High-Frequency Cross-Sectional Identification of Military News Shocks

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OUTLINE

Introduction

HFXS Framework & Identification

Empirical Results

Application: US GDP XS-Multipliers

Conclusion



MOTIVATION

- Economists are interested in the effects of defense spending because it provides:
 - Exogenous variation in government spending (causal inference)
 - Multiplier estimates of military build-ups (policy relevance)
- Identification challenges:
 - Effects of government spending are anticipated (Ramey, 2011)
 - Measuring expectations is tricky

\rightarrow Research Question:

- "How does the economy respond to **anticipated** changes in defense spending?" &
- "How can we effectively measure expectations about future defense spending?

LITERATURE REVIEW

- Macro shocks need to be unanticipated (Ramey, 2016)
 - Fiscal foresight
 Mertens and Ravn (2010) (gov. spending), Leeper et al. (2013) (taxes)
 - Measurement delays (Briganti et al., 2025)
 - → Non-invertibility of fiscal shocks

INTRODUCTION

- → **Unanticipated measures** of government spending shocks:
 - VAR Restrictions: Blanchard and Perotti (2002) (short-run restrictions), Ben Zeev and Pappa (2017) (medium run restrictions (Barsky and Sims, 2011)), Ascari et al. (2023) (sign restrictions (Mountford and Uhlig, 2009))
 - Narrative Instruments:
 Ramey and Shapiro (1998) (war dates), Ramey (2011)+Ramey and Zubairy (2018) (def. news)
 - Bartik Instruments: Nakamura and Steinsson (2014), Dupor and Guerrero (2017), Demyanyk et al. (2019), Auerbach et al. (2020), Muratori et al. (2023), Barattieri et al. (2023), Auerbach et al. (2024).
 - Stock-Price-Based Instruments:
 Fisher and Peters (2010), McClure and Yding (2024)(narrative+high frequency).
 - High Frequency Instruments: Bandeira et al. (2025) (Brazil Deficit), Wiegand (2025)+
 Gomez-Cram et al. (2025)+Hazell and Hobler (2025)+Bi et al. (2025)(US Deficits)

CONTRIBUTION: HFXS IDENTIFICATION

- We introduce a novel method to quantify expectations of future military spending
 - I. Identify HF-fiscal events using narrative analysis augmented with LLM searches
 - II. Leverage stock price XS-variation to quantify expected shifts in defense expenditure

Benefits:

- $\scriptstyle\rm I.$ Model consistent methodology grounded in asset pricing theory
- II. Self-validating: it estimates and allows statistical validation of each event (testing)
- III. Generalizable to contexts where units are heterogeneously impacted by aggregate shocks
- IV. Parsimony and objectivity (i.e., minimizes subjectivity in narrative approaches)

Contributions:

- I. Novel LLM-augmented narrative analysis: key fiscal events (2001-2023)
- II. Novel military news shocks series (2001-2023)
- III. Novel XS-multiplier estimates (MSA / 2001-2023)

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A SIMPLE MODEL OF STOCK PRICES

• Profits $D_{i,t}$ of firm i at time t

$$D_{i,t} := (1 - au_t) \cdot \underbrace{\left(V_{i,t} + G_{i,t}\right)}_{ ext{TOTAL SALES}} \cdot \left(1 - rac{1}{\mu_i}\right)$$

- $-V_{i,t}$ is private sales
- $-G_{i,t}$ is government sales
- $-\mu_i$ is the markup and τ_t is a corporate tax
- Gordon (1959):

$$P_{i,t} := \sum_{h=0}^{\infty} \frac{D_{i,t+h}^e}{\prod_{\tau=0}^h (1 + i_{t,t+\tau}^e)}$$

- $-P_{i,t}$ is the stock price of firm i
- $i_{t,t+ au}^e$ is the expected (t+ au)-period ahead interest rate at time t

- Under (i)-(ii):
 - I. Expected profits are proxied by current profits
 - II. Expectations hypothesis of the term structure holds

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

→ The stock prices are proportional to government sales

Let us focus on cross-section (XS) of contractors i

- Denote Reliance on DoD by $\lambda_i := \frac{G_i}{G_i + V_i}$; define $G_i := \theta_i \cdot G$
- Log-Differentiate (1) around a **HF fiscal event**:

$$\underbrace{\frac{d\log P_i}{\text{Stock Return}}} = \alpha + \underbrace{\lambda_i}_{\text{Reliance}} \cdot \left(\underbrace{\frac{d\log G^e}{\text{Shock}}} + d\log \theta_i^e - d\log V_i^e\right) + \varepsilon_i$$
 (2)

- $-\alpha$: time FEs (e.g., \mathbb{E} change in corporate taxes);
- $-\varepsilon_i$: firm-specific FEs (e.g., \mathbb{E} change in markups)

HFXS IDENTIFICATION: THEOREM

GENERALIZATION

Under weak Assumptions, regressing stock returns $(d \log P_i)$ on reliance on DoD contracts (λ_i) :

$$d\log P_i = \alpha + \gamma \cdot \lambda_i + e_i \tag{3}$$

yields

$$\hat{\gamma}_{\mathsf{OLS}} \stackrel{p}{\to} d \log G^e$$

That is, $\hat{\gamma}_{OLS}$ consistently estimates expected changes in defense spending $(d \log G^e)$

"If Lockheed's reliance on DoD (λ_i) is 71% and Boeing's is 30%, a positive shock will affect Lockheed's price more, mirroring its larger profit potential."

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EMPIRICAL RESULTS •00000000

EMPIRICAL RESULTS

EVENTS THAT SHIFTED US EXPECTED MILITARY SPENDING (2000-2023)

Date	Sign	Description of the Event
11 September 2001	+	9/11 terrorist attacks $+$ ensuing invasion of Afghanistan in October 2001
20 March 2003	+	U.Sled invasion of Iraq opens a second major war
10 January 2007	+	President Bush's Iraq "Surge" address
4 November 2008	-	Barack Obama elected U.S. president after campaigning to end the Iraq War
2 August 2011	-	Budget Control Act of 2011 signed amid debt-ceiling crisis
1 March 2013	-	U.S. Government Sequestration takes effect after Congress fails to agree on deficit reductions
18 March 2014	+	Russia's illegal annexation of Crimea
22 September 2014	+	Extremist group ISIS seizes large parts of Iraq & Syria
8 November 2016	+	Trump wins 2016 U.S. Elections campaigning on military build-up
9 February 2018	+	Bipartisan Budget Act of 2018 lifts strict BCA spending caps for FY 2018–19
2 August 2019	+	${\it Bipartisan \; Budget \; Act \; of \; 2019 \; raises \; defense \; spending \; caps \; + \; ends \; sequestration-era \; limits}$
24 February 2022	+	Russia invades Ukraine

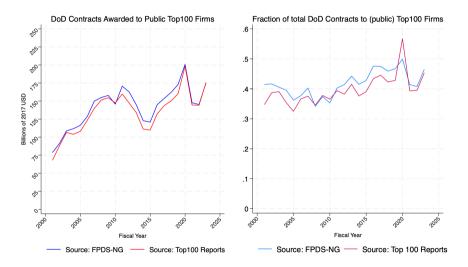
Defense Contractors Data

- Annual official Top100 Report (available from 1958)
- \rightarrow 430 Top100 Contractors from FY2001
- Three conditions:
 - Publicly Traded (NYSE or NASDAQ)
 - \rightarrow 57 contractors
 - II. Salience: investors associate contractors to "defense"
 - → Appear at least four times in Top100 report (e.g., rules out **Moderna**)
 - III. Relevance: stock price non-negligibly affected by gov. contracts
 - \rightarrow Median reliance \geq 1% (e.g., rules out **BP**):

$$\mathsf{Median}\left(\lambda_{i,t}
ight) \geq 1\%, \quad \lambda_{i,t} := rac{\mathsf{DoD}\;\mathsf{Contracts}_{i,t}}{\mathsf{Tot.}\;\mathsf{Sales}_{i,t}}$$

- → 33 Contractors meet conditions I-III
 - Median reliance is 20%. Interquartile range is [3.7%,39.9%] Descriptive State

33 companies = 40% total DoD Procurement spending!



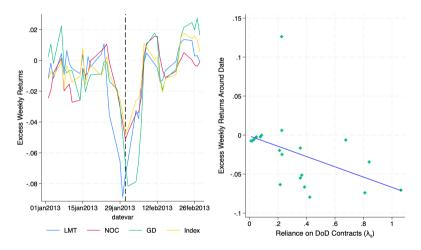
MODEL-IMPLIED XS-REGRESSION

- We have:
 - Set of Narrative Dates T
 - Set of 33 publicly traded, salient and relevant defense contractors
- → Implement HFXS Regressions
- For each date $\tau \in \mathcal{T}$ estimate empirical analog of Equation (3):

$$\underbrace{\frac{\mathbf{v}_{i|t=\tau}}{\approx d \log P_{i,t}}} = \alpha + \gamma_{t=\tau} \cdot \underbrace{\frac{\lambda_{i|t=\tau}}{\text{Reliance}}} + \epsilon_i \quad \forall \tau \in \mathcal{T}, \ \forall i \in \mathcal{I}_{\tau},$$
(4)

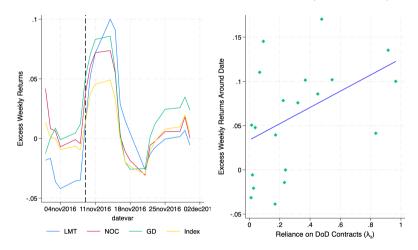
- Vilt=: weekly excess returns
 - Constructed using Fama-French 3 factors model
 - Frequency: five trading days
- $-\lambda_{i|t=\tau}$: reliance on DoD purchases in the quarter of the event
- We have:
 - Set of Narrative Dates T
 - Set of 33 publicly traded, salient and relevant defense contractors
- → Implement HFXS Regressions

EXAMPLE 1: BUDGET SEQUESTRATIONS (2013Q1)



 \rightarrow **Estimated Slope** $(\hat{\gamma})$: -0.066 (0.015)

EXAMPLE 2: TRUMP ELECTION (2016Q4)



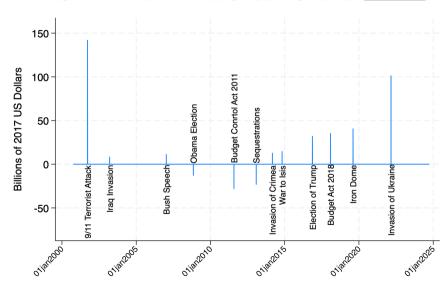
 \rightarrow Estimated Slope ($\hat{\gamma}$): +0.092 (0.024)

ESTIMATES OF HFXS MILITARY NEWS SHOCKS

Shock Trading Date	Expected Sign	$\mathbf{d} \log \mathbf{G_t} \ (\gamma_{\mathbf{t}= au})$	pvalue	N	Defense Index
September 21, 2001	+	0.629	0.000	14	+5.2%
March 19, 2003	+	0.029	0.406	20	+ 6.4%
January 11, 2007	+	0.028	0.117	20	+3.1%
November 6, 2008	-	-0.031	0.327	18	-2.3%
August 2, 2011	-	-0.065	0.002	23	-3.1%
January 31, 2013	-	-0.066	0.000	21	-4.7%
March 5, 2014	+	0.038	0.086	21	+1.5%
29 October 2014	+	0.047	0.065	23	+3.3%
November 14 2016	+	0.092	0.042	23	+4.9%
January 31 2018	+	0.091	0.024	23	+5.8%
9 August, 2019	+	0.101	0.002	23	+3.7%
March 1. 2022	+	(0.028) 0.273	0.000	23	+10.4%
	September 21, 2001 March 19, 2003 January 11, 2007 November 6, 2008 August 2, 2011 January 31, 2013 March 5, 2014 29 October 2014 November 14 2016 January 31 2018 9 August, 2019	September 21, 2001 + March 19, 2003 + January 11, 2007 + November 6, 2008 - August 2, 2011 - January 31, 2013 - March 5, 2014 + 29 October 2014 + November 14 2016 + January 31 2018 + 9 August, 2019 +	September 21, 2001 + 0.629 (0.133) March 19, 2003 + 0.029 January 11, 2007 + 0.028 (0.017) November 6, 2008 0.031 (0.030) August 2, 2011 0.065 (0.019) January 31, 2013 0.066 (0.015) March 5, 2014 + 0.038 (0.021) 29 October 2014 + 0.047 (0.024) November 14 2016 + 0.092 (0.043) January 31 2018 + 0.091 (0.038) 9 August, 2019 + 0.101 (0.028)	September 21, 2001 + 0.629 (0.133) March 19, 2003 + 0.029 (0.035) January 11, 2007 + 0.028 (0.017) November 6, 2008 - - -0.031 (0.030) August 2, 2011 - -0.065 (0.019) -0.002 (0.019) January 31, 2013 - -0.066 (0.015) -0.006 (0.015) March 5, 2014 + 0.038 (0.021) 29 October 2014 + 0.047 (0.024) November 14 2016 + 0.092 (0.042) January 31 2018 + 0.091 (0.038) 9 August, 2019 + 0.101 (0.028)	September 21, 2001 + 0.629 (0.133) March 19, 2003 + 0.029 (0.046) 20 January 11, 2007 + 0.028 (0.017) 0.117 (0.017) November 6, 2008 - - -0.031 (0.030) 0.327 (0.030) August 2, 2011 - -0.065 (0.002 (0.019)) 0.002 (0.019) January 31, 2013 - -0.066 (0.000 (0.015)) 0.055 (0.002 (0.015)) March 5, 2014 + 0.038 (0.021) 0.086 (0.021) 29 October 2014 + 0.047 (0.065 (0.024)) November 14 2016 + 0.092 (0.042 (0.024)) January 31 2018 + 0.091 (0.038) 9 August, 2019 + 0.101 (0.028)

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%.

HFXS MILITARY NEWS SHOCK SERIES RZIS COMPARISON



OUTLINE

Introduction

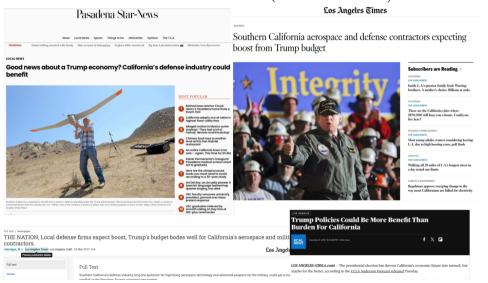
HFXS FRAMEWORK & IDENTIFICATION

EMPIRICAL RESULTS

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MILITARY NEWS SHOCKS ARE (REGIONALLY) SALIENT!



REGIONAL ECONOMIC EFFECTS

$$\frac{Y_{\ell,t+h} - Y_{\ell,t-1}}{Y_{\ell,t-1}} = \underbrace{\beta_h}_{\text{XS-MULTIPLIER}} \cdot \frac{G_{\ell,t+h} - G_{\ell,t-1}}{Y_{\ell,t-1}} + \alpha_\ell^h + \lambda_t^h + \varepsilon_{\ell,t+h}$$

- $Y_{\ell,t}$ real GDP, $G_{\ell,t}$ real DoD Contracts, α_{ℓ}^h & λ_{t}^h location & time FE; (N = 377; T = 24)
- ! Endogeneity of $G_{\ell,t}$: Reverse Causality (Mintz, 1992), Anticipation (Auerbach et al., 2020)
- → shift-share (Bartik) instrument:

