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When War Hits Close: Did the Russian invasion of Ukraine affect French firms' ability to adjust their capital structure?

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Abstract: Empirical literature suggests firms gradually adjust their capital structure in an active pursuit of optimal leverage. This paper examines whether the Russian invasion of Ukraine disrupted this adjustment behavior. Using a sample of French listed firms, we conduct an event study to measure heterogeneous market reaction and assign firms to groups based on their cumulative abnormal return (CAR). We then estimate the speed of adjustment (SOA) towards target leverage for each group, following the Flannery and Rangan (2006) partial adjustment model. We find that the Russian invasion of Ukraine did not stop French firms from gradually adjusting towards their target leverage. However, descriptive evidence suggests the observed adjustment was driven by constrained financing options rather than active pursuit of optimal leverage. More precisely, firms most impacted by the shock experienced negative operating profitability, limiting their access to equity and thereby pushing them towards debt financing regardless of rebalancing intent.

Keywords: Capital structure; Speed of adjustment; Cumulative abnormal return; Trade-off theory; Geopolitical shock

Supervisor: Milda Tylaite

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1 Introduction

After the fall of the Soviet Union in 1991 the strained relationship between Europe and Russia began recovering. This was marked by the 1994 EU-Russia Partnership and Cooperation Agreement (European Union, 1997), as well as NATO cooperation frameworks like the Partnership for Peace (NATO, 1994) and the 1997 Founding Act (NATO, 1997). However, whether due to Vladimir Putin's official appointment as President of Russia in 2000 or as a result of NATO's expansion into former Soviet territory (NATO, 2024), tensions began to emerge once again. In Munich in 2007, Putin stated NATO's eastward expansion was a threat to Russian security (Putin, 2007). When NATO officials discussed the future membership of Georgia and Ukraine in Bucharest in 2008 (NATO, 2008), Russia decided it had endured enough. What followed was a series of Russian military operations, particularly the 16-day war in Georgia in August 2008 (EurasiaNet, 2009) and the annexation of Crimea in 2014 (Council of the European Union, 2025), which ultimately led to the full scale invasion of Ukraine on the 24th of February 2022 (NATO, 2022). It not only affected the geopolitical landscape in Europe, but also introduced economic uncertainty, with potential implications for firm behavior and capital structure decisions.

Academic literature exists which covers the heterogeneous impact of economy-wide policy shocks (Li and Qiu, 2020), but literature on the heterogeneous impact of geopolitical shocks and subsequent capital structure adjustments is limited. This study uses cumulative abnormal returns (CAR) to capture the heterogeneous impact of the shock, which reflects the market's perception of the shock's impact on firms (MacKinlay, 1997), explained further in Section 2.3.

To measure the subsequent capital structure adjustments, we follow Flannery and Rangan (2006), an extensive study on capital structure adjustments. Their paper is based on the dynamic trade-off theory, which states that each firm has an optimal target leverage, and that there are frictions which inhibit an immediate adjustment towards that target. These frictions lead firms to only close a fraction of the gap between actual and target leverage each year, which they measure as speed of adjustment (SOA). Their findings confirm the logic behind dynamic trade-off theory, with firms closing on average one-third of the gap each year.

Importantly, Flannery and Rangan (2006) have a long U.S. panel dataset covering the time-period 1965–2001, which both dilutes the effects of geopolitical shocks and looks at a time-period which doesn't cover the Russian invasion of Ukraine. As such, their findings don't cover how firms respond to sudden increases in geopolitical uncertainty, such as the Russian invasion of Ukraine. This study therefore aims to test the robustness of their findings by examining whether the underlying logic of dynamic trade-off theory continues to hold in the presence of a geopolitical shock. Accordingly, this study examines the following research question:

> *Did the Russian invasion of Ukraine affect firms' ability to adjust their capital structure?*

This question is answered by testing the following hypotheses:

> H_0: Firms adjust at the same speed whether they belong to the high CAR tercile or low CAR tercile
>
> H_1: Firms in the low CAR tercile exhibit a slower SOA than firms in the high CAR tercile

Our contribution to the literature is two-layered. First, we test if Flannery and Rangan's (2006) findings on SOA hold in the event of a geopolitical shock. Second, we relate to existing literature and theoretical frameworks to explain whether and why the SOA mechanism holds or breaks under such conditions. This allows us not only to assess whether the direction of SOA holds under pressure, but also explain the underlying mechanisms that either sustain its stability or cause its deviations.

In practice, we test this using data from France, a major European economy with an active role in NATO. We conduct an event study around the 24th of February 2022, estimating CARs for each firm. Matching these firms with their fundamentals data pulled from Compustat, we obtain a final working sample of 248 firms with data spanning the 2019–2023 period. These firms are split into terciles, with Group 1 representing the firms most negatively affected according to the market (most negative CAR), and Group 3 representing the firms least negatively impacted. We estimate leverage targets for each firm, then estimate the SOA of each group, and finally test whether the SOA differs between both groups.

We find no significant difference in the SOA between the groups. We fail to reject the null hypothesis. This reinforces the empirical results of Flannery and Rangan (2006), namely that firms actively adjust towards a target leverage even during times of uncertainty. However, descriptive evidence illustrates a marginally significant post-invasion divergence in leverage, driven by slower equity growth in the shocked group caused by a decline in operating profitability. We suggest that whilst the SOA coefficient persists during times of uncertainty, it likely reflects shocked firms' operational survival rather than deliberate pursuit of their target, the main finding of Flannery and Rangan (2006).

This paper is organized as follows. Section 2 reviews capital structure theories and literature on capital structure adjustments. Section 3 covers the construction of our sample, leverage measure, and model we use to estimate the speed of adjustment. Section 4 presents the findings of the regression and examines the equity and debt channels which might have impaired firms' ability to adjust, complemented by robustness checks of the regression. Section 5 interprets the main findings and discusses their theoretical implications. Section 6 presents a summary of contributions, followed by limitations and suggested further research.

2 Theory and Literature Review

2.1 Capital Structure Theory and the Speed of Adjustment (SOA)

The concept of an optimal capital structure originates from the fundamental propositions of Modigliani and Miller (1958). In the first version, Modigliani and Miller assume perfectly efficient markets. Under this assumption, they demonstrate that capital structure has no effect on firm value. In their second version, they relax the perfectly efficient market assumption by introducing the tax benefit of debt. Debt creates firm value through a tax shield, resulting in a positive relationship between leverage and firm value that argues for 100% debt financing. Although Modigliani and Miller contribute to the understanding of capital structure decisions, their propositions remain too limited to be applied in real-life scenarios.

The static trade-off theory builds on the second version of the Modigliani and Miller propositions by introducing the concept of financial distress costs (Myers, 1984). This change is reflected in the following equation:

$$V_L = V_U + PV(\text{Interest Tax Shield}) - PV(\text{Financial Distress Costs})$$

where V_L is the firm's value with leverage, and V_U is the value of the firm without leverage.

In contrast to the 1958 framework, trade-off theory assumes firms balance the interest tax shield against the financial distress costs arising from fixed payment claims. As a result, the theory implies that there is an optimal capital structure at which firm value is maximized. Beyond this point, financial distress costs outweigh the benefits of taking on more debt, resulting in a decline in firm value. Therefore, firms below their target leverage are incentivized to increase debt to fully utilize the interest tax shield, whilst firms above are incentivized to reduce leverage to reduce their financial distress costs.

