging. In measuring actual disasters during the 20th century to calibrate disaster risk, Barro (2006) observes that the largest economic disasters are related to wars—provided they take place on a country’s soil. This is a fate that advanced economies have essentially escaped over the past several decades. But even for a country not directly involved in a war, disaster risk increases if a war breaks out in its vicinity. Because stock markets are sensitive to changes in disaster risk, they are bound to react accordingly (Berkman et al., 2011; Gourio, 2012).¹

We provide evidence in support of this hypothesis by studying the stock market response to the Russian invasion of Ukraine. Our key insight is that the invasion increased the risk of a rare economic disaster in other countries due to a possible regional escalation of the war. In order to identify this effect, we use the fact that it should depend on geographic proximity. Figure 1 provides some initial suggestive evidence. It shows the stock market response, measured in terms of cumulative returns since December 1, 2021, for two sets of countries: first, for Ukraine’s first- and second-degree neighbors in Europe (“Neighbors”), and second, for a group of “Other Countries” located further away from Ukraine.² The vertical green dashed line indicates the start of the war on February 24. The green shaded area in the figure demarcates the period from two weeks prior to, until two weeks after, the start of the war (“event window”).

The difference across groups is stark: Within the four weeks around the start of the war, the neighbors experienced an average stock market decline of over 20 percent (solid blue line), which contrasts with a decline of only six percent in the more distant countries (red dashed line).³ In the subsequent weeks, the gap narrowed but remained large. Proximity to war clearly appears to be crucial for the market response. The right panel of Figure 1 underscores the specific geographic differentiation triggered by the war in Ukraine. It shows the cumulative stock market returns over a four-week window around eight selected major financial or geopolitical events, alongside the Ukraine war episode.⁴

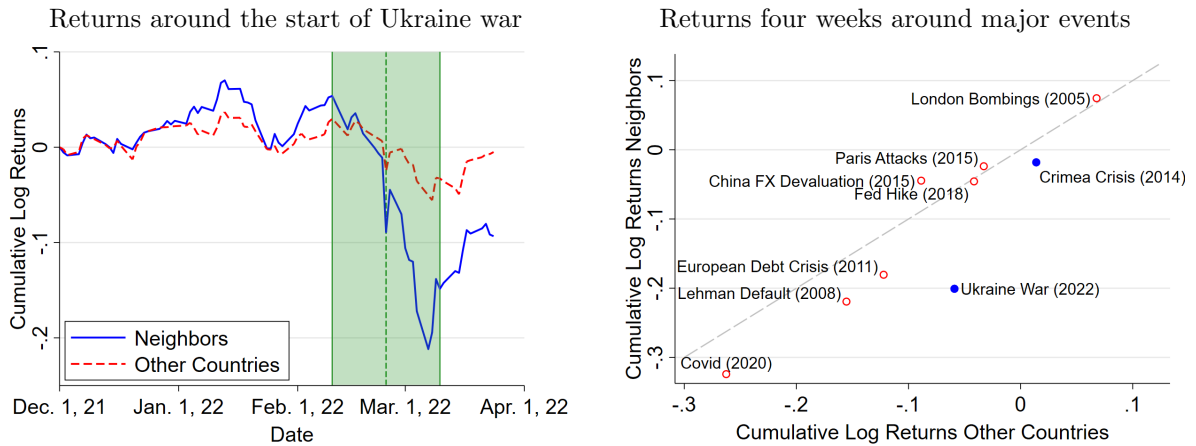
¹In the analysis of Farhi and Gabaix (2016) countries’ riskiness differs when exposed to a common disaster because of different “recovery rates.” Differences in distance offers a complementary and perhaps even more natural explanation of why the perceived riskiness of countries differs in the face of disasters.

²We describe our data set in Section 2 below.

³The decline in the “Neighbors” group corresponds to the 2nd percentile of the historical distribution of 4-week returns since 2002, underscoring the magnitude of the sell-off.

⁴Specifically, we consider: the collapse of Lehman Brothers (September 1, 2008 - September 29,

Figure 1: Cumulative Stock Market Returns



Notes: “Neighbors” is unweighted average of 15 European first- and second-degree neighbors of Ukraine; “Other Countries” is average of remaining 51 countries in our sample. Russia and Ukraine are excluded from both groups. Returns are computed based on Morgan Stanley Capital International (MSCI) country indices. Left panel shows cumulative log return since December 1, 2021. Green shaded area (“event window”) demarcates period from two weeks prior to the start of the war until two weeks after, i.e., from February 10 to March 10, 2022. Right panel measures cumulative log returns over four weeks around major geopolitical or financial events for Neighbors (vertical axis) and Other Countries (horizontal axis).

Again, we compare the average performance of Ukraine’s neighbors, measured along the vertical axis, with that of the *Other Countries*, measured along the horizontal axis. The war in Ukraine stands out: not only are the stock market losses for the *Neighbors* very large in absolute terms but they also differ to an exceptionally large extent from losses recorded elsewhere.

Our analysis quantifies the apparent “proximity penalty” systematically, exploiting observations at both the country and the firm level. Importantly, the proximity penalty may not only reflect disaster risk due to the possibility of military spillovers. Even without a regional escalation of the fighting, countries closer to the war zone are likely to suffer adverse spillovers via trade linkages. After all, distance is a key barrier to trade, so neighbors tend to trade more and hence be more exposed to each other than countries far apart (Head and Mayer, 2014). Accordingly, in our econometric specification we control for adverse trade effects in order to quantify how the stock market response to an increase

2008), the invasion of Crimea (February 13, 2014 - March 13, 2014), the start of the Covid-19 pandemic (February 13, 2020 - March 12, 2020), the Russian invasion of Ukraine (February 10, 2022 - March 10, 2022), the Paris terror attacks (November 12, 2015 - December 10, 2015), the London bombings (July 6, 2005 - August 4, 2005), the European sovereign debt crisis (July 24, 2011 - August 21, 2011), the last Fed Hike in the 2015-18 cycle (December 5, 2018 - January 1, 2009), and China’s unexpected foreign exchange devaluation (August 10, 2015 - September 7, 2015). For unforeseeable events, the event window starts one day prior to the event. Otherwise it is centered around the event.

in disaster risk varies with the proximity to the war.

Working with a sample of 66 countries, we obtain a concrete measure of the proximity penalty. While a direct neighbor to the conflict (at a distance of zero) suffers a cumulative stock market decline of 23.1 percent by the end of the second week of the war, this effect empirically diminishes by about 2.6 percentage points for every 1,000 km of distance from Ukraine. Accounting, in a second step, for spillovers via the trade channel (including the impact of sanctions) reduces the proximity penalty to 1.1 percentage points per 1,000 km. Thus, trade spillovers appear to be quantitatively important but still leave a meaningful role for perceived disaster risk in driving stock returns. This picture crystallizes further when we take a more granular perspective and evaluate our much larger firm-level data set. In particular, we find that proximity to war also influences stock market returns *within* countries. We also support the interpretation of our results with evidence based on additional indicators, including military aid flows to Ukraine and the tail risk priced in exchange-rate options.

From a methodological point of view, our analysis is straightforward because it exploits a quasi-natural experiment. Based on the assumption that the war in Ukraine is waged for geopolitical and not for economic reasons, we can identify its spillovers without further identifying assumptions. As a limitation, we recognize that our findings do not easily generalize to other contexts without resorting to a structural model (Fuchs-Schündeln and Hassan, 2016; Nakamura and Steinsson, 2018). Nonetheless, we believe our main insight has wider relevance: The market response to a foreign military conflict with inherent spillover risk is bound to depend on the proximity to that conflict, insofar as it reflects specific changes in disaster risk.

Our study brings together several strands of the literature. First, there is a body of relevant work on how financial markets respond to (expected) conflict (Leigh et al., 2003; Guidolin and La Ferrara, 2007; Zussman and Ørregaard Nielsen, 2008; Caldara and Iacoviello, 2022) and, more broadly, policy-related uncertainty (Baker et al., 2016; Born et al., 2019). Second, a limited number of studies have explicitly looked into the role of proximity or distance as a determinant of conflicts and their spillovers (Murdoch and Sandler, 2002, 2004; Mueller et al., 2022). Third, adverse spillovers from wars via trade and production networks have been documented before, also based on the 2014 Russia-Ukraine conflict (Glick and Taylor, 2010; Couttenier and Piemontese, 2022; Korovkin and Makarin, 2021). Finally, two other papers independently study the stock market response to the war in Ukraine (Deng et al., 2022; Boungou and Yatié, 2022). What sets our work apart from these studies is our effort to identify the change in disaster risk by analyzing the relationship between stock market returns and the proximity to war.

2 Methodology and Data

In order to quantify the proximity penalty we employ a set of simple ordinary least square regressions based on the following form:

$$CumRet_i^\tau = \alpha + \rho * DistanceUkraine_i + \gamma * controls_i + \varepsilon_i. \quad (1)$$

Here, i indexes either countries or firms, depending on the specification. τ indexes the event window in days relative to the start of the war. In our main analysis, we measure the cumulative stock market returns, $CumRet_i^\tau$, in logs within a 4-week window, $\tau = [-14, 14]$, centered around February 24, 2022. This date is widely accepted as the beginning of the war—an interpretation that is supported by the large negative reaction of equity markets in Ukraine’s neighboring countries on that day, visualized in Figure 1. The event window is centered around the start date of the war to capture the market impact of the Russian invasion, including possible anticipation effects observed in the days leading up to the attack. Even though Russia’s intentions remained unclear until right up to the invasion, there were growing signs of escalation, especially once Russia moved to recognize the two Russian-controlled statelets in the Donbas region of Ukraine on February 21. Correspondingly, Figure 1 illustrates that the MSCI indices of neighbors reacted at least a few days prior to the outbreak of the war as the information flow turned increasingly negative.

At the country level, we measure stock-market returns based on national MSCI indices. Our final sample comprises MSCI returns for 66 countries around the globe. At the firm level, $CumRet_i^\tau$ denotes the cumulative log return for firm i in the event window. Our sample comprises 16,929 different firms from 54 countries. Indices and firms pertaining to Russia and Ukraine were excluded from our samples since we focus on the externalities of the war. We obtain both the country-level MSCI data and the firm-level pricing data from Thomson Reuters Datastream. We provide further details on data sources, the construction of our control variables, and sample selection in the online appendix.

For our country-level analysis, we measure the distance from Ukraine in 1,000 km, using the city database of Simplemaps. It contains over 40,000 cities and their geographical coordinates. We calculate the distance between two countries as the smallest distance between any possible pair of cities across those countries. Neighboring countries, accordingly, are coded to have very small, if non-zero, distances of a few kilometers. Intuitively, the closest countries to Ukraine are its direct neighbors, whereas the countries farthest from Ukraine include New Zealand (15,960 km), Chile (11,714 km), and Argentina (11,272 km). The average distance from Ukraine in our country sample is about 3,959 km, and

the median distance is 2,494 km.

For firms, we likewise measure distance in 1,000 km starting from the postal codes of firms' headquarters obtained from Thomson Reuters Datastream. We supplement this information with the gazetteer database Geonames⁵, which contains data on 4.8 million populated places around the globe. We match the country-postal code combinations in our stock price sample with the Geonames database to obtain the latitudes and longitudes of the headquarters of each firm. For all firms, we then calculate the distance between their headquarters and the closest postal code in Ukraine. The firm located closest to Ukraine in our sample is headquartered in *Sanok*, a city in South-Eastern Poland located 35 km from the Ukrainian border. In contrast, the most distant Polish firm in our sample is located in *Szczecin*, which is 655 km from Ukraine.

3 Results

Turning to our results, we begin with the country-level analysis of stock returns. Next, we show that the proximity penalty is equally apparent in firm-level stock prices. We then test the robustness of our results by exploring the role of membership in supranational organizations, non-linear effects in the distance from Ukraine, and variation in the event window. Finally, we turn to the interpretation of the proximity penalty and present several pieces of evidence directly pointing to military spillover risk as a relevant driver. Specifically, we document, first, a positive association between proximity to Ukraine and the geopolitical risk index developed by Caldara and Iacoviello (2022). Second, we show that defense stocks provide an informative counterpoint to our general findings, as they command a significant proximity *premium* in countries close to Ukraine. Third, we look beyond equities and turn to currencies, where we observe a notable rise in option-implied tail risk premia for countries close to Ukraine. Lastly, we find proximity to Ukraine to be positively associated with military aid but uncorrelated with humanitarian and financial help provided to Ukraine. Together, these findings lend weight to the hypothesis that markets are sensitive to changes in disaster risk related to regional military spillovers from the war in Ukraine.

