The Effects of the War on Ukraine on Global Corporate Investment*

Dario Caldara   Mike McHenry   Matteo Iacoviello   Immo Schott†

December 2025

Abstract

We study the investment effects of the Russia–Ukraine war using a novel, text-based measure of firm-level exposure derived from earnings call transcripts. Combining this measure with financial statement data for over 6,500 firms across 50 countries, we show that exposure to the conflict led to sizable and persistent declines in corporate investment. Firms that discussed the war in early 2022 invested significantly less than otherwise similar firms. The results hold across multiple empirical strategies and highlight the role of geopolitical risk in shaping firm behavior during global crises.

*We thank conference participants, the editor, and an anonymous referee for feedback and suggestions. The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System.

† Federal Reserve Board. Division of International Finance, 20th and C Streets, NW, Washington, DC 20551, United States.

1 Introduction

Russia's invasion of Ukraine in February 2022 triggered a major geopolitical shock with wide-ranging implications for the global economy. The conflict intensified uncertainty, disrupted global trade and energy flows, and led to sharp swings in commodity prices and financial markets. From the outset, investors, firms, and policymakers anticipated that the war would weigh on global activity while fueling inflationary pressures.[1] Yet despite the scale of the disruption, systematic evidence on how the conflict affected real economic behavior—particularly at the firm level—remains limited. Did firms' exposure to the war influence investment decisions, and if so, to what extent?

This paper provides new evidence on the investment effects of the Russia–Ukraine war using a large panel of over 6,500 publicly listed firms from 50 countries. We combine financial statement data with a new, firm-level measure of war exposure, based on textual analysis of quarterly earnings call transcripts. Our approach captures how often managers and analysts discussed the conflict across more than 125,000 firm-quarter observations. We then estimate how exposure to the war shaped corporate investment, both in the aggregate and at the micro level, using complementary econometric strategies.

We make two contributions. First, we develop a novel measure of firm-level exposure to the Russia–Ukraine war. Our approach builds on the recent literature that extracts forward-looking indicators from corporate disclosures (Hassan, Hollander, van Lent, and Tahoun, 2019; Caldara, Iacoviello, Molligo, Prestipino, and Raffo, 2019; Gormsen and Huber, 2025), and applies proximity-based keyword searches to identify war-related content in earnings calls. Second, we provide evidence that exposure to the war weighed significantly on investment. Firms that mentioned the conflict in their earnings calls in 2022 invested roughly 10 percent less than comparable firms that did not, with effects that persisted over several quarters. This investment response holds across different empirical methods—difference-in-differences, synthetic control, and local projections.

Section 2 describes the data construction and the measurement of firm-level exposure to the Russia–Ukraine war. We compile a global dataset of earnings call transcripts from the *S&P Global Machine-Readable Transcripts database*, spanning 2016 to 2024. Using proximity-

[1] See, e.g., Federal Reserve Chair Powell's May 2022 press conference: https://www.federalreserve.gov/mediacenter/files/FOMCpresconf20220504.pdf.

based text searches, we identify conflict-related mentions. We audit the results to ensure robustness, assess false positives, and validate our measure by comparing it to external indices of geopolitical risk. Mentions of the conflict surged in early 2022, especially among European firms, and remained elevated through 2023. A word cloud analysis reveals that these mentions often reference concrete operational impacts—such as supply chains, inflation, and energy costs—rather than generic geopolitical commentary.

Section 3 examines the aggregate investment effects of war exposure. We begin by documenting cross-country variation in exposure intensity and corporate investment using asset-weighted investment indices. Countries with more frequent firm-level mentions of the conflict experienced larger post-invasion declines in investment. Next, we divide firms into "exposed" and "non-exposed" groups based on whether they mentioned the war around the time of the invasion. A difference-in-differences comparison shows that investment at exposed firms diverged meaningfully from that of non-exposed firms, beginning in mid-2022. We then implement a synthetic control approach to construct a counterfactual investment path for exposed firms, confirming that the observed divergence is unlikely to be driven by pre-existing trends or composition effects.

Section 4 turns to firm-level panel regressions. Using local projections, we estimate the dynamic response of investment to a shock in exposure. A one-standard-deviation increase in war mentions reduces investment-to-capital ratios by 1.5 percent at peak, with effects materializing immediately and persisting for several quarters. These results are robust to alternative specifications, including a binary treatment indicator, and align closely with the macro-level estimates from the previous section.

Our analysis complements and extends a growing literature on the economic effects of the war on Ukraine. The war elevated global economic policy uncertainty (Anayi, Bloom, Bunn, Mizen, Thwaites, and Yotzov, 2022), reduced global GDP (Caldara, Conlisk, Iacoviello, and Penn, 2024), and disrupted financial markets (Federle, Meier, Müller, and Sehn, 2025). Research focused on Europe highlights the key role of energy and trade linkages in shaping macroeconomic spillovers (Bachmann, Baqaee, Bayer, Kuhn, Löschel, Moll, Peichl, Pittel, and Schularick, 2024). Relative to these contributions, we focus on firm-level investment behavior and develop a new measure of exposure to the Russia-Ukraine conflict using textual data. Our findings also connect to the broader literature on the effects of wars and military expenditures on economic activity (Barro, 2006; Ramey, 2011; Hall and Sargent, 2022; Federle, Meier, Müller, Mutschler, and Schularick, 2024), and to recent work on extracting risk perceptions and shocks from corporate language (Hassan et al., 2019; Caldara et al., 2019).

2 Measuring firm-level exposure to the conflict

We construct a measure of firm-level exposure to the Russia-Ukraine War using textual analysis of earnings call transcripts from publicly listed firms. Earnings calls are quarterly conference calls during which senior management presents recent financial results, outlines expectations for the upcoming period, and answers questions from financial analysts and institutional investors. Transcripts of these calls record verbatim remarks from executives (e.g., the CEO or CFO) and the questions posed by analysts, making them a rich source of qualitative information on firms' strategic priorities, perceived risks, and evolving outlooks (Frankel, Johnson, and Skinner, 1999). Because publicly listed firms are required to disclose material information, the content of these calls is publicly available through commercial databases. Our primary data source is the *S&P Global Machine-Readable Transcripts* database, which archives quarterly earnings calls for publicly traded firms worldwide (S&P Global Market Intelligence, 2025). Our sample covers the years from 2016 through 2024 and includes approximately $195,000$ transcripts of non-financial firms, an average of about $5,400$ per quarter. Transcripts are consistently structured and timestamped.

To identify mentions of the Russia-Ukraine conflict, we construct two sets of keywords. The first set includes country-specific terms: *Russia, Russian, Ukraine, Ukrainian.* The second set includes war-related terms: *attack, war*, conflict, military, sanction*, invasion, invad**, where the asterisk denotes a wildcard operator. We then apply two proximity-based text searches to the earnings call transcripts.

The first search identifies instances where a war-related term appears within five words of any country-specific term. The second search captures mentions in which any Russia-related term appears within ten words of any Ukraine-related term. This second condition allows us to detect references to the conflict that do not include explicit war-related language but still convey geopolitical relevance—for example, phrases discussing access to Russian and Ukrainian markets.

To illustrate, consider *BASF*, a German-based company and the largest chemical producer in the world. In its 2022 year-end earnings call, the firm stated:

> *"In addition, production growth was impacted by longer spells of trough in several regions, as well as production disruptions in Ukraine as a result of the war."*

This excerpt qualifies as a valid mention under the first search criterion: the war-related term "war" appears within five words of the country term "Ukraine." This example shows that the co-occurrence of a war-related term with either "Ukraine" or "Russia" is typically sufficient to indicate a reference to the Russia-Ukraine conflict.

A second example, taken from the March 2022 earnings call of the Texas-based *Commercial Metals Company*, illustrates a valid mention under the second search criterion:

> *"On the supply side, you mentioned, obviously, lack of supply coming from Russia, Ukraine, Belarus. We're hearing a lot about [how] very high power costs put some [Electric Arc Furnaces] in Europe temporarily out of commission. Is that something you're seeing that's further tightening up the market there?"*

The passage mentions Russia and Ukraine in close proximity without referring to any war-related terms.

We define the variable, $RU_{i,t}$, as the number of valid conflict-related mentions in transcript i at time t, divided by the transcript's total word count. This variable captures the intensity of firm-level exposure to the Russia-Ukraine War. To avoid counting overlapping matches multiple times, we impose the constraint that only one mention may be recorded per ten-word window.[2]

Figure 1 plots the monthly share of firms mentioning the conflict at least once in their earnings calls. The blue line aggregates all firms in the sample, while the red and gray lines European and non-European firms, based on the country where a firm is headquartered. At the onset of the war in early 2022, over 60 percent of European firms referenced the conflict—— compared to nearly 40 percent globally. Mentions declined over time but remained elevated: by mid-2023, around 20 percent of European firms continued to reference the war, underscoring the persistence of geopolitical concerns at the firm level.

Figure 2 provides a complementary geographic breakdown, plotting the exposure to the Russia-Ukraine war by country, using transcripts of earnings calls that took place between March 1, 2022, and December 31, 2022. The patterns observed in Figure 1 are echoed here:

[2]For example, a segment like "Russia-Ukraine conflict" may contain multiple keyword matches across both searches. We consolidate these into a single count if they occur within a ten-word span.

European firms exhibit the highest frequency of mentions, with higher exposure depending on their proximity to the conflict and stronger economic linkages with Russia.[3] Countries more exposed to Russian energy and trade—such as Germany, Italy, and Poland—show a particularly sharp rise in war-related references. By contrast, firms based in more geographically and economically distant countries, including the United States, Canada, and those in Latin America, report substantially fewer mentions.

