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Geopolitical Shocks and Default Probabilities of European Firms: A Sectoral Heterogeneity Analysis

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Abstract

This paper estimates sector-specific sensitivities of European firms' default probabilities to geopolitical risk shocks, providing empirical counterparts to δ_k in the reverse stress testing framework of Hurlin et al. (2026). Using Local Projections on a panel of 1,324 European firms from January 2021 to April 2026, I estimate impulse responses of the logit-transformed Bloomberg 5-year default probability to a one-standard-deviation shock in the standardized first difference of the Caldara and Iacoviello (2022) GPR Index. Results show strong cross-sector heterogeneity. Consumer Staples and Consumer Discretionary display the largest, most persistent responses, exceeding 0.018 after four months; Industrials, Materials, and Health Care also respond positively. Energy and Communication Services remain insignificant, while Financials are positive but less sensitive. At industry-group level, Automobiles & Components drives Consumer Discretionary, while Banks and Insurance show similar patterns. Robustness checks confirm the findings, and estimated $\hat{\delta}_{k,h}$ help calibrate sector-level credit portfolio models.

Keywords: Geopolitical Risk, Corporate Default Probability, Local Projections, Sectoral Heterogeneity, Credit Risk.
JEL Classification: C23, G33, C58, G21.

1 Introduction

European supervisory authorities have explicitly recognized geopolitical risk (GPR) as a first-order concern for financial stability. In a special feature of the 2024 Financial Stability Review entitled *Turbulent times: Geopolitical risk and its impact on Euro Area financial stability*, the European Central Bank (ECB) writes: "Geopolitical risk, which has increased of late, can be a threat to financial stability. [...] Adverse geopolitical events can trigger rapid shifts in market sentiment and sharp increases in uncertainty, exposing existing vulnerabilities in financial institutions and markets" (European Central Bank, 2024). Also, the European Stability Mechanism and the European Banking Authority, in their joint publication *Enhancing Europe's resilience against rising geopolitical risks*, investigate the impact of GPR on the banking sector and construct an analytical framework in which GPR is transmitted to banks through three primary channels: financial markets, the real economy, and the political environment (European Banking Authority and European Stability Mechanism, 2025). The present study focuses on the real-economy transmission channel, examining the impact of geopolitical shocks on the default probabilities of European corporations.

The literature on GPR has expanded substantially in recent years, in part due to the introduction by Caldara and Iacoviello (2022) of the Geopolitical Risk Index (GPR Index), which quantifies GPR as the proportion of newspaper articles that discuss adverse geopolitical events and associated threats. From a banking perspective, the existing literature has predominantly examined the effects of GPR on the stability and behavior of banking institutions (see, for instance, Avril et al., 2025; Martins et al., 2023; Phan et al., 2022). A substantial body of research has examined the effects of GPR on equity markets, treating the Russian invasion of Ukraine as an exogenous shock (Ahmed et al., 2022; Boungou and Yatié, 2022; Federle et al., 2024). A robust finding across these studies is that stock return responses are heterogeneous at the firm level, varying systematically with geographic proximity to the conflict, economic sector, and firm size. The relationship between GPR—almost invariably proxied by the GPR Index—and the volatility of equity and commodity markets has also been extensively investigated (Smales, 2021; Zhang et al., 2023).

By contrast, the impact of GPR and armed conflicts on credit risk has received comparatively less attention than their effects on equity markets. A notable contribution in this area is Téllez Valle et al. (2026), who analyzes the behavior of credit default swap (CDS) spreads for the most liquid firms in the EuroStoxx 600 at the onset of the Russian invasion of Ukraine, and finds that the banking sector is the most adversely affected, whereas some energy firms experience a beneficial impact. Huang (2025) construct a firm-level, cost-weighted GPR index and show that high exposure to GPR is associated with wider CDS spreads, higher default probabilities, and an increased likelihood of credit rating downgrades. Furthermore, Huang and Qiu (2025) and Bahukhandi et al. (2026) provide evidence that both GPR and

uncertainty regarding energy costs exacerbate corporate credit risk.

This paper contributes to this literature by estimating sector-specific sensitivities of default probabilities to exogenous geopolitical shocks. Building on the theoretical reverse stress testing framework for GPR developed by Hurlin et al. (2026) and employing the Local Projections (LP) econometric methodology of Jordà (2005), I analyze the transmission of these shocks to a sample of 1,324 European firms drawn from the Bloomberg Europe Large, Mid & Small Cap Index. Firms' default probabilities are proxied by a forward-looking indicator from Bloomberg Issuer Default Risk model, which is based on a modified structural Merton–Black–Cox framework. This metric integrates market-based information with firm-level fundamentals and is calibrated on realized default events. The use of this measure enables the extension of default risk analysis to a broad cross-section of firms for which alternative market-based indicators, such as CDS spreads, are unavailable.

2 Data

Hurlin et al. (2026) develop a reverse stress testing framework for GPR in which a state vector, $s = \begin{pmatrix} g, \\ x \end{pmatrix} \in \mathcal{S}$, with x capturing variations in the macro-financial environment (interest rates, commodity prices, etc.) and g representing the level of GPR, influences both the default probabilities and the loss given default of a bank's credit portfolio.

Focusing on default probabilities, Hurlin et al. propose to partition banks' credit exposures into sectors $k = 1, \ldots, K$ and to assume that the sensitivity of the log-odds of default to geopolitical and macro-financial factors is homogeneous within each sector. The functional form they adopt for the transmission of GPR to the default probability of exposure i in sector $k(i)$ is:

$$\ell_{i,t}(g, x) = \ell_{i,t}^0 + \beta_{k(i)}^\top x + \delta_{k(i)}\, g. \tag{1}$$

where $\ell_{i,t} \equiv \log\big(\mathrm{PD}_{i,t}/(1 - \mathrm{PD}_{i,t})\big)$ is the logit-transformed default probability of firm i at time t, and $\delta_{k(i)}$ denotes the sector-specific sensitivity of the log-odds of default to the GPR factor g. The objective of this study is to quantify the cross-sectoral and temporal variation in the parameter δ_k.

The financial data for the firms are sourced from Bloomberg. For the 1,543 companies included in the Bloomberg Europe Large, Mid & Small Cap Index, I collect 5-year default probabilities (from now on PD) based on the Bloomberg Issuer Default Risk model, total assets as a proxy for firm size, return on assets, and leverage (defined as total debt divided by total assets) from January 2021 to April 2026. In addition, I obtain information on country of domicile, sector, industry, and industry group as defined by the Global Industry Classification Standard. The PDs are available at a monthly frequency, whereas the accounting variables

are reported on an annual basis. From the original sample, I excluded the firms for which PD was not available, resulting in a final unbalanced sample of 1,324 firms. Descriptive statistics for the sample are presented in Table 1.

Table 1: Descriptive Statistics by GICS Sector (Firm-Level Averages)

Sector	N	PD (5-yr)	Total Assets	ROA	Leverage
Communication Services	72	0.0245	52,300	8.533	30.929
Consumer Discretionary	150	0.0334	33,700	5.890	33.566
Consumer Staples	88	0.0164	32,000	6.121	26.776
Energy	44	0.0321	223,000	5.099	22.771
Financials	212	0.0144	581,000	3.292	17.583
Health Care	110	0.0233	30,900	2.341	26.019
Industrials	312	0.0238	38,100	6.067	25.919
Information Technology	80	0.0180	24,300	8.210	19.104
Materials	112	0.0254	26,200	6.009	23.566
Real Estate	87	0.0327	26,900	3.056	37.893
Utilities	57	0.0258	60,100	3.572	35.224
Total	1,324	0.0236	129,000	5.222	26.261

Notes: Firm-level time-series averages over January 2021 – April 2026. N refers to the number of firms with non-missing PD. PD (5-yr) is the Bloomberg 5-year default probability. Total Assets are in millions of €. ROA is Return on Assets (%). Leverage is Total Debt to Total Assets (%).

The PD is defined on $[0, 1]$ and has low mean values: 2.36% (Table 1). To make the dependent variable suitable for linear regression and consistent with Equation 1, I apply a logit transformation, $\ell = \log\big(PD/(1-PD)\big)$. To capture variation in the macro-financial environment (the x component of the state vector in Hurlin et al.), I employ monthly time series for Brent crude oil prices (U.S. Energy Information Administration, 2026), the global price of natural gas for the European Union (International Monetary Fund, 2026), the three-month interbank rate for the euro area (Organization for Economic Co-operation and Development, 2026b), and long-term government bond yields for the euro area (Organization for Economic Co-operation and Development, 2026a). The inflation rate, together with other variables that vary only at annual frequency, is absorbed by year fixed effects. To approximate the g component of the state vector, following the approach recommended by the original authors, I use the global GPR Index constructed by Caldara and Iacoviello (2022), which is available at a monthly frequency. I take the first difference of the GPR Index and standardize it by computing its Z-score, so that the corresponding regressor can be interpreted as a geopolitical shock and the associated coefficient as the response to a one-standard-deviation increase in geopolitical risk.

3 Methodology

The econometric methodology employed to estimate the sensitivity of $\ell_{i,t}$ to GPR is the Local Projections (LP) approach, originally introduced by Jordà (2005). LP provide a flexible framework for estimating impulse response functions directly, without the need to specify and estimate a full vector autoregressive system. The approach consists of running a separate regression for each horizon h, projecting the future value of the variable of interest at $t+h$ onto the current shock g_t and a set of controls. The coefficient on g_t in each regression directly yields the impulse response at that horizon. Iterating this procedure over $h = 0, 1, \ldots, H$ traces the full impulse response function without imposing any dynamic restrictions on its shape. Here h is measured in months.

The econometric specification is:

$$\ell_{i,t+h} = \beta_h g_t + \sum_{k=2}^{K} \theta_{k,h} \left(g_t \times D_{ik} \right) + \rho_h \ell_{i,t-1} + \phi_h^\top x_{i,t-1} + \alpha_i + \eta_s + u_{i,t+h}, \tag{2}$$

where i indexes firms and $h = 0, 1, \ldots, H$ indexes forecast horizons. $\ell_{i,t+h}$ is the level of the logit-transformed default probability at horizon h; g_t is the geopolitical shock at month t; and D_{ik} is an indicator variable equal to one if firm i belongs to sector k. The term $\ell_{i,t-1}$ is the lag-augmentation term of Montiel Olea and Plagborg-Møller (2021), included to capture persistence in firm-level default risk and to attenuate the moving-average error structure induced by LP at long horizons. The vector $x_{i,t-1}$ captures variation in the macro-financial environment and contains predetermined firm-level controls, namely Brent oil prices, natural gas prices, short- and long-term interest rates, return on assets, leverage, and the logarithm of total assets, all measured at $t-1$. The term α_i denotes firm fixed effects, η_s denotes year fixed effects, and $u_{i,t+h}$ is the idiosyncratic error term.

This specification tackles an important econometric issue. By construction, LP residuals are serially correlated, with nonzero autocorrelation up to lag $h-1$: when Equation 2 is estimated at horizon $h > 0$, overlapping observation windows make adjacent residuals dependent. This does not affect the consistency of the estimates—since g_t and $x_{i,t-1}$ are predetermined—but it produces downward-biased standard errors and overly narrow confidence intervals if not accounted for. The lag-augmentation term $\ell_{i,t-1}$ both captures persistence in the data and attenuates this MA(h) problem. Standard errors are clustered at the firm level throughout, following Jordà and Taylor (2025).

The model is estimated on the full sample of firms for each horizon $h = 0, \ldots, 6$. Since sector membership is time-invariant at the firm level, sector dummies are absorbed by firm fixed effects and are not separately identified. By contrast, the interaction terms between the geopolitical shock and the sector indicators remain identified, allowing the response to geopolitical risk to vary freely across sectors. The coefficient β_h captures the response of the

reference sector at horizon h, while each coefficient $\theta_{k,h}$ measures the differential response of sector k relative to the reference category.

To recover economically meaningful sector-specific impulse responses, I compute the absolute marginal effect of the geopolitical shock for each sector at each horizon:

$$\widehat{IRF}_{k,h} = \frac{\partial \ell_{i,t+h}}{\partial g_t} = \begin{cases} \hat{\beta}_h, & \text{for the reference sector,} \\ \hat{\beta}_h + \hat{\theta}_{k,h}, & \text{for sector } k \neq 1. \end{cases} \tag{3}$$

The sequence $\{\widehat{IRF}_{k,h}\}_{h=0}^{H}$ traces the dynamic sector-level response of default risk to a geopolitical shock and constitutes the empirical counterpart to the sensitivity parameter δ_k in Hurlin et al.. Standard errors are clustered at the firm level throughout.

This specification serves two purposes. First, it allows the sensitivity of firm-level default risk to geopolitical shocks to differ across sectors while preserving a unified estimation framework on the full sample. Second, by iterating across horizons, it traces the temporal propagation of the shock, capturing not only cross-sectional heterogeneity in exposure to geopolitical risk but also differences in the persistence of that exposure across sectors.