⁵*Simplemaps* provides greater country coverage for our MSCI sample, *Geonames* provides more granular data on a postal code level. Differences in the obtained distances are negligible.

3.1 Country-Level Evidence

Our results are based on different variants of the linear regression model (1). We report them in Table 1. As already suggested by Figure 1, we find that a country’s geographical proximity to Ukraine is indeed a significant differentiator of cumulative stock returns in the early stages of the war. Column (1) of Table 1 provides a simple benchmark that relates stock returns during our event window exclusively to countries’ distance from Ukraine. We can infer from this regression that Ukraine’s immediate neighbors (that is, countries at a distance of virtually zero) incurred, on average, a negative log return of 23.1% (p -value < 0.001) during the four-week period centered around the start of the war. Moving away from Ukraine improves the return by 2.6 percentage points per 1,000 km of distance (p -value < 0.001).

In column (2), we introduce as additional regressors the stock markets’ historical “alpha” and “beta” capturing, respectively, the average excess return and sensitivity to global stock returns.⁶ More sensitive (i.e., higher-beta) stock markets would tend to underperform during global sell-offs and vice versa. As such, the negative sign on the estimated coefficient is intuitive, although it is not statistically significant (p -value = 0.314). Similarly, the alpha is not significantly different from zero (p -value = 0.815). The other estimated coefficients are little affected.

In column (3), we turn to a regression that also controls for direct trade-related spillover effects. Our trade variables are transformed to z-scores to facilitate the interpretation of coefficients. We include variables measuring countries’ pre-war import and export dependence vis-à-vis Russia and Ukraine scaled by the countries’ GDP. The idea is to capture the (negative) effect of close pre-war trade ties with one or both of the warring countries as such ties are likely to be disrupted by the war. The extent of trade dependence on Russia turns out to be both statistically and economically significant. Specifically, the log equity return in our event window drops by 10.6 percentage points for a one standard deviation rise in the dependence on Russia as an export destination (p -value < 0.001). In our sample, one standard deviation represents 0.56% of GDP. We find this result plausible insofar as exports to Russia were set to suffer a particularly sharp collapse, given the breadth of sanctions imposed since the start of the war.⁷

Direct commercial linkages with Russia or Ukraine are not the only conceivable trade

⁶We describe the construction of these and other control variables in the online appendix.

⁷The interpretation of coefficients is, however, affected by the high correlation between the different trade variables. Notably, imports from Russia are very highly (81.2%) correlated with exports to Russia. This is likely to explain the insignificant coefficient estimate for the import variable. Indeed, re-running the regression without the $ExportsToRussia_i$ variable leads the $ImportsFromRussia_i$ coefficient to become negative and highly significant.

Table 1: Country-Level Stock Market Response to the Ukraine War

	(1)	(2)	(3)	(4)	(5)
	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$
$DistanceUkraine_i$	0.0263 (0.00474) {0.000}	0.0257 (0.00458) {0.000}	0.0170 (0.00453) {0.000}	0.0171 (0.00453) {0.000}	0.0113 (0.00444) {0.014}
$\hat{\alpha}_i$		8.213 (34.88) {0.815}	31.99 (27.91) {0.257}	31.78 (28.43) {0.269}	35.10 (29.22) {0.235}
$\hat{\beta}_{i,world}$		-0.0565 (0.0558) {0.314}	-0.0337 (0.0508) {0.510}	-0.0374 (0.0520) {0.475}	-0.00737 (0.0537) {0.891}
$z(ImportsFromRussia_i)$			0.0314 (0.0240) {0.195}	0.0333 (0.0241) {0.172}	-0.0225 (0.0614) {0.715}
$z(ExportsToRussia_i)$			-0.106 (0.0213) {0.000}	-0.107 (0.0222) {0.000}	-0.0754 (0.0423) {0.081}
$z(ImportsFromUkraine_i)$			-0.00305 (0.0287) {0.915}	-0.000584 (0.0304) {0.985}	0.00262 (0.0292) {0.929}
$z(ExportsToUkraine_i)$			-0.00212 (0.0130) {0.871}	-0.00305 (0.0137) {0.824}	0.000211 (0.0131) {0.987}
$z(SensitiveCommodities_i)$				-0.00902 (0.0203) {0.659}	-0.0128 (0.0184) {0.490}
EU_i					-0.0742 (0.0459) {0.112}
$EU_i * z(ImportsFromRussia_i)$					0.0659 (0.0650) {0.315}
$EU_i * z(ExportsToRussia_i)$					-0.0382 (0.0549) {0.490}
Constant	-0.231 (0.0297) {0.000}	-0.196 (0.0450) {0.000}	-0.171 (0.0396) {0.000}	-0.169 (0.0404) {0.000}	-0.146 (0.0439) {0.002}
Adj. R^2	0.32	0.33	0.53	0.52	0.52
N	66	66	64	64	64

Notes: Standard errors are heteroscedasticity robust and denoted in round brackets. P-values are reported in curly brackets. The event window is $\tau = [-14, 14]$.

channel. Given the important role both countries play as exporters of energy and metals (Russia) as well as agricultural goods (both Russia and Ukraine), disruptions in their

exports may affect—via higher prices—even countries that procure relevant commodities elsewhere on the world market. To allow for this indirect trade spillover, regression (4) also includes countries’ total imports (again scaled by GDP) of all goods that are among the top 10 exports of either Russia or Ukraine according to the Harvard University Atlas of Economic Complexity. The coefficient on this variable is negative as one would expect but not statistically significant (p -value = 0.659).

Importantly, the inclusion of all these trade variables still leaves our distance measure highly significant, with a point estimate of 1.7 percentage points (p -value < 0.001). This suggests that, even after controlling for direct and indirect trade linkages, simply being located, say, 3,000 km further away from Ukraine improved a country’s equity returns by more than 5 percentage points during our event window, all else fixed.

Finally, we also add, in regression (5), control variables for countries’ membership in the EU, as this might affect the extent of spillovers. In particular, the imposition of EU-coordinated sanctions during the event window could intensify trade-related shocks.⁸ We include not only the EU dummy but also its interaction with the countries’ pre-war import and export levels with Russia. Neither of the coefficients turn out statistically significant. Meanwhile, the inclusion of these control variables reinforces the finding that our distance measure captures a distinct non-trade spillover channel: the distance coefficient remains statistically significant and suggests a 1.1-percentage point improvement in cumulative equity returns for every 1,000 km of distance from Ukraine (p -value = 0.014), all else fixed. In other words, countries close to Ukraine still appear to be suffering a notable “proximity penalty” even after controlling for trade-related spillovers in various ways. Throughout, our regressions explain between one-third and one-half of the total variation of returns in our cross-section of countries.

3.2 Firm-Level Evidence

We now take a more granular view and assess to what extent our results also hold at the firm level. In doing so, we employ country fixed effects to control for country-specific characteristics or policies that might explain part of the stock market reaction. This allows us to interpret the coefficient ρ in model (1) as the effect on stock returns of an intra-country increase in the distance from Ukraine.

The firm-level regression also features industry fixed effects, the stock’s market capitalization as well as its historical alpha and its betas capturing sensitivities to the global equity market, the Russian equity market, and the Ukrainian equity market, respectively.

⁸In a related study, Huang and Lu (2022) quantify the stock market response to sanctions.

We include the specific betas for Russia and Ukraine to account for firms with inherently high exposure to these countries, for instance, because of direct revenue sources from either or both.

Table 2 provides results for three distinct samples: First, Columns (1) and (2) report the results of regressions restricted to firms headquartered in first- or second-degree neighbors of Ukraine. Second, Columns (3) and (4) report results for the entire sample of European firms. Third, results in Columns (5) and (6) pertain to the entirety of our sample without any geographic pre-selection. For each of these samples, we consider two different models: (i) a baseline model which features $DistanceUkraine_i$ as the sole regressor; (ii) an expanded model which also includes the firms' historical alphas ($\hat{\alpha}_i$) and their sensitivities to the global equity market ($\hat{\beta}_{i,world}$), the Russian market ($\hat{\beta}_{i,russia}$) and the Ukrainian market ($\hat{\beta}_{i,ukraine}$), along with the market value of the firms ($MarketValue_i$) and country as well as industry fixed effects.

Examining the results within the neighboring country sample, we find the distance from Ukraine to be a key determinant for (abnormal) stock market returns across all specifications. In the baseline model, an increase in the firms' distance from Ukraine by 1,000 km is associated with an increased return of 10.5 percentage points (p -value < 0.001). Moving to the expanded model, we still find greater distance to be significantly associated with returns, which increase by 4.9 percentage points for each 1,000 km (p -value = 0.042).

The results are similar but quantitatively smaller as we turn to the European sample in Columns (3) and (4). We still find $DistanceUkraine_i$ to be a significant driver across both model specifications. In the baseline model, we find an increase in the distance from Ukraine to be associated with extra returns of 3.4 percentage points per 1,000 km (p -value < 0.001). In the expanded model of Column (4), the effect is 4.1 percentage points (p -value = 0.023).

Lastly, we move to the global sample in Columns (5) and (6). The baseline model in column (5) indicates that an increase in the distance by 1,000 km is associated with increased returns of 1.2 percentage points (p -value < 0.001). The effect, however, becomes insignificant in Column (6) due to the inclusion of country fixed effects (p -value = 0.190).

Our firm-level analysis reveals three intuitive properties: (1) all three betas are consistently negative across all model specifications. This seems reasonable in a bearish market environment and with negative externalities arising from economic interconnect- edness with the Russian and Ukrainian economies. Moreover, the historical alphas are, across all regressions, positive and statistically significant, which may result from anticipatory effects regarding the conflict within our estimation period: stocks that, due

Table 2: Firm-Level Stock Market Response to the Ukraine War

	Neighbors		Europe		World	
	(1)	(2)	(3)	(4)	(5)	(6)
	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$
$DistanceUkraine_i$	0.105 (0.0106) {0.000}	0.0487 (0.0240) {0.042}	0.0342 (0.00486) {0.000}	0.0410 (0.0180) {0.023}	0.0119 (0.000365) {0.000}	0.00377 (0.00287) {0.190}
$\hat{\alpha}_i$		7.573 (3.386) {0.025}		8.830 (2.514) {0.000}		4.599 (1.114) {0.000}
$\hat{\beta}_{i,world}$		-0.0219 (0.00665) {0.001}		-0.0205 (0.00542) {0.000}		-0.0162 (0.00237) {0.000}
$\hat{\beta}_{i,ukraine}$		-0.0125 (0.0147) {0.397}		-0.0156 (0.00974) {0.109}		-0.00771 (0.00434) {0.076}
$\hat{\beta}_{i,russia}$		-0.0299 (0.0138) {0.031}		-0.0351 (0.00982) {0.000}		-0.0118 (0.00470) {0.012}
$MarketValue_i$		-0.000542 (0.000244) {0.026}		-0.0000123 (0.0000954) {0.898}		-0.0000556 (0.0000469) {0.236}
Constant	-0.237 (0.00885) {0.000}	-0.271 (0.0511) {0.000}	-0.200 (0.00586) {0.000}	-0.391 (0.0502) {0.000}	-0.160 (0.00241) {0.000}	-0.0841 (0.0533) {0.114}
Industry FE	No	Yes	No	Yes	No	Yes
Country FE	No	Yes	No	Yes	No	Yes
Adj. R^2	0.07	0.27	0.01	0.18	0.07	0.19
N	1,568	1,568	4,414	4,414	16,929	16,929

Notes: Standard errors are heteroscedasticity robust and denoted in round brackets. P-values are reported in curly brackets. The event window is $\tau = [-14, 14]$.

to the emerging conflict, had experienced negative excess returns in the period leading up to our event window plausibly were also affected the most by the outbreak of the war. (2) The $DistanceUkraine_i$ coefficient consistently decreases as we move toward a broader sample of firms, likely because, in the presence of country fixed effects, the measured intra-country differences lose their relevance in countries located far from Ukraine. To give a concrete example, unlike for Bulgaria and Poland, we would not expect the northeast of Argentina to be more affected by its relative proximity to Ukraine than the southwest of Argentina. (3) A global firm-level model with trade controls but without country fixed effects corroborates the results obtained from our country-level analysis displayed in Column (5) of Table 1; see Table C2 in the online appendix. Strikingly, we find that the distance coefficient of the firm-level analysis (0.0112) is nearly identical to the distance coefficient in our country-level analysis (0.0113).