2.1 Understanding the exposure measure and audit

We begin by summarizing key facts about the exposure measure introduced in the previous subsection. Out of the 9,656 transcripts identified as referencing the conflict, 7,546 (78.2 percent) are captured by the first search, and the remaining 2,110 (21.8 percent) are picked up by the second. The second search contributes meaningfully to coverage, particularly after the outbreak of the war: roughly 85 percent of the mentions identified by the second search occur after February 24, 2022, suggesting that they are indeed war-related rather than incidental references to Russia or Ukraine.

To evaluate the accuracy of our exposure measure, we conduct a manual audit. We randomly sample 5 percent of all transcripts containing at least one conflict mention. For transcripts with multiple hits, we randomly select one instance for review. In this sample, 39 mentions are judged to be false positives, corresponding to a relatively low error rate of 7.8 percent. Most of these false positives occur before the invasion, further confirming the informativeness of our search strategy in the post-invasion period.

An additional concern might be that conflict mentions reflect beneficial rather than adverse effects. In an additional audit, we assess the sentiment of 200 randomly selected earnings calls from the first half of 2022. Only about 5 percent of these calls express positive sentiment about the impact of the war, and such cases are strongly concentrated in defense-related firms. This small share relative to the overall sample is unlikely to materially affect our baseline estimates.[4]

Panel (a) of Figure 3 reports the frequency of individual term matches from the first search. The most common is "war*," which appears nearly 10,000 times, followed by "conflict." Terms

[3] See also Appendix Figure A.1 for a zoomed-in view of Europe.

[4] In Section 4 we confirm that our baseline results are essentially unchanged when we control for a military-industry dummy and its interaction with the conflict–exposure measure in our empirical analysis.

such as “attack” and “military” appear less frequently. While “war*” and “conflict” account for the majority of mentions, the remaining terms contribute approximately 25 percent of the total. Their inclusion is therefore important, as it captures additional relevant references that would otherwise be missed.

Panel (b) of Figure 3 shows alternative measures of the global share of firms that mention the conflict at least once in their earnings calls. A measure exclusively based on the first search is highly correlated with our benchmark measure. When we exclude the situation-specific search terms “invad*”, “invasion”, and “sanction*” from the search, the resulting measure is also highly correlated with the benchmark. While not crucial for our results, the second search and the use of situation-specific terms improve the exposure measure by capturing references that would otherwise be missed.

To better understand the context of mentions, we construct a word cloud, presented in Figure 4, showing the 50 most frequent terms that appear within ten words of a Russia–Ukraine mention. Variations of the search terms themselves, as well as stop words defined in the SMART lexicon, are excluded. The results highlight key economic terms—such as *supply chains*, *inflation*, and *energy*—that point to diverse transmission channels through which the war may affect firm operations. The most prominent term is “impact,” suggesting that firms are either directly experiencing the consequences of the war or are concerned about its potential repercussions.

As a final validation step, Figure 5 compares our standardized time series of the share of transcripts referencing the conflict to the standardized version of the geopolitical risk (GPR) index constructed by Caldara and Iacoviello (2022). While the GPR index is more volatile—reflecting geopolitical events beyond the Russia–Ukraine conflict—the two series are positively correlated and both spike in early 2022 in response to the invasion. Importantly, while both series begin to decline in the second half of 2022, the transcript-based measure falls at a slower rate than the GPR index, exhibiting greater persistence. This suggests that firm-level references to the war remained elevated even as media coverage of geopolitical tensions subsided.

Taken together, these checks confirm that our exposure measure reliably captures firm-level references to the Russia–Ukraine conflict. Moreover, the time series aligns closely with independent measures of geopolitical tension. The remainder of the paper examines how this conflict exposure affects firm-level investment behavior.

3 Aggregate investment effects

We begin by quantifying how the Russia-Ukraine war shaped *aggregate* corporate investment. First, we show visually that firms in more exposed countries saw larger reductions in investment. We then define firms as exposed to the war if they mention the war in their earnings calls and show that at the country-level more exposed firms reduced their investment by more. Finally, we follow a synthetic control approach to confirm these findings.

3.1 Balance sheet data

To analyze the relationship between firm-level exposure to the war and corporate investment decisions, we merge the earnings call transcripts with firm balance sheet data from Capital IQ, a proprietary database maintained by S&P Global Market Intelligence which provides standardized balance sheet data for tens of thousands of publicly listed firms worldwide. We use quarterly data for non-financial firms headquartered both inside and outside the United States, spanning the period from 2016Q1 to 2024Q4. Linking Capital IQ to the earnings call transcripts yields a panel of $143,762$ firm-quarter observations, covering $8,482$ firms across 83 countries. We restrict the sample to firms with available data for at least four quarters both before and after the outbreak of the war in 2022Q1. In addition, we exclude country-quarters with fewer than five firms reporting earnings calls to ensure adequate coverage at the country level. These filters yield a final estimation sample of 126,386 observations across 6,611 firms in 50 countries.

We then construct quarterly firm-level investment rates. Investment is based on the year-to-date capital expenditure variable `capxy` in Capital IQ, which we convert to quarterly frequency. We then define the investment rate as the quarterly change in capital expenditures divided by the lagged stock of total assets (`atq`). This construction follows standard practice in corporate finance and macroeconomic investment research.[5] Specifically, our firm-level measure

[5] For details on the data cleaning procedures and robustness checks using alternative investment measures, see Appendix A. For related methodologies, see Gutiérrez and Philippon (2017), among others. An alternative to using lagged total assets in the denominator is to use property, plant, and equipment (`ppentq`). For data availablitly reasons, we use `atq`. However, results are quantitatively very similar for firms were both variables are observed.

of investment is

$$I_{i,t} \;=\; \frac{\texttt{capxy}_{i,t} - \texttt{capxy}_{i,t-1}}{\texttt{atq}_{i,t-1}} \tag{1}$$

for a firm i at time t. This series is then normalized to 100 based on its average during the first three quarters of 2021:[6]

$$I^*_{i,t} = 100 \times \frac{I_{i,t}}{\frac{1}{3}\sum_{s\in 2021\text{Q1–Q3}} I_{i,s}}. \tag{2}$$

The resulting series, $I^*_{i,t}$, is our firm-specific *investment index*.

3.2 Country-level investment patterns

We start the analysis by correlating firm investment and exposure to the war by country. Figure 6 displays a world map that shows changes in investment indices $I^*_{i,t}$. Country-level investment indices are computed as weighted means of firm-level investment indices $I^*_{i,t}$, using a firm's total assets as weights,

$$I_{c,t} \;=\; \frac{\sum_{i\in\mathcal{F}_c} \texttt{atq}_{i,t}\cdot I^*_{i,t}}{\sum_{i\in\mathcal{F}_c} \texttt{atq}_{i,t}}, \tag{3}$$

where $\mathcal{F}_c \;=\; \Big\{ i \,:\, \text{firm } i \text{ is located in country } c \Big\}$.[7] Figure 6 shows the 'investment gap', ΔI_c, in the year after the beginning of the Russian invasion of Ukraine. It is computed as the average level of $I_{c,t}$ from 2021Q4–2022Q3 minus the average level between 2020Q4–2021Q3:

$$\Delta I_c \;=\; \frac{1}{4}\left(\sum_{t=2021\text{Q4}}^{2022\text{Q3}} I_{c,t} \;-\; \sum_{t=2020\text{Q4}}^{2021\text{Q3}} I_{c,t}\right) \tag{4}$$

The patterns in Figure 6 closely resemble those in the country exposure-intensity map shown in Figure 2. In particular, countries with the highest mention frequencies—particularly in Europe—also register some of the largest investment gaps.[8] Conversely, more geographically distant economies like the U.S. and Canada exhibit more moderate drops. This visual analysis suggests a negative relationship between exposure to the war and aggregate investment activity.

[6] In 2021Q4 the invasion risk was already widely discussed; On November 13, 2021, Ukrainian President Zelensky publicly warned that over $100,000$ Russian troops were massed at the border. U.S. intelligence sources also alerted allies that a large-scale offensive could occur as early as January 2022.

[7] We require firms to be in the sample for all quarters in 2021–2023 in order to be included in the calculation of investment gaps in (4). This reduces the number of countries shown in Figure 6 and 7 to 30.

[8] See also Appendix Figure A.2 for a zoomed-in view of Europe.

This relationship is confirmed by a cross-sectional regression in which we regress a country's ΔI_c on the country-level change in mentions of war-related terms in earnings calls, ΔRU_c.[9] The estimated coefficient is -8.25 and statistically significant, indicating that a one standard deviation increase in exposure is associated with an 8.25 point decline in the investment index. Figure 7 provides a visual representation of the data and the regression line.[10] A regression on geographical distance from Kyiv delivers similar results.

3.3 A difference-in-difference approach.

The cross-country patterns above suggest that firms with exposure to the Russia–Ukraine conflict reduced investment relative to those without such exposure. To explore this relationship in a more systematic way, we now implement two complementary empirical approaches that summarize investment dynamics for exposed and non-exposed firms using earnings calls.

Let $\mathcal{I}_i^{RU}$ denote a time-invariant indicator that equals one if firm i mentioned the conflict in any earnings call during 2021Q4 or 2022Q1 and zero otherwise. Firms with $\mathcal{I}_i^{RU} = 1$ are henceforth referred to as *exposed*, those with $\mathcal{I}_i^{RU} = 0$ as *non-exposed*. In the full sample, 33 percent of firms are classified as exposed, with 56.8 percent of exposed European firms and 29 percent of exposed U.S. firms.[11]

We compute an *investment index* separately for exposed and non-exposed firms in each country c and quarter t. Mirroring the construction of country-level investment indexes described in equations (1)–(2), we define the group-specific investment rate as

$$I_{c,t}^{j} = \frac{\sum_{i:\mathcal{I}_i^{RU}=j} \texttt{capxy}_{i,t} - \texttt{capxy}_{i,t-1}}{\sum_{i:\mathcal{I}_i^{RU}=j} \texttt{atq}_{i,t-1}}, \qquad j \in \{0,1\}, \tag{5}$$

and then compute a country-specific investment index for each group of firms:

$$I_{c,t}^{*,j} = 100 \times \frac{\widetilde{I}_{c,t}^{j}}{\frac{1}{3}\sum_{s\in 2021\text{Q1–Q3}} \widetilde{I}_{c,s}^{j}}. \tag{6}$$

[9] See Appendix A for details.

[10] We regress $\Delta I_c = \alpha + \beta\, \Delta RU_c + \varepsilon_c$. When using country-level total assets as weights, the coefficient is -9.71 and statistically significant.

[11] We excluded from our sample 817 firms that have $RU_{i,t} > 0$ between 2021Q1 and 2021Q3. Firm exposure up until 2021Q3 is not measurement error, but mostly reflects existing exposure to the conflict associated with the Russian annexation of Crimea. However, we exclude these firms from the analysis because we want to isolate the effects of the war that started in 2022.

To reduce reporting volatility – the degree to which a firm's financial disclosures are unevenly clustered within the calendar year – we use smoothed investment $\widetilde{I}^{j}_{c,t}$ in equation (6), constructed using a four-quarter moving sum of capital expenditures and a four-quarter moving average of lagged assets. The smoothing has no qualitative effect on our findings.

Finally, to analyze investment patterns at the global level, we construct a global investment index $\mathbf{I}^{j}_{t}$ for each group aggregating the group-specific investment indices $I^{*,j}_{c,t}$ across countries, using total country-level lagged assets (`atq`) as weights. Details of the aggregation are shown in Appendix A.

The global indices are plotted in Figure 8, which tracks global investment dynamics separately for exposed and non-exposed firms. The solid blue line depicts the index for firms that did not mention the war; the dashed red line shows the index for firms that did.

Two patterns emerge. First, the investment indices for the exposed and non-exposed groups track each other closely through the end of 2021 and into early 2022. Second, beginning in mid-2022—roughly two quarters after the invasion—the gap between the two series opens significantly. Firms that explicitly mentioned the war in their earnings calls exhibit investment rates between 5 and 10 percent lower than those of non-exposed firms. The divergence is especially pronounced in Europe: the peak difference in investment indices reaches 8.2 percent for European firms, compared to 4.7 percent for non-European firms (not shown).

Second, Figure 8 shows that both indices increase steadily from 2021Q1 onward, reflecting a broad post-COVID investment recovery. The flatter trajectory of the exposed group suggests that war-related exposure significantly dampened the investment rebound.

Overall, the evidence indicates that firms that explicitly discussed the conflict in early 2022 persistently curtailed investment in its aftermath.

3.4 A synthetic control approach

The results in Figure 8 may reflect pre-existing cross-country differences rather than the causal effect of war exposure. To assess whether the investment trajectory of exposed firms diverged from what would have occurred in the absence of war-related exposure, we apply a version of the synthetic control method using the global investment indices constructed above. This approach builds on the framework introduced by Abadie, Diamond, and Hainmueller (2010) and is commonly used in comparative case studies where standard difference-in-differences techniques may be biased by time-varying confounders (Abadie, 2021).

Our implementation departs from the standard use of synthetic control methods, which typically evaluate the impact of an intervention on a single treated unit, such as a country or region. In our setting, we define treatment at the firm level based on textual exposure to the war, and then aggregate investment outcomes at the country-treatment group level, before computing global indices. The global investment index for exposed firms, $\mathbf{I}_t^1$, serves as the observed outcome for the "treated" group.

To construct the control group, we estimate a synthetic counterpart of the investment index $\mathbf{I}_t^0(\mathbf{w})$, defined as a convex combination of country-level investment indices for non-exposed firms, $I_{c,t}^{*,0}$. The weight vector $\mathbf{w}$ consists of non-negative weights summing to one, chosen to minimize the distance between the exposed and synthetic control group in the pre-treatment period. Specifically, the weights are selected to closely match the pre-war investment dynamics and covariates of the exposed group.[12] The resulting synthetic control, $\mathbf{I}_t^0(\mathbf{w}^*)$, provides a counterfactual for the investment path that exposed firms would have followed in the absence of war-related exposure. To ensure a balanced panel, we implement additional data restrictions. We exclude countries with limited coverage (Greece, Philippines, Singapore, and United Arab Emirates) and retain only firms with consecutive earnings call and investment data available for at least one year before and one year after 2022Q1. This leaves us with 81,912 firm-quarter observations.

The results, shown in Figure 9, broadly confirm the findings from the difference-in-differences analysis. Firms that mention the war in their earnings calls exhibit significantly lower investment rates relative to the synthetic control group. The series begin to diverge one quarter after the onset of the war in 2022Q1, with the gap peaking at approximately 5.8 percentage points by 2023Q1, before gradually narrowing. Both the timing and magnitude of the divergence align closely with the patterns shown in Figure 8.[13]

We conduct several robustness checks to assess the reliability of these results. First, we study a key diagnostic in synthetic control applications, the root mean squared prediction error (RMSPE). It measures the difference between the treated unit and its synthetic counterpart in

[12] We use investment indices from 2021Q1 to 2021Q4 and aggregate total assets as predictors in the matching procedure. Total assets, a commonly used measure of firm size, are included to ensure that treated and control units are of comparable economic scale.

[13] The treated firms exposed to the war are best represented by a control group combining the United States (w = 0.58), Finland (0.04), Spain (0.025), and Germany (0.024). The large weight given to the United States is reasonable considering that the method matches total assets between treated and control groups.

the pre-treatment period and is equal to 0.91 for our baseline model. A close pre-treatment fit (low RMSPE) increases confidence in the validity of the counterfactual. We find that the RMSPE increases by a factor of 3.2 in the post-treatment period relative to the pre-treatment fit. Post-treatment increases in the RMSPE provide evidence of treatment effects and suggest that the observed divergence is not due to noise.

Second, we perform placebo tests by reassigning treatment status to each country in the control group, one at a time. These placebo paths do not exhibit a comparable post-2022Q1 divergence in investment, further supporting the validity of the main results. Finally, we confirm that excluding large economies from the control pool, or extending the pre-treatment matching window by one additional year, does not materially alter the estimates. Together, these exercises demonstrate that our findings are not sensitive to model specification or sample composition.

4 Dynamic investment effects

To complement the aggregate investment patterns documented so far, in this section we study how the war impacted investment using firm-level variation. To this end, we estimate panel local projections, which allow us to trace the dynamic effects of an exposure shock without imposing strong parametric restrictions on its propagation (Jordà, 2005). This micro-level approach complements the aggregate analysis by capturing dynamic adjustment patterns across heterogeneous firms and enables assessing whether exposure to the war systematically altered firms' investment behavior. For each horizon $h = 0, \ldots, H$, we estimate two specifications. In the first, we run following regression:

$$y_{i,t+h} = \alpha_i + \delta_{t,\kappa(i)} + \beta_h \, RU_{i,t} + \mathbf{X}'_{i,t-1}\gamma_h + \varepsilon_{i,t+h}, \tag{7}$$

where $y_{i,t+h} \equiv 100 \cdot \log(I/K)_{i,t+h}$ is the log investment rate of firm i at horizon h. The regressor $RU_{i,t}$ measures a firm's exposure to the Russia–Ukraine war, defined as the normalized frequency of war-related terms in its earnings call in quarter t. Firm fixed effects α_i absorb time-invariant heterogeneity, while $\delta_{t,\kappa(i)}$ are time fixed effects interacted with industry dummies, which control for industry-specific macroeconomic shocks. The control vector $\mathbf{X}_{i,t-1}$ includes predetermined firm-level covariates—including two lags of the dependent variable—to mitigate concerns about persistence and omitted variables. Because $RU_{i,t}$ is normalized, the sequence $\{\beta_h\}_{h=0}^{H}$ traces the cumulative average effect of a one-standard-deviation increase in $RU_{i,t}$ on investment out to horizon h.

In the second, alternative specification, we replace the continuous exposure variable $RU_{i,t}$ with a binary indicator, $\mathcal{I}^{RU}_{i,t}$, equal to one if $RU_{i,t} > 0$, i.e., if a firm mentions the war in a given quarter. For each horizon $h = 0, \ldots, H$, we then estimate:

$$y_{i,t+h} = \alpha_i + \delta_{t,\kappa(i)} + \beta_h \, \mathcal{I}^{RU}_{i,t} + \mathbf{X}'_{i,t-1}\gamma_h + \varepsilon_{i,t+h}. \tag{8}$$

The dummy specification allows us to assess whether mere exposure is associated with systematically different investment behavior, regardless of intensity. It isolates extensive-margin responses, where even a brief mention of geopolitical risk may trigger precautionary adjustments. Additionally, the binary indicator is less sensitive to potential measurement error in the frequency measure and to differences in transcript length or language style across firms.

Our results for the two specifications are presented in Figure 10. Panel (a) plots the estimated impulse responses of the log investment rate, $\log(I/K)$, to a one-standard-deviation increase in war-exposure intensity, $RU_{i,t}$. The point estimates (solid line) and their 90 percent confidence band (shaded area) reveal three key features.

First, investment falls significantly on impact. This immediate response underscores that exposure to geopolitical risk had direct and meaningful effects on managerial decision-making. Rather than waiting to assess conditions over time, firms adjusted investment in the same quarter, consistent with a forward-looking response to the war events and the associated uncertainty. This interpretation is reinforced by the timing of earnings calls, which typically occur near the end of the quarter or shortly thereafter. The exposure measure $RU_{i,t}$, derived from the content of those calls, therefore serves as a proxy for contemporaneous uncertainty––capturing the information environment that shaped firms' decisions during the quarter.

Second, the cumulative investment response bottoms out at $h = 2$, when the coefficient on $RU_{i,t}$ equals -1.48, before gradually attenuating. Because the dependent variable is in logs and scaled by 100, the coefficient can be interpreted as a semi-elasticity: a one-unit (one-standard-deviation) increase in $RU_{i,t}$ reduces $\log(I/K)_{i,t+h}$ by 1.48 units, corresponding to approximately a 1.5 percent decline in the investment-to-capital ratio.

Third, the estimate aligns well with the aggregate investment index results reported above. Those earlier estimates captured the *average* investment gap between firms that mentioned the war and those that did not. In our sample, war-mentioning firms have an average $RU_{i,t}$

value roughly three standard deviations higher than non-mentioning firms. Assuming linearity, this implies an average effect of approximately -4.5 percent, which is in the same ballpark as the 8.2 percentage point gap from the aggregate index.

Panel (b) of Figure 10 presents results from the alternative specification in equation (8), where we use a binary indicator for exposure. The estimated impulse responses closely mirror the shape and timing of the baseline specification. The peak effect is a coefficient of -4.61, implying that firms mentioning the war experience a reduction in investment rates of approximately 4.6 percent at the trough. This estimate is consistent with the scaled marginal effect from the continuous specification and with the difference-in-means estimate from the investment index analysis. The dummy-based results confirm that extensive-margin exposure—whether a firm references the conflict at all—is associated with a significant short-run decline in investment.

The effects of the war are likely to be heterogeneous across industries. In particular, firms operating in the defense and military industries might benefit from the war through increased demand for weapons and related products, and consequently increase their investment. To test this hypothesis, we re-estimate equation (7) by including an interaction term between $RU_{i,t}$ and a military industry dummy. The resulting impulse responses are reported in Figure 11. For non-military firms, the responses are virtually identical to the baseline estimates in panel (a) of Figure 10. By contrast, for firms in the military industry, the estimated coefficients are consistently positive at most horizons. While the confidence intervals are wider, reflecting the relatively small number of such firms in our sample, the point estimates suggest that war exposure is associated with an increase in investment for firms operating in these industries.

5 Conclusion

This paper studies the effects on private investment of the war on Ukraine using a novel firm-level measure of geopolitical risk exposure derived from earnings call transcripts. We show that firms exposed to the war subsequently reduced investment relative to non-exposed firms, with effects that are sizable, persistent, and robust across empirical methods.

The combination of text-based exposure measures and firm-level panel data provides a powerful lens to study how global events shape corporate decision-making. The timeliness of both the textual and investment data makes this approach particularly well suited for real-time monitoring and policy analysis. While our focus is on a specific episode—the Russia–Ukraine war—the methods and findings speak to broader questions about how firms perceive and respond to geopolitical developments. Future work can build on this framework to study other conflicts and quantify the effects of geopolitical risk on other dimensions of firm behavior.

References

Abadie, A. (2021): "Using Synthetic Controls: Feasibility, Data Requirements, and Methodological Aspects," *Journal of Economic Literature*, 59, 391–425.

Abadie, A., A. Diamond, and J. Hainmueller (2010): "Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program," *Journal of the American Statistical Association*, 105, 493–505.

Anayi, L., N. Bloom, P. Bunn, P. Mizen, G. Thwaites, and I. Yotzov (2022): "The impact of the war in Ukraine on economic uncertainty," VoxEU column.

Bachmann, R., D. Baqaee, C. Bayer, M. Kuhn, A. Löschel, B. Moll, A. Peichl, K. Pittel, and M. Schularick (2024): "What if? The macroeconomic and distributional effects for Germany of a stop of energy imports from Russia," *Economica*, 91, 1157–1200.

Barro, R. J. (2006): "Rare Disasters and Asset Markets in the Twentieth Century*," *The Quarterly Journal of Economics*, 121, 823–866.

Caldara, D., S. Conlisk, M. Iacoviello, and M. Penn (2024): "Do Geopolitical Risks Raise or Lower Inflation?" Mimeo, Board of Governors of the Federal Reserve System.

Caldara, D. and M. Iacoviello (2022): "Measuring Geopolitical Risk," *American Economic Review*, 112, 1194–1225.

Caldara, D., M. Iacoviello, P. Molligo, A. Prestipino, and A. Raffo (2019): "Does Trade Policy Uncertainty Affect Global Economic Activity?" FEDS Notes, Board of Governors of the Federal Reserve System.

Federle, J., A. Meier, G. J. Müller, W. Mutschler, and M. Schularick (2024): "The price of war," Tech. rep., Kiel Working Paper.

Federle, J., A. Meier, G. J. Müller, and V. Sehn (2025): "Proximity to War: The Stock Market Response to the Russian Invasion of Ukraine," *Journal of Money, Credit and Banking*, forthcoming.

Frankel, R., M. Johnson, and D. J. Skinner (1999): "An Empirical Examination of Conference Calls as a Voluntary Disclosure Medium," *Journal of Accounting Research*, 37, 133–150.

Gormsen, N. J. and K. Huber (2025): "Corporate Discount Rates," *American Economic Review*, 115, 2001–49.

Gutiérrez, G. and T. Philippon (2017): "Investmentless Growth An Empirical Investigation," *Brookings Papers on Economic Activity*, 89–169.

Hall, G. J. and T. J. Sargent (2022): "Three World Wars: Fiscal–Monetary Consequences," *Proceedings of the National Academy of Sciences*, 119.

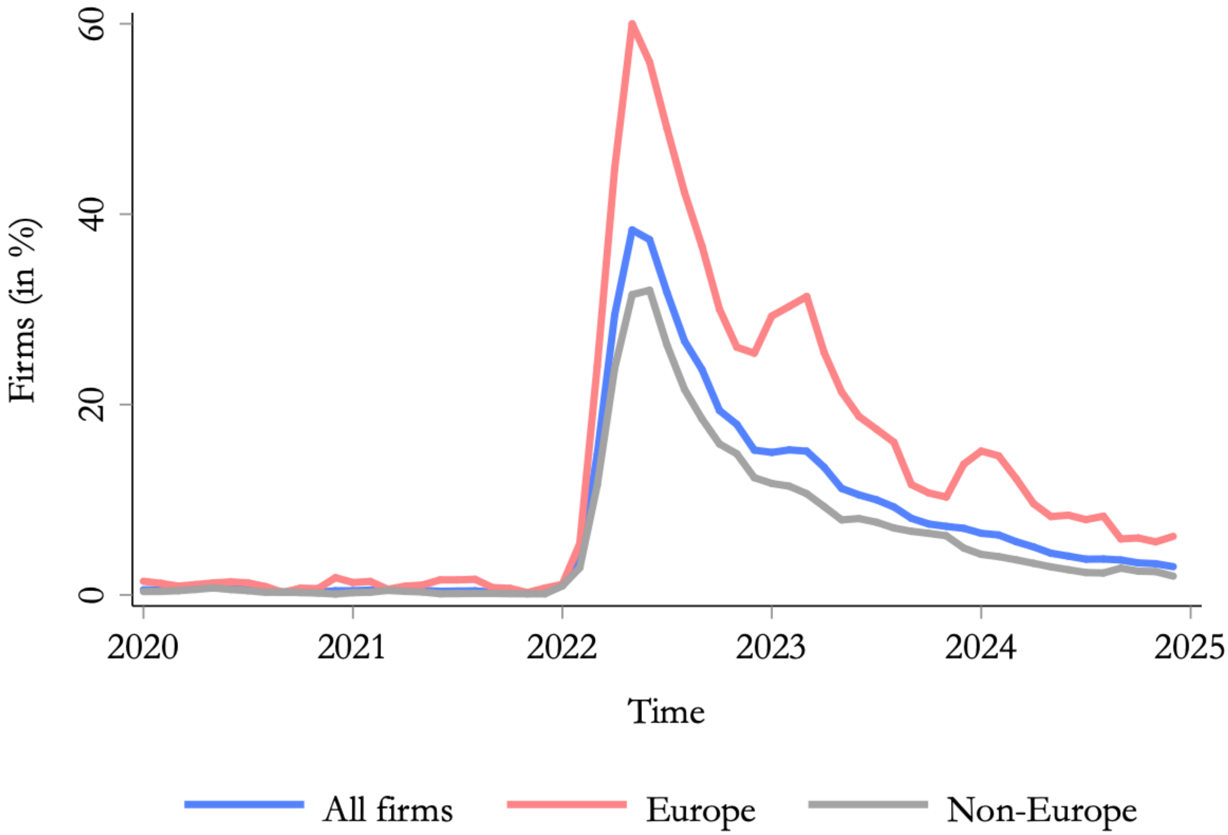
Hassan, T. A., S. Hollander, L. van Lent, and A. Tahoun (2019): "Firm-Level Political Risk: Measurement and Effects," *The Quarterly Journal of Economics*, 4, 2135–2202.

Jordà, Ò. (2005): "Estimation and Inference of Impulse Responses by Local Projections," *American Economic Review*, 95, 161–182.

Ramey, V. A. (2011): "Identifying Government Spending Shocks: It's all in the Timing," *The Quarterly Journal of Economics*, 126, 1–50.

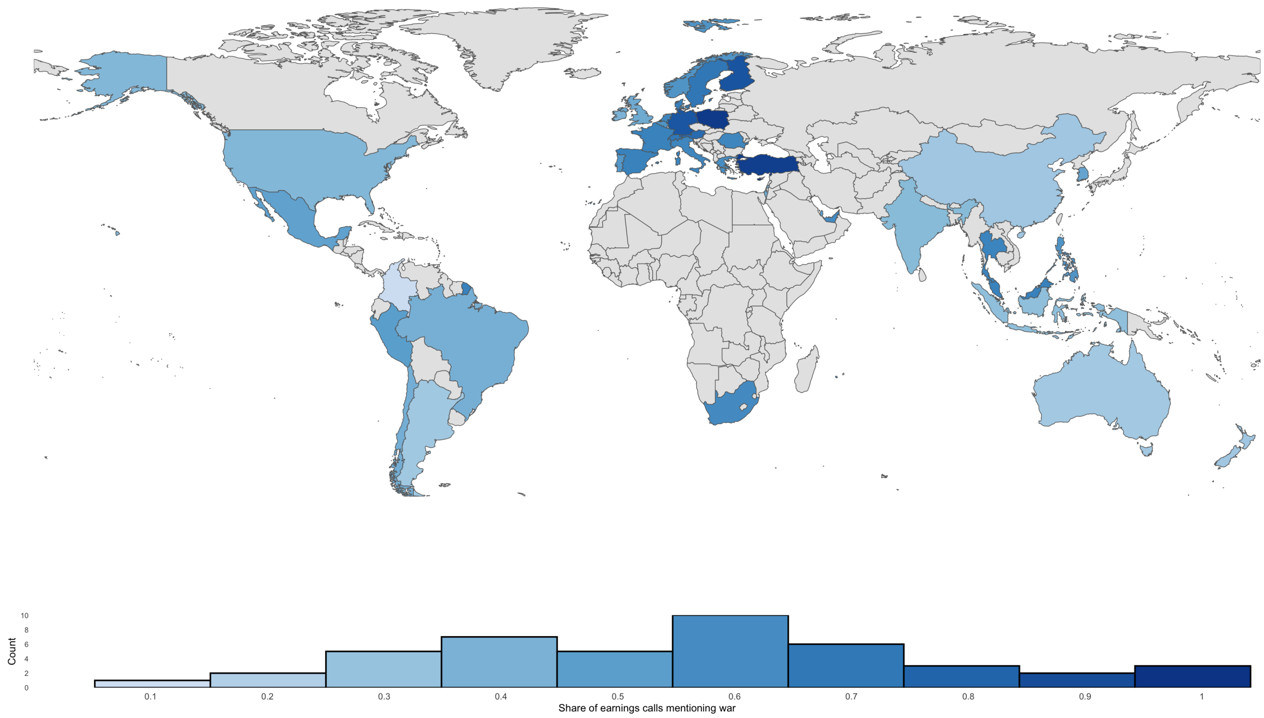
S&P Global Market Intelligence (2025): "Transcripts Data Feed," https://www.spglobal.com/marketintelligence/en/solutions/events-and-transcripts.

Figure 1: Firm-Level Mentions of the Russia-Ukraine War: 2020-2025



Note: 3-month moving average share of firms' earnings calls mentioning the Russia-Ukraine war. A firm's region is determined by the location of its headquarters. Source: Federal Reserve Board staff calculations; S&P Global Market Intelligence.

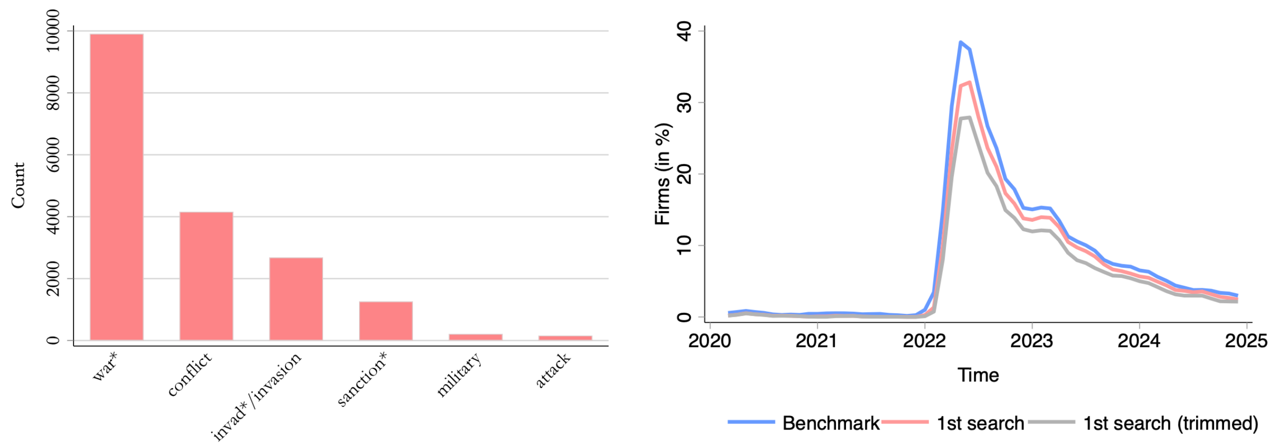
Figure 2: Firm-Level Geopolitical Concerns by Country in 2022



Note: Exposure of a country to the Russia-Ukraine war, calculated using the share of firms' earnings calls mentioning the Russia-Ukraine war, based on the country where the firm is headquartered. The earnings call share is calculated for countries with at least five earnings calls between March 1, 2022, and December 31, 2022. All other countries are shown in gray. Deeper shades of blue indicate a larger fraction of firms mentioning concerns related to the conflict. Source: Federal Reserve Board staff calculations; S&P Global Market Intelligence.

Figure 3: Exposure measure: Details

(a) Counts of Conflict Terms Near Russia-Ukraine Terms (b) Alternative measures of firm-level mentions

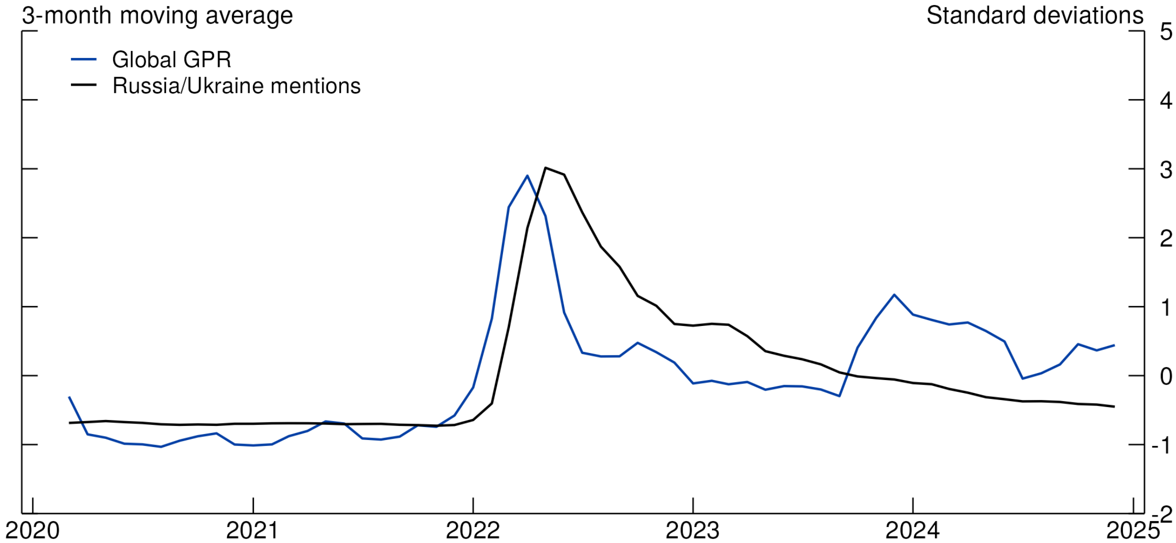


Note: Panel (a): Count of all conflict terms within five words of either “Russia”, “Russian”, “Ukraine”, or “Ukrainian”. The asterisk symbol * is a wildcard indicating any number of characters of any type may follow the prefix. Panel (b): Alternative measures of firm-level mentions. The line ‘benchmark’ is the same as what is shown in Figure 1. The red line relies only the first search criterion. The gray line relies only the first search excluding the terms “invad*”, “invastion”, and “sanction”. Source: Federal Reserve Board staff calculations; S&P Global Market Intelligence.