The main results are presented using the GICS sector classification. Appendix A reports a more granular disaggregation based on GICS industry groups, estimated with the same interacted specification. Appendix B presents two robustness checks: a specification in which the geopolitical shock is replaced by a dummy variable equal to one in months in which the change in the GPR Index exceeds two standard deviations, and a long-difference LP specification that includes a lag-augmentation term following Montiel Olea and Plagborg-Møller (2021).

4 Results

Table 2 reports estimates of Equation 2 for the full pooled sample at horizon $h = 0$. At this horizon the specification collapses to a level-on-level regression, and the output allows us to assess the overall fit and the role of individual controls. The overall R^2 is very high (0.977), driven primarily by the lag augmentation term: the coefficient on $\ell_{i,t-1}$ is 0.922, confirming the strong persistence in firm-level default risk. Among macro-financial controls, Brent crude oil and natural gas prices enter with positive and highly significant coefficients, consistent with the interpretation that commodity price increases raise credit risk across the sample. The short-term interest rate enters with a negative and significant coefficient (-0.023), and the long-term rate with a positive one (0.016): these signs are consistent with the post-2022 normalization, in which monetary tightening coincided with declining default probabilities and a steepening yield curve. Among firm-level controls, leverage increases default risk as expected, ROA enters negatively and marginally significantly, and the logarithm of total

assets has a small positive coefficient.[1]

Table 3 reports the sector-level impulse responses $\widehat{IRF}_{k,h}$ from Equation 2 across horizons $h = 0, \ldots, 6$. Each cell measures the change in the logit of the 5-year default probability following a one-standard-deviation increase in geopolitical risk, and constitutes the empirical counterpart to the parameter δ_k in Hurlin et al. (2026).

Consumer Discretionary and Consumer Staples. Consumer Discretionary and Consumer Staples display the largest and most precisely estimated responses. For Consumer Discretionary, a one-standard-deviation geopolitical shock raises the logit of the default probability by 0.011 on impact and the response grows to 0.019 at $h = 4$, remaining significant and relatively stable through $h = 6$ at 0.016. The sector is highly exposed to disruptions in critical raw material supply chains—most notably, the automotive industry relies on palladium for catalytic converters and nickel for electric-vehicle batteries, and depended heavily on Ukraine for wiring harnesses before 2022. Consumer Staples shows a similarly large and persistent response: 0.011 at $h = 0$, peaking at 0.018 at $h = 4$. Globally diversified food, beverage, and household-product firms are directly exposed to trade disruptions and commodity-price spikes induced by geopolitical shocks, and many exited the Russian market following the invasion of Ukraine. In both sectors, the effects are statistically significant at all horizons and show no sign of reverting within the six-month window.

Industrials, Materials, and Health Care. Industrials and Materials show positive, significant, and persistent responses at all horizons, with impulse responses ranging from 0.008 on impact to 0.016 and 0.014 at $h = 4$ respectively. Both sectors are capital-intensive and tightly integrated into European production networks, making them vulnerable to trade disruptions, raw-material constraints, and energy-price fluctuations—channels that are activated almost immediately by a geopolitical shock. Health Care displays a comparable pattern (0.008 at $h = 0$, rising to 0.016 at $h = 4$), reflecting its dependence on globally integrated pharmaceutical supply chains and exposure to sanctions and export controls on active pharmaceutical ingredients.

Financials. The financial sector also shows positive and statistically significant impulse responses at every horizon, ranging from 0.006 at $h = 0$ to 0.019 at $h = 4$. The magnitude is somewhat smaller than in the sectors above, which is consistent with the different transmission mechanism: banks and insurers are not directly exposed to supply-chain disruptions or commodity inputs, but are affected through credit risk repricing, higher market volatility, and the deterioration of macroeconomic conditions induced by the geopolitical shock.

[1] Although this may seem counterintuitive, the fixed-effects estimator identifies the within-firm effect of asset growth, not the between-firm level effect. A correlated random-effects specification shows a positive between-firm effect and a negative within-firm effect.

Table 2: Pooled Model – Baseline Results at Horizon $h = 0$

	Coefficient	Std. err.	t	$P > \|t\|$	95% conf.	interval
Reference sector (Communication Services) × g_t						
g_t	0.0010	0.0026	0.38	0.704	−0.0041	0.0061
Sector × g_t interactions (differential response vs. reference)						
Consumer Discret. × g_t	0.0096	0.0030	3.22	0.001	0.0038	0.0155
Consumer Staples × g_t	0.0095	0.0035	2.70	0.007	0.0026	0.0164
Energy × g_t	−0.0008	0.0039	−0.20	0.844	−0.0084	0.0069
Financials × g_t	0.0047	0.0028	1.69	0.091	−0.0007	0.0102
Health Care × g_t	0.0073	0.0033	2.23	0.026	0.0009	0.0138
Industrials × g_t	0.0066	0.0028	2.36	0.018	0.0011	0.0121
Info. Technology × g_t	0.0017	0.0035	0.48	0.633	−0.0052	0.0086
Materials × g_t	0.0068	0.0031	2.18	0.029	0.0007	0.0129
Real Estate × g_t	0.0040	0.0035	1.14	0.254	−0.0029	0.0109
Utilities × g_t	0.0071	0.0033	2.12	0.034	0.0005	0.0136
Controls						
$\ell_{i,t-1}$	0.9220	0.0049	187.86	0.000	0.9123	0.9316
Natural gas$_{t-1}$	0.0008	0.0001	8.84	0.000	0.0007	0.0010
Brent$_{t-1}$	0.0006	0.0001	6.87	0.000	0.0004	0.0008
Long-term rate$_{t-1}$	0.0163	0.0028	5.89	0.000	0.0109	0.0217
Short-term rate$_{t-1}$	−0.0235	0.0021	−11.39	0.000	−0.0275	−0.0194
ROA$_{t-1}$	−0.0005	0.0003	−1.83	0.068	−0.0010	0.0000
Leverage$_{t-1}$	0.0038	0.0006	6.88	0.000	0.0027	0.0049
Log Total Assets$_{t-1}$	0.0311	0.0045	6.83	0.000	0.0221	0.0400
Constant	−0.7918	0.0575	−13.76	0.000	−0.9047	−0.6789
Firm and Year FE			Yes			
Observations			82,423			
Number of clusters			1,318			
R^2			0.9767			
Within R^2			0.8979			
Root MSE			0.1873			

Notes: OLS estimation of Equation 2 at horizon $h = 0$ on the pooled sample. The dependent variable is $\ell_{i,t}$, the level of the logit-transformed 5-year default probability. g_t is the standardized first difference of the GPR Index. The row labelled g_t reports the coefficient for the reference sector (Communication Services); rows labelled Sector × g_t report interaction coefficients measuring the differential response of each sector relative to the reference. The absolute impulse response for each sector is $\hat{\beta}_0 + \hat{\theta}_{k,0}$, as reported in Table 3. All controls in $x_{i,t-1}$ are lagged one period. Robust standard errors clustered at the firm level.