Static trade-off theory assumes frictionless adjustments, meaning once the target leverage is known, firms will adjust towards the target immediately. The dynamic trade-off theory builds on static trade-off theory by keeping the underlying logic of there being an optimal firm-level leverage ratio, but introducing the concept of adjustment costs (Fischer et al., 1989). In essence, the dynamic trade-off theory suggests that firms are expected to gradually move towards their target at a certain SOA, rather than adjusting immediately.

Flannery and Rangan (2006) applied the dynamic trade-off framework to capital structure adjustments. They define the target leverage using industry norms and firm-characteristics identified in previous literature, commonly referred to as the determinants of capital structure (Rajan and Zingales, 1995; Hovakimian, 2003; Hovakimian et al., 2001; Fama and French, 2002). Using a partial adjustment model and a long U.S. panel dataset covering the time-period 1965–2001, they find that firms close 34% of the gap each year, supporting dynamic trade-off

theory. Further literature has applied the same model to different countries, with Öztekin and Flannery (2012) finding that French firms have an average SOA of 27.66%, using a French panel dataset from 1991 to 2006. Crucially, these findings reflect mean adjustment over a long period of time, meaning that capital structure adjustments during times of heightened uncertainty are absorbed.

2.2 Constraints of Capital Structure Adjustments

The gradual adjustments found in Flannery and Rangan (2006) reflect the presence of constraints which limit firms' ability to rebalance their capital structure. Their findings reveal that these constraints slow down the SOA rather than breaking it. The central question we cover is whether a geopolitical shock amplifies these constraints to the point of either slowing down the SOA further or breaking it down completely. The following section reviews how these constraints can influence firms' financing decisions following the Russian invasion of Ukraine, and, by extension, their impact on adjustment behavior.

An important constraint that affects capital structure decisions is explained by Baker and Wurgler (2002)who examine how market timing theory influences capital structure decisions. Using U.S. firm-level data, they find that firms tend to issue equity when their market valuation is high and repurchase equity when their valuation is low. Most notably, they find that firms' current leverage reflects their historical attempts to time the market. This has important implications for our setting. After the Russian invasion of Ukraine, firms may experience significant changes in their market valuations. According to market timing theory, firms with low (high) valuation are incentivized to repurchase (issue) equity. However, if firms more affected by the invasion experience a financial squeeze, they will be unwilling to issue equity due to the low valuation. This leads to increased reliance on debt financing, pushing book-debt-ratio (BDR) upwards, despite potentially moving further away from target leverage.

This logical order of events is supported by pecking order theory, which was articulated by Myers (1984). He considered three sources of financing available to firms in order of preference: internal funds, debt, and equity. The argument behind this hierarchy is the issue of adverse selection, that is, how each financing source signals information and is perceived by the market under conditions of asymmetric information. When firms issue equity, its firm value typically drops because rational investors perceive the issuance as a signal that management believes the firm is overvalued or financially weak (Berk and DeMarzo, 2023). If French firms experiencing negative abnormal returns around the invasion of Ukraine issue equity, it tells investors that their valuation reflects reality and not something temporary. As a result, in times of uncertainty, firms avoid issuing equity and prefer debt financing.

In essence, theory and prior literature suggest firms may be unable to adjust their capital structure towards a target leverage ratio during periods of uncertainty. Firms experiencing valuation declines from the shock will be unwilling to issue equity, pushing them toward debt financing. If

these firms also face a financial squeeze following the invasion, their reliance on debt financing is further reinforced. The amplification of these constraints from the Russian invasion of Ukraine therefore suggests firms more exposed to the shock may slow or break the SOA mechanism, as they are pushed to take on more debt regardless of their target leverage, going against the predictions of trade-off theory. In contrast, firms less exposed will align more with the logical argument presented by Flannery and Rangan (2006) due to sustained financial flexibility. These heterogeneous predictions form the basis for the hypothesis developed in section 2.4.

Though there exists numerous other behavioral theories of capital structure decisions, this paper primarily adopts a neoclassical perspective. This is complemented by market timing theory, which alongside trade-off theory and pecking order theory constitutes the three dominant frameworks in capital structure literature (Frank and Goyal, 2009). The neoclassical perspective is adopted for reasons of simplicity, as it allows us to interpret the complexities of reality, similar to previous literature such as Flannery and Rangan (2006). Where the market timing theory is applied, it is on the basis of objective financing costs implications rather than managerial biases.

2.3 Empirical Evidence on Market Reactions to Geopolitical Shocks

Bloom (2009) demonstrates how uncertainty spikes after major geopolitical shocks, drawing on data from the OPEC oil price shock and 9/11. He found that geopolitical shocks increase stock volatility by up to 200% and that they are correlated with cross-sectional shifts in firm and industry level earnings growth, output and employment. Since firm value is priced using present value of future earnings (Fama, 1970), the market prices these changes in expected output through stock price movements in the market.

Li and Qiu (2020) observe how economy-wide policy shocks impact firms differently according to their exposure to the shock. Their most important argument is that the same shock will generate different capital structure pressures depending on how exposed the firm is to the shock. In this thesis, we will capture the heterogeneous impact on French firms from the Russian invasion of Ukraine through an event study by measuring CARs around the invasion.

CAR reflects the market perception of a firm's total exposure to the shock, where a highly negative CAR can be attributed to direct exposure such as revenue stream, supply chain or manufacturing coming from Russia or Ukraine, or indirect exposure to broader macroeconomic and industry specific volatility. Fundamentally, a negative CAR signals that the market expects diminishing future cash flows. If this were to materialise, affected firms' earnings and equity value would decrease, increasing reliance on debt financing. The limited financing flexibility caused by the invasion would provide an explanation for deviations from the SOA findings of Flannery and Rangan (2006).

2.4 Hypotheses Development

Based on the logic discussed in the previous sections, this study expects that the Russian invasion of Ukraine amplified the adjustment frictions. To test if this geopolitical event significantly affected French firms' ability to adjust their capital structure, we test the following hypotheses:

> H_0: Firms adjust at the same speed whether they belong to the high CAR tercile or low CAR tercile
>
> H_1: Firms in the low CAR tercile exhibit a slower SOA than firms in the high CAR tercile

To further examine the results of the model, we complement the results with additional descriptive evidence on the adjustment channels.

3 Methodology

3.1 Sample Construction

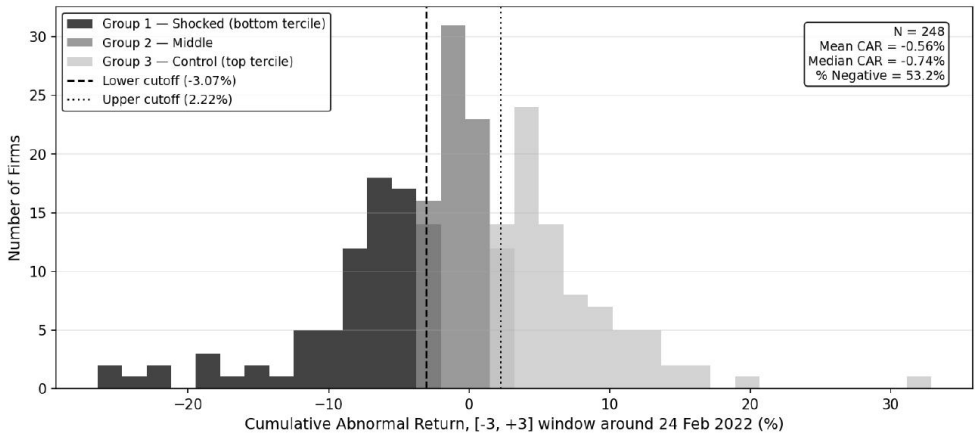
The empirical analysis is grounded in a sample of French companies listed on the stock exchange observed over the 2019–2023 period. This period is chosen to isolate as much as possible the impact of the invasion. First, an event study is carried out following the methodology of MacKinlay (1997) to calculate the CARs around the Russian invasion of Ukraine. Second, we construct a panel of accounting fundamentals for firms which have an assigned CAR, applying filters in accordance with Flannery and Rangan (2006). Third, the CAR and fundamentals are merged, retaining only the firms with valid data in both datasets. The final sample contains 248 French listed firms suitable for analysis.

