NBER WORKING PAPER SERIES

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Working Paper 29837
http://www.nber.org/papers/w29837

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
March 2022

We are grateful to David Brown, Mustafa Caglayan, Mark Flannery, Eric Hughson, Sehoon Kim, Nitish Kumar, Mahendrarajah Nimalendran, Sarah Quincy, Ahmed Rahman, Valerie Ramey, Jay Ritter, Mike Ryngaert, Mike Schwert, Matt Spiegel, Jenny Tucker, Baolian Wang, Nick Ziebarth, and seminar participants at the Catholic University of Brasília, the SEA Annual Meeting, and the University of Florida for helpful suggestions. We thank Someswar Amujala, Umut Arac, Peixin Li, and Suzannah Thomas for excellent research assistance. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 29837
March 2022
JEL No. E30,G1,H56,N12

ABSTRACT

U.S. stock volatility is 33 percent lower during wartime and periods of conflict. This is true even for World Wars I and II, which would seemingly increase uncertainty. In a seminal paper, Schwert (1989) identified the "war puzzle" as one of the most surprising facts from two centuries of stock volatility data. We propose an explanation for the puzzle: the profits of firms become easier to forecast during wartime due to massive government spending. We test this hypothesis using newly-constructed data on more than 100 years of defense spending. The aggregate analysis finds that defense spending reduces stock volatility. The sector level regressions show that defense spending predicts lower stock volatility for firms that produce military goods. Finally, an event-study demonstrates that earnings forecasts of defense firms by equity analysts become significantly less disperse after 9/11 and the invasions of Afghanistan (2001) and Iraq (2003).

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1 Introduction

Schwert's (1989) seminal paper on stock volatility found that economic variables such as industrial production, interest rates, money supply, and inflation explain a small fraction of the time series variation of stock market volatility.[1] He also identified two major puzzles in his classic paper: the "Great Depression volatility puzzle" and the "war volatility puzzle." The first refers to Schwert's observation that stock volatility was much higher during the Great Depression than any other period in U.S. history. Stock volatility peaked at 75 percent on an annual basis during the 1930s.[2] The second puzzle refers to the counter-intuitive finding that stock markets do not display volatile behavior during wars even though military conflicts are periods of heightened uncertainty and economic volatility. In his own words, Schwert (1989, p.1146) states that: *"The volatility of inflation and money growth rates is very high during war periods, as is the volatility of industrial production. Yet the volatility of stock returns is not particularly high during wars."* Indeed, stock volatility is 33 percent lower during major wars and periods of conflict since 1921.

With respect to the war puzzle, Schwert (1989) hypothesizes that if investors knew that wars only had short-term effects, stock volatility would likely be affected less than the volatility of inflation or other macroeconomic variables. However, he also points out that U.S. stock volatility is quite low even during World War I, World War II, and the Korean War. This is surprising because major wars should raise the prospects of a U.S. defeat, increasing uncertainty and stock volatility.[3]

In this paper, we investigate the war puzzle, which has remained unanswered for over 30 years.[4] First, we point out that all major American conflicts (except for the War of 1812 and the American Civil War) have been fought on foreign soil. This is an important stylized fact that reduces stock volatility because the U.S. capital stock is not being damaged or destroyed. Second, we hypothesize that military spending might also be an important factor in explaining the war puzzle: government-guaranteed contracts during wartime reduce the uncertainty of firms' expected profits, which de-

[1] Schwert's (1989) seminal work is listed as one of the "Top Cited Articles of All Time" in the history of the *Journal of Finance*. See https://onlinelibrary.wiley.com/page/journal/15406261/homepage/top_cited_articles_of_all_time.htm.

[2] Merton (1987) and Schwert (1989) hypothesized that the persistently high level of stock volatility during the 1930s might be explained by the rise of communism that threatened the survival of market capitalism.

[3] A related literature in asset pricing examines stock returns and volatility during rare historical events associated with "consumption disasters," like wars, banking crises, and economic depressions (e.g., Rietz (1988), Barro (2006), Gabaix (2012), Wachter (2013), Koudijs (2016), Muir (2017), and Cortes, Taylor, and Weidenmier (2022)).

[4] With respect to the Great Depression volatility puzzle, Cortes and Weidenmier (2019) show that the volatility of building permits—a forward-looking measure of construction—explains the bulk of the variation in stock volatility between January 1928 and December 1938.

creases stock volatility. Using new, hand-collected U.S. military spending data for over 100 years, we run a simple regression of the determinants of stock volatility. The empirical analysis demonstrates that defense expenditures as a fraction of total expenditures has a large and significant negative effect on stock volatility. The coefficient on the defense spending ratio is greater than the coefficient on corporate leverage, but with a negative sign—as opposed to the usual positive sign on leverage.

We then follow-up the baseline tests by breaking down U.S. defense spending into four categories: Army, Navy, Air Force, and other defense agencies. Then we re-estimate the stock volatility regression using leverage and macro variables in addition to defense spending ratios for the Army, Navy, Air Force, and other agencies. The empirical analysis demonstrates that spending of the Navy, Air Force, and other defense agencies has a large and statistically significant negative effect on aggregate stock volatility. Interestingly, this is not the case for the Army. A couple of factors may explain this result. Department of Defense data show that the Navy, Air Force, and other defense agencies spend a higher percentage of their budget on "Procurement" and "Research, Development, Test, and Evaluation." These departments have a higher proportion of civilian contracts, which plausibly leads to large spillover effects to the private sector. Consistent with this explanation, these departments may have large capital-to-labor ratios relative to the Army given that the Air Force and Navy rely on large sophisticated ships, carriers, and planes that require superior civilian expertise.

Turning to a more micro-level analysis, we next test the impact of military spending on the volatility of sector-specific stock portfolios as defined by the Fama and French (1997) 30-industry classification. Again, the empirical analysis shows that military spending reduces stock volatility for many sectors that produce goods and services for the U.S. military, including carry (aircraft and ships), oil (petroleum and natural gas), steel, and coal. On the other hand, we find that military spending does not reduce stock volatility in non-defense sectors such as books, beer, or finance industries. These sectors are crowded out in favor of military goods, especially during periods of conflict.

We then formally test the hypothesis that military conflict makes firms' profits easier to forecast due to expectations of massive government purchases. Taking an even further disaggregated approach at the firm level, we look at the dispersion of earnings-per-share forecasts for four recent conflicts. Consistent with our proposed channel, we find that the dispersion of earnings-per-share forecasts following 9/11 and the ensuing invasions of Afghanistan (2001) and Iraq (2003) significantly decline for defense *vis-à-vis* non-defense firms. The increase in military spending that occurred following the outbreak of the war on terrorism likely explains the decline in the dispersion of earnings-per-share for defense firms. Interestingly, we find that the dispersion of forecasts for defense firms versus non-defense firms was not significantly different for the Gulf War (1990) and the War for Kosovo (1997). An explanation for this result is that the U.S. was downsizing the military at this time due to the end of the Cold War in the 1990s, meaning that our proposed channel is unlikely to bind in a less belligerent context.

We finish the empirical analysis with an international extension of our empirical model. Specifically, we investigate the relation between global stock volatility and U.S. defense spending. We test the hypothesis that U.S. military spending may act as a deterrent to global conflict, affecting the volatility of global stock markets. Using a standard GARCH(1,1) model, we find a negative relationship between U.S. defense spending and global stock volatility, consistent with the hypothesis.

The remainder of the paper proceeds as follows. First, we motivate the empirical analysis by examining the impact on corporate America of massive government purchases of military goods and services during World War II (1939–1944). Then we discuss the data used in the empirical analysis and our baseline specifications. Next, we analyze the impact of military spending on aggregate and sector stock volatility. This is followed by event studies that examine the response of defense and non-defense stocks to the outbreak of conflict. We close out the empirical analysis looking at the relationship between U.S. defense spending and global stock volatility. The final section concludes with a discussion of the results for future research.

2 Narrative Evidence: Corporate America in World War II

We motivate the empirical analysis by showing some narrative evidence of the close relationship between corporate America and the U.S. military during WWII. Figure 1 presents photos from the Library of Congress' World War II Collection to illustrate some of the ways that large U.S. corporations contributed to the war economy. Panel A shows a Boeing plant in Seattle, WA, assembling hundreds of B-17 ("Flying Fortresses") heavy bombers instead of commercial aircraft. Boeing produced an estimated 12,741 of the four-engine bombers during the war. The B-17 helped secure the Allied merchant sea lanes of the Atlantic from the German "U-boats" between 1939 and 1945. Panel B of Figure 1 shows workers in a Chrysler factory in Detroit, MI, engaging in the mass assembly of

