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Analysis of the Effects and Transmission Mechanisms of Fiscal Policy in the United States

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The Dissertation of Edoardo Briganti is approved, and it is acceptable in quality and form for publication on microfilm and electronically.

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EPIGRAPH

Truth is a pathless land.

Jiddu Krishnamurti

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Chapter 3, in full, has been submitted for publication and has been co-authored with Professor Carlo Favero and Professor Madina Karamysheva. The dissertation author was the primary investigator and author of this paper.

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ABSTRACT OF THE DISSERTATION

Analysis of the Effects and Transmission Mechanisms of Fiscal Policy in the United States

by

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Understanding the effects and transmission mechanism of fiscal policy is crucial for designing efficient policies and enhancing efficacy assessments. This dissertation leverages recent trends in accurate data measurement and network data usage to enhance our understanding of fiscal policy's transmission mechanisms.

Chapter 1 presents evidence that early impacts of defense news shocks on GDP stem from increased business inventories as contractors prepare for new defense contracts. These do not impact government spending until payment-on-delivery, occurring 3 quarters later. Data on defense procurement obligations reveal that contract awards Granger-cause shocks to government spending identified via Cholesky decomposition, highlighting that Cholesky shocks miss early

inventory changes, resulting in underestimated multipliers.

Chapter 2 introduces novel data on defense contracts to study government purchase effects in the US, developing new facts about their transmission mechanism. The data includes a new quarterly series of US military prime contracts starting from 1947. These contracts are shown to be exogenous to output fluctuations and provide robust measures for timing shocks, eliminating the need for narrative analysis. Findings suggest that positive shocks to defense contracts enhance output, consumption, labor earnings, and productivity, supported by "*learning-by-doing*" effects in military production.

Chapter 3 investigates fiscal consolidations' effects in the United States and their network propagation. Using a narrative approach, we identify exogenous fiscal adjustments and employ a spatial autoregression (SAR) model to differentiate direct and network effects. Tax-based consolidations exhibit a more pronounced recessionary impact than expenditure-based ones, with about 27% of tax-based effects attributable to network spillovers versus 11% for expenditure-based adjustments. This difference in network effects highlights the stronger propagation of tax increases compared to spending cuts.

Chapter 1

Why Does GDP Move Before Government Spending? It Is All in the Timing

1.1 Introduction

The fiscal policy literature has long aimed to quantify the effects of government spending (G) and its underlying transmission mechanism.[1] To do so, researchers must first identify unpredictable government spending shocks that are exogenous to the business cycle. According to Ramey (2016), the two most commonly used approaches for identification are the Cholesky decomposition (Blanchard and Perotti (2002)) and the narrative method (Ramey (2011)). The Cholesky decomposition approach places G first in a vector autoregressive (VAR) model, relying on the assumption that G is predetermined due to decision lags. Practically, this entails regressing G on its lags and on lags of other pertinent state variables, and assuming that the resulting OLS residuals represent structural shocks (henceforth Cholesky shocks). By contrast, the narrative approach uses an instrument (e.g., defense news shocks) which reflects the anticipated shifts in defense spending brought on by exogenous military events, and places this instrument first in a VAR. Both approaches are valid under the right assumptions. Yet, the Cholesky-based method estimates smaller multipliers than the narrative method (i.e., "multiplier-gap"), especially at small horizons. This chapter provides an empirical explanation of the multiplier-gap.

[1] Government Spending (G) is the sum of government consumption expenditure and gross investments. It is one component of GDP in the classical decomposition Y = C + I + NX + G. More information on the accounting origin of G in the National Income and Product Account is reported in the Online Appendix D.1.

We start from the key empirical finding that GDP increases immediately while G increases with a delay following narratively-identified shocks to government spending.[2] Since narrative shocks predict Cholesky-identified shocks to G, proponents of the narrative approach argue that Cholesky-identified shocks fail to account for anticipation effects of fiscal policy. For instance, Ramey (2011) shows that war-dates Granger-cause (or predict) Cholesky shocks, thus leading to an identification problem since those shocks capture military build-ups with a delay. Moreover, delaying war-dates in the VAR can reconcile resulting estimates from the two methods (i.e., "*it's all in the timing*").

However, one question still remains. What causes GDP to move before G in response to narrative shocks? Ramey (2011) suggests that it is Ricardian behavior of agents which drives the anticipation effect of government spending. In particular, the existence of implementation lags during military build-ups leads to a time-mismatch between the agents' expectations of future G and actual change in G. Since Ricardian agents respond to changes in the present discounted value of G and taxes, GDP responds even before any actual change in G. However, the strength of this mechanism is still a matter of debate among economists.[3]

We provide empirical evidence of an alternative mechanism. In particular, we show that an increase in business inventories accounts for the early movement of GDP following a narrative shock. We trace back the inventory effect to an increase in newly awarded defense procurement contracts following a defense news shock. However, war-related contract awards and associated early-stage production occur several quarters before payment-on-delivery. Since government spending tracks payments, early-stage production is recorded in aggregate inventories until delivery. The differential response of aggregate inventories explains the difference in government spending multipliers calculated via the narrative method and via Cholesky decomposition (i.e.,

[2]See Ramey and Shapiro (1998), Edelberg, Eichenbaum, and Fisher (1999), Burnside, Eichenbaum, and Fisher (2004), Eichenbaum and Fisher (2005), Ramey (2011), Barro and Redlick (2011), Ben Zeev and Pappa (2017) and Ramey and Zubairy (2018). Leeper, T. Walker, and S.-C. S. Yang (2013)'s also suggests to control for anticipation effects to correctly identify fiscal shocks.

[3]For instance, Monacelli and Perotti (2008), Galí, López-Salido, and Vallés (2007) and Gabaix (2020) propose theoretical models which can dampen the strength of this mechanism. Coibion, Gorodnichenko, and Weber (2020) find little survey evidence in support of a strong negative income effect.

"*it's all in the measurement*").

We start by decomposing the increase in GDP after a defense news shock, using quarterly data from the National Income and Product Accounts (NIPA). At the aggregate level, we observe that G responds two quarters after the defense news shock, while GDP has a positive and significant response on impact and in the first quarter. The impact (horizon 0) response is entirely driven by durable consumption, but is not robust to the exclusion of the Korean war from the sample.[4] The horizon 1 response is entirely driven by a strong and robust increase in aggregate investment, and more specifically the business inventories component of investment. Even more specifically, we find from a panel of manufacturing industries that the increase in inventories after war events is driven exclusively by higher real inventories in defense sectors. In other words, the response of inventories is a result of contractors ramping-up production.

We directly document the time delay between obligations and payments using our novel quarterly time-series of defense procurement spending and defense procurement obligations. We find that obligations precede payments (and G) by an average of 2-3 quarters. The time-mismatch is discussed in the Department of Commerce's Government Transaction Methodology Paper, which shows that the production of government contractors is not immediately reflected in government spending. Rather, G primarily tracks payments which occur after the delivery of the ordered items, and defense production takes time. In other words, the recorded time-delay between payments and new orders provides an accounting origin of the positive response of inventories during a military build-up, driven primarily by unpaid production-in-progress which does not yet show up in G.

We estimate shocks to obligated government funds by ordering defense procurement obligations first in a VAR. We show that these shocks Granger-cause Cholesky shocks to government spending. However, shocks to obligations do not predict defense news shocks. Intuitively, fluctuations in real government spending, as measured by NIPA, reflect changes in defense spending brought on by military events. Cholesky shocks to NIPA government spending

[4] This is a well-known fact in the fiscal policy literature (see Perotti (2014) and Ramey (2016)).

thus capture these fluctuations. The timing of these shocks, however, is delayed relative to the initial economic impact of a military event reflected in new government orders. As a result, shocks to defense procurement obligations predict the Cholesky shocks. On the other hand, defense news shocks are recorded at the start of a military build-up, when new contracts are awarded and contractors increase production. As a result, defense news shocks are not predictable by shocks to defense procurement obligations.

Finally, we show that more than 84% of the multiplier-gap (the difference between narratively-identified and Cholesky-identified fiscal multipliers) is explained by the differential response of inventories. In other words, whenever defense production is characterized by long time-to-build, and contractors are paid after-delivery, the Cholesky shocks will overlook the initial production by defense contractors that is recorded in inventories. Therefore, under these conditions, our findings support the robustness of the narrative method in accurately (i) identifying government spending shocks, and (ii) estimating fiscal multipliers. Under the assumption that obligated funds are predetermined, identification via Cholesky decomposition is still valid as long as the government spending variable is set to obligations, which better captures the timing of federal funds as soon as they are committed to be spent.

The idea that inventories absorb the time-to-build of defense contractors can be traced back to Hickman (1955)'s analysis of the US economy during the Korean war. He argues that changes in government spending have effects before the actual disbursement of money captured by G, and that these effects are temporarily reflected in inventories.[5] Therefore, researchers should take into account new government orders to fully understand the impact of government spending changes. To overcome this implementation lag problem, Leduc and Wilson (2013) study the effects of local fiscal policy using obligations rather than outlays.

Similarly, Brunet (2020) suggests that the National Income and Product Account "mea-

[5]Extract from page 10 of their NBER book, "It is apparent that a defense mobilization will provide a stimulus to economic expansion if government expenditures increase the aggregate demand for goods and services. However, the expansion need not await the actual growth of government expenditures. In the first place, some government expenditures for defense will lag behind the placement of orders. For a time, the increased production consequent on the orders will be reflected in private inventory investment rather than in government expenditures."

sures G too late in the process", and constructs an annual measure of funds appropriations by the Department of Defense, termed budget authority. Brunet finds that this measure leads G and uses it to estimate a fiscal multiplier between 1.3 and 1.6, which is higher than typical estimates from the national multiplier literature (see Ramey (2016)). Brunet attributes the difference to implementation-lags and time-to-build in the government spending process, which leads to increased production reflected in private inventory investment before government expenditures.

Our work contributes to this literature in a few ways. To the best of our knowledge, we are the first to study the aggregate and sectoral effects of fiscal shocks on inventories.[6] Although Ginsburg (1952) also studies inventories, the analysis is restricted to the outbreak of the Korean War. Moreover, we focus on national government spending multipliers and relate them to aggregate obligations. This builds on the local cross-sectional analysis of Leduc and Wilson (2013), who use obligations to study the effects of state-level highway-construction expenditure, and estimate cross-sectional government spending multipliers.[7]

We also build on the work of Brunet (2020), who provides accounting evidence on the behavior of inventories during a military build-up. We verify this theory empirically using both an aggregate and sectoral analysis of inventories. Additionally, our novel quarterly measure of federal defense procurement obligations has several advantages relative to Brunet (2020)'s annual budget authority series. Firstly, our measure is available at the quarterly frequency rather than annual, which (i) considerably increases the sample size, (ii) allows for a more direct comparison with the other quarterly multiplier estimates from the literature, and (iii) allows us to understand the time-mismatch between contracts and payments at sub-annual frequencies.

With two quarterly series on defense procurement obligations and defense procurement spending, we are able to precisely quantify the time-mismatch between newly awarded contracts

[6]Researchers have historically overlooked the role of inventories in analyzing government spending shocks, likely due to the use of log-transformations in VAR models, which cannot handle negative inventory values. However, the adoption of other transformation of the data, such as the Gordon and Krenn (2010)'s transformation, does not require the adoption of logs and allows us to analyze the response of aggregate inventories to fiscal policy shocks.

[7]It is well-known that national and local multipliers are two different objects. In particular, the local multiplier is a rough lower bound of the deficit-financed, closed-economy, no-monetary-policy-response national multiplier (see Chodorow-Reich (2019)).

and payment to contractors. The focus on defense contracts illustrates the role of time-to-build in generating an accounting delay. Our results show that obligations precede payments (and G) by an average of 2-3 quarters, which could not have been detected with annual data. Finally, we directly relate this accounting delay to the anticipation effect measured by Ramey (2011), and use our findings to reconcile the difference in multiplier estimates obtained using narrative and Cholesky shocks.

The chapter is organized as follows. Section 1.2 establishes the positive response of contractor inventories following a defense news shock. Section 1.3 carries out the sectoral level analysis of inventories. Section 1.4 studies the underlying economic and accounting mechanisms driving the response of inventories using novel procurement data. Section 1.5 explores implications of our results in estimating government spending multipliers. Section 1.6 concludes.

1.2 Response of Inventories to Fiscal Shocks

In this section, we decompose changes in the components of real output that are driven by news about future government spending rather than actual government spending. We find that the early response of GDP to defense news shocks is driven by a positive and robust response in business inventories.[8] Our starting point is Ramey (2011), who finds that aggregate output reacts immediately to news about future war-related defense spending (defense news shocks), while government spending itself has a delayed response.[9] We replicate this result in the top panels of Figure 1.1. Note that GDP responds immediately, while G only responds starting from the second period, marked with a dashed red line.

[8]Note that we use the term "inventories" to refer to "Aggregate Changes in Business Inventories", which is one component (along with fixed - residential plus non-residential - investment) of I in the decomposition $GDP = C + I + G + NX$.

[9]See similar results in Ramey and Shapiro (1998), Edelberg, Eichenbaum, and Fisher (1999), Eichenbaum and Fisher (2005), Ben Zeev and Pappa (2017).

In particular, we estimate the quarterly impulse response function (IRF) of some outcome y_t of interest (e.g., GDP) using lag-augmented local projections:[10]

$$y_{t+h} = \theta_h \cdot \text{Shock}_t + \beta \cdot \mathbf{X}_t + \varepsilon_{t+h} \tag{1.1}$$

where y_{t+h} is the outcome, Shock_t is the updated series of narratively identified defense news shocks from Ramey and Zubairy (2018), and $\mathbf{X}_t$ is a vector of four lags of shocks, government spending, consumption, investments, net-exports, hours worked by the private sector, the three-month Treasury Bill rate and a linear time trend. Following Ramey and Zubairy (2018), we divide all nominal variables by real potential output and the GDP price deflator.

To further investigate the underlying mechanism here, we decompose GDP and estimate the aggregate response of consumption, fixed investment, inventories, government spending, and net-exports to defense news shocks. Note that the IRF of GDP (top-left panel) can be obtained by summing up the ones of all its components.[11]

The middle-left panel of Figure 1.1 shows the IRF of Fixed Investments, the middle-right panel the one of Inventories, the bottom-left panel the one of consumption and, finally, the bottom-right panel the one of net-export. Values are normalized by the peak response of G.

Firstly, consumption at horizon 0 is almost 50% of the peak response of government spending and accounts for almost all of the impact response of GDP. However, it is a well-known fact in the fiscal policy literature that this response is driven by durable consumption at the onset of the Korean war.[12] Secondly, the positive response of inventories at horizon 1 is equal to more than 50% of the peak response of G. Since we detect either negative or insignificant responses of

[10]See Jordà (2005) for local projections, LPs, and Montiel Olea and Plagborg-Møller (2021) for econometric details on lag-augmented LPs. Notice that the IRFs obtained via LPs are asymptotically equivalent to the IRFs estimated via VAR (Plagborg-Møller and C. K. Wolf (2021)). LPs are more precise in terms of bias-reduction than VAR, however, this comes at a great efficiency cost (Li, Plagborg-Møller, and C. Wolf (2021)). We use LPs for their simplicity and to compare with the literature (e.g. Ramey and Zubairy (2018)).

[11]This follows from (i) the linearity of the OLS estimator used in local projections and (ii) the way NIPA constructs GDP, as the sum of the components of final demand. See Online Appendix A for the formal proof.

[12]See Ginsburg (1952), Hickman (1955), Ramey (2016) and Binder and Brunet (2021). Consistently with the literature, we detect no significant effect of durables in samples which exclude the Korean war.

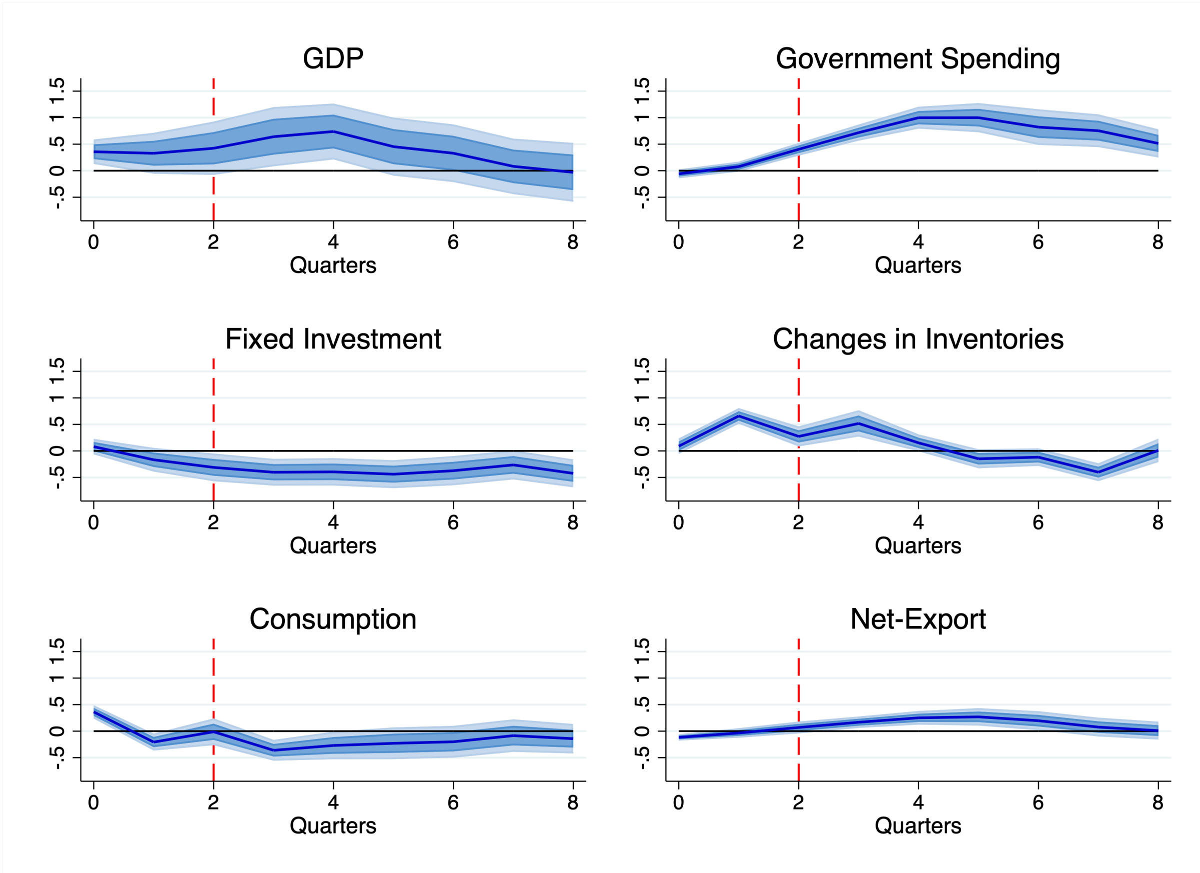


Figure 1.1. Response of GDP and Its Components to a Defense News Shock

Notes: IRFs of GDP, G, Investment and Changes in Inventories to a defense news shock are obtained via lag-augmented local projections. Bands represent the 68% and 90% heteroskedasticity robust standard errors. Defense news shocks are obtained from the updated series in Ramey and Zubairy (2018). Sample goes from 1947Q1 to 2015Q4. Values in the Figures are normalized by the peak response of G.

fixed investment (middle-left panel), consumption (bottom-left panel) and net-export (bottom-right panel) at horizon 1, it is clear that the early increase in GDP relative to G following a defense news shock initially shows up as an increase in inventories. To the best of our knowledge, we are the first to detect positive effects of inventories to defense news shocks and relate it to the anticipation effect of G detected in Ramey (2011).[13]

Robustness: The positive response of inventories is robust to the exclusion of the Korean War

[13] Fatas and Mihov (2001) estimate the effect of shocks to G identified via Cholesky decomposition on several variables and also find a positive early response of inventories. They do not discuss this result in the paper.

(the largest military build-up after World War II) from the sample, indicating that the response of inventories is not driven by periods in which defense shocks dominate.[14] Moreover, we find that the positive response of inventories is robust to the adoption of other types of fiscal shocks. In particular, we use the Cholesky shocks and shocks identified from a VAR which orders defense procurement obligations first, where defense procurement obligations capture the all universe of defense prime contract awards (we will discuss the construction of this variable in the next sections). We report all robustness checks in the Online Appendix B.

Next, we show in the panel of manufacturing industries that the aggregate response of inventories is driven by an increase in industries which heavily contract to the federal government.

1.3 Industry Analysis: Who is Responding?

Given the positive and robust aggregate response of inventories, we study heterogeneity in this response across industries in response to war events. We find that the positive response is driven by defense industries which increase inventories during a military build-up. To do so, we use monthly data from the Bureau of Economic Analysis (BEA) to construct a panel of real inventories for 18 manufacturing industries between January 1959 and December 1997.[15]

The production of defense goods is concentrated in the manufacturing sector (see e.g., Ramey and Shapiro (1998), Nekarda and Ramey (2011) and Cox et al. (2023)). However, the level of government involvement varies greatly among manufacturing sub-industries. For example, the "Other Transportation Equipment" sector has 34% of its sales directly from the government. Accounting for indirect sales via input-output connections, the sector's dependence on government purchases rises to 42% and 44% with first and second order downstream connections included (as done in Nekarda and Ramey (2011)). This heavy reliance on government purchases

[14] We believe that it is important to include the largest war events in the sample as they mimic natural experiments involving government spending. However, we are aware of potential confounding factors (see Perotti (2007), Fisher and Peters (2010), Perotti (2014) and Ramey (2016)).

[15] We thank Valerie Ramey for providing this data. Our data ends in 1997, however, most of the variation in defense spending comes from before the Nineties (Vietnam War and Soviet invasion of Afghanistan).

is unsurprising given that the sector includes sub-industries like Aircraft, Ship Building, Guided Missiles, and Space Vehicles. Conversely, the "Wood Products" sector has no sales to the government as it does not include any defense item producers.

Therefore, we construct a weight θ_i for each industry which captures the long-run average share of industry sales coming from government purchases. Using industry-by-industry input-output matrices, our weights include up to second-order downstream connections.[16] Then we estimate the following equation:

$$\text{Invt}_{i,t+h} = \lambda_{ih} + \alpha_h \cdot \text{War}_t + \beta_h \cdot \text{War}_t \cdot \theta_i + \sum_{p=1}^{12} \varphi_{ph} \cdot \text{Invt}_{i,t-p} + \varepsilon_{i,t+h} \tag{1.2}$$

where $h = 0, 1, ..., 24$, Invt_{it} is total real inventories of industry i in month t, λ_{ih} is an industry fixed-effect, and War_t is war dates.[17] Consistent with Ramey and Shapiro (1998) and Eichenbaum and Fisher (2005), our war event variable is a weighted dummy with value 1 on March 1965 and 0.3 on January 1984 to indicate the start of the Vietnam War and Soviet invasion of Afghanistan, respectively.

We are interested in the estimands α_h and $\alpha_h + \beta_h$. The former is the response of inventories for those industries not connected to the government (i.e., $\theta_i = 0$). The latter is the response of industries which are highly connected to the government through government purchases (i.e., $\theta_i = 1$). If war dates have a differential positive effect on sectoral inventories which is proportional to the degree of connection to the government, we expect $\beta_h > 0$.[18]

Figure 1.2 shows a significant positive and long-term differential response ($\alpha_h + \beta_h$) of

[16]We don't find that downstream linkages matter beyond the second order degree of connection. See Online Appendix C.2 for a detailed derivation of industry weights.

[17]We use war dates instead of defense news shocks since the former can easily be converted into monthly frequency to match our inventories data.

[18]Our approach differs from traditional shift-share methods, such as those examined in Goldsmith-Pinkham, Sorkin, and Swift (2020) and Borusyak, Hull, and Jaravel (2022). Unlike those studies, which primarily focus on cross-sectional frameworks and require instrumental variables, we investigate the impact of an aggregate exogenous shock (i.e., war-dates) on sectoral inventories and its heterogeneous effects on defense industries, as captured by the interaction between the shock and industry weights. Moreover, since we use long-run averages for our industry weights and we account for any time-invariant fixed effects through industry fixed effects, we are not concerned about the potential endogeneity of our industry weights.

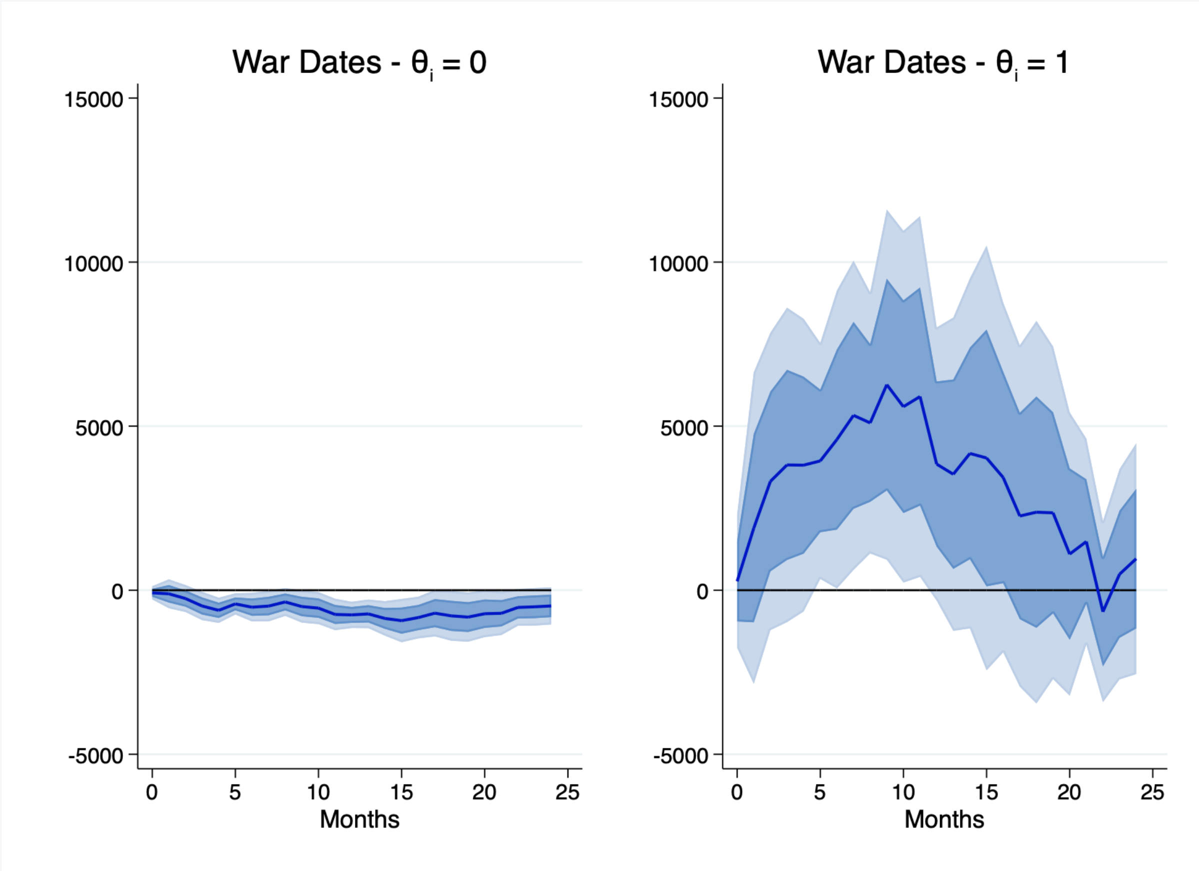


Figure 1.2. RESPONSE OF SECTORAL INVENTORIES TO WAR EVENTS

Notes: Left panel shows estimates of α_h (response when $\theta_i = 0$), right panel reports estimates of $\alpha_h + \beta_h$ (response when $\theta_i = 1$). Weights are normalized by maximum weight (i.e. the one of Other Transportation Equipment Manufacturing). Since Real Inventories are trending, data is filtered using Hamilton (2018)'s filter (we set $h = 24$ and $p = 12$, that is two years lag plus one more year of lags). The unit of real inventories is millions of 2005 chained dollars. Sample goes from 1959-Jan to 1997-Dec and uses 18 sectors breakdown of Manufacturing. Confidence bands are 68% and 90%. Standard errors are obtained via Bootstrap (standard Stata routine for `xtreg`: we use `vce(boot)` and set the seed for replicability of results; Stata uses a non-parametric type of bootstrap which resamples data with replacement).

defense industries' inventories to war dates. On the other hand, the change in inventories for those industries who do not supply the government (α_h) is negative and close to zero. Therefore, all of the effect of war dates on inventories is explained by the degree of connection of each sector to the government.

Robustness: We verify that this differential response of defense industries' inventories is not driven by their different sensitivity to the business-cycle. In particular, we replace War_t with monetary policy shocks constructed narratively by C. D. Romer and D. H. Romer (2004) and updated by Wieland and M.-J. Yang (2020) and estimate the differential response ($\alpha_h + \beta_h$) to be statistically indistinguishable from zero. This confirms that the reaction of federal contractors to defense news shocks is driven by war-related forces and not the associated business-cycle fluctuations.[19]

Furthermore, we make sure that the differential response of defense industries during a military build-up is not driven by spurious correlation. In particular, we re-estimate Equation (1.2) using randomly re-shuffled weights as commonly done in the production network literature (e.g. see Ozdagli and Weber (2020)). Again, we estimate the differential response ($\alpha_h + \beta_h$) to be statistically indistinguishable from zero and we report the results of these robustness checks in the Online Appendix C.1.

1.4 Why Inventories and not G?

This section explains why the early stage production of defense industries during a military build-up is absorbed by inventories and not government spending (G). Briefly, part of the production process occurs between contract award and delivery, and contractors are paid after delivery. Since G is constructed primarily using payments, it measures production with delay (see also Brunet (2020)). To accurately track production as it happens, NIPA uses inventories to align the timing of production with the contract award and payment. Chapter 7 of NIPA's Handbook states:[20]

> "*A general principle underlying NIPA accounting is that production should be recorded at the time it occurs. [...] The recording of movements of goods in inventory — materials and supplies, work-in-process, and finished goods — and from inventories to final sales provides the means to allocate production to the period in which it occurred.*"

[19] We thank Juan Herreño for suggesting this test.

[20] We thank Junyuan Chen and Valerie Ramey to bring up to our attention this meaningful passage.

The Procurement Process:

In the defense procurement process, obligations and spending are two distinct stages. The process starts with the award of a contract, which is when the government is legally bound to pay for goods/services. Although contractors are notified of contract opportunities before the award date through pre-award solicitations. Using contracts' solicitations data from the 2000, we find that these solicitations are typically posted in the same quarter as the award date.[21]

After contracts are awarded, contractors launch a potentially long production process. In particular, contract-level data indicates that the mean and median duration of $1 defense procurement contract are 4.2 and 5.4 years, respectively. We measure duration as the period of performance, or the number of days between award date and contract end (full delivery) date. We find that total defense procurement spending is dominated by few very large contracts with very long duration. Using the same data, Cox et al. (2023) report a very short average contract duration. However, their estimated duration is not weighted by contract size. Weighting is necessary to find the duration of $1 of spending and not the average duration of contracts. This difference matters, since most of procurement spending comes from few very large contracts. If we do not weigh by contract size, our results are consistent.[22]

Given that production takes a long time, when do associated payments actually occur? According to the Federal Acquisition Regulation (FAR), the canonical rule for payments to federal contractors from government agencies is *payments-after-delivery* (see FAR 32.904).[23] Finally, NIPA constructs G using mainly outlays, that is, payments to contractors (see Brunet (2020)).

Therefore, NIPA's accounting rules result in a delay in tracking defense production due to the time it takes to produce items. In the following sections, we create a measure of defense

[21] Nowadays, solicitations are posted on beta.sam.gov and are linked to the eventual contract award using the solicitation ID. Further discussion can be found in the Online Appendix D.5

[22] We use defense contract data from the federal procurement data system (FPDS) from 2000 to 2020. FPDS encompasses every federal transaction at daily frequency. We report results in the Online Appendix D.2.

[23] Certain contracts are also subject to partial-delivery-payments. However, given the multiple year average duration of $1 of procurement spending, we still observe several quarter-long delays in partial deliveries. We further clarify this point in the Online Appendix D.3.

procurement spending and obligations to directly observe the time gap between the start of production (when the contract is awarded) and when NIPA records it (at delivery).

Construction of Defense Procurement Spending and Obligations

We construct a novel database of defense procurement spending and obligations. Spending measures payments from federal agencies to contractors, while obligations measure the total value of federal funds as soon as they are contractually obligated to firms. To construct the spending series, we use the accounting identity discussed in Cox et al. (2023):[24]

$$\begin{aligned}
(\text{Procurement Spending})_t &\approx (\text{Intermediate Goods \& Services Purchased})_t + \\
&+ (\text{Change in Government Fixed Assets})_t + \\
&- (\text{Investment R\&D})_t \\
&\approx (\text{Payment to Contractors})_t,
\end{aligned}$$

where all variables are obtained from the National Income and Product Accounts (NIPA).

Figure 1.3 plots this measure of defense procurement spending along with the annual measure of procurement spending of Dupor and Guerrero (2017), aggregated over states. The two measures are virtually identical before 1984, but afterwards the Dupor and Guerrero (2017) series omits contract actions with value less than $25,000 and thus systematically underestimates our NIPA-based series. From 2000 onward, we also aggregate federal agency payments from the universe of procurement contracts, available in the Federal Procurement Data System (FPDS), and find that our measure is consistent.

To construct the obligations series, we aggregate the value of procurement contracts awarded by the Department of Defense (DoD) from the universe of procurement contracts recorded in the Federal Procurement Data System (FPDS). Since this data is only available from 2000 onward, we also collect historical information from the periodical *Business Conditions*

[24]Further details on the accounting origin of procurement spending is discussed in the Online Appendix D.1.

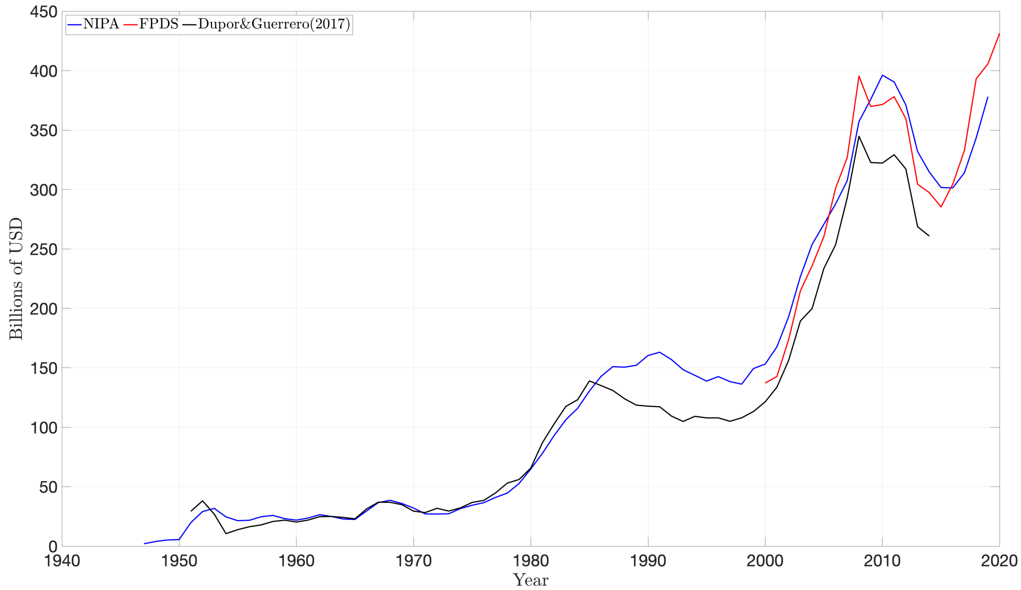


Figure 1.3. ANNUAL DEFENSE PROCUREMENT SPENDING

Digest (henceforth BCD) which is available from January 1951 to November 1988. We use information from the contract and spending data to impute missing quarters and construct a quarterly time series of defense procurement obligations.[25]

Direct Evidence of Time Mismatch in Defense Procurement

Figure 1.4 plots spending and obligations from Jan 1951-Nov 1988. From the figure it appears that spending lags behind obligations.[26] The bottom-right panel reports the lead-lag correlation.[27] From the right panel, the average lead-lag correlation significantly peaks in the North-East quadrant of the map. This suggests that changes in obligations are more highly correlated with delayed changes in spending rather than current changes in spending. The results

[25] Many thanks to Valerie Ramey for providing the BCD data. We remand to our Online Appendix D.4 for extra details on the sources of contract level data and the construction of the series.

[26] We recognize the significant disparities in the two series during and after the Korean War period. These disparities are likely due to the broad awarding of contracts, subsequent cancellations, and the accounting methods utilized by the Department of Defense before McNamara's term. We appreciate Emi Nakamura for pointing out this issue, initially identified during the drafting of Nakamura and Steinsson (2014).

[27] Lead-lag correlations are useful for studying relationships in time between variables. For example, Smets, Tielens, and Van Hove (2019) use it to study the timing of propagation of inflation from upstream to downstream sectors.

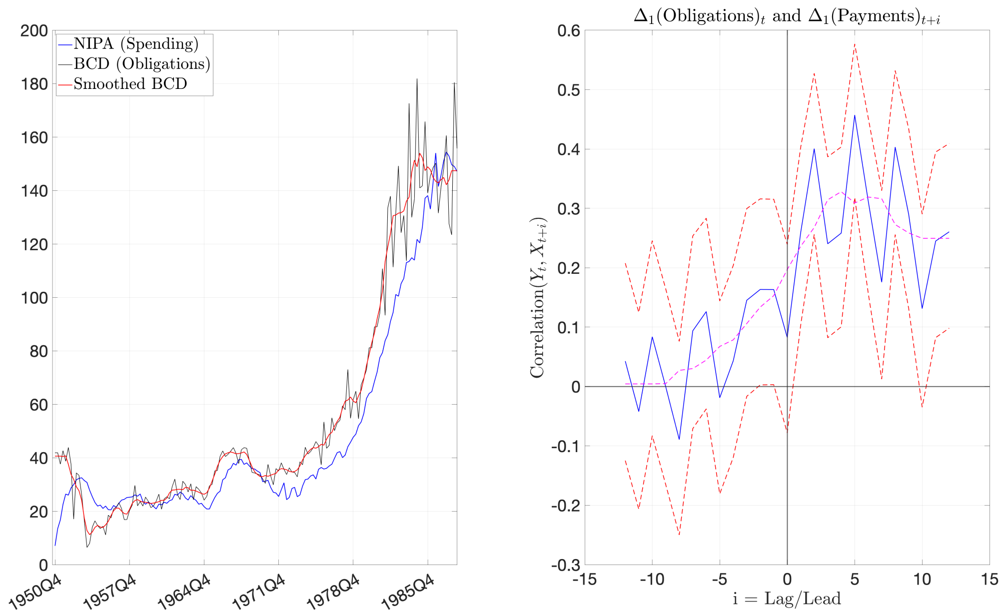


Figure 1.4. TIME LAG IN "BCD"

Notes: Lead-lag correlation map between NIPA's spending (i.e. payments) and obligations: $Corr\left(\Delta_1(\text{Obligations})_t, \Delta_1(\text{Payments})_{t+i}\right)$, where Δ_1 is the first difference operator. Sample: 1951Q1 to 1988Q4.

replicate for more recent obligations data obtained from FPDS and when we look at quarterly year-to-year changes instead of simple changes. We report these robustness checks in the Online Appendix D.2. On average, we find that obligations lead spending by 2-3 quarters.

The payment (or government outlay) thus occurs several quarters after the defense contract award. This finding is consistent with the results of Leduc and Wilson (2013) and Brunet (2020) in the context of highway spending and the aggregate annual defense budget. Moreover, this is confirmed directly by the Department of Commerce's Government Transaction Methodology Paper:[28]

> "*The largest timing difference is for national defense gross investment for relatively long-term production items, such as aircraft and missiles, for which the work in progress is considered as part of business inventories until the item is completed and delivered to the Government.*"

[28] Many thanks to Gillian Brunet for redirecting us to that document.

In other words, early-stage production associated with long procurement contracts is recorded at an aggregate level in inventories until the delayed payment-on-delivery. The value of completed and paid contract work is then moved from inventories to G. We can observe the delay between defense contract awards and payment directly from our data.

Finally, in the Online Appendix E, we distinguish between the response of defense contractors to actual contract awards and the anticipation of future contract awards. Firms may increase their inventories in preparation for future awards, whether to minimize adjustment costs or reduce delivery times (i.e., production smoothing). While we identify evidence of the latter, it is of lesser importance compared to the response to actual contract awards.

1.5 Implications for the Government Spending Multiplier

In this section, we argue that the Cholesky shocks to government spending as measured by NIPA do not capture early-stage production associated with newly awarded federal procurement contracts during a military build-up. This leads to lower multiplier estimates relative to the narrative method. We show that 84% of the difference in multipliers (multiplier gap) is driven by a differential early response of inventories following a defense news shock.

Shock Predictability:

Ramey (2011) shows that narrative shocks predict (Granger-cause) the Cholesky shocks, which implies that those shocks are missing part of the early response in GDP. To show that the missing early response is associated with early-stage production related to defense procurement contracts, we further show that shocks to defense procurement obligations Granger-cause the Cholesky shocks to G, while do not Granger-cause defense news shocks. We construct defense procurement obligation shocks by ordering defense procurement obligations first in a VAR.[29] In turn, we use two series of defense procurement obligations: one which goes from 1947Q1 to 1988Q4, which uses data from BCD ("*BCD series*") and one which uses information from

[29]The variables employed here are identical to the ones utilized in Section 1.2.

defense procurement spending and FPDS to extend the BCD data up to 2015Q4 ("*extended series*"). Our full sample spans 1947Q1 to 2015Q4, and Table 1.1 summarizes the results.

Table 1.1. PREDICTABILITY OF CHOLESKY SHOCKS VIA OBLIGATIONS

Predicted	Predictor	F	Pvalue	Korea
Cholesky Shocks	Obligation Shocks (Extended Series)	5.63	0.0%	Yes
Cholesky Shocks	Obligation Shocks (BCD Series)	3.45	0.1%	Yes
Cholesky Shocks	Obligation Shocks (Extended Series)	4.24	0.0%	No
Cholesky Shocks	Obligation Shocks (BCD Series)	2.41	1.9%	No
Obligation Shocks (Extended Series)	Cholesky Shocks	1.07	38.7%	Yes
Obligation Shocks (BCD Series)	Cholesky Shocks	0.57	84.2%	Yes
Obligation Shocks (Extended Series)	Cholesky Shocks	1.67	10.7%	No
Obligation Shocks (BCD Series)	Cholesky Shocks	1.12	35.31%	No
Defense News Shocks	Obligation Shocks (Extended Series)	0.73	66.1%	Yes
Defense News Shocks	Obligation Shocks (BCD Series)	0.75	64.4%	Yes
Defense News Shocks	Obligation Shocks (Extended Series)	0.32	95.7%	No
Defense News Shocks	Obligation Shocks (BCD Series)	0.59	78.7%	No

Notes: Granger Causality test is a Wald test on the 8 lags of the predictor while controlling for 4 lags of the predicted variable. In Appendix F, we report analogous results for Cholesky shocks to an index of Top 3 defense contractor excess returns, constructed as in Fisher and Peters (2010). We find no significant predictability in either direction for this index.

The top panel of Table 1.1 shows that shocks to defense procurement obligations predict the Cholesky shocks. On the other hand, the second panel shows a much weaker relationship in the other direction, especially when you omit the Korean War from the sample. Our results are consistent with Ramey (2011). The bottom panel shows that shocks to defense procurement obligations do not predict defense news shocks. This indicates that early economic effects of newly awarded contracts, which are missed by the Cholesky shocks to G, are captured using defense news shocks.

Government Spending Multipliers:

In most macroeconomic studies, researchers are interested in the economic effects of government spending from the moment funds are contractually obligated and contractors begin reacting. In this setting, the actual transfer of cash is not the main focus. Given our results from the previous section, we argue that the Cholesky shocks are capturing transfers of cash rather than obligation of funds. We consider an illustrative example of this problem around the outbreak of the Korean War in Figure 1.5.

In the summer of 1950 (Q3), we observe a large defense news shock associated with

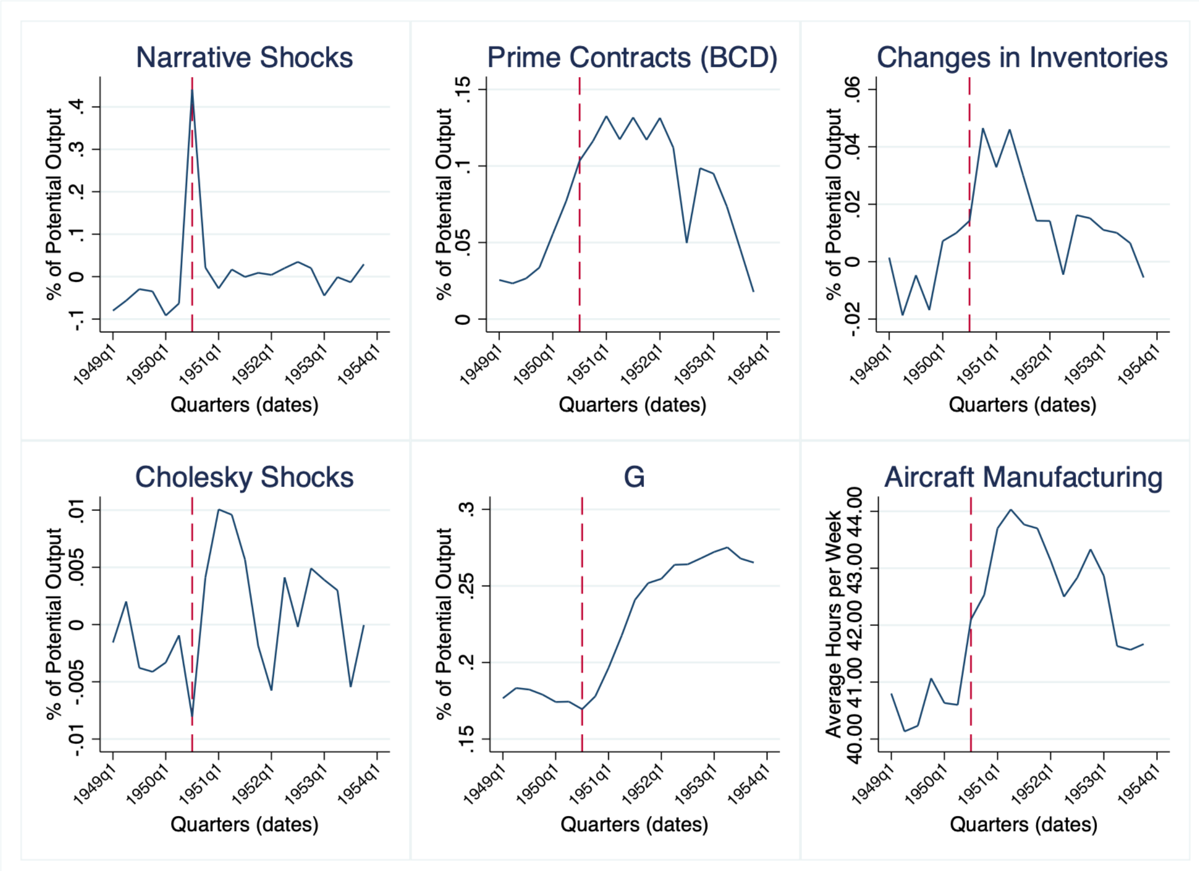


Figure 1.5. Illustration of the Delay - Korean War

the outbreak of the Korean War. However, the Cholesky shock to NIPA's measure of G does not spike until 2-3 quarters later. Unsurprisingly, G has a slow positive response. On the other hand, defense procurement obligations react almost immediately to the shock. In other words, the DoD begins awarding defense procurement contracts at the onset of the war. We also observe quick increases in inventories starting from 1950Q4 as well as in defense production, proxied by average hours of production and non-supervisory workers in the aircraft industry.[30] Therefore, the Cholesky shocks fail to capture the initial production of defense industries in response to

[30]Production workers account for 82% of total private employment, on average (see Nekarda and Ramey (2020)). We choose the Aircraft industry since it specializes in defense production and we use average hours of production workers since total hours is a lagged measure of production (see Bils and Cho (1994) and Fernald (2012)). We further clarify this point in the Online Appendix C.3. Furthermore, in the Online Appendix C.1 we show that this measure of defense production responds strongly and positively to both defense news shocks and defense procurement obligations.

newly granted contracts at the onset of the Korean war. This is consistent with our previous Granger-causality test results.

We now show that this delay leads to the underestimation of the fiscal multiplier when using Cholesky decomposition as an identification method. In particular, we show that, on average, 84% of the difference in fiscal multipliers estimated using the Cholesky and narrative methods is explained by a difference in capturing the early response of inventories. Following Ramey (2016), we estimate cumulative fiscal multipliers using LP-IV with both Cholesky shocks to G and narratively identified defense news shocks. We use the following estimation equation:[31]

$$\sum_{h=0}^{H} y_{t+h} = \gamma_H + \mathscr{M}(H) \cdot \underbrace{\sum_{h=0}^{H} g_{t+h}}_{\text{instrument with Shock}_t} + \text{lags}_t + \varepsilon_{t+h}, \tag{1.3}$$

where $\mathscr{M}(H)$ is the cumulative government spending multiplier at horizon H, y_t is GDP at time t, g_t is government spending at time t, Shock_t is an exogenous instrument for cumulative government spending, and lags_t contains lagged values of the shock, government spending, consumption, investment, hours worked and 3 months T-Bill rate. We rescale nominal variables by potential output. The narrative method sets Shock_t equal to the defense news shock variable, while the Cholesky identification is equivalent to setting Shock_t equal to G.

The left panel of Figure 1.6 shows that the Cholesky method delivers uniformly lower point estimates of the multiplier relative to the narrative method. To investigate how much of the multiplier gap can be explained by a differential response in inventories, we break down the multiplier in different components, each accruing to one of the components of GDP.

We start from the result discussed in Ramey (2016) and Stock and Watson (2018), that the one-step LP-IV approach delivers an estimate of the multiplier which is analytically equivalent to the one obtained following a two steps procedure consisting in (i) estimating the cumulative

[31]More technical details on LP-IV are available in Stock and Watson (2018).

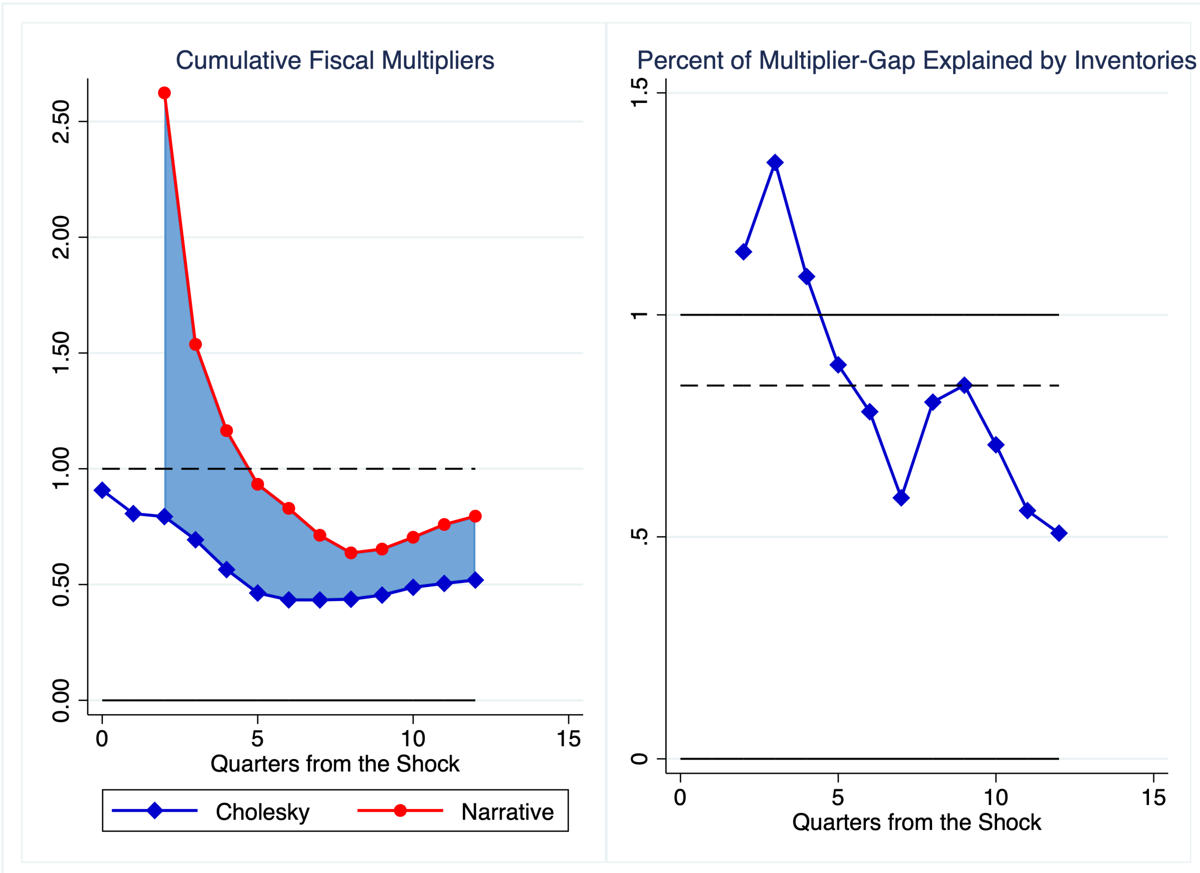


Figure 1.6. CONSEQUENCES OF THE DELAY - MULTIPLIER UNDERESTIMATION

Notes: compares the point estimates of the calculated fiscal multipliers from horizon 0 to 12 quarters. Sample: 1947Q1 to 2015Q4. The bottom-right panel shows the share of *multipliers-gap* explained by the differential response of inventories (dashed black line is the average of the response). Share is calculated only when the multiplier gap is finite.

impulse response functions of GDP and G to a government spending shock via local projections and (ii) by taking their ratio:[32]

$$\hat{\mathscr{M}}_{GDP}(H) = \frac{\sum_{h=0}^{H} \hat{\theta}_{GDP,h}}{\sum_{h=0}^{H} \hat{\theta}_{G,h}}, \quad \forall H = 0, 1, \ldots.$$

where $\hat{\theta}_{GDP,h}$ and $\hat{\theta}_{G,h}$ are the estimated IRFs of G and GDP to a government spending shock. For instance, if we used defense news shocks, they would be equal to the estimated IRFs of GDP and G shown in the top-left and top-right panel of Figure 1.1. Furthermore, since the IRF of

[32]The ˆ denotes an estimate.

GDP can be obtained by summing up the IRFs of each of its components, we can break down the fiscal multiplier as follows:

$$\underbrace{\frac{\sum_{h=0}^{H}\hat{\theta}_{GDP,h}}{\sum_{h=0}^{H}\hat{\theta}_{G,h}}}_{\hat{\mathscr{M}}_{GDP}(H)} = 1 + \underbrace{\frac{\sum_{h=0}^{H}\hat{\theta}_{C,h}}{\sum_{h=0}^{H}\hat{\theta}_{G,h}}}_{\hat{\mathscr{M}}_{\text{C}}(H)} + \underbrace{\frac{\sum_{h=0}^{H}\hat{\theta}_{I_{\text{Fixed}},h}}{\sum_{h=0}^{H}\hat{\theta}_{G,h}}}_{\hat{\mathscr{M}}_{I_{\text{Fixed}}}(H)} + \underbrace{\frac{\sum_{h=0}^{H}\hat{\theta}_{I_{\text{Invy}},h}}{\sum_{h=0}^{H}\hat{\theta}_{G,h}}}_{\hat{\mathscr{M}}_{I_{\text{Invy}}}(H)} + \underbrace{\frac{\sum_{h=0}^{H}\hat{\theta}_{NX,h}}{\sum_{h=0}^{H}\hat{\theta}_{G,h}}}_{\hat{\mathscr{M}}_{\text{NX}}(H)}$$

Notice that each component of the fiscal (GDP) multiplier corresponds to the ratio of the area under the IRF of the corresponding component of GDP and the area under the IRF of G. For instance, the inventory-multiplier obtained via defense news shocks, $\hat{\mathscr{M}}_{I_{\text{Invy}}}^{\text{News}}(H)$, is equal to the area under the IRF of inventories up to horizon H, shown in the middle-right panel of Figure 1.1, divided by the one of Government spending, plotted in the top-right panel of the same figure.

If we differentiate the above expression, and divide by the left-hand side, we obtain:

$$\begin{aligned}
(\forall H) \quad 1 &= \underbrace{\frac{d\hat{\mathscr{M}}_{I_{\text{Invy}}}(H)}{d\hat{\mathscr{M}}_{GDP}(H)}}_{:=\Delta\% I_{\text{Invy}}(H)} + \underbrace{\frac{d\hat{\mathscr{M}}_{\text{C}}(H)}{d\hat{\mathscr{M}}_{GDP}(H)} + \frac{d\hat{\mathscr{M}}_{I_{\text{Fixed}}}(H)}{d\hat{\mathscr{M}}_{GDP}(H)} + \frac{d\hat{\mathscr{M}}_{\text{NX}}(H)}{d\hat{\mathscr{M}}_{GDP}(H)}}_{\Delta\%\text{Other}(H)} \\
1 &= \Delta\% I_{\text{Invy}}(H) + \Delta\%\text{Other}(H),
\end{aligned}$$

where $\Delta\% I_{\text{Invy}}(H)$ represents the share of the multiplier-gap, $d\hat{\mathscr{M}}_{GDP}(H)$, explained by differences in the response of inventories, $d\hat{\mathscr{M}}_{I_{\text{Invy}}}(H)$, while $d\Delta\%\text{Other}(H)$ refers to all the other components of GDP.

Therefore, we calculate and breakdown the fiscal multiplier using both defense news shocks (News) and Cholesky shocks (Chol), then we calculate the share of multiplier gap explained by inventories, as suggested by the previous expression:

$$\Delta\% I_{\text{Invy}}(H) = \frac{\hat{\mathscr{M}}_{I_{\text{Invy}}}^{\text{News}}(H) - \hat{\mathscr{M}}_{I_{\text{Invy}}}^{\text{Chol.}}(H)}{\hat{\mathscr{M}}_{\text{GDP}}^{\text{News}}(H) - \hat{\mathscr{M}}_{\text{GDP}}^{\text{Chol.}}(H)}$$

which computes the proportion of the multiplier gap (denominator) arising from using the narrative and Cholesky methods, explained by differences in the inventory multiplier (numerator). The right panel of Figure 1.6 plots $\Delta\% I_{\text{Invy}}(H)$ up to horizon 12 (solid blue line with diamonds) along with its average (dark dash line). On average, 84% of the multiplier gap can be explained by the differential response of inventories as captured by the shocks. In the Online Appendix F, we show that this result is robust to the exclusion of the Korean War.

To summarize, the identification of government spending shocks via Cholesky decomposition fails to fully capture early-stage defense production which is reflected in inventories, which results in underestimated multipliers. This is due to NIPA G's delayed tracking of defense production during military build-ups. Our Granger-causality test results are consistent with this intuition. This finding raises a major challenge in identifying government spending shocks through the Cholesky decomposition, provided there exists a long enough time-mismatch between orders and payments in the government spending process.

1.6 Conclusion

The National Income and Product Accounts (NIPA) tracks production by monitoring changes in inventories. During a military buildup, defense industries increase production in response to new procurement contracts, which results in a rise in inventories and GDP. Once the production of defense items, such as aircraft and missiles, is finished, they are delivered to the government and the contractors receive payment. This causes inventories to decrease and government spending (G) to increase as payments are recorded. The onset of a war results in GDP responding faster than G due to (1) accounting procedures and (2) the time required for production in the defense sector.

The findings of our study support the idea that the early rise in GDP relative to G after a defense news shock, as described by Ramey (2011), can be attributed to an increase in inventories. Our analysis of manufacturing sector data reveals that defense industries are responsible for the rise in inventories. By creating new quarterly time series that track defense procurement contract awards and payments, we were able to observe a 2-3 quarter gap between the two. This delay provides evidence for the existence of a time-to-build period for defense production.

Our study has three significant implications. Firstly, it provides a straightforward explanation for the early reaction of GDP compared to G in response to a defense news shock, which was previously believed to be due to households' Ricardian behavior (negative wealth effect). Secondly, the results indicate that shocks to defense procurement obligations predict Cholesky shocks to government spending, which is a major issue in the identification of macroeconomic shocks (as noted by Ramey (2016)). Lastly, the delay in these shocks leads to an under-estimation of the response of inventories which is responsible for 84%, on average, for the under-estimation of the fiscal multiplier estimated by the narrative method.

Our findings highlight the significance of the early effects of G, as reflected in the increase in inventories. Policymakers and economists should take into account measurement delays in government spending when evaluating the impact of government purchases on the economy.

1.7 Appendix

1.7.1 Breaking Down the Response of GDP

In this section, we decompose the response of GDP to a defense news shock into its underlying components. To do so, we exploit the linearity of the OLS estimates which are used to construct the impulse response functions (IRFs) via local projection.

In particular, we first calculate the IRF of GDP to a defense news shock by regressing GDP on defense news shocks and four lags of investment, government spending, net-export, consumption total hours worked in the private sector, the 3-months T-Bill rate, defense news shocks and a linear time trend. We divide all nominal variables by nominal potential GDP (we take real potential GDP from Ramey and Zubairy (2018) and multiply it by the GDP price deflator). In particular, we group this set of lagged variables and the time trend into matrix X_t, and the IRF of GDP is the coefficient θ_h^{GDP} in the following linear equation:

$$\text{GDP}_{t+h} = \theta_h^{\text{GDP}} \cdot \text{News}_t + X_t \cdot \boldsymbol{\beta}^{\text{GDP}} + \varepsilon_{t+h} \quad h = 0, 1, ..., 8.$$

We report the estimated IRF of GDP in the left panel of Figure 1 in the main text. Repeating this procedure for all four components of GDP, we estimate the following set of linear equations:

$$\begin{aligned}
\text{G}_{t+h} &= \theta_h^{\text{G}} \cdot \text{News}_t + X_t \cdot \boldsymbol{\beta}^{\text{G}} + \varepsilon_{t+h}^{G} \quad h = 0, 1, ..., 8 \\
\text{C}_{t+h} &= \theta_h^{\text{C}} \cdot \text{News}_t + X_t \cdot \boldsymbol{\beta}^{\text{C}} + \varepsilon_{t+h}^{C} \quad h = 0, 1, ..., 8 \\
\text{I}_{t+h} &= \theta_h^{\text{I}} \cdot \text{News}_t + X_t \cdot \boldsymbol{\beta}^{\text{I}} + \varepsilon_{t+h}^{I} \quad h = 0, 1, ..., 8 \\
\text{NX}_{t+h} &= \theta_h^{\text{NX}} \cdot \text{News}_t + X_t \cdot \boldsymbol{\beta}^{\text{NX}} + \varepsilon_{t+h}^{NX} \quad h = 0, 1, ..., 8
\end{aligned}$$

Given that the decomposition of GDP is additive and all equations have the same set of controls

X_t, it is easy to show that:

$$\hat{\theta}_h^{\text{GDP}} = \hat{\theta}_h^{\text{G}} + \hat{\theta}_h^{\text{C}} + \hat{\theta}_h^{\text{I}} + \hat{\theta}_h^{\text{NX}} \quad \text{for all } h = 0, 1, ..., 8.$$

where the ˆ denotes an OLS estimate. Therefore, we decomponse IRF of GDP to a defense news shock into its four underlying components, reported in Figure 1.7.

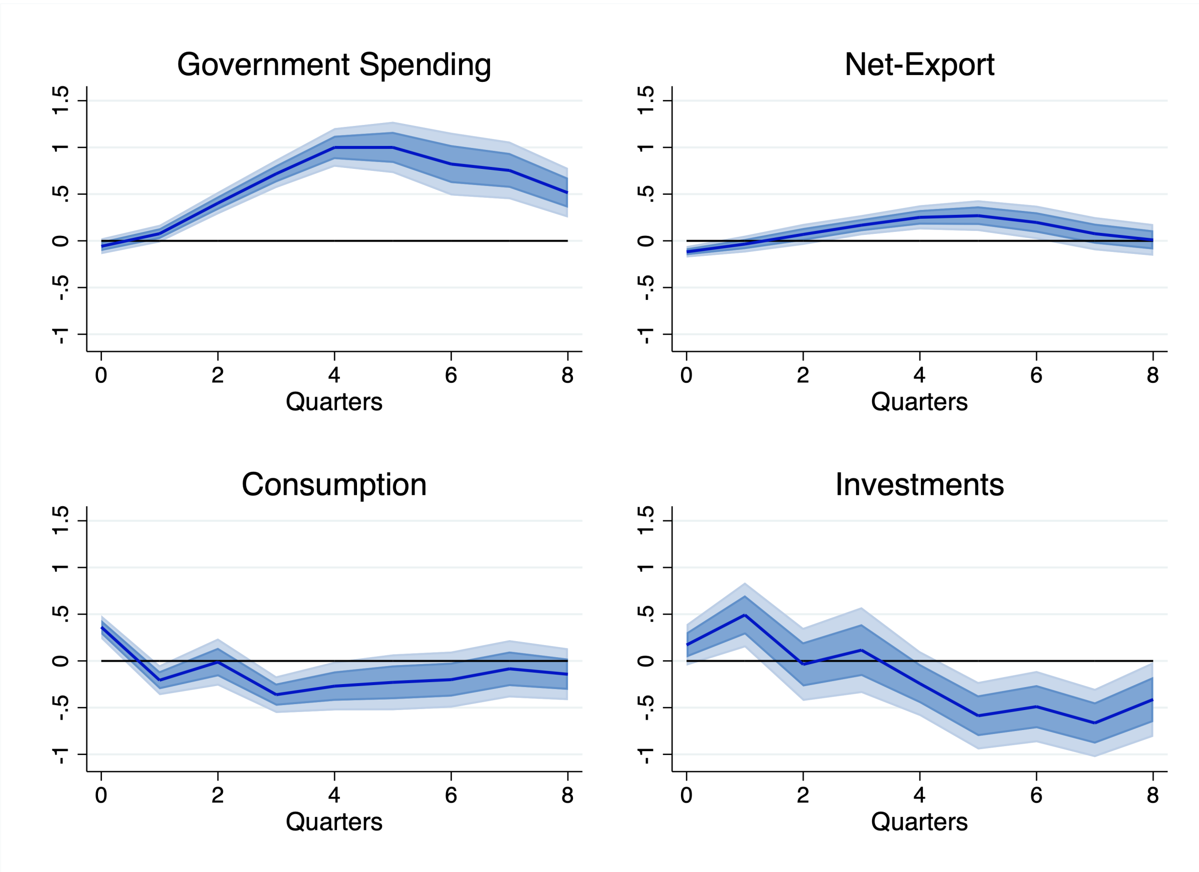


Figure 1.7. Response of GDP Components to a Defense News Shock

Notes: IRFs of GDP, G, Investment and Changes in Inventories to a defense news shock are obtained via lag-augmented local projections. Bands represent the 68% and 90% heteroskedasticity robust standard errors. Defense news shocks are obtained from the updated series in Ramey and Zubairy (2018). Sample goes from 1947Q1 to 2015Q4. Values in the Figures are normalized by the peak response of G.

Figure 1.7 shows that aggregate consumption at horizon 0 and aggregate investment at horizon 1 drive the early increase in GDP after a defense news shock.

Consumption and Investment

We can further decompose the responses of consumption and investment to better understand what drives their early response. In particular, we apply the same methodology to estimate the IRFs of inventories and residential plus non-residential fixed investment (components of investment) to a defense news shock. Similarly, we estimate the IRFs of durable consumption and the sum of non-durable and service consumption. As before, we consider variables in nominal terms, divide by the GDP price deflator and multiply by real potential output (Gordon and Krenn (2010) transformation).

We report the IRFs of these four components of consumption and investments to a defense news shocks in Figure 1.8. We observe that the horizon 0 response of consumption largely shows up in durables while the horizon 1 response of investment is driven by inventories.

1.7.2 Robustness - Section 1.2

In Figure 1.9, we verify that the positive response of inventories is robust to the inclusion of the Korean War in the sample period. In particular, we estimate IRFs of inventories via lag-augmented local projections with respect to three different fiscal shocks (narratively identified, recursively identified, and shocks to obligations) over two samples. The first sample includes the Korean war and goes from 1947Q1 to 2015Q4 (top row of Figure 1.9). The second sample runs from 1954Q1 to 2015Q4 and excludes the Korean war (bottom row of Figure 1.9).

For all results, we control for a linear time trend and four lags of government spending, consumption, investment, net-export, hours in the private sectors and 3-months T-Bill rate. To implement the narrative method, we include defense news shocks and its four lags and estimate the IRF using the OLS coefficients associated with defense news shocks (first column of Figure 1.9). To implement the recursive method, we add contemporaneous government spending and obtain the IRF from its OLS coefficient (second column of Figure 1.9). Finally, we consider shocks to defense procurement obligations. We control for four lags of obligations using the series discussed in the main text of the first chapter, and estimate the IRF from the OLS coefficient

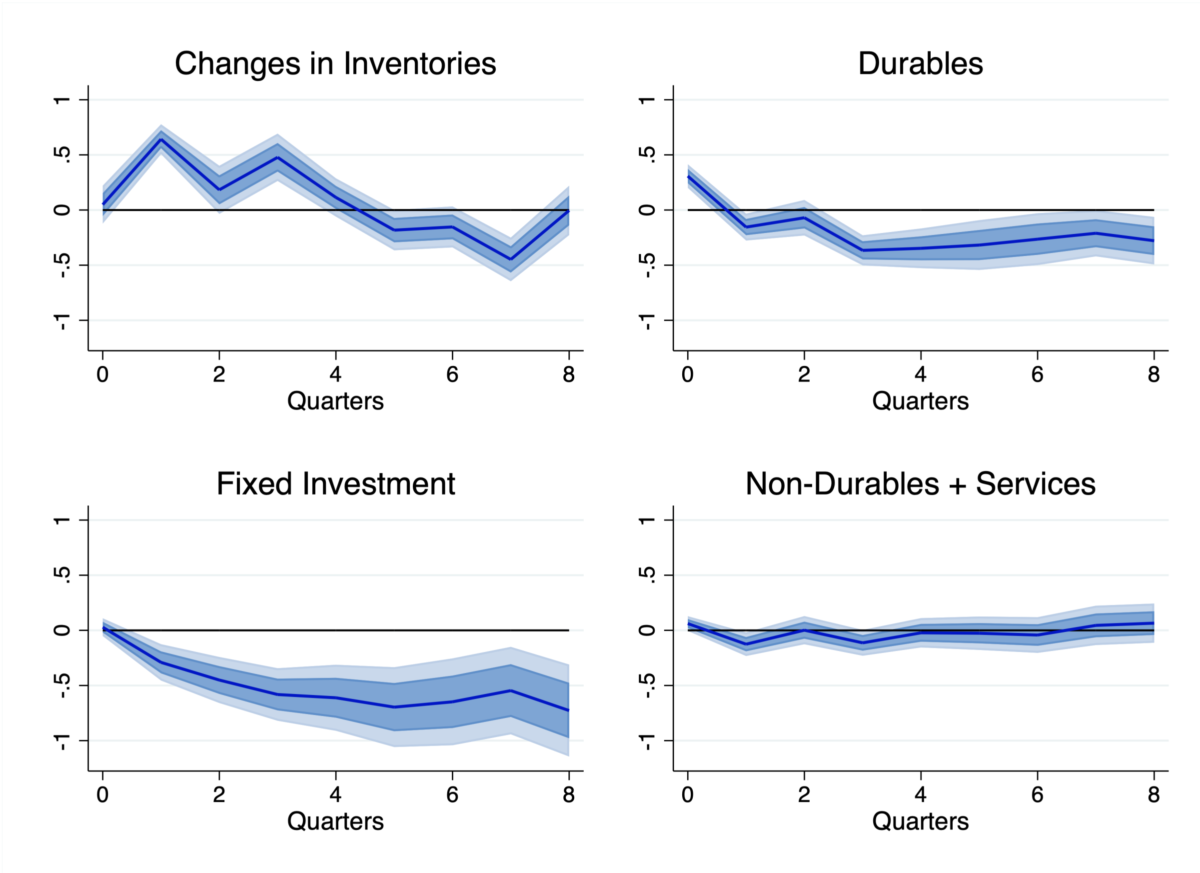


Figure 1.8. Response of Consumption and Investment to a Defense News Shock

Notes: See notes of Figure 1.7

on contemporaneous defense procurement obligations (third column of Figure 1.9).

Although excluding the Korean War from the sample leads to less precise estimates of the IRF, our results are still significant especially at early horizons. The difference in precision is not a surprising result since the Korean War represents the largest military build-up after WWII. As discussed in the first chapter, we support the idea of including the Korean war in the sample since wars represent natural experiments where G increases exogenously.

1.7.3 Details on Industry Level Analysis

In this section, we implement robustness checks for the industry-level analysis of inventories (see Appendix 1.7.3) and provide details on our construction of industry weights θ_i (see

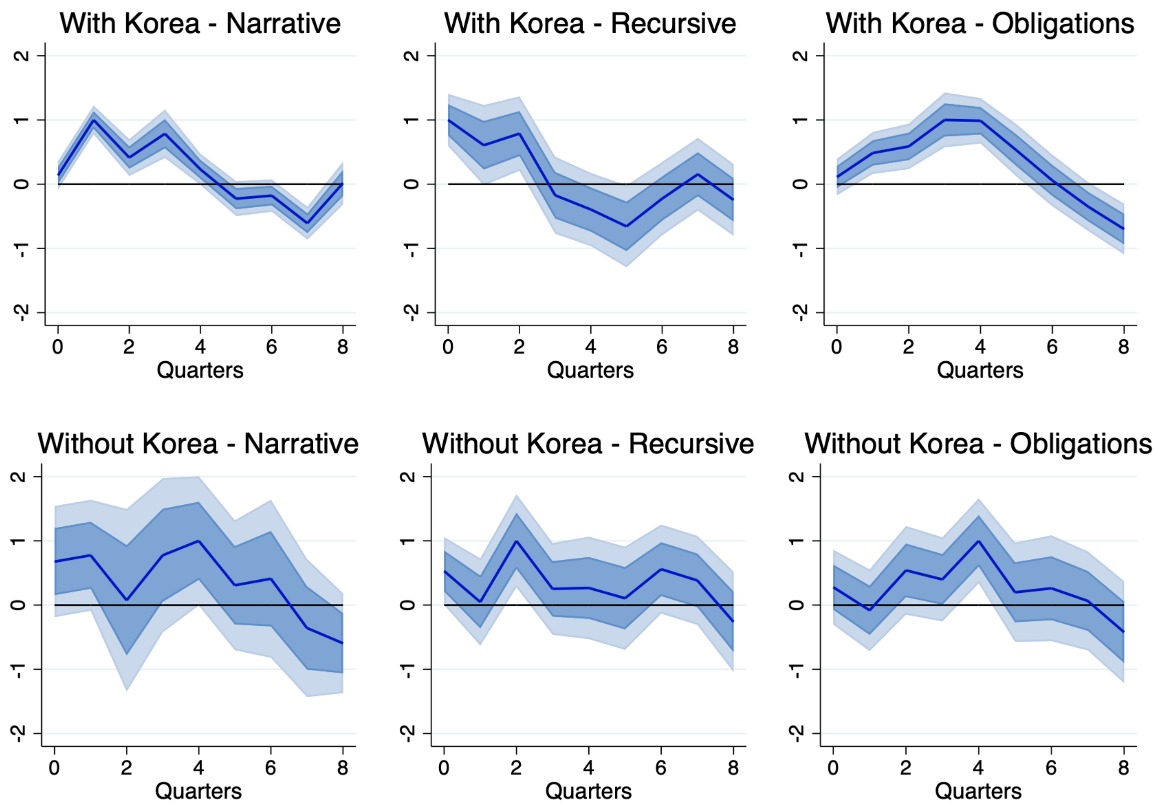


Figure 1.9. RESPONSE OF INVENTORIES - ROBUSTNESS

Notes: Response of inventories to different fiscal shocks over two samples (with and without Korean war). All the rest is identical to notes of Figure 1.7.

Appendix 1.7.3).

Robustness - Section 1.3

Figure 1.10 shows the results of the robustness checks associated with Section II of the main text. The first column replicates the results reported in the first chapter, where our $Shock_t$ variable is war dates and industry weights (θ_i) are baseline weights constructed directly from the BEAs Make and Use tables. We report IRFs conditional on setting $\theta_i = 0$ (top panel) and $\theta_i = 1$ (bottom panel). Recall that setting $\theta_i = 0$ indicates the effect of a shock on a sector not connected to the government while setting $\theta_i = 1$ indicates the effect of such a shock on a sector which is fully connected to the government.

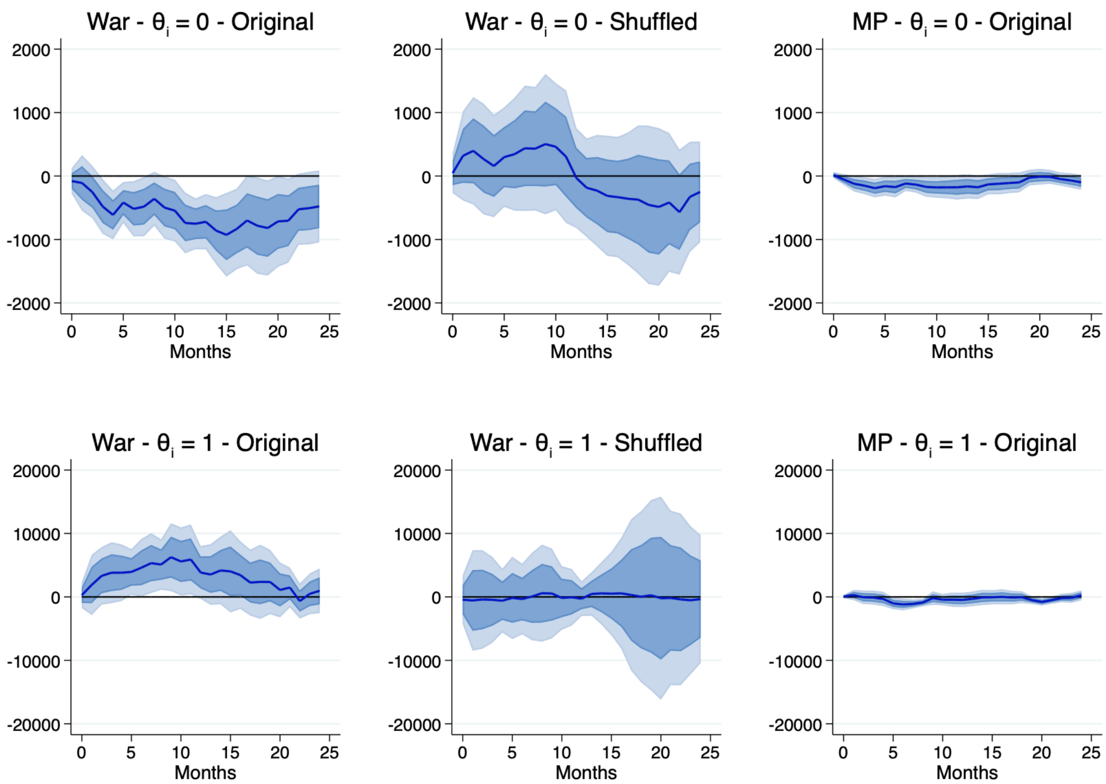


Figure 1.10. RESPONSE OF SECTORAL INVENTORIES TO WAR EVENTS - ROBUSTNESS

Notes: See notes of Figure 1.2.

Additionally, in the middle panels we report the same results using shuffled weights. In this case, we randomly assign a weight θ_j to an industry i to verify that the result is not driven by the aggregate distribution of weights. Lastly, the right panels report the results when the weights are fixed at their empirical value, but where the shock is a monetary policy shock rather than a war date. The goal of this robustness check is to verify that the result is not driven by industry-level exposure to the business cycle. Notice that the inventory response of industries connected to the government $\theta_i = 1$ (bottom panels) vanishes for both robustness checks.

The Response of the Aircraft Industry:

Here we estimate the following lag-augmented local projection:

$$\bar{h}^{aircraft}_{t+h} = \beta_h \cdot Shock_t + lags_t + \varepsilon_{t+h}$$

where $\bar{h}^{aircraft}_{t+h}$ is average hours of production workers in the aircraft industry in quarter t+h, $Shock_t$ is either defense news shocks or defense procurement obligations, $lags_t$ is four lags of the dependent variable and four lags of the shock. We believe average hours of production workers in the aircraft industry is an excellent proxy for defense production (see Appendix 1.7.3). We report IRFs in Figure 1.11. We observe that defense production quickly ramps up in response to defense news or newly awarded procurement contracts.

Construction of Industry Weights

To construct industry weights, we combine information from the Make and Use table with more than 60 non-government sectors between 1963 to 1996. Following Horowitz and Planting (2009), we derive direct requirement industry-by-industry matrices A_t and direct sales from the private sectors to the government. We use these two elements to construct our final industry weights as follows.

Government Direct Purchases:

We construct a vector of government purchases (i.e., direct requirements) relative to industry output:

$$\underset{n\times 1}{\boldsymbol{\gamma}_{0,t}} = \begin{bmatrix} \frac{\text{SALES}_{1\to G,t}}{\text{SALES}_{1,t}} \\ \vdots \\ \frac{\text{SALES}_{n\to G,t}}{\text{SALES}_{n,t}}, \end{bmatrix}$$

where t denotes the year, n is the number of manufacturing sub-industries, G denotes the federal general government, and the 0 subscript in a vector's name refers to the order of included input-output connections (e.g., a zero subscript suggests that the vector only accounts for direct

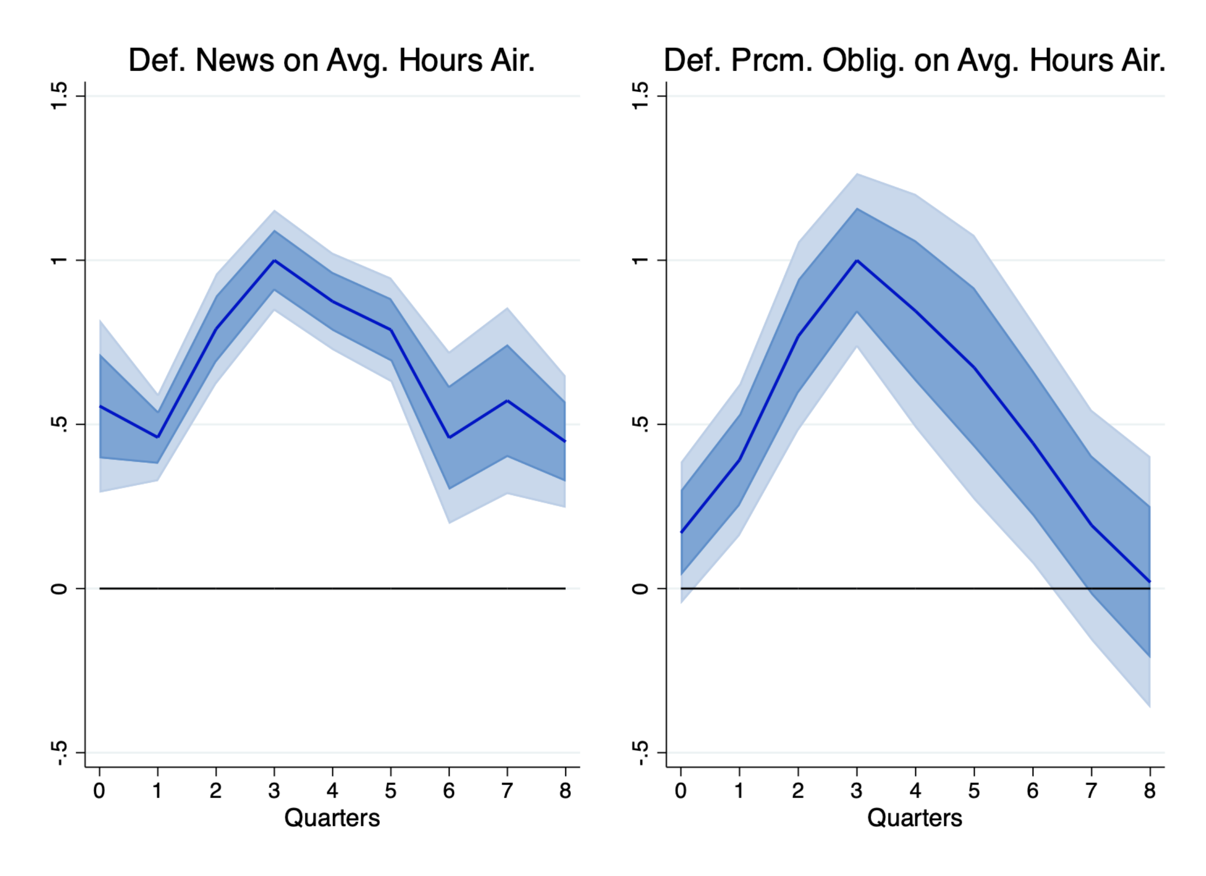


Figure 1.11. EFFECTS OF MILITARY BUILD-UPS ON DEFENSE PRODUCTION

Notes: IRFs are obtained via lag-augmented local projections. Sample goes from 1947Q1 to 2002Q4 (sample stops in 2002 because data are no longer available). Data Source: BLS Discontinued Databases. Standard errors are heteroskedasticity robust. Confidence bands are 90% and 68%.

sales to the government). Moreover, $\text{SALES}_{i\to G,t}$ for a given sector i includes government gross investments, which show up as final uses in the Use tables. We report the time-average values of $\boldsymbol{\gamma}_{0,t}$ in the third column of Table 1.2.

Government Indirect Purchases:

Following Nekarda and Ramey (2011), we also include downstream input-output linkages to account for indirect sales to the government. In order to do so, we construct yearly $n \times n$

input-output matrices A_t in which (i,j)th element of matrix A_t is given by:

$$\frac{\text{SALES}_{i\to j,t}}{\text{SALES}_{i,t}}.$$

We then construct a vector of direct and first-order indirect sales shares as follows:

$$\boldsymbol{\gamma}_{1,t} = (I_n + A_t)\cdot \boldsymbol{\gