High-Frequency Cross-Sectional Identification of Military News Shocks

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Abstract

This study develops a two-step procedure to identify and quantify fiscal news shocks. First, we augment a narrative identification strategy using Large Language Model searches to compile events (2001–2023) that altered the expected path of U.S. defense expenditure. Second, for each event, we estimate market-implied shifts in expected defense spending with cross-sectional regressions of contractors' stock returns on their reliance on military revenues. We show that this approach statistically validates each event, quantifies each shock in an intuitive, model-consistent fashion, and readily generalizes to other macroeconomic contexts. Employing the estimated shocks in a shift-share analysis yields a two-year MSA-level GDP multiplier of approximately 1 for U.S. military build-ups.

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I. Introduction

How does the economy respond to *anticipated* changes in government spending? This question lies at the intersection of two core strands of macroeconomic research: the debate over fiscal multipliers and the effects of agents' expectations on aggregate economic outcomes. While the former has been extensively explored through alternative identification strategies for government spending shocks (Ramey and Shapiro, 1998; Blanchard and Perotti, 2002; Ramey, 2011), the latter has suffered from a lack of widely accepted methods for estimating the impact of expectations on macroeconomic aggregates. We address this gap by introducing a two-step procedure that combines narrative identification enhanced by Large Language Models (LLMs) with the cross-sectional analysis of defense contractors' stock market performance. By leveraging firms' differential exposure to anticipated changes in government spending, we extract robust measures of military news shocks.

We begin by narratively identifying salient military events that shifted U.S. defense spending expectations since 2000. We carry out this analysis with a detailed historical review, enhanced with OpenAI's most advanced model, cross-checking each event against established narrative series (Ramey, 2011; Ramey and Zubairy, 2018) or documenting thoroughly the new events we introduce. Next, we validate each episode and quantify investors' anticipation by examining abnormal fluctuations in defense contractors' stock returns. Finally, we extract the anticipated fiscal shocks via cross-sectional regressions derived from standard asset pricing models, exploiting each contractor's differential elasticity to government spending as proxied by its *reliance* on Department of Defense (DoD) procurement.

Intuitively, a simple asset pricing model predicts that, around an event of interest, a firm whose revenues depend on government purchases will exhibit returns proportional to the expected change in spending, multiplied by its reliance. Reliance thus measures the firm's exposure to fiscal shocks, measured here by the ratio of DoD contract revenues to total sales. For example, if Lockheed Martin and Boeing derive respectively 70% and 30% of their sales from DoD contracts, a given military news shock should, on average, affect Lockheed Martin's stock price more than Boeing's.

Leveraging this insight, we use cross-sectional variation in contractors' returns to quantify the expected *aggregate* fiscal shock. For each event, we regress weekly excess returns on firms' reliance measures and interpret the estimated slope coefficient as the expected percent change in defense spending. In other words, by adopting a broadly established asset pricing framework, we let the data reveal the magnitude of fiscal shocks around each narratively identified episode.

We label this methodology *high-frequency cross-sectional* identification. We highlight three main advantages. First, it is grounded in standard, parsimonious, and intuitive asset-pricing models and is readily generalizable to any context in which treated units are differentially exposed to an aggregate shock. Second, it is self-validating: it explicitly tests the statistical significance (hence the *sign*) of each shock in the cross section of returns. Third, it delivers a data-driven, robust quantification of shocks' magnitudes by exploiting high-frequency fluctuations of priced-in expectations embedded in stock market responses. In summary, the methodology achieves a transparent, testable and less subjective quantification of fiscal shocks.

We apply this methodology to the U.S., identifying 12 events from 2000 to 2023. For each, we estimate the cross-sectional regressions described above and extract a novel daily series of expected military spending news shocks. Hence, we study the real economic effects of these shocks in a *shift-share* empirical framework by calculating a cross-sectional fiscal multiplier at the Metropolitan Statistical Area (MSA) level. Whereas the literature typically uses a Bartik-type instrument with national changes in defense procurement as the "*shift*", we use our high-frequency cross-sectional (HFXS) series of news shocks. In our baseline sample, the F-statistic for our instrument increases over time, peaking two years after the shock at a value of 30. The corresponding estimated two-year cross-sectional multiplier is approximately 1, i.e., an MSA receiving an additional dollar in defense spending sees its GDP stimulated two years from the shock by $1 relative to the average MSA.

Related Literature This paper places itself in the fiscal policy literature discussing the effects of news shocks on economic outcomes. In particular, Ramey (2011) and Ramey and Zubairy (2018) (RZ18) construct a series of defense news shocks by means of a narrative analysis. Fisher and Peters (2010) (FP10) build a stock market index of cumulative excess returns on defense contractors and use it as an internal instrument in a VAR to identify anticipated changes in government expenditure. Leeper, Richter, and Walker (2012) measures fiscal news using the Survey of Professional Forecasters, while Ben Zeev and Pappa (2017) employ medium-run restrictions in a VAR to identify defense spending news shocks (Barsky and Sims, 2011).

Our method combines the narrative approach of RZ18 with a high-frequency identification strategy, and uses fluctuation in military contractors' stock prices in a similar but distinct fashion to FP10. More precisely, we broaden and enrich the narrative identification of *fiscal events* with the aid of Large Language Models (LLMs), identifying 12 major episodes that shifted the medium-run trajectory of U.S. defense spending after the 2000.

Related contemporaneous work by Bandeira et al. (2025) use LLMs to identify announcement shocks to Brazilian primary surplus; Bi, Phillot, and Zubairy (2025) use a high-frequency approach

in bond auctions to identify Treasury supply shocks; Gomez-Cram, Kung, and Lustig (2025) and Wiegand (2025) use federal budget related information to build high-frequency series of deficit news shocks; Hazell and Hobler (2025) uses a narrative based high-frequency identification to study the effects of fiscal policy on inflation; McClure and Yding (2024) construct a stock market index of excess returns for defense contractors and use its variation around the release of fiscal information to identify shocks.
In contrast, our methodology focuses on *estimating* shocks leveraging cross-sectional variation in contractors' returns around narratively pre-identified events.

A major contribution of this study to the current debate is the introduction of a cross-sectional dimension to the high-frequency identification strategy. We show that a single, theory-consistent cross-sectional regression can be used to extract the aggregate shock from the heterogeneous response of defense contractors around the identified events, and that the estimated slope coefficient *directly* quantifies the sign and the magnitude of the shock. Testing each event's relevance and extracting the shock thus serves as a "*first-stage*" regression which allows to empirically claim that a fiscal event is indeed a news shock to expected military spending.[1] Besides, we also show how this method generalizes to any macroeconomic context in which publicly traded firms are differentially exposed to an *expected* aggregate shock. Equivalently, the approach we introduce can be interpreted as a two-step, high-frequency adaptation of a *shift-share* framework à la Bartik (1991), as in studies that exploit differential industry (Nekarda and Ramey, 2011) and regional (Nakamura and Steinsson, 2014) exposure to national changes in military spending.

Our analysis also relates to the fiscal foresight literature. Leeper, Walker, and Yang (2013) and Mertens and Ravn (2010) show that VAR innovations cannot recover true fiscal shocks in the presence of agents' foresight due to non-invertibility of the shocks (Montiel-Olea et al. (2025)). Forni and Gambetti (2016) use expectational data from the the Survey of Professional Forecasters (SPF) to explain why anticipated increases in government spending are associated with depreciation in the exchange rate. Ascari et al. (2023) employ RZ18's defense news shock series to study state-dependent effects of news under different fiscal and monetary regimes. We introduce a new identification approach for military spending news shocks and show that they have real and substantial economic effects in the context of MSA-level regional multipliers.

The paper is structured as follows. Section II presents the asset-pricing model and derives the cross-sectional regression. Section III describes the data construction and conducts the narrative analysis enhanced by LLMs. Section IV extracts the military news shocks from the cross-section of

[1] We are grateful to Johannes Wieland and Juan Herreño for encouraging us to explore this point in an early presentation of this project (Spring 2022).

returns for each event. Section V applies the method to estimate U.S. regional multipliers. Section VI concludes.

II. High-Frequency Cross-Sectional Identification: A Framework

This study proposes a novel method to identify and quantify fiscal shocks to expected military spending, using a high-frequency cross-sectional approach. After identifying a set of relevant events, we leverage the differential stock price responses of government contractors to extract quantitative military news shocks. More precisely, we implement a two step procedure: first, using Large Language Models (LLMs), we perform a narrative high-frequency identification of events predictive of future military spending; and second, we establish the magnitude of each spending shock by analyzing the cross-sectional variations in contractors' stock prices around the identified events.

The central idea is intuitive: as long as an event entails an expected increase (decrease) in military procurement spending, investors will react by buying (selling) stocks of contractors proportionally to how much each contractor is exposed to the shock. This approach presents several advantages over traditional narrative analysis. Importantly, it develops a disciplined, data-driven framework to address the non-trivial quantification of a fiscal shock. This represents a step forward over existing methodologies. For instance, Ramey and Zubairy (2018) adopts multiple sources to propose measures of the present discounted value of future expected defense spending, such as media outlets, e.g. Business Week and the New York Times, and CBO estimates. Additionally, a further strength of the proposed framework is that it allows us to empirically verify whether any identified event truly signals a change in expected military spending by testing for statistically significant market responses around that date. We expand on these and other advantages below.

Model Consider a simple class of models of stock prices inspired by Gordon (1959). The profits of firm i at time t are proportional to its total sales:

$$D_{i,t} := (1-\tau_t) \cdot \underbrace{(V_{i,t} + G_{i,t})}_{\text{Total Sales}} \cdot \left(1 - \frac{1}{\mu_i}\right)$$

where total sales are equal to the sum of private sales, $V_{i,t}$, and government purchases, $G_{i,t}$, τ_t is a corporate profit tax, and μ_i is an average firm-specific price-cost markup.

The stock price of firm i at time t is equivalent to the present discounted value of future profits:

$$P_{i,t} := \sum_{h=0}^{\infty} \frac{D^e_{i,t+h}}{\Pi_{\tau=0}^{h}(1 + i^e_{t,t+\tau})}$$

where $i^e_{t,t+\tau}$ is the expected $(t + \tau)$-period ahead interest rate at time t.

Let us consider the dynamics of stock price changes around an event of interest.[2] For simplicity, assume that (*i*) expected future profits are proxied by current profits, and that (*ii*) the expectations hypothesis of the term structure holds, i.e., long-term interest rates can be obtained by compounding short-term rates.[3] Then, the stock price around the event can be approximated by:

$$P_{i,t} = \frac{D_{i,t}}{1 - \frac{1}{1-i_t}} = \frac{1 + i_t}{i_t} \cdot \underbrace{(1 - \tau_t) \cdot (V_{i,t} + G_{i,t}) \cdot \left(1 - \frac{1}{\mu_i}\right)}_{D_{i,t}} \tag{1}$$

We show that, by log-differentiating (1) around the occurrence of a shock at t, we obtain a relationship with the following structure:[4]

$$d\log P_{i|t} = \alpha_{|t} + \underbrace{\frac{G_{i|t}}{V_{i|t} + G_{i|t}}}_{\textit{Reliance} \text{ on DoD}} \underbrace{d\log G^e_{i|t}}_{\text{Shock}} + \varepsilon_{i|t} \tag{2}$$

where α is a constant that absorbs any firm invariant change around the event, e.g., a contemporaneous expected change in the corporate profit tax affecting every firm or an expected change in interest rates; ε_i is a fixed effect which absorbs any firm-specific variation; the *Reliance on DoD* term measures the share of firm sales attributable to defense procurement, while the *Shock* term captures the expected percentage change in defense spending at time t.

Denoting by $\lambda_{i|t}$ the *reliance* of a contractor i around the date of the event t, we can rewrite Equation (2) as an estimating cross-sectional regression equation:

$$d\log P_{i|t} = \alpha \ + \underbrace{d\log G^e_t}_{\gamma_t} \cdot \lambda_{i|t} \ + \ \varepsilon_i \tag{3}$$

That is, around the occurrence of a military event at time t, contractors' stock price change reacts proportionally (γ_t) to their degree of reliance on DoD purchases. For instance, in our sample, Lockheed Martin reliance on DoD contracts is about 71%, while Boeing's is 30%. In response to

[2] Section III develops an identification scheme for the selection of such events of interest.
[3] Then, $\Pi^e_{i,t+h} = \Pi_{i,t}$ and $\Pi_{\tau=0}^{h}(1 + i^e_{t,t+\tau}) = (1 + i_t)^h$.
[4] A complete derivation is provided in Appendix A.

a positive shock, we expect Lockheed Martin's stocks to appreciate more than Boeing's, reflecting its higher expected increase in sales.

Therefore, equation (3) implies that regressing stock market returns ($d\log P_{i|t}$) on reliance on DoD contracts ($\lambda_{i|t}$) around an event allows to estimate the expected percentage increase in defense procurement spending ($d\log G_{|t}$) associated with that event. That is, it enables us to leverage contractors' differential exposure to a shock and their variation in stock prices *to extract the shock itself*.

Furthermore, equation (3) allows us to directly test the importance of each identified candidate event, by simply verifying the statistical significance of the slope coefficient, γ, estimating the expected increase in procurement spending. Intuitively, if the estimated slope around a specific date is statistically insignificant, we would conclude that investors did not perceive such a date as a shock to military expenditure. Equivalently, a significant slope coefficient would constitute evidence that stock prices' adjusted, reflecting an anticipated shift in the path of defense expenditure.

While we relegate to Appendix A a rigorous discussion[5] of Equation (2) a few remarks follow. First, Equation (3) assumes that investors interpret the shock as a change in expected military procurement without any systematic reallocation of contracts toward or away from publicly traded contractors. For instance, if military procurement is expected to rise by 10% in response to an event, investors anticipate that publicly and non-publicly traded contractors will benefit homogeneously, *on average*; that is, the investors' expected increase in contracts is 10%, *on average*, for both groups.[6]

Second, we assume that investors perceive future private sales as unaffected, *on average*, by the expected defense shock ($\mathbb{E}[d\log V^e_{i|t}] = 0$). Private sales may move in both directions in response to newly awarded procurement contracts. For instance, Lee (2024) finds that new contracts crowd-in private sales via learning-by-doing, while Ilzetzki (2023) shows that capacity constraints during WWII may have limited the ability of contractors to expand private demand. Giovanni et al. (2023) finds crowding-out on impact, and crowding-in after one year after winning a contract. Thus, we consider a zero *average* expected change in private sales consistent with empirical evidence.

Lastly, unless systematically correlated with reliance on DoD purchases, $\lambda_{i|t}$, any military crowding-out (or -in) effects or expected changes in the price-cost markups do not constitute a threat to identification (i.e, omitted variable bias).