Before calculating CARs, we apply the four data quality filters used by MacKinlay (1997): late IPO firms, i.e., without a large enough estimation window, are filtered out; non-trading firms during the event window are filtered out; those with more than 50 per cent of their daily returns at zero in the event window are removed, and finally firms with a market capitalisation beneath 100 million euros are removed. These filters narrow down the original sample of 864 firms to an event-study sample of 330 firms. Using the filtered sample, CAR is estimated in accordance with the standard market model proposed by MacKinlay (1997). The index used to estimate CAR, the CAC 40 index, represents the French market. Return parameters for each firm are estimated using OLS over a 250-trading-day estimation window up to 10 days before the event. These parameters are used to calculate the abnormal returns for each firm and then cumulated over a symmetrical seven-day event window of $[-3, +3]$ trading days around 24 February 2022.

The accounting fundamentals and market equity dataset, using Compustat Global for years 2019 to 2023, is used to create the final sample. Firms from the financial sector (GICS sector 40) and utilities sector (GICS sector 55) are excluded. In line with Flannery and Rangan (2006), such firms are subject to regulatory capital restrictions that cannot be compared to the non-financial corporations. The resulting dataset is combined with the CAR dataset using an inner merge, effectively removing 81 firms from the working sample due to them being filtered out or because they could not be matched across datasets. One additional firm is removed due to missing data for the book value of total assets in at least one year, leading to an undefined BDR.

The final working sample is made up of 248 firms that were observed in five fiscal years resulting in 1,218 firm-year observations. Following Flannery and Rangan (2006) and Frank and Goyal (2009), descriptive statistics are reported for the full sample, while the regression is estimated on the subset of firms with complete lagged observations. All variables are winsorised to the 1st and 99th percentile, as per Flannery and Rangan (2006).

Figure 1: Distribution of CARs and Tercile Group Assignment



Notes: The figure displays the distribution of cumulative abnormal returns (CARs) estimated over the [-3, +3] event window around 24 February 2022 for the final sample of 248 French listed firms. Firms are assigned to tercile groups based on the full-sample CAR distribution. The lower dashed vertical line indicates the upper bound of Group 1 (CAR $< -3.07\%$) and the upper dashed vertical line indicates the lower bound of Group 3 (CAR $\geq 2.22\%$).

The tercile group assignment is done once all filters are applied, and cutoffs are calculated on the final 248-firm sample. Group 1 (the shocked group) comprises the 83 firms in the bottom tercile, where CARs are less than -3.07% and this group represents the firms that had the worst market reaction to the invasion. Group 3 (the control group) includes the 83 firms in the top third, whose CARs are 2.22% or higher. The other 82 firms in the middle tercile constitute Group 2. This is a group-based design based on Byoun (2008) who encourages a comparison based on terciles instead of using a continuous treatment variable. Figure 1 demonstrates the tercile cuts and the distribution of CARs among the groups.

Table 1: Mean Determinants across CAR Groups, 2021

	G1 Mean	G1 Std	G2 Mean	G2 Std	G3 Mean	G3 Std	p-value (G1 vs G3)	Sig
BDR	0.2875	0.1715	0.3152	0.1694	0.2720	0.1678	0.5577	
MDR	0.3281	0.2335	0.3239	0.2419	0.2619	0.2325	0.0691	*
EBIT_TA	0.0297	0.1480	0.0234	0.1473	0.0314	0.1576	0.9446	
MB	1.4995	2.5376	2.1395	3.9295	2.2774	3.3463	0.0935	*
DEP_TA	0.0381	0.0274	0.0345	0.0295	0.0358	0.0271	0.5895	
LnTA	7.1804	2.0461	7.2538	2.2293	7.3631	1.9858	0.5602	
FA_TA	0.2120	0.1488	0.1818	0.1383	0.1813	0.1526	0.2061	
IND_Median	0.2883	0.0588	0.2901	0.0604	0.2569	0.0463	0.0002	***

Notes: The table reports mean firm characteristics for Group 1 (Shocked, bottom CAR tercile) and Group 3 (Control, top CAR tercile) in fiscal year 2021, the final pre-invasion year. p-values are from Welch's two-sided t-test comparing Group 1 and Group 3 means. BDR is total debt scaled by total assets. MDR is total debt scaled by total debt plus market equity. EBIT_TA is earnings before interest and taxes scaled by total assets. MB is the market-to-book ratio of assets. DEP_TA is depreciation scaled by total assets. LnTA is the natural logarithm of total assets. FA_TA is net PP&E scaled by total assets. IND_Median is the median BDR of all firms in the same GICS industry group. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

A treatment validation exercise compares the important firm characteristics of Group 1 and Group 3 in fiscal year 2021, the final pre-invasion year, using Welch's two sided t-test. The findings, as presented in Table 1, indicate that the two groups are generally similar in terms of their pre-invasion BDR ($p = 0.558$), profitability ($p = 0.945$), size ($p = 0.560$), asset tangibility ($p = 0.206$), and depreciation ($p = 0.590$). Two characteristics are significantly different: Group 1 firms have a mean industry-median leverage ($p = 0.001$) and a slightly lower market-to-book ratio ($p = 0.094$). The observed pre-invasion homogeneity in firm characteristics across both groups reveal that CAR does not capture variation driven by these characteristics. Rather, CAR captures firm's heterogeneous sensitivity to the shock, which is not explained by these characteristics, supporting the group-based identification strategy.

The main regression model accounts for the differences in market-to-book ratio (MB) and industry median (IND Median) by incorporating both variables as determinants of the unique leverage target for each firm. Instead of having a common target across all firms, the partial adjustment model estimates firm-specific targets as a function of firm characteristics, meaning the differences in MB and IND Median are reflected in each firm's target accordingly. This results in differences in SOA capturing how quickly each firm adjusts towards its own target. Importantly, the difference in these two firm characteristics does not give reason to invalidate the comparability of both groups.

3.2 Determinants of Capital Structure

Target leverage is modeled on both industry norms and firm-specific characteristics. These factors are generally referred to as the determinants of capital structure and are well established

in previous literature. Although there is a consensus among existing literature on the influence most determinants have on target leverage, a few of the determinants remain debatable (Frank and Goyal, 2009). For methodological consistency, we adopt the determinants employed by Flannery and Rangan (2006). This selection allows us to more accurately compare our findings against theirs. Thus, the expected influence between each determinant and target leverage is detailed as follows:

Profitability (EBIT / Total Assets): The most controversial of the determinants used by Flannery and Rangan (2006). Under static trade-off theory, more profitable firms face lower financial distress costs and therefore find the tax shield more valuable, indicating a positive relationship between profitability and leverage. In contrast, Myers (1984) pecking order theory implies a negative relationship between profitability and debt, as firms prefer internal funds over debt. Frank and Goyal (2009) find empirical evidence supporting the negative relationship implied by the pecking order theory.

Size (Log of Total Assets): Larger sized firms tend to exhibit greater diversification, transparency, and have stronger bargaining power with creditors. These factors collectively indicate low default risk. While pecking order theory suggests size has a negative relationship with debt by implying that mature firms have had more time to accumulate internal funds, Frank and Goyal (2009) find empirical evidence for a positive relationship. This aligns with trade-off theory, which suggests lower bankruptcy costs increases debt capacity.

Growth Opportunities (Market-to-Book Ratio of Assets): Higher MB, or growth stock, signals that the firm has valuable future opportunities, which firms tend to protect by taking on less debt. Frank and Goyal (2009) find empirical evidence supporting a negative relationship between growth and leverage.

Tangibility (Net PP&E / Total Assets): Firms with more tangible assets are easier to be valued than firms with a higher proportion of intangible assets, allowing them to put up collateral which lowers expected distress costs and increases debt capacity. Frank and Goyal (2009) find empirical evidence supporting a positive relationship between tangibility and leverage.

Depreciation (Depreciation / Total Assets): Depreciation is a non-debt tax shield, which offers a tax benefit that replaces the one from debt. High depreciation firms will have less incentive to engage in debt due to tax reasons and this means that there will be an inverse relationship between depreciation and leverage. Flannery and Rangan (2006) find empirical evidence supporting a negative relationship between depreciation and leverage.

Industry Median Leverage: Measures the median book debt ratio of all firms within the same industry. Firms tend to gravitate towards financing norms of other firms in the same industry, as they frequently share similar asset structures, business risk, and sensitivity to financial distress (Rajan and Zingales, 1995). Industry median controls for industry characteristics not captured by

the firm-characteristic variables. Hovakimian et al. (2001) find empirical evidence supporting a positive relationship between industry median and leverage.

3.3 The Flannery & Rangan (2006) Partial Adjustment Model

To evaluate whether the Russian invasion of Ukraine affected the ability of French firms to adjust their capital structure, an empirical model that estimates how fast firms can move towards a leverage target is appropriate. This allows a comparison of adjustment speeds across groups of firms with various shock exposures. For this purpose, the partial adjustment model of Flannery and Rangan (2006) is adopted.

The baseline is a simple observation: if adjustment is costless, firms would adjust towards their target immediately. In reality, this is not the case because of transaction costs, market conditions, and financing frictions which constrain adjustment and thus firms only close the gap between current and target leverage partially every year (Fischer et al., 1989). The rate at which they do so is the speed of adjustment (SOA), denoted λ. A λ of 0 means a firm does not adjust at all; a λ of 1 means a firm adjusts towards the target in a year. Previous literature has established λ should fall in between these two extremes.

The leverage target of each firm $BDR^*_{i,t}$ is not fixed; it varies across firms and over time as a function of the six determinants discussed in 3.2. Formally:

$$BDR^*_{i,t} = \boldsymbol{\beta}\mathbf{X}_{i,t-1} \tag{1}$$

where $\mathbf{X}$ is the vector of lagged firm determinants and $\boldsymbol{\beta}$ is the vector of coefficients to be estimated. Lagged values are used to avoid reverse causality, meaning the firm determinants in year $t-1$ predict the target in year t.

The partial adjustment model states that every year a firm closes a fraction, λ, of the gap between the actual leverage and the target:

$$BDR_{i,t} - BDR_{i,t-1} = \lambda(BDR^*_{i,t} - BDR_{i,t-1}) + \varepsilon_{i,t} \tag{2}$$

The left-hand side of the equation represents the firm's leverage change each year. The right-hand side indicates that change is a fraction λ of the gap that the firm would need to close to reach its target. Replacing the target leverage expression and rearranging the equation yields the reduced equation:

$$BDR_{i,t} = (\lambda\boldsymbol{\beta})\mathbf{X}_{i,t-1} + (1-\lambda)BDR_{i,t-1} + \varepsilon_{i,t} \tag{3}$$

This is the equation we estimate directly. The regression yields a coefficient on lagged BDR,

$(1-\lambda)$. A greater coefficient on lagged BDR means slower adjustment; a smaller coefficient means faster adjustment.

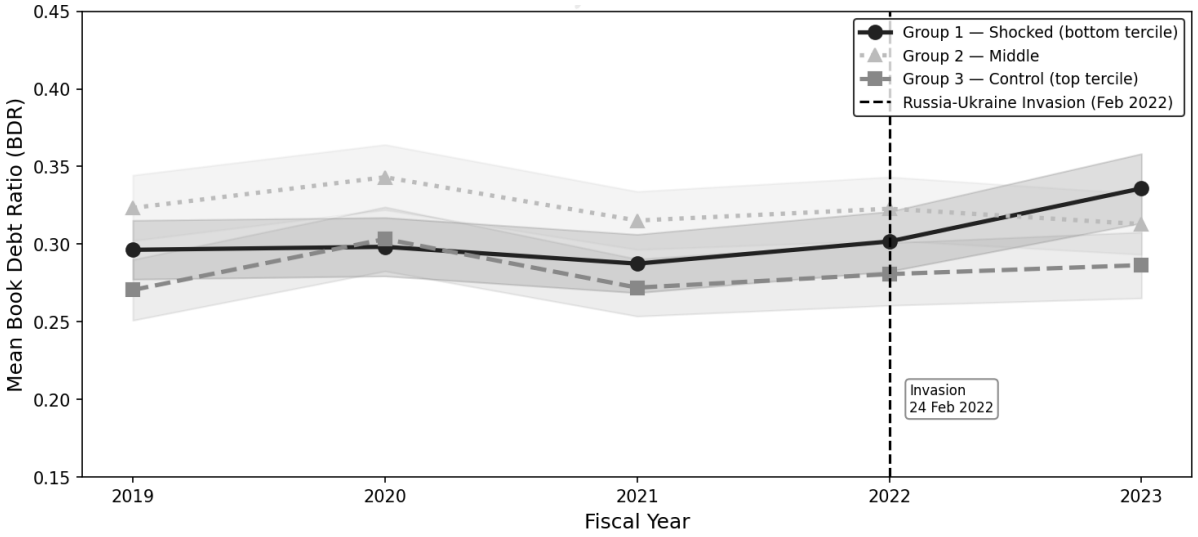
Following Flannery and Rangan (2006), the lagged market debt ratio ($MDR_{i,t-1}$) serves as an instrument for the lagged book debt ratio ($BDR_{i,t-1}$) in an IV regression. The market and book debt ratios are highly correlated as they measure the same underlying leverage with different denominators, satisfying the relevance condition. While MDR uses market equity that is influenced by market fluctuations, BDR is built on book values and remains isolated from market fluctuations. This means MDR does not determine book leverage, which satisfies the exclusion restriction. The first-stage F-statistics of 311.25 and 134.12 for Group 1 and Group 3 respectively confirm that lagged MDR is a strong instrument, exceeding the weak instrument threshold of $F > 10$ (Stock and Yogo, 2005) (see Table A1). The standard errors at the firm level are clustered to account for the serial correlation that arises from observing each firm over multiple consecutive years. All specifications include year fixed effects to absorb common macroeconomic patterns that all firms are affected by at the same time including the aggregate effects of the invasion itself.