Table 3: Sector-Level Impulse Responses of Default Risk to Geopolitical Shocks ($\widehat{IRF}_{k,h}$)

	$h=0$	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$	$h=6$	N
Communication Serv.	0.001	−0.001	−0.003	−0.004	−0.003	−0.005	−0.001	82,423
Consumer Discret.	0.011***	0.013***	0.017***	0.018***	0.019***	0.015***	0.016***	82,423
Consumer Staples	0.011***	0.008**	0.009***	0.016***	0.018***	0.010**	0.009*	82,423
Energy	0.000	−0.005	−0.000	−0.005	0.016***	0.015**	0.010*	82,423
Financials	0.006***	0.008***	0.015***	0.015***	0.019***	0.013***	0.013***	82,423
Health Care	0.008***	0.006**	0.017***	0.014***	0.016***	0.012***	0.015***	82,423
Industrials	0.008***	0.010***	0.014***	0.010***	0.016***	0.012***	0.015***	82,423
Info. Technology	0.003	0.004	0.012***	0.010**	0.012**	0.014***	0.022***	82,423
Materials	0.008***	0.005**	0.011***	0.008**	0.014***	0.012***	0.014***	82,423
Real Estate	0.005**	0.002	−0.003	−0.004	0.001	−0.003	−0.005	82,423
Utilities	0.008***	−0.000	−0.003	−0.000	0.004	−0.000	−0.003	82,423

Notes: Each cell reports $\widehat{IRF}_{k,h} = \hat{\beta}_h + \hat{\theta}_{k,h}$ from Equation 2, estimated on the pooled sample with sector–shock interactions. The dependent variable is the level $\ell_{i,t+h}$ of the logit-transformed 5-year default probability at horizon h. The impulse response measures the change in $\ell_{i,t+h}$ following a one-standard-deviation increase in the geopolitical shock g_t. All specifications include firm and year fixed effects and the full set of macro-financial and firm-level controls in $x_{i,t-1}$. Standard errors clustered at the firm level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. N is the number of observations at $h = 0$; the sample shrinks at longer horizons due to forward projection.

Information Technology. The Information Technology sector displays an initially muted response: the impulse responses at $h = 0$ and $h = 1$ are positive but small and statistically indistinguishable from zero (0.003 and 0.004). From $h = 2$ onward, however, the responses become positive and significant, growing monotonically to 0.022 at $h = 6$. This pattern suggests that the sector is not directly exposed to the immediate first-round effects of a geopolitical shock, but is instead affected through the indirect channels of weaker aggregate European demand and tightening financial conditions, which operate with a delay.

Energy, Real Estate, and Utilities. The Energy sector shows negligible and statistically insignificant responses at short horizons, but positive and significant effects at $h = 4$ (0.016), $h = 5$ (0.015), and marginally at $h = 6$ (0.010). This delayed pattern is consistent with the mixed transmission mechanism for European integrated oil and gas producers: higher energy prices induced by geopolitical events support their revenues in the short run, but uncertainty about demand, sanctions, and asset stranded values accumulates over time and eventually raises credit risk. Real Estate and Utilities show a very different profile: both sectors exhibit a small positive and significant response on impact (Real Estate 0.005, Utilities 0.008), but the response reverts toward zero or turns negative within one to two months and remains indistinguishable from zero thereafter. For Real Estate, this likely reflects the indirect channel through interest rates, which tends to affect valuations gradually rather than at impact. For Utilities, the pattern is consistent with a sector that, in the European con-

text, combines firms directly exposed to energy-price volatility with renewables and nuclear operators that benefit from higher commodity prices, resulting in a near-zero net effect over the medium run.

Communication Services. The Communication Services sector shows no statistically significant response at any horizon, with coefficients close to zero and alternating in sign. European telecommunication and media providers operate in highly regulated domestic markets with subscription-based revenues, locally anchored infrastructure, and limited dependence on global value chains or critical raw materials. These structural features insulate the sector from geopolitical shocks.

Taken together, these results confirm that geopolitical risk transmits to corporate default probabilities in a heterogeneous way across sectors. The magnitude of the response ranges from essentially zero in Communication Services to 0.019 in Consumer Discretionary and Financials at $h = 4$, a difference that is both statistically significant and economically meaningful given the typical level of the logit-transformed default probability in the sample. The responses are also heterogeneous in their dynamic profile: some sectors respond immediately and persistently (Consumer Staples, Industrials), others display a delayed but growing reaction (Information Technology), and others show only a transient impact effect (Utilities, Real Estate).

5 Conclusions

This paper has estimated sector-specific impulse responses of the logit-transformed 5-year default probability of European firms to a one-standard-deviation geopolitical shock, using the Local Projections framework of Jordà (2005) on a panel of 1,324 firms over the period January 2021–April 2026. The estimated sequences $\{\widehat{IRF}_{k,h}\}_{h=0}^{6}$ constitute the empirical counterpart to the sensitivity parameter δ_k in the reverse stress testing framework of Hurlin et al., providing sector-level inputs for the calibration of geopolitical risk in banks' credit portfolio models.

The main findings can be summarized as follows. The sectors most sensitive to geopolitical shocks are Consumer Staples and Consumer Discretionary, with impulse responses that are positive, statistically significant at all horizons, and increase monotonically up to a four- to five-month horizon before stabilizing. Industrials, Materials, and Health Care display broadly similar patterns, consistent with their capital intensity, dependence on imported raw materials, and integration into European production networks. Financials show positive and significant sensitivity throughout, reflecting indirect transmission through credit risk repricing and market volatility rather than direct supply-chain exposure. Information Technology responds with a delay, with negligible effects on impact and growing significance from the

second month onward. Conversely, the Energy and Communication Services sectors show no statistically significant response at any horizon, consistent with the offsetting effects of higher commodity revenues for energy firms and the domestically anchored, regulated revenue structure of European telecoms. Real Estate and Utilities display only a transient impact effect that dissipates rapidly, suggesting that their exposure to geopolitical shocks is limited and indirect. Disaggregation at the industry group level confirms these patterns and reveals additional within-sector heterogeneity, most notably the dominant role of Automobiles & Components within Consumer Discretionary and of Household & Personal Products—the group with the largest coefficients in the entire sample—within Consumer Staples.

Several limitations merit discussion. First, the analysis does not support a causal interpretation. The Local Projections framework identifies the conditional correlation between geopolitical shocks and subsequent changes in default risk, controlling for observable macro-financial and firm-level factors, but omitted variables and reverse causality cannot be fully excluded. The estimated $\hat{\delta}_{k,h}$ should therefore be interpreted as empirical sensitivity measures rather than structural causal effects.