3.3 Robustness

To ensure the robustness of our results, we test a variety of alternative model specifications. Specifically, we account for countries' memberships in supranational organizations, non-linearities, and different event window specifications.⁹ We find that the stock markets of North Atlantic Treaty Organization (NATO) members and of former Soviet Union countries exhibit significant negative excess returns. This seems intuitive as both groups of countries are arguably exposed to a higher probability of military involvement in the conflict. However, upon inclusion of our distance measure in the regression, both NATO and former Soviet Union affiliation become insignificant, suggesting that distance from Ukraine captures the ostensible link between the NATO/Soviet Union affiliations and stock returns.

To account for a potential non-linear relationship between distance from Ukraine and stock returns, we replicate the regression results shown in Table 1 now including a higher-order term of the distance from Ukraine. The point estimates suggest that the proximity penalty increases exponentially in the proximity to Ukraine. However, the measured non-linear effects are only statistically significant in the parsimonious model specifications. Very high variance inflation factors suggest that the expanded regressions exhibit strong multicollinearity, hampering statistical inference. We therefore prefer to focus on the linear model.

We also consider alternative event window lengths. Specifically, we replicate our main results outlined in Tables 1 and 2 for all τ with $\tau \in \{-1, 7, [-7, 7], [-1, 14], [-14, 14], [-28, 28]\}$. The obtained results largely mirror our earlier findings. The economic and statistical significance of the $DistanceUkraine_i$ coefficient, however, appears to increase in the event window size. This is consistent with random noise cancelling out in longer observation periods and with the notion of spillover threats building up over some time. In particular, it is highly plausible that, due to anticipatory effects, some of the proximity penalty already seeped into market prices prior to the Russian invasion of Ukraine. Similarly, some perceived spillover risks may have increased in the weeks following the start of the war, as exemplified by tensions in Moldova that intensified amid reported Russian plans to advance toward the South-west of Ukraine.¹⁰

⁹Detailed results are available in the online appendix: The robustness tests regarding international organization membership are provided in Table B3; our analyses regarding non-linear distance effects are provided in Table B4; and the results of the country-level and firm-level event window variations are outlined in Tables B5-B6 and C5-C10, respectively.

¹⁰See "Ukraine war casts shadow over Transnistria as security alerts sow fear," Financial Times, May 3, 2022.

Finally, another potential concern about our findings could be that countries close to Ukraine might differ from other countries in a way that hampers their general capacity to cope with (economic) crisis. We address this concern by examining other events that affected global stock markets. The right panel of Figure 1 visualizes these placebo tests. In all of the examined crises, except for the specific two instances of the Russia/Ukraine conflict, the returns of Ukraine’s neighbors are similar to those of other countries, suggesting no systematic difference.

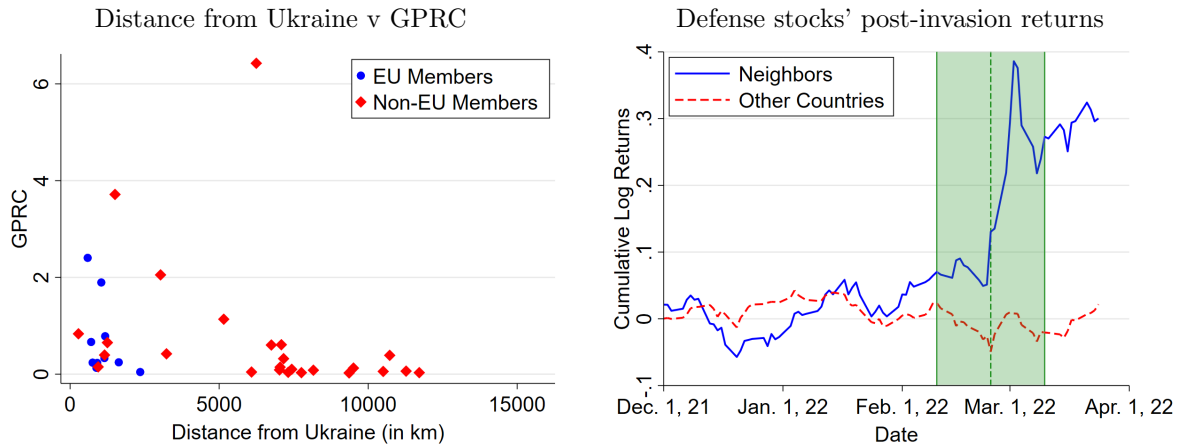
3.4 Interpretation of the Proximity Penalty

Our findings show a sizeable and robust stock market response to the war in Ukraine, differentiated across countries and firms. We find that stock prices suffer larger declines in economies closest to the conflict zone, even after controlling for EU membership and trade relations with the countries at war. A similar finding also applies to firm-level stock prices. This incremental “proximity penalty” may reflect different factors. Prominent among these is fear of direct military entanglement or collateral damage, the latter perhaps related to the potential use of weapons of mass destruction in the neighboring country, or to the risk of military activity causing an accident in a nuclear power plant—both commonly discussed as potential risks for the war in Ukraine. Put differently, the fighting in Ukraine creates a (tail) risk of economic disaster for other economies, and this risk increases in the proximity to Ukraine. Incidentally, a perceived increase of this risk may not only be a natural consequence of “fighting next door”. Rather, it could also be deliberately provoked by a warring party to deter other countries from supporting its adversary. This is certainly one way to interpret Russia’s repeated references to the risk of nuclear escalation.

In the remainder of this section, we consider four pieces of evidence that support the notion of military spillovers and, hence, increased disaster risk as a relevant differentiator in the current context.

First, we show in the left panel of Figure 2 how our distance measure relates to an independent and objective measure of geopolitical risk, namely the Geopolitical Risk Index for individual countries (GPRC) compiled by Caldara and Iacoviello (2022). The GPRC should capture the geopolitical risk affecting countries in our sample as the war in Ukraine unfolded. As is apparent from the figure, geopolitical risk increases clearly in the proximity to Ukraine. This conforms with the view that neighbors face greater risks of direct kinetic escalation or other military spillovers than faraway countries. The only data point going against the grain of this idea is the high assessed geopolitical risk of the US (the maximum value in the sample). Indeed, we would argue that this risk assessment

Figure 2: Proximity to War and Military Spillover Risk



Notes: Left panel correlates the GPRC in March 2022 and distance from Ukraine. The outlier, at about 6300 km, represents the USA. Right panel shows the returns of aerospace & defense equities as defined by Thomson Reuters in first-/second-degree neighbor countries and other countries. Russia and Ukraine are excluded from both panels.

overstates *de facto* military threats posed to the US by the war in Ukraine, although there is no denying that a standoff with Russia qualifies as heightened geopolitical risk for the US more broadly.

Second, in the right panel of Figure 2 we turn to the equity market performance of a specific enterprise sector that is likely to be a rare beneficiary of military escalation: the aerospace and defense sector (Phillips, 2015). If military spillover risk affects neighbors of the warring countries more than faraway countries, it would be natural to expect greater prospective orders and activity for defense companies in neighboring countries compared to those further away. The extent to which this hypothesis is borne out in the data is quite impressive: companies in this sector experience average positive returns as high as 30% in the neighbor group, whereas their peers in other countries show zero returns. This is even more remarkable if we consider two complicating facts: (i) there are bound to be some positive spillovers for global defense companies, irrespective of where they are located; and (ii) the sector includes not only pure defense companies but also airlines and integrated air/defense companies for whom war is likely to have a negative effect. Nonetheless, defense companies in neighboring countries appear to derive a strong proximity premium, the exact mirror image of the proximity penalty suffered by the broader stock market in these countries.

Third, we examine whether countries located close to Ukraine were more likely to provide financial, humanitarian, or military support to Ukraine. We obtain data on country-level aid from the Ukraine Support Tracker compiled by Antezza et al. (2022). The

database contains the total aid by category provided by 31 Western governments. For each category, we test whether the amount spent on helping Ukraine, normalized by the respective countries' GDP, varies with their distance from Ukraine. We find that countries' distance from Ukraine is not associated with the amount of humanitarian and financial help in a statistically significant way. By contrast, there is a statistically significant negative association with military aid. In other words, the countries closest to Ukraine tend to provide distinctly more military help to Ukraine than those which are further away. In fact, the five countries which provided the largest military support to Ukraine, scaled by their own GDP, are all first- or second-degree neighbors of Ukraine.¹¹ In total, the extra military help provided by first- and second-degree neighbors amounted to USD 9.0 billion.¹² These results underscore the prominence of the military dimension and support the notion that military risks are central to the residual proximity penalty (i.e., once trade-related effects are controlled for). A detailed outline of the data and results is provided in Section D in the online appendix.

Lastly, we present direct evidence that the reaction of financial markets to the war in Ukraine is—at least partially—driven by a perceived increase in tail or disaster risk. To this end, we note that the arguments developed and tested above for the case of stock prices can also be applied to exchange rates. Specifically, greater economic exposure to Russia and/or Ukraine may cause countries' economies to suffer as the war proceeds and lead to weaker exchange rates. The depreciation of national currencies could be related, for instance, to declining exports to the countries at war, weaker growth prospects as a result of economic, political or military disruption, or broader threats to economic and political stability that discourage capital inflows. Just like with stock prices, exchange-rate movements may also be driven by expectations of rare economic disasters. To measure these, we focus on tail risk premia apparent from currency option pricing.

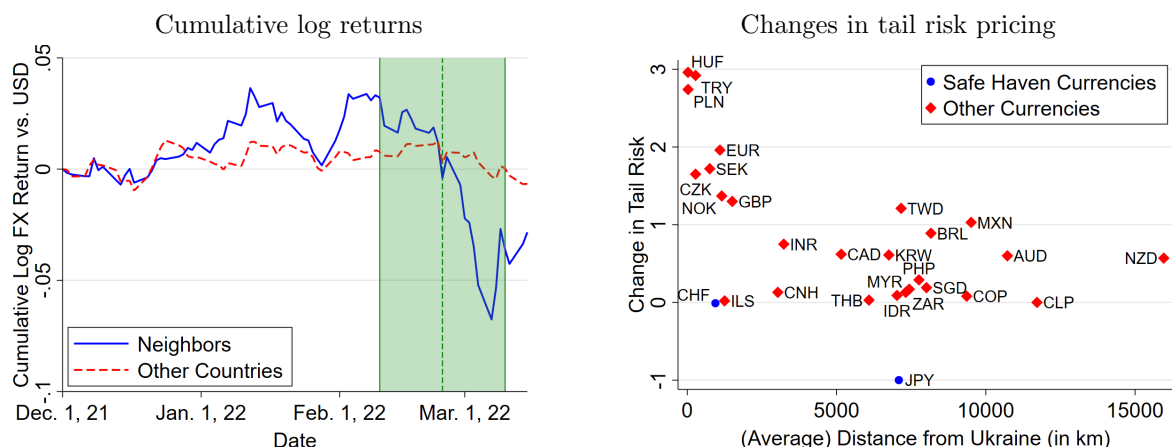
We start by replicating Figure 1, now using countries' exchange rates against the US dollar instead of stock indices. As before, we distinguish between neighbors and other countries. The results are displayed in the left panel of Figure 3. Note that the two samples are now smaller than before, as the list of countries with flexible exchange rates and reasonably liquid currency markets is much shorter than the list of countries with MSCI equity indices.¹³ Nonetheless, the broad picture is remarkably similar to Figure 1. Although the currencies of neighbors and other countries showed limited divergence prior to the event window, the neighboring countries' exchange rates started to weaken significantly more than the other countries' exchange rates as tensions in Ukraine escalated and especially

¹¹These are Estonia, Latvia, Poland, the Slovak Republic and Lithuania. Related, we find that first- and second-degree neighbors, on average, spent 0.15 percentage points of their GDP more on military help for Ukraine than other countries—an association that is significant at the 5% level.

¹²The Ukraine Support Tracker comprises data for the period from January 24 through April 23.

¹³Details are provided in Section D of the online appendix.

Figure 3: Exchange Rate Dynamics



Notes: Left panel shows the cumulative foreign exchange spot return of first- and second-degree neighbors and other countries against USD. Right panel shows the change in tail risk pricing of first- and second-degree neighbor vs. non-neighbor currencies.

once the Russian invasion got underway.

