Corporate Responses to Perceived Stakeholder Signals

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Abstract

We study how firms interpret signals about consumer sentiment when their political or geopolitical actions become publicly salient. Using data on multinational firms' responses to the 2022 invasion of Ukraine and high-frequency consumer spending data for U.S. retail locations, we find limited evidence of broad-based changes in consumer demand following public scrutiny of firms operating in Russia. Nevertheless, firms respond to short-run fluctuations in their own sales, even when these movements largely reflect idiosyncratic variation rather than systematic demand shifts. Financial markets provide a complementary, forward-looking signal: abnormal returns tied to firms' own actions predict subsequent exit decisions. These findings suggest that firms rely on multiple, imperfect signals when evaluating stakeholder reactions, placing disproportionate weight on noisy demand fluctuations while also incorporating market feedback tied to their own actions in a politically charged environment.

Keywords: Corporate exit, economic sanctions, consumer boycotts, multinational firms, Russia–Ukraine war, reputational risk, firm behavior, SafeGraph mobility data

JEL Classification: D22, F23, F51, D12

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1 Introduction

Corporate engagement in political and social issues has become increasingly common. Firms frequently take public positions on contentious topics, ranging from regulatory debates to broader social movements through public statements, advocacy campaigns, or other symbolic actions. While such stance-taking may help firms appeal to particular consumer segments or align with the expectations of their stakeholders, it also exposes them to potential consumer backlash (Bhagwat et al. 2020) and various forms of "private sanctions" imposed by consumers or investors whose political preferences conflict with corporate behavior (Hart, Thesmar and Zingales 2024). Once firms publicly signal political or social commitments, consumers may come to expect consistency between those commitments and corporate behavior. As a result, both the positions themselves and perceived deviations from them may provoke demand responses from consumers whose views differ.

For firms that take such positions, an important question is how consumers respond. More broadly, firms must interpret imperfect signals about stakeholder reactions in environments where reputational or political pressure increases the salience of those signals, despite limited information about how they map into underlying demand or long-run consequences. Firms may observe public reactions through channels such as social media discourse or media coverage, but these signals can be difficult to interpret as indicators of actual consumer behavior (Chatterji and Toffel 2019). Public criticism or praise may reflect expressive or reputational incentives rather than genuine changes in purchasing decisions (Bénabou and Tirole 2011), and highly visible online backlash may be driven by a vocal subset of consumers whose behavior does not represent broader demand (Barberá and Rivero 2015). Consumer spending therefore provides a more direct measure of consumer response. Yet interpreting such signals is also challenging. Short-run movements in sales often reflect many factors unrelated to political behavior, including local economic conditions, seasonality, and routine fluctuations in consumer purchasing patterns. Because firms primarily observe their own sales rather than the broader aggregate consumer response, they face a signal-extraction problem when interpreting consumer demand, making it difficult to distinguish meaningful ideological reactions from ordinary demand fluctuations.

To study how firms interpret such signals in practice, when their political or geopolitical exposure becomes publicly salient, we examine U.S. consumer reaction to multinational firms' announcements regarding their operations in Russia following the February 2022 invasion of Ukraine. We link two data sources capturing firms' geopolitical actions and the consumer

demand they face. The first is the Kyiv School of Economics (KSE) Institute's weekly database tracking multinational corporations' decisions to exit the Russian market (Kyiv School of Economics 2022). The second consists of high frequency consumer spending data for U.S. retail locations from the SafeGraph Spend dataset (SafeGraph 2025), which allows us to track firm-level consumer demand responses over time.

We begin by examining whether consumers adjust their spending following the public release of the so-called Yale list (Yale Chief Executive Leadership Institute 2022, Sonnenfeld et al. 2022), which identified multinational firms continuing to operate in Russia following the invasion of Ukraine and intensified public scrutiny of corporate geopolitical exposure (Hart, Thesmar and Zingales 2024).[1] The publication of the list increased attention to firms' geopolitical exposure and generated widespread media coverage and online discussion, creating a salient information shock for consumers. If consumers respond to firms' geopolitical positions through their purchasing behavior, one would expect to observe shifts in spending following this disclosure. Using high-frequency consumer spending data, we estimate a difference-in-differences specification comparing spending at brands associated with firms identified on the list to comparable brands in the broader spending dataset around the list's release.

Consumer spending shows little evidence of systematic change following the disclosure. Spending responses appear limited across most brands in the sample, with any declines modest on average and concentrated on a small number of highly visible consumer-facing firms. Only a small number exhibit patterns consistent with boycott-like behavior (Friedman 1999), with one prominent example being McDonald's, which experienced a temporary decline in spending, potentially reflecting both heightened public pressure (Russ 2022), and the presence of close experiential substitutes such as Burger King.

Despite the absence of broad-based changes in consumer demand, firms may still attempt to infer consumer sentiment from short-run fluctuations in their own sales. We next examine whether firms respond to these idiosyncratic changes in consumer demand surrounding announcements related to their Russian operations. We find that firms respond to these relative demand movements even when they are not accompanied by broader shifts in consumer demand. These findings suggest that firms may interpret idiosyncratic fluctuations in their own demand as signals of consumer approval or backlash, even when systematic demand responses are limited, consistent with evidence that firms respond to noisy or imperfect signals when making real decisions (Baker, Stein and Wurgler 2003, Edmans, Goldstein and Jiang 2012, Dessaint et al. 2019).

Our findings suggest that firms face a fundamental signal-extraction problem when

[1] At the time the Yale list was first disseminated, the KSE database was not yet publicly available.

interpreting consumer sentiment in politically salient environments. While consumer demand can, in principle, discipline firms' political behavior, the short-run movements firms observe in their own sales may not always reflect systematic shifts in consumer sentiment (Lucas 1972, Bikhchandani, Hirshleifer and Welch 1992). In such settings, firms may place disproportionate weight on idiosyncratic fluctuations in their own demand, interpreting these movements as evidence of consumer approval or backlash. More broadly, the results suggest that firms facing reputational pressure may rely on imperfect demand signals when assessing stakeholder reactions, shaping corporate behavior even when underlying consumer responses are limited.

In addition to consumer demand, firms may also infer stakeholder reactions from financial markets, which provide a forward-looking assessment of the consequences of corporate actions. Stock market responses aggregate investors' expectations about future cash flows, incorporating both anticipated demand shifts and potential operational frictions associated with maintaining operations in Russia. We therefore complement our analysis of consumer spending with an examination of abnormal stock returns around key events related to firms' Russia exposure. While consumer demand captures realized purchasing behavior, these market-based measures may reflect expectations about firms' geopolitical positioning.

We find that market reactions differ sharply across events. The invasion itself is associated with significant negative abnormal returns, reflecting a reassessment of firms' fundamental exposure to Russia, whereas the subsequent release of the Yale list generates little evidence of systematic repricing. However, when incorporated into firms' withdrawal decisions, a more nuanced pattern emerges: consumer demand signals are most closely associated with earlier-stage actions, such as initial withdrawal or escalation decisions, whereas stock market reactions tied to firms' own actions play a more prominent role in later-stage decisions, namely full exit. This contrast reflects financial markets responding strongly to shocks affecting expected cash flows, but less so to reputational or salience-driven disclosures that primarily reorganize existing information, with firms correspondingly placing greater weight on signals that convey information about fundamentals when making high-stakes decisions.

Overall, our evidence indicates that firms rely on two complementary sources of information when assessing stakeholder reactions: realized demand, which provides a noisy and firm-specific signal of consumer sentiment, and financial market responses, which aggregate forward-looking expectations about the consequences of firm actions. The relative importance of these signals appears to shift across decision stages, with firms responding more strongly to demand fluctuation in earlier-stage withdrawal actions such as announcements and partial suspensions, and placing weight on market-based signals when making higher-stakes decisions, such as on full exit.

These patterns also raise the question of why firms respond to market-based signals.

In standard settings, managers are typically better informed about their own operations than outside investors, suggesting that stock market reactions should not, in themselves, provide new information about firm fundamentals. However, in environments characterized by heightened public scrutiny and substantial operational uncertainty, firms may face ambiguity about both the economic consequences of their actions and how those actions will be perceived by stakeholders. In such settings, market reactions may serve as a useful, albeit imperfect, signal of broader stakeholder expectations.

This paper contributes to three strands of literature. First, it relates to a growing body of work examining corporate engagement in political and social issues and the role of consumer reactions in shaping firm behavior. Prior research shows that consumers increasingly align brand choices with political identity and may reward or punish firms for their political or social positions (Schoenmueller, Netzer and Stahl 2023, Bhagwat et al. 2020, Chatterji and Toffel 2019). These dynamics reflect broader trends in political polarization and identity-driven economic behavior documented in recent work on political consumerism and media-driven polarization (Gentzkow, Shapiro and Taddy 2019, Allcott and Gentzkow 2017, Guriev and Papaioannou 2022, Conway and Boxell 2026). While this literature primarily focuses on whether consumers respond to corporate political behavior, we instead study how firms interpret the signals they observe, in environments with noisy and imperfect information, about consumer sentiment. Our findings suggest that firms may respond to idiosyncratic fluctuations in their own sales as if they reflected ideological approval or backlash, even when systematic shifts in consumer demand are limited.

Second, the paper contributes to a broader literature linking political ideology, political risk, and corporate decision-making. Prior work has shown that political preferences influence economic behavior and firm outcomes, shaping investment decisions, financing conditions, and corporate policies (Hong and Kostovetsky 2012, Chava 2014, Hutton, Jiang and Kumar 2015). Prior work shows that firms respond to political and geopolitical uncertainty (Hassan et al. 2019, Caldara and Iacoviello 2022) and may undertake socially or politically salient actions in response to stakeholder pressures and reputational incentives (Baron 2001, Bénabou and Tirole 2010, Fioretti, Saint-Jean and Smith 2026). We contribute to this literature by studying how firms use both realized consumer demand and financial market signals to infer the consequences of their geopolitical exposure and incorporate those signals into corporate decisions.

Finally, our findings connect to a literature on firm behavior under uncertainty and social learning. Firms often make strategic decisions in environments where information about underlying demand or stakeholder reactions is incomplete and may rely on observable signals or the actions of peers when forming beliefs about underlying conditions (Bikhchandani,

Hirshleifer and Welch 1992, Banerjee 1992, Haunschild 1993, Lieberman and Asaba 2006). We contribute to this literature by showing that firms appear to rely on multiple, imperfect signals when evaluating stakeholder reactions, facing a signal-extraction problem: short-run fluctuations in firm-level demand, which may not reliably reflect broader consumer sentiment but are nonetheless treated by firms as informative signals, and financial market responses, which aggregate forward-looking expectations about the consequences of firms' actions. These signals can shape corporate behavior even when they do not reliably reflect broader shifts in underlying stakeholder sentiment.

2 Data

Our analysis combines data on firm withdrawal decisions, consumer spending, and the political composition of firms' U.S. customer bases. We begin with firm-level withdrawal action data from the Kyiv School of Economics (KSE) "LeaveRussia" database (Kyiv School of Economics 2022), which tracks multinational firms' operational responses in Russia following the 2022 invasion of Ukraine, covering over 4,255 firms operating in Russia. We supplement these data with the Yale School of Management's list of corporate withdrawal announcements (Yale Chief Executive Leadership Institute 2022), which represents an early and widely circulated public subset of the firms covered in the KSE dataset. The list received extensive coverage in major news outlets and circulated widely on social media, quickly becoming a focal reference for public discussion of firms' responses to the invasion.

To measure consumer responses, we use SafeGraph transaction data (SafeGraph 2025), which report weekly brand-level spending across U.S. counties, allowing us to track changes in local consumer demand for firms following the public disclosure of their Russia exposure.

Finally, we incorporate county-level political and demographic characteristics to capture differences in the political composition of firms' U.S. customer bases. Democrat–Republican vote margins in the 2020 presidential election are obtained from the MIT Election Data and Science Lab (MIT Election Data and Science Lab 2025), while demographic characteristics are drawn from the American Community Survey (U.S. Census Bureau 2023). These additional datasets allow us to examine how consumer responses vary across local ideological environments.

2.1 Firm Withdrawal Actions

Information on firms' withdrawal status is drawn from the Kyiv School of Economics (KSE) database described above, which we treat as the canonical record of multinational firms with

exposure to the Russian market following the 2022 invasion of Ukraine. The database tracks firms' operational statuses in Russia over time based on publicly available announcements, corporate filings, and media reports, providing several detailed labels describing different stages of withdrawal from the Russian market.

For our analysis, we collapse these labels into a four-step withdrawal ladder reflecting progressively greater disengagement from operations in Russia.

0. **Operating.** Firms continuing normal operations in Russia with no announced or implemented changes to their activities.

1. **Announced.** Firms that have publicly announced intentions to scale back or exit the Russian market, or have begun early stages of scaling down operations, but have not yet implemented substantial operational withdrawals.

2. **Partially Exited.** Firms that have suspended operations or implemented substantial operational withdrawals but have not yet fully exited the Russian market.

3. **Fully Exited.** Firms that have completed their withdrawal and fully exited the Russian market.

These states form the ordered withdrawal ladder used in the hazard analyses described in Section 3.2. Figure 1 illustrates this withdrawal ladder.

Figure 2 shows the distribution of firms across these withdrawal states. Most firms remain in the *Partially Exited* state, while fewer firms progress toward eventual full exit. This distribution highlights the substantial heterogeneity in firms' responses to the invasion and indicates that complete withdrawal represents only one of several strategies adopted by multinational firms. The full KSE dataset version of this figure is shown in Figure 3.

The SafeGraph-linked sample is necessarily restricted to firms with a significant consumer-facing presence, as the SafeGraph data capture spending at retail and service locations visited by U.S. consumers. As a result, the analysis focuses on firms for which consumer demand is directly observable at high frequency. This restriction arises naturally from our research design and is well-suited to our objective of studying how firms interpret consumer demand signals. While many firms in the broader KSE dataset operate in business-to-business sectors that do not appear in the SafeGraph data, this does not affect the internal validity of our analysis, which relies on within-firm variation in demand and firm decisions over time. Rather, it implies that our findings are most directly applicable to consumer-facing firms, where reputational pressures and demand-based signals are likely to be most salient.

In addition to the cross-sectional distribution of withdrawal states, the panel structure of the KSE dataset allows us to examine the timing of firms' initial responses. Figure 4 shows

the distribution of the timing of firms' first withdrawal actions following the invasion. Many firms took their first action in the weeks immediately after the invasion, with the frequency of new actions declining over time. At the same time, the distribution exhibits a long tail, indicating that some firms delayed their initial response for several months. The full KSE dataset version of this figure is shown in Figure 5.

While the KSE dataset provides the underlying record of firms' operational responses, public awareness of these responses was shaped by a widely circulated list compiled by researchers at Yale University (Yale Chief Executive Leadership Institute 2022). Following the invasion on February 24, 2022, media outlets, policymakers, and civil society organizations began scrutinizing multinational firms' continued operations in Russia, and the Yale list quickly became a focal public reference tracking firms' Russia exposure (Pietsch 2022). The earliest publicly archived instance of the list that we identify dates to March 8, 2022, when it was circulated on Twitter by Sir William Browder.[2]

The Yale list largely represents a subset of the broader firm universe documented by the Kyiv School of Economics (KSE), but provides a publicly visible classification of firms' responses that was widely disseminated to consumers and the media. Early versions of the list classified firms into two categories: firms that continued operating in Russia and firms that had curtailed operations through suspensions, scale-backs, or exits. In the terminology used throughout this paper, the *Remained* category loosely corresponds to firms that were reported to have continued normal operations, while *Curtailed* includes firms that had announced or begun suspensions, scale-backs, or exits. In terms of the withdrawal ladder defined in Section 2.1, this distinction broadly corresponds to whether a firm remained in the *Operating* state or transitioned to withdrawal states.

2.2 Consumer Spending Data

To measure consumer responses to firms' withdrawal decisions, we use consumer spending data from the SafeGraph Spend dataset. SafeGraph aggregates anonymized debit and credit-card transaction data sourced from a financial data aggregator and reports spending totals at the point-of-interest (POI) level across the United States. For our analysis, we aggregate these data to the brand-county-week level, allowing us to track how local consumer demand for a brand evolves over time.

Because SafeGraph reports spending at the brand rather than firm level, firms in the KSE dataset must be mapped to their corresponding consumer brands. We match SafeGraph brands to KSE corporate entities using high-threshold name matching combined with USPTO

[2]Twitter post by Sir William Browder, March 8, 2022, circulating the Yale Chief Executive Leadership Institute list of companies operating in Russia: https://x.com/billbrowder/status/1501095884779626502.

trademark ownership records (United States Patent and Trademark Office 2025). Candidate matches are then manually verified to retain only high-probability links between brands and their parent firms.

To construct the spending panel used in our analysis, we require firms to have observable county-level consumer spending in the pre-invasion period (2021). This baseline allows us to measure the geographic distribution of each firm's U.S. consumer demand and construct county-weighted spending measures. After applying this requirement, the SafeGraph-linked sample contains 207 firms.

2.3 Summary Statistics

Table 1 reports summary statistics for the consumer spending panel used in the spending-response analysis. The SafeGraph data provide extensive geographic coverage, with brand–county spending observed across more than 3,000 U.S. counties. Average weekly brand–county spending is $1,300 in weekly spending per brand–county observation.

Table 2 reports summary statistics for the firm-level sample used in the hazard analysis. The SafeGraph-linked sample contains 207 firms with observable consumer spending in the pre-invasion period. Spending response measures capture short-run changes in county-weighted consumer demand following firms' withdrawal actions and around the initial dissemination of the Yale list, measured relative to contemporaneous county-level spending trends. On average these responses are close to zero but exhibit substantial dispersion, indicating considerable variation in consumer reactions across firms.

To capture differences in firms' exposure to both the U.S. consumer market and the Russian economy, we include several firm-level characteristics. These include measures derived from SafeGraph spending data, such as total U.S. consumer spending, and the number of U.S. counties in which a firm operates. We also incorporate measures of firms' exposure to the Russian market, including 2021 Russian revenue and employment where available, as reported in the KSE dataset. These variables are later included as firm controls and exposure measures in the hazard analysis of firms' withdrawal decisions. We also report county-level controls to capture the political and demographic composition of firms' customer bases.

3 Empirical Findings

3.1 Consumer Demand Responses

3.1.1 Empirical Strategy

To assess whether consumers adjust their spending in response to this information, we estimate event-time spending responses using a stacked difference-in-differences design with matched controls at the brand–county–week level. Because the early Yale list distinguishes between firms that *Remained* in Russia and those that *Curtailed* operations, we construct two separate matched panels corresponding to these categories. In each panel, treated brands are those appearing on the Yale list in the relevant category.

For each treated brand–county pair, we construct a matched control drawn from brands that appear in neither the Yale nor the KSE lists but operate in the same county and industry. Industry matching is based primarily on SafeGraph *top categories* (e.g., Restaurants, Traveler Accommodation, Automotive). When SafeGraph categories are missing or overly granular, we supplement them with manually assigned coarse industry groupings to ensure that treated brands are matched with comparable businesses. Matching is based on similarity in pre-event spending levels and trajectories, ensuring comparable demand patterns prior to the information shock.

We estimate dynamic treatment effects using the following event-study specification:

$$\ln(\text{Spend}_{bct}) = \sum_{k \neq -1} \beta_k \mathbf{1}[\tau = k] \times \text{Treated}_{bc} + \mu_{bc} + \lambda_{gt} + \epsilon_{bct}, \tag{1}$$

where τ indexes weeks relative to the Yale list release and Treated_{bc} indicates brands appearing on the Yale list in the relevant category. The specification includes brand–county fixed effects μ_{bc} and cohort–week fixed effects λ_{gt} for matched treated–control cohorts. Identification therefore comes from within-cohort differences between treated and control brands over time.

3.1.2 Remained vs Curtailed Comparison

We begin by examining how consumer spending responds to the information shock generated by the public release of the Yale list. Figure 6 plots event-time estimates of normalized firm-level spending around the list's initial publication, while Table 3 reports the corresponding stacked difference-in-differences estimates.

Counterfactual brand–county pairs are matched based on spending levels and trajectories in the five weeks prior to the Yale list's release ($t = -5$ to $t = -1$, with the list released

during the week of February 28, 2022), forming cohorts of treated and control observations. Event-study and difference-in-differences estimates are then computed within a symmetric $[-5, +5]$ week window around the release.

Prior to the list's publication, treated firms and their matched controls exhibit similar spending trajectories, indicating comparable pre-period trends. Following the release, firms classified as continuing to operate in Russia (*Remained*) exhibit a modest decline in normalized consumer spending relative to matched controls. The decline appears with a short lag following the list's release, which may reflect the gradual diffusion of information as the list circulated through news coverage and social media. The difference-in-differences estimates in Table 3 indicate an average post-period decline of approximately 12 percent, though as later shown in Section 3.1.3, this effect masks substantial heterogeneity across firms. In contrast, firms categorized as already having *Curtailed* operations in Russia show little systematic change in spending relative to their matched controls, and the corresponding estimates are small and statistically insignificant.

The results of the two event studies offer little evidence of systematic consumer reward for firms that curtailed operations, and only modest evidence of demand declines for firms that were reported to have continued operating in Russia following the Yale list salience shock.

Figures 7 and 8 examine heterogeneity in spending responses across county demographic and political characteristics, including Ukrainian ancestry shares, education, political preferences, income, and population density. The patterns are broadly similar across regions, suggesting that the observed spending responses are not driven by a particular geographic or demographic segment. Spending declines among *Remained* firms do not appear to be systematically larger in counties with stronger pro-Ukraine sentiment or particular political leanings, suggesting that the modest demand response does not appear to reflect a systematic ideological boycott across firms or geographic areas.

3.1.3 Case Study: McDonald's, Starbucks, & Papa John's

To better understand the modest aggregate decline observed among firms that continued operating in Russia, we first examine the composition of consumer spending within the *Remained* subset. Figure 9 reports 2021 SafeGraph spending shares for brands linked to firms classified as remaining in Russia at the time of the Yale list's initial publication. Consumer spending within this group is highly concentrated among a small number of large consumer-facing restaurant chains. McDonald's alone accounts for approximately 60% of observed spending in the *Remained* sample, while Starbucks and Papa John's account for an additional 15% and 8%, respectively. Together, these three brands represent more than 80% of total spending among firms classified as continuing operations in Russia.

Outside of these three firms, the remaining brands account for relatively small shares of observed spending. Moreover, 19 of the remaining 22 brands correspond to hotel chains. Because hotel stays are often booked weeks in advance, short-run spending measures may reflect pre-existing reservations rather than contemporaneous consumer reactions to newly available information. As such, demand responses among these firms may be less visible in short event windows.

We therefore begin by separating these three firms: McDonald's, Starbucks, and Papa John's ("Focus 3"), from the remaining firms classified as continuing to operate in Russia. Figure 10 compares event-time spending responses for the Focus 3 against the remaining brands in the *Remained* category. We estimate these responses using the same matched difference-in-differences specification described in the previous subsection. The figure shows that the aggregate decline is highly concentrated among the focal brands; firms in the *Remained* category excluding the Focus 3 exhibit spending patterns that remain close to zero or are slightly positive throughout the post-period, while the Focus 3 brands, in aggregate, display a clear decline in normalized consumer spending relative to matched controls shortly after the initial dissemination of the Yale list. Table 4 reports the corresponding difference-in-differences estimates, confirming a large negative post-period response for the Focus 3 and a small positive estimate for the remaining brands. This concentration also implies that the demand signals observed by most firms are likely to be weak and idiosyncratic, rather than reflecting broad shifts in consumer sentiment.

We next examine spending responses separately for each of the three focal brands. Figure 11 presents event-time estimates for McDonald's, Starbucks, and Papa John's individually. These firms were among the most publicly visible consumer-facing brands discussed in the early corporate withdrawal debate, but they differed in the scale and structure of their Russian operations as well as in the timing of their responses.

McDonald's exhibits a sharp and persistent decline in spending beginning roughly two weeks after the list's publication. This pattern is consistent with the firm's high visibility in Russia and the intense public attention surrounding its response. McDonald's announced a temporary closure of its Russian restaurants on March 8, 2022 and later announced a full exit from the market on May 16, 2022 (McDonald's Corporation 2022*a*,*b*). Papa John's also displays a negative trajectory over the post-period, although spending for this brand begins trending downward prior to the event, making causal interpretation more cautious. Relative to McDonald's, Papa John's Russian presence was organized through a franchise structure, which made its exposure and withdrawal process somewhat different and became part of the public discussion at the time. The company suspended operations in Russia on March 11, 2022, though contemporaneous reporting noted the continued role of local franchise

arrangements (Feuer 2022, Creswell 2022). By contrast, Starbucks does not appear to exhibit any significant systematic spending response. Starbucks halted Russian sales in early March and later exited the Russian market in May 2022 (BBC News 2022, Sophia 2022). Compared with McDonald's, however, Starbucks appears to have attracted less sustained demand-side response in our data despite being part of the same broader wave of public scrutiny. One possible explanation is that Starbucks faces fewer close substitutes within the quick-service restaurant category, which may limit short-run consumer switching.

Table 5 reports the corresponding difference-in-differences estimates at the individual brand level. McDonald's and Papa John's exhibit large negative post-period estimates of approximately 20%, while Starbucks shows no detectable change in spending. In summary, the results indicate that even among the brands connected to firms classified as *Remained* in the Yale list, the modest aggregate decline in spending is primarily driven by a small number of highly visible consumer-facing brands, while the majority of firms exhibit little systematic demand response following the list's release. These patterns suggest that increased public salience of firms' Russia exposure was not, by itself, sufficient to generate widespread consumer boycotts.

3.2 Firm Response to Demand Signals

3.2.1 Empirical Strategy

The KSE dataset records firms' operational status using several detailed categories (e.g., continuing operations, announcing future changes, suspending operations, or exiting the market). For tractability, we collapse these statuses into a coarser ordered "withdrawal ladder" consisting of four states: *Operating*, *Announced*, *Partially Exited*, and *Fully Exited*.

The preceding consumer demand analysis in Section 3.1 shows that the public dissemination of the Yale list generated, at most, modest average declines in spending for firms that remained active in Russia, with these effects concentrated among a small number of highly visible consumer-facing brands. However, as shown in the summary statistics in Table 2 and Figure 12, firm-level spending responses around corporate actions also exhibit substantial dispersion. While the average response is close to zero, individual firms experience both strongly positive and strongly negative demand realizations.

Importantly, firms observe only their own sales, and cannot cleanly observe the distribution of demand responses among their market competitors. Managers may therefore interpret these firm-specific demand fluctuations relative to broader local spending as signals of consumer approval or backlash, even when these fluctuations do not necessarily reflect systematic shifts in underlying demand.

To investigate whether firms respond to these demand signals, we estimate a hazard model of firms' decisions to change their operations in Russia. The dependent variable indicates whether firm f transitions to a more advanced withdrawal state in week t.

The estimating equation takes the form

$$Pr(\text{Action}_{ft} = 1) = F(\beta \cdot \text{Demand Signal}_{f,t-1} + X_f + \gamma_t + \delta_s)$$

where $\text{Demand Signal}_{f,t-1}$ measures firm-specific changes in consumer spending, X_f denotes firm-level characteristics, γ_t are week fixed effects capturing common time shocks, and δ_s are coarse industry fixed effects. In the hazard regressions, demand signal variables are standardized to have mean zero and unit variance so that coefficients correspond to the effect of a one–standard deviation change in firm-level spending signals. The coefficient β captures how firm-specific demand signals affect the likelihood of announcing operational changes. A negative β indicates that firms are more likely to move toward operational withdrawal following negative demand signals.

The control vector X_f includes two sets of firm characteristics. The first set captures *Firm Controls* related to firms' size and geographic footprint in the United States. These include *log 2021 Spending*, defined as the logarithm of total SafeGraph consumer spending at the firm level during the pre-invasion period, and *log Counties*, defined as the logarithm of the number of U.S. counties in which the firm records spending activity. These variables proxy for firm scale and geographic reach in the U.S. consumer market.

The second set captures firms' *Russian Exposure*. These include *log Russian Revenue*, defined as the logarithm of total firm revenue generated in Russia in 2021, and *log Russian Staff*, defined as the logarithm of the number of employees located in Russia in 2021. These variables capture firms' operational and financial exposure to the Russian market prior to the invasion.

The demand signal itself is constructed from firm-level consumer spending following each status change. We measure firm spending relative to total spending in the same county-week to remove common local demand fluctuations and aggregate this measure across counties using fixed 2021 geographic spending weights. The signal is defined as the change in average spending between the two weeks after the action and the two weeks before it. In the time-varying hazard specifications, the signal is updated after each new status change and enters the hazard once the post-action window has elapsed. Appendix Section A.1 outlines this computation in finer detail.

We exploit the ordered structure of the withdrawal ladder by estimating hazards for three distinct transitions between KSE status categories:

1. **First Action (Operating → Announced / Partially Exited / Fully Exited).** We first estimate the hazard that a firm moves away from continued operations (*Operating*) to any withdrawal state on the ladder. This captures the decision to take an initial public action in response to the post-invasion environment.

2. **Escalation (Announced → Partially Exited / Fully Exited).** Conditional on having made an announcement, we estimate the hazard that firms escalate their response by transitioning from the *Announced* category to a more substantive operational withdrawal.

3. **Full Exit (Announced / Partially Exited → Fully Exited).** Finally, we estimate the hazard that firms ultimately reach the *Fully Exited* category, representing complete withdrawal from the Russian market. The risk set begins at the week of each firm's first move away from *Operating* and includes firms in intermediate ladder states that have not yet exited.

These specifications allow us to distinguish between firms' decisions to signal responsiveness and their decisions to implement more costly operational changes. We estimate the model using a complementary log-log specification, which corresponds to a discrete-time proportional hazard model in which the hazard of transitioning states evolves continuously within each period (Allison 1982, Jenkins 1995). As a robustness check, we also report linear probability models with the same risk sets and fixed effects; the results are qualitatively unchanged.

3.2.2 First Action

We begin by analyzing the determinants of firms' initial responses following the invasion of Ukraine. The first stage captures the hazard that a firm takes any withdrawal-related action, typically a symbolic announcement or limited suspension of operations.

Table 6 reports complementary log–log hazard estimates for the transition from continued operations to a first withdrawal-related step. The specifications include a firm-level demand signal, *Demand Signal (Yale)*, measuring changes in normalized consumer spending following the circulation of the Yale list and capturing the immediate demand environment firms may have observed after the list's release.

Across specifications, the coefficient on *Demand Signal (Yale)* is small and statistically insignificant, indicating that on average, shifts in consumer spending following the list's circulation do not independently predict the timing of firms' first withdrawal actions. Rather, the timing of firms' first withdrawal actions appears to be more strongly associated with public identification on the Yale list than with short-run demand movements. In Section 3.2.5,

we examine interactions between the demand signal and firms' Yale list classifications to test whether demand responses become more informative for firms facing direct public scrutiny.

In contrast, firms' public classification on the Yale list strongly predicts early responses. Firms identified as continuing operations in Russia exhibit substantially higher transition hazards. In the baseline specification, firms classified as *Curtailed* face a transition hazard roughly 3.6 times higher than the omitted group, while firms classified as *Remained* face a hazard that is approximately five times higher, with both effects statistically significant at the 1% level. These patterns remain broadly stable when firm characteristics are introduced. Controlling for firm size and geographic footprint yields similar estimates, while the coefficient on *Yale Remained* becomes smaller and only marginally significant once Russian exposure measures are included, reflecting the smaller sample available for these firms.

Overall, the results indicate that firms publicly identified as continuing or partially continuing operations in Russia were substantially more likely to initiate withdrawal-related actions following the circulation of the Yale list, consistent with reputational pressure generated by public scrutiny contributing to firms' early responses.

Firm characteristics play a more limited role in predicting the timing of first actions. The coefficients on firm size and geographic reach are generally modest, although firms operating in a larger number of counties exhibit somewhat higher hazards of taking an initial step. Firms with greater Russian revenue exposure also appear more likely to initiate withdrawal-related actions once exposure controls are included. This pattern is consistent with the relatively low operational cost of initial announcements, suggesting that reputational considerations play a more prominent role than firm fundamentals in driving firms' initial responses.

3.2.3 Escalation

We next turn to whether firms escalate their responses after taking an initial symbolic action. At this stage, firms decide whether to move beyond announcements toward more substantive operational withdrawal.

Table 7 reports hazard estimates for the transition from *Announced* to more advanced withdrawal states. The specifications include two demand signals. *Demand Signal (Yale)* captures spending responses following the circulation of the Yale list, while *Demand Signal (First)* measures the idiosyncratic shift in normalized consumer spending following a firm's first withdrawal-related action, i.e., the week of the firm's first deviation away from the *Operating* stage in the withdrawal ladder described in Section 3.2.

Escalation decisions are strongly associated with firm-specific demand signals following the initial action (*Demand Signal (First)*). A one standard deviation decline in the demand signal, indicating weaker relative spending following the firm's initial action, is associated

with a roughly 70% increase in the weekly hazard of escalation. The magnitude remains similar when firm controls and Russian exposure measures are included. Firms experiencing weaker relative spending following their initial response are therefore significantly more likely to escalate toward deeper operational withdrawal. In contrast, *Demand Signal (Yale)* plays a limited role in predicting escalation decisions. The coefficient is small and statistically insignificant in the baseline and firm-control specifications, although it becomes negative and statistically significant when Russian exposure controls are included. Public classification on the Yale list is also less predictive at this stage. Firms classified as *Yale Curtailed* exhibit somewhat higher escalation hazards across specifications, while the *Yale Remained* indicator is not statistically significant. Operational exposure to Russia remains positively associated with escalation decisions once exposure controls are included. Firms with larger Russian revenue streams are more likely to move beyond symbolic actions, consistent with greater exposure creating stronger incentives to demonstrate substantive withdrawal.

Unlike the shift from *Operating* to *Announced* on the withdrawal ladder, escalation beyond the *Announced* stage typically involves more costly operational changes. Firms may therefore place greater weight on realized demand responses, despite their noisiness, when deciding whether to intensify their withdrawal. At the same time, the reputational pressure generated by the Yale list may have already been partially addressed by the first symbolic action, making subsequent escalation more dependent on firm-specific demand signals, rather than their original Yale list classification following their initial announcement.

3.2.4 Full Exit

Finally, we examine firms' decisions to fully exit the Russian market, capturing the transition from intermediate withdrawal states to complete operational exit.

Table 8 reports hazard estimates for the transition to full exit. The specifications include three demand signals corresponding to different stages of the withdrawal process: *Demand Signal (Yale)*, *Demand Signal (First)*, and *Demand Signal (Current)*, capturing spending responses following the Yale list release, firms' initial withdrawal action, and their most recent withdrawal step.

Across specifications, none of these demand signals significantly predict full exit decisions. In the baseline specification, the coefficients on *Demand Signal (Yale)*, *Demand Signal (First)*, and *Demand Signal (Current)* are statistically insignificant and remain so when firm controls and Russian exposure measures are introduced. These results suggest that while consumer demand responses influence earlier withdrawal decisions, they are less informative for firms' ultimate decisions to exit the Russian market entirely. Public classification on the Yale list also plays a limited role at this stage. Firms identified as *Yale Remained* exhibit a higher exit

hazard in the baseline specification, but the estimate becomes statistically insignificant once Russian exposure measures are included. The *Yale Curtailed* indicator is not statistically significant across specifications.

Instead, Operational exposure appears more important in explaining exit decisions. Russian revenue exposure enters with a negative and statistically significant coefficient, while Russian staffing exposure is positive and statistically significant. Because transitioning to the *Fully Exited* state entailed relinquishing all Russian revenue and involves heightened reversal costs, this variable likely reflects the income loss associated with complete withdrawal. Therefore, one interpretation is that firms with greater revenue dependence on the Russian market face larger financial costs from fully exiting, while conditional on revenue exposure, larger staffing footprints may increase the operational costs of maintaining continued presence.

A clear pattern emerges across the hazard specifications: as firms progress along the withdrawal ladder, reputational pressures dominate early responses, while later decisions are increasingly governed by operational costs and constraints.

3.2.5 Heterogeneity: Yale Demand Signal Interaction

Arguably, firms that were not publicly identified as continuing operations in Russia at the time of the Yale list's circulation may have had weaker incentives to extract information from short-run demand signals. By contrast, firms named on the list, particularly those classified as continuing operations, may have faced heightened reputational pressure and uncertainty regarding potential consumer backlash. To examine whether demand signals were more salient for these firms, we interact *Demand Signal (Yale)* with the *Yale Curtailed* and *Yale Remained* indicators. These interaction terms capture whether the relationship between consumer demand responses and firms' withdrawal decisions differs for firms publicly identified as continuing operations in Russia.

Table 9 reports complementary log–log hazard estimates for each stage of the withdrawal ladder. Column (1) examines the transition from continued operations to a first withdrawal-related action, Column (2) examines escalation beyond an initial announcement, and Column (3) examines the transition to full exit.

The interaction results suggest that consumer demand responses following the Yale list release may have been particularly salient for firms publicly identified as continuing operations in Russia.In the first-action hazard, the interaction between *Yale Remained* and *Demand Signal (Yale)* is negative and statistically significant. This estimate indicates that firms classified as *Remained* may be more sensitive to adverse consumer demand signals following the Yale list release, exhibiting a substantially higher weekly hazard of taking an initial withdrawal-related action when spending declines. One interpretation is that firms publicly

identified as holdouts faced heightened reputational pressure and uncertainty, potentially making them disproportionately sensitive to shifts in consumer demand, even if those demand signals were noisy or difficult to interpret.

The magnitude of this coefficient should be interpreted with caution, however. The number of firms classified as *Yale Remained* with SafeGraph spending data is relatively small, and the extreme coefficient likely reflects the limited number of observations identifying this interaction in the hazard specification. In contrast, the interaction effect between *Yale Curtailed* and *Demand Signal (Yale)* is small and statistically insignificant, and none of the interaction terms are significant for the escalation or full-exit hazards. The evidence suggests that demand responses following the Yale list release may have been most relevant for firms publicly identified as continuing operations in Russia when deciding whether to take an initial withdrawal step.

3.2.6 Investor Responses

The preceding sections examine how consumer demand responds to firms' Russia-related actions and how firms subsequently adjust their withdrawal decisions in response to those demand signals. Financial markets provide an additional source of information that firms may use when evaluating their strategic responses under public scrutiny.

Stock Market Response to the Invasion. We first assess whether financial markets priced firms' exposure to Russia at the onset of the invasion. Using daily stock return data from CRSP, we compute cumulative abnormal returns (CARs) over standard event windows around February 24, 2022. For firm i, listed in the KSE dataset, the CAR over window $[a, b]$ is defined as:

$$\mathrm{CAR}_i[a, b] = \sum_{t=a}^{b} \mathrm{AR}_{it},$$

where abnormal returns are computed as market-adjusted returns:

$$\mathrm{AR}_{it} = r_{it} - r_{mt},$$

with r_{it} referring to the firm's daily return, and r_{mt} denoting the return on the CRSP value-weighted market index.

We compare firms with high versus low operational exposure to Russia, where high exposure is defined as firms whose share of total global revenue in 2021 generated in Russia exceeds the sample median (0.65% of total revenue) among firms in the CRSP-matched sample.

Table 10 reports the results. Firms with above-median exposure experienced significantly lower abnormal returns around the invasion. For instance, over the $[-1, +1]$ window, high exposure firms underperform by approximately 2.2 percentage points relative to low-exposure firms, with similar magnitudes across alternative event windows. Firms with below-median exposure, on the other hand, exhibit no statistically significant abnormal performance. These findings indicate that investors rapidly priced firms' underlying exposure to Russia at the onset of the invasion, penalizing firms with greater exposure, even though the median firm had relatively modest exposure to Russia.

Stock Market Response to the Yale List. We next evaluate whether financial markets reacted differently to firms listed in the initial publication of the Yale list, first circulated during the week of February 28, 2022 (2022-W09). Because investors had already been processing information about firms' Russia exposure through sanctions announcements, corporate disclosures, and media coverage, the Yale list likely served primarily to organize firms that were already under scrutiny rather than introducing entirely new information to the market. Instead, the list plausibly increased the salience of firms' Russia-related activities and placed their responses under greater public attention.

To assess the impact of this public classification on investor behavior, we estimate differences-in-differences specifications using weekly abnormal returns, measured as market-adjusted returns at the firm-week level, consistent with the definition used in the preceding event-study analysis. All specifications include firm and calendar-week fixed effects, so identification arises from the differential changes in returns around the period in which the Yale list began circulating.

We first test for differences in abnormal returns between firms appearing on the Yale list and other firms in the KSE sample:

$$AR_{it} = \alpha_i + \gamma_t + \beta_1 \left(\text{Yale Listed}_i \times \text{Post}_t\right) + \epsilon_{it},$$

where Yale Listed_i indicates firms included in the Yale list, and Post_t denotes weeks following its initial public circulation. This specification captures whether the public identification of firms' Russia exposure generated a differential stock market response.

We then restrict the sample to firms appearing on the Yale list and compare firms categorized as having *Remained* in Russia to those that *Curtailed* their operations:

$$AR_{it} = \alpha_i + \gamma_t + \beta \left(\text{Yale Remained}_i \times \text{Post}_t\right) + \epsilon_{it}.$$

This within-list comparison isolates whether investors penalized firms differently given

their exit statuses, conditional on being under public scrutiny.

Finally, we estimate a pooled specification on the full KSE sample that jointly captures both margins:

$$AR_{it} = \alpha_i + \gamma_t + \beta_1 \left(\text{Yale Listed}_i \times \text{Post}_t\right) + \beta_2 \left(\text{Yale Remained}_i \times \text{Yale Listed}_i \times \text{Post}_t\right) + \epsilon_{it},$$

where β_1 reflects the average effect of Yale list inclusion, and β_2 captures the incremental effect of firms categorized as remaining in Russia.

Table 11 reports the results. Across all specifications, estimated effects are economically small and statistically indistinguishable from zero. Firms included on the Yale list do not exhibit significantly different abnormal returns relative to other firms in the KSE sample. Moreover, within the set of listed firms, those categorized as remaining in Russia do not experience significantly different returns relative to those that curtailed operations. The pooled specification presents the same pattern, with no evidence of either broad Yale-list effect, or an incremental penalty for remained firms.

These findings indicate no meaningful additional market repricing following the public circulation of the Yale list. Given that investors plausibly could have already incorporated information about firms' Russia exposure and actions into prices, the Yale list largely represents a public salience shock rather than new fundamental information. This pattern is consistent with investors having already incorporated information about firms' Russia exposure prior to the lists' circulation, with the Yale list primarily increasing public salience rather than introducing new information.

As with the evidence on consumer demand, financial markets did not systematically penalize firms that remained active in Russia following the publication of the Yale list. Yet the absence of a strong aggregate response does not imply that firms ignored investor sentiment. Instead, during periods of heightened reputational pressure, firms may look to firm-specific stock market reactions to their own actions as signals of investor approval or concern.

Post-Action Stock Market Signals. To evaluate the influence of financial markets in firms' withdrawal decisions, we construct cumulative abnormal returns (CARs) around key events in the withdrawal process. Table 12 reports summary statistics for these post-event abnormal returns. On average, abnormal returns following the Yale list release are slightly negative, while returns around firms' withdrawal-related actions are close to zero. Across all events, the distributions exhibit substantial dispersion and include both positive and negative realizations. Figure 13 illustrates the distribution of these responses. While most

events generate relatively small abnormal returns, the distributions exhibit both positive and negative realizations, indicating substantial heterogeneity in investor reactions across firms and withdrawal stages.

Next, we test whether these market reactions predict subsequent movements along the withdrawal ladder. We augment the baseline hazard specification with abnormal returns around key withdrawal-related events in order to isolate the incremental predictive content of market reactions observed at decision-relevant milestones. Abnormal returns around the invasion primarily reflect the initial reassessment of firms' exposure to Russia following the onset of the war, whereas the withdrawal-related CARs, namely those following the Yale list release and subsequent withdrawal-related actions, are tied to subsequent public classifications and firm actions that coincide with firms' withdrawal decisions. Accordingly, we focus on abnormal returns around these withdrawal-related events rather than around the invasion itself. Table 13 incorporates post-action abnormal returns into the hazard specifications. The table includes abnormal returns around three stages of the withdrawal process: the Yale list release (*Post-Action CAR (Yale)*), firms' first withdrawal-related action (*Post-Action CAR (First)*), and the most recent withdrawal step (*Post-Action CAR (Current)*). For the hazard regressions, these abnormal return measures are standardized to have mean zero and unit variance, facilitating comparison of economic magnitudes across the different CAR measures, which correspond to distinct events and exhibit different underlying return volatility.

To ensure that abnormal returns reflect information available to firms at the time of decision-making, all CAR measures are constructed using post-event windows and enter the hazard specification only after the corresponding event window has elapsed. Specifically, each CAR variable is masked until the end of its event window (e.g., two weeks after the relevant event), so that abnormal returns are strictly predetermined with respect to subsequent withdrawal decisions and do not mechanically overlap with the timing of firm actions.

The introduction of the abnormal return variables does not materially effect the estimated coefficients on Yale classification nor the demand signal variables relative to the baseline results, suggesting that the baseline relationships are robust to controlling for contemporaneous abnormal returns and are not mechanically explained by investor responses. For the first-action hazard, abnormal returns around the Yale listing are not statistically significant, and the baseline results on Yale classification remain unchanged. Similarly, in the escalation hazard, abnormal returns following either the Yale listing or the first action do not significantly predict escalation decisions. In contrast, the consumer demand signal associated with the first action remains negative and statistically significant.

For the full-exit hazard, stock market reactions appear more informative. In particular, a one standard deviation increase in abnormal returns following the first withdrawal-related

action is associated with a substantial rise in the weekly exit hazard, corresponding to roughly a 2.5-fold increase. Abnormal returns around the most recent action, by contrast, enter with a negative effect, indicating that more negative investor reactions are associated with a higher likelihood of full exit.

These patterns suggest that firms respond to market feedback when evaluating whether to proceed to full exit. While abnormal returns around the Yale list release are significant predictors of exit in baseline specifications, this effect disappears once firms' underlying exposure to Russia is taken into account, as shown in Table 14. By contrast, abnormal returns associated with firms' own withdrawal-related actions remain informative for exit decisions, indicating that market reactions tied to firm-specific decisions may be more relevant than those associated with broader public events or exposure shocks.

One interpretation is that firms may use market reactions as feedback when updating their withdrawal decisions. More favorable investor reactions following an initial withdrawal-related action may be interpreted as validation of the firm's chosen course, encouraging further steps toward exit. Conversely, adverse market reactions at later stages may signal that the firm's current level of disengagement is not fully aligned with investor expectations, increasing the likelihood of a full exit.

When combined, the evidence suggests that consumer demand signals are most closely associated with earlier-stage withdrawal decisions, whereas investor reactions, particularly those tied to firms' own actions, are more informative for later-stage decisions, such as full exit. Firms may treat consumer responses as capturing relatively isolated signals of reputational pressure, while stock market reactions reflect both reputational concerns and investors' expectations about firms' underlying fundamentals.

Early CARs versus Russia Exposure. Table 14 compares direct measures of Russia exposure with market-based measures derived from abnormal returns. For comparability with the other CAR measures in the hazard specifications, we construct invasion-period abnormal returns over the same $[0, +2]$-week window, even though cross-sectional event-study regression of abnormal returns uses narrower daily windows. As shown in Column (1), exposure, as captured by Russia revenue and staff, is strongly associated with exit decisions. By contrast, abnormal returns around the invasion do not enter significantly once exposure is included, despite reflecting investors' initial reassessment of firms' Russia exposure. This suggests that invasion-period abnormal returns primarily reflect a repricing of underlying exposure, rather than provide an independent signal that firms incorporate into their exit decisions. Similarly, abnormal returns around the Yale list release are not robust once exposure is accounted for.

Although financial markets rapidly priced firms' exposure to Russia at the onset of the

invasion, firms' subsequent exit decisions appear to align more closely with their underlying economic exposure than with contemporaneous stock price movements. In this sense, market reactions around broad events appear to reflect a repricing of existing exposure rather than a source of additional investor pressure shaping firms' decisions. This distinction suggests that the relevance of market-based signals may depend on the context in which they arise, particularly whether firms face heightened public scrutiny.

Post-Action Yale CAR Interaction. Motivated by this distinction, we next analyze heterogeneous investor reactions to the Yale list release across firms' public classifications on the list. To do so, we interact *Post-Action CAR (Yale)* with the *Yale Curtailed* and *Yale Remained* indicators.

Table 15 reports the resulting hazard estimates across the withdrawal ladder. In the first-action specification, the interaction terms enter with large negative and statistically significant coefficients, suggesting that firms publicly identified on the Yale list may be more responsive to investor reactions following the list's release, particularly in environments where heightened scrutiny increases uncertainty about the consequences of their actions. Firms facing heightened reputational pressure may therefore have placed greater weight on stock market signals, which could plausibly reflect investors' expectations about the financial consequences of maintaining operations in Russia. The introduction of the abnormal return interactions does not materially diminish the significance of the Yale categorization or the Demand Signal variables relative to the baseline results, suggesting that the reputational scrutiny associated with inclusion on the Yale list reflects forces beyond investor reactions captured in the abnormal return measures.

For the escalation and full-exit hazards, the interaction terms are smaller and statistically insignificant. These results suggest that sensitivity to investor reactions is most pronounced at the initial stage of the withdrawal process, when firms face the greatest uncertainty and reputational pressure. In the analogous consumer demand interaction analysis in Section 3.2.5, sensitivity to demand responses appears primarily among firms classified as *Remained*, consistent with early actions reflecting responses to immediate consumer backlash. Heightened public scrutiny appears to increase firms' sensitivity to external signals, even when those signals are noisy or difficult to interpret.

3.2.7 Robustness Checks

Sanction-Prone Industries. As a robustness check, we examine the role of exposure to industries directly targeted by Western sanctions regulations in firms' withdrawal decisions. We construct a binary indicator for firms operating in sectors subject to major sanctions

measures, including finance and banking (e.g., SWIFT restrictions), energy (import bans and price caps), electronics and telecommunications (export controls), logistics and shipping, and industrial equipment and aerospace subject to dual-use export bans. In total, 36 of the 207 firms in our sample fall into these sanction-prone industries.

Table 16 reports hazard estimates that incorporate this indicator. The coefficient on the *Sanction Prone* variable is small and statistically insignificant across the first-action, escalation, and full-exit hazards. Moreover, the estimated effects of the key explanatory variables remain largely unchanged relative to the baseline specifications.

These findings suggest that firms' withdrawal decisions are not primarily explained by exposure to sectors directly targeted by sanctions regulations. Instead, the patterns documented above appear more consistent with reputational pressure and firm-specific demand signals shaping firms' responses.

Alternative CAR Measurement. We verify that the market-based results are not sensitive to the event window used to construct abnormal returns. Table 17 re-estimates the full-exit hazard using alternative CAR windows. The results are qualitatively similar across specifications. In particular, abnormal returns following firms' first withdrawal-related actions remain positive and statistically significant predictors of full exit decisions across both alternative windows, with economically comparable magnitudes. Abnormal returns associated with the most recent action retain a consistent negative sign across specifications, although their statistical significance is attenuated when using the shorter $[0, +1]$ window. By contrast, abnormal returns around the Yale list release are not statistically significant under either alternative CAR window, consistent with earlier evidence that such market reactions may primarily reflect underlying exposure rather than an independent signal.

Combined with the timing structure of the CAR variables, which ensures that abnormal returns enter the hazard only after the corresponding event window has elapsed, these findings indicate that the market-based results are not driven by mechanical timing or a particular return specification.

Alternative Hazard Specification. We re-estimate the hazard specifications using linear probability models (LPMs). While the complementary log–log specification is standard for discrete-time hazard models and maps covariates into transition probabilities through a nonlinear link function, the LPM provides a linear approximation that facilitates a more direct interpretation of marginal effects.

Table 18 reports linear probability model estimates for the three transitions: *First Action*, *Escalation*, and *Full Exit*, on the withdrawal ladder using the fully controlled specification

that includes firm characteristics and measures of Russian operational exposure. The results are broadly consistent with the complementary log–log estimates reported in Section 3.2.6. In particular, firms identified as *Yale Curtailed* or *Yale Remained* exhibit a higher probability of taking a first action, the consumer demand signal remains negatively associated with escalation decisions, and the exposure variables continue to play a more prominent role in explaining full exit decisions.

Although the magnitudes differ due to the linear probability interpretation, the signs and statistical significance of the key coefficients remain largely unchanged, indicating that the main findings are robust to the choice of hazard specification.

4 Conclusion

Corporate engagement with political and geopolitical issues has become increasingly visible, raising questions about how consumers respond and how firms interpret the signals they observe in response to those actions. This paper examines these dynamics in the context of multinational firms' reactions to Russia's 2022 invasion of Ukraine. Using high-frequency consumer spending data combined with detailed information on firms' withdrawal decisions, we study both whether consumers adjust their purchasing behavior following heightened public scrutiny and how firms interpret the signals they observe when making subsequent decisions.

We find little evidence of large, systematic shifts in consumer demand following the public dissemination of information about firms' continued operations in Russia. While a small number of highly salient consumer brands experienced temporary declines in spending, most firms exhibit spending patterns that do not meaningfully deviate from pre-event trajectories. These findings suggest that widespread consumer boycotts or coordinated purchasing responses were limited in this setting, consistent with evidence that public discourse and online backlash may not always translate into measurable changes in consumer behavior (Barberá and Rivero 2015, Bénabou and Tirole 2011). More broadly, they highlight the difficulty of inferring underlying consumer sentiment from highly visible but potentially unrepresentative signals such as social media activity or media coverage (Chatterji and Toffel 2019).

Despite the absence of large aggregate demand responses, firms appear to respond to short-run fluctuations in their own consumer spending when determining whether to escalate their withdrawal from Russia. Firms experiencing weaker relative demand following initial actions are significantly more likely to undergo further operational withdrawal. Because these firm-level demand movements largely reflect idiosyncratic variation rather than systematic shifts in consumer sentiment, the results suggest that firms may interpret these fluctuations as

informative signals of consumer approval or backlash, even when they may not reliably reflect broader demand conditions. Consistent with this interpretation, firms publicly identified on the Yale list appear particularly sensitive to these demand signals when deciding whether to take an initial withdrawal-related step. In this sense, firms appear to treat short-run fluctuations in their own demand as signals when making decisions in politically salient environments, consistent with theories of decision-making under imperfect information and social learning (Lucas 1972, Bikhchandani, Hirshleifer and Welch 1992, Banerjee 1992).

Our additional analyses suggest that financial markets may provide a complementary source of feedback when firms consider later-stage withdrawal decisions. While equity markets did not exhibit meaningful repricing following the publication of the Yale list on average, and abnormal returns around its release do not predict exit decisions after controlling for underlying operational exposure to Russia, abnormal returns associated with firms' own withdrawal-related actions contain predictive information for exit decisions. Firms experiencing more negative investor reactions following their own actions are more likely to ultimately exit the Russian market, suggesting that market-based signals tied directly to firm actions may be more informative than those associated with broader public disclosures

These findings suggest that investor responses may serve as a complementary source of feedback alongside consumer demand signals, particularly when firms evaluate the costly decision to fully unwind their operations, and that such signals are most informative when directly tied to firm-specific decisions.

In environments where reputational or political pressure makes stakeholder reactions highly salient, firms face a fundamental challenge in separating signal from noise when interpreting the feedback they observe. When signals from consumers and investors are noisy or heterogeneous, firms may rely on imperfect signals, including firm-specific demand fluctuations and short-run market reactions, when determining how far to escalate politically salient actions. As a result, corporate responses to public pressure may reflect firms' interpretations of imperfect signals rather than systematic shifts in underlying stakeholder preferences.

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5 Figures

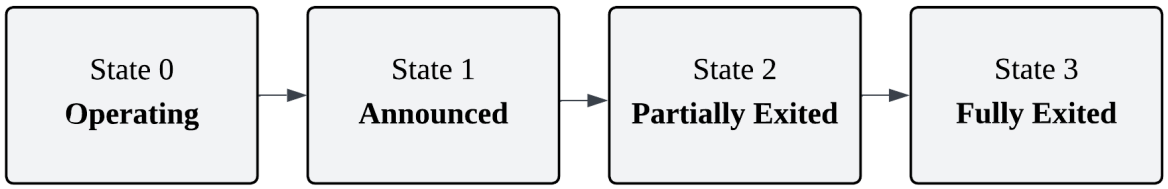


Figure 1: Firm Withdrawal Ladder. Firms in the KSE dataset move along an ordered ladder of withdrawal states, ranging from continued operation in Russia (State 0) to full exit (State 3).

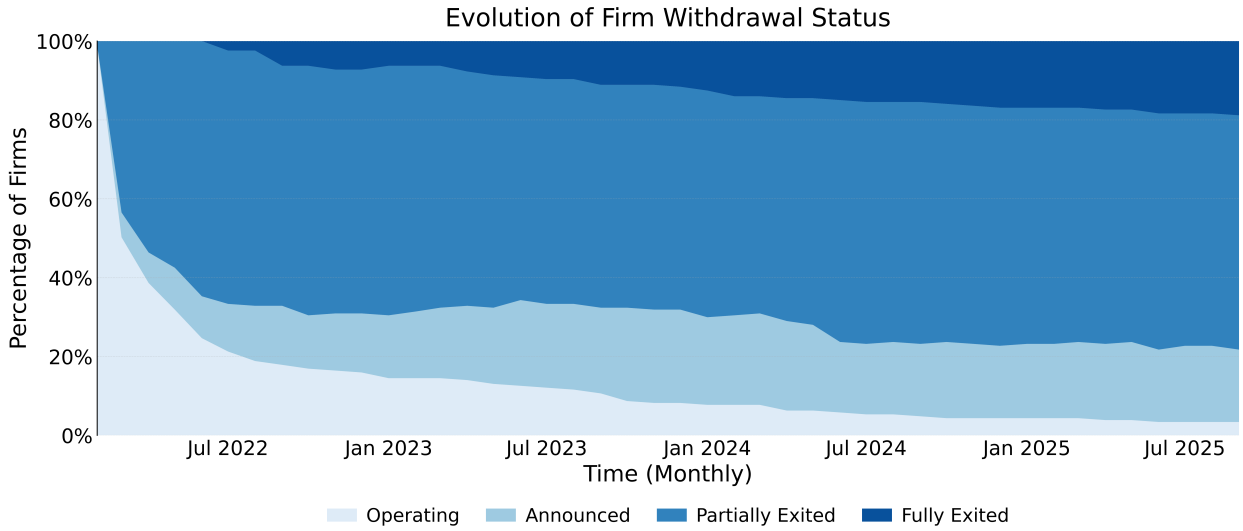


Figure 2: Distribution of Firms Across Withdrawal States. This figure shows the distribution of firms across withdrawal states in the KSE-SafeGraph intersected dataset.

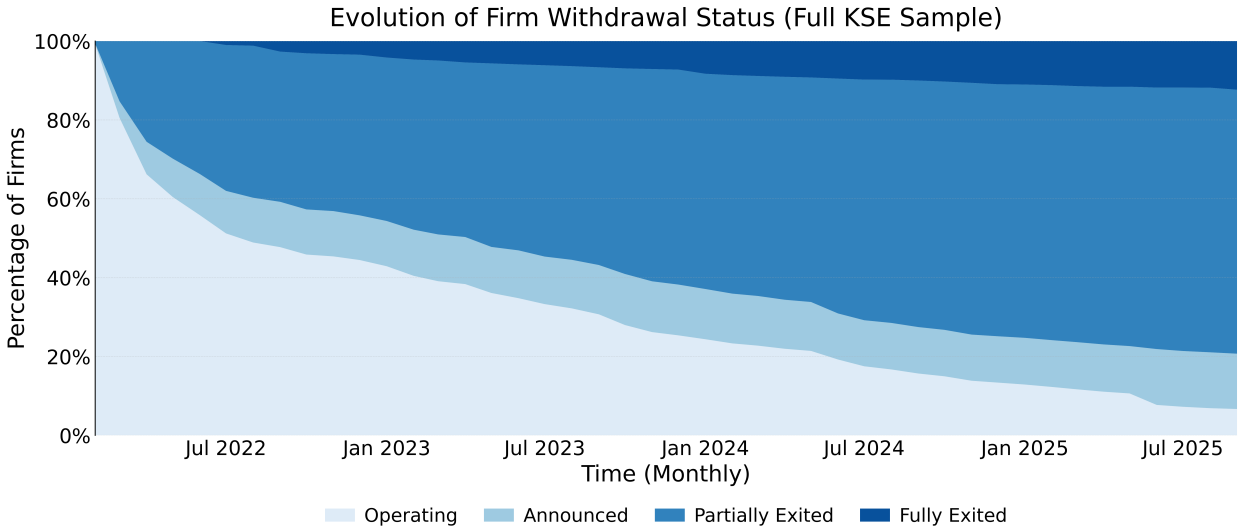


Figure 3: Distribution of Firms Across Withdrawal States. This figure shows the distribution of firms across withdrawal states in the full KSE dataset.

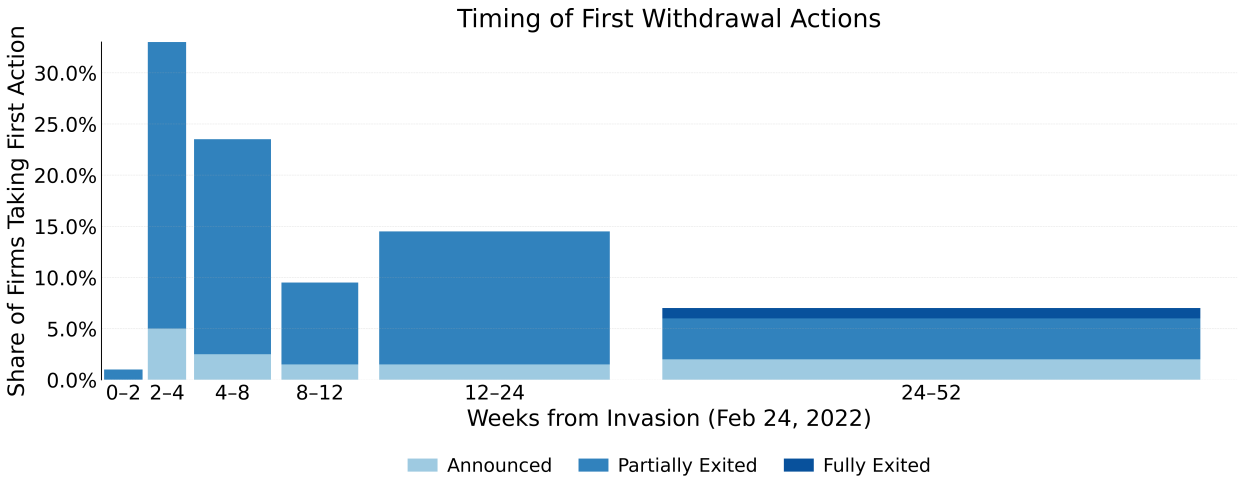


Figure 4: Timing of Firms' First Withdrawal Actions. This figure shows the distribution of weeks between Russia's invasion of Ukraine and firms' first withdrawal-related actions in the KSE-SafeGraph intersected dataset.

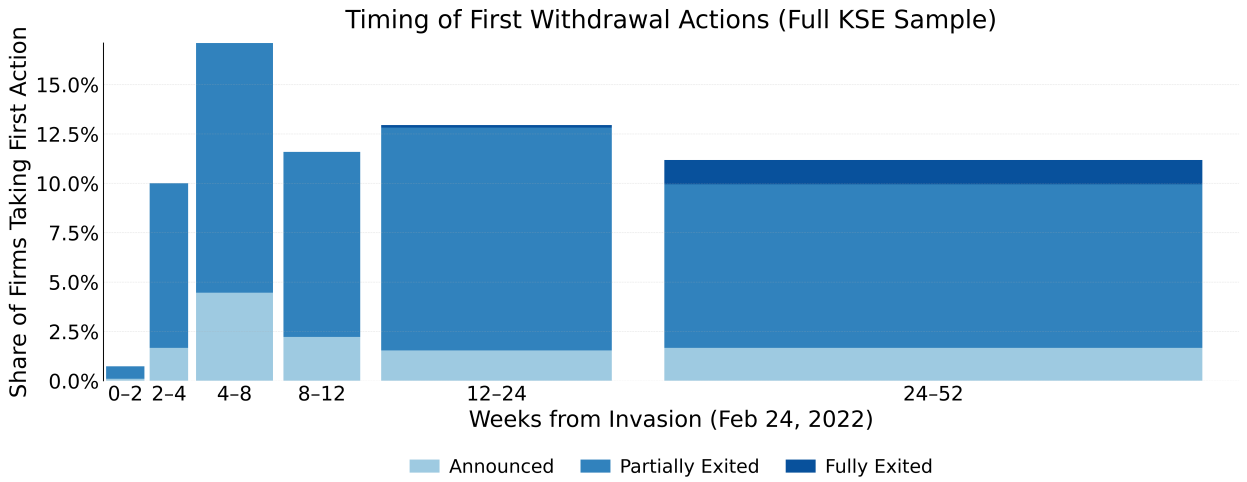


Figure 5: Timing of Firms' First Withdrawal Actions. This figure shows the distribution of weeks between Russia's invasion of Ukraine and firms' first withdrawal-related actions in the full KSE dataset.

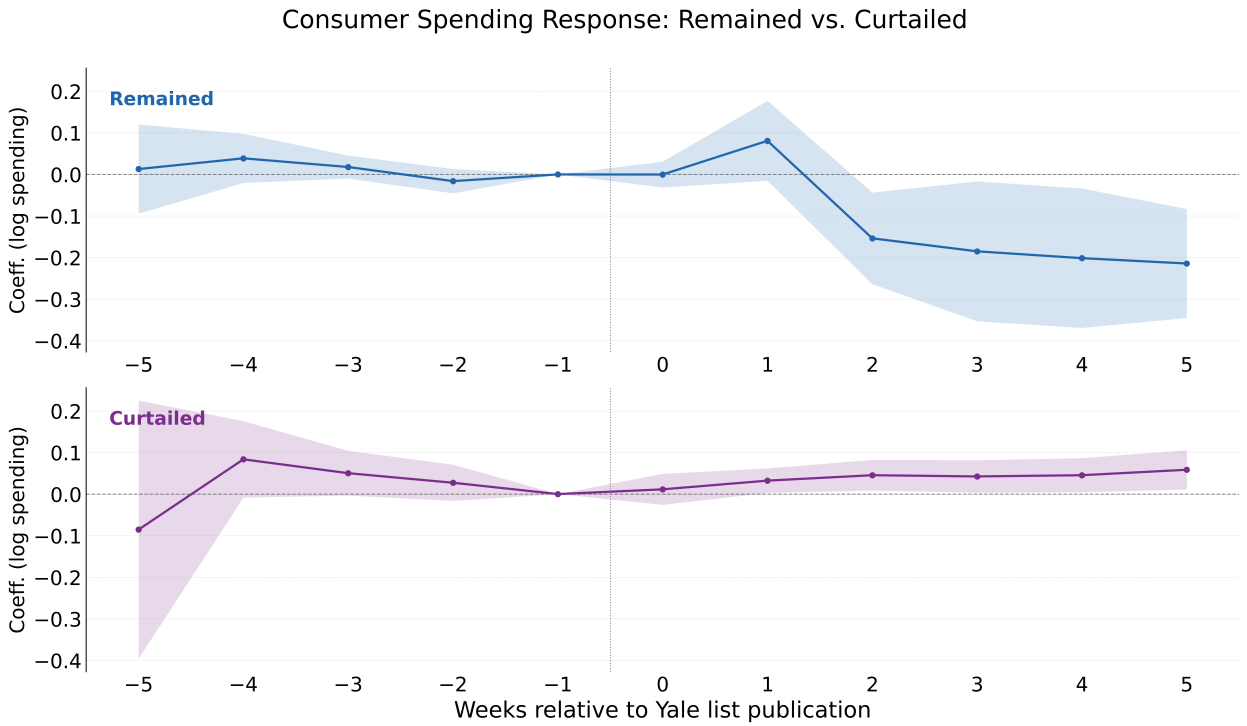


Figure 6: Spending Responses. Event-time estimates of normalized firm-level spending around the Yale list release. Estimates are shown for firms classified as continuing to operate (*Remained*), and firms that had begun curtailing operations (*Curtailed*). The omitted period is the week prior to the list's release. Shaded bands indicate 95% confidence intervals

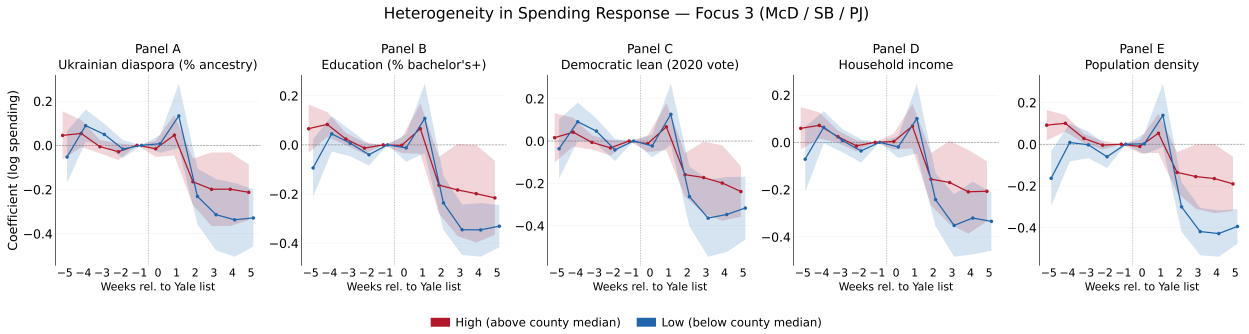


Figure 7: Regional Heterogeneity in Spending Responses: Focus Brands. Event-time estimates of normalized consumer spending around the Yale list release for the three largest consumer-facing firms in the sample (McDonald's, Starbucks, and Papa John's). Each panel splits counties based on whether the indicated characteristic is above or below the county-level median: Ukrainian ancestry share, share of adults with a bachelor's degree or higher, Democratic vote share in the 2020 presidential election, median household income, and population density. The omitted period is the week prior to the list's publication. Shaded bands indicate 95% confidence intervals.

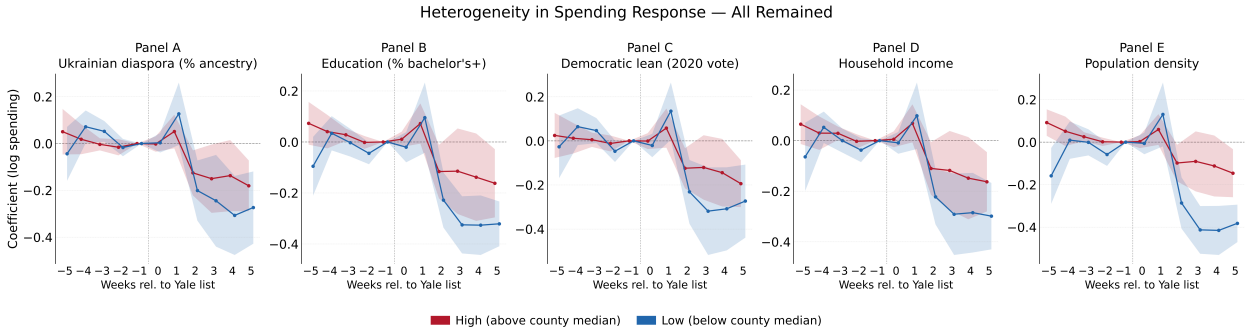


Figure 8: Regional Heterogeneity in Spending Responses: Firms Remaining in Russia. Event-time estimates of normalized consumer spending around the Yale list release for firms classified as continuing to operate in Russia. Each panel splits counties based on whether the indicated characteristic is above or below the county-level median: Ukrainian ancestry share, share of adults with a bachelor's degree or higher, Democratic vote share in the 2020 presidential election, median household income, and population density. The omitted period is the week prior to the list's publication. Shaded bands indicate 95% confidence intervals.

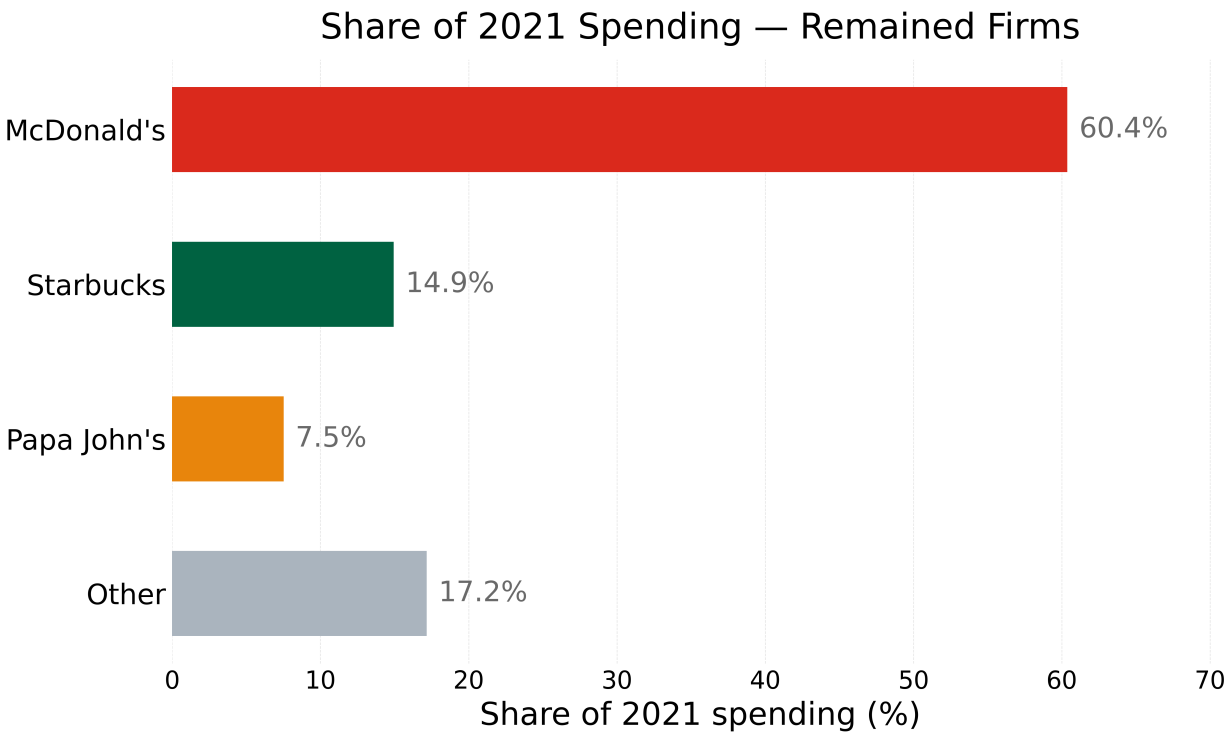


Figure 9: Spend Shares Among Firms Remaining in Russia. Horizontal bar chart comparing 2021 SafeGraph spending shares for the three largest brands linked to firms classified as *Remained* in the March 8 Yale list (McDonald's, Starbucks, and Papa John's) with the combined share of all other brands in the sample.

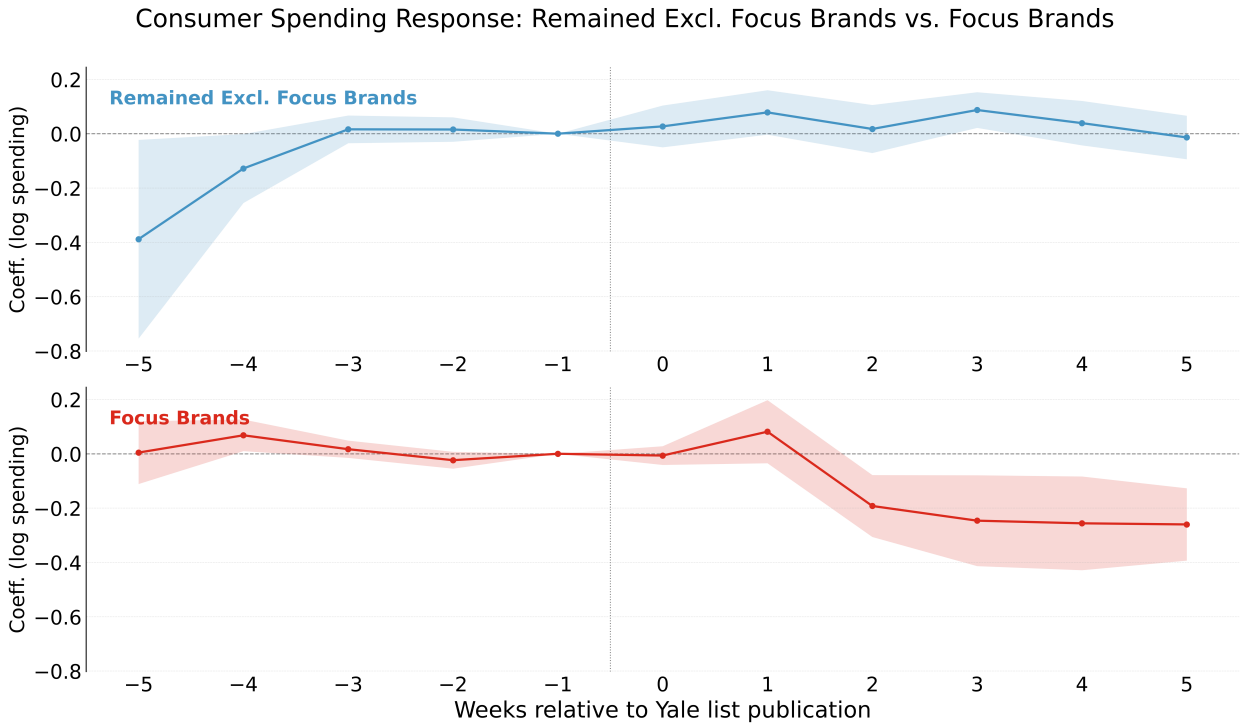


Figure 10: Spending Responses: Focus Brands vs. Other Remaining Firms. Event-time estimates of normalized consumer spending around the Yale list release. The figure compares firms classified as continuing to operate in Russia excluding the three largest consumer-facing brands ("Remained Excl. Focus 3") with those focal brands themselves ("Focus 3": McDonald's, Starbucks, and Papa John's). The omitted period is the week prior to the list's release. Shaded bands indicate 95% confidence intervals.

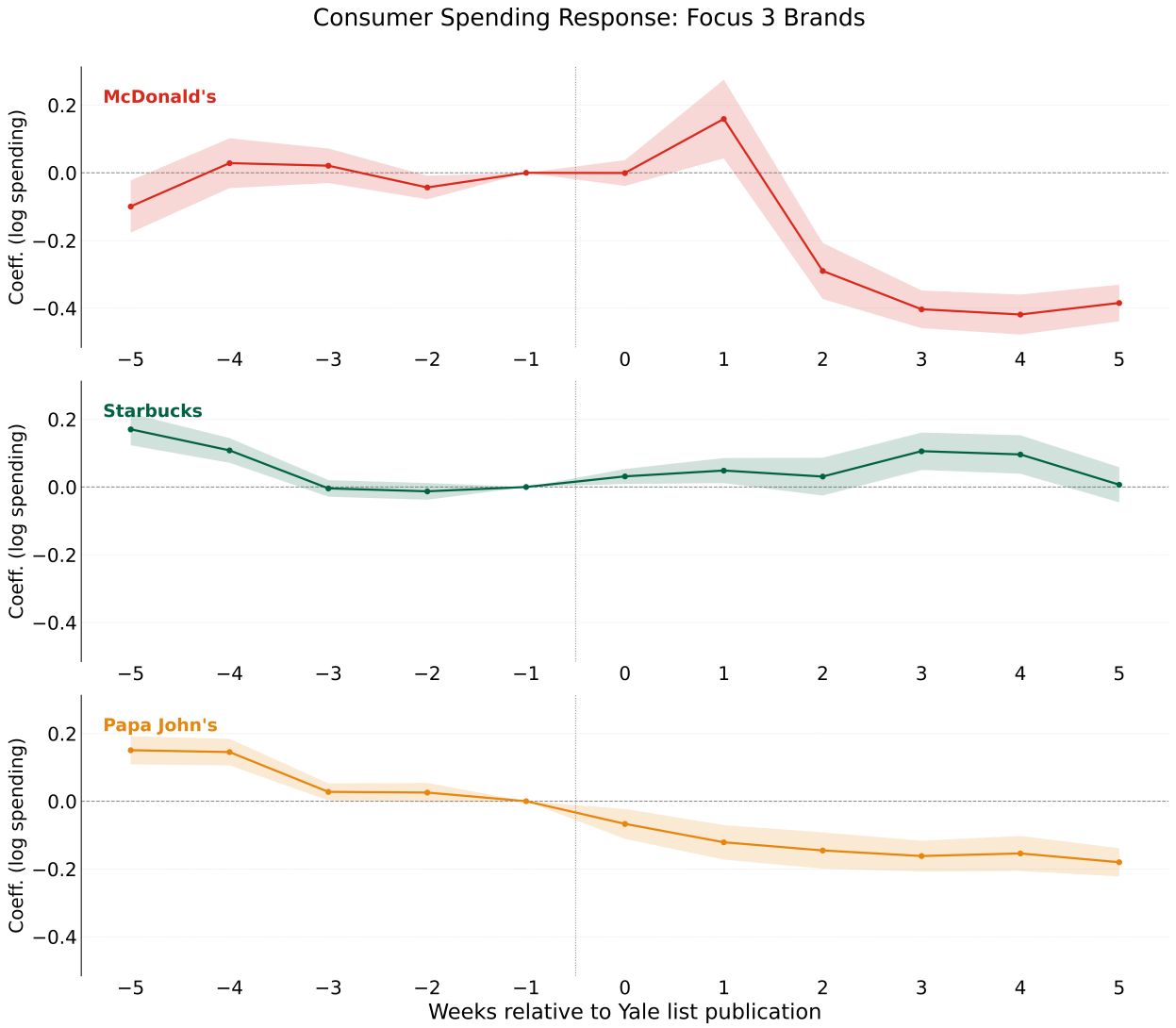


Figure 11: Spending Responses: Focus Brands. Event-time estimates of normalized consumer spending for the three largest consumer-facing firms in the sample—McDonald's, Starbucks, and Papa John's, around the initial release of the Yale list. The omitted period is the week prior to the list's publication. Shaded areas indicate 95% confidence intervals.