[5] and the formal proof of the consistency of our estimator: $\hat{\gamma}_{\text{OLS}} \xrightarrow{p} d\log G^e$.

[6] The right panel of Figure 1 confirms that the share of defense contracts awarded to publicly traded contractors remains relatively stable over time.

Generalization We introduce the high-frequency cross-sectional identification method in the context of military news shocks, but we show that the same approach can be readily generalized to other macroeconomic settings. This subsection briefly remarks on this.

Consider an event identified to be a source of a shock — such as an FOMC meeting, a military news release, or a change in banking regulation (Drechsel and Miura, 2025) – and denote it by ε_t. If such exogenous variation affects firms' sales heterogeneously, the framework we propose allows to exploit that heterogeneity to quantify the shock *directly* from the cross-sectional response around the event.

Let $Z_{i,t}$ be the dollar value of sales affected by the shock for firm i at time t, and define

$$Z_{i,t} = \lambda_{i,t} \cdot S_{i,t},$$

where $S_{i,t}$ is total sales and $\lambda_{i,t} \in [0,1]$ is the fraction of sales exposed to the shock. Conditional on the occurrence of the news shock (high frequency identification), firm i's stock returns satisfy

$$d \log P_{i,t} \;=\; \lambda_{i,t} \frac{d \log Z_{i,t}}{d\varepsilon_t}\, d\varepsilon_t.$$

If we assume $Z_{i,t} = f_i(\varepsilon_t)$ for some (possibly nonlinear) isoelastic function f_i, then the elasticity of affected sales with respect to the shock is

$$\xi_i = \frac{f_i'(\varepsilon_t)}{f_i(\varepsilon_t)},$$

and hence

$$d \log P_{i,t} = \underbrace{\underbrace{\lambda_{i,t}}_{(i)} \cdot \underbrace{\xi_i}_{(ii)}}_{\text{Heterogenous Exposure}} \cdot \underbrace{d\varepsilon_t}_{(iii)-\text{Shock}}$$

In other words, the stock return of firm i around the news event at time t depends on (*i*) the fraction of sales exposed to the shock, $\lambda_{i,t}$, (*ii*) the elasticity of sales with respect to the shock, ξ_i and (*iii*) the magnitude of the shock, $d\varepsilon_t$. Conditioning on observing a measure of $\lambda_{i,t}$ and ξ_i, $d\varepsilon_t$ is identifiable via high-frequency cross-sectional regression.

In our context, $\lambda_{i,t}$ is the share of DoD sales in firm i's revenue, thus $\xi_i = 1$, i.e., investors perceive the narrative shock as reallocating a homogeneous fraction of procurement across firms. In other contexts, $\lambda_{i,t}$ may equal one (i.e., *total reliance* on the shock), while ξ_i may require structural assumptions: for instance, an automaker whose *entire* demand is affected by changes in interest rates (McKay and Wieland, 2021), ξ_i would represent the elasticity of car sales to rate variations. In turn, firms whose demand is heterogeneously affected by interest rates may provide a source of cross-sectional variation which would allow to extract high-frequency monetary policy shocks from their stock returns.

Remark (Generalization). *If (i) units are heterogeneously affected by a shock ε_t and (ii) that heterogeneity can be modeled or observed ($\lambda_{i,t}, \xi_i$), then a cross-sectional regression around the analyzed event like* (3) *identifies the magnitude of the shock.*

III. Identification of Fiscal Policy Shocks

III.1. Complementing Narrative Identification: Strategy

We propose to identify fiscal shocks using a combination of narrative analysis and high-frequency methods. In particular, we implement a two-steps procedure. First, we establish relevant events/-dates to predict future military spending; we refer to this step as a *narrative high-frequency identification*. Second, we quantify the scope of the shock associated with each event (and we test it) using cross-sectional variation in the stock prices of contractors around the event. Jointly, we label the procedure *high-frequency cross-sectional* (HFXS) identification.

Identifying Events We carry out a narrative analysis using a combination of several sources. First, we use Ramey and Zubairy (2018)'s events as baseline to establish a portion of the defense news shocks. Their events extends to 2015, and the last recorded shock in the series is in 2013. Hence, we complement their narrative analysis using OpenAI's LLM to aid our identification of relevant episodes.[7] As the nascent large language models literature recommends caution when using AI in research, we adopt a conservative prompting strategy that either relies on highly non-controversial examples or defines a very narrow context[8]. Appendix B provides examples of the actual prompts we employed, and discusses variations around them.

We extensively cross-check all identified events manually for validation and historical contextualization. Overall, we identify 12 dates/events from 2000 to 2024 which affected the expected trajectory of defense spending. Table 1 lists each one, together with the original source, the sign of the expected shock and a brief description of the event. Appendix C details a thorough historical synopsis of each considered event.

[7]Specifically, we use the *deep research* function of *ChatGPT*, available to premium subscribers.

[8]Furthermore, we conduct this analysis by initiating separate chats for each prompt, rather than reusing the same chat, in order to mitigate what the artificial intelligence literature refers to as "*hallucination*" problems.

Table 1: Events That Changed The Expected Path of Military Spending

Date	*Source*	*Sign*	*Description of the Event*
11 September 2001	R&Z18 + LLM	+	The 9/11 terrorist attacks on the U.S. (and the ensuing invasion of Afghanistan in October 2001) marked the start of the "War on Terror," prompting a sharp surge in defense procurement and spending. This inflection led to much higher military budgets in the post-9/11 years than previously expected.
20 March 2003	R&Z18 + LLM	+	The U.S.-led invasion of Iraq opened a second major war. Congress soon approved emergency war funding (e.g. a $79 billion supplemental in April 2003, expanding military operations and procurement needs beyond prior forecasts (positive shock).
10 January 2007	LLM	+	President Bush's Iraq "Surge" address: The White House asked Congress for an immediate $5.6 billion plus a much larger FY 2007 supplemental, signaling that operations costs would jump.
4 November 2008	R&Z18 + LLM	-	Barack Obama was elected U.S. president after campaigning to end the Iraq War. Democratic administration shift signaled expectations of a more restrained defense posture to prior years, though immediate cuts were moderated by ongoing conflicts and lower war spending compared through September and confirmed that Congress would keep writing very large off-budget checks for the wars.
2 August 2011	R&Z18 + LLM	-	The Budget Control Act of 2011 was signed amid a debt-ceiling crisis, imposing ten years of caps on defense (and non-defense) discretionary spending. These caps effectively aimed to reduce defense budgets by roughly $1 trillion over 2012–2021 versus previous plans lowering the expected trajectory of Pentagon procurement.
1 March 2013	R&Z18+LLM	-	U.S. government sequestration took effect after Congress failed to agree on deficit reductions, triggering abrupt across-the-board budget cuts. Defense programs were hit with forced funding cuts under the Budget Control Act's enforcement, disrupting procurement plans and prompting warnings of a "doomsday" impact on the military.
18 March 2014	LLM	+	Russia's annexation of Crimea and intervention in Ukraine signaled a return of great-power conflict. This geopolitical jolt ended assumptions of post-Cold War stability in Europe and spurred U.S./NATO leaders to reconsider defense spending increases to deter Russian aggression.
22 September 2014	LLM	+	The extremist group ISIS seized large parts of Iraq and Syria (capturing Mosul in June). By August, the U.S. launched airstrikes (Operation Inherent Resolve) to combat ISIS; announced by Pentagon Press Secretary on September 22. This unexpected new campaign reversed the prior drawdown of U.S. military operations, necessitating renewed procurement of munitions and equipment for ME operations.
8 November 2016	LLM	+	Donald Trump won the 2016 U.S. presidential election on a platform of rebuilding the military. His surprise victory (over forecasts of a status-quo defense posture) led to expectations of significantly higher defense procurement budgets, as Trump pursued a large defense buildup after years of budget caps.
9 February 2018	LLM	+	A bipartisan budget deal (Bipartisan Budget Act of 2018) was enacted, which lifted the strict BCA spending caps for FY2018–2019. This deal enabled a major jump in Pentagon funding (about a 15% increase in defense budget authority), signaling a notable upward revision in near-term procurement spending plans.
2 August 2019	LLM	+	A bipartisan budget deal (Bipartisan Budget Act of 2019) was signed, raising the defense spending caps for FY2020 and FY2021 and essentially ending the decade of sequestration-era limits. The law boosted defense cap levels by roughly $172 billion over two years compared to previous law, locking in higher procurement funding than earlier baseline projections.
24 February 2022	LLM	+	Russia invades Ukraine, igniting the largest conflict in Europe since WWII and dramatically shifting U.S./NATO threat perceptions. This crisis fundamentally altered assumptions about U.S. defense needs, spurring bipartisan support for higher Pentagon funding (positive shock). Leaders in Congress acknowledged that the invasion meant the defense budget "has to be bigger than we thought," as Russia's war created strong political momentum for increased military spending.

Notes: *Source* column refers whether the event is from Ramey and Zubairy (2018) (R&Z18) and/or through the LLM-enhanced analysis. The *Sign* column refers to the sign of the expected change in the trajectory of spending: "+" ("-") if an increase (decrease) is expected.

III.2. Data Construction

The next step in implementing equation (3) is to identify firms that satisfy the following criteria: (*i*) each is a publicly traded military contractor; (*ii*) it is *perceived* by the market as a defense-related company; and (*iii*) its financial performance is significantly linked to military procurement. We refer to condition (*ii*) as *salience* and to condition (*iii*) as *relevance*.

Identifying Defense Contractors Since 1958, the Department of Defense has compiled detailed annual reports on the Top 100 contractors, specifying the total dollar value of contracts awarded and the fraction of DoD contracts allocated to each.[9] We collect information on the Top 100 contractors by fiscal year from 2001 onward, identifying 430 unique firms.

Then, we determine which of the identified firms are publicly traded on the New York Stock Exchange (NYSE) or the NASDAQ using the tickers retrieved from Yahoo Finance's API. Each match is manually reviewed to ensure precise association between tickers and firms. Of the 430 total contractors, 57 publicly traded companies are successfully matched and have available stock market data from Compustat. Then, we proceed to filter each according to the criteria of salience and relevance defined above.

Salience Condition (ii) requires that publicly traded firms whose revenues depend on military sales must be recognized by investors as defense contractors. This condition allows us to unambiguously link military news shock with expected variation in each identified company's stock market valuation. To meet this requirement, we restrict our sample to firms appearing in the publicly available Top 100 Defense Contractors Report for at least four fiscal years over the past 24 years. An example of excluded company is Moderna, who entered the Report only once, during the COVID-19 pandemic – due to its vaccine supply — and saw its defense contracts fall to near zero once the pandemic subsided. We then exclude it, as it is clear that Moderna is not perceived as a primary provider of defense-related hardware and services. In summary, only firms consistently listed among the Top 100 are kept, as their stock prices can be expected to reflect meaningful information about future defense spending.

Relevance To satisfy condition (iii), we identify firms whose stock prices are *significantly* affected by defense spending. This allows us to relate episodes when the expected path of defense spending changed with meaningful stock price variation. For example, British Petroleum North America (BP) ranked 21^{st} among defense contractors in 2005, totaling \$1.5 billion in DoD contracts. In the same year, its total annual sales amounted to \$240 billion, making federal govern-

[9] Fisher and Peters (2010) represents the first work to use this data for research purposes.

ment's contracts 0.6% of its revenues. Hence, we conclude its stock price changed likely conveyed minimal information about future military expenditure. Relevance underscores that not all major defense contractors' stock valuations serve as reliable indicators of defense spending expectations, as their financial performance is not necessarily reliant on procurement contracts.

Then, we construct a firm-level measure of *reliance* on government purchases to *quantify* the degree of relevance of each contractor. First, we cumulate quarterly sales at yearly frequency from Compustat by fiscal year. Second, we divide the official value of DoD contracts awarded to each contractors ($G_{i,t}$) by the yearly sales figure:

$$\lambda_{i,t} := \frac{G_{i,t}}{\text{Sales}_{i,t}}. \tag{4}$$

The value of $\lambda_{i,t}$ is indicative of how much each contractor's revenues depend on government purchases, and, by our framework in Section II, represents a measure of its stock price' elasticity to military news shocks. More precisely, this expression reflects exactly the $\lambda_{i,t}$ specified on the right-hand side of Equation (3).

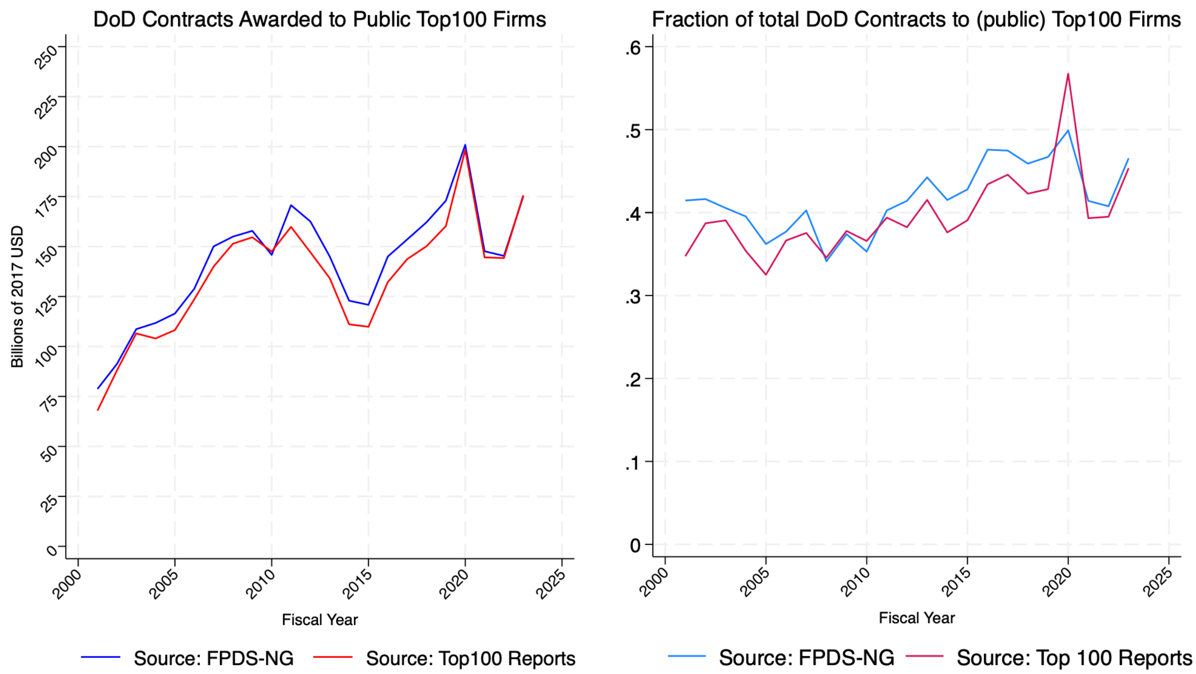
We retain only firms with a median reliance of at least 1%. Altogether, we are left with a sample of 33 contractors, with a median time-averaged reliance λ_i of 20% across contractors, and with an interquartile range of [3.7%,39.9%]; the four firms with the largest reliance are VSE Corp (86%), L3 Harris Technologies (82%), Huntington Ingalls Industries (73%) and Lockheed Martin (71%).