To complement this simple analysis of *average* exchange rate movements, we next investigate the market’s perception of currency *tail risk* as apparent from exchange rate options. Specifically, the right panel in Figure 3 visualizes the difference between each currency’s average “risk reversal” during February 24, 2022 to March 10, 2022 and their average risk reversal value during 2021. The risk reversal is defined as the difference between the price of an out-of-the-money put option on the currency and the price of an out-of-the-money call option. Intuitively, if markets become more worried about disasters, put options that provide insurance against such outcomes become relatively more valuable than call options, which would pay out in the event of large appreciation. Thus, a rising risk reversal reflects greater market concern over the risk of sharp exchange rate weakness. As Figure 3 shows, this metric is clearly and inversely related to distance from Ukraine, once again suggesting the importance of geographic proximity for economic risk reflected in asset prices.

A higher perceived tail risk for neighboring countries aligns with our hypothesis that the proximity penalty partly captures military spillover risk: the direct involvement of neighboring countries in the conflict may have low *ex ante* probability, but implies high *ex post* costs if the disaster materializes. This type of risk should have *some* impact on basic asset prices like equity prices or exchange rates but become more clearly apparent from option prices that directly reflect tail assessments. In the present case, the increased disaster risk premium apparent from currency options suggests that financial markets

did indeed become more concerned about such “unlikely but highly impactful” events occurring in countries closer to Ukraine. One instructive special case is the Taiwan Dollar. Although Taiwan is far away from Ukraine, the apparent rise in Taiwan Dollar tail risk is particularly large in our sample. Proximity to Ukraine clearly is not the reason. And yet, a direct link to the war in Ukraine is very plausible insofar as markets became more attuned, in the wake of Russia’s attack on Ukraine, to the possibility of future hostilities between China and Taiwan.¹⁴

To sum up, supplementary evidence from a geopolitical risk variable, defense sector stock prices, military aid flows to Ukraine and the currency options market all support the notion that the “proximity penalty” is at least partly related to disaster risk. This risk may not be particularly high but would generate a large impact if the war were to escalate beyond Ukraine’s borders.

4 Conclusion

During times of war, a country’s proximity to the conflict zone is a key determinant for the economic spillovers it is exposed to. Focusing on the specific case of the war in Ukraine, we show that the behavior of stock markets around the start of the war shows a strong sensitivity to changes in perceived disaster risk. Geography turns out to be key in this regard. In countries geographically close to the war, markets suffered a sizeable proximity penalty, in the form of sharply negative returns, during the first couple of weeks of the war. Countries farther away fared much better in comparison. About one-half to two-thirds of this effect can be attributed to trade links, which, all else equal, tend to be closer among neighbors. The remainder is likely to reflect military spillover risks. Indeed, Ukraine’s neighbors generally experienced a greater rise in independent measures of geopolitical risk, provided greater levels of military support to Ukraine, saw their domestic defense companies outperform the general stock market more significantly, and suffered higher perceptions of disaster risk as reflected in currency options. In conclusion, geography matters for the economic spillovers of war. These spillovers, in turn, are likely to feed back into geopolitics and perhaps influence the course of the war itself.

¹⁴See “Investors in Taiwan seek to hedge against risk of conflict with China,” *Financial Times*, March 15, 2022.

References

- Antezza, A., A. Frank, P. Frank, L. Franz, E. Rebinskaya, and C. Trebesch (2022). The ukraine support tracker: Which countries help ukraine and how? Kiel Working Paper No. 2218.
- Baker, S. R., N. Bloom, and S. J. Davis (2016, 07). Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics* 131(4), 1593–1636.
- Barro, R. J. (2006). Rare Disasters and Asset Markets in the Twentieth Century. *The Quarterly Journal of Economics* 121(3), 823–866.
- Berkman, H., B. Jacobsen, and J. B. Lee (2011). Time-varying rare disaster risk and stock returns. *Journal of Financial Economics* 101(2), 313–332.
- Born, B., G. J. Müller, M. Schularick, and P. Sedláček (2019). The Costs of Economic Nationalism: Evidence from the Brexit Experiment. *The Economic Journal* 129(623), 2722–2744.
- Boungou, W. and A. Yatié (2022). The impact of the ukraine–russia war on world stock market returns. *Economics Letters*, 110516.
- Caldara, D. and M. Iacoviello (2022). Measuring Geopolitical Risk. *American Economic Review* 112(4), 1194–1225.
- Couttenier, Mathieu, N. M. and L. Piemontese (2022). The economic costs of conflict: A production network approach. *CEPR Discussion Papers* 16984.
- Deng, M., M. Leippold, A. F. Wagner, and Q. Wang (2022). Stock prices and the russia-ukraine war: Sanctions, energy and esg. *Swiss Finance Institute Research Paper No. 22-29*.
- Farhi, E. and X. Gabaix (2016). Rare disasters and exchange rates. *The Quarterly Journal of Economics* 131(1), 1–52.
- Fuchs-Schündeln, N. and T. Hassan (2016). Natural experiments in macroeconomics. In *The Handbook of Macroeconomics*, Volume 2, pp. 923–1012. Elsevier.
- Glick, R. and A. M. Taylor (2010). Collateral damage: Trade disruption and the economic impact of war. *The Review of Economics and Statistics* 92(1), 102–127.
- Gourio, F. (2012, May). Disaster risk and business cycles. *American Economic Review* 102(6), 2734–2766.
- Guidolin, M. and E. La Ferrara (2007). Diamonds are forever, wars are not: Is conflict bad for private firms? *Economica* 97(5), 1978–1993.
- Head, K. and T. Mayer (2014). Chapter 3 - Gravity Equations: Workhorse, Toolkit, and Cookbook. In *Handbook of International Economics*, Volume 4, pp. 131–195. Elsevier.
- Huang, L. and F. Lu (2022). The cost of russian sanctions on the global equity markets. *Available at SSRN*.

- Korovkin, V. and A. Makarin (2021). Conflict and inter-group trade: Evidence from the 2014 russia-ukraine crisis. *Available at SSRN*.
- Leigh, A., J. Wolfers, and E. Zitzewitz (2003). What Do Financial Markets Think of War in Iraq? *NBER Working Paper 9587*.
- Mueller, H., D. Rohner, and D. Schönholzer (2022, 06). Ethnic Violence Across Space. *The Economic Journal* 132(642), 709–740.
- Murdoch, J. C. and T. Sandler (2002). Economic growth, civil wars, and spatial spillovers. *The Journal of Conflict Resolution* 46(1), 91–110.
- Murdoch, J. C. and T. Sandler (2004). Civil wars and economic growth: Spatial dispersion. *American Journal of Political Science* 48(1), 138–151.
- Nakamura, E. and J. Steinsson (2018). Identification in macroeconomics. *Journal of Economic Perspectives* 32(3), 59–86.
- Phillips, B. J. (2015). Civil war, spillover and neighbors' military spending. *Conflict Management and Peace Science* 32(4), 425–442.
- Rietz, T. A. (1988). The equity risk premium a solution. *Journal of Monetary Economics* 22(1), 117–131.
- Veronesi, P. (2004). The peso problem hypothesis and stock market returns. *Journal of Economic Dynamics and Control* 28(4), 707–725.
- Zussman, Asaf, N. Z. and M. Ørregaard Nielsen (2008). Asset market perspectives on the israeli–palestinian conflict. *Economica* 75(297), 84–115.

Online Appendix

A Data Sources and Variable Construction

We retrieve the daily price MSCI indices of all countries available on Thomson Reuters Eikon. Our sample comprises 69 countries from around the world. As we observe significant data anomalies in the MSCI price index of Lebanon, we drop the country from our analyses. We further exclude Ukraine and Russia to focus on the externalities of the war for other countries. Accordingly, our primary analysis comprises 66 countries.¹⁵ We also obtain price levels of the MSCI World, MSCI Russia, and MSCI Ukraine from Thomson Reuters Datastream for our beta estimations. Throughout this section, all price levels are obtained in US dollars.

For our country-level analysis, we estimate the “alphas” and “betas” of all country stock markets in our sample. We use the returns of the MSCI World as a measure of global equity market performance. Considering weekly returns for the year leading up to the start of our event window, we compute the country-specific alpha and beta as the coefficients from a regression of a country’s stock market return on the global return and a constant.

To capture trade linkages, we consider a set of variables which we expect to matter for the economic spillover effects of the war. Specifically, we use $ImportsFromRussia_i$ to denote imports from Russia by country i and $ExportsToRussia_i$ to denote exports of country i to Russia. Similarly, the variables $ImportsFromUkraine_i$ and $ExportsToUkraine_i$ denote the imports of country i from Ukraine and the exports of country i to Ukraine, respectively. The import and export variables pertain to 2019 (thus avoiding distortions related to Covid-19) and are all scaled by the country’s respective GDP. We obtain the country-level trade statistics from the International Monetary Fund. The data on countries’ GDP is provided by the World Bank.¹⁶ A detailed outline of the variables is provided in Section B of this appendix.

Russian and Ukrainian trade restrictions may increase the prices and limit the availability of their top export goods on the global market. Countries with a higher import rate for such goods may therefore be negatively affected even if they do not directly import goods from Russia or Ukraine. To control for these indirect trade spillover effects, we compute each country’s total import value, across all trading partners, of the top-10 Russian and Ukrainian export goods, scaled by GDP and denoted $SensitiveCommodities_i$. The largest 10 export goods for Russia and Ukraine, respectively, are determined based on 4-digit SITC codes, excluding special transactions and unclassified commodities. Combining the two top-10 lists produces a list of 18 items (due to partial overlap in the largest export goods). We calculate each country’s aggregate import value accounted for by items on this list. We retrieve data on commodity-specific trade flows from the Harvard University Atlas of Economic Complexity database. As before we use 2019 values and scale by GDP for the same year.

¹⁵See Section B for a detailed overview.

¹⁶Due to incomplete data coverage, we need to drop Jamaica and Taiwan when including the trade statistics, reducing our sample to 64 countries.

For our firm-level analysis, we retrieve daily pricing data and the headquarters' domicile countries and postal codes of all equities available on Thomson Reuters Eikon. We restrict our sample to active, exchange-traded equities. The sample is further restricted to primary quotes with a linked Reuters Instrument Code and major securities as defined by Datastream. The resulting sample comprises 48,403 different firms around the globe. We drop firms with missing postal codes and those we could not match with the Geonames database. We further drop all firms for which we did not obtain valid pricing data on at least 90% of all days as measured by the stock for which we have the most valid day-firm observations. We linearly interpolate the remaining missing values. As the Aerospace & Defense sector likely profits from proximity to Ukraine, we exclude those firms from our analyses. Furthermore, we exclude firms from Ukraine and Russia to only capture the externalities of the war on third-party countries. Moreover, we only include firms in our analysis for which we obtained the market value of equity from Thomson Reuters Eikon on at least one day. Lastly, we drop firms with a market value of equity which is lower than \$10 millions as they likely exhibit a deficient liquidity.¹⁷ After applying those filters, our sample size is reduced to 16,929 firms across 54 different countries and 8,954 postal codes. A detailed outline of how many firms are dropped in each step as well as a country-firm overview is provided in Section C of this appendix.

Within our sample there is a total of 1,568 firms headquartered in first- or second-degree neighbor countries of Ukraine. Similarly, a total of 4,414 firms in our sample is located in Europe.¹⁸

The betas included in the firm-level regression are estimated on weekly-aggregated observations within the year preceding the event-window. The MSCI World was used as a proxy for the global equity return and we assumed a flat risk-free interest rate of 0%. The MSCI Ukraine and MSCI Russia were used to account for the firms' sensitivity to the respective countries' economies. Summarizing, for each firm separately, we estimated their respective alphas and betas using the following ordinary least squares regression:

$$\begin{aligned} \text{LogRet}_{n,t} = & \alpha_n + \hat{\beta}_{n,\text{world}} * \text{MSCILogRet}_{t,\text{world}} + \hat{\beta}_{n,\text{russia}} * \text{MSCILogRet}_{t,\text{russia}} \\ & + \hat{\beta}_{n,\text{ukraine}} * \text{MSCILogRet}_{t,\text{ukraine}} + \varepsilon_{n,t}, \end{aligned} \quad (2)$$

where $\text{LogRet}_{t,n}$ denotes the log return of firm n on day t and $\text{MSCILogRet}_{t,\text{world}}$, $\text{MSCILogRet}_{t,\text{russia}}$, and $\text{MSCILogRet}_{t,\text{ukraine}}$ denote the log returns of the MSCI World, MSCI Russia, and MSCI Ukraine on day t , respectively. The resulting coefficients of the regression resemble our firm-level control alphas and betas.