 \rightarrow We replace the Shift:

$$Z_{\ell,t+h}^{ ext{Bartik}} = rac{s_{\ell}\left(G_{t+h} - G_{t-1}
ight)}{Y_{\ell,t-1}}$$

$$Z_{\ell,t+h}^{\rm HFXS} = \frac{s_\ell \, \mathbb{E}_t \big(\mathit{G}_{t+1} \big)}{Y_{\ell,t-1}}$$

- $-s_{\ell}$ (Share): DoD contracts share MSA ℓ
- $\mathbb{E}_t(G_{t+1})$: HFXS MILITARY NEWS SHOCKS

- G_t (Shift): National DoD contracts

2-year XS Multiplier of ≈ 1

Horizon	IV: HFXS	Military	News Shocks
	Coefficient	pvalue	Effective F
Impact	2.647 (2.307)	0.252	1.462
Year 1	1.352 (0.369)	0.000	14.939
Year 2	0.953 (0.271)	0.000	30.558
Year 3	0.614 (0.338)	0.070	6.257

Notes: 377 MSAs, 2001-23. GDP price deflator from BEA, base year 2017. Robust SE in parentheses, clustered at MSA level. Montiel Olea and Pflueger (2013) F calculated with weakivtest.

→ Military news shocks have real economic effects

Horizon	IV: HFXS	Military I	News Shocks	IV: Standard Bartik					
	Coefficient	pvalue	Effective F	Coefficient	pvalue	Effective F			
Impact	2.647 (2.307)	0.252	1.462	0.095 (0.044)	0.030	17.088			

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CONCLUSION

Conclusion

- New model-consistent methodology to identify military news shocks
 - Estimate & Test shocks from the data!
 - A. Identify narrative events
 - B. Run model-implied HFXS-regressions around events
 - → **Self-validating** (sign & significance)
 - **Generalizable** to contexts of aggregate shock/heterogeneous exposure
- Application: US Military Spending post-2000:
 - Document novel series of key US military events
 - Construct **new** (HFXS) defense news shocks
 - \rightarrow Defense news shocks have significant effects on regional GDP (2-year XS- $\mathcal{M} \approx 1$)

Thank You!



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APPENDIX



EXAMPLE OF PROMPT WITH NON-CONTROVERSIAL EVENTS BACK



"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."

- 9/11: defense news shock according to Ramey and Zubairy (2018).
- Budget Sequestrations: exogenous fiscal consolidation by Alesina et al. (2014).
- Trump's 2016 election: marginal win + campaign on "peace through strength"



PROMPT FOR NARROWER PERIODS WITHOUT EXAMPLES (BACK)



- Context: Iraq & Afghanistan wars followed from 9/11 and prompted increased spending
- Then, we ask:

"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."



ASSUMPTIONS FOR IDENTIFICATION BACK

- Assumption 1. $\lambda_i \perp d \log V_i^e$
- Assumption 2. $\mathbb{E}[d \log V_i^e] = 0$ Private sales may move in both directions:
 - Lee (2024): new contracts crowd-in private sales via learning-by-doing.
 - Ilzetzki (2023): capacity constraints during WWII may have limited the ability of contractors to expand private
 - di Giovanni et al. (2023): crowding-out on impact, and crowding-in after one year after winning a contract.
- Assumption 3. $\lambda_i \perp d \log \pi_i^e := \frac{d \log \mu_i^e}{\mu_i 1}$ If investors form expectations about future contractors' profitability, those expectations must be independent of reliance
- Assumption 4. $\lambda_i \perp d \log \theta_i^e$
- Assumption 5. $\mathbb{E}[d \log \theta_i^e] = 0$ If investors form expectations about future contractors' profitability, those expectations must be independent of reliance and average out to zero