Cross-validation and Aggregation We cross-validate contract-level data from the Top 100 Reports with data from the universe of DoD contracts from fiscal year 2001 to 2024, sourced by the Federal Procurement Data System Next Generation (FPDS-NG). We link the 33 firms in our sample to FPDS-NG and aggregate their data by parent company of contract recipient, across MSAs and quarters[10]. Thus, we assemble a novel panel that, for each firm, records its stock ticker, total and proportional DoD contract values from the Top 100 reports, quarterly and MSA-level contract amounts from FPDS-NG, and balance-sheet data from Compustat.

Figure 1 plots the time-series evolution of total DoD contract value for our 33 defense contractors (left panel); the near-perfect overlap of FPDS-NG (blue) and Top 100 Reports (red) confirms the validity of our aggregation protocol. Furthermore, the percentage discrepancy between contract values in the Top 100 Reports and the aggregated FPDS-NG data is close to 0%, corroborating the soundness of our aggregation.

[10]FPDS-NG consistently reports parent companies of each contract recipient, allowing us to accurately identify subsidiaries of the 33 firms in our sample

Figure 1: **Publicly Traded Top 100 Defense Contractors in Our Sample**



Notes: The figures are constructed using data from only the 33 defense contractors in our final sample.

The right panel of Figure 1 traces the share of DoD contracts captured by our 33 firms. This share averages 40.4 % (SD 4.6 %), mirroring the strong concentration documented by Cox et al. (2024). These contractors are highly salient to investors: in fact, Lockheed Martin (14.7 % of 2023 contracts), Raytheon (6.5 %), General Dynamics (5.0 %), Boeing (4.7 %), and Northrop Grumman (3.4 %) are widely covered in financial news and embedded in key U.S. industrial hubs. Together, they account for 34.3 % of DoD procurement in 2023, making their stock-price movements a rich source of information on expected defense spending.

Construction of Excess Returns Finally, we employ the three factor model of Fama and French (1993) to construct weekly excess returns of the stock price of our top defense contractors. In particular, we estimate via OLS the following firm-by-firm regression:

$$r_{i,t} = \alpha_i + \beta_i^1 \cdot \mathrm{MKT}_t + \beta_i^2 \cdot \mathrm{SML}_t + \beta_i^3 \cdot \mathrm{HML}_t + v_{i,t} \tag{5}$$

where $r_{i,t}$ are the contractors' weekly returns and MKT_t, SML_t and HML_t represent the three Fama & French factors.[11] We download the daily returns of the three factors model from Ken French's website and cumulate the return of day t up to day $t-4$ to create (daily) rolling weekly returns (i.e., five trading days window). We interpret the OLS residuals $v_{i,t}$ as weekly excess returns.

IV. Empirical Results

In this section, we show how to extract the shock to expected military spending from the cross-sectional variation in stock returns. For each date $\tau \in \mathcal{T}$ of identified events, we estimate the empirical analog of Equation (3):

$$v_{i|t=\tau} = \alpha_{t=\tau} + \gamma_{t=\tau} \cdot \lambda_{i|t=\tau} + \epsilon_{i|t=\tau} \quad \forall \tau \in \mathcal{T},\ \forall i \in \mathcal{I}_\tau, \tag{6}$$

where $v_{i|t=\tau}$ denotes each contractor's weekly excess return and $\lambda_{i|t=\tau}$ its reliance on DoD purchases. Each specification is a purely cross-sectional regression over the set $\mathcal{I}_\tau$ of contractors appearing in the Top 100 Report during the fiscal year that contains event τ.

Illustrations and Results To illustrate, we leverage two insightful events from the set identified in Table 1: the Budget Sequestrations news releases at the end of January 2013 (Figure 2), and the election of Donald Trump on November 9, 2016 (Figure 3). A detailed historical synopsis of all narratively identified events is provided in Appendix C.

On 1 March 2013, budget sequestration took effect after Congress failed to avert the automatic cuts in the Budget Control Act; the market had largely priced this in during late January, following heavy media coverage and official warnings, which sparked a sell-off in defense stocks: the left panel of Figure 2 shows excess weekly returns for Lockheed Martin (LMT), Northrop Grumman (NOC), General Dynamics (GD), and an index equal to the arithmetic mean of the top five contractors' returns, all of which fell sharply and bottomed on 31 January.[12] Hence, we examine the cross-sectional distribution of excess weekly returns among the publicly listed defense contractors on January 31st, 2013.

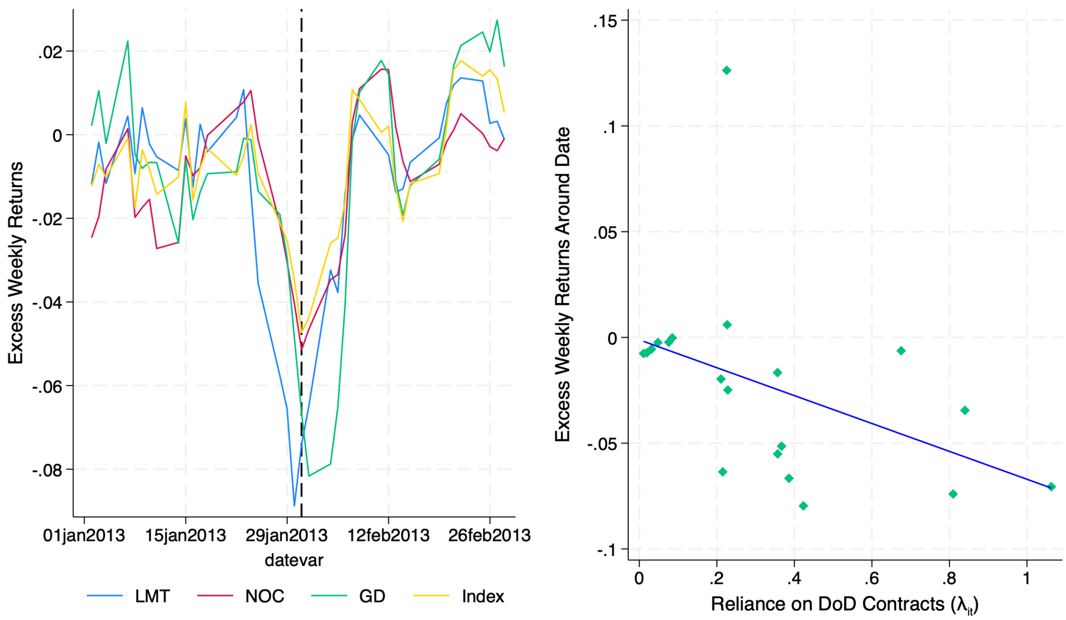
Figure 2's right panel shows a bin-scatterplot of weekly returns and the corresponding reliance on

[11] $\text{MKT}_{i,t}$ are the returns from the market portfolio minus the risk free rate; $\text{SML}_{i,t}$ is the size factor and represents the difference between the returns of a portfolio with only small firms and one with only large firms; HML is the value factor and represents the difference between the returns of a portfolio made of firms with high book-to-market ratio and one made of firms with low book-to-market ratio. We defer to Ken French's website for further details.

[12] In insightful contemporaneous work, McClure and Yding (2024) construct a defense index of contractors to quantify defense news shocks around fiscal events. Similarly, Fisher and Peters (2010) construct an index of defense contractors and use it as an internal instrument in a VAR to identify fiscal shocks.

DoD purchases (i.e., $\lambda_{i,t}$). Crucially, the estimated slope of the least squares line represents our estimate of $d \log G^e_{|t}$. That is, it captures the expected decline in defense spending embedded in the stock market's response to this specific event—i.e., the *shock*.

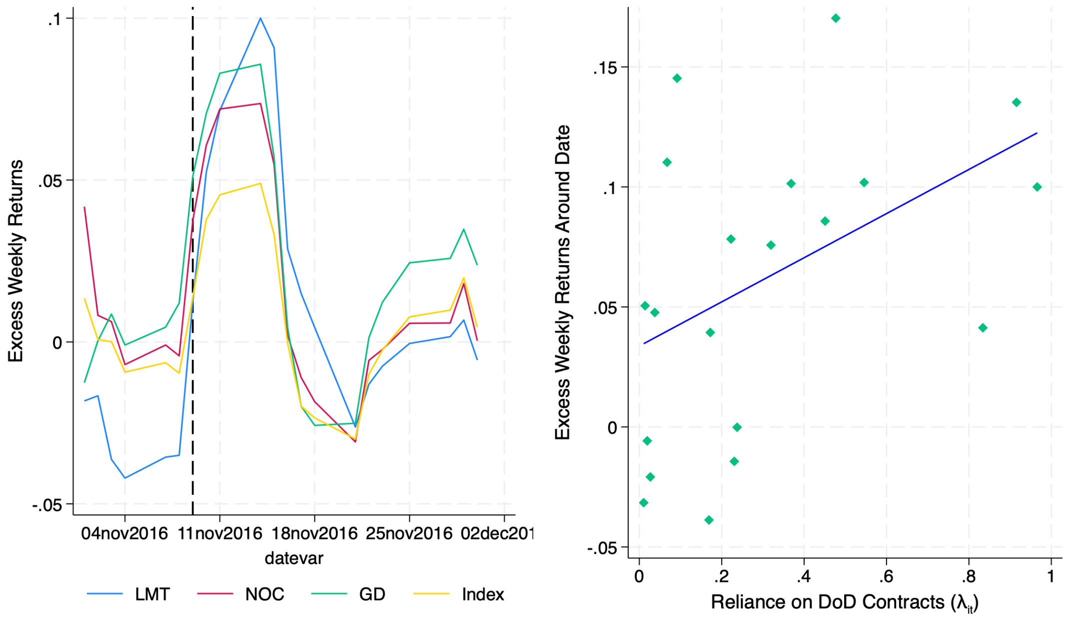
Figure 2: **Stock Market Response to Budget Sequestrations**



Notes: Left: Stock market (excess) returns of Lockheed Martin (LMT), Northrop-Grumman (NOC), General Dynamics (GD) around January 31 2013; Right: Linear relationship between excess returns and reliance; in green, the contractors in the sample.

Note that this procedure is ex-ante agnostic about the size *and* sign of the military event, as we let stock market fluctuations pin them down through the differential elasticities of military contractors on government purchases. Nevertheless, the estimated slope for this date (31 January 2013) is negative as expected, indicating that companies more reliant on the government experienced larger losses in response to the news. Specifically, and in line with our framework in Section II, the estimated slope is -0.066, meaning that investors expected DoD contracts to fall by 6.6%. The sample size on this particular occasion was 21, and, despite the relatively small number, the effect is statistically significant at the 1% confidence level. Table 2 reports the estimates of the slope for all the identified events. For each one, the expected and realized signs of the shock coincide.

Figure 3: **Stock Market Response to 2016 Donald Trump's Election**



Notes: Left: Stock market (excess) returns of Lockheed Martin (LMT), Northrop-Grumman (NOC), General Dynamics (GD) around November 14 2016; Right: Linear relationship between excess returns and reliance; in green, the contractors in the sample.

Let us consider another instance with an opposite sign. Figure 3 reports the same analysis for the 2016 Presidential Elections won by a narrow margin by Donald Trump, and causing widespread surprise in the stock market. Donald Trump campaigned vigorously on large increases in military spending under a "*Peace through Strength*" foreign-policy framework. Unsurprisingly, defense contractors' stock prices jumped after the election, peaking at the market reopening on Monday, November 14th (Figure 3's left panel). We calculate excess weekly returns on November 14th and plot them against contractors' reliance in the right panel of Figure 3. The least-squares line slopes upward, and its estimated coefficient – again, reported in Table 2 —is 0.092, implying that the market expected a 9.2% increase in defense spending following President Trump's election.

Table 2: Extraction of Shock from Cross-Sectional Variation

Event	Shock Trading Date	*Expected Sign*	$d\log G_t^e$	*pvalue*	*N*	Defense Index
9/11 Terrorist Attack	*September 21, 2001*	+	0.629 (0.133)	0.000	14	+5.2%
Invasion of Iraq	*March 19, 2003*	+	0.029 (0.035)	0.406	20	+ 6.4%
Bush Speech on Iraq	*January 11, 2007*	+	0.028 (0.017)	0.117	20	+3.1%
Obama Election	*November 6, 2008*	-	-0.031 (0.030)	0.327	18	-2.3%
Budget Control Act 2011	*August 2, 2011*	-	-0.065 (0.019)	0.002	23	-3.1%
Sequestrations	*January 31, 2013*	-	-0.066 (0.015)	0.000	21	-4.7%
Russia's Invasion of Crimea	*March 5, 2014*	+	0.038 (0.021)	0.086	21	+1.5%
War to Isis	*29 October 2014*	+	0.047 (0.024)	0.065	23	+3.3%
First Trump Election	*November 14 2016*	+	0.092 (0.043)	0.042	23	+4.9%
Bipartisan Budget Act 2018	*January 31 2018*	+	0.091 (0.038)	0.024	23	+5.8%
Bipartisan Budget Act 2019 + Iron Dome	*9 August, 2019*	+	0.101 (0.028)	0.002	23	+3.7%
Invasion of Ukraine	*March 1, 2022*	+	0.273 (0.041)	0.000	23	+10.4%

Notes: Robust standard errors in parentheses. Last column (Defense Index), refers to the excess weekly returns of the Defense Index. Interquartile range of excess weekly returns of Defense Index is [-1.0%,+1.0%], 10th and 90th percentiles are -2.2% amd +2.1%.