We obtain both the currency spot returns and the data on FX risk reversals (the difference between out-of-the-money call and put option premia) from Bloomberg Finance L.P.

For the purpose of external validation, we retrieve the most recent Geopolitical Risk Index (GPRC) from Caldara and Iacoviello (2022). The GPRC measures country-specific geopolitical risk as of March 1, 2022, using an automated textual analysis of newspaper articles. It is updated on a monthly basis and available for 39 countries in our analysis.

¹⁷Throughout our analyses we consistently used the first non-missing market value of equity of firm n provided by Thomson Reuters Eikon within our sample period.

¹⁸We classified the firms' countries as European according to the United Nations geoscheme for Europe.

Regarding the country-level support of Ukraine, we use the Ukraine Support Tracker compiled by Antezza et al. (2022). Specifically, our analysis relies on the latest version of the database which was updated on May 02, 2022.

Lastly, we obtain daily market prices for all active equities operating in the Aerospace and Defense sector from Thomson Reuters Datastream. In total, we retrieved data for 650 Aerospace and Defense equities across 29 different countries. After dropping all stocks for which we did not obtain complete data on market prices and the respective company’s domicile country for 2020-22, we are left with 480 equities.

B Country Level Analysis

Table B1: Geographical and Geopolitical Properties of Sample Countries

	Distance from Ukraine (in km)	First-Degree Neighbor	Second-Degree Neighbor	EU Member	GPRC
Argentina	11,272	No	No	No	0.06
Australia	10,723	No	No	No	0.39
Austria	390	No	Yes	Yes	-
Bahrain	2,496	No	No	No	-
Bangladesh	4,925	No	No	No	-
Belgium	1,175	No	No	Yes	0.78
Bosnia and Herzegovina	464	No	No	No	-
Botswana	6,979	No	No	No	-
Brazil	8,161	No	No	No	0.08
Bulgaria	184	No	Yes	Yes	-
Canada	5,155	No	No	No	1.14
Chile	11,715	No	No	No	0.03
China	3,034	No	No	No	2.05
Colombia	9,360	No	No	No	0.03
Croatia	409	No	Yes	Yes	-
Czech Republic	277	No	Yes	Yes	-
Denmark	881	No	No	Yes	0.13
Estonia	669	No	Yes	Yes	-
Finland	909	No	Yes	Yes	0.23
France	1,045	No	No	Yes	1.90
Germany	589	No	Yes	Yes	2.40
Ghana	4,646	No	No	No	-
Hong Kong	7,045	No	No	No	0.14
Hungary	24	Yes	No	Yes	-
India	3,233	No	No	No	0.42
Indonesia	7,025	No	No	No	0.09
Ireland	2,032	No	No	Yes	-
Israel	1,249	No	No	No	0.65
Italy	704	No	No	Yes	0.67
Jamaica	9,122	No	No	No	-
Japan	7,086	No	No	No	0.61
Jordan	1,321	No	No	No	-
Kazakhstan	527	No	No	No	-
Kenya	4,568	No	No	No	-

Lithuania	266	No	Yes	Yes	-
Malaysia	7,316	No	No	No	0.04
Mauritius	7,551	No	No	No	-
Mexico	9,507	No	No	No	0.13
Morocco	2,494	No	No	No	-
Netherlands	1,151	No	No	Yes	0.33
New Zealand	15,960	No	No	No	-
Nigeria	3,983	No	No	No	-
Norway	1,154	No	Yes	No	0.40
Pakistan	2,955	No	No	No	-
Peru	10,505	No	No	No	0.06
Philippines	7,759	No	No	No	0.03
Poland	27	Yes	No	Yes	-
Portugal	2,352	No	No	Yes	0.04
Romania	3	Yes	No	Yes	-
Russia	14	Yes	No	No	7.84
Serbia	303	No	Yes	No	-
Singapore	8,012	No	No	No	-
Slovenia	474	No	Yes	Yes	-
South Africa	7,436	No	No	No	0.10
South Korea	6,751	No	No	No	0.60
Spain	1,631	No	No	Yes	0.24
Sri Lanka	5,692	No	No	No	-
Sweden	753	No	No	Yes	0.24
Switzerland	941	No	No	No	0.15
Taiwan	7,162	No	No	No	0.32
Thailand	6,086	No	No	No	0.04
Trinidad and Tobago	8,560	No	No	No	-
Tunisia	1,572	No	No	No	-
Turkey	279	No	No	No	0.83
Ukraine	0	No	No	No	7.74
United Kingdom	1,506	No	No	No	3.72
United States	6,245	No	No	No	6.43
Vietnam	6,244	No	No	No	-
<i>N</i>	68				

Notes: Table provides an overview of the properties of the countries comprised in our country-level analysis.

Table B2: Trade Statistics of Sample Countries (Scaled by GDP)

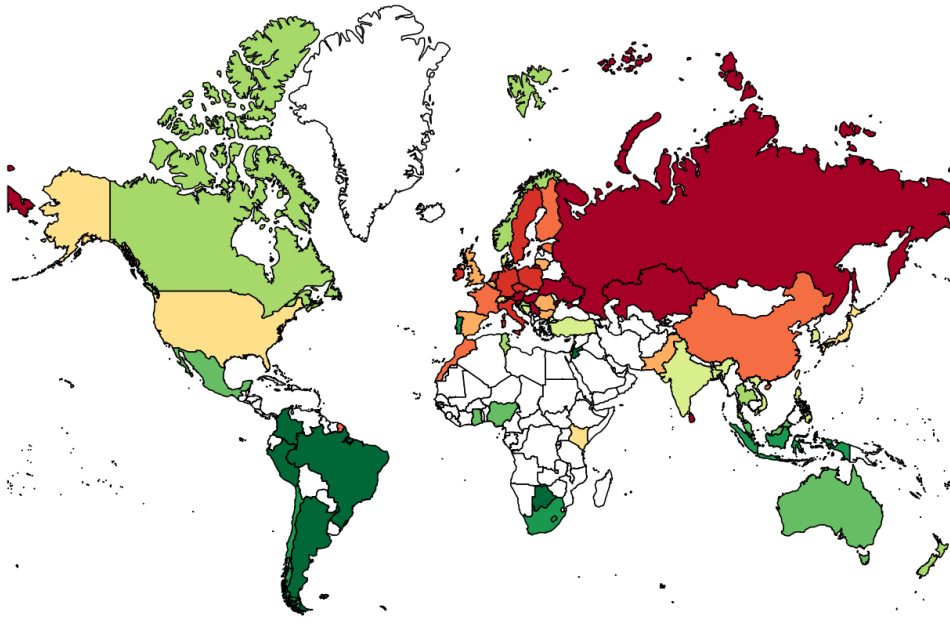
	<i>ExportsToRussia_i</i>	<i>ImportsFromRussia_i</i>	<i>ExportsToUkraine_i</i>	<i>ImportsFromUkraine_i</i>	<i>SensitiveCommodities_i</i>
Argentina	0.18%	0.07%	0.01%	0.00%	1.36%
Australia	0.05%	0.01%	0.01%	0.00%	2.10%
Austria	0.59%	0.79%	0.15%	0.13%	3.39%
Bahrain	0.03%	0.09%	0.00%	0.03%	4.83%
Bangladesh	0.32%	0.37%	0.03%	0.15%	3.18%
Belgium	0.45%	1.26%	0.10%	0.13%	6.77%
Bosnia and Herzegovina	0.49%	0.19%	0.07%	0.10%	5.45%
Botswana	0.05%	0.15%	0.01%	0.01%	5.54%
Brazil	0.11%	0.13%	0.01%	0.00%	1.33%
Bulgaria	0.84%	3.93%	0.67%	0.70%	7.01%
Canada	0.05%	0.05%	0.01%	0.00%	2.46%
Chile	0.33%	0.03%	0.02%	0.00%	4.24%
China	0.38%	0.38%	0.06%	0.03%	3.02%
Colombia	0.04%	0.05%	0.03%	0.01%	2.11%
Croatia	0.31%	2.39%	0.08%	0.06%	6.66%
Czech Republic	1.46%	1.87%	0.46%	0.36%	4.61%
Denmark	0.34%	0.92%	0.08%	0.07%	2.29%
Estonia	1.56%	7.88%	0.47%	0.45%	5.92%
Finland	1.30%	3.74%	0.10%	0.02%	3.70%
France	0.31%	0.24%	0.06%	0.02%	2.47%
Germany	0.65%	0.72%	0.15%	0.06%	3.38%
Ghana	0.13%	0.18%	0.29%	0.12%	1.32%
Hong Kong	0.13%	0.22%	0.02%	0.02%	10.14%
Hungary	1.39%	2.45%	0.76%	0.96%	5.87%
India	0.14%	0.25%	0.03%	0.07%	5.47%
Indonesia	0.15%	0.07%	0.03%	0.07%	2.57%
Ireland	0.40%	0.11%	0.04%	0.04%	1.60%
Israel	0.21%	0.36%	0.05%	0.16%	2.82%
Italy	0.54%	0.71%	0.10%	0.12%	3.54%
Jamaica	0.56%	0.01%	-	-	9.05%
Japan	0.17%	0.22%	0.02%	0.00%	2.94%

Jordan	0.06%	0.82%	0.04%	0.38%	8.53%
Kazakhstan	2.94%	7.53%	0.25%	0.20%	1.23%
Kenya	0.09%	0.16%	0.01%	0.07%	3.84%
Lithuania	1.05%	6.37%	2.09%	0.75%	8.10%
Malaysia	0.48%	0.31%	0.06%	0.05%	9.84%
Mauritius	0.07%	0.01%	0.01%	0.01%	6.88%
Mexico	0.09%	0.12%	0.01%	0.01%	4.05%
Morocco	0.42%	0.64%	0.08%	0.25%	7.15%
Netherlands	0.44%	4.93%	0.08%	0.20%	10.50%
New Zealand	0.10%	0.09%	0.01%	0.00%	1.92%
Nigeria	0.01%	0.08%	0.00%	0.04%	2.05%
Norway	0.12%	0.70%	0.07%	0.01%	1.73%
Pakistan	0.13%	0.06%	0.03%	0.02%	4.68%
Peru	0.12%	0.12%	0.01%	0.01%	3.14%
Philippines	0.11%	0.18%	0.01%	0.05%	4.73%
Poland	0.85%	2.07%	0.69%	0.55%	3.98%
Portugal	0.23%	0.30%	0.03%	0.12%	4.28%
Romania	0.58%	1.28%	0.26%	0.40%	3.57%
Russia	-	-	0.41%	0.19%	0.32%
Serbia	2.03%	2.96%	0.34%	0.50%	5.08%
Singapore	0.16%	0.61%	0.01%	0.05%	21.06%
Slovenia	1.89%	0.90%	0.45%	0.07%	7.50%
South Africa	0.21%	0.07%	0.02%	0.01%	3.55%
South Korea	0.48%	0.99%	0.02%	0.02%	7.34%
Spain	0.24%	0.18%	0.06%	0.11%	3.97%
Sri Lanka	0.34%	0.13%	0.05%	0.07%	4.56%
Sweden	0.42%	0.44%	0.09%	0.01%	3.14%
Switzerland	0.39%	0.53%	0.22%	0.02%	8.69%
Taiwan	-	-	-	-	-
Thailand	0.32%	0.11%	0.04%	0.06%	7.21%
Trinidad and Tobago	0.00%	0.18%	0.02%	0.00%	5.60%
Tunisia	0.34%	1.23%	0.05%	0.87%	12.47%
Turkey	0.65%	2.78%	0.31%	0.34%	4.85%

Ukraine	3.12%	4.78%	-	-	6.89%
United Kingdom	0.14%	0.46%	0.03%	0.02%	4.68%
United States	0.06%	0.06%	0.01%	0.00%	1.11%
Vietnam	1.44%	0.43%	0.16%	0.04%	8.46%
<i>N</i>	68				

Notes: Table provides an overview of countries' trade relationships with Russia and Ukraine as well as their dependence on commodities which rank among the top-10 import and export goods from Russia or Ukraine, respectively. All variables are scaled by their countries' GDP.

Figure B1: Geographic Variation of Stock Market Returns



Notes: Map illustrates geographical distribution of cumulative log returns, measured in 4-week event window around February 24, 2022. Dark green (red) countries exhibited the highest (lowest) returns within period. Countries for which we did not obtain any data are white.

Table B3: Country-Level Responses to the Ukraine War (With Affiliation Dummies)

	(1)	(2)	(3)	(4)
	$CumRet_i^T$	$CumRet_i^T$	$CumRet_i^T$	$CumRet_i^T$
$NATO_i$	-0.105 (0.0402) {0.011}	-0.0899 (0.0428) {0.039}	0.0190 (0.0476) {0.691}	0.0545 (0.0557) {0.332}
$Soviet_i$		-0.219 (0.143) {0.132}	-0.159 (0.114) {0.166}	-0.0928 (0.139) {0.509}
$DistanceUkraine_i$			0.0257 (0.00603) {0.000}	0.0135 (0.00472) {0.006}
$\hat{\alpha}_i$				37.42 (29.18) {0.206}
$\hat{\beta}_{i,world}$				-0.0200 (0.0571) {0.728}
$z(ImportsFromRussia_i)$				-0.00466 (0.0663) {0.944}
$z(ExportsToRussia_i)$				-0.0701 (0.0425) {0.106}
$z(ImportsFromUkraine_i)$				-0.00476 (0.0341) {0.890}
$z(ExportsToUkraine_i)$				0.00511 (0.0205) {0.804}
$z(SensitiveCommodities_i)$				-0.0131 (0.0190) {0.496}
EU_i				-0.105 (0.0537) {0.055}
$EU_i * z(ImportsFromRussia_i)$				0.0630 (0.0606) {0.304}
$EU_i * z(ExportsToRussia_i)$				-0.0450 (0.0523) {0.394}
Constant	-0.0881 (0.0268) {0.002}	-0.0831 (0.0246) {0.001}	-0.228 (0.0448) {0.000}	-0.150 (0.0445) {0.001}
Adj. R^2	0.07	0.13	0.34	0.52
N	66	66	66	64

Notes: Standard errors are heteroscedasticity robust and denoted in round brackets. P-values are reported in curly brackets. The applied event window is $\tau = [-14, 14]$. Table complements the analysis given by Equation (1) and outlined in Table 1 with a dummy indicating NATO and former Soviet Union membership.

Table B4: Country-Level Responses to the Ukraine War (Non-Linear)

	(1)	(2)	(3)	(4)	(5)
	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$
$DistanceUkraine_i$	0.0474 (0.0119) {0.000}	0.0424 (0.0120) {0.001}	0.0187 (0.0142) {0.191}	0.0205 (0.0139) {0.147}	0.00471 (0.0148) {0.752}
$DistanceUkraine_i^2$	-0.00189 (0.000802) {0.022}	-0.00149 (0.000820) {0.074}	-0.000140 (0.000990) {0.888}	-0.000269 (0.000977) {0.784}	0.000492 (0.00108) {0.651}
$\hat{\alpha}_i$		4.911 (34.57) {0.887}	31.68 (28.53) {0.272}	31.19 (29.08) {0.288}	36.48 (30.10) {0.231}
$\hat{\beta}_{i,world}$		-0.0397 (0.0571) {0.489}	-0.0318 (0.0504) {0.531}	-0.0341 (0.0515) {0.511}	-0.0114 (0.0534) {0.832}
$z(ImportsFromRussia_i)$			0.0312 (0.0243) {0.204}	0.0331 (0.0245) {0.182}	-0.0246 (0.0613) {0.690}
$z(ExportsToRussia_i)$			-0.105 (0.0225) {0.000}	-0.106 (0.0235) {0.000}	-0.0754 (0.0431) {0.086}
$z(ImportsFromUkraine_i)$			-0.00235 (0.0295) {0.937}	0.000969 (0.0315) {0.976}	-0.000117 (0.0304) {0.997}
$z(ExportsToUkraine_i)$			-0.00196 (0.0130) {0.881}	-0.00282 (0.0138) {0.839}	0.000334 (0.0133) {0.980}
$z(SensitiveCommodities_i)$				-0.00977 (0.0205) {0.635}	-0.0117 (0.0187) {0.534}
EU_i					-0.0804 (0.0479) {0.099}
$EU_i * z(ImportsFromRussia_i)$					0.0688 (0.0648) {0.293}
$EU_i * z(ExportsToRussia_i)$					-0.0402 (0.0551) {0.469}
Constant	-0.259 (0.0347) {0.000}	-0.228 (0.0524) {0.000}	-0.175 (0.0473) {0.001}	-0.177 (0.0475) {0.000}	-0.130 (0.0526) {0.017}
Adj. R^2	0.34	0.33	0.52	0.51	0.52
N	66	66	64	64	64

Notes: Standard errors are heteroscedasticity robust and denoted in round brackets. P-values are reported in curly brackets. The applied event window is $\tau = [-14, 14]$. This analysis replicates the analysis given by Equation (1) and outlined in Table 1 with a higher-order term for the distance from Ukraine, as denoted by $DistanceUkraine_i^2$. With very high variance inflation factors in Columns (3) - (5), the models suffer from substantial multicollinearity.

Table B5: Country-Level Responses with Event Window Variations (Baseline)

	$\tau = [-1, 7]$ (1)	$\tau = [-7, 7]$ (2)	$\tau = [-1, 14]$ (3)	$\tau = [-1, 28]$ (4)	$\tau = [-28, 28]$ (5)
	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$
<i>DistanceUkraine_i</i>	0.0155 (0.00337) {0.000}	0.0208 (0.00412) {0.000}	0.0169 (0.00317) {0.000}	0.0147 (0.00379) {0.000}	0.0236 (0.00531) {0.000}
Constant	-0.123 (0.0239) {0.000}	-0.180 (0.0295) {0.000}	-0.154 (0.0219) {0.000}	-0.101 (0.0238) {0.000}	-0.156 (0.0283) {0.000}
Adj. R^2	0.24	0.27	0.26	0.15	0.22
N	66	66	66	66	66

Notes: Standard errors are heteroscedasticity robust and denoted in round brackets. P-values are reported in curly brackets. This table replicates Column (1) of Table 1 for different event window specifications.

Table B6: Country-Level Responses with Event Window Variations (Expanded)

	$\tau = [-1, 7]$	$\tau = [-7, 7]$	$\tau = [-1, 14]$	$\tau = [-1, 28]$	$\tau = [-28, 28]$
	(1)	(2)	(3)	(4)	(5)
	$CumRet_i^T$	$CumRet_i^T$	$CumRet_i^T$	$CumRet_i^T$	$CumRet_i^T$
$DistanceUkraine_i$	0.00227 (0.00448) {0.614}	0.00369 (0.00496) {0.461}	0.00645 (0.00347) {0.068}	0.00690 (0.00532) {0.200}	0.0135 (0.00623) {0.035}
$\hat{\alpha}_i^{sep}$	-25.30 (18.97) {0.188}	-10.58 (28.19) {0.709}	6.342 (16.24) {0.698}	13.25 (21.13) {0.533}	52.42 (29.27) {0.079}
$\hat{\beta}_{i,world}^{sep}$	-0.00458 (0.0200) {0.820}	-0.00720 (0.0280) {0.798}	0.0164 (0.0359) {0.650}	0.0867 (0.0560) {0.128}	0.111 (0.0785) {0.163}
$z(ImportsFromRussia_i)$	-0.0590 (0.0573) {0.308}	-0.0708 (0.0724) {0.333}	-0.0163 (0.0520) {0.756}	-0.00458 (0.0565) {0.936}	-0.0201 (0.0627) {0.750}
$z(ExportsToRussia_i)$	-0.0466 (0.0380) {0.226}	-0.0575 (0.0481) {0.238}	-0.0612 (0.0398) {0.130}	-0.0850 (0.0422) {0.049}	-0.0903 (0.0459) {0.054}
$z(ImportsFromUkraine_i)$	-0.00391 (0.0217) {0.857}	-0.00613 (0.0288) {0.832}	0.00601 (0.0185) {0.746}	0.00572 (0.0200) {0.776}	0.0145 (0.0263) {0.582}
$z(ExportsToUkraine_i)$	-0.00414 (0.00710) {0.562}	0.00419 (0.00958) {0.663}	-0.0103 (0.00945) {0.279}	-0.0127 (0.00843) {0.139}	-0.00611 (0.0121) {0.615}
$z(SensitiveCommodities_i)$	-0.00665 (0.0119) {0.579}	-0.00480 (0.0155) {0.758}	-0.0122 (0.0120) {0.314}	-0.00564 (0.0111) {0.614}	-0.0104 (0.0134) {0.440}
EU_i	-0.0321 (0.0338) {0.346}	-0.0620 (0.0401) {0.127}	-0.0335 (0.0375) {0.375}	-0.0194 (0.0393) {0.624}	-0.0650 (0.0446) {0.151}
$EU_i * z(ImportsFromRussia_i)$	0.0890 (0.0586) {0.135}	0.106 (0.0740) {0.158}	0.0529 (0.0540) {0.332}	0.0318 (0.0579) {0.585}	0.0515 (0.0674) {0.448}
$EU_i * z(ExportsToRussia_i)$	-0.00275 (0.0475) {0.954}	-0.0194 (0.0607) {0.751}	-0.0167 (0.0461) {0.719}	0.0414 (0.0491) {0.403}	0.0206 (0.0590) {0.729}
Constant	-0.0719 (0.0290) {0.017}	-0.102 (0.0334) {0.004}	-0.115 (0.0294) {0.000}	-0.119 (0.0442) {0.009}	-0.162 (0.0588) {0.008}
Adj. R^2	0.58	0.57	0.48	0.34	0.35
N	64	64	64	64	64

Notes: Standard errors are heteroscedasticity robust and denoted in round brackets. P-values are reported in curly brackets. This table replicates Column (5) of Table 1 for different event window specifications. We observe strictly positive coefficients regarding the $DistanceUkraine_i$ variable with varying significance levels. As denoted by the superscript *sep*, alphas and betas for the event window variations have been estimated in the year preceding the beginning of the earliest event window to preclude event and separation window overlappings.

C Firm-Level Analysis

Table C1: Firm-Level Responses to the Ukraine War (With Higher-Order Distance Term)

	Neighbors		Europe		World	
	(1)	(2)	(3)	(4)	(5)	(6)
	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$
$DistanceUkraine_i$	0.0616 (0.0376) {0.101}	-0.0400 (0.0710) {0.573}	0.0789 (0.0149) {0.000}	0.0199 (0.0471) {0.672}	0.0267 (0.000916) {0.000}	-0.00558 (0.00802) {0.487}
$DistanceUkraine_i^2$	0.0286 (0.0245) {0.243}	0.0488 (0.0383) {0.203}	-0.0181 (0.00549) {0.001}	0.00928 (0.0201) {0.644}	-0.00120 (0.0000679) {0.000}	0.000508 (0.000417) {0.223}
$\hat{\alpha}_i$		7.526 (3.387) {0.026}		8.845 (2.514) {0.000}		4.590 (1.114) {0.000}
$\hat{\beta}_{i,world}$		-0.0215 (0.00666) {0.001}		-0.0205 (0.00543) {0.000}		-0.0162 (0.00237) {0.000}
$\hat{\beta}_{i,ukraine}$		-0.0124 (0.0148) {0.403}		-0.0156 (0.00975) {0.111}		-0.00768 (0.00434) {0.077}
$\hat{\beta}_{i,russia}$		-0.0296 (0.0139) {0.033}		-0.0350 (0.00982) {0.000}		-0.0118 (0.00470) {0.012}
$MarketValue_i$		-0.000535 (0.000243) {0.028}		-0.0000113 (0.0000955) {0.906}		-0.0000562 (0.0000470) {0.232}
Constant	-0.225 (0.0137) {0.000}	-0.240 (0.0545) {0.000}	-0.223 (0.00946) {0.000}	-0.382 (0.0532) {0.000}	-0.190 (0.00303) {0.000}	-0.0459 (0.0606) {0.449}
Industry FE	No	Yes	No	Yes	No	Yes
Country FE	No	Yes	No	Yes	No	Yes
Adj. R^2	0.07	0.27	0.01	0.18	0.09	0.19
N	1,568	1,568	4,414	4,414	16,929	16,929

Notes: Standard errors are heteroscedasticity robust and denoted in round brackets. P-values are reported in curly brackets. The applied event window is $\tau = [-14, 14]$. Table complements the analysis given by Equation (1) and outlined in Table 2 with a higher-order term for $DistanceUkraine_i$. The deteriorating effect of the distance from Ukraine seems to exponentially increase in the proximity.

Table C2: Firm-Level Responses to the Ukraine War (Detailed)

	Neighbors			Europe			World		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$
$DistanceUkraine_i$	0.105 (0.0106) {0.000}	0.105 (0.0109) {0.000}	0.0487 (0.0240) {0.042}	0.0342 (0.00486) {0.000}	0.0216 (0.00486) {0.000}	0.0410 (0.0180) {0.023}	0.0119 (0.000365) {0.000}	0.0112 (0.000374) {0.000}	0.00377 (0.00287) {0.190}
$\hat{\alpha}_i$		7.003 (3.390) {0.039}	7.573 (3.386) {0.025}		7.904 (2.510) {0.002}	8.830 (2.514) {0.000}		2.793 (1.027) {0.007}	4.599 (1.114) {0.000}
$\hat{\beta}_{i,world}$		-0.0180 (0.00644) {0.005}	-0.0219 (0.00665) {0.001}		-0.0203 (0.00523) {0.000}	-0.0205 (0.00542) {0.000}		-0.0127 (0.00218) {0.000}	-0.0162 (0.00237) {0.000}
$\hat{\beta}_{i,ukraine}$		-0.0110 (0.0147) {0.453}	-0.0125 (0.0147) {0.397}		-0.0180 (0.00996) {0.071}	-0.0156 (0.00974) {0.109}		-0.0176 (0.00423) {0.000}	-0.00771 (0.00434) {0.076}
$\hat{\beta}_{i,russia}$		-0.0276 (0.0137) {0.044}	-0.0299 (0.0138) {0.031}		-0.0409 (0.00987) {0.000}	-0.0351 (0.00982) {0.000}		-0.0181 (0.00440) {0.000}	-0.0118 (0.00470) {0.012}
$MarketValue_i$		-0.000499 (0.000238) {0.036}	-0.000542 (0.000244) {0.026}		0.000163 (0.0000985) {0.097}	-0.0000123 (0.0000954) {0.898}		0.00000263 (0.0000455) {0.954}	-0.0000556 (0.0000469) {0.236}
Constant	-0.237 (0.00885) {0.000}	-0.276 (0.0364) {0.000}	-0.271 (0.0511) {0.000}	-0.200 (0.00586) {0.000}	-0.334 (0.0441) {0.000}	-0.391 (0.0502) {0.000}	-0.160 (0.00241) {0.000}	-0.252 (0.0244) {0.000}	-0.0841 (0.0533) {0.114}
Industry FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Country FE	No	No	Yes	No	No	Yes	No	No	Yes
Adj. R^2	0.07	0.26	0.27	0.01	0.15	0.18	0.07	0.15	0.19
N	1,568	1,568	1,568	4,414	4,414	4,414	16,929	16,929	16,929

Notes: Standard errors are heteroscedasticity robust and denoted in round brackets. P-values are reported in curly brackets. The applied event window is $\tau = [-14, 14]$. This table extends Table 2 by also outlining the results of estimating Equation (1) with trade controls and industry fixed effects but without country fixed effects.

Table C3: Firm Sample Selection

Total Firms	48,403
./ Firms with missing postal codes	9,222
./ Firms with postal codes we could not match with GeoNames	14,425
./ Firms with too many missing prices	6,075
./ Firms without data on market value of equity	10
./ Firms with market value of equity smaller than \$10m	1,484
./ Firms in aerospace & defense sector	100
./ Firms from Russia or Ukraine	158
Final sample global	16,929
Final sample Europe	4,414
Final sample first-/second-degree neighbor countries of Ukraine	1,568

Notes: Table outlines the initial firm sample obtained from Thomson Reuters Datastream and the number of firms dropped in each step of the sample selection.

Table C4: Country-Firm Overview

	Average HQ Distance from Ukraine (in km)	Total Firms
Argentina	12,158	8
Australia	13,185	1,065
Austria	501	47
Bangladesh	5,192	131
Belgium	1,311	101
Bermuda	7,158	44
Brazil	10,128	6
Canada	7,602	1,171
Chile	12,915	14
Croatia	602	8
Cyprus	1,104	11
Czech Republic	429	2
Denmark	923	132
Faeroe Islands	2,155	2
Finland	1,178	38
France	1,456	366
Germany	927	899
Hungary	265	22
Iceland	2,946	18
India	4,470	1,619
Ireland	2,037	31
Isle of Man	1,902	15
Italy	1,002	244
Japan	7,615	3,398
Latvia	559	5
Liechtenstein	957	3
Lithuania	315	1
Luxembourg	1,176	6
Macedonia	672	2
Malaysia	7,724	700
Malta	1,522	11
Mexico	10,236	76
Monaco	1,253	6
Netherlands	1,270	98

New Zealand	16,223	102
Norway	1,306	205
Pakistan	3,458	142
Philippines	8,204	124
Poland	284	316
Portugal	2,654	21
Romania	153	16
Serbia	413	1
Singapore	8,009	172
Slovenia	650	8
South Africa	8,178	147
South Korea	6,823	1,260
Spain	2,212	95
Sweden	938	534
Switzerland	1,062	216
Thailand	6,721	564
Turkey	531	284
United Kingdom	1,674	945
United States	8,204	1,476
Uruguay	12,072	1
Observations	54	

Notes: Table provides an overview of firms' origins and their average headquarters' distance from Ukraine.

Table C5: Neighbor Countries' Firms' Responses Event Window Variations (Baseline)

	$\tau = [-1, 7]$ (1)	$\tau = [-7, 7]$ (2)	$\tau = [-1, 14]$ (3)	$\tau = [-1, 28]$ (4)	$\tau = [-28, 28]$ (5)
	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$
<i>DistanceUkraine_i</i>	0.0882 (0.00875) {0.000}	0.0931 (0.0102) {0.000}	0.0976 (0.00901) {0.000}	0.0897 (0.00972) {0.000}	0.0993 (0.0128) {0.000}
Constant	-0.136 (0.00822) {0.000}	-0.191 (0.00913) {0.000}	-0.161 (0.00769) {0.000}	-0.102 (0.00832) {0.000}	-0.149 (0.0104) {0.000}
Adj. R^2	0.08	0.07	0.08	0.05	0.04
N	1,568	1,568	1,568	1,568	1,568

Notes: Standard errors are heteroscedasticity robust and denoted in round brackets. P-values are reported in curly brackets. This table replicates Column (1) of Table 2 for different event window specifications.

Table C6: Neighbor Countries' Firms' Responses Event Window Variations (Expanded)

	$\tau = [-1, 7]$	$\tau = [-7, 7]$	$\tau = [-1, 14]$	$\tau = [-1, 28]$	$\tau = [-28, 28]$
	(1)	(2)	(3)	(4)	(5)
	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$
$DistanceUkraine_i$	0.00290 (0.0169) {0.864}	0.0110 (0.0212) {0.605}	0.0179 (0.0200) {0.373}	0.0239 (0.0232) {0.302}	0.0939 (0.0323) {0.004}
$\hat{\alpha}_i^{sep}$	1.807 (2.177) {0.407}	7.728 (2.844) {0.007}	-0.449 (2.551) {0.860}	1.999 (3.238) {0.537}	12.02 (7.214) {0.096}
$\hat{\beta}_{i,world}^{sep}$	0.00957 (0.00447) {0.032}	-0.00499 (0.00518) {0.336}	0.00419 (0.00536) {0.434}	0.0212 (0.00649) {0.001}	0.00820 (0.00917) {0.371}
$\hat{\beta}_{i,ukraine}^{sep}$	-0.00446 (0.0132) {0.735}	-0.00886 (0.0148) {0.550}	0.00233 (0.0153) {0.879}	-0.00890 (0.0145) {0.541}	-0.00921 (0.0241) {0.703}
$\hat{\beta}_{i,russia}^{sep}$	-0.00758 (0.00889) {0.394}	-0.0187 (0.0132) {0.156}	0.0120 (0.0110) {0.276}	-0.00192 (0.0125) {0.879}	-0.0168 (0.0175) {0.338}
$MarketValue_i$	-0.000559 (0.000243) {0.021}	-0.000581 (0.000265) {0.029}	-0.000369 (0.000205) {0.072}	-0.000293 (0.000189) {0.122}	-0.000475 (0.000260) {0.067}
Constant	-0.238 (0.0427) {0.000}	-0.300 (0.0463) {0.000}	-0.212 (0.0328) {0.000}	-0.209 (0.0416) {0.000}	-0.130 (0.0415) {0.002}
Adj. R^2	0.28	0.24	0.29	0.27	0.21
N	1,568	1,568	1,568	1,568	1,568

Notes: Standard errors are heteroscedasticity robust and denoted in round brackets. P-values are reported in curly brackets. This table replicates Column (2) of Table 2 for different event window specifications. As denoted by the superscript *sep*, alphas and betas for the event window variations have been estimated in the year preceding the beginning of the earliest event window to preclude event and separation window overlappings.

Table C7: European Firms' Responses Event Window Variations (Baseline)

	$\tau = [-1, 7]$ (1)	$\tau = [-7, 7]$ (2)	$\tau = [-1, 14]$ (3)	$\tau = [-1, 28]$ (4)	$\tau = [-28, 28]$ (5)
	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$
<i>DistanceUkraine_i</i>	0.0192 (0.00383) {0.000}	0.0325 (0.00438) {0.000}	0.00568 (0.00420) {0.177}	-0.000180 (0.00467) {0.969}	0.0133 (0.00602) {0.027}
Constant	-0.0886 (0.00480) {0.000}	-0.154 (0.00538) {0.000}	-0.0975 (0.00505) {0.000}	-0.0348 (0.00559) {0.000}	-0.0978 (0.00703) {0.000}
Adj. R^2	0.01	0.01	0.00	-0.00	0.00
N	4,414	4,414	4,414	4,414	4,414

Notes: Standard errors are heteroscedasticity robust and denoted in round brackets. P-values are reported in curly brackets. This table replicates Column (3) of Table 2 for different event window specifications.

Table C8: European Firms' Responses Event Window Variations (Expanded)

	$\tau = [-1, 7]$	$\tau = [-7, 7]$	$\tau = [-1, 14]$	$\tau = [-1, 28]$	$\tau = [-28, 28]$
	(1)	(2)	(3)	(4)	(5)
	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$
$DistanceUkraine_i$	0.0111 (0.0128) {0.386}	0.0155 (0.0149) {0.297}	0.0185 (0.0151) {0.218}	0.0250 (0.0181) {0.167}	0.0597 (0.0246) {0.015}
$\hat{\alpha}_i^{sep}$	3.815 (1.626) {0.019}	7.122 (1.831) {0.000}	3.587 (1.919) {0.062}	6.650 (2.244) {0.003}	19.41 (4.216) {0.000}
$\hat{\beta}_{i,world}^{sep}$	0.00841 (0.00356) {0.018}	-0.00423 (0.00389) {0.278}	0.00134 (0.00423) {0.752}	0.0151 (0.00438) {0.001}	0.00680 (0.00631) {0.281}
$\hat{\beta}_{i,ukraine}^{sep}$	-0.00941 (0.00777) {0.226}	-0.0206 (0.00913) {0.024}	-0.00840 (0.00863) {0.330}	-0.00376 (0.00975) {0.700}	-0.00696 (0.0159) {0.661}
$\hat{\beta}_{i,russia}^{sep}$	-0.00890 (0.00636) {0.162}	-0.0241 (0.00792) {0.002}	0.0000420 (0.00744) {0.995}	-0.000585 (0.00822) {0.943}	-0.00546 (0.0121) {0.652}
$MarketValue_i$	-0.000164 (0.0000676) {0.016}	-0.0000213 (0.0000880) {0.809}	-0.000131 (0.0000676) {0.053}	-0.0000820 (0.0000787) {0.298}	0.0000322 (0.000118) {0.785}
Constant	-0.259 (0.0295) {0.000}	-0.354 (0.0348) {0.000}	-0.284 (0.0355) {0.000}	-0.269 (0.0428) {0.000}	-0.230 (0.0597) {0.000}
Adj. R^2	0.13	0.14	0.17	0.14	0.14
N	4,414	4,414	4,414	4,414	4,414

Notes: Standard errors are heteroscedasticity robust and denoted in round brackets. P-values are reported in curly brackets. This table replicates Column (4) of Table 2 for different event window specifications. As denoted by the superscript *sep*, alphas and betas for the event window variations have been estimated in the year preceding the beginning of the earliest event window to preclude event and separation window overlappings.