Second, the sample period is short. The estimation window spans January 2021 to April 2026, a period in which major geopolitical shocks have been relatively few and concentrated. Much of the identified variation is likely driven by the Russian invasion of Ukraine in February 2022 and its direct consequences for European firms. More recent conflicts enter the estimates only at short horizons due to data availability, and the identification of longer-horizon effects rests on limited post-shock observations. Extending the analysis to a longer sample, if and when suitable default probability data become available, remains a natural next step.

Third, despite the inclusion of the lag-augmentation term of Montiel Olea and Plagborg-Møller (2021), residual serial correlation in the error term cannot be fully eliminated. By construction, LP residuals at horizon h follow an MA(h) process, and while lag augmentation attenuates this problem, firm-level clustering may not fully capture the remaining cross-sectional and temporal dependence at longer horizons. As a consequence, standard errors at $h \geq 4$ may still be somewhat underestimated, and the significance of coefficients at the longest horizons should be interpreted with appropriate caution.

Fourth, the default probability measure used in this study is derived from the Bloomberg Issuer Default Risk model, which is based on a structural Merton–Black–Cox framework and is therefore equity-based in nature. This implies that the estimated PD is heavily influenced by short-term equity price dynamics, which may reflect transient market sentiment rather than fundamental changes in credit quality. To the extent that geopolitical shocks primarily affect equity prices in the short run, the estimated impulse responses may partly capture equity market reactions rather than genuine changes in firms' underlying default risk. This limitation is inherent to any market-based PD measure and is difficult to address without alternative credit risk data at the same breadth of coverage.

Notwithstanding these limitations, the analysis provides a set of empirical results that are directly actionable for practitioners and regulators. The estimated sector-level impulse responses offer a transparent, data-driven basis for calibrating the geopolitical risk sensitivity of credit portfolios, complementing scenario-based stress testing approaches with quantitative, horizon-specific inputs. As geopolitical risk becomes an increasingly central concern for European supervisory authorities, the availability of granular, sector-specific estimates of GPR transmission to corporate default risk represents a concrete contribution to the operationalization of geopolitical stress testing in banking supervision.

A Industry Group Disaggregation

This appendix reports the sector-level impulse responses estimated using the GICS Industry Group classification, which disaggregates the eleven GICS sectors into 25 more granular industry groups. The econometric specification is identical to Equation 2, with industry group indicators replacing sector indicators in the interaction terms. The dependent variable and all controls are unchanged. Results are reported in Table 4.

Table 4: Industry Group – Impulse Responses of Default Risk to Geopolitical Shocks ($\widehat{IRF}_{k,h}$)

	$h=0$	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$	$h=6$
Automobiles & Components	0.015***	0.022***	0.029***	0.026***	0.030***	0.021***	0.011*
Banks	0.007***	0.009***	0.016***	0.015***	0.021***	0.016***	0.011***
Capital Goods	0.007***	0.010***	0.017***	0.012***	0.015***	0.012***	0.015***
Commercial & Professional Serv.	0.009***	0.010**	0.011**	0.012**	0.016***	0.010**	0.020***
Consumer Discret. Distribution	0.008***	0.005	0.005	0.010**	0.013***	0.015**	0.019***
Consumer Durables & Apparel	0.012***	0.014***	0.018***	0.022***	0.013*	0.008	0.013*
Consumer Services	0.008***	0.010**	0.016***	0.011**	0.020***	0.016**	0.019***
Consumer Staples Dist. & Retail	0.004	−0.006	−0.001	0.006	0.011	0.006	0.000
Energy	0.000	−0.005	−0.000	−0.005	0.016***	0.015**	0.010*
Equity REITs	0.005	−0.003	−0.006	−0.007	−0.002	−0.010*	−0.012***
Financial Services	0.004*	0.008***	0.014***	0.016***	0.016***	0.011***	0.018***
Food, Beverage & Tobacco	0.011***	0.010**	0.008**	0.014***	0.016***	0.008	0.006
Health Care Equip. & Services	0.009***	0.008**	0.014**	0.014***	0.017***	0.009	0.013**
Household & Personal Products	0.018***	0.021**	0.030***	0.044***	0.038***	0.028**	0.041***
Insurance	0.006***	0.007***	0.013***	0.015***	0.020***	0.012***	0.008***
Materials	0.008***	0.005**	0.011***	0.008**	0.014***	0.012***	0.014***
Media & Entertainment	0.003	0.004	0.005	0.009	0.008	0.004	0.009
Pharma, Biotech & Life Sciences	0.008***	0.005	0.019***	0.014**	0.015***	0.015**	0.016**
Real Estate Mgmt & Development	0.005	0.005	−0.001	−0.003	0.002	0.001	−0.001
Semiconductors & Equip.	0.002	0.017**	0.015**	0.007	0.011	0.009	0.031***
Software & Services	0.003	0.005	0.011**	0.011*	0.015**	0.019**	0.026***
Tech Hardware & Equipment	0.003	−0.002	0.012	0.010	0.009	0.009	0.012
Telecommunication Services	−0.002	−0.007	−0.013**	−0.018***	−0.016**	−0.016**	−0.013**
Transportation	0.011***	0.010**	0.004	0.002	0.021***	0.013**	0.007
Utilities	0.008***	−0.000	−0.003	−0.000	0.004	−0.000	−0.003

Notes: Each cell reports $\widehat{IRF}_{k,h} = \hat{\beta}_h + \hat{\theta}_{k,h}$ from a variant of Equation 2 in which GICS industry group indicators replace GICS sector indicators in the interaction terms with g_t. The dependent variable is the level $\ell_{i,t+h}$ of the logit-transformed 5-year default probability at horizon h. The sample consists of 82,423 observations at $h=0$. All specifications include firm and year fixed effects and the full set of macro-financial and firm-level controls. Standard errors clustered at the firm level. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

B Robustness Checks

This appendix presents two robustness checks for the main results reported in Table 3. Section B.1 re-estimates the baseline specification replacing the continuous geopolitical shock with a binary indicator. Section B.2 re-estimates the model in long differences to address the potential non-stationarity of the dependent variable.

B.1 Long-Difference Specification

Although the baseline specification in levels is aligned with the theoretical framework of Hurlin et al. (2026), the logit-transformed default probability may be non-stationary for a subset of firms in the sample, as suggested by standard panel unit root tests. To address this concern, this section re-estimates Equation 2 replacing the level $\ell_{i,t+h}$ with the cumulative long difference $\ell_{i,t+h} - \ell_{i,t-1}$ as the dependent variable and including a lag-augmentation term $(\ell_{i,t-1} - \ell_{i,t-2})$ among the regressors, following Montiel Olea and Plagborg-Møller (2021). All other controls, fixed effects, and clustering remain unchanged. The results are reported in Table 5.

Table 5: Robustness B.1 – Long-Difference Specification ($\widehat{IRF}_{k,h}$)

	$h=0$	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$	$h=6$
Communication Serv.	0.001	−0.002	−0.003	−0.003	−0.003	−0.006	0.001
Consumer Discret.	0.013***	0.016***	0.023***	0.026***	0.028***	0.025***	0.029***
Consumer Staples	0.015***	0.013***	0.018***	0.026***	0.031***	0.026***	0.026***
Energy	0.002	−0.002	−0.002	−0.005	0.014	0.011	0.010
Financials	0.007***	0.009***	0.017***	0.018***	0.022***	0.016***	0.017***
Health Care	0.010***	0.009***	0.023***	0.022***	0.025***	0.024***	0.028***
Industrials	0.010***	0.013***	0.018***	0.016***	0.023***	0.020***	0.025***
Info. Technology	0.002	0.004	0.017***	0.016***	0.020***	0.023***	0.034***
Materials	0.011***	0.009***	0.018***	0.017***	0.025***	0.026***	0.027***
Real Estate	0.008***	0.006	−0.000	0.001	0.005	0.001	0.004
Utilities	0.012***	0.005	0.000	0.005	0.009	0.004	0.006

Notes: Each cell reports $\widehat{IRF}_{k,h}$ from a variant of Equation 2 in which the dependent variable is the cumulative long difference $\ell_{i,t+h} - \ell_{i,t-1}$ and the lag-augmentation term $(\ell_{i,t-1} - \ell_{i,t-2})$ replaces $\ell_{i,t-1}$ among the regressors. All other controls, fixed effects, and clustering are unchanged. Standard errors clustered at the firm level. $^{***}\,p < 0.01$, $^{**}\,p < 0.05$, $^{*}\,p < 0.1$.

The long-difference results are closely consistent with the baseline. The sectoral ranking is preserved: Consumer Discretionary, Consumer Staples, Health Care, Industrials, and Materials display positive, significant, and persistent impulse responses at all horizons, while Communication Services and Energy remain indistinguishable from zero at short horizons. Financials confirms its positive and significant pattern across all horizons, with coefficients

ranging from 0.007 at $h = 0$ to 0.022 at $h = 4$. Information Technology again shows a delayed reaction, with negligible effects at $h = 0$ and $h = 1$ and growing significance from $h = 2$ onward, reaching 0.034 at $h = 6$. Real Estate and Utilities show only a small positive and significant coefficient on impact (0.008 and 0.012 respectively) with no persistence thereafter, confirming the pattern observed in the baseline. Overall, the long-difference results support the conclusion that the baseline findings are not driven by non-stationarity of the dependent variable.

B.2 Binary Shock Indicator

The baseline specification measures the geopolitical shock as the standardized first difference of the GPR Index, a continuous variable. To assess robustness to the measurement of the shock, this section replaces the continuous variable g_t with a binary indicator $\mathbb{1}[g_t > 2]$, equal to one in months in which the change in the GPR Index exceeds two standard deviations, and zero otherwise. This indicator identifies episodes of unusually sharp geopolitical escalation. The dependent variable remains the level $\ell_{i,t+h}$, and all other elements of the specification are unchanged. Because the shock variable is now binary, the impulse responses measure the change in the logit of the default probability in months of extreme geopolitical escalation relative to tranquil months; they are not directly comparable in scale to the baseline coefficients. Results are reported in Table 6.

Table 6: Robustness B.2 – Binary Shock Indicator ($\widehat{IRF}_{k,h}$)

	$h=0$	$h=1$	$h=2$	$h=3$	$h=4$	$h=5$	$h=6$
Communication Serv.	0.011	−0.013	−0.070*	−0.040	−0.003	0.015	0.015
Consumer Discret.	0.082***	0.071***	0.026	0.030	0.050*	0.049*	0.039
Consumer Staples	0.062***	0.057**	0.026	0.051	0.058	0.050	0.061*
Energy	0.015	−0.032	−0.036	0.008	0.089**	0.095**	0.033
Financials	0.039***	0.032***	−0.000	−0.009	−0.011	−0.030**	−0.051***
Health Care	0.069***	0.038*	0.021	0.052*	0.068**	0.069**	0.082***
Industrials	0.065***	0.056***	0.020	0.027	0.052***	0.045***	0.047***
Info. Technology	0.055***	0.046**	0.026	0.054	0.091**	0.114***	0.111***
Materials	0.066***	0.049***	0.025	0.049*	0.077***	0.085***	0.084***
Real Estate	0.048***	0.016	−0.057**	−0.014	0.062***	0.074***	0.056**
Utilities	0.053***	0.008	−0.077**	−0.065*	−0.002	0.038	0.063

Notes: Each cell reports $\widehat{IRF}_{k,h}$ from a variant of Equation 2 in which g_t is replaced by a binary indicator equal to one in months in which the standardized change in the GPR Index exceeds two standard deviations. The dependent variable is the level $\ell_{i,t+h}$. Coefficients measure the change in the logit of the default probability in months of extreme geopolitical escalation relative to all other months, and are not directly comparable in scale to those in Table 3. Standard errors clustered at the firm level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The binary shock results broadly confirm the cross-sectoral ranking of the baseline, with

some differences in precision and dynamic profile attributable to the different nature of the identified variation. Consumer Discretionary, Consumer Staples, Health Care, Industrials, and Materials all show large positive and significant responses on impact, consistent with their baseline counterparts. Information Technology, which displayed a delayed reaction in the baseline, here shows an immediate and significant positive response (0.055 at $h = 0$), suggesting that its default risk reacts sharply to extreme geopolitical episodes even if it is less sensitive to the average level of geopolitical risk captured by the continuous measure. Materials shows the most consistent and persistent profile across both measures, with significant responses at most horizons.

The main divergence relative to the baseline concerns Financials, whose impulse responses turn negative and significant at $h = 5$ (-0.030) and $h = 6$ (-0.051). This pattern may reflect the behavior of bank and insurance default probabilities during episodes of extreme geopolitical escalation: large shocks tend to trigger immediate monetary and fiscal policy responses, including central bank interventions that temporarily compress financial sector credit risk at medium horizons. A similar pattern of sign reversal is observed for Real Estate and Utilities at $h = 2$–$h = 3$, consistent with a transient overshooting followed by partial recovery. Communication Services remains insignificant throughout, confirming the baseline result. Overall, the sign and significance structure of the main results is robust to the use of a binary shock measure, with the qualifications noted above for Financials and, to a lesser extent, Real Estate and Utilities.

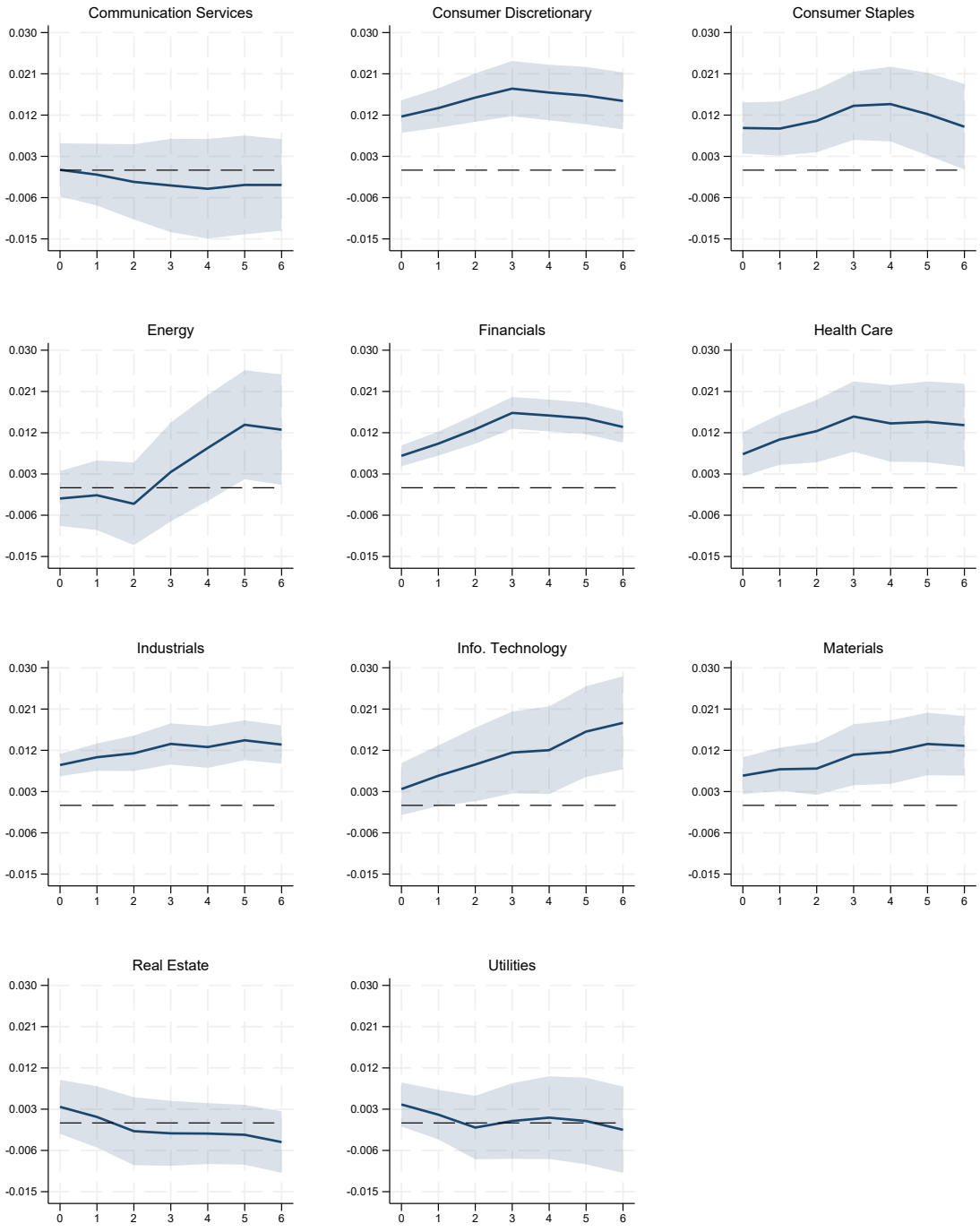
C Smoothed Impulse Response Functions

The LP estimator produces unbiased point estimates of the impulse response at each horizon, but the resulting IRF can appear jagged due to sampling variability across adjacent horizons. Following Jordà and Taylor (2025), the figures in this appendix apply a centred three-period moving average to the estimated coefficients and their confidence intervals. Formally, the smoothed estimate at horizon h is:

$$\widetilde{IRF}_{k,h} = \frac{1}{3}\left(\widehat{IRF}_{k,h-1} + \widehat{IRF}_{k,h} + \widehat{IRF}_{k,h+1}\right),$$

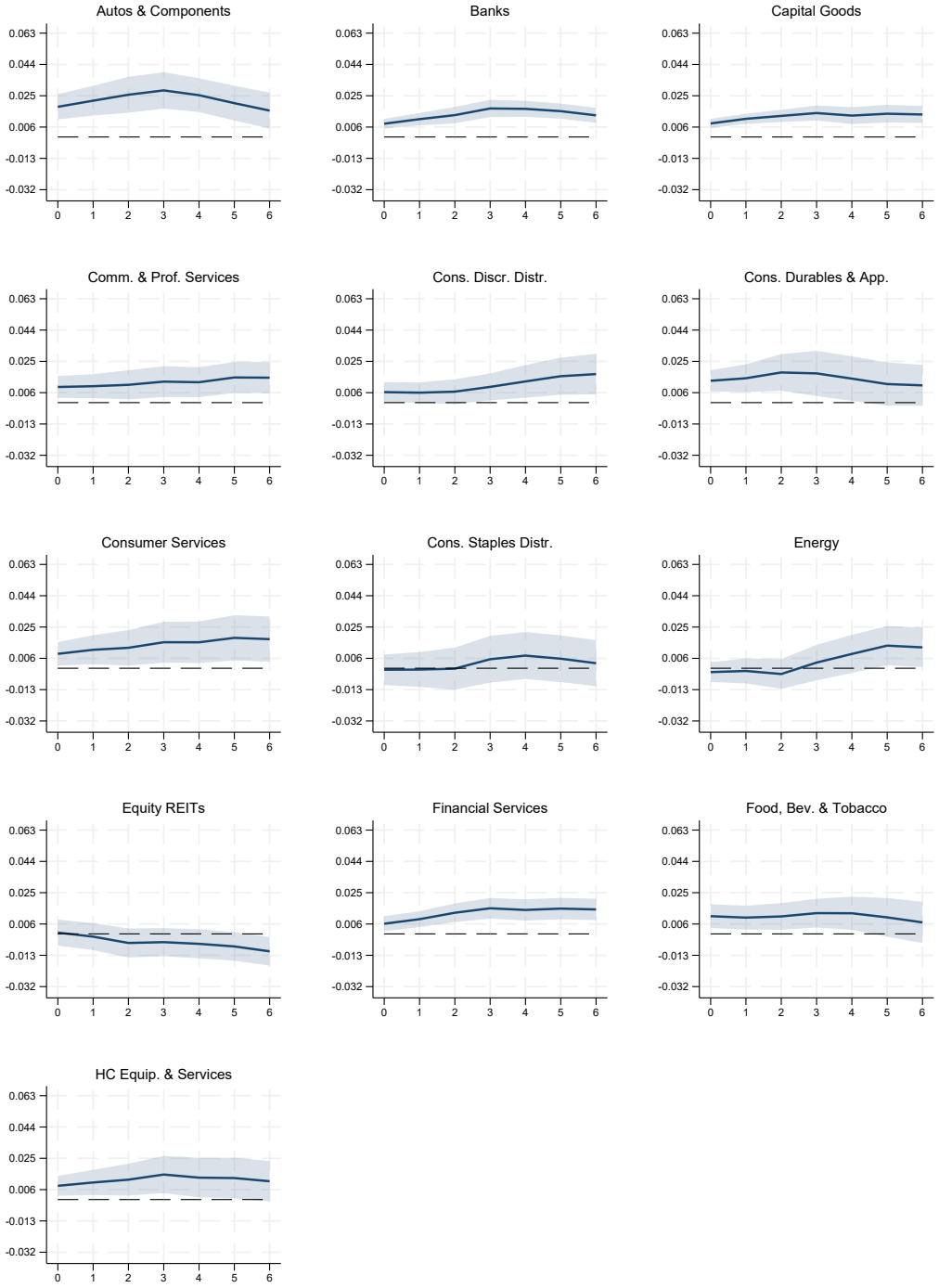
with boundary corrections at $h = 0$ and $h = 6$, where the average is taken over the two available adjacent horizons. The same smoothing is applied to the upper and lower bounds of the confidence intervals, so that the shaded bands represent the smoothed 95% confidence intervals. The smoothing reduces variance at the cost of a negligible bias if the true IRF is itself smooth, which is the expected property for a slowly-evolving credit risk variable. The unsmoothed estimates are reported in Tables 3 and 4.

IRF by GICS Sector: $\delta_{k,h}$



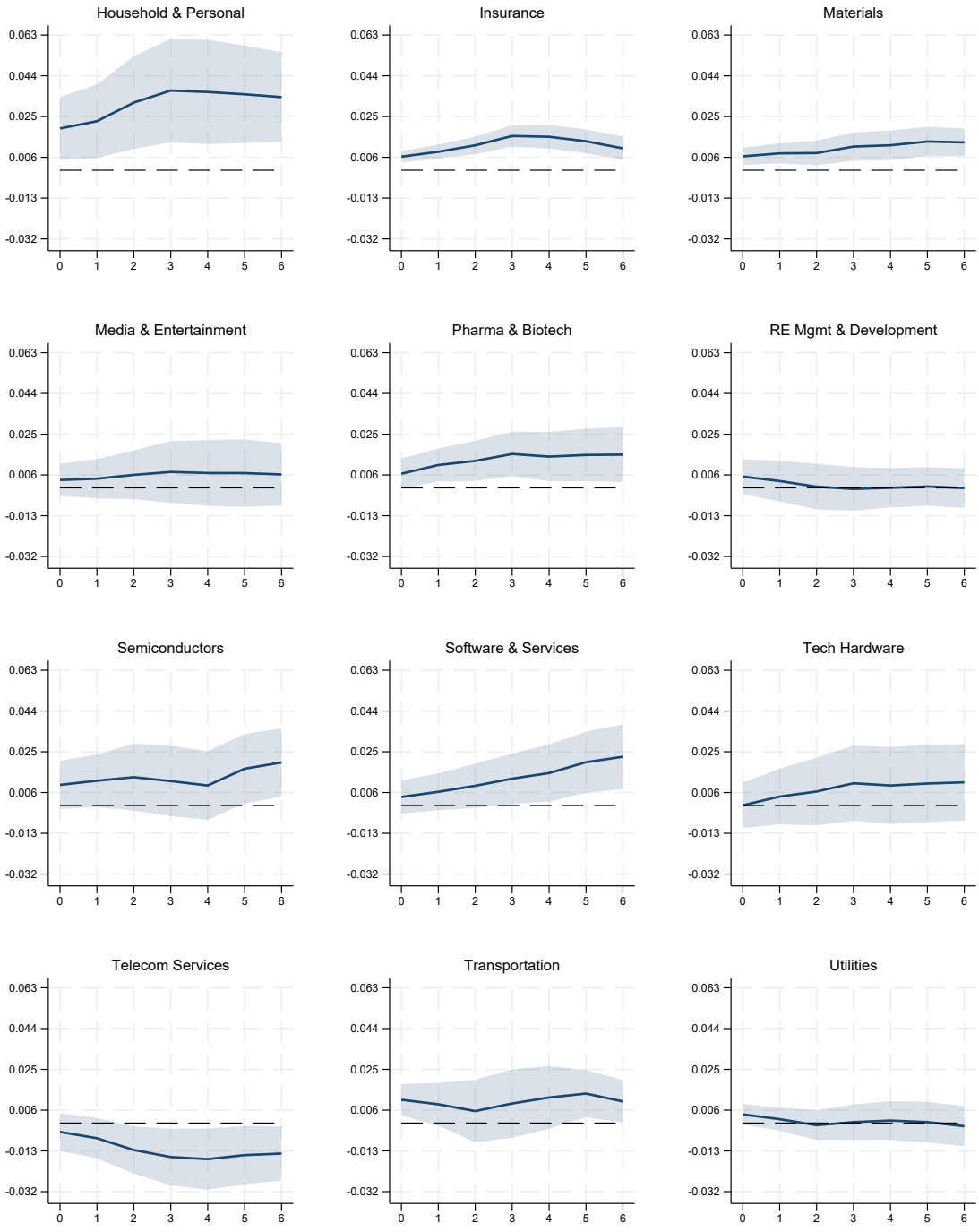
Smoothed IRF (3-period centred MA). Shaded areas: smoothed 95% CI.
Robust SE clustered at firm level.

IRF by Industry Group (1/2): $\delta_{k,h}$



Smoothed IRF (3-period centred MA). Shaded areas: smoothed 95% CI.
Robust SE clustered at firm level.

IRF by Industry Group (2/2): $\delta_{k,h}$



Smoothed IRF (3-period centred MA). Shaded areas: smoothed 95% CI.
Robust SE clustered at firm level.

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