The model is estimated on Group 1 (73 shocked firms, 275 firm-year observations), and Group 3 (76 control firms, 290 firm-year observations), after discarding the 2019 base year (lag construction). Relative to the 83 firms per tercile in the descriptive sample, 10 and 7 firms are excluded from Group 1 and 3 due to missing observations in one or more regression variables across all years. The null hypothesis is that the SOAs of the two groups are equal: $H_0 : \lambda_1 = \lambda_3$. We test this with a 2-sided z-test on the difference between the two estimated coefficients of λ, with the standard error of the difference being the square root of the sum of the squared standard errors of each estimate. Our findings, further discussed in the following section, show no significant difference in SOA between Group 1 and Group 3.

3.4 Descriptive Statistics

The descriptive statistics confirm both groups are comparable. The validation is done by demonstrating that Group 1 and Group 3 were similar prior to the invasion and that the tercile assignment reflects genuine cross-sectional variation from the invasion and not a sector-specific phenomenon.

Figure 2: Mean BDR by CAR Group, 2019–2023



Notes: The figure plots mean book debt ratio (BDR) for each CAR group over the 2019–2023 period. Shaded bands represent ±1 standard error around the group mean. The vertical dashed line marks the date of the Russian invasion of Ukraine (24 February 2022).

Figure 2 is a plot of the mean BDR of each CAR group between 2019 and 2023, with the ±1 standard error bands and the date of the invasion indicated by a vertical dashed line. Before the invasion, the three groups trace very similar paths with no single group tracing a systematically different path than the others. After the invasion, both groups experienced an increase in BDR, although Group 1 experienced a sharper increase than Group 3.

Table 2: Year-by-year Welch t-test on pre-invasion years for Groups 1 and 3

Year	G1 Mean BDR	G3 Mean BDR	Difference	p-value	Sig
2019	0.2964	0.2705	0.0259	0.3440	*n.s.*
2020	0.2983	0.3033	-0.0050	0.8576	*n.s.*
2021	0.2875	0.2720	0.0155	0.5577	*n.s.*

Notes: The table reports Welch's two-sided t-tests on mean BDR between Group 1 (Shocked) and Group 3 (Control) for each pre-invasion year separately. *n.s.* = not significant

Table 3: One-way ANOVA on Groups 1 and 3 in pre-invasion years

Statistic	Value
F-statistic	0.1863
p-value	0.6662
Significant?	No

Notes: The table reports a one-way ANOVA testing equality of mean BDR between Group 1 (Shocked) and Group 3 (Control) across the full pre-invasion period (2019–2021).

Table 2 presents the Welch t-tests of Group 1 and Group 3 BDR across each pre-invasion year. In no year is the difference statistically significant, with p-values of 0.344 in 2019, 0.858 in 2020, and 0.558 in 2021. The differences are economically insignificant, with a range of -0.005 to $+0.026$. Together with the one-way ANOVA in Table 3, limited to Group 1 and Group 3 over the entire pre-invasion period, which yields an F-statistic of 0.186 and a p-value of 0.666, these tests reveal that the two groups are not significantly different in terms of BDR before the invasion. This does not give us a reason to reject the parallel trends assumption and provides credibility for the group-based identification strategy.

Table 4: GICS Sector Composition by CAR Group

	Group 1 (Shocked, N=83)	**Group 2 (Middle, N=82)**	**Group 3 (Control, N=83)**
Industrials	16.9%	29.3%	20.5%
Cons. Discretionary	24.1%	18.3%	9.6%
Health Care	10.8%	8.5%	21.7%
Info. Technology	7.2%	8.5%	21.7%
Real Estate	10.8%	12.2%	3.6%
Comm. Services	9.6%	9.8%	6.0%
Materials	7.2%	6.1%	7.2%
Cons. Staples	10.8%	6.1%	2.4%
Energy	2.4%	1.2%	7.2%

Notes: The table reports the share of firms from each GICS sector within each CAR group. Financial sector (GICS 40) and utilities sector (GICS 55) firms are excluded from the sample in line with Flannery and Rangan (2006).

Table 4 shows the GICS sector composition of each group. No single sector dominates in any of the studied groups, with the largest share of 24.1% (Consumer Discretionary in Group 1) confirming the tercile split is not the result of sector-specific dynamics. Group 1 is more concentrated in Consumer Discretionary (24.1%), traditionally highly sensitive to consumer confidence, consistent with these firms having more negative market responses to a macroeconomic shock. Group 3 is more concentrated in Healthcare (21.7%) and Information Technology (21.7%), traditionally less leverage-intensive sectors that have more defensive earnings characteristics, consistent with the lower industry median BDR recorded in Table 2. Industrials, the largest sector in the sample, is represented similarly in both groups, proving industrials do not drive the cross-group differences. In general, Table 4 supports the validity of the CAR-based tercile design: the group assignment captures real variation in market-perceived exposure to the shock as opposed to reflecting the leverage norms of specific industries.

4 Empirical Results and Adjustment Mechanisms

4.1 Results of the Regression

The results of the partial adjustment model of Flannery and Rangan (2006) were estimated separately for Group 1 and Group 3, followed by a formal test of the difference in the SOA between the two groups. Notably, due to the lag construction, Group 1 consists of 73 firms (275 observations) and Group 3 contains 76 firms (290 observations) suitable for the regression.

Table 5a: Group 1 (Shocked) Results

	Group 1 (Shocked)
λ (Speed of Adjustment)	0.1304
SE (λ)	(0.0844)
N observations	275
N firms	73
Coeff on lagged BDR $(1-\lambda)$	0.8696
EBIT/TA (lagged)	-0.2501^{***}
	(0.0876)
Market-to-Book (lagged)	-0.0005
	(0.0015)
Depreciation/TA (lagged)	0.2206
	(0.3296)
Log Total Assets (lagged)	0.0037
	(0.0047)
Tangibility (lagged)	-0.0018
	(0.0539)
Industry Median BDR (lagged)	-0.0156
	(0.2021)

Notes: The table reports IV estimates of the Flannery and Rangan (2006) partial adjustment model for Group 1 (Shocked, bottom CAR tercile), comprising 73 firms and 275 firm-year observations. The lagged market debt ratio (MDR) instruments for the lagged book debt ratio (BDR). The speed of adjustment λ is recovered as one minus the coefficient on lagged BDR. Standard errors are clustered at the firm level and reported in parentheses. All specifications include year fixed effects. The 2019 base year is excluded due to lag construction. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5a presents the regression results of the 73 firms in the bottom CAR tercile. The SOA of Group 1 is estimated at 0.1304, that is, the shocked firms close an estimated 13% of the gap between their actual and target BDR annually. The small time dimension ($T = 4$) should be taken into account when interpreting these results, as some studies suggest the IV estimator could be subject to downward bias in short panels (Nickell, 1981). Of the determinants of target

leverage, profitability (EBIT/TA) alone is statistically significant, with a coefficient of -0.2501 ($p < 0.01$), aligning with the pecking order prediction that profitability and debt are negatively related. None of the other determinants attain statistical significance.

Table 5b: Group 3 (Control) Results

	Group 3 (Control)
λ (Speed of Adjustment)	0.1800
SE (λ)	(0.0494)
N observations	290
N firms	76
Coeff on lagged BDR $(1-\lambda)$	0.8200
EBIT/TA (lagged)	-0.1386^{***}
	(0.0444)
Market-to-Book (lagged)	0.0007
	(0.0014)
Depreciation/TA (lagged)	0.2863
	(0.2476)
Log Total Assets (lagged)	-0.0017
	(0.0022)
Tangibility (lagged)	0.0753^{**}
	(0.0368)
Industry Median BDR (lagged)	-0.0277
	(0.0943)

Notes: The table reports IV estimates of the Flannery and Rangan (2006) partial adjustment model for Group 3 (Control, top CAR tercile), comprising 76 firms and 290 firm-year observations. The lagged market debt ratio (MDR) instruments for the lagged book debt ratio (BDR). The speed of adjustment λ is recovered as one minus the coefficient on lagged BDR. Standard errors are clustered at the firm level and reported in parentheses. All specifications include year fixed effects. The 2019 base year is excluded due to lag construction. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The regression findings for the 76 companies in Group 3 are reported in Table 5b. The estimated SOA is $\lambda = 0.1800$, indicating control firms close 18% of the distance between the target and actual BDR annually. Two determinants are significant: profitability (EBIT/TA) has a coefficient of -0.1386 ($p < 0.01$), again consistent with the prediction of pecking order theory that firms with higher earnings require less debt; and tangibility has a coefficient of 0.0753 ($p < 0.05$), consistent with the prediction of trade-off theory that firms with higher asset collateral support higher leverage targets.

Table 5c: Z-test on difference between Group 1 and Group 3 SOAs

	Estimate
λ Group 1 (Shocked)	0.1304
SE (λ Group 1)	(0.0844)
λ Group 3 (Control)	0.1800
SE (λ Group 3)	(0.0494)
Difference $(\lambda_1 - \lambda_3)$	-0.0496
SE (Difference)	(0.0978)
z-statistic	-0.5068
p-value (two-sided)	0.6123 *n.s.*
Null hypothesis	Cannot reject H_0: $\lambda_1 = \lambda_3$

Notes: The table reports a two-sided z-test on the difference in speed of adjustment (SOA) between Group 1 (Shocked) and Group 3 (Control), based on the IV estimates in Tables 5a and 5b. The standard error of the difference is computed as the square root of the sum of the squared standard errors of each group's λ estimate. *n.s.* denotes not significant.

Table 5c provides the formal two-sided z-test comparing the SOA between Group 1 and Group 3. The difference is equal to -0.0496, meaning shocked firms adjust towards their target leverage slower than control firms. However, the standard error is 0.0978, which is approximately twice the size of the difference itself and yields a z-statistic of -0.507 and a p-value of 0.612. We cannot reject the null hypothesis.

The result is contrary to the predictions in Section 2. The result is particularly noteworthy considering the observed visual post-invasion BDR divergence illustrated in Figure 2, an inconsistency that warrants further attention. Therefore, to clarify the mechanisms behind the result, Section 4.3 examines the debt and equity channels, preceded by a series of robustness tests.

4.2 Robustness

The following robustness tests verify that the results yielded by the model, specifically the failure to reject the null hypothesis, is not driven by the modelling choices made throughout the paper. Three distinct tests are conducted. First, an interaction specification is employed to test for the difference in SOA between groups within a single regression using a pooled sample of firms. Second, firms are divided into quartiles instead of terciles. Third, the SOA is estimated using OLS instead of IV. Across each test, the null hypothesis cannot be rejected, reinforcing the robustness of the findings in Section 4.1.

*Table 6: Interaction Specification (*BDR $\times$ SHOCKED*)*

	Estimate
N observations $(G1+G3)$	565
N firms $(G1+G3)$	149
λ Group 3 (Control)	0.1603
λ Group 1 (Shocked)	0.1219
Interaction coeff (γ)	0.0384
SE (γ)	(0.0513)
p-value (γ)	0.4539 *n.s.*
Difference $(\lambda_{G3}-\lambda_{G1})$	-0.0384

Notes: The table reports IV estimates from a pooled regression of Group 1 and Group 3 firms (149 firms, 565 firm-year observations) augmented with a SHOCKED $\times$ BDR interaction term. Rather than estimating through split-sample regressions, this specification assesses whether the coefficient on lagged BDR differs significantly between groups within a single model. The interaction coefficient γ captures the differential speed of adjustment, where a positive γ indicates that shocked firms adjust more slowly than control firms. Standard errors are clustered at the firm level. All specifications include year fixed effects. *n.s.* denotes not significant.

An additional test for the difference in SOA is conducted by extending the sample by pooling Group 1 and Group 3 firms into a single regression using the interaction term $SHOCKED \times BDR_{i,t}$. Rather than estimating through split-sample regressions, this specification assesses whether the coefficient on lagged BDR is significantly different between groups in a single model, where the interaction coefficient γ captures SOA. A negative γ indicates that shocked firms adjust faster than control firms, whereas a positive γ indicates the opposite.

The interaction specification in Table 6 uses a sample of 149 firms and 565 firm-year observations. The result yield $\gamma = 0.0384$ with a standard error of 0.0513 and a p-value of 0.454. Whilst the SOA for Group 1 (0.1219) and Group 3 (0.1603) remain directionally consistent with our split-sample estimates, the difference remains statistically insignificant. Thus, the null hypothesis cannot be rejected.

Table 7: Quartile-split (Group 1 and Group 4)

	Q1 (Most Negative)	**Q4 (Highest CAR)**
λ (SOA)	0.1707	0.1845
SE (λ)	(0.1058)	(0.0616)
Coeff on lagged BDR $(1-\lambda)$	0.8293	0.8155
N observations	204	208
N firms	54	55
CAR cutoff	CAR $< -4.18\%$	CAR $> 4.04\%$
Difference $(\lambda_{Q1} - \lambda_{Q4})$	-0.0138	
SE (Difference)	(0.1225)	
z-statistic	-0.1129	
p-value (two-sided)	0.9101 *n.s.*	

Notes: The table reports IV estimates for a quartile-based robustness check, where Q1 (CAR $< -4.18\%$, 54 firms) and Q4 (CAR $> 4.04\%$, 55 firms) replace the tercile-based Groups 1 and 3. The difference in SOA is tested using a two-sided z-test, where the standard error of the difference is computed as the square root of the sum of the squared standard errors of each group's λ estimate. Standard errors are clustered at the firm level. All specifications include year fixed effects. *n.s.* denotes not significant.

This paper divides the sample into terciles based on their CAR distribution. To test whether the null result is sensitive to this specific threshold, Table 7 divides firms into quartiles and their SOA is compared. Consequently, Group 1 and Group 4 are made up of 54 and 55 firms respectively. The estimation yields a SOA of 0.1707 for Group 1 and a SOA of 0.1845 for Group 4, with a standard error of 0.1225 and a p-value of 0.910. The null hypothesis cannot be rejected under this new grouping method, confirming the main result is not driven by the tercile grouping.

Table 8: OLS regression instead of IV

	Group 1 (Shocked)	**Group 3 (Control)**
λ (SOA)	0.1244	0.1509
SE (λ)	(0.0564)	(0.0332)
Coeff on lagged BDR $(1-\lambda)$	0.8756	0.8491
N observations	275	290
N firms	73	76
Difference $(\lambda_{G1} - \lambda_{G3})$	-0.0265	
SE (Difference)	(0.0655)	
z-statistic	-0.4053	
p-value (two-sided)	0.6853 *n.s.*	

Notes: The table reports OLS estimates of the partial adjustment model for Group 1 (Shocked, 73 firms, 275 observations) and Group 3 (Control, 76 firms, 290 observations), treating lagged BDR as exogenous. This specification is included as a robustness check on the main IV model to verify that the choice of instrument does not drive the null result. The difference in SOA is tested using a two-sided z-test, where the standard error of the difference is computed as the square root of the sum of the squared standard errors of each group's λ estimate. Standard errors are clustered at the firm level. All specifications include year fixed effects. *n.s.* denotes not significant.

The main model uses an IV with lagged MDR instrumenting for the BDR. To verify that the null result is not driven by the choice of instrument, Table 8 re-estimates the model using OLS, treating lagged BDR as exogenous. While OLS introduces a new set of potential biases, it is a standard robustness check to ensure the instrumenting of lagged BDR is not affecting the result of the model (Flannery and Rangan, 2006). Under the OLS specification, the SOA is 0.1244 for Group 1 and 0.1509 for Group 3, where both estimates are lower than the IV estimates. With a standard error of 0.0655 and p-value of 0.685, the null hypothesis cannot be rejected, confirming the result of the main model is robust to the choice of estimator.

4.3 The Adjustment Mechanism

Whilst the two year post-invasion period limits the statistical power of a regression, conducting additional descriptive statistics on BDR and its components enables a deeper understanding of the visual divergence observed in Figure 2.

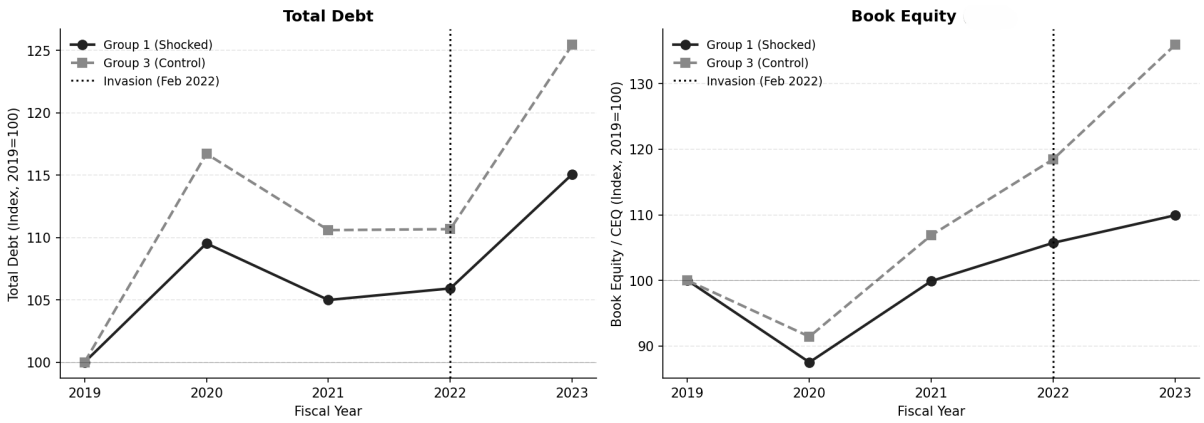
Table 9: Pre and post-invasion mean BDR level across groups

	Group 1 (Shocked)	**Group 3 (Control)**	**Difference**	**p-value**	**Sig.**
Pre-invasion mean (2019–2021)	0.2940	0.2820	0.0121	0.4415	n.s.
Post-invasion mean (2022–2023)	0.3181	0.2835	0.0346	0.0958	*
Change (post − pre)	0.0199	0.0026	0.0173		
N firms	83	83			

Notes: The table reports mean BDR for Group 1 (Shocked) and Group 3 (Control) across the pre-invasion (2019–2021) and post-invasion (2022–2023) periods, along with the cross-group difference. The p-value for the pre and post-invasion differences is from a Welch's two-sided t-test comparing group means. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. *n.s.* denotes not significant.

Table 9 displays the difference in pre and post-invasion mean BDR between Group 1 and Group 3. As discussed in Section 3.4, the pre-invasion difference of 0.0121 is insignificant ($p = 0.442$), supporting the comparison of both groups. In contrast, the post-invasion difference of 0.035 is marginally significant ($p = 0.096$), supporting the visual interpretation of Figure 2. To further examine this divergence in BDR, the following figures compare the variation in the two main components of BDR, debt and book equity, between both groups for the 2019–2023 period.

Figure 3: Debt and Book Equity by CAR Group between 2019 and 2023



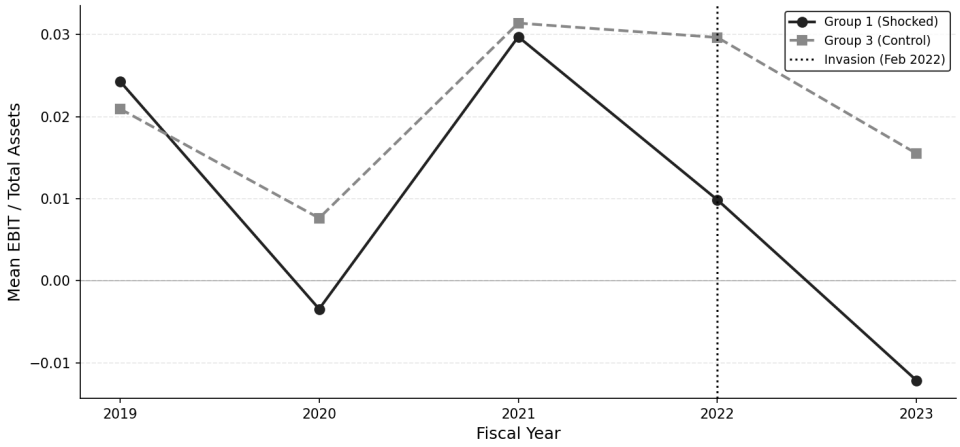
Notes: The figure plots indexed total debt (left panel) and book equity (right panel) for Group 1 (Shocked) and Group 3 (Control) over the 2019–2023 period, with 2019 = 100. The vertical dashed line marks the date of the Russian invasion of Ukraine (24 February 2022).

Figure 3 is a plot of debt and book equity over the 2019–2023 period. Both measures are indexed to 100 in 2019. The left panel plotting total debt shows both groups follow a similar path throughout the period. However, the right panel plotting book equity shows paths diverge after the invasion, where Group 3 firms steadily grow their equity to over 130, as opposed to Group 1 only reaching 111 over the same period.

According to Figure 3, book equity is the main driver of the BDR divergence. Diving deeper

into why equity accumulated slower for Group 1, we chose to study the impact of the invasion on profitability. An initial attempt using $ROE = Net\ Income/Book\ Equity$ proved too noisy to reliably distinguish the effects of the invasion. Therefore, following Flannery and Rangan (2006), we use $EBIT/TA$ to measure profitability.

Figure 4: Operating Profitability (EBIT/TA) by CAR Group, 2019–2023



Notes: The figure plots mean operating profitability, measured as earnings before interest and taxes scaled by total assets (EBIT/TA), for Group 1 (Shocked) and Group 3 (Control) over the 2019–2023 period. The vertical dashed line marks the date of the Russian invasion of Ukraine (24 February 2022).

Figure 4 reports the operating profitability for both groups between 2019 and 2023. Group 3 exhibits a slight decrease in profitability, although it remains above 1%. On the contrary, Group 1 firms experience a sharp decline in profitability, dropping below -1% in 2023. Both groups had similar levels of operational profitability in 2021 around 3%.