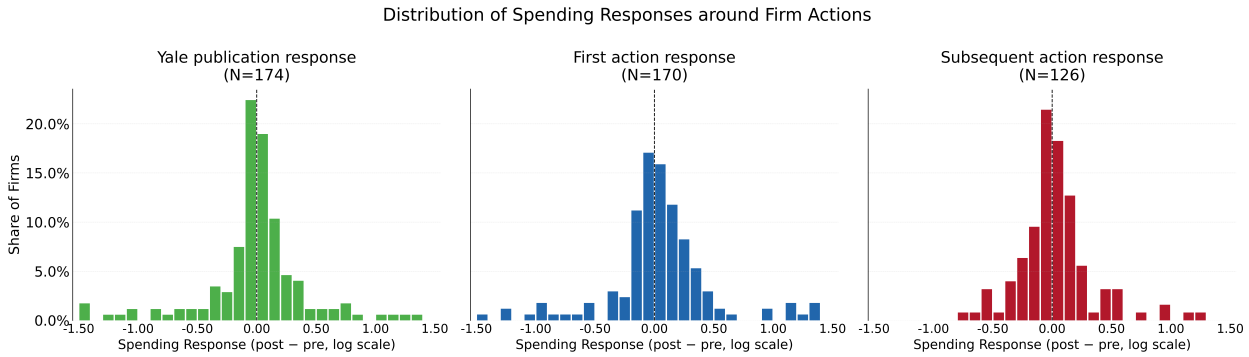


Figure 12: Distribution of firm-level spending responses around status changes. The figure shows the change in log normalized spending between the two weeks after and two weeks before each event, separately for the Yale list publication, as well as first and subsequent actions.

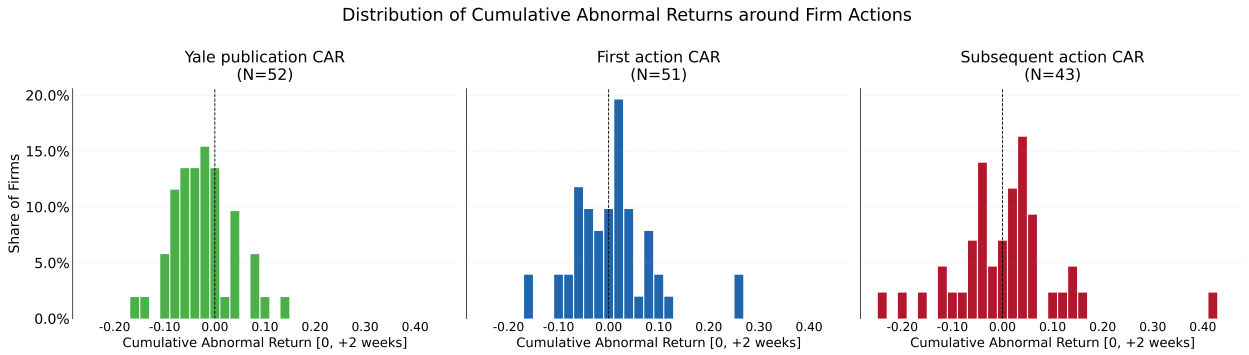


Figure 13: Distribution of CAR responses around status changes. The figure shows the cumulative market-adjusted returns in the [0,+2] week window following the Yale list publication, as well as first and subsequent actions.

6 Tables

Table 1: Summary Statistics: Consumer Spending Sample

	N	Mean	SD	Min	Max
Panel A: Consumer Spending					
Log weekly brand–county spending	171,987	6.88	1.63	0.001	15.304
Panel B: County Characteristics					
Democratic vote share (2020)	3,154	0.341	0.164	0.031	0.945
Median household income ($1,000s)	3,143	63.312	16.820	17.900	170.463
Share with bachelor's degree	3,144	23.491	10.060	0.000	78.871
Log population density	3,144	3.779	1.805	−3.303	11.193
Ukrainian diaspora share	3,144	0.156	0.328	0.000	9.654

Notes: This table reports summary statistics for the SafeGraph consumer spending sample used in the event-study analysis. Log weekly spending is measured at the brand–county level. County characteristics are measured using pre-period data.

Table 2: Summary Statistics: Firm Withdrawal Sample

	N	Mean	SD	Min	Max
Panel A: Spending Responses					
Spend response to Yale list release	174	0.075	0.966	−3.113	5.568
Spend response to first action	170	0.064	1.186	−5.726	7.640
Spend response to subsequent action	156	0.008	0.936	−4.514	5.425
Panel B: Firm Characteristics					
Log total SafeGraph spending, 2021	207	13.933	3.916	0.000	22.053
Log number of U.S. counties	207	3.689	2.064	0.693	7.894
Log Russia revenue	98	4.552	2.011	0.000	8.836
Log Russia employees	97	5.967	1.951	2.639	11.035

Notes: This table reports summary statistics for the firm-level sample used in the hazard analysis. Panel A reports spending responses, defined as the difference in mean county-weighted relative spending between the two weeks after and two weeks before each firm action: $Resp_f = \bar{y}_{f,[\tau+1,\tau+2]} - \bar{y}_{f,[\tau-2,\tau-1]}$, where $y_{ft} = \sum_c w_{fc}\big[\log(1+S_{fct}) - \log(1+T_{ct})\big]$ and weights w_{fc} are fixed at 2021 county spending shares. *Yale list release* corresponds to the week of the initial public circulation of the Yale list identifying firms continuing operations in Russia. *First action* denotes the initial transition from continued operations (status 0) to any withdrawal-related step (status 1+). *Subsequent actions* refer to later escalations in withdrawal status. Panel B reports firm characteristics. SafeGraph spending and county counts are available for all 207 sample firms; Russian revenue and employment are available for a smaller subset sourced from the KSE Institute database.

Table 3: Event-Study Estimates by Brand Sample

	(1) All Remained	(2) Curtailed
Post × Treat	-0.123^{***}	0.014
	(0.037)	(0.033)
Brand-County FE	Yes	Yes
Cohort-Week FE	Yes	Yes
Observations	157,260	161,024
R^2	0.967	0.953

Notes: Each column reports event-study estimates from a stacked difference-in-differences specification. The outcome is log weekly brand–county spending. Post × Treat captures the average post-treatment spending response relative to matched controls. Standard errors clustered by brand are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 4: Event-Study Estimates: Focus 3 Brands vs Other Remained Brands

	(1) Focus 3 (McD/SB/PJ)	(2) Remained (excl. Focus 3)
Post × Treat	-0.160^{***}	0.067^{**}
	(0.033)	(0.029)
Brand-County FE	Yes	Yes
Cohort-Week FE	Yes	Yes
Observations	91,814	65,446
R^2	0.980	0.887

Notes: Each column reports event-study estimates from a difference-in-differences specification. The outcome is log weekly brand–county spending. Post × Treat captures the average post-treatment spending response relative to matched controls. Column (1) includes McDonald's, Starbucks, and Papa John's. Column (2) includes all other *Remained* firms. Standard errors clustered by brand are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 5: Event-Study Estimates: McDonald's, Starbucks, Papa John's

	(1) McDonald's	(2) Starbucks	(3) Papa John's
Post × Treat	-0.205^{***}	0.005	-0.206^{***}
	(0.017)	(0.018)	(0.017)
Brand-County FE	Yes	Yes	Yes
Cohort-Week FE	Yes	Yes	Yes
Observations	49,504	22,044	20,266
R^2	0.979	0.983	0.977

Notes: Each column reports event-study estimates from a difference-in-differences specification. The outcome is log weekly brand–county spending. Post × Treat captures the average post-treatment spending response relative to matched controls. Standard errors clustered by brand are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 6: First Action Hazard (0 → 1+): Reputational Pressure

	(1) Baseline	(2) + Firm Controls	(3) + Russia Exposure
Yale Curtailed	1.267***	1.328***	1.267***
	(0.262)	(0.268)	(0.385)
Yale Remained	1.642***	1.543***	0.633*
	(0.208)	(0.209)	(0.354)
Demand Signal (Yale)	−0.068	−0.081	0.010
	(0.134)	(0.145)	(0.116)
Log 2021 Spending		−0.084	−0.263**
		(0.054)	(0.108)
Log Counties		0.192**	0.522***
		(0.097)	(0.199)
Log Russia Revenue			0.254**
			(0.105)
Log Russia Staff			0.020
			(0.089)
Week FE	Yes	Yes	Yes
Coarse Industry FE	Yes	Yes	Yes
Observations	4,904	4,904	2,008
Firms	205	205	91
Events	198	198	87

Notes: Complementary log-log hazard estimates of the probability that a firm takes its first withdrawal-related action following the invasion of Ukraine. Standard errors clustered by firm are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 7: Escalation Hazard (1 → 2+): Demand Signal Mechanism

	(1) Baseline	(2) + Firm Controls	(3) + Russia Exposure
Yale Curtailed	1.018***	1.165***	0.970**
	(0.379)	(0.389)	(0.398)
Yale Remained	0.543	0.399	0.842
	(0.668)	(0.766)	(0.834)
Demand Signal (Yale)	−0.041	−0.074	−0.482**
	(0.214)	(0.236)	(0.191)
Demand Signal (First)	−0.538**	−0.596***	−0.584***
	(0.226)	(0.229)	(0.180)
Log 2021 Spending		−0.171	−0.551***
		(0.107)	(0.152)
Log Counties		0.346*	0.897***
		(0.191)	(0.302)
Log Russia Revenue			0.532**
			(0.231)
Log Russia Staff			−0.198
			(0.201)
Week FE	Yes	Yes	Yes
Coarse Industry FE	Yes	Yes	Yes
Observations	6,906	6,906	2,475
Firms	84	84	45
Events	58	58	45

Notes: Complementary log-log hazard estimates of the probability that firms escalate beyond an initial symbolic action. Demand Signal corresponds to the spending response following the first action. Standard errors clustered by firm.

Table 8: Exit Hazard (1–2 → 3): Withdrawal Completion

	(1) Baseline	(2) + Firm Controls	(3) + Russia Exposure
Yale Curtailed	0.437	0.487	0.043
	(0.396)	(0.408)	(0.359)
Yale Remained	1.191*	1.079*	0.285
	(0.655)	(0.630)	(0.761)
Demand Signal (Yale)	0.200	0.253	0.009
	(0.139)	(0.169)	(0.159)
Demand Signal (First)	−0.528	−0.610	−0.152
	(0.626)	(0.655)	(0.537)
Demand Signal (Current)	0.075	0.086	−0.557
	(0.653)	(0.672)	(0.571)
Log 2021 Spending		−0.133	−0.422**
		(0.087)	(0.194)
Log Counties		0.322*	0.834**
		(0.177)	(0.342)
Log Russia Revenue			−0.349***
			(0.103)
Log Russia Staff			0.586***
			(0.135)
Week FE	Yes	Yes	Yes
Coarse Industry FE	Yes	Yes	Yes
Observations	29,593	29,593	11,312
Firms	198	198	87
Events	40	40	38

Notes: Complementary log-log hazard estimates of the transition to full exit from Russia. Standard errors clustered by firm.

Table 9: Hazard Robustness: Demand Signal (Yale) Interactions

	(1) First Action	(2) Escalation	(3) Full Exit
Yale Curtailed	1.267***	1.021***	0.440
	(0.259)	(0.377)	(0.384)
Yale Remained	1.468***	0.509	0.840
	(0.303)	(0.676)	(0.690)
Demand Signal (Yale)	−0.063	−0.042	0.098
	(0.141)	(0.231)	(0.237)
Demand Signal (First)		−0.539**	−0.633
		(0.233)	(0.624)
Demand Signal (Current)			0.109
			(0.651)
Yale Remained × Demand Signal (Yale)	−107.562***	−0.352	−4.028
	(13.129)	(3.519)	(3.932)
Yale Curtailed × Demand Signal (Yale)	−0.121	0.032	0.280
	(0.423)	(0.580)	(0.288)
Week FE	Yes	Yes	Yes
Coarse Industry FE	Yes	Yes	Yes
Observations	4,904	6,906	29,593
Firms	205	84	198
Events	198	58	40

Notes: Complementary log-log hazard estimates interacting the Yale category indicators with the Demand Signal (Yale) measure. Each column reports a separate hazard corresponding to a different transition on the withdrawal ladder. Standard errors clustered by firm are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 10: Stock Market Responses: Invasion of Ukraine

	(1) [-1,+1]	(2) [0,+1]	(3) [-1,+3]	(4) [-3,+3]
High Exposure	-0.0222^{***}	-0.0228^{***}	-0.0323^{**}	-0.0273^{*}
	(0.0077)	(0.0065)	(0.0143)	(0.0152)
Observations	431	431	431	431
R^2	0.017	0.030	0.017	0.011

Notes: Each column reports cross-sectional regressions of cumulative abnormal returns (CARs) around the invasion of Ukraine on an indicator for high Russia exposure. High Exposure is defined as firms with 2021 Russian revenue share above the sample median. CAR windows (in trading days) are centered around February 24, 2022, the invasion onset, as indicated in column headings. Standard errors (in parentheses) are heteroskedasticity-robust (HC3). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 11: Stock Market Responses: Yale List Release

	(1) Yale vs Non-Yale	(2) Within Yale	(3) Pooled
Yale × Post	0.0015		0.0011
	(0.0037)		(0.0044)
Remained × Post		0.0018	
		(0.0048)	
Remained × Yale × Post			0.0018
			(0.0047)
Firm FE	Yes	Yes	Yes
Week FE	Yes	Yes	Yes
Observations	4,253	913	4,253
Within R^2	-0.0002	-0.0012	-0.0005

Notes: The dependent variable is weekly abnormal returns. Column (1) compares firms listed on the Yale list to other firms in the KSE sample. Column (2) restricts to Yale-listed firms and compares firms categorized as remaining in Russia to those that curtailed operations. Column (3) reports a pooled specification including both effects. All specifications include firm and week fixed effects. Standard errors clustered at the firm level are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 12: Summary Statistics: Post-Action Cumulative Abnormal Returns

	N	Mean	SD	Min	Max
$[0, +2]$ week CAR response to Yale list release	52	−0.014	0.093	−0.154	0.503
$[0, +2]$ week CAR response to first action	51	0.005	0.080	−0.163	0.268
$[0, +2]$ week CAR response to subsequent action	43	0.003	0.106	−0.242	0.410

Notes: Cumulative abnormal returns (CARs) are computed as the sum of market-adjusted weekly returns over the $[0, +2]$ week window following each event. Abnormal returns are defined as $AR_{i,w} = R_{i,w} - R_{m,w}$, where $R_{m,w}$ denotes the CRSP value-weighted market return. *Yale list release* corresponds to the week of the initial public circulation of the Yale list identifying firms continuing operations in Russia. *First action* denotes the initial transition from continued operations (status 0) to any withdrawal-related step (status 1+). *Subsequent actions* refer to later escalations in withdrawal status (e.g., status 1→2 or 2→3). The sample is restricted to publicly traded firms with valid CRSP–Compustat linkages.

Table 13: Investor Responses: Hazard Estimates with Post-Event CARs

	(1) First Action	(2) Escalation	(3) Full Exit
Yale Curtailed	1.316***	0.895**	0.472
	(0.258)	(0.418)	(0.417)
Yale Remained	1.645***	0.542	1.013
	(0.213)	(0.630)	(0.687)
Demand Signal (Yale)	−0.042	−0.142	0.065
	(0.134)	(0.258)	(0.147)
Demand Signal (First)		−0.422*	−0.363
		(0.252)	(0.569)
Demand Signal (Current)			−0.057
			(0.604)
Post-Yale CAR	−0.093	−0.524	−0.962**
	(0.118)	(0.488)	(0.427)
CAR Missing (Yale)	−0.358*	0.352	−1.847
	(0.199)	(0.402)	(1.274)
Post-Action CAR (First)		0.087	0.908***
		(0.968)	(0.345)
CAR Missing (First)		−1.084	2.189
		(0.940)	(1.523)
Post-Action CAR (Current)			−0.721**
			(0.297)
CAR Missing (Current)			1.783
			(1.275)
Week FE	Yes	Yes	Yes
Coarse Industry FE	Yes	Yes	Yes
Observations	4,904	6,906	29,593
Firms	205	84	198
Events	198	58	40

Notes: Complementary log-log hazard estimates incorporating abnormal stock returns around firms' prior withdrawal-related actions. The first-action specification adds CARs around the Yale list release; the escalation specification adds CARs around the first action and Yale list release; the full-exit specification adds CARs around the first action, most recent action, and Yale list release. Standard errors clustered by firm are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 14: Full Exit Hazard: Exposure and Market-Based Measures

	(1) + Russia Exposure	(2) + Invasion CAR	(3) + Yale CAR	(4) + Both CARs
Yale Curtailed	−0.299	−0.295	−0.210	−0.298
	(0.367)	(0.364)	(0.370)	(0.401)
Yale Remained	0.254	0.022	0.077	0.021
	(0.817)	(0.751)	(0.773)	(0.757)
Demand Signal (First)	0.021	−0.234	−0.158	−0.233
	(0.597)	(0.589)	(0.550)	(0.589)
Demand Signal (Current)	−0.636	−0.505	−0.536	−0.506
	(0.644)	(0.644)	(0.610)	(0.643)
Demand Signal (Yale)	−0.107	−0.095	−0.147	−0.095
	(0.143)	(0.176)	(0.144)	(0.175)
Post-Invasion CAR		0.480		0.487
		(0.378)		(0.549)
Post-Yale CAR			0.339	−0.018
			(0.641)	(1.072)
CAR Missing (Invasion/Yale)		−1.260**	−1.205**	−1.258**
		(0.490)	(0.500)	(0.500)
Log Russia Revenue	−0.390***	−0.419***	−0.415***	−0.419***
	(0.085)	(0.094)	(0.091)	(0.094)
Log Russia Staff	0.662***	0.767***	0.772***	0.767***
	(0.121)	(0.157)	(0.161)	(0.159)
Week FE	Yes	Yes	Yes	Yes
Coarse Industry FE	Yes	Yes	Yes	Yes
Observations	11,312	11,312	11,312	11,312
Firms	87	87	87	87
Events	38	38	38	38

Notes: Complementary log-log hazard estimates for full exit. Column (1) includes direct measures of Russia exposure. Columns (2)–(4) sequentially add abnormal returns around the invasion, the Yale list release, and both measures jointly. The missing indicator is common across Post-Invasion and Post-Yale CARs in this sample, as the two are perfectly colinear. Standard errors clustered by firm are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 15: Investor Responses: Post-Action CAR (Yale) Interactions

	(1) First Action	(2) Escalation	(3) Full Exit
Yale Curtailed	1.262***	0.547	0.409
	(0.262)	(0.436)	(0.422)
Yale Remained	1.572***	0.767	0.387
	(0.259)	(0.589)	(0.942)
Demand Signal (Yale)	−0.049	−0.087	0.061
	(0.137)	(0.269)	(0.152)
Demand Signal (First)		−0.444*	−0.382
		(0.251)	(0.567)
Demand Signal (Current)			−0.039
			(0.600)
Post-Yale CAR	−0.068	−0.258	−0.878**
	(0.111)	(0.477)	(0.411)
CAR Missing (Yale)	−0.255	0.644	−1.593
	(0.203)	(0.395)	(1.398)
Post-Action CAR (First)		0.084	0.874**
		(1.076)	(0.431)
CAR Missing (First)		−1.109	2.112
		(0.948)	(1.545)
Post-Action CAR (Current)			−0.579
			(0.370)
CAR Missing (Current)			1.737
			(1.321)
Yale Remained × Post-Yale CAR	−8.337***	1.001	−3.305
	(0.903)	(3.551)	(3.563)
Yale Curtailed × Post-Yale CAR	−15.772***	−5.022***	−0.706
	(1.728)	(1.221)	(1.829)
Week FE	Yes	Yes	Yes
Coarse Industry FE	Yes	Yes	Yes
Observations	4,904	6,906	29,593
Firms	205	84	198
Events	198	58	40

Notes: Complementary log-log hazard estimates interacting the Yale category indicators with the Post-Action CAR (Yale) measure. Each column reports a separate hazard corresponding to a different transition on the withdrawal ladder. Standard errors clustered by firm are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 16: Hazard Robustness: Sanction-Prone Industry Controls

	(1) First Action	(2) Escalation	(3) Full Exit
Yale Curtailed	1.270***	0.986**	0.466
	(0.261)	(0.386)	(0.403)
Yale Remained	1.643***	0.534	1.198*
	(0.207)	(0.659)	(0.653)
Demand Signal (Yale)	−0.068	0.009	0.161
	(0.134)	(0.224)	(0.148)
Demand Signal (First)		−0.621***	−0.391
		(0.239)	(0.635)
Demand Signal (Current)			−0.026
			(0.655)
Sanction Prone	0.051	0.503	−0.987
	(0.357)	(0.501)	(0.874)
Week FE	Yes	Yes	Yes
Coarse Industry FE	Yes	Yes	Yes
Observations	4,904	6,906	29,593
Firms	205	84	198
Events	198	58	40

Notes: Complementary log-log hazard estimates adding an indicator for firms in sanction-prone industries. Each column reports a separate hazard corresponding to a different transition on the withdrawal ladder. Standard errors clustered by firm are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 17: Hazard Robustness: Alternative CAR Windows

	(1) $[-1,+1]$ CARs	(2) $[0,+1]$ CARs
Yale Curtailed	0.603	0.528
	(0.425)	(0.417)
Yale Remained	1.405**	1.243*
	(0.668)	(0.653)
Demand Signal (Yale)	0.064	0.153
	(0.169)	(0.170)
Demand Signal (First)	−0.157	−0.316
	(0.611)	(0.600)
Demand Signal (Current)	−0.249	−0.127
	(0.635)	(0.625)
Post-Action Yale CAR	−0.576	−0.391
	(0.418)	(0.398)
CAR Missing (Yale)	0.198	−0.921
	(1.487)	(2.239)
Post-Action CAR (First)	1.169***	0.623*
	(0.343)	(0.337)
CAR Missing (First)	2.340	1.578
	(1.668)	(2.521)
Post-Action CAR (Current)	−0.548**	−0.300
	(0.239)	(0.268)
CAR Missing (Current)	−0.451	0.555
	(1.410)	(2.219)
Week FE	Yes	Yes
Coarse Industry FE	Yes	Yes
Observations	29,593	29,593
Firms	198	198
Events	40	40

Notes: Complementary log-log hazard estimates for full exit (status 1–2 $\rightarrow$ 4), replicating the Spec 5 CAR specification across alternative event windows. Column (1) uses $[-1,+1]$ windows; column (2) uses $[0,+1]$ windows. All specifications include CARs around the first action, most recent action, and Yale list release, with 0-fill and missing indicators for firms without CRSP coverage. Standard errors clustered by firm are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 18: Hazard Robustness: Linear Probability Models

	(1) First Action	(2) Escalation	(3) Full Exit
Yale Curtailed	0.1099**	0.0140**	−0.0006
	(0.0470)	(0.0063)	(0.0010)
Yale Remained	0.1327***	0.0269	0.0039
	(0.0506)	(0.0166)	(0.0073)
Demand Signal (Yale)	0.0148	−0.0038	−0.0001
	(0.0099)	(0.0045)	(0.0008)
Demand Signal (First)		−0.0078*	−0.0015
		(0.0044)	(0.0014)
Demand Signal (Current)			−0.0004
			(0.0014)
Log 2021 Spending	−0.0200***	−0.0072***	−0.0008**
	(0.0075)	(0.0021)	(0.0004)
Log Counties	0.0363***	0.0117***	0.0015**
	(0.0128)	(0.0039)	(0.0007)
Log Russia Revenue	0.0219**	0.0067**	−0.0012***
	(0.0105)	(0.0029)	(0.0004)
Log Russia Staff	0.0153*	−0.0027	0.0018***
	(0.0085)	(0.0031)	(0.0004)
Week FE	Yes	Yes	Yes
Coarse Industry FE	Yes	Yes	Yes
Observations	2,008	2,475	11,312
Firms	91	45	87
Events	87	45	38

Notes: Linear probability models estimated on the same risk sets as the main hazard specifications, using the fullest specification that adds firm controls and Russian exposure measures. Standard errors clustered by firm are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

A Appendix

A.1 Construction of Firm-Level Spending Response Measures

This section describes the construction of the firm-level consumer spending response measure used in the hazard analyses.

A.1.1 County-Level Normalized Spending

The underlying data consist of weekly consumer spending at the firm–county level. Let S_{fct} denote consumer spending at firm f in county c during week t, and let T_{ct} denote total consumer spending in county c during the same week.

To remove common local demand fluctuations, we define normalized firm spending as

$$y_{fct} = \log(1 + S_{fct}) - \log(1 + T_{ct}). \tag{2}$$

This transformation measures firm spending relative to the overall level of consumer spending in the county-week, thereby removing variation driven by common county-level shocks, such as local economic conditions or seasonality.

A.1.2 Aggregation to Firm-Week Spending

We aggregate the normalized county-level measure to the firm-week level using fixed county weights reflecting the geographic distribution of each firm's spending prior to the invasion.

Let

$$w_{fc} = \frac{S_{fc}^{2021}}{\sum_c S_{fc}^{2021}} \tag{3}$$

denote the share of firm f's total consumer spending occurring in county c during 2021. These weights sum to one across counties for each firm.

Firm-level normalized spending in week t is then defined as

$$y_{ft} = \sum_c w_{fc}\, y_{fct}. \tag{4}$$

Using fixed pre-period weights ensures that changes in geographic composition do not mechanically influence the measured spending response following firm actions.

A.1.3 Post-Action Spending Response

For each firm action occurring in week τ, we define the short-run spending response as the change in average firm-level spending between the two weeks following the action and the two weeks preceding it:

$$Resp_f(\tau) = \frac{1}{2}\sum_{k=1}^{2} y_{f,\tau+k} - \frac{1}{2}\sum_{k=1}^{2} y_{f,\tau-k}. \tag{5}$$

This measure captures the short-run change in consumer demand following a firm's announcement. Observations are included only when at least one non-missing observation is available in both the pre- and post-action windows.

A.1.4 Time-Varying Demand Signal

In hazard specifications that follow firms through multiple status changes, the demand signal is updated after each new action.

For each status change at week τ, the spending response $Resp_f(\tau)$ is computed using the same two-week pre- and post-action window described above. The corresponding response is assigned to firm-weeks only after the post-action window has fully elapsed (i.e., for weeks $t > \tau + 2$). This ensures that the demand signal entering the hazard model is strictly predetermined with respect to the outcome being predicted and does not mechanically overlap with the timing of firm actions.

A.1.5 Construction of the Demand Signal Measure

This quantity represents the firm-level spending response associated with the action occurring in week τ. In the hazard regressions, the demand signal variable $\text{Demand Signal}_{ft-1}$ corresponds to the most recent realized response available prior to week t:

$$\text{Demand Signal}_{ft-1} = Resp_f(\tau^*)$$

where $\tau^* = \max\{\tau : \tau + 2 < t\}$. This construction ensures that the demand signal reflects realized firm-specific demand fluctuations available at the time of decision-making, rather than ex post outcomes.