Table C9: Global Firms' Responses Event Window Variations (Baseline)

	$\tau = [-1, 7]$ (1)	$\tau = [-7, 7]$ (2)	$\tau = [-1, 14]$ (3)	$\tau = [-1, 28]$ (4)	$\tau = [-28, 28]$ (5)
	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$
<i>DistanceUkraine_i</i>	0.00878 (0.000242) {0.000}	0.0105 (0.000283) {0.000}	0.00916 (0.000291) {0.000}	0.00719 (0.000359) {0.000}	0.00828 (0.000472) {0.000}
Constant	-0.0648 (0.00166) {0.000}	-0.113 (0.00197) {0.000}	-0.0898 (0.00195) {0.000}	-0.0428 (0.00226) {0.000}	-0.0909 (0.00303) {0.000}
Adj. R^2	0.10	0.09	0.07	0.03	0.02
N	16,929	16,929	16,929	16,929	16,929

Notes: Standard errors are heteroscedasticity robust and denoted in round brackets. P-values are reported in curly brackets. This table replicates Column (5) of Table 2 for different event window specifications.

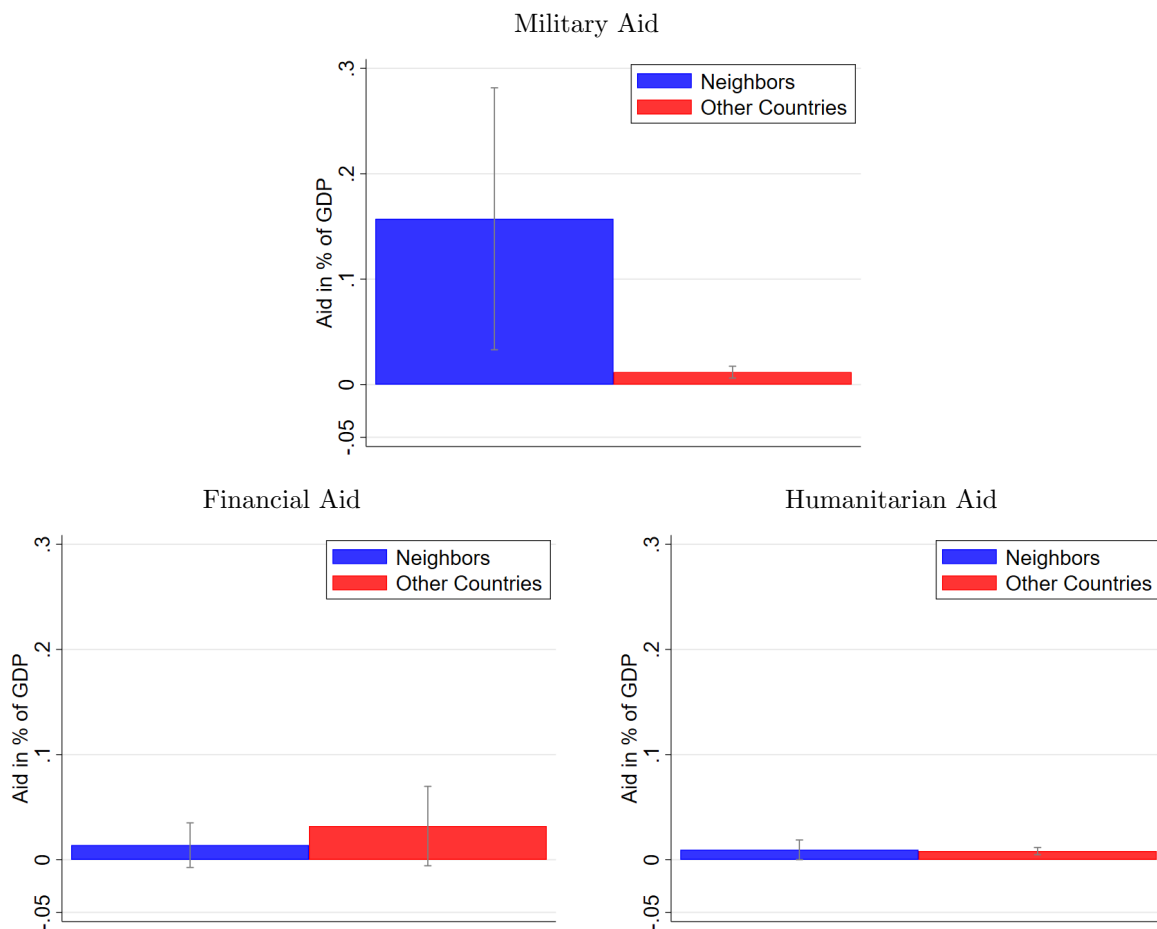
Table C10: Global Firms' Responses Event Window Variations (Expanded)

	$\tau = [-1, 7]$	$\tau = [-7, 7]$	$\tau = [-1, 14]$	$\tau = [-1, 28]$	$\tau = [-28, 28]$
	(1)	(2)	(3)	(4)	(5)
	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$	$CumRet_i^\tau$
$DistanceUkraine_i$	0.0000997 (0.00176) {0.955}	-0.0000730 (0.00202) {0.971}	0.00181 (0.00230) {0.432}	-0.000867 (0.00278) {0.755}	0.00417 (0.00365) {0.253}
$\hat{\alpha}_i^{sep}$	3.791 (0.664) {0.000}	5.255 (0.750) {0.000}	2.936 (0.886) {0.001}	3.655 (1.220) {0.003}	9.115 (1.662) {0.000}
$\hat{\beta}_{i,world}^{sep}$	0.00849 (0.00150) {0.000}	-0.00585 (0.00163) {0.000}	0.00454 (0.00191) {0.017}	0.0200 (0.00250) {0.000}	0.0110 (0.00321) {0.001}
$\hat{\beta}_{i,ukraine}^{sep}$	-0.00187 (0.00293) {0.525}	-0.0155 (0.00342) {0.000}	0.000861 (0.00381) {0.821}	0.00939 (0.00519) {0.070}	0.00371 (0.00670) {0.580}
$\hat{\beta}_{i,russia}^{sep}$	-0.000111 (0.00258) {0.966}	-0.00985 (0.00309) {0.001}	0.00524 (0.00346) {0.130}	0.0192 (0.00436) {0.000}	0.0228 (0.00569) {0.000}
$MarketValue_i$	-0.0000632 (0.0000344) {0.066}	0.0000174 (0.0000351) {0.621}	-0.000126 (0.0000476) {0.008}	-0.0000158 (0.0000585) {0.787}	0.000128 (0.0000587) {0.029}
Constant	-0.0268 (0.0300) {0.372}	-0.0436 (0.0422) {0.302}	-0.0834 (0.0401) {0.037}	0.0475 (0.143) {0.740}	0.152 (0.146) {0.298}
Adj. R^2	0.20	0.22	0.19	0.13	0.11
N	16,929	16,929	16,929	16,929	16,929

Notes: Standard errors are heteroscedasticity robust and denoted in round brackets. P-values are reported in curly brackets. This table replicates Column (6) of Table 2 for different event window specifications. As denoted by the superscript *sep*, alphas and betas for the event window variations have been estimated in the year preceding the beginning of the earliest event window to preclude event and separation window overlappings.

D Interpretation Analysis

Figure D1: Ukraine Aid by Type



Notes: Top panel shows average military aid provided to Ukraine by first- and second degree neighbors and other countries scaled by the respective countries' GDP. Bottom left and bottom right panel shows the same statistic for financial and humanitarian help, respectively. Grey markers indicate the 5% confidence bands in each direction, respectively. The only category exhibiting significant differences between first- and second-degree neighbors and other countries is military aid.

Table D1: Currency Overview

Symbol	Name	Mean Distance from Ukraine (in km)	Countries in MSCI Sample
AUD	Australian Dollar	10,723	Australia
BRL	Brazilian Real	8,161	Brazil
CAD	Canadian Dollar	5,155	Canada
CHF	Swiss Franc	941	Switzerland
CLP	Chilean Peso	11,715	Chile
CNH	Chinese Yuan (Offshore)	3,034	China
COP	Colombian Peso	9,360	Colombia
CZK	Czech Koruna	277	Czech Republic
EUR	Euro	1,095	Austria, Estonia, Finland, France, Germany, Ireland, Italy, Lithuania, Netherlands, Portugal, Slovenia, Spain
GBP	Pound Sterling	1,506	United Kingdom
HUF	Hungarian Forint	24	Hungary
IDR	Indonesian Rupiah	7,025	Indonesia
ILS	Israeli New Shekel	1,249	Israel
INR	Indian Rupee	3,233	India
JPY	Japanese Yen	7,086	Japan
KRW	South Korean Won	6,751	South Korea
MXN	Mexican Peso	9,507	Mexico
MYR	Malaysian Ringgit	7,316	Malaysia
NOK	Norwegian Krone	1,154	Norway
NZD	New Zealand Dollar	15,960	New Zealand
PHP	Philippine Peso	7,759	Philippines
PLN	Polish Zloty	27	Poland
SEK	Swedish Krona	753	Sweden
SGD	Singapore Dollar	8,012	Singapore
THB	Thai Baht	6,086	Thailand
TRY	Turkish Lira	279	Turkey
TWD	New Taiwan Dollar	7,162	Taiwan
ZAR	South African Rand	7,436	South Africa

Notes: Table provides an overview of currencies examined in Figure 3. Each currency was merged with all countries from our MSCI analysis that use the respective currency as main currency. If a currency comprises multiple countries, the mean distance of countries using the currency was taken as the currency distance.

Table D2: Regression of Risk Reversal Change on Distance from Ukraine

	(1)	(2)	(3)	(4)	(5)
	ΔRR_i	ΔRR_i	ΔRR_i	ΔRR_i	ΔRR_i
$DistanceUkraine_i$	-0.129 (0.0436) {0.007}	-0.372 (0.0897) {0.000}	-0.178 (0.102) {0.093}	-0.178 (0.121) {0.156}	-0.0444 (0.127) {0.731}
$DistanceUkraine_i^2$		0.0197 (0.00554) {0.002}	0.0110 (0.00535) {0.053}	0.0107 (0.00628) {0.103}	0.00351 (0.00687) {0.617}
$z(ImportsFromRussia_i)$			0.759 (0.185) {0.000}	0.654 (0.175) {0.001}	0.959 (0.180) {0.000}
$z(ExportsToRussia_i)$			-0.186 (0.108) {0.100}	-0.281 (0.121) {0.031}	-0.662 (0.266) {0.024}
$z(ImportsFromUkraine_i)$				0.192 (0.423) {0.655}	0.212 (0.269) {0.443}
$z(ExportsToUkraine_i)$				0.0200 (0.497) {0.968}	-0.154 (0.359) {0.674}
$z(SensitiveCommodities_i)$					-0.111 (0.0833) {0.201}
EU_i					1.308 (0.260) {0.000}
$EU_i * z(ImportsFromRussia_i)$					-0.171 (0.413) {0.685}
$EU_i * z(ExportsToRussia_i)$					0.184 (0.302) {0.551}
Constant	1.507 (0.315) {0.000}	1.907 (0.333) {0.000}	1.237 (0.353) {0.002}	1.247 (0.411) {0.007}	0.620 (0.386) {0.128}
Adj. R^2	0.29	0.44	0.67	0.65	0.75
N	28	28	27	27	27

Notes: Standard errors are heteroscedasticity robust and denoted in round brackets. P-values are reported in curly brackets. Regression follows roughly Equation (1) with i , however, denoting currency i here and the change in risk reversal, ΔRR_i , being the dependent variable. We calculate the change in risk reversal, ΔRR_i as the difference between each currency's average risk reversal between February 24, 2022 and March 10, 2022 and their average risk reversal value during 2021. With very high variance inflation factors, the expanded models are prone to substantial multicollinearity. In the more extensive models we dropped the Taiwan New Dollar as we did not obtain import/export statistics for Taiwan (c.f., Appendix B).