5 Discussion

5.1 Interpreting the Main Findings

The empirical results reveal no statistically significant difference in the SOA between firms with highly negative CAR and those with less severe market reactions. Therefore, we fail to reject the null hypothesis. The persistence of an economically meaningful SOA across both groups reinforces the robustness of the empirical findings by Flannery and Rangan (2006), indicating that the trade-off mechanism remains functional even amidst periods of geopolitical uncertainty. This observation aligns with Graham (2000), who suggests that firms are generally underleveraged. Therefore, the SOA likely reflects firms utilizing their inherent debt capacity buffer to finance their operations during periods of heightened uncertainty.

The lack of a significant difference in SOA between the groups is interesting given the BDR divergence following the invasion, as shown in Figure 2. While the two-year post-invasion period limits the statistical power of a regression, the descriptive evidence in Table 9 confirms that the post-invasion difference in BDR between the two groups is marginally significant. A decomposition analysis of the BDR in Figure 3 illustrates that the divergence is not driven by debt, as both firms increase debt at similar rates, but rather by a slower book equity growth for the shocked group.

Figure 4 provides an additional explanation, as it illustrates that the shocked group experienced a severe decline in operating profitability, going into the negatives in 2023. This suggests that the CAR grouping did not merely reflect market sentiment, but accurately predicted the impairment of future operational value creation. Negative operating profit means the firm failed to generate internal funds, which directly eroded book equity, supporting the divergence in BDR.

5.2 Theoretical Implications

The descriptive evidence in Section 4.3 is explained by the neoclassical perspective we adopted throughout the paper. While both groups increase their debt levels, the underlying motives diverge. The control group can take on more debt because greater profitability enables firms to benefit more from the tax shield without incurring excessive financial distress (Fischer et al., 1989). In contrast, the shocked group's debt increase reflects forced adjustments due to a lack of viable financing alternatives.

Negative operating profitability reduces internal funds, which according to pecking order theory (Myers, 1984) means firms' best alternative is to finance their operations with debt, given the adverse signaling costs of issuing equity. Market timing theory (Baker and Wurgler, 2002) reinforces the reluctance to issue equity, as weak operating profitability following the invasion amplifies the adverse signaling costs. Although trade-off theory (Fischer et al., 1989) strongly incentivizes reducing leverage to decrease bankruptcy risk during a financial squeeze, Figure 3 suggests that the adjustment costs, specifically the adverse signaling costs of equity issuance,

outweigh the distress costs of additional debt.

6 Conclusion

6.1 Summary of Contributions

Our empirical analysis does not invalidate Flannery and Rangan's (2006) findings, but rather questions whether firms deliberately move towards their target during times of uncertainty. While both groups exhibit statistically indistinguishable and economically meaningful SOA, we show that the Russian invasion of Ukraine constrained the shocked firms' financing flexibility more than the control group. Amidst negative operating profitability, shocked firms continued to accumulate debt to maintain their operations while equity growth slowed, moving leverage upwards regardless of any rebalancing intent. Therefore, we contribute by showing that although the SOA coefficient persists, it likely reflects shocked firms' operational survival rather than deliberately pursuing their target.

6.2 Limitations

The primary limitation of this study is the inability to directly observe firm-level targets. Although the partial adjustment model estimates targets for each firm every year, only the SOA coefficient is observable. Consequently, the adjustment could either reflect firms actively moving towards their target, or firms' own target being pulled closer to their actual leverage. This is particularly relevant for the analysis of the shocked group, whose declining profitability lowered the target leverage in the model, potentially narrowing (widening) the gap for underlevered (overlevered) firms. Flannery and Rangan (2006) acknowledge this limitation in their paper as well. As such, it should be kept in mind when interpreting the results, and constitutes our main suggestion for further research.

A further limitation of this study is the short panel length of $T = 4$. With only four observations per firm after lag construction, the IV estimator struggles to accurately identify the difference in SOA between groups, with standard errors reaching almost twice the size of the observed difference in the z-test *(Table 5c)*. Furthermore, the estimated SOA values of 13% and 18% are notably lower than the 27.66% reported for French firms by Öztekin and Flannery (2012), who use a panel with $T = 16$ periods and 661 French firms. The null result found in Section 4.1 should be interpreted accordingly, as the lack of a statistically significant difference between both groups does not necessarily mean there is no real difference.

Finally, firm fixed effects are omitted throughout the regression. Firm fixed effects capture the time-invariant heterogeneity in leverage targets across firms, and including them is shown to meaningfully affect the SOA estimates (Flannery and Rangan, 2006). An attempt at including firm fixed effects yielded an unrealistic SOA coefficient above 70% (see Table A2), meaning they absorbed nearly all within-variation. Their omission means that time-invariant firm characteristics may bias the estimated SOA, and the results should be interpreted accordingly. However, the model partially accounts for time-invariant variation. Lagged BDR bases each firm's estimate

on its leverage ratio in the previous year. This means a firm which is already highly leveraged will have a high lagged BDR for each period, and the model will account for this by focusing on year-on-year variation rather than absolute levels.

6.3 Suggestions for Future Research

A natural extension of this study would be to examine how geopolitical shocks affect leverage targets rather than focusing solely on the speed of adjustment toward them. As discussed in the limitations, the partial adjustment model does not differentiate between firms actively pursuing a leverage target and targets shifting in response to the shock. Future research could estimate targets separately for pre and post-invasion periods, allowing the model to determine whether the invasion caused a shift in optimal leverage. This approach would need a longer post-invasion window to reliably estimate the determinants used in the calculation of the target, a condition that will be met naturally as time passes and more observations become available.

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Appendix

Table A1: First-Stage IV Diagnostics

	Group 1 (Shocked)	**Group 3 (Control)**
N observations	275	290
First-stage F-statistic	311.25	134.12
p-value	0.000	0.000
First-stage R^2	0.688	0.657
Weak instrument threshold ($F > 10$)	Satisfied	

Notes: The first stage regresses the endogenous variable (lagged BDR) on the instrument (lagged MDR), the six lagged determinants of capital structure, and year fixed effects using OLS. The F-statistic tests the null hypothesis that the coefficient on lagged MDR is zero, i.e., that the instrument is irrelevant.

Table A2: IV estimation with firm fixed effects

	Group 1 (Shocked)	**Group 3 (Control)**
λ (SOA)	0.7277	0.7525
SE (λ)	(0.2125)	(0.1004)
Coeff on lagged BDR $(1-\lambda)$	0.2723	0.2475
N observations	275	290
N firms	73	76
Difference $(\lambda_{G1} - \lambda_{G3})$	-0.0248	
SE (Difference)	(0.2350)	
z-statistic	-0.1055	
p-value (two-sided)	0.9160 *n.s.*	

Notes: The table reports IV estimates of the Flannery and Rangan (2006) partial adjustment model using firm fixed effects for Group 1 (shocked, bottom CAR tercile) and Group 3 (control, top CAR tercile). The lagged market debt ratio (MDR) instruments for the lagged book debt ratio (BDR). The speed of adjustment λ is recovered as one minus the coefficient on lagged BDR. Standard errors are clustered at the firm level. All specifications include year fixed effects. The difference in SOA is tested using a two-sided z-test, where the standard error of the difference is computed as the square root of the sum of the squared standard errors of each group's λ estimate. *n.s.* denotes not significant.

Generative AI Disclosure

In accordance with SSE guidelines, the following AI tool was used during the writing of this thesis. All AI-generated content was reviewed, verified and remains the responsibility of the authors.

- **Claude** (Anthropic, 2025): Used for Python coding assistance and LaTeX formatting.