Figure 4: Terms Surrounding Geopolitical Mentions

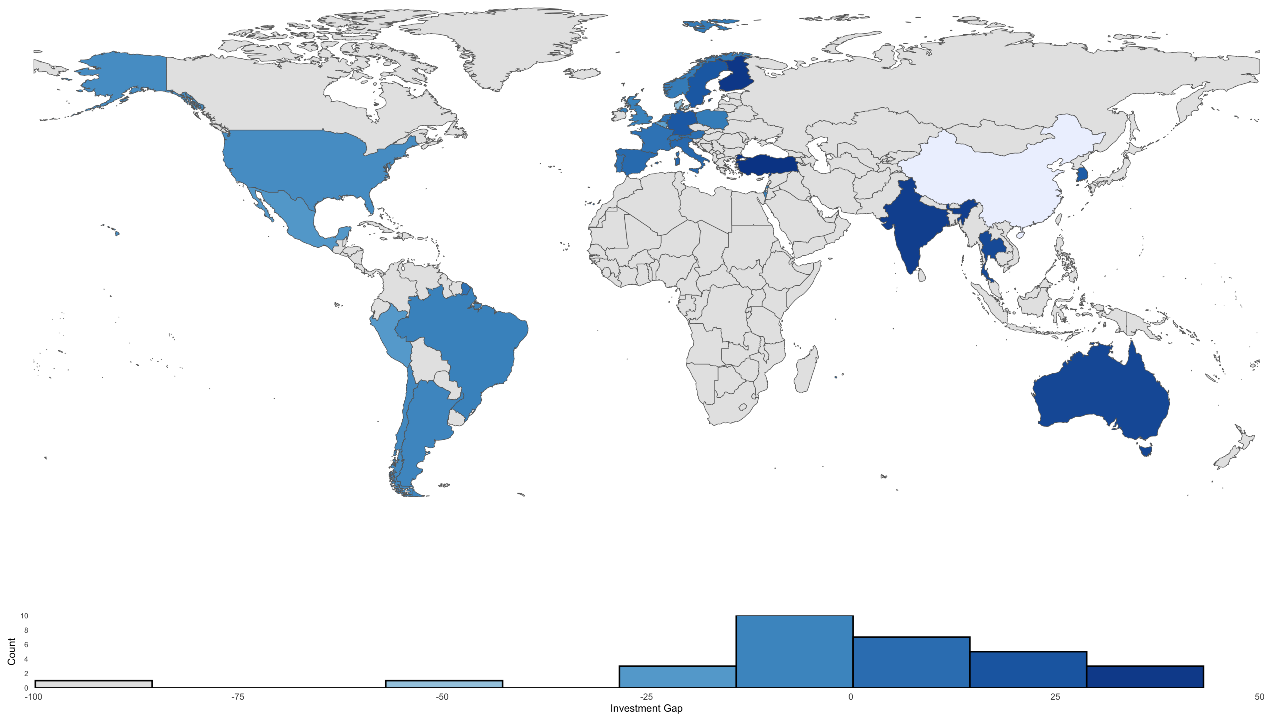
Note: The word cloud displays terms that are within 10 words of a Russia-Ukraine mention, excluding stop words and terms included in the initial searches. Terms with higher frequency are larger and shown in darker colors. Source: Federal Reserve Board staff calculations; S&P Global Market Intelligence.

Figure 5: Comparison of Russia-Ukraine Mentions to Geopolitical Risk Index



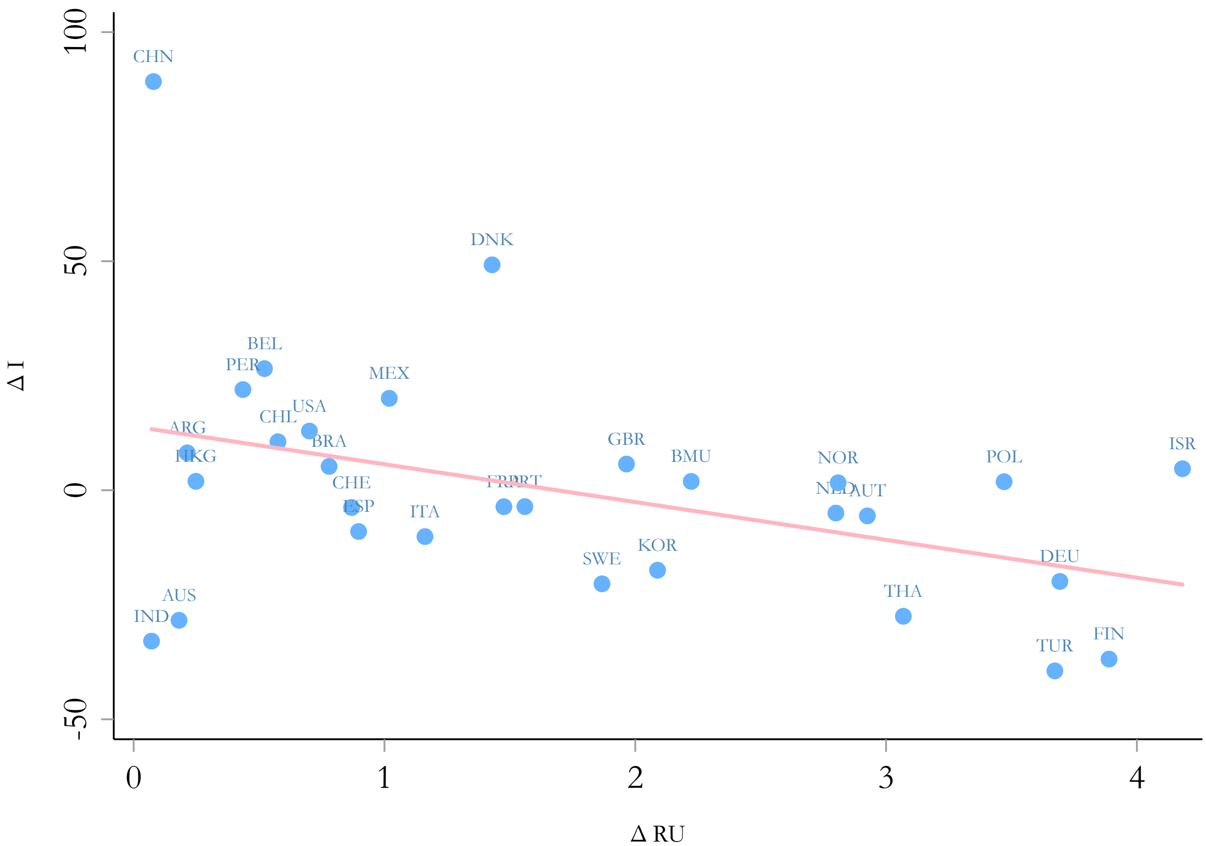
Note: The black line is the share of firms' earnings calls mentioning the Russia-Ukraine war and the blue line is the geopolitical risk index from Caldara and Iacoviello (2022). Both series are standardized over 2020-2024 and shown as 3-month moving averages. Source: Caldara and Iacoviello (2022); Federal Reserve Board staff calculations; S&P Global Market Intelligence.

Figure 6: Investment Gaps by Country



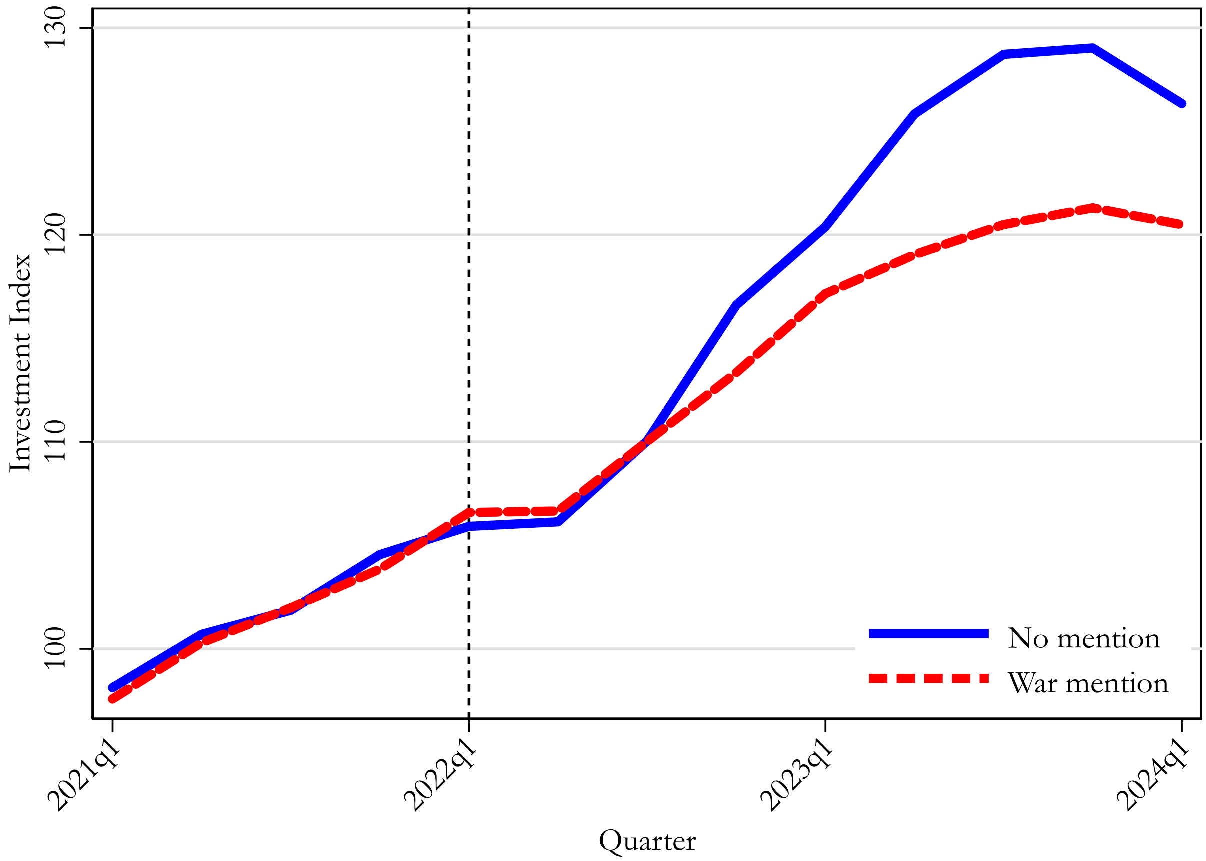
Note: This chart depicts the 'investment gap', ΔI_c, in the year after the beginning of the Russian invasion of Ukraine. Deeper shades of blue represent larger negative changes in investment. Source: Federal Reserve Board staff calculations; Capital IQ; S&P Global Market Intelligence.

Figure 7: Investment Gaps and War Mentions by Country



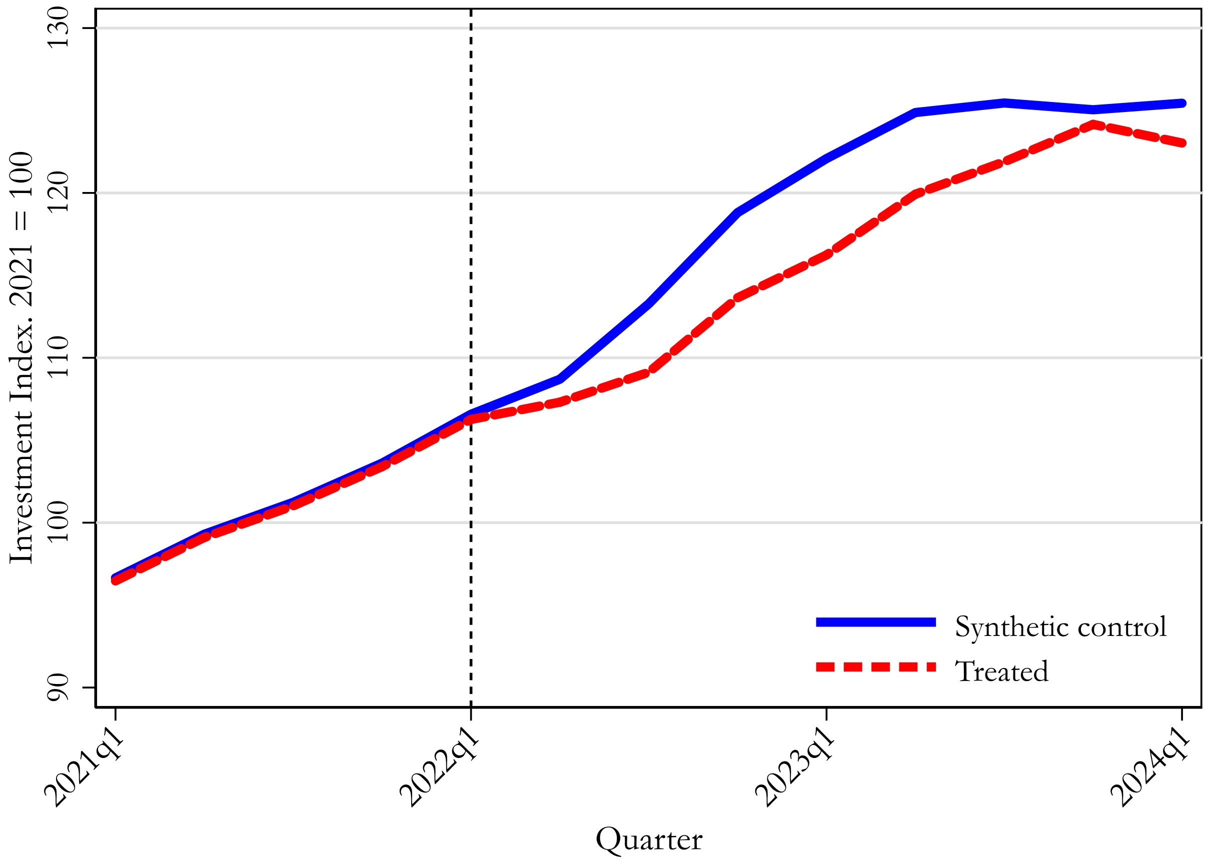
Note: Relationship between a country's investment gap ΔI_c and its change in mentions of war-related terms in earnings calls, ΔRU_c. The slope of the corresponding regression line is -8.25. Source: Federal Reserve Board staff calculations; Capital IQ; S&P Global Market Intelligence.

Figure 8: Investment index for Firms with and without War Mentions



Note: The blue solid line plots the investment index for firms that do not mention the war. The red dashed line shows results for firms that mention the war. Firms are aggregated across all countries. The investment index is normalized to 100 in the first three quarters of 2021. Source: Federal Reserve Board staff calculations; Capital IQ; S&P Global Market Intelligence.

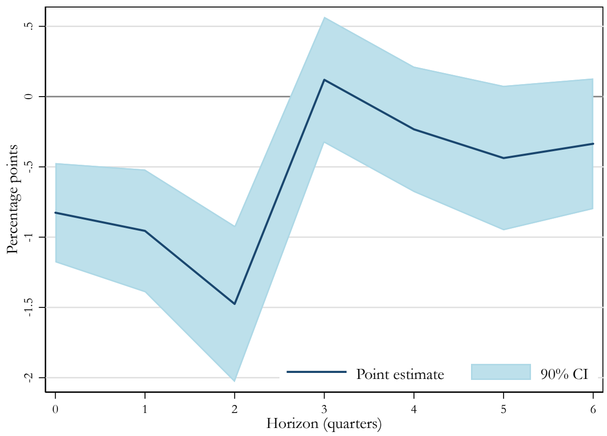
Figure 9: Synthetic control: The effect of the War on Investment



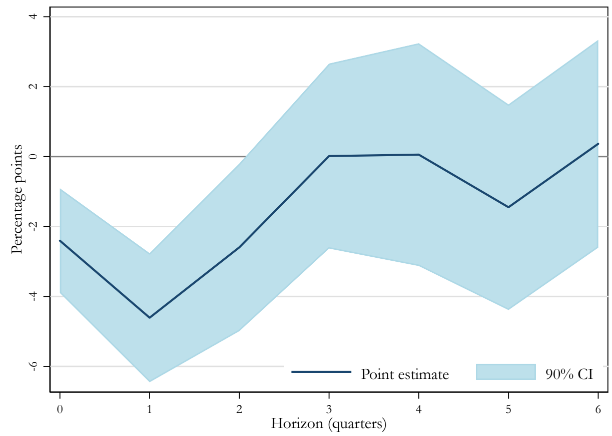
Note: The red dashed line plots the observed trajectory of the investment index of treated firms over time. The solid blue line plots the corresponding synthetic control—a weighted average of donor-pool units chosen to match the treated unit on pre-intervention levels and trends. The vertical line denotes 2022Q1, the beginning of the war. The investment index is normalized to 100 in the first three quarters of 2021. Source: Federal Reserve Board staff calculations; S&P Global Market Intelligence.

Figure 10: Local projections: The effect of $RU_{i,t}$ on investment

(a) Baseline specification



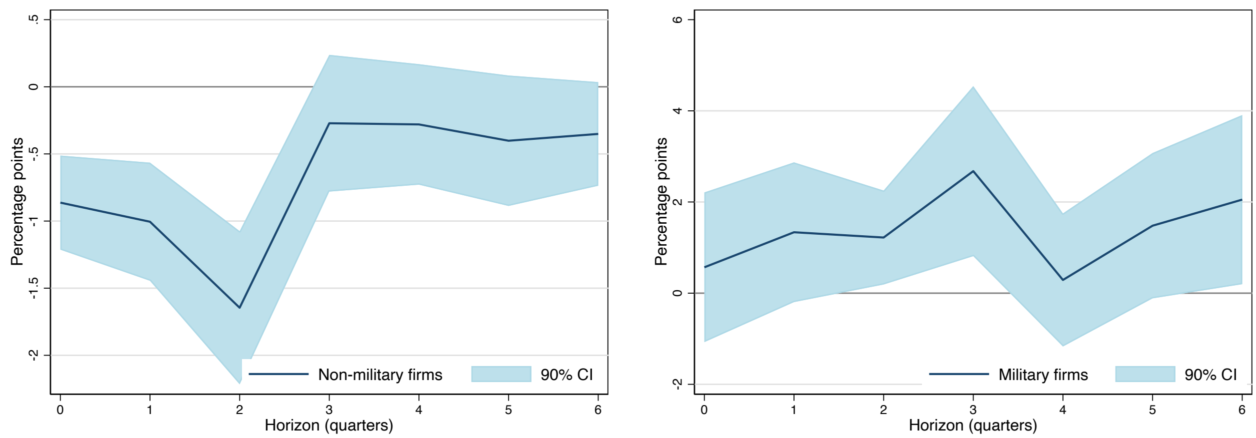
(b) Dummy specification



Note: The figure presents impulse-response estimates obtained via local projections. For each horizon h, we regress the outcome variable Y_{t+h} on the level of $RU_{i,t}$ (panel (a)) or a dummy $RU_{i,t} > 0$ (panel (b)) at time t, (in addition to the controls and fixed effects). The vertical axis measures the change in log firm-level investment rates. The horizontal axis denotes quarters since the shock. The solid line shows the point estimates of the response at each horizon, while the shaded area denotes 90% confidence intervals. Standard errors are clustered at the firm level to account for serial correlation in firm-specific shocks. Source: Federal Reserve Board staff calculations; S&P Global Market Intelligence.

Figure 11: Local projections: Adding military interaction term

(a) Non-military (b) Military



Note: The figure presents impulse-response estimates obtained via local projections. For each horizon h, we regress the outcome variable Y_{t+h} on the level of $RU_{i,t}$ and an interaction between $RU_{i,t}$ and a military industry dummy. Panel (a) shows the estimated coefficients for non-military firms, panel (b) shows the result for military firms. All regressions include the same controls and fixed effects as our baseline specification. The vertical axis measures the change in log firm-level investment rates. The horizontal axis denotes quarters since the shock. The solid line shows the point estimates of the response at each horizon, while the shaded area denotes 90% confidence intervals. Standard errors are clustered at the firm level to account for serial correlation in firm-specific shocks. Source: Federal Reserve Board staff calculations; S&P Global Market Intelligence.

Appendix

A Data appendix

In this appendix we present additional details on how we cleaned the Capital IQ data. We also include additional robustness measures.

Country-level changes in RU. We first define $\mathrm{RU}_{c,t}$ as a country-level, asset-weighted mean of firm-level $\mathrm{RU}_{i,t}$:

$$\mathrm{RU}_{c,t} \;=\; \frac{\sum_{i\in\mathcal{F}_c} \texttt{atq}_{i,t}\cdot \mathrm{RU}^*_{i,t}}{\sum_{i\in\mathcal{F}_c} \texttt{atq}_{i,t}}, \tag{9}$$

We then define

$$\Delta\mathrm{RU}_c = \frac{1}{4}\left(\sum_{t=2021\text{Q4}}^{2022\text{Q3}} \mathrm{RU}_{c,t} \;-\; \sum_{t=2020\text{Q4}}^{2021\text{Q3}} \mathrm{RU}_{c,t}\right). \tag{10}$$

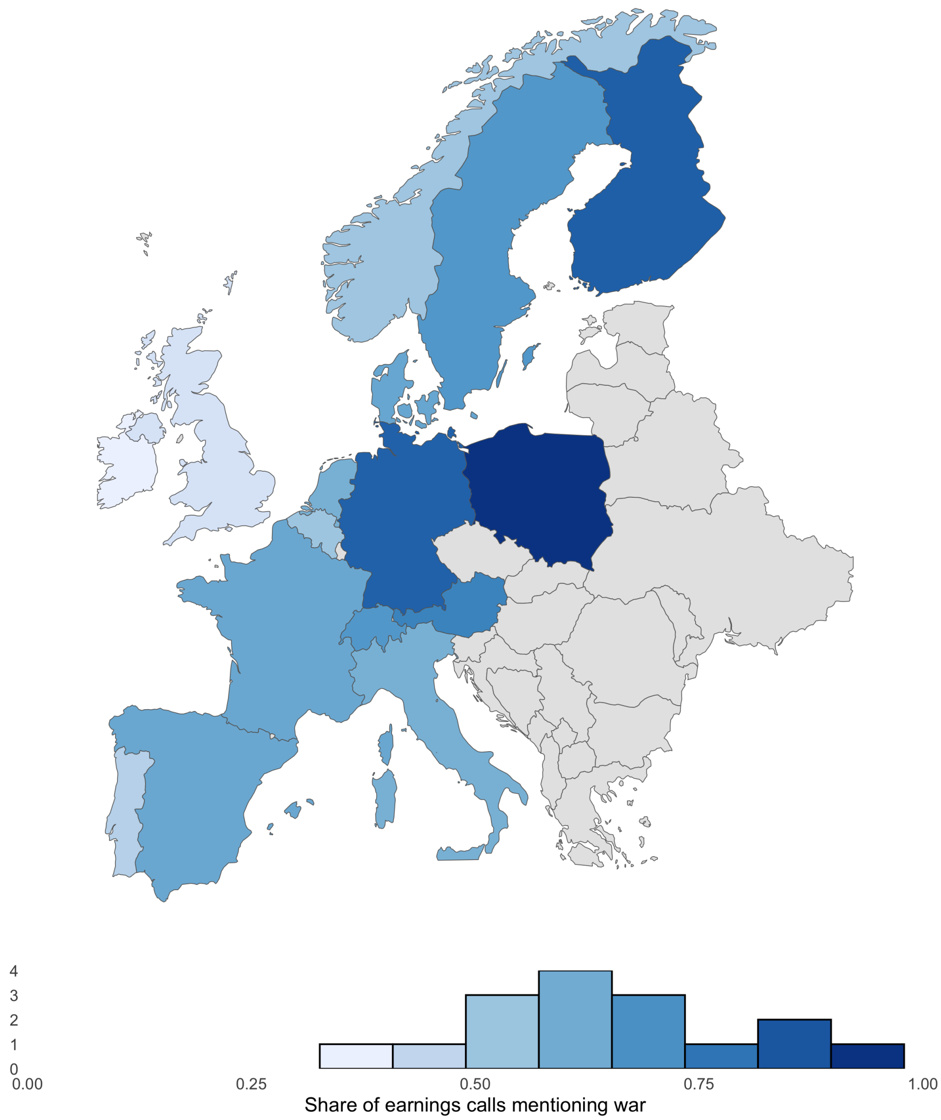
Global investment index. To summarize investment patterns at the global level, we construct an investment index for the exposed and non-exposed groups. For each country and quarter, we compute total capital expenditures and lagged assets at the group level, using country-level total assets `atq` as weights. Weighing countries by the number of firm observations yields very similar results. For each group $j \in \{0,1\}$ and each quarter t, we then compute a four-quarter moving sum of capital expenditures and a four-quarter moving average of lagged total assets. These are aggregated across all firms within group j and then combined into a smoothed global investment rate:

$$\widetilde{I}_t^j = \frac{\sum_{i:\mathcal{I}_i^{RU}=j} \sum_{s=t-3}^{t}\left(\texttt{capxy}_{i,s} - \texttt{capxy}_{i,s-1}\right)}{\sum_{i:\mathcal{I}_i^{RU}=j} \frac{1}{4}\sum_{s=t-3}^{t} \texttt{atq}_{i,s-1}}.$$

We then normalize this smoothed series to 100 based on its average during the first three quarters of 2021:

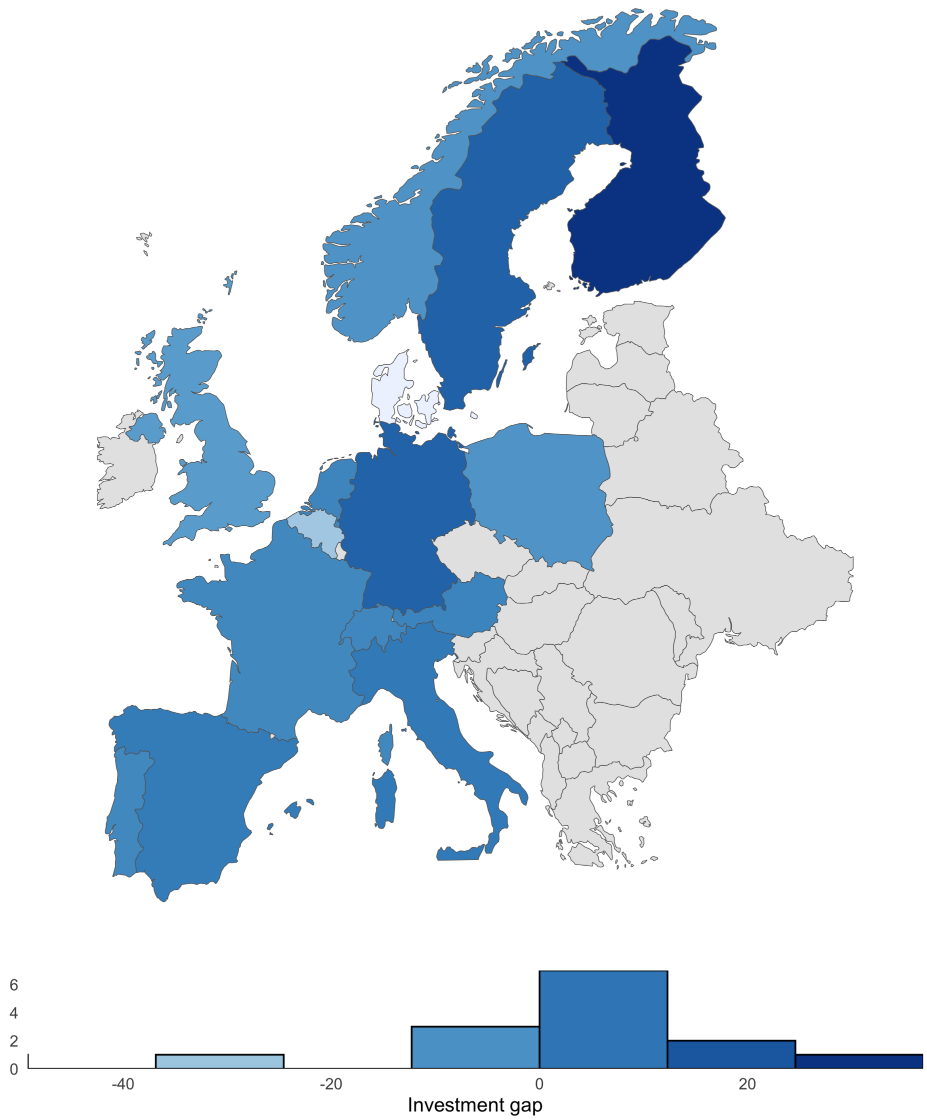
$$\mathbf{I}_t^j = 100 \times \frac{\widetilde{I}_t^j}{\frac{1}{3}\sum_{s\in 2021\text{Q1–Q3}} \widetilde{I}_s^j}.$$

Figure A.1: Firm-Level Geopolitical Concerns in Europe in 2022



Note: This chart depicts the exposure of a country to the Russia-Ukraine war, calculated using the share of firms' earnings calls mentioning the Russia-Ukraine war, based on the country where the firm is headquartered. Earnings call share is calculated for countries with at least five earnings calls between March 1, 2022, and May 13, 2022. Other countries are shown in gray. Deeper shades of blue indicate a larger fraction of firms mentioning concerns related to the conflict. Source: Federal Reserve Board staff calculations; S&P Global Market Intelligence.

Figure A.2: Investment Gap in Europe in 2022



Note: This chart depicts the 'investment gap', ΔI_c, in the year after the beginning of the Russian invasion of Ukraine. Deeper shades of blue represent larger negative changes in investment. Source: Federal Reserve Board staff calculations; Capital IQ; S&P Global Market Intelligence.