Framework Generalizable to Broader Macro Contexts

BACK

• It is possible to show that:

$$d \log P_{i,t} = \underbrace{\lambda_{i,t} \cdot \xi_i}_{(i) \quad (ii)} \cdot \underbrace{d\varepsilon_t}_{(iii)-\mathsf{Shoc}}$$
Heterogeneous Exposure

- I. $\lambda_{i,t}$: fraction of sales exposed to the news shock
- II. ξ_i : elasticity of sales with respect to the shock
- III. $d\varepsilon_t$: shock you want to identify

Proposition: Generalization

Let units experience a common shock ε_t with heterogeneous loadings captured by observable (or parametrizable) terms $(\lambda_{i,t}, \xi_i)$. Then, estimating the cross-sectional regression around the event yields an estimate of the shock magnitude.



LARGEST FIRMS IN THE SAMPLE BACK

- Median reliance is 20%. Interquartile range is [3.7%,39.9%].
- Top 3 firms by (median) reliance:
 - VSE Corp (86%) (Aviation Services)
 - L3 Harris Technologies (82%) (Avionics)
 - Huntington Ingalls Industries (73%) (Ship building)
- Top 3 firms by fraction of DoD Contracts (FY23):
 - Lockheed Martin (14.7%) (Aerospace)
 - Raytheon (RTX) (6.5%) (Weapons and Electronics)
 - **General Dynamics** (5.0%) (Aerospace, Submarines, Vehicles)
- Data cross-validation:
 - We match these companies with universe of micro-contracts from FPDS
 - We compare FPDS data with Top100 Report data
 - → The two data sources match!



CONSTRUCTION OF EXCESS RETURNS BACK

• Need to "clean" the returns → extract excess returns

• Fama and French (1993) three factor model:

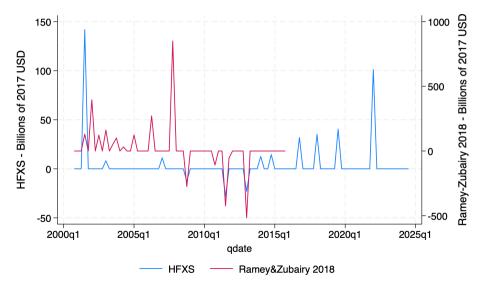
$$r_{i,t} = \alpha_i + \beta_i^1 \cdot \mathsf{MKT}_t + \beta_i^2 \cdot \mathsf{SML}_t + \beta_i^3 \cdot \mathsf{HML}_t + v_{i,t} \quad \forall i \in \mathcal{I}$$

- $-r_{i,t}$: contractors' weekly returns (WRDS)
- Three factors: MKT (market), SML (size) and HML (value)
- $\rightarrow v_{i,t}$: OLS residuals weekly excess returns



HFXS AND RZ18 SHOCKS ARE SIMILAR BUT NOT IDENTICAL







ROBUSTNESS: EXCLUSION OF 9/11 BACK

		Robustne	ss - Sample: 2	00	2-2023 (With	out 9/11)	- 377 MSAs				
Horizon	IV: HFXC Military News Shocks				IV: Standard Bartik				OLS		
	Coefficient	pvalue	Effective F		Coefficient	pvalue	Effective F		Coefficient	pvalue	
Impact	-0.112 (0.209)	0.594	9.428		0.124 (0.047)	0.008	17.575		0.009 (0.018)	0.622	
Year 1	0.609 (0.301)	0.044	17.868		0.494 (0.120)	0.000	100.184		0.052 (0.025)	0.042	
Year 2	0.571 (0.268)	0.033	12.293		0.437 (0.142)	0.002	42.991		0.078 (0.046)	0.090	
Year 3	0.620 (0.427)	0.147	6.656		0.638 (0.271)	0.019	10.163		0.123 (0.069)	0.074	

Notes: 377 MSAs, 2001-23. GDP price deflator from BEA, base year 2017. Robust standard errors in parentheses, clustered at MSA level. Montiel Olea and Pflueger (2013) effective F is calculated with weakivtest, coincides with Kleibergen and Paap (2006) statistic for single instrument