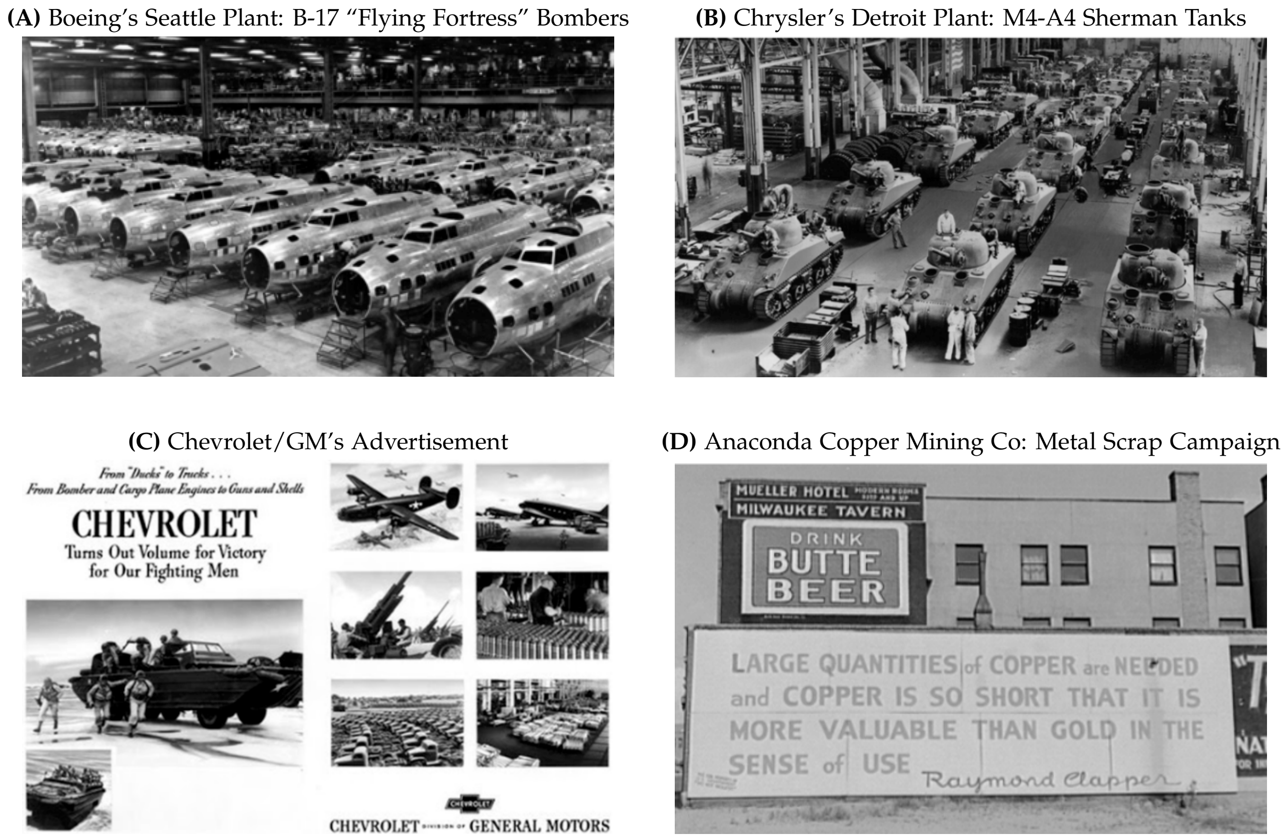


Figure 1. Corporate America and the War Effort: The Library of Congress' World War II Collection. This figure shows photographs from the Library of Congress, World War II Collection. The original photographs are available in the Library of the Congress.

M4-A4 Sherman tanks. Despite German Panzers and Tiger tanks being technologically superior to the Allied tanks, the outstanding industrial power of the U.S. economy—which obviously includes corporate America—allowed the Allies to overwhelm the Axis forces with 88,479 tanks produced between 1940 and 1945 (Dear and Foot (2001, Statistics, Table 2)).[5] The consensus among military historians of WWII is that this "quantity-over-quality" advantage paved the way for the Allied victory in 1945 (Dear and Foot (2001)). Panel C shows an advertisement from Chevrolet, a division of General Motors. The ad noted *"From 'ducks' to trucks, from bomber and cargo plane engines to guns and shells,"* along with pictures of hundreds of military trucks, artillery, planes, amphibious vehicles, and bomb shells. Finally, Panel D shows how Anaconda Copper Company in Butte, MT, provided metals valuable for the production of military goods. Copper was considered *"more valuable than*

[5]For example, the National WWII Museum of New Orleans estimates that Ford Motor Company alone produced over 12,500 Sherman tanks of the M4-A3 specification in 1943.

gold" during wartime.[6] The main takeaway from Figure 1 is that many sectors of the U.S. economy had to retool their production to meet the demands of the military during WWII.

We follow-up this narrative evidence with an analysis of balance sheet data on U.S. corporations during WWII. To examine the economic impact of massive government purchases of goods and services, we hand-collect sales data on all 30 companies that were components of the Dow–Jones Industrial Average (DJIA) index in 1939. We then examine the growth rate of sales for DJIA firms from 1939 through 1944.[7] The sample should capture the effect of moving from a peacetime economy to a "command economy," in which large government purchases drive a significant portion of firms' profits. Panel A of Figure 2 reports the 1939–1944 growth rate of net sales for the 30 components of the DJIA.

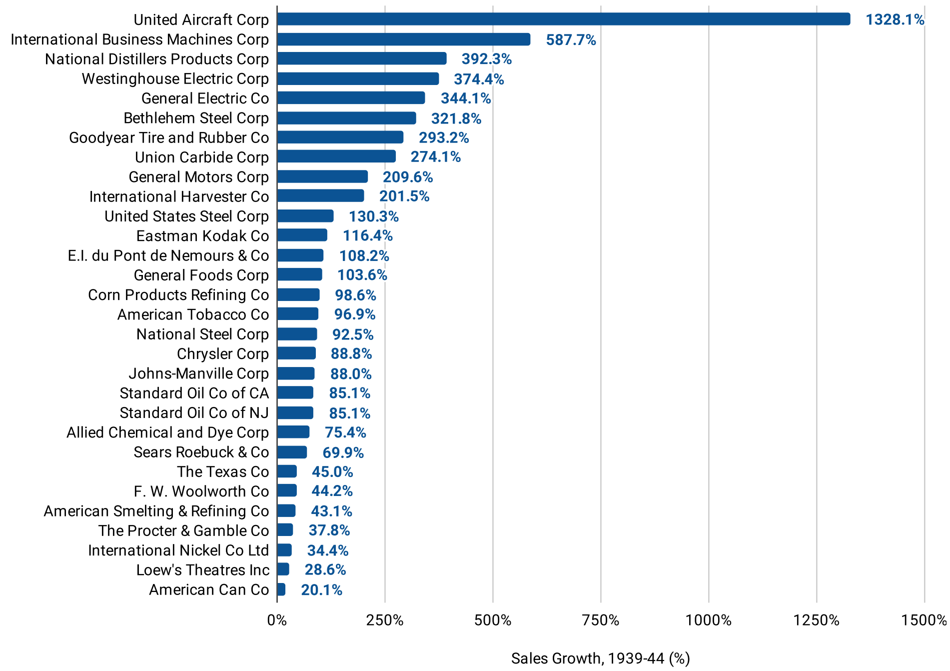
Fourteen of the 30 firms on the DJIA had growth rates in excess of 100 percent between 1939 and 1944. United Aircraft Corporation had the highest growth rate in net retail sales of all DJIA firms. Net retail sales for the plane company rose more than 1,300 percent. IBM had the second highest growth rate, expanding net sales growth by 587.5 percent during World War II. The computer company developed the radiotype that transmitted coded text messages from one electric typewriter to another by shortwave radio or wire (da Cruz (2021)). Net sales for National Distillers Product Corporation grew 392.3 percent between 1939 and 1944, putting the company in third place. Alcohol was needed to produce ammunition and to make synthetic rubber for trucks and planes. Ranked in the fourth position, net sales for Westinghouse grew by 374.4 percent. The firm made important developments in radar, bombsights, and atomic energy. They also improved the engines of U.S. Navy battleships (Pennsylvania Historical and Museum Commission (2022)). Rounding out the top five, net retail sales at General Electric increased 344.1 percent during WWII. General Electric constructed a 12,000 horsepower engine for Navy destroyers. The corporation also developed the first American jet engine in 1942. Nearly three quarters of the Navy's total propulsion and auxiliary turbine horsepower was built by General Electric (Stowe (2020)).

A small group of firms listed on the Dow 30 conducted very little (or no) business with the U.S. military. As shown in Panel A of Figure 2, Loew's Theatres is ranked 29th in net sales growth

[6] In several photographs—unreported here for brevity—one can see how Anaconda Copper and other companies organized large-scale aluminum scrap campaigns to avoid the waste of metals that were essential for the war economy.

[7] We choose 1944 because the war economy was undergoing demobilization following the surrender of Nazi Germany and Imperial Japan in 1945. Since many companies file their SEC annual reports in the second half of the year, using 1945 as the end date would conflate the effects of war and peace.

(A) Dow-Jones Industrial Average Companies' Sales Growth: 1939–1944



(B) RFC Defense-Related Investment: Top 25 Companies (Million USD, 1945)

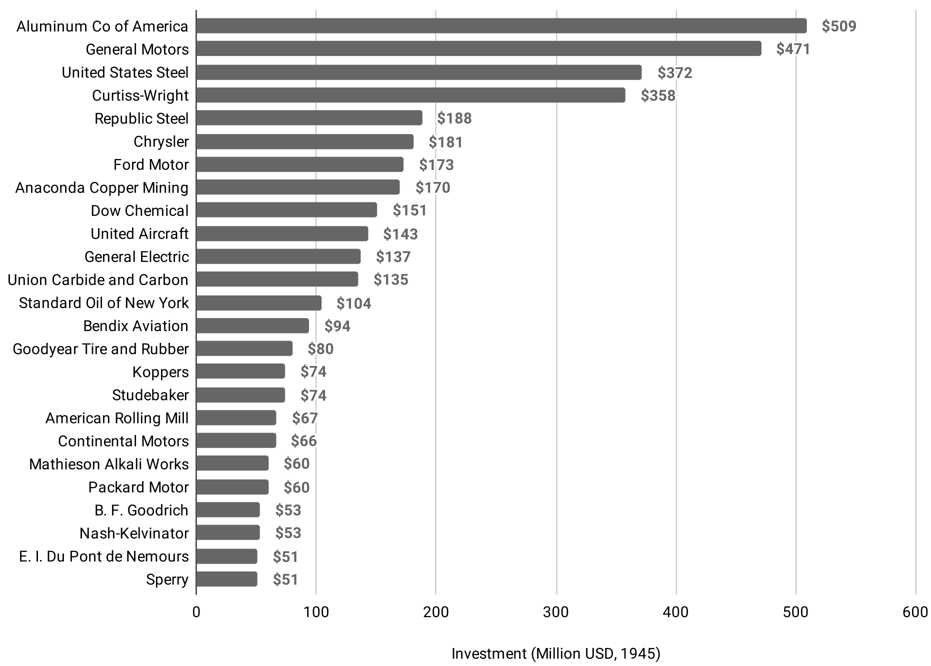


Figure 2. Corporate America and the World War II Effort: Sales Growth of DJIA Companies and Top Companies by Investments from the RFC. This figure shows evidence of the substantial economic expansion experienced by U.S. corporations during World War II. Panel A shows the total growth rate of all 30 Dow-Jones Industrial Average companies between 1939 and 1944. The data are from the companies' SEC filings reproduced in the *Moody's Industrial Manuals*. Panel B shows the leading corporations operating DPC Facilities during WWII as of June, 1945. The data refer to investment funds from the Reconstruction Finance Corporation's Defense Plant Corporation (DPC) to private corporations to finance projects related to the war effort. Data are from the Comptroller General of the United States (1947) *apud* White (1980, Table 1).

during WWII. Woolworth and Procter and Gamble are firms with relatively low growth rates that produced a wide range of home and consumer products. Nevertheless, each company still experienced solid growth rates, which may suggest positive spillover effects from defense spending. Overall, the analysis of net sales growth during WWII demonstrates the importance of government spending on the earnings of firms listed on the DJIA.

Many companies listed on the DJIA also received direct investment from the government during World War II. As of June 1945, the Reconstruction Finance Corporation's (RFC) Defense Plant Corporation (DPC) invested almost $4 billion in 1945-denominated dollars in companies supplying the U.S. military with goods and services (White (1980)). Panel B of Figure 2 plots the top 25 corporations receiving funds from the DPC for developing projects specifically related to national defense. Aluminum Company of America topped the list with more than a half billion dollars ($509 million) invested during wartime, followed by General Motors with roughly another half-billion dollars ($471 billion). United Aircraft received $143 million in investment, likely contributing to the large growth rate in net retail sales shown earlier in Panel A. The DPC gave General Electric $137 million. Direct government investment and large-scale procurement contracts with firms helped propel the large growth rates in net sales, which reduced the uncertainty of future profits for many U.S. firms.

Finally, scientific research and innovation for defense purposes is another channel through which corporations can receive substantial inflows of military resources. During World War II, the Office of Scientific and Research Development (OSRD) had multi-million dollar contracts with many large U.S. companies (Baxter (1946)).[8] Gross and Sampat (2020, Table 3) hand-collected data on all government contracts with the OSRD and list the top ten largest firms, reproduced here in Table 1.

[Insert Table 1 About Here]

Western Electric, for example, had a 15 million-dollar contract with the government. This was followed by General Electric ($7.6 million), Radio Corporation of America ($6 million), DuPont de Nemours ($5.4 million), and Monsanto Chemical Company ($4.5 million). The OSRD financed many important military projects during World War II, including the development of radar and

[8] Anticipating an eventual entry into the war, a group of prominent American scientists approached President Franklin Roosevelt in June 1940 with a proposal to create a National Defense Research Committee, later reorganized into the OSRD to apply scientific research to military problems. The OSRD quickly grew from a one-page proposal to a 1,500 person, multi-billion dollar federal agency engaging tens of thousands of scientists around the country in research to support the war effort (Gross and Sampat (2020, p.7)).

the atomic bomb. Many of the technological advances in rocketry, radio, and electronic computing had commercial applications after the war (Gross and Sampat (2020)). The OSRD is another example of a government funding source during World War II that plausibly contributed to reducing the uncertainty of future profits for firms.

3 Data and Empirical Strategy

3.1 Data Sources and Variable Construction

The empirical analysis uses monthly data from January 1890 to December 2017. We combine various sources to assemble a database with macroeconomic, financial, and defense variables to explain movements in stock volatility for more than a century.

Defense Expenditures. We use U.S. Treasury statements from 1890 to 2017 to construct a monthly data series of defense expenditures, total expenditures, and total receipts. From 1890 to 1980, we use the *Annual Report of the Secretary of the Treasury on the State of Finances for the Fiscal Year*. From 1980 to 2017, we use the *Monthly Treasury Statement of Receipts and Outlays of the United States Government*. Defense spending is reported annually from 1890–1900, quarterly from 1900–1916, annually from 1916–1921, and monthly from 1921 to present. Total receipts and total expenditures are reported monthly throughout the entire sample period.

Our novel defense variable is calculated from expenditures for military, war, or national defense purposes. Our series does not include expenditures for civilian purposes even if it was through a military branch or defense department. Furthermore, we break down defense spending into the three military department (Army, Navy, and Air Force) and other defense agencies using the annual and monthly reports. We then construct ratios of defense expenditures to total expenditures, Army expenditures to total expenditures, Navy expenditures to total expenditures, Air Force expenditures to total expenditures, other defense agencies expenditures to total expenditures, and total receipts to total expenditures. This allows us to identify the impact of each military department on stock volatility. Appendix A.1.1 presents more details on the collection process of defense data.

Macroeconomic Data. For a monthly measure of economic activity, we use the industrial production (IP) series constructed by the Federal Reserve System that begins in 1919. In empirical tests that include data before 1919, we use Miron and Romer's (1990) IP series, who extend the Fed's series back to 1884.[9] Data for the money supply (M1) are taken from the website of the Federal Reserve Bank of St. Louis (FRED) while consumer prices are provided by Global Financial Data (GFD).

Aggregate Stock Volatility. We follow Schwert (1989) and construct our measure of realized stock return volatility by calculating the monthly standard deviation of stock returns from daily data using CRSP.

Financial Leverage. The financial leverage measure is taken from Jordà, Schularick, and Taylor (2016), the most comprehensive source of long-term macro-financial data.[10] We calculate leverage as the sum of *"tloans"* (Total loans to non-financial private sector) and *"tmort"* (Mortgage loans to non-financial private sector), scaling it by *"gdp"* (nominal GDP). As in Cortes and Weidenmier (2019), we interpolate the annual series of financial leverage into monthly data.

Sector-Level Stock Volatility. Data for returns on stock portfolios of 30 Fama and French (1997) sectors (FF-30 hereafter) are from Ken French's data library.[11] We again follow Schwert (1989) and compute monthly standard deviations from the daily stock returns of each sector. Our choice of the FF-30 classification is driven by practical problems that arise from the long time series of our sample. While choosing more granular aggregations (e.g., the Fama and French 49 industries classification) is beneficial for gauging with more precision the stock volatility of different sectors in the economy, doing so is unfeasible in our long sample. The evolving life cycles of industries and the long-run dynamics of the U.S. economy imply that choosing more granular classifications makes the sector indices too sparse in the first half of the sample. Sectors that are too modern (e.g., "software" in the FF-49 classification) only begin in the last few decades of the sample, which does not allow us to exploit the heterogeneity across sectors over the entire sample period. The Fama and French 30-sector classification provides the best combination of sectoral disaggregation and time-series coverage in the early decades of our sample.

[9] Appendix A.1.2 details the IP series constructed by Miron and Romer (1990) and their splicing procedure.

[10] We thank Òscar Jordà, Moritz Schularick, and Alan Taylor for making their data publicly available at www.macrohistory.net/data.

[11] Available on: mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Summary Statistics. We present summary statistics in Table 2 by breaking down our sample into peace and conflict periods. "All Wars" are all conflicts and wars fought by the U.S. in the Correlates of War Database (Sarkees and Wayman (2010)). We consider "Major Wars" to be the conflicts with the largest increases in military expenditures: World War I, World War II, and Korean War.

[Insert Table 2 About Here]

As noted by Schwert (1989), stock volatility is lower during wartime. Stock volatility is 0.009 during periods of no conflict and 0.006 during periods of conflict, meaning that stock volatility is 33 percent lower during periods of conflict. This is true both for major and non-major wars. A difference-in-means test between the peace and conflict periods is statistically significant at the one percent level. For the remaining variables, leverage is lower during wartime while defense expenditures are much higher during periods of conflict. Growth in industrial production, CPI, and M1 are also higher during conflict periods.

3.2 Empirical Strategy

With our monthly data series, our baseline regression of the determinants of stock volatility follows Schwert (1989) and is given by:

$$\begin{aligned} \textit{Stock Vol}_t = \beta_0 &+ \sum_{m=1}^{11} \beta_{1,m} \cdot D_m + \sum_{p=1}^{12} \beta_{2,p} \cdot \textit{Stock Vol}_{t-p} + \sum_{p=1}^{12} \beta_{3,p} \cdot \textit{Lev}_{t-p} \\ &+ \sum_{p=1}^{12} \beta_{4,p} \cdot \textit{Defense Expenditure Ratio}_{t-p} + \sum_{p=1}^{12} \beta_{5,p} \cdot \textit{Macro}_{t-p} + \epsilon_t, \end{aligned} \tag{1}$$

where *Stock Vol* is our monthly measure of stock market volatility (standard deviation of stock returns), D_m is a set of seasonal monthly indicators, *Lev* is the market value of aggregate corporate leverage, and *Macro* is a vector of macroeconomic determinants of stock volatility that includes industrial production growth ($\%\Delta IP$), money supply growth ($\%\Delta M1$), and the inflation rate calculated from the consumer price index ($\%\Delta CPI$). We also include the ratio of federal receipts to expenditures to disentangle defense-specific spending from general deficit spending. Also following Schwert (1989), the autoregressive specification includes 12 lags of each variable.

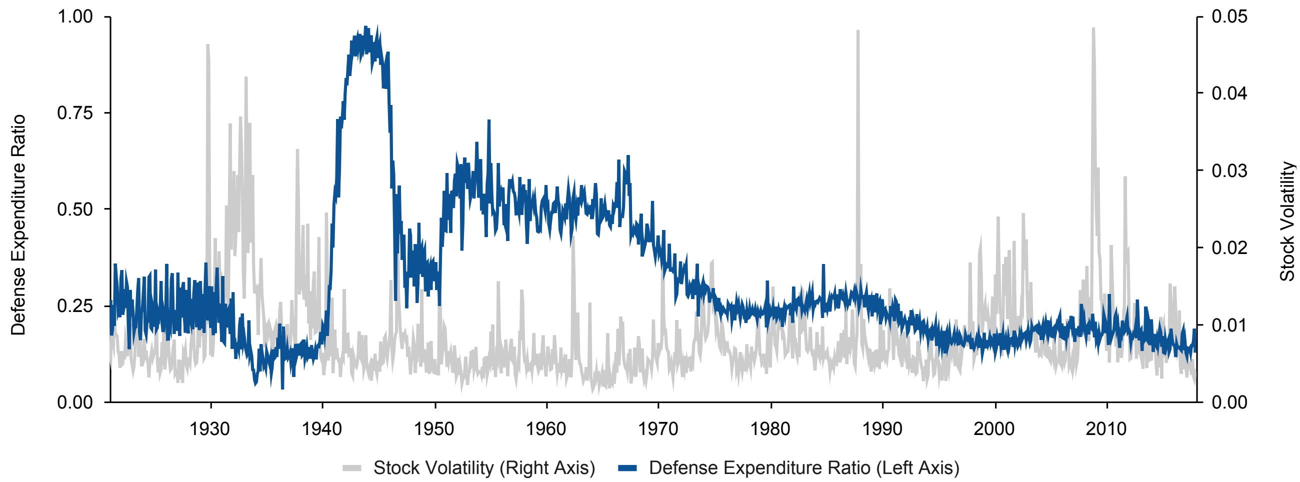


Figure 3. Monthly Stock Volatility and Defense Expenditures over Total Expenditures: 1921:M1–2017:M12. This figure shows monthly time series of stock volatility (right axis, in gray) and defense expenditures as a share of total government expenditures (left axis, in blue).

4 Results

4.1 Aggregate Analysis: Time Series Evidence

Figure 3 shows our monthly series of the ratio of defense expenditures to total expenditures (blue) and stock volatility (gray) from 1921 to 2017. The figure shows evidence of an inverse relationship, where a higher (lower) defense expenditure ratio is associated with lower (higher) volatility. There is a –0.26 correlation between the defense spending ratio and stock volatility time series.

We then model the data using the linear regression specification in Equation (1). We begin with a simple aggregate specification, where the outcome variable is stock volatility in month-year t. Results for four models are displayed in Table 3. In the first specification of Table 3 (column (1)), the controls include 12 lags of stock volatility and month indicators. Column (1) shows that 12 lags of stock volatility predict stock volatility. In column (2), we add 12 lags of leverage to the autoregressive model. Leverage is positive and statistically significant at the 10 percent level. Next, in column (3), we add 12 lags of the new defense expenditure variable to the stock volatility specification. Leverage remains positive and statistically significant. Defense spending is negative and significant at the one percent level and its inclusion increases the R-squared. One explanation for this result is that defense spending and government-guaranteed military contracts make it easier for investors to forecast the future profits of firms.

[Insert Table 3 About Here]

In column (4), we add 12 lags of industrial production growth, money growth, and inflation to the right hand side of the stock volatility model, along with leverage and the defense expenditure ratio. In this specification, the sample begins at a later date because data for M1 is not available earlier than 1918. The defense variable is negative and significant at the one percent level. Industrial production and money growth are also statistically significant. Column (4) also includes the ratio of federal receipts to federal expenditures as a control variable. This variable is insignificant, ensuring that our defense result is not simply driven by deficit spending.[12]

To investigate whether major wars account for our findings, we run three specifications: one where the sample is limited to major wars (World War II and the Korean War), all wars, and peacetime (omitting all wars from the sample). We consider the specification (4) in the previous table, which has 12 lags of each of the 7 variables. Table 4 presents the results for the defense expenditure variable.

[INSERT TABLE 4 ABOUT HERE]

With only major wars, the defense expenditure ratio variable has an even larger coefficient and greater statistical significance. Military spending reduces stock volatility during World War II and the Korean War. The same is true when we restrict the sample to all wars. When we omit all conflicts, as Table 4 demonstrates, we still find strong and robust results for the defense expenditure ratio.

To ensure that our results are not driven by a particular episode in American history, Table 4 also presents results where we restrict the sample into seven sub-periods: Spanish American War and WWI (1890–1928), Great Depression/Pre-World War II (1921–1940), World War II and Korean War (1941–1953), Vietnam Era (1954–1974), Cold War Era (1975–1997), and Middle East conflicts and global terrorism before the Global Financial Crisis (1998–2007) and after (2008–2017). Again, we see that defense spending has a negative and statistically significant effect in all seven periods. The Middle East conflicts before the Global Financial Crisis has an unusually large coefficient of negative 25. We attribute the outlier to the short sample period of only 120 observations. We further explore this time period in Section 5 with an event study analysis using granular firm-level data. Overall, the baseline empirical results demonstrate that defense spending lowers stock volatility.

[12]We also consider a specification that controls for unemployment (civilian population unemployment rate) and political uncertainty (proxied by Baker, Bloom, and Davis's (2016) economic policy uncertainty index). Our results remain robust, despite information criteria suggest overfitting when these variables are added.

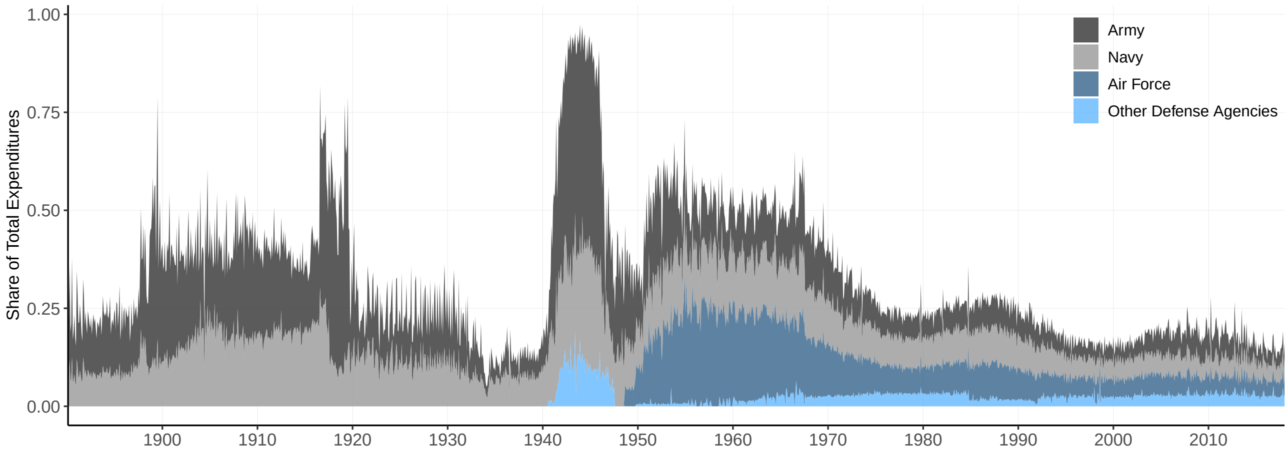


Figure 4. Share of Total Defense Expenditures by Military Branch: Army, Navy, Air Force, and Other Defense Agencies. This figure shows stacked monthly time series of Army expenditures over total expenditures, Navy expenditures over total expenditures, Air Force expenditures over total expenditures, and Other Agencies' expenditures over total expenditures.

4.2 Disaggregate Analysis

4.2.1 Military Branch-Level Evidence

Since military branches vary by capital expenditures, labor workforce, and civilian contracts, we investigate if a particular branch drives the empirical result that defense spending lowers stock volatility. We construct four new variables, including expenditures for the Department of the Army (formerly the War Department), the Department of the Navy, the Department of the Air Force, and Other Defense Agencies. The latter group includes expenditures for national defense or military activities that do not fall under the three departments. In the Treasury reports, these are often labeled as "Other agencies under the Secretary of Defense" or "Other Military Activity Expenditures." Under the present Department of Defense, other agencies include the Defense Advanced Research Projects Agency (DARPA), Defense Intelligence Agency, Missile Defense Agency, among many others.[13] Figure 4 presents a stacked column graph of our monthly series by each branch's expenditures over total expenditures. The earlier decades show the Army and the Navy with roughly similar shares, becoming even more balanced as other branches (Air Force and Other Defense Agencies) gain prominence after WWII.

We estimate specification (4) from Table 3 with each branch's expenditures (as a ratio of total expenditures) instead of total defense expenditures. The results are reported in Table 5. The em-

[13] Appendix Figure A.1 presents a detailed organizational chart of the Department of Defense with all divisions under the Secretary of Defense as of 2013.

pirical analysis suggests that Navy, Air Force, and Other Defense Agencies expenditures reduce aggregate stock volatility. Army spending, on the other hand, is positive and statistically significant at the one percent level. It is important to note, however, that model selection criteria show strong preference for the model with aggregate defense expenditures over the specification where we divide expenditures into the various military branches.[14]

[Insert Table 5 About Here]

These results are consistent with our hypothesis that military expenditures lower volatility because they reduce the uncertainty of firms' future profits. The branch-level findings show that Navy, Air Force, and Other Defense Agencies spending are particularly important for reducing stock volatility. This may reflect several factors. Starting in the 1980s until present, the Monthly Treasury Statements outline how each branch spends money. The Navy, Air Force, and Other Defense Agencies use a higher proportion of their expenditures on "Procurement" and "Research, Development, Test, and Evaluation." The Army uses a higher proportion of their expenditures on "Personnel" and "Operation and Maintenance." This suggests that the Navy, Air Force, and Other Defense Agencies engage in more contracts with civilians than the Army. Second, their contracts are often long in duration since they involve research and development for large construction projects like aircraft carriers and other expensive military equipment such as destroyers, guided missile cruisers, and military planes (Koyama, Rahman, and Sng (2021)). It also appears to be the case that their capital-to-labor ratio is higher than the Army, which means that their military goods are more intertwined with the stock of private and publicly traded firms (Biolsi (2019)). Our Navy results are related to Rahman (2020) who shows how the presence of Navy officers influences regional military spending and local economies. Similarly, Rahman (2020) does not find this effect for the Army.

4.2.2 Sector-Level Evidence: Defense Industries and Stock Volatility

We follow-up the baseline analysis by examining the impact of defense spending on stock volatility at the sector level. First, we use daily returns starting in January 1926 on portfolios of 30 sectors using the Fama–French classification. Monthly stock volatility is calculated by taking the standard

[14] While each branch reports its expenditures, it is important to note that the branch definitions change over time. For instance, the predecessor to the United States Air Force, the United States Army Air Forces, was under the Army's command. Similarly, the U.S. Coast Guard, which typically operates under the Department of Homeland Security, has been transferred to the Department of the Navy during wartime.

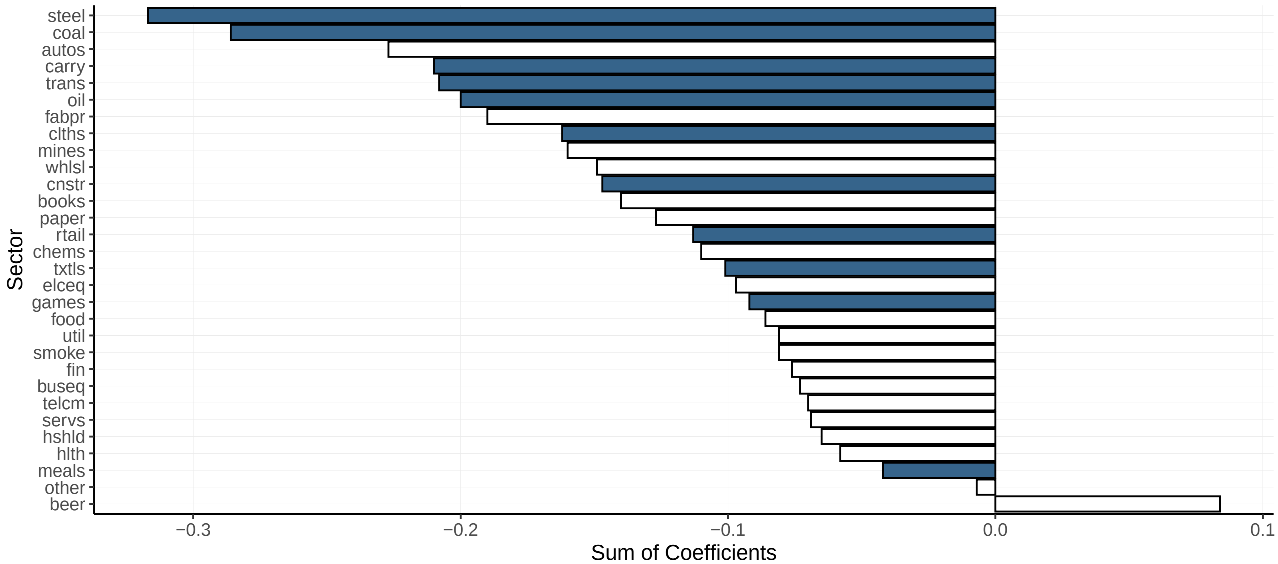


Figure 5. Sector-Level Analysis: Sums of Coefficients of Defense Expenditure Ratio on Disaggregated Stock Volatility. This figure shows disaggregated analysis of sector-level stock volatility constructed using the Fama–French 30 sector classification. Blue bars refer to cases in which the statistical significance of the sum of coefficients is at least 10% as given by a joint-significance F test.

deviation of daily returns in a given month. We then specify autoregressive time series models, similar to that of Equation (1). The dependent variable is now stock volatility of a given sector. The covariates are identical to the independent variables in the aggregate model, except that the lagged dependent variables are also lags of sector volatility instead of aggregate market volatility. Figure 5 presents the empirical results for the sector analysis.

The bar plot shows that the sums of coefficients for the defense expenditure ratio are all negative (29 sectors), except for the beer sector. Sectors for which the sum of coefficients is statistically different from zero are depicted in blue. Eleven of the 30 sectors have a negative effect that is statistically significant at the 10 percent level or greater. Several well-known military sectors have a large and significant coefficient on the ratio of defense spending to total spending including carry (aircraft and ships, −0.210), construction materials (−0.147), coal (−0.286), oil (−0.200), steel (−0.317), and transportation (−0.208). Intuitively, we find that the sectors with the strongest impact on volatility are steel and coal. Naturally, steel is the basis for producing countless military goods (e.g., tanks, artillery, ships, planes). Although coal is often an input for blast furnaces in steelworks producing such military goods, it also became a crucial input for synthetic fuel. On April 5, 1944, the U.S. Congress passed the Synthetic Liquid Fuels Act, authorizing $30 million for a five-year effort for: *"...the construction and operation of demonstration plants to produce synthetic liquid fuels from coal (...) in order to aid the prosecution of the war."*

The overall message of the industry-level regressions is that military spending reduces stock volatility for many different sectors in the economy. While network effects from military spending have been widely discussed in the economics literature, the topic has received much less attention in the finance literature.[15] For example, the retail sector has a statistically significant defense coefficient with a point estimate of (-0.113). The meal and clothing sectors have large and statistically significant defense coefficients of (-0.042) and (-0.162), respectively. Military spending also lowers stock volatility for textiles (-0.101). We also see a significant decrease in volatility of "games" (-0.092), which also includes "boat building and repairing" in the FF-30 classification. The result is likely explained by how important shipbuilding and repair becomes during wartime. For example, the Bureau of Labor Statistics's (1944) *Monthly Labor Review* published an article on earnings in ship-repair yards in the Spring of 1943. In it, the BLS documents that *"ship-repair work plays a vital part in our war economy. From a small peacetime industry (...) this industry has increased greatly in size since the outbreak of WWII, from the standpoint of both the number of yards and the number of workers. It is estimated that the number of workers now engaged in ship-repair work is more than 6 times as great as it was at the start of the war."* (Bureau of Labor Statistics (1944, p.140)).

Overall, the empirical analysis demonstrates that military spending has far reaching spillover effects in reducing stock volatility for non-military sectors. These results align with Auerbach, Gorodnichenko, and Murphy (2020), who find Department of Defense spending has large positive spillover effects for both intermediate inputs and general equilibrium spillovers.[16]

5 Firm-Level Evidence: Conflict and Dispersion of Analysts' Forecasts

We now use a difference-in-differences setting to formally test the hypothesis that military conflict makes firms' profits easier to forecast due to expectations of massive government purchases. We identify this effect by analyzing the dispersion of earnings per share (EPS) forecasts released by equity analysts for each firm in the I/B/E/S data. Since the EPS forecast data starts in 1990, we can

[15] See Auerbach, Gorodnichenko, and Murphy (2020) for a recent study.

[16] Nickelsburg (2020) and Hultquist and Petras (2012) also demonstrate how military expenditures spillover to local economic activity.

cover only the four most recent conflicts: (i) Gulf War (1991); (ii) War for Kosovo (1998); (iii) the 9/11 terrorist attacks and the ensuing invasion of Afghanistan (2001); and (iv) the invasion of Iraq (2003).

For our dependent variable, we follow an extensive literature (e.g., Diether, Malloy, and Scherbina (2002); Da and Warachka (2009)) and construct a cross-sectional measure that aggregates the dispersion of equity analyst forecasts on firms' earnings-per-share (EPS). Dispersion is defined as the standard deviation of earnings forecasts scaled by the absolute value of the mean earnings forecast. If the mean earnings forecast is zero, then the stock is assigned to the highest dispersion category.[17] We consider shorter and longer horizons of EPS forecasts: 1 quarter, 2 quarters, 3 quarters, 1 year, and 2 years.

We then define firms as defense- and non-defense-related based on their share of revenues coming from federal government procurement contracts. The firm-level measure of federal procurement intensity is from Baker, Bloom, and Davis (2016), who hand-match each firm and its subsidiaries to their parent company using *Dun & Bradstreet's* data and the universe of Federal government procurement contracts between 2000–2016. We consider a firm to be a defense-related company if it is in the top decile of the distribution of federal procurement contracts relative to total revenues. The cutoff is equivalent to including firms with roughly 20% of their revenues coming from federal government contracts. To assess the validity of this criteria, Baker, Bloom, and Davis (2016) document that companies at the top of the distribution are from 3-digit SIC industries with significant revenues from producing military goods: *ordnance and accessories* (39% of revenues are from federal procurement contracts), *search, detection, navigation, guidance & aeronautical systems* (27%); engineering services (21%); aircraft and parts (20%); ship and boat building and repairing (15%). In our difference-in-differences (DID) framework, defense-related firms are the "treated" group, while non-defense firms are part of the "control" group.

Finally, we must define the time dimension of our DID specification. Defining an excessively narrow time window is challenging because some of our conflicts have key developments spanning more than one month. For example, the terrorist attacks of September, 11, 2001 were followed immediately by the American invasion of Afghanistan in October, 7, 2001. To ensure the forecasts of equity analysts incorporate all relevant information about each conflict, we choose a three-month

[17] As in Diether, Malloy, and Scherbina (2002), excluding observations with a mean earnings forecast of zero does not significantly affect the results. Moreover, our results remain virtually unchanged if we use the ratio of the standard deviation of earnings forecasts to the book equity per share as an alternative measure of dispersion.

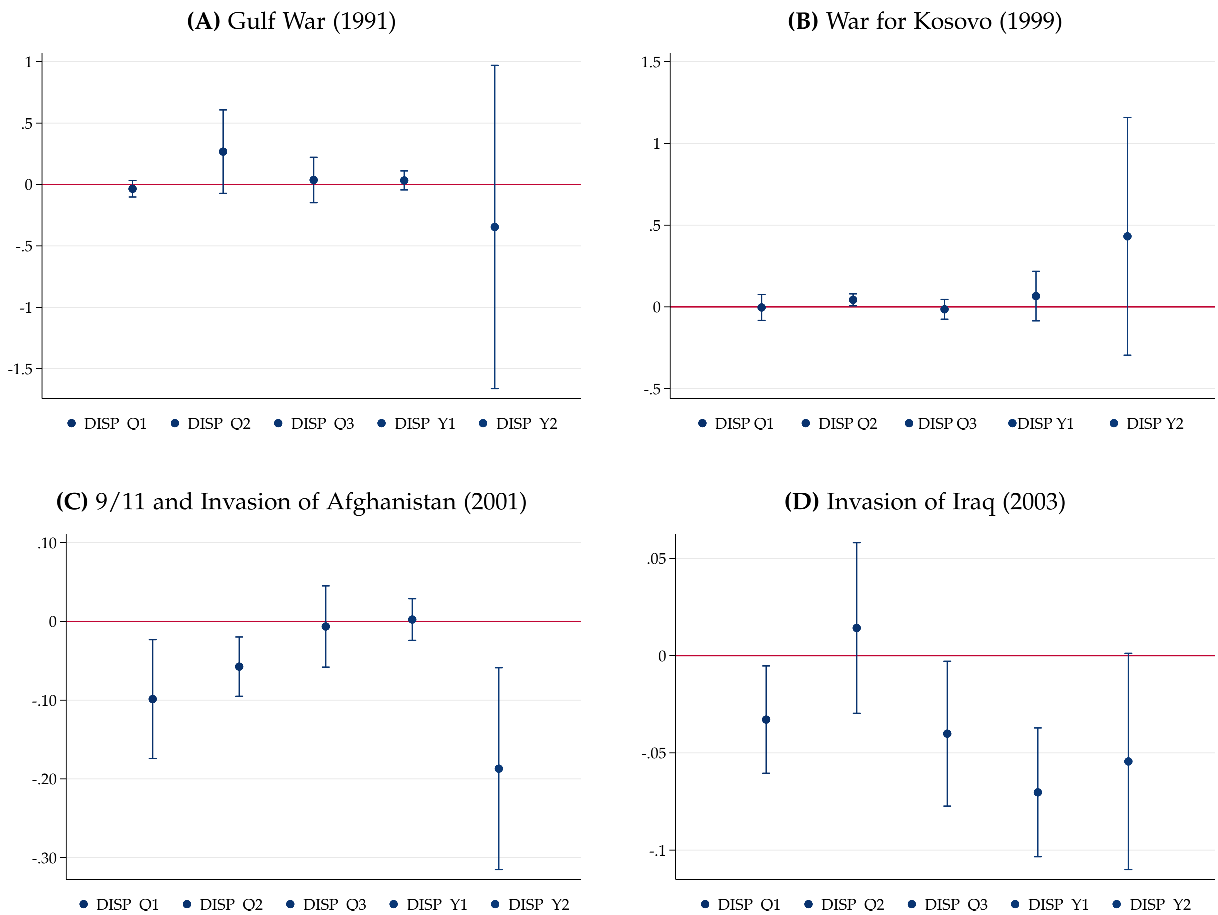


Figure 6. Monthly dispersion in earnings-per-share forecasts for defense vs. non-defense companies: DID Coefficients. This figure shows difference-in-differences (DID) coefficients (and 95% confidence intervals) estimated in Equation (2). Panel A shows the results for the Gulf War's outbreak in January 1991. Panel B shows the results for the outbreak of the war for Kosovo in March 1999. Panel C depicts the results for the 2001 terrorist attacks of 9/11 and the following invasion of Afghanistan in October of that year. Panel D displays results for the invasion of Iraq in March 2003. The forecast dispersion variable, $Disp(h)_{i,t}$, is the standard deviation of earnings forecasts scaled by the absolute value of the mean earnings forecast. $Disp(h)_{i,t}$ is defined for each firm i, in month t, and EPS forecast horizon $h \in \{$1 quarter, 2 quarters, 3 quarters, 1 year, 2 years$\}$ ahead.

time window. Formally, the empirical specification can be written as:

$$Disp(h)_{i,t} = \beta_0 + \beta_1 \cdot Defense\ Related_i + \beta_2 \cdot Post_t + \beta_3 \cdot [Defense\ Related_i \times Post_t] + \lambda_i + \lambda_t + \varepsilon_{i,t}, \quad (2)$$

where the dependent variable is the dispersion of earnings-per-share forecasts of firm i, at monthly date t, for forecast horizon of $h \in \{$1 quarter, 2 quarters, 3 quarters, 1 year, 2 years$\}$. *Defense Related*$_i$ is an indicator variable that is one if firm i meets the criterion discussed above (top decile in procurement). *Post*$_t$ is an indicator variable relative to the monthly date of each war event ($t = 0$). It equals one if $t \in \{+1, +2, +3\}$, and zero otherwise ($t \in \{-3, -2, -1\}$). Our main interest is to estimate the interaction coefficient β_3, which captures the DID effect on the change of the forecast dispersion of defense-related firms after the war event *vis-à-vis* their non-defense peers. The λ terms capture time and firm fixed effects. The estimated β_3 coefficients (with 95% confidence intervals) for each war and forecast horizon are reported in Figure 6.

Figure 6 shows that defense-intensive firms did not have significantly lower dispersion in earnings forecasts compared to non-defense companies following the outbreaks of the Gulf War in 1991 (Panel A) and the War for Kosovo in 1999 (Panel B). This is not surprising given that these conflicts came shortly after the end of the Cold War, when the U.S. was downsizing its military.

Defense spending began to increase again in 2001, following the attacks of 9/11 and the ensuing war on terrorism. As shown in Panel C of Figure 6, the dispersion of earnings forecasts of defense firms falls significantly more than their non-defense peers following 9/11 and the invasion of Afghanistan. The dispersion in earnings forecasts declines significantly in shorter horizons (the one- and two-quarter-ahead forecast dispersion) and even one of the long-run horizons (two-year-ahead forecast dispersion). With respect to the invasion of Iraq in March 2003 (Panel D), the EPS forecasts of professional equity analysts covering defense firms became significantly less disperse than non-defense firms in three relevant forecast horizons following the American invasion of Iraq. Two of the significant declines occurred in short-run forecast horizons (one- and three-quarters ahead) and the other is a longer horizon (one-year ahead).

Overall, the empirical evidence in Figure 6 is consistent with our hypothesis and our proposed explanation of the war puzzle. The expectation of large future government purchases of military goods and services seems to reduce the uncertainty of future profits for defense firms.

6 U.S. Defense Spending and Global Stock Volatility

Finally, we provide an international perspective to analyze how U.S. defense spending affects global stock volatility. The analysis is motivated by the hypothesis that U.S. defense spending is a deterrent to global conflict. This would imply that higher U.S. defense spending lowers global stock volatility, all else equal. An alternative hypothesis is that U.S. defense spending is destabilizing and increases global stock volatility. To test these hypotheses, we use two world equity indices from Global Financial Data (GFD) at the monthly frequency. One world index contains the U.S., while the second excludes American stocks.[18]

Taking a global approach requires us to adapt our model to deal with some data limitations. Since daily stock returns are not available for the global index over a long period of time, we use a GARCH(1,1) model to estimate the monthly volatility of global equity returns. We follow an extensive literature that uses GARCH models to construct estimates of the one-step ahead conditional volatility (e.g., Chan, Chan, and Karolyi (1991); Karolyi (1995); Flannery and Protopapadakis (2002); Cortes and Weidenmier (2019)). The outcome variable is returns at time t, and the covariate is returns at $t-1$. The U.S. defense expenditure ratio is placed in the variance equation of the GARCH model along with a measure of global leverage, calculated from the panel dataset of developed countries assembled by Jordà, Schularick, and Taylor (2016). The leverage measure follows the same definition of our U.S.-specific leverage variable described in Section 3.[19] The GARCH(1,1) sample period also ends in 2017, but it can only start in 1950 because the global leverage variable is not available before then. Table 6 shows the estimation results.

[Insert Table 6 About Here]

Columns (1) and (2) of Table 6 only include a measure of global leverage in the variance term. In column (2), the leverage variable is positive and statistically significant at the one percent level. Columns (3) and (4) report the results when the defense expenditure ratio is also included in the variance. The defense variable is negative and significant for both global stock indices. The leverage covariate is no longer significant. The empirical specifications show that U.S. defense spending reduces global stock volatility by more than one percent. The effect is statistically significant at the one percent level. The results suggest that U.S. defense spending lowers global volatility by acting as a deterrent to conflict.

7 Concluding Remarks

We investigate the war puzzle first identified by Schwert (1989) in his classic paper on stock volatility. Curiously, U.S. stock volatility during World War I, World War II, and the Korean War was

[18] The other economies in the indices are Australia, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom.

[19] We construct our global leverage variable using an equally weighted average of country-level leverages of the economies that comprise the GFD global index.

surprisingly low. We hypothesize that stock volatility is low during war and periods of conflict for two reasons. First, virtually all major U.S. military conflicts except the War of 1812 and the American Civil War have been fought on foreign soil. This fact spares the U.S. from damage or destruction of the capital stock. Second, massive military spending and government-guaranteed contracts during periods of conflicts reduce uncertainty about the future profitability of firms. Using the ratio of defense spending to total spending, we document that there is a negative and statistically significant impact of military spending on aggregate stock volatility, especially during periods of major wars and conflict. Disaggregating defense spending into Army, Navy, Air Force, and Other Defense Agencies components, we find that the decline in aggregate stock volatility is largely explained by Navy, Air Force, and Other Defense Agencies spending. We believe that this result can be explained by the fact that these branches have large, long-term contracts with significant spillovers to private firms. Next, we look at the relationship between stock volatility and defense spending at the sector level. Again, we find strong evidence of a negative relationship between stock volatility at the sector level and military spending on goods and services.

We then use a difference-in-differences setting to formally test the hypothesis that military conflict makes firms' profits easier to forecast due to expectations of massive government purchases. We identify this effect by analyzing the dispersion of earnings per share forecasts released by equity analysts for each firm. Overall, we find empirical evidence consistent with our hypothesis and our proposed explanation of the war puzzle. The expectation of large future government purchases of military goods and services seems to reduce the uncertainty of future profits for defense firms, making it easier for analysts and investors to forecast future profits and lowering stock volatility.

Finally, we examine the impact of U.S defense spending spending on global stock return volatility. A simple GARCH(1,1) model shows that U.S. military spending lowers global stock volatility. The result suggests that U.S. military spending may act as a deterrent to global conflict. Overall, the empirical analysis demonstrates that government spending plays an important role in explaining why U.S. stock volatility is so low during periods of conflict. Our paper provides an economic explanation for an important puzzle identified in one of the most influential papers in the history of finance (Schwert (1989)).

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Tables

Table 1. Top 10 OSRD Contractors, by Contract Obligations. This table reproduces the data from Table 2 in Gross and Sampat (2020). The table presents the top 10 firms with R&D contract obligations with the Office for Scientific Research and Development. Percentages measure each contractor's percent of total OSRD research spending.

Rank	Contractor	Total Obligation (Million $)	Share of Total OSRD Obligations (%)
1	Western Electric Co	$15.2	3.3%
2	General Electric Co	$7.6	1.6%
3	Radio Corp of America	$6.0	1.3%
4	E.I. DuPont De Nemours	$5.4	1.2%
5	Monsanto Chemical Co	$4.5	1.0%
6	Eastman Kodak	$4.3	0.9%
7	Zenith Radio Corp	$4.2	0.9%
8	Westinghouse Electric Corp	$3.9	0.8%
9	Remington Rand	$3.7	0.8%
10	Sylvania Electric	$3.1	0.7%
	Total	$57.81	12.5%

Table 2. Summary Statistics. This table presents averages of our variables from 1921–2017. "Major Wars" includes WWII and the Korean War. "All Wars" includes major wars as well as short-lived conflicts. "Peacetime" is defined when "All Wars" equals 0.

Variable	Full Sample	Major Wars	All Wars	Peacetime
Stock Volatility	0.008	0.006	0.006	0.009
Defense Expenditure Ratio	0.311	0.649	0.516	0.262
Leverage	0.446	0.199	0.346	0.470
%ΔIndustrial Production	0.296	0.764	0.542	0.237
%ΔConsumer Price Index	0.233	0.358	0.330	0.209
%ΔM1	0.089	0.264	0.172	0.068
Receipts-to-Expenditures	0.879	0.624	0.792	0.899
Observations (T)	1,152	110	223	929

Table 3. Aggregate Time Series Results: Defense Expenditure and Stock Volatility. This table shows the OLS estimates of Equation (1) with HAC standard errors (24 lags). Specifically:

$$Stock\ Vol_t = \beta_0 + \sum_{m=1}^{11} \beta_{1,m} \cdot D_m + \sum_{p=1}^{12} \beta_{2,p} \cdot Stock\ Vol_{t-p} + \sum_{p=1}^{12} \beta_{3,p} \cdot Lev_{t-p} + \sum_{p=1}^{12} \beta_{4,p} \cdot Def\ Exp\ Rat_{t-p} + \sum_{p=1}^{12} \beta_{5,p} \cdot Macro_{t-p} + \epsilon_t,$$

Coefficients are the sum of all 12 lags of a variable, and test statistics in parentheses refer to joint-significance F-tests. Stock Volatility is multiplied by 100 for numerical precision. Significance levels: * p <0.10, ** p <0.05, *** p <0.01.

	Stock Vol$_t$			
Lags of Variables ($p = 12$)	(1)	(2)	(3)	(4)
Stock Volatility	0.859***	0.856***	0.847***	0.829***
	(820.97)	(802.98)	(677.56)	(850.39)
Leverage		0.111*	0.056***	–0.024**
		(20.09)	(25.09)	(24.26)
Defense Expenditure Ratio			–0.072***	–0.123***
			(31.62)	(29.52)
%ΔIndustrial Production				0.010*
				(19.57)
%ΔM1				–0.174*
				(20.45)
%ΔCPI				–0.016
				(6.71)
Receipts-to-Expenditures				–0.096
				(15.37)
Month Effects	Yes	Yes	Yes	Yes
Sample Period	1890:M1–2017:M12	1890:M1–2017:M12	1890:M1–2017:M12	1918:M8–2017:M12
Observations	1,525	1,525	1,525	1,176
R-Squared	0.511	0.518	0.522	0.604

Table 4. Subsample Results. Results for the defense expenditure ratio variable when we restrict the sample to particular eras. OLS estimates are the sum of all lags of a variable, and test statistics in parentheses refer to joint-significance F-tests. *Stock Volatility* is multiplied by 100 for numerical precision. These specifications include monthly indicators and 12 lags of stock volatility, leverage, defense expenditures, industrial production, M1, CPI, and receipts-to-expenditures. An exception is the 1890–1929 sample, which excludes M1 because that variable does not go back to 1890. Significance levels: * p <0.10, ** p <0.05, *** p <0.01.

Time Subsample	Defense Expenditure Ratio	*F*-test statistic
Major Wars	-1.117^{***}	(73.60)
All Wars	-0.227^{***}	(53.51)
Peacetime	-0.217^{***}	(37.05)
1890–1928, Spanish American War & WWI	-0.094^{***}	(34.85)
1929–1940, Great Depression	-0.284^{***}	(35.25)
1941–1953, WWII & Korean War	-1.060^{***}	(62.39)
1954–1974, Vietnam Era	-0.383^{***}	(68.27)
1975–1997, Cold War Era	-0.253^{**}	(23.36)
1998–2007, Middle East Conflicts, Pre-GFC	-25.903^{***}	(77.11)
2008–2017, Middle East Conflicts, Post-GFC	-2.728^{***}	(48.07)

Table 5. Military Branch Results. Results for the expenditure ratio variables by military branches. OLS estimates with HAC standard errors (24 lags). Estimates are the sum of all 12 lags of a variable, and test statistics in parentheses refer to joint-significance F-tests. These specifications include monthly indicators and 12 lags of stock volatility, leverage, each branch's expenditures, industrial production, M1, CPI, and receipts-to-expenditures. Stock Volatility is multiplied by 100 for numerical precision. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Variable	Estimates	F-test statistic
Stock Volatility	0.800^{***}	(619.24)
Leverage	0.164^{**}	(24.62)
%ΔIndustrial Production	0.014^{*}	(20.07)
%ΔM1	-0.241^{***}	(31.07)
%ΔCPI	0.005	(6.41)
Receipts-to-Expenditures	–0.134	(18.27)
Army Expenditures/Total Expenditures	0.309^{***}	(44.03)
Navy Expenditures/Total Expenditures	-0.201^{***}	(25.84)
Air Force Expenditures/Total Expenditures	-0.489^{*}	(18.43)
Other Defense Expenditures/Total Expenditures	-1.195^{**}	(24.77)
Month Effects	Yes	
Observations	1,176	

Table 6. Global Stock Volatility and U.S. Defense Spending. This table shows maximum-likelihood estimates and standard errors (in parentheses) for the GARCH(1,1) model. World Return is calculated as monthly returns on the GFD world equity index that includes the following countries: Australia, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. *Leverage* has the same definition as in Table 3, but is an equally weighted average of the leverage of the respective individual countries using the Jordà, Schularick, and Taylor (2016) country-level data. *Defense Expenditure Ratio* is defined as in Table 3. Significance levels: * p <0.10, ** p <0.05, *** p <0.01.

	World Return	*World Return* (without U.S.)	*World Return*	*World Return* (without U.S.)
	(1)	(2)	(3)	(4)
Mean Equation				
World Return$_{t-1}$	0.056	0.119***	0.056	0.124***
	(0.041)	(0.038)	(0.041)	(0.039)
Variance Equation				
Leverage$_{t-1}$	0.502	1.062**	–0.841	–1.014
	(0.462)	(0.502)	(0.780)	(0.677)
Defense Expenditure Ratio$_{t-1}$			–2.718**	–4.535***
			(1.327)	(1.068)
ARCH term (1 lag)	0.126***	0.124***	0.131***	0.134***
	(0.026)	(0.025)	(0.027)	(0.028)
GARCH term (1 lag)	0.807***	0.830***	0.794***	0.770***
	(0.038)	(0.034)	(0.041)	(0.049)
Sample Period	1950–2017	1950–2017	1950–2017	1950–2017
Observations	816	816	816	816

A Appendix

A.1 Data Details

Below we present details on the data and the construction of the variables used in our empirical tests.

A.1.1 Defense Expenditures and Total Expenditures

We use U.S. Treasury statements from 1890 to 2017 to construct a monthly data series of defense expenditures, total expenditures, total receipts, Army expenditures, Navy expenditures, Air Force expenditures, and other defense agencies expenditures. From 1890 to 1980, we use the *Annual Report of the Secretary of the Treasury on the State of Finances for the Fiscal Year*. These reports were also employed in Hall and Sargent (2020) and Hall, Payne, Sargent, and Szke (2021) to construct data series on war financing. From 1980 to 2017, we use the *Monthly Treasury Statement of Receipts and Outlays of the United States Government*. Monthly receipts and expenditures (outlays) are reported consistently from 1890 to 2019.

Defense and branch spending are reported annually from 1890-1900, quarterly from 1900-1916, annually from 1916-1921, and monthly from 1921 to present. We interpolate the earlier years to create a monthly series beginning in 1890. Before the establishment of the Department of Defense or the Office of the Secretary of Defense, defense expenditures are defined by expenditures for "National Defense," "War Activities," "National Military Establishments," or "Military Functions," often encompassing expenditures by the War Department (Army) and the Navy Department. Once the Office of the Secretary of Defense and the Department of Defense are established, defense expenditures are the total expenditures of that department for military purposes. We do not include any expenditures for "civil functions" by the Department of Defense or the branches in our calculations, only "military functions."

Other agencies defense expenditures are expenditures for military functions that do not fall under the three departments. In the Treasury reports, these are often labeled as "Other agencies under the Secretary of Defense" or "Other Military Activity Expenditures." Under the present Department of Defense, other agencies include Defense Advanced Research Projects Agency (DARPA), Defense Intelligence Agency, Missile Defense Agency, among many others.

A.1.2 Industrial Production

We splice the Miron and Romer (1990) industrial production (IP) index with the Federal Reserve Board's (FRB) industrial production index using the procedure described in the Appendix of Romer (1994), which we briefly summarize here. We adjust the Miron–Romer index of industrial production for 1884 to 1918 to be more consistent with the modern FRB index. We run a regression between the two series over the period 1923 to 1928. The specification that we use regresses the log level of the FRB index (not seasonally adjusted) on a constant, a trend, 11 monthly dummy variables, the contemporaneous log level of the Miron–Romer index, and six lags and six leads of the Miron–Romer index. The contemporaneous value of the Miron–Romer series is included to capture the main relationship of interest. The constant and the monthly dummies are present to take into account seasonal fluctuations. The results of this regression suggest that there is a very close relationship between the two industrial production series. The R^2 of the regression is 90%. The sum of the coefficients on the lags and leads of the Miron–Romer index is 0.67 with a standard error of 0.10. To form the adjusted Miron–Romer index for the period before World War I, we first regress the Miron–Romer index for 1884 to 1918 on a constant, a trend, and 11 monthly dummy variables and form a seasonally adjusted series by removing the effect of the monthly dummy variables. We then use the estimated coefficients from the regression for the 1920s to combine the lags and leads of this index. Because the seasonal effects are removed in a separate step, we do not use the seasonal coefficients in forming these fitted values. This procedure allows for the possibility that seasonal movements may have changed between the turn of the century and the 1920s. The final prewar index of industrial production that we use merges the adjusted Miron–Romer series for 1884 to 1918 with the FRB index for 1919 to 1940. By construction, the series match up very closely in 1919.

A.2 Additional Figures and Tables

This subsection presents additional figures and tables.

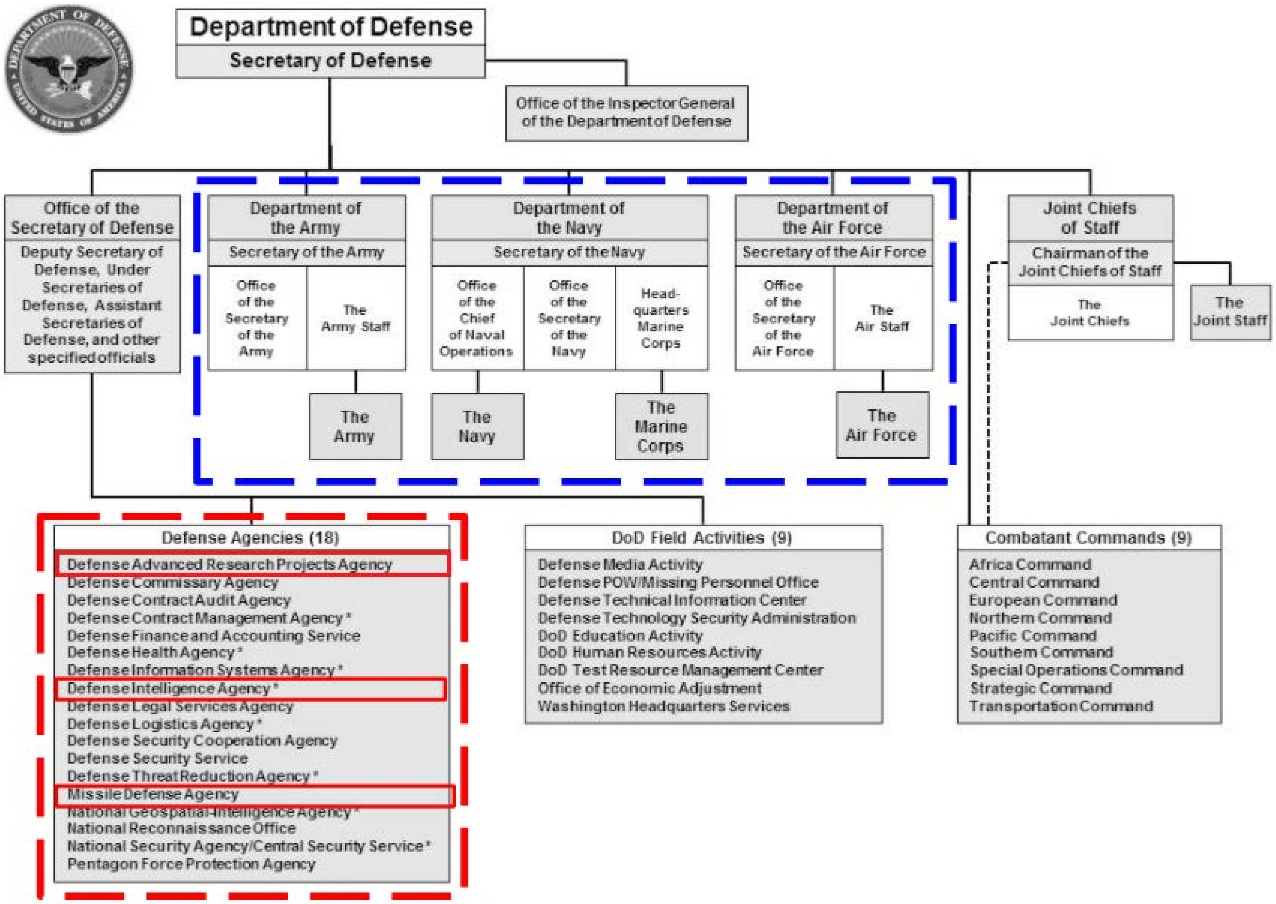

Figure A.1. Organization of the Department of Defense. This figure shows the organizational chart of the Department of Defense as of 2013. The dashed blue line highlights the three branches of the U.S. Military (Department of the Army, Department of the Navy, and Department of the Air Force). The red dashed line highlights the eighteen Defense Agencies of the DoD. We further highlight in red rectangles the agencies mentioned in the main text (Defense Advanced Research Projects Agency, Defense Intelligence Agency, and Missile Defense Agency). The source is the website of the U.S. Department of Defense.