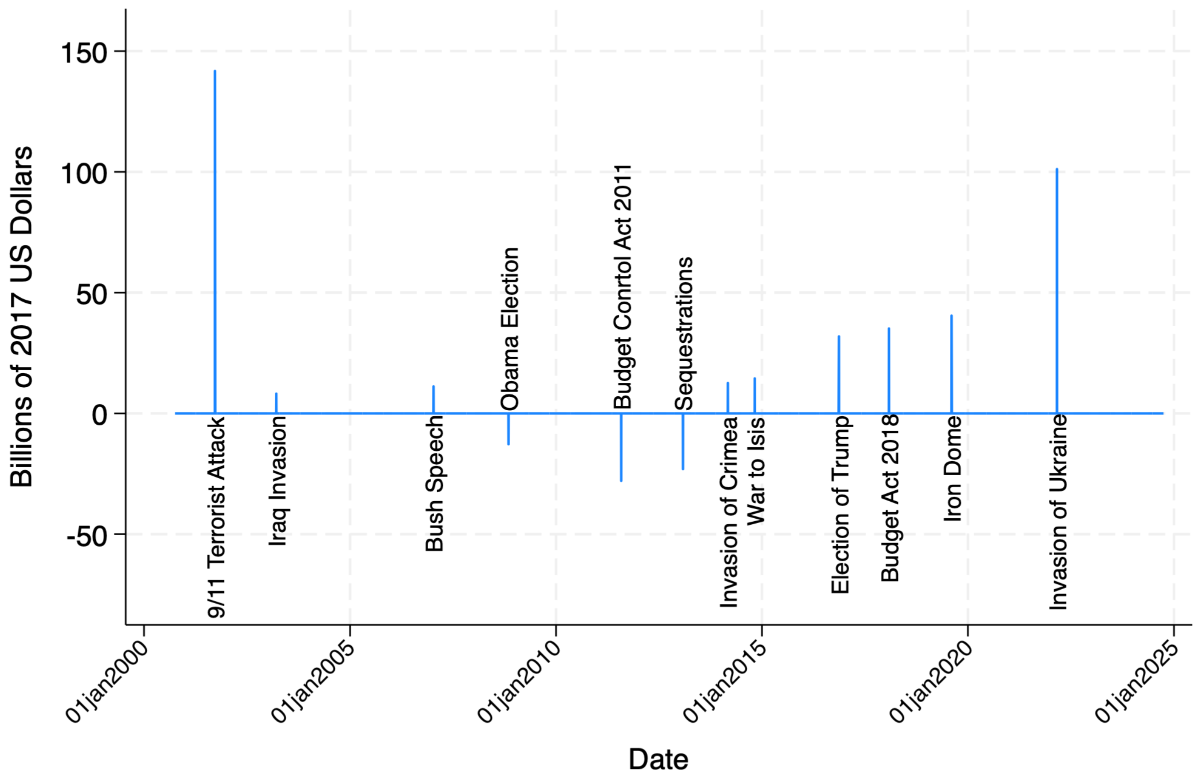
A New Series of Defense News Shocks We apply the above procedure to all military events listed in Table 1. For each, we extract the expected percentage increase in military spending from the cross-sectional stock price response (Table 2) and convert it into a dollar shock by multiplying it by that fiscal year's total defense contracts; the resulting daily series of defense news shocks is plotted in Figure 4 and constitutes a central contribution of this study.

One potential limitation of this methodology is the relatively small sample of Top 100 publicly traded defense contractors. This might cause two types of concerns: affect (*i*) estimate precision; and undermine (*ii*) representativeness. We address both.

On precision, nine out of twelve events produce estimates significant at least at the 10% level, and a tenth is marginally below that threshold. Thus, even with a limited sample, we reliably detect statistically significant stock–price responses.

On representativeness, firms in our regressions account for about 40% of total DoD procurement on average (Figure 1's right panel). This pronounced and stable concentration among a small number of contractors accords with previous estimates in the literature (Cox et al., 2024) and supports the notion that a handful of firms captures most of the aggregate dynamics of defense-contract awards.

Figure 4: **High-Frequency Cross-Sectional Military News Shocks**

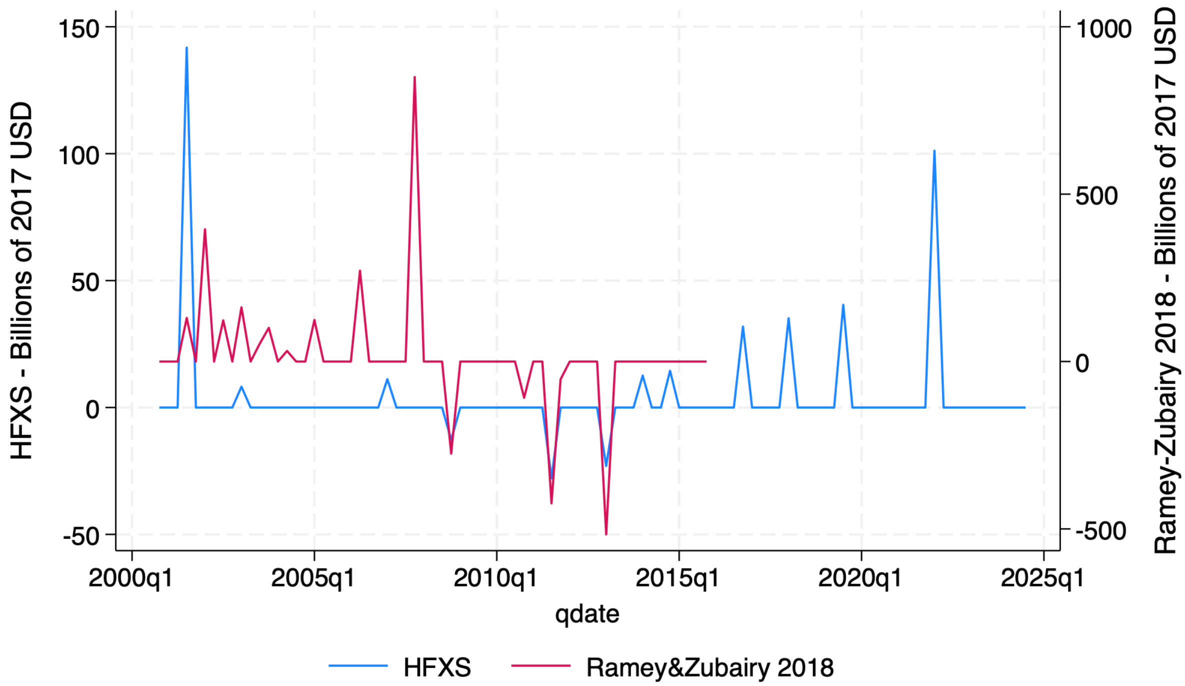


Notes: High-frequency military-news shocks (billions of 2017 USD). Vertical bars show estimated magnitudes around identified events. Positive values signal upward revisions in anticipated spending; negative values signal cuts. Sample: 2000-2024.

IV.1. Comparison with Ramey and Zubairy's Defense News Shock Series

In this section, we compare the most widely used fiscal shock series in the literature — the Ramey and Zubairy (2018) defense news shock series — with ours. Figure 5 plots in blue (left axis) the high-frequency cross-sectional shock series (HFXS) that we construct, and in red, the defense news shock series constructed by Ramey (2011) and updated in Ramey and Zubairy (2018).

Figure 5: **HFXS shocks and Ramey & Zubairy (2018) shocks**



Notes: Comparison between HFXS shocks and RZ18. Sample: 2000-2024 (HFXS); 2000-2015 (RZ18).

First, the shocks differ in magnitude: RZ18 shocks are substantially larger than HFXS shocks. This disparity arises from their construction. RZ18 use the present discounted value of predicted defense spending several years ahead. For instance, they record a shock of $395 billion (2017 dollars) in 2002 Q1, obtained as the present discounted value of New York Times' and budget projections over the next five years. In contrast, HFXS estimates a 62% increase in military contracts in 2001, which yields an expected amount of $141 billions, representing our largest shock. Our cross-sectional regression returns the expected one-year increase in contracts as priced in by the market[13]. Consequently, HFXS shocks reflect a one-year rather than a multi-year horizon, making our shocks smaller than those in RZ18. Consider the 9/11 Terrorist Attacks case: RZ18 report values from the New York Times, which cites two contemporaneous emergency appropriations and an expected increase *for the following year*. Then, the shock horizon is very short and therefore comparable to that of the HFXS market-implied shocks. Unsurprisingly, the RZ18 shock in that quarter amounts to $130 billion (2017 dollars), remarkably close to our estimated $141 billion.

Second, the LLM-enhanced search returns a narrower set of events than those reported in news

[13]The one-year horizon follows by construction: we interact the estimated shock (in percentage terms) with the current fiscal-year value of military contracts.

sources captured by RZ18, with few notable exceptions. In the pre-Sequestration era (before President Obama's election), we identify only (*i*) the 9/11 terrorist attack; (*ii*) the Bush ultimatum preceding the U.S. invasion of Iraq in March 2003; and (*iii*) President Bush's January 2007 speech requesting supplemental funds for the wars in Afghanistan and Iraq. HFXS shocks tend to capture only major events that affected the long-term trajectory of military procurement. For example, the largest RZ18 shock in our sample period occurs in 2007 Q4, and it is sourced from ten-year defense spending forecasts in a *CNN Money* article dated October 24, 2007. However, our stock market index of the top defense contractors shows no abnormal behavior in October or November 2007. A possible interpretation is that the two series differ in how they measure expectations: RZ18 may capture household expectations, while HFXS reflects only major procurement shifts reflected in the stock market.

Two notable exceptions are worth mentioning. RZ18's last measured shock is the implementation of sequestration in January 2013. However, we report two events not included in the RZ18 series: the Russian annexation of Crimea in February 2014 and the escalation of the conflict in Iraq—with the rise of ISIS—following the September 2014 announcement and subsequent news of increased spending in October. These events reversed the downward trajectory of defense procurement spending that had resulted from the Sequestrations.

Lastly, concerning negative shocks, both HFXS and RZ18 consistently capture President Obama's election in 2008, the Budget Control Act of 2011, and the onset of sequestration in 2013 Q1.

V. Empirical Application: The Regional Effects of Military News Shocks

In this section, we investigate the real effects of military news shocks on economic activity by leveraging broad regional variation in defense spending across U.S. Metropolitan Statistical Areas (MSAs). As discussed in Auerbach, Gorodnichenko, and Murphy (2020), MSAs constitute an appealing regional level of analysis, as they comprise collections of counties that function as integrated commuting zones, behaving like small open economies. Hence, this feature helps mitigate spillovers across regions. MSAs are smaller than states, yet numerous enough to maximize sample size, and therefore variation in government contracts.

Following the literature on the regional effects of government purchases, we estimate:[14]

$$\frac{Y_{\ell,t+h} - Y_{\ell,t-1}}{Y_{\ell,t-1}} = \beta^h \cdot \frac{G_{\ell,t+h} - G_{\ell,t-1}}{Y_{\ell,t-1}} + \alpha_\ell^h + \lambda_t^h + \varepsilon_{\ell,t+h} \tag{7}$$

where $Y_{\ell,t}$ is real GDP in MSA ℓ in year t, $G_{\ell,t}$ denotes defense contracts, α_ℓ^h and λ_t^h are respectively location and time fixed effects. Our baseline sample covers the period between 2000 and 2023 and includes 377 MSAs.

Data All nominal series are deflated using the BEA's GDP price deflator (2017 = 100). MSA-level real GDP is available for 2001–2023; to include 2000 — and thus capture 9/11 — we impute $Y_{\ell,2000}$ by regressing GDP on regional employment, personal income, and wages for each MSA from 2001 to 2023, then extrapolating to 2000 using the 2000 values of those covariates[15]. All MSA-level data on employment, income, and wage originate from the BEA.

Defense-contract values are drawn from FPDS by summing DoD awards annually, assigning each contract to an MSA via its primary place-of-performance ZIP code, and mapping ZIP code to counties and MSAs using Census crosswalks[16] [17].

Identification Estimating (7) by OLS raises two issues: (*i*) regional changes in contracts, $G_{\ell,t+h} - G_{\ell,t-1}$, may reflect anticipation of awards (Auerbach, Gorodnichenko, and Murphy (2020); Briganti et al. (2024)); (*ii*) contract allocations may be endogenous to local political cycles (Mintz, 1992; Nakamura and Steinsson, 2014; Choi, Penciakova, and Saffie, 2023). A standard solution to both is the implementation of a shift-share (Bartik) instrument:

$$Z_{\ell,t+h}^{\text{Bartik}} = \frac{s_\ell \left(G_{t+h} - G_{t-1}\right)}{Y_{\ell,t-1}}, \tag{8}$$

where $s_\ell = \frac{1}{T}\sum_t G_{\ell,t} \big/ \sum_\ell G_{\ell,t}$ is the historical share of DoD contracts in MSA ℓ, and G_t is national DoD contracts. Identification requires exogeneity of either the shift or the share (Goldsmith-Pinkham, Sorkin, and Swift (2020); Borusyak, Hull, and Jaravel (2022)). Shares are driven by

[14] See Nekarda and Ramey (2011) (industry level); Nakamura and Steinsson (2014) and Dupor and Guerrero (2017) (State level); Demyanyk, Loutskina, and Murphy (2019), Auerbach, Gorodnichenko, and Murphy (2020), Muratori, Juarros, and Valderrama (2023) and Auerbach, Gorodnichenko, and Murphy (2024) (MSA level).

[15] Specifically, for each region ℓ, we estimate $Y_{\ell,t} = \delta_0 + \delta_1 \,\text{Emp}_{\ell,t} + \delta_2 \,\text{PI}_{\ell,t} + \delta_3 \,\text{W}_{\ell,t} + u_{\ell,t}$ over $t = 2001, \ldots, 2023$, and compute $\hat{Y}_{\ell,2000}$ using the 2000 covariates.

[16] If primary place of performance zip code is missing, we use recipient zip-code, which is never missing.

[17] Because FPDS covers only Q4 2000 (the first quarter of FY 2001), we annualize 2000 totals by multiplying Q4 figures by four. Our results remain unchanged if 2000 (and the 9/11 shock) is excluded. Excluding year 2000 altogether (i.e., dropping both the 9/11 shock) does not qualitatively alter our findings.

long-standing military bases locations, widely considered as plausibly exogenous, while (national) shifts reflect geopolitical events unrelated to regional GDP.

We complement this line of analysis with a novel instrument based on high-frequency cross-sectional (HFXS) news shocks:

$$Z^{\text{HFXS}}_{\ell,t+h} = \frac{s_\ell \, \mathbb{E}_t(G_{t+1})}{Y_{\ell,t-1}} \quad \forall h \geq 0, \tag{9}$$

where $\mathbb{E}_t(G_{t+1})$ is the yearly aggregated expected change in defense spending we estimated in the previous Section (Figure 4). This instrument (*i*) mitigates anticipation concerns by identifying (by construction) unexpected military news shocks and (*ii*) directly estimates the effect of news shocks rather than realized spending changes. We use a two-stage least squares estimator with *either* instruments to address endogeneity in regional contract changes.

The top-left panel of Table 3 highlights in green the estimated regional fiscal multipliers by horizon for the baseline sample, which includes the 9/11 terrorist attack. The bottom panel provides a robustness test: it displays the same results excluding the 9/11 shock, which represents the largest shock in the sample.

Table 3: Effects of Military News Shocks on Regional GDP

Baseline Sample: 2001-2023 - 377 MSAs								
Horizon	*IV: HFXS Military News Shocks*			*IV: Standard Bartik*			*OLS*	
	Coefficient	*pvalue*	*Effective F*	*Coefficient*	*pvalue*	*Effective F*	*Coefficient*	*pvalue*
Impact	2.647	0.252	1.462	0.095	0.030	17.088	0.010	0.573
	(2.307)			(0.044)			(0.017)	
Year 1	1.352	0.000	14.939	0.539	0.000	95.193	0.061	0.017
	(0.369)			(0.125)			(0.025)	
Year 2	0.953	0.000	30.558	0.484	0.001	46.408	0.090	0.029
	(0.271)			(0.148)			(0.041)	
Year 3	0.614	0.070	6.257	0.639	0.013	15.239	0.124	0.074
	(0.338)			(0.256)			(0.069)	
Robustness - Sample: 2002-2023 (Without 9/11) - 377 MSAs								
Horizon	*IV: HFXS Military News Shocks*			*IV: Standard Bartik*			*OLS*	
	Coefficient	*pvalue*	*Effective F*	*Coefficient*	*pvalue*	*Effective F*	*Coefficient*	*pvalue*
Impact	-0.112	0.594	9.428	0.124	0.008	17.575	0.009	0.622
	(0.209)			(0.047)			(0.018)	
Year 1	0.609	0.044	17.868	0.494	0.000	100.184	0.052	0.042
	(0.301)			(0.120)			(0.025)	
Year 2	0.571	0.033	12.293	0.437	0.002	42.991	0.078	0.090
	(0.268)			(0.142)			(0.046)	
Year 3	0.620	0.147	6.656	0.638	0.019	10.163	0.123	0.074
	(0.427)			(0.271)			(0.069)	

Notes: Sample includes 377 MSAs from 2001 to 2023. GDP price deflator from BEA, base year 2017. Robust standard errors in parentheses, clustered at the MSA level. Montiel Olea and Pflueger (2013) effective F is calculated with `weakivtest`; 5% critical values with one instrument are 15.06

Military news shocks have no significant effect on either GDP or regional government spending *on impact*, as indicated by the low first-stage F-statistics (top-left panel).

One year after the shock, the estimated multiplier is statistically significant and equal to 1.3. The corresponding first-stage F-statistics reaches nearly 15, which lies within the critical value range provided by Montiel Olea and Pflueger (2013) (between 11 and 23), indicating a statistically relevant, moderate response of military contracts to news.

The highest F-statistics is observed at the two-year horizon, where it reaches 30 and the estimated multiplier is just below one. In other words, baseline 2SLS estimates suggest that a one-dollar news shock in an MSA raises its GDP by approximately \$1 after two years, relative to the average MSA. The gradual increase in F-statistics is consistent with a delayed rise in regional military procurement in response to news, as they do not immediately translate into higher regional procurement spending.

The middle panels show GDP multipliers estimated using the standard Bartik instrument. Overall, the two approaches yield qualitatively similar multiplier profiles, though HFXS multipliers tend to be somewhat larger. Auerbach, Gorodnichenko, and Murphy (2024) provide[18] a potential explanation arguing that standard Bartik instruments may not fully exclude anticipation effects, potentially biasing the estimates downwards.[19] Then, given that markets price-in anticipation, HFXS defense news shocks are expected to properly account for it, so delivering higher multiplier estimates.

Robustness The bottom panel of Table 3 reports estimates excluding the year 2001. This exclusion is motivated by two factors: first, 2001 includes our most influential shock—the 9/11 terrorist attacks (see blue line in Figure 5); second, incorporating this event entails extrapolating regional GDP data for 2000, which is of lower quality.[20]

The results excluding the 9/11 shock (bottom-left panel) remain qualitatively similar. First, there is no significant effect on impact, but estimates become significant thereafter. Second, the F-statistics are lower on impact, peak at horizon one, and then decline—replicating the dynamics observed in the baseline sample. However, the overall F-statistics are (expectedly) smaller due to the exclusion

[18]See their footnote 12.

[19]Note that Auerbach, Gorodnichenko, and Murphy (2024) (AGM) report impact MSA-level GDP multipliers of about 1 using the Bartik instrument—compared to our estimates hovering around 0.5. These discrepancies likely stem from the sample period (we use 2001–2023), the GDP price deflator (they use a 2001 deflator; we use a 2017 deflator), and the treatment of contract values: AGM distribute DoD contract awards over their duration, while we allocate the full award amount to the award year. As a result, the computed contract shares differ; for example, the Washington–Alexandria–Arlington MSA accounts for nearly 20% of DoD spending in AGM, but only for about 12% in our sample.

[20]The first observed outcome observation is $(Y_{\ell,2001} - Y_{\ell,2000})/Y_{\ell,2000}$, but BEA's GDP estimates at MSA level begin in 2001. Therefore, we extrapolated values of $Y_{\ell,2000}$.

of the largest shock. The estimated multipliers are also smaller, similarly reflecting the exclusion of the 2002 output response following the 9/11 attacks. Overall, even in the restricted sample, the point estimates of the multipliers remain larger than those obtained using the standard Bartik instrument, although the confidence bands are too wide to suggest a statistically significant difference.

In summary, our estimated HFXS defense news shocks are robust and can successfully be used to identify significant real economic effects of increased military spending.

VI. Conclusions

In this paper, we develop and demonstrate a novel approach we label *high-frequency cross-sectional* (HFXS) identification to isolate fiscal shocks. It consists of a two-step procedure: first, it identifies relevant events using a narrative high-frequency analysis augmented by Large Language Models methods; then, it employs cross-sectional regressions of excess returns on firm-level reliance on DoD contracts to yield a transparent, model-consistent estimate of the percentage change in expected military spending around each identified event. These event-specific estimates represent a new series of defense news shocks that extends through 2023.

The approach rests on a tight link between theory and data. Asset pricing logic yields disciplined, intuitive moment conditions: each firm's excess return is proportional to its reliance on government revenues times the surprise component of expected spending, while the narrative step keeps identification free of structural assumptions. Publicly available stock prices around the identified events, combined with contractors' balance-sheet data, therefore suffice to recover market-implied fiscal shocks under a standard, parsimonious model.

Beyond its use in this paper in providing new estimates of the regional GDP multipliers for the United States, the methodology we present offers several advantages for empirical macroeconomic research. First, it directly tests whether investors perceive a given narrative event as a shock to government spending, self-validating its identification via the sign and the statistical significance of the cross-sectional slope. Second, it is immediately exportable to other non-fiscal contexts – essentially, any setting in which exogenous shocks heterogeneously affect publicly traded firms, assets or commodities.

We use our market-implied news shocks (HFXS) as instruments in a shift-share empirical design to estimate the regional real effects of military spending. At the MSA level, using our HFXS instrument in place of the standard Bartik, we find that while news-driven procurement shocks have no significant effects on GDP at impact, they generate economically and statistically significant multipliers after that. We estimate a value of 1.3 one year after the shock, and of about 1 two years after the shock, with a peak F-statistics of 30.

Overall, the high-frequency cross-sectional identification approach is a valuable instrument in the causal inference toolkit of modern macroeconomists. It combines the appealing features of narrative analysis with the discipline of market-implied quantification within a parsimonious, generalizable framework, and it delivers novel and robust estimates of policy-relevant economic effects.

A Model Identification and Consistency of (3)

As argued in Section II, the stock price around the event can be approximated by:

$$P_{i,t} = \frac{D_{i,t}}{1-\frac{1}{1-i_t}} = \frac{1+i_t}{i_t} \cdot \underbrace{(1-\tau_t)\cdot(V_{i,t}+G_{i,t})\cdot\left(1-\frac{1}{\mu_i}\right)}_{D_{i,t}} \tag{10}$$

Focusing on a window of five trading days, we can drop the subscript t and log-differentiate (10) around the occurrence of a shock:

$$d\log P_i = \underbrace{\left(\tfrac{1}{i}-1\right)di - \tfrac{1}{1-\tau}\,d\tau}_{:=\alpha \text{ (Time FE)}} + \underbrace{\frac{G_i}{G_i+V_i}}_{\lambda_i}\left(d\log G_i^e - d\log V_i^e\right) + \underbrace{d\log V_i^e + \tfrac{1}{\mu_i-1}\,d\log\mu_i^e}_{:=\varepsilon_i \text{ (Error)}} \tag{11}$$

where α is a constant that absorbs any firm-invariant change around the event, e.g., a contemporaneous expected change in the corporate profit tax, $d\tau^e$, or a high frequency change in interest rates, di, λ_i is the *Reliance on DoD*; high-frequency expected changes in private sales $d\log V_i^e$ and markups $d\log\mu_i^e$ collapse into a firm-varying error ε_i. Therefore, the reduced-form data generating process of Equation (11) can be rewritten as:

$$d\log P_i = \alpha + (d\log G_i^e - d\log V_i^e)\cdot\lambda_i + \varepsilon_i \tag{12}$$

A.1. Consistency of γ_t

Our stated goal is to back out the expected change in defense spending from Equation (2), by regressing high-frequency firm-level changes in the stock prices of publicly traded defense contractors on their measure of reliance around a narratively identified event.

Therefore, we run the following high-frequency cross-sectional regression:

$$d\log P_i = \alpha + \gamma_t\cdot\lambda_i + e_i. \tag{13}$$

Theorem 1 provides the asymptotic convergence of the OLS estimator of γ_t under a set of exogeneity conditions and the sufficient conditions for it to estimate the expected policy shift, i.e., the shock.

Assumption 1. $\lambda_i \perp d\log V_i^e$

Assumption 2. $\mathbb{E}[d\log V_i^e] = 0$

Assumption 1 states that, around the event, if investors also expect changes in the private sales of military contractors, i.e., $d\log V_i^e \neq 0$, these expected changes are orthogonal to the reliance on DoD purchases.
Assumption 2 states that, if investors form expectations about changes in future private sales in response to the shock, these expectations average out to zero.

Private sales could increase if government purchases crowd-in private demand through learning-by-doing effects, as found in Lee (2024). Conversely, private sales could be crowded out if government demand pushes firms on their production capacity constraints—an outcome that may occur during a transition to a war economy, as documented in Ilzetzki (2023) for WW II.
We deem highly implausible that even the most sophisticated investors form expectations about the potential crowding-in/out effects of private sales, particularly in the absence of any documented theory. We believe it is (very) safe to assume $d\log V_i^e = 0$, which is stronger than, but consistent with, Assumption 1 and 2.

Assumption 3. $\lambda_i \perp d\log \pi_i^e := \frac{d\log \mu_i^e}{\mu_i - 1}$

Assumption 3 is about the expected change in the *profit rate* $d\log \pi_i^e$, as positively related to the price-cost markup: $\pi_i := 1 - 1/\mu_i$. It states that if investors form expectations about changes in the profit rate around an event, then these expectations are orthogonal to the reliance on DoD purchases.

The behavior of price-cost mark-ups in response to increased spending is the subject of a long-standing debate in the fiscal policy literature.[21] In fact, firm-level mark-up measures suffer from identification challenges due to the lack of unit-price data, as reported by Bond et al. (2021).
Therefore, we conclude there is no plausible claim that investors form expectations about mark-up evolution in response to our identified set of events. Moreover, it is additionally unrealistic to conjecture such expectations are systematically correlated with the reliance measure.

Finally, consider expected changes in government sales, $d\log G_i^e$, as the sum of expected changes in total defense procurement spending, $d\log G^e$ (the shock) and expected changes in the fraction of spending going to firm i, which we denote by $d\log \theta_i^e$.[22] In other words, $d\log G_i^e = d\log G^e + d\log \theta_i^e$. Then,

[21] Studies using Blanchard and Perotti (2002)'s identification find evidence of mark-up counter-cyclicality conditional on a spending shock (Monacelli and Perotti, 2008). In contrast, studies using narrative methods document mild mark-ups procyclicality, as in Nekarda and Ramey (2020) and Auerbach, Gorodnichenko, and Murphy (2024).

[22] We have that $G_{i,t} := \theta_{i,t} \cdot G_t$, that is, government purchases from firm i are equal to the fraction $\theta_{i,t}$ of total purchases G_t going to firm i.

Assumption 4. $\lambda_i \perp d\log\theta_i^e$

Assumption 5. $\mathbb{E}[d\log\theta_i^e] = 0$

Assumptions 4 and 5 state that if investors form expectations about how an aggregate narrative shock will affect the reallocation of resources across contractors—i.e., $d\log\theta_i^e \neq 0$—then these expectations must be uncorrelated with reliance and must average out to zero.

In fact, there is no obvious reason why firms with higher reliance on DoD purchases would see this reliance further increased in response to a military shock. Then, it may be reasonable to even assume $d\log\theta_i^e = 0$ for all firms. Regardless, even if investors did form such expectations, a systematic correlation with λ_i appears even more implausible. Similarly, a potential concern would arise if investors expected a reallocation of contracts either toward our set of publicly traded contractors ($\mathbb{E}[d\log\theta_i^e] > 0$) or away from them ($\mathbb{E}[d\log\theta_i^e] < 0$). Again, we see no compelling reason to consider such scenarios.

Theorem 1 below, formalizes the identification strategy formulated in Section II:

Theorem 1. *Given the data generating process* (11)*, under Assumptions 1, 3 and 4, we have that*

$$\hat{\gamma}_{OLS} \xrightarrow{p} d\log G^e + \mathbb{E}[d\log\theta_i^e] - \mathbb{E}[d\log V_i^e]$$

Moreover, under additional Assumptions 2 & 5, we obtain

$$\hat{\gamma}_{OLS} \xrightarrow{p} d\log G^e$$

that is, HFXS-regression (13) *estimates consistently the expected spending shock.*

Proof of Theorem 1

The data generating process is given by Equation (11):

$$d\log P_i = \alpha + \lambda_i \cdot (d\log G^e + d\log\theta_i^e - d\log V_i^e) + d\log V_i^e + \frac{1}{\mu_i - 1} \cdot d\log\mu_i^e$$

We estimate via OLS the following cross-sectional regression:

$$d\log P_i = \alpha + \gamma \cdot \lambda_i + e_i$$

The OLS estimator of parameter γ is given by the simple univariate OLS formula:

$$\hat{\gamma}_{\text{OLS}} := \frac{\sum_{i=1}^{N}(\lambda_i - \bar{\lambda}) \cdot (d \log P_i - \frac{1}{N}\sum_{j=1}^{N} d \log P_j)}{\sum_{i=1}^{N}(\lambda_i - \bar{\lambda})^2}$$

where $\bar{\lambda} := \frac{1}{N}\sum_{j=1}^{N} \lambda_j$. Using the DGP equation, we have:

$$\begin{aligned}
d \log P_i - \frac{1}{N}\sum_{j=1}^{N} d \log P_j = \alpha + \lambda_i \cdot (d \log G^e + d \log \theta_i^e - d \log V_i^e) + d \log V_i^e + \frac{d \log \mu_i^e}{\mu_i - 1} - \\
- \frac{1}{N}\sum_{j=1}^{N}\left(\alpha + \lambda_j \cdot \left(d \log G^e + d \log \theta_j^e - d \log V_j^e\right) + d \log V_j^e + \frac{d \log \mu_j^e}{\mu_j - 1}\right) \\
= (\lambda_i - \bar{\lambda}) \cdot d \log G^e + \left(\lambda_i \cdot d \log \theta_i^e - \frac{1}{N} \cdot \sum_j \lambda_j \cdot d \log \theta_j^e\right) - \\
- \left(\lambda_i \cdot d \log V_i^e - \frac{1}{N} \cdot \sum_j \lambda_j \cdot d \log V_j^e\right) + \left(d \log V_i^e - \frac{1}{N} \cdot \sum_j d \log V_j^e\right) + \\
+ \left(\frac{d \log \mu_i^e}{\mu_i(1 - \mu_i)} - \frac{1}{N}\sum_j \frac{d \log \mu_j^e}{\mu_j - 1}\right).
\end{aligned}$$

Replacing the above expression into the OLS formula we have:

$$\begin{aligned}
\hat{\gamma}_{\text{OLS}} = d \log G^e + \frac{\sum_{i=1}^{N}(\lambda_i - \bar{\lambda}) \cdot (\lambda_i \cdot d \log \theta_i^e - \frac{1}{N}\sum_{j=1}^{N} \lambda_j \cdot d \log \theta_j^e)}{\sum_{i=1}^{N}(\lambda_i - \bar{\lambda})^2} - \\
- \frac{\sum_{i=1}^{N}(\lambda_i - \bar{\lambda}) \cdot (\lambda_i \cdot d \log V_i^e - \frac{1}{N}\sum_{j=1}^{N} \lambda_j \cdot d \log V_j^e)}{\sum_{i=1}^{N}(\lambda_i - \bar{\lambda})^2} + \\
+ \frac{\sum_{i=1}^{N}(\lambda_i - \bar{\lambda}) \cdot (d \log V_i^e - \frac{1}{N}\sum_{j=1}^{N} d \log V_j^e)}{\sum_{i=1}^{N}(\lambda_i - \bar{\lambda})^2} + \\
+ \frac{\sum_{i=1}^{N}(\lambda_i - \bar{\lambda}) \cdot \left(\frac{d \log \mu_i^e}{\mu_i - 1} - \frac{1}{N}\sum_j \frac{d \log \mu_j^e}{\mu_j - 1}\right)}{\sum_{i=1}^{N}(\lambda_i - \bar{\lambda})^2}
\end{aligned}$$

By the Continuous Mapping Theorem and the Weak Law of Large numbers, we obtain:

$$\begin{aligned}
\hat{\gamma}_{\text{OLS}} \xrightarrow{p} d \log G^e + \frac{\mathbb{C}ov(\lambda_i, \lambda_i \cdot d \log \theta_i^e)}{\mathbb{V}(\lambda_i)} - \frac{\mathbb{C}ov(\lambda_i, \lambda_i \cdot d \log V_i^e)}{\mathbb{V}(\lambda_i)} + \\
+ \underbrace{\frac{\mathbb{C}ov(\lambda_i, d \log V_i^e)}{\mathbb{V}(\lambda_i)}}_{=0 \text{ (Assumption 1)}} + \underbrace{\frac{\mathbb{C}ov(\lambda_i, \frac{d \log \mu_i^e}{\mu_i - 1})}{\mathbb{V}(\lambda_i)}}_{=0 \text{ (Assumption 3)}}
\end{aligned}$$

Under Assumption 1, we have that $\mathbb{C}ov(\lambda_i, d\log V_i^e) = 0$. Under assumption 3, we have $\mathbb{C}ov(\lambda_i, \frac{d\log\mu_i^e}{\mu_i - 1}) = 0$. Furthermore,

$$\begin{aligned}\mathbb{C}ov(\lambda_i, \lambda_i \cdot d\log V_i^e) &= \mathbb{E}[\lambda_i^2 \cdot d\log V_i^e] - \mathbb{E}[\lambda_i] \cdot \mathbb{E}[\lambda_i \cdot d\log V_i^e] \\ &= \mathbb{E}[\lambda_i^2] \cdot \mathbb{E}[d\log V_i^e] - \mathbb{E}[\lambda_i]^2 \cdot \mathbb{E}[d\log V_i^e] = \mathbb{V}(\lambda_i) \cdot \mathbb{E}[d\log V_i^e]\end{aligned}$$

Similarly, under Assumption 4 we have

$$\begin{aligned}\mathbb{C}ov(\lambda_i, \lambda_i \cdot d\log \theta_i^e) &= \mathbb{E}[\lambda_i^2 \cdot d\log \theta_i^e] - \mathbb{E}[\lambda_i] \cdot \mathbb{E}[\lambda_i \cdot d\log \theta_i^e] \\ &= \mathbb{E}[\lambda_i^2] \cdot \mathbb{E}[d\log \theta_i^e] - \mathbb{E}[\lambda_i]^2 \cdot \mathbb{E}[d\log \theta_i^e] = \mathbb{V}(\lambda_i) \cdot \mathbb{E}[d\log \theta_i^e].\end{aligned}$$

Therefore, under Assumption 1,3 and 4, we have that:

$$\hat{\gamma}_{\text{OLS}} \xrightarrow{p} d\log G^e + \mathbb{E}[d\log \theta_i^e] - \mathbb{E}[d\log V_i^e]$$

Trivially, additionally imposing Assumption 2 and 5 proves the statement of Theorem 1.

B LLMs – Prompts

Below, instanced of prompts with examples we used:

"*Compile a list of dates or events—from 2000 onward—that signal a potential shift in the expected path of US military procurement spending. Include both positive and negative shocks. Examples: (a) September 11, 2001 terrorist attacks: widely seen as a precursor to higher defense spending; (b) Failure in February/March 2013 of President Obama and Congress to reach a budget agreement: triggered automatic cuts (sequestration) and reduced defense spending; (c) Unexpected election victory of Donald Trump, November 2016: he campaigned on increasing military outlays. Use a similar standard to identify and briefly justify each additional event you list.*"

In this case, the 9/11 is already listed by Ramey and Zubairy (2018) as a clear precursor of military spending, the 2013 sequestrations are listed as both a defense news shock by Ramey and Zubairy (2018) and as an exogenous expenditure-based fiscal consolidation by Alesina et al. (2017); the election of Donald Trump by a narrow margin was widely regarded by news and industry expert as a defense news shock, given he campaigned using a "*peace through strength*" slogan. Therefore, all examples are highly non-controversial in the sense they are all clearly precursors of military spending expansions or cuts, which indeed materialized.

Lastly, an example of prompt without specifying examples within a narrower context is the following:

"*List the defining moments/events of the war in Iraq and Afghanistan that (a) had large media coverage in the US around the years 2004-2008 and (b) which also gave the impression of an expected increase in military spending in the US.*"

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C Supplemental: Narrative Analysis of Each Identified Event

In this section we provide a detailed analysis of the high frequency events windows that we choose. To help visualize the shocks, we plot the stock price of three major defense contractors: Lockheed Martin (LMT), Northrop Grumman (NOC) and General Dynamics (GD). We also construct a simple defense index using the excess return of these three defense contractors plus those ones of other two major defense contractors: Raytheon (RTX) and Boeing (BA). We prefer to plot the stock prices of LMT, NOC and GD instead of RTX and BA, as their stock price elasticity to the military news is smaller. In fact, RTX and BA have much smaller reliances (λ_i) than the other three contractors.

9/11 Terrorist Attacks The stock market closed on September 11th following the first strike to the World Trade Center. It re-opened on September 17th. The stock price of RTX and BA fell on opening as large part of their business was linked to air traveling. On the contrary, LMT, GD and NOC experienced record high increases. The spike of the defense index occurred on September 21st, that, is, exactly five trading days after September 10th.

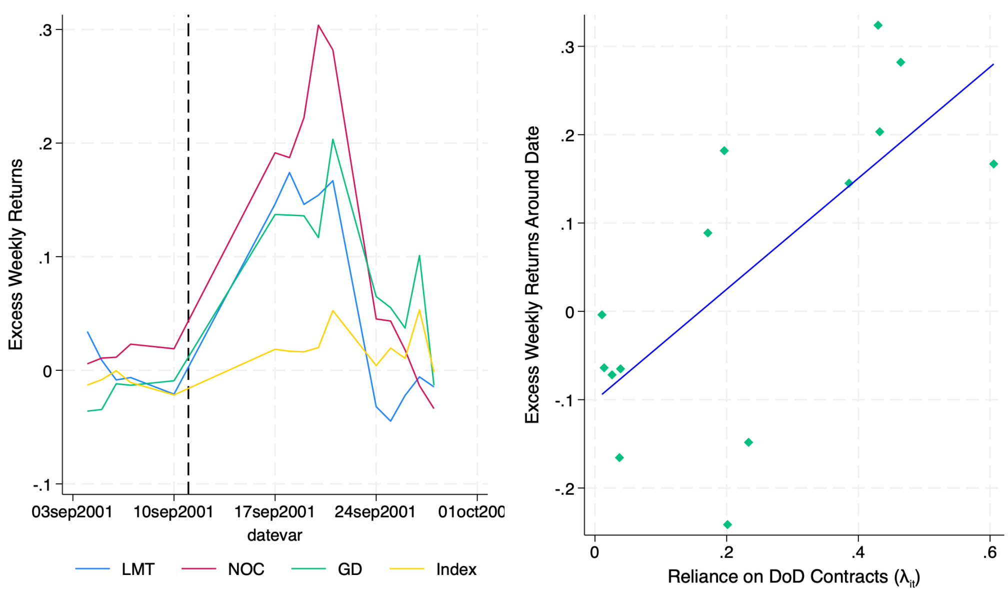

Figure 6: **9/11 Terrorist Attack**: shock date 21 Sep 2001

US led invasion of Iraq On Mon 17 Mar 2003, 8 p.m. EST, President Bush gave a 48-hour ultimatum. Televised Oval-Office address broadcast live on every major network. Newspapers and 24-h cable channels immediately framed it as the formal “go” for war. The speech removed virtually all remaining uncertainty: unless Saddam fled within two days, an invasion was assured.

Financial desks reported a "war-relief" rally the next morning—defense names led gains. On Wed 19 Mar 2003, 9:34 p.m. EST (20 Mar 05 : 34 Baghdad): first cruise-missile strike. Networks cut to breaking news of explosions over Baghdad; the President addressed the nation about 15 minutes later. The ultimatum on the evening of the 17th gave investors one and a half trading days (Tue 18 Mar and Wed 19 Mar) to price-in an almost certain shooting war before the first bombs actually fell. The defense index jumped up to almost 6% on March 19th.

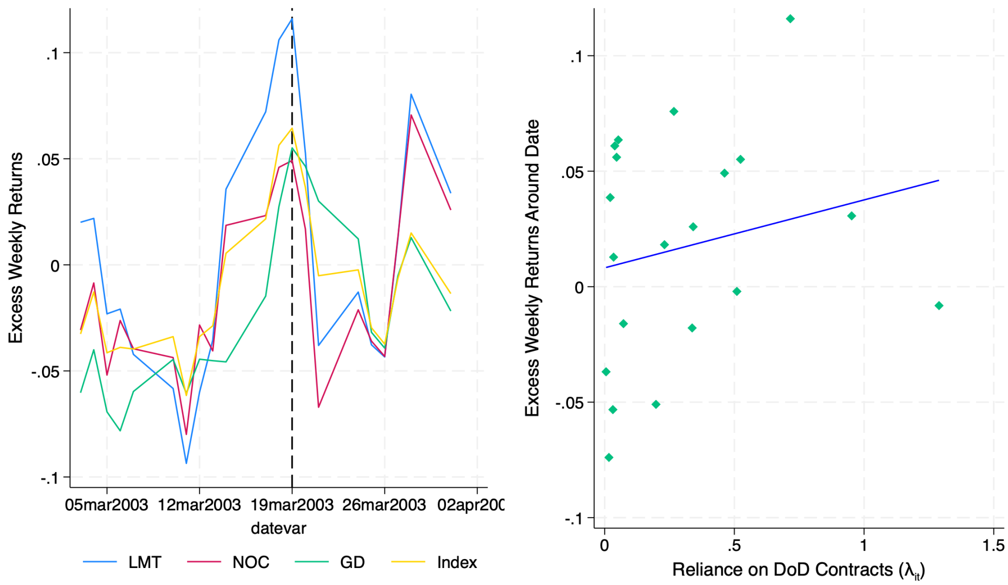

Figure 7: **Invasion of Iraq (Bush Ultimatum)**: shock date 19 Mar 2003

Bush Speech for Extra Funds for Iraq The White House asked Congress for an immediate $5.6 billion plus a much larger FY 2007 supplemental, signaling that operations costs would jump. The speech was given on January 10th 2007 around 9pm ET.[23] The day after, weekly returns increase. However, the stock price jump on the day after, January 11th 2007, was not particularly strong, as information leakages (Washington Post and NY Times) about the President willingness to increase troops, had already put upward pressures on stock prices.

[23] link to speech.

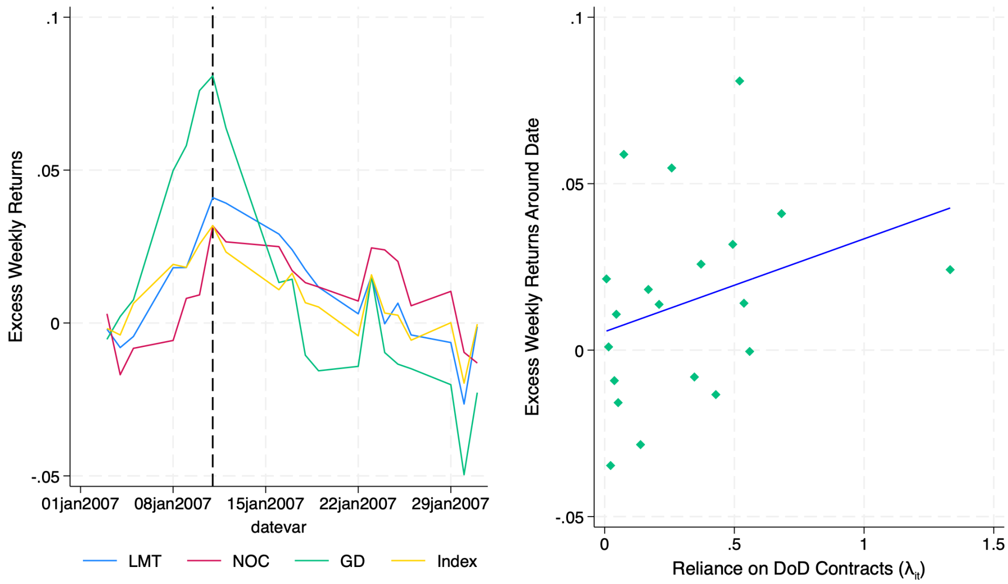

Figure 8: **Bush Speech**: shock date 11 Jan 2007

Election of President Obama Barack Obama was elected U.S. president after campaigning to end the Iraq War. A Democratic administration shift signaled expectations of a more restrained defense posture to prior years, though immediate cuts were moderated by ongoing conflicts and lower war spending compared through September and confirmed that Congress would keep writing very large off-budget checks for the wars. On November 5th Obama resulted as the clear winner. The stock prices of major defense contractors appear to decline the day after. Therefore, we choose Thursday November 6th 2008 as the shock date for the weekly returns.

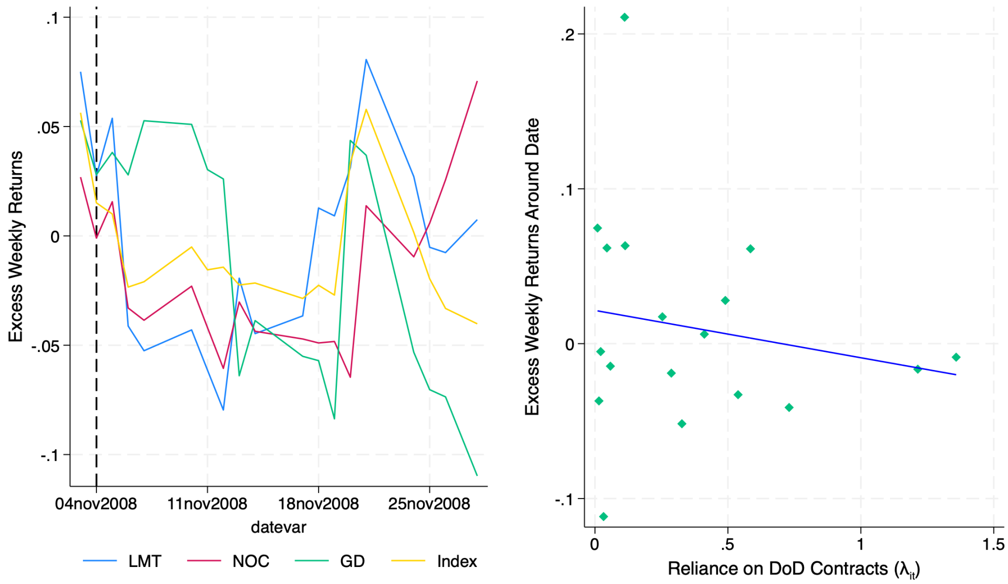

Figure 9: **Election of Obama**: shock date 6 Nov 2008

Budget Control Act of 2011 The Budget Control Act of 2011 was enacted on August 2, 2011, as a legislative response to a looming U.S. sovereign default due to the debt ceiling crisis. The act emerged from a tense political standoff between the Obama administration and a Republican-controlled Congress, aiming to simultaneously raise the debt ceiling and impose measures to curb the federal deficit. It authorized a multi-step increase in the debt limit totaling up to $2.1 trillion and included an initial $917 billion in discretionary spending cuts over a ten-year horizon. These cuts were split between defense and non-defense categories and capped annual discretionary appropriations, imposing tight constraints on future budget growth.

A central feature of the law was the creation of the Joint Select Committee on Deficit Reduction, commonly known as the “Super Committee,” which was tasked with identifying an additional $1.2 trillion in deficit reduction. When the committee failed to reach an agreement by its November 2011 deadline, a mechanism known as sequestration was triggered. Sequestration mandated automatic, across-the-board cuts beginning in 2013, evenly divided between defense and non-defense discretionary spending. This automatic enforcement mechanism was designed to be deliberately severe in order to incentivize compromise, but instead, it took effect and reshaped the structure of federal spending.

The consequences for the Department of Defense were substantial. The combination of the spending caps and the sequester led to an estimated $500 billion reduction in planned defense budget authority from 2013 to 2021. These cuts affected a wide range of defense activities, including troop levels, procurement programs, operations, and maintenance. The defense community criticized the cuts as blunt and inflexible, arguing they undermined strategic planning and national security preparedness. The BCA's legacy was one of deep fiscal restraint, but also policy gridlock, as Congress increasingly resorted to temporary funding extensions and stopgap measures to navigate its constraints.

Stock prices of defense contractors fell sharply starting from the Friday before the enactment, which occurred on Tuesday. The dip was reached on the day of the signing, August 2 2011, therefore, we choose this date as the shock date for the weekly returns.[24]

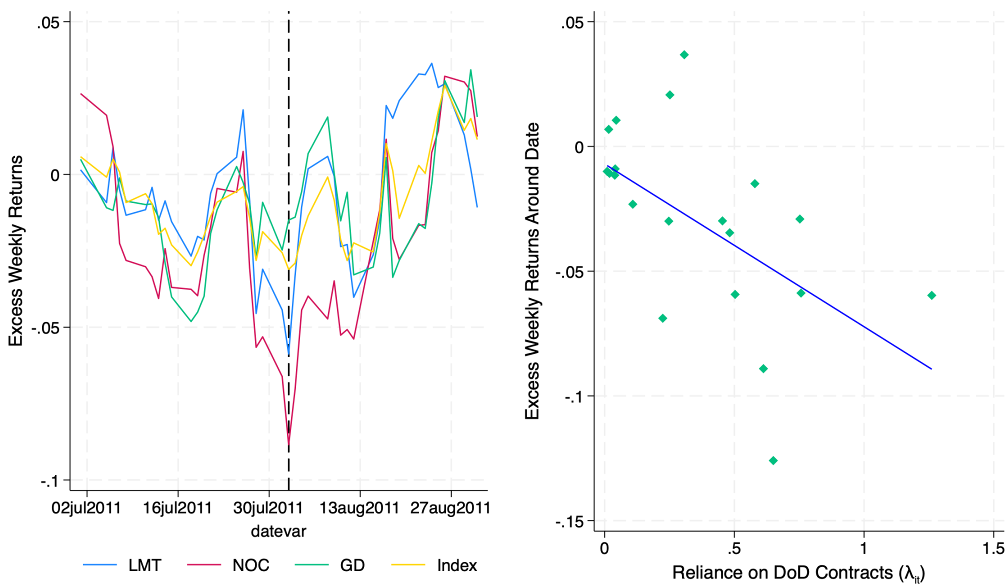

Figure 10: **Budget Control Act 2011**: shock date 2 Aug 2011

Sequestrations of 2013 The BCA of 2011, passed in August 2011, set caps on federal spending and included a provision for across-the-board cuts (sequestration) to both defense and non-defense spending, starting in 2013, unless a bipartisan deficit reduction deal was reached. By early 2013, it had become increasingly clear that no such deal would be reached. The deadline for sequestration was March 1, 2013. On January 30, 2013, the Department of Defense and major government agencies were preparing for deep budget cuts, including reductions in procurement, furloughs for civilian workers, and delays in contracts. Around that date, market sentiment shifted, with increasing media coverage and official warnings from the Pentagon that the sequestration would severely impact defense budgets.

[24] See Reuters article and this CNN Money article.

On January 31st, weekly returns on our defense index fell to almost -5%; therefore, we set January 31st as a shock date for our cross-sectional regression. By consequence, around March 1st when sequestrations took place, the stock price responses of defense contractors only experienced a mild contraction, as budget cuts had already been incorporated into the stock price of defense contractors.

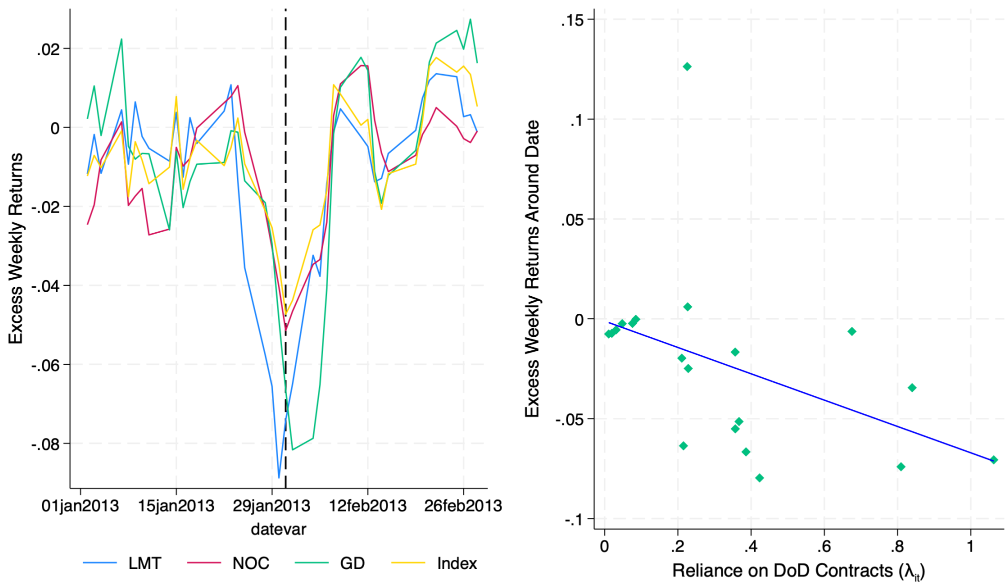

Figure 11: **Sequestrations**: shock date 31 Jan 2013

Annexation of Crimea On February 27, amid chaotic political developments in Ukraine, Russian troops invaded Crimea. On March 1, President Obama confirmed the Russian intervention, and in the following days, several press conferences were held to discuss and condemn Russia's actions. Between March 4 and 5, we observe a spike in the excess weekly returns of U.S. defense contractors, reflecting market expectations of increased defense spending. Finally, on March 18, 2014, Russia formally annexed Crimea, which was accompanied by another localized increase in defense contractor stock prices. However, the primary stock market response occurred in late February, immediately following the start of the invasion.

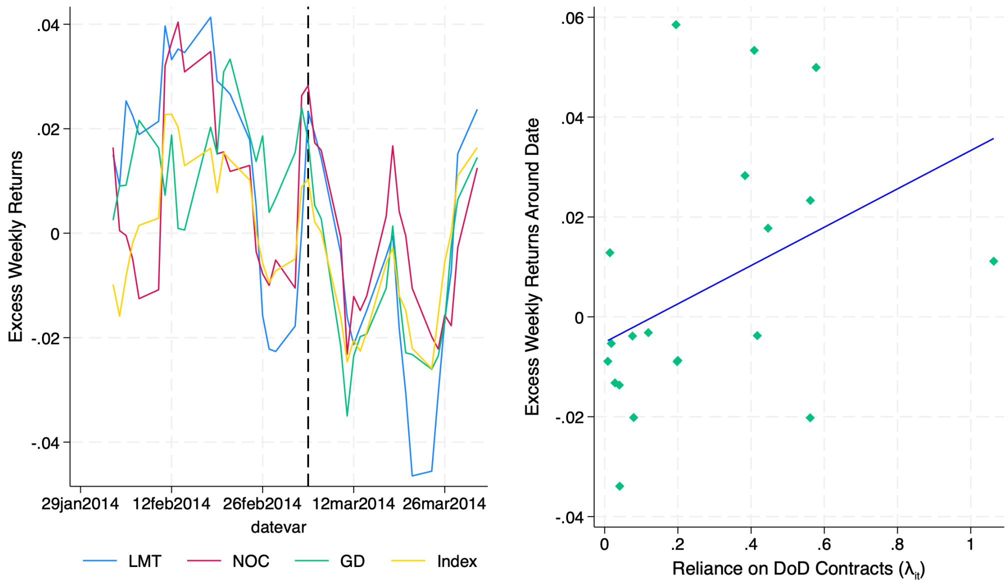

Figure 12: **Annexation of Crimea**: shock date 5 Mar 2014

The military intervention in Ukraine signaled a return of great-power conflict. This geopolitical jolt ended assumptions of post-Cold War stability in Europe and spurred U.S./NATO leaders to reconsider defense spending increases to deter Russian aggression.

War to ISIS Build-up On September 22nd 2014, the extremist group ISIS seized large parts of Iraq and Syria (capturing Mosul in June). By August, the U.S. launched airstrikes (Operation Inherent Resolve) to combat ISIS; announced by Pentagon Press Secretary on September 22. This unexpected new campaign reversed the prior drawdown of U.S. military operations.

The defense index experienced a big jump in the week that closed Friday 31 October 2014, originating from a cluster of bullish headlines that all landed within four trading days, giving investors unusually clear signals that both near-term revenues and longer-term budget prospects were improving for the prime contractors. The spike occurred around the 28-29th of October, therefore, we pick October 29th as the trading shock date. Major events:

- Reuters broke the news that the Pentagon and Lockheed Martin had reached a tentative \$4 billion deal for Low-Rate Initial Production (LRIP) Lot 8 of 43 F-35s.[25] The F-35 is the single largest procurement program for every major U.S. contractor involved (Lockheed, Northrop, BAE, Raytheon/RTX, Pratt & Whitney/RTX). A fresh production lot signaled continuity after

[25] Link to article.

the mid-year engine fire and grounding.

- A string of formal contract actions followed: (i) 28 Oct — \$392 m sustainment contract to Lockheed for delivered F-35s; (b) on 30 Oct — \$793 m Lot 8 engine order to Pratt & Whitney for F-35s.[26] These DoD awards confirmed the Reuters scoop and showed money flowing, not just a handshake. The cumulative value (airframes + engines + support) pushed the week's announced F-35 obligations to well over \$5 billion.

- By 30 Oct analysts estimated U.S. air-campaign costs against ISIS had already neared \$1 billion, implying a coming supplemental request. Moreover, Polls pointed to a likely Republican takeover of the Senate in the 4 Nov mid-term elections, a scenario viewed as friendlier to higher defense top-lines. Both factors strengthened the view that the FY-15 base budget cap could be eased and that Overseas Contingency Operations (OCO) funding would rise, extending revenue visibility for contractors.

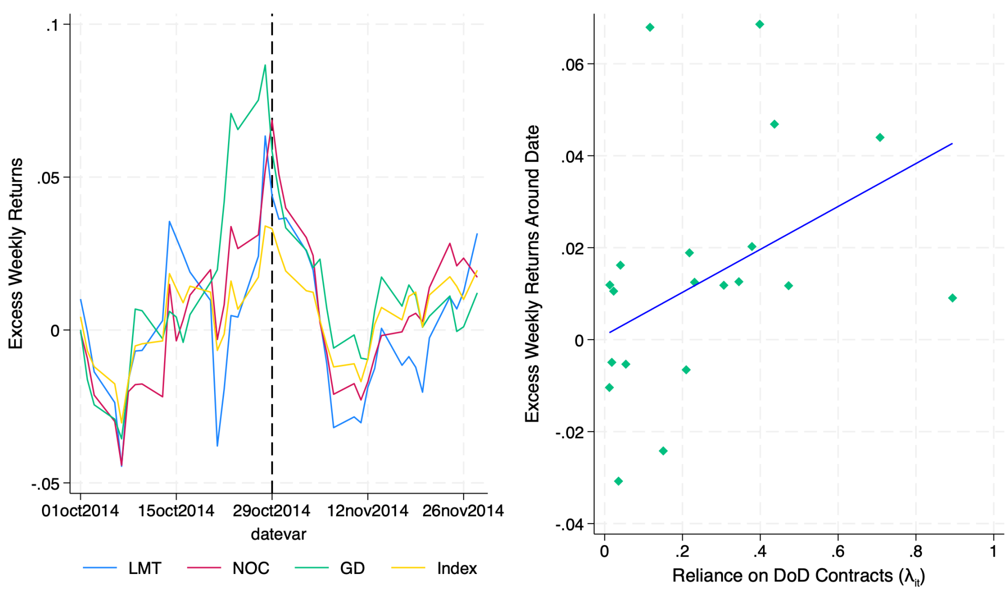

Figure 13: **War to ISIS**: shock date 29 Oct 2014

First President Trump Election In a scripted national-security speech at Philadelphia's Union League on 7 September 2016, Trump called for ending the Budget Control Act sequester and submitting[27] "*a new budget to rebuild our military:*";"*Rebuild our military… it is so depleted.*"

[26] Link to Defense.gov contracts' announcements for (a) and (b).
[27] See this The Guardian's article.

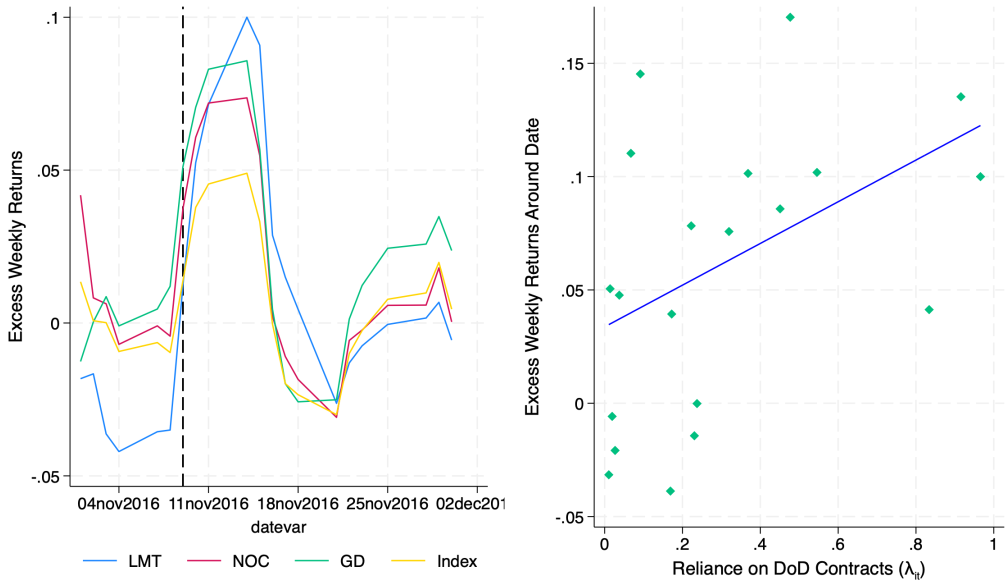

Figure 14: **First President Trump Election**: shock date 14 Nov 2016

As a consequence, stock prices of defense contractors soared following his first election.[28]

Bipartisan Budget Act of 2018 The White House was preparing a $716 bn FY-2019 defense request which leaked late 25 January. Washington Post, Axios and Bloomberg all reported that President Trump would ask for $716 bn—about 7% above the still-unfunded FY-2018 plan and 13% above FY-2017—marking the biggest one-year jump since the Iraq Surge years. Markets got the story after the close on 25 January and bid up defense names in pre-market trading on the 26th and following days.[29] The spike of the Defense Index occurred on January 31st, reaching a value of +5.8% in weekly excess returns.

Following those days, a bipartisan budget deal (bipartisan Budget Act of 2018) was enacted on 9 February 2018, which lifted the strict BCA spending caps for FY2018–2019. This deal enabled a major jump in Pentagon funding (about a 15% increase in defense budget authority), signaling a notable upward revision in near-term procurement spending plans.

[28] See this this Breaking Defense article.
[29] See the article by The Washington Post.

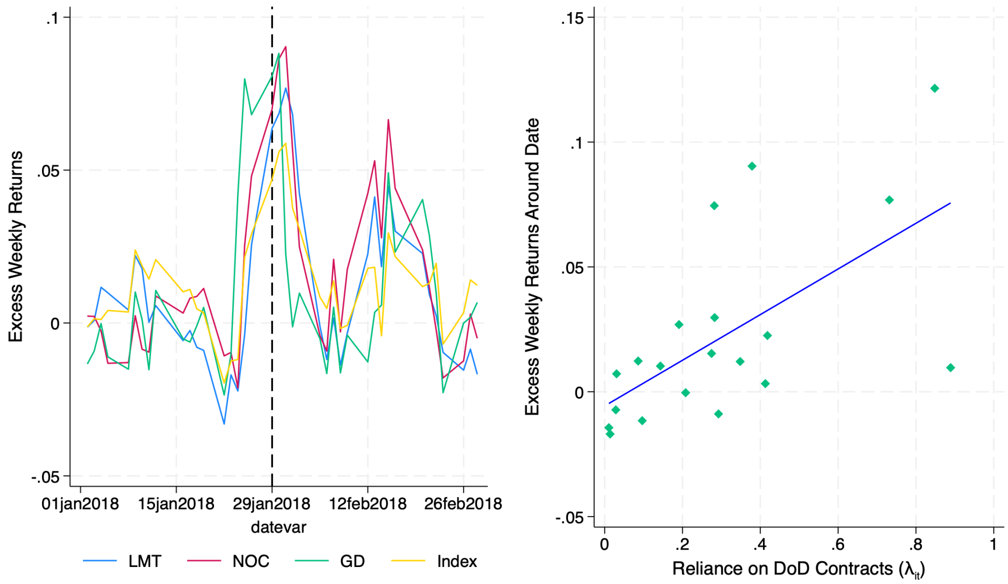

Figure 15: **Bipartisan Budget Act 2018**: shock date 31 Jan 2018

Bipartisan Budget Act of 2019 On July 22nd 2019, the White House and Capitol Hill stroke a two-year budget-cap deal. The draft of the Bipartisan Budget Act of 2019 lifted the FY-2020 defense cap to \$738 bn (up \$22 bn over 2019) and suspended the debt ceiling through mid-'21, eliminating the risk of automatic sequestration.[30] The deal signaled higher funding for at least two fiscal years and removed the threat of a fall government shutdown. The very next trading sessions (from Tuesday 23rd to Friday 26th July) investors treated the bill signings as nearly locked-in future funds for the defense firms. By consequence, the defense sector stock prices increased, in particular, on July 25th the defense index spiked to +2.4% (see Figure 16).

[30] See this article by Reuters. See this article by Axios.

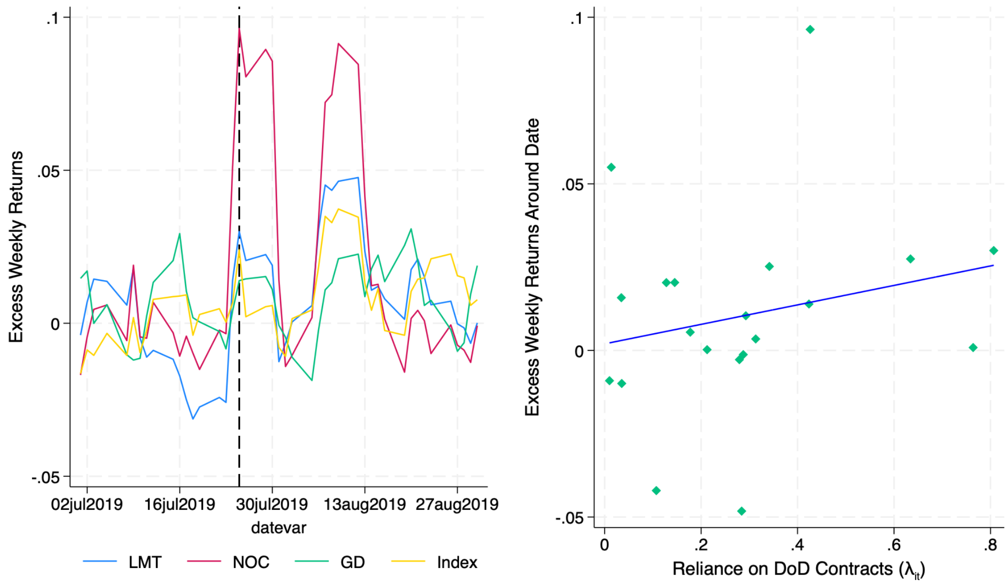

Figure 16: Bipartisan Budget Act 2019 (House), 25 July 2019

Eventually, the budget deal was signed by the President on August 2nd; raising the defense spending caps for FY2020 and FY2021 and essentially ending the decade of sequestration-era limits. The signing of the bill canceled any uncertainty relative to future defense contracts. Moreover, the US, after alleging Russian non-compliance, announced its suspension of obligations under the INF treaty (Inter-range Nuclear Forces Treaty) and formally withdrew on August 2, 2019.[31] That opened an unbudgeted lane for new missile, launcher and sensor programs—prime territory for Lockheed, Raytheon and Northrop. For instance, Lockheed received a $176 m Aegis SPY-1 weapons-system support deal (9 Aug). The Army finalized the Iron Dome buy (Raytheon/Rafael) on 12 Aug but news of those contracts were discussed in the days before the awards.[32]

The defense index spiked on August 9th to +3.7%, therefore, we set as a weekly excess returns trading shock date August 9th (see Figure 17).

[31] See Pentagon announcement.

[32] See contracts announcements for Lockheed and Raytheon for the Iron Dome.

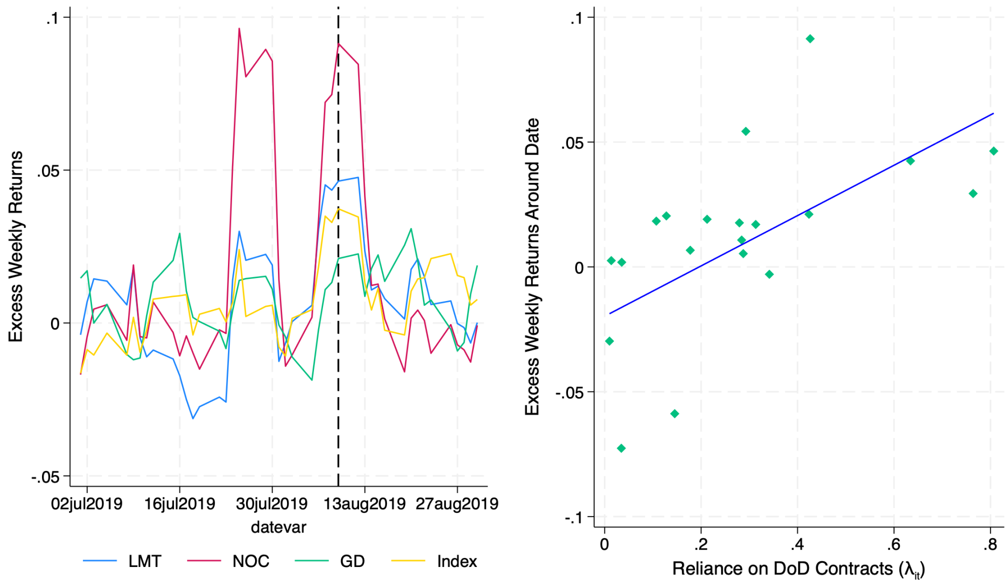

Figure 17: Bipartisan Budget Act 2019 (Senate) and Iron Dome shock, 9 Aug 2019

Russian Invasion of Ukraine In late 2021, Russia began amassing tens of thousands of troops along Ukraine's borders and issued ultimatums demanding that NATO bar Ukraine from ever joining the alliance. After repeatedly denying any invasion plans, on February 24, 2022 President Vladimir Putin launched what he called a "special military operation," with air strikes and a multi-pronged ground assault from the north (via Belarus toward Kyiv), the south (from Crimea) and the east (from the Donbas). Following the invasion, the stock price of US military contractors began increasing and spiked on March 1st, which is chosen as trading shock date for the excess weekly returns.

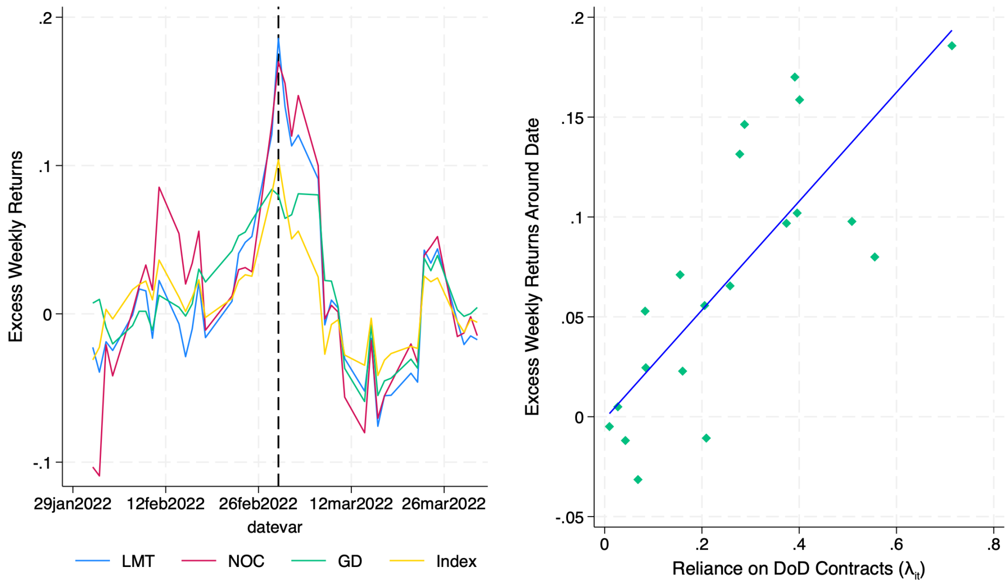

Figure 18: **Russian Invasion of Ukraine**: shock date 1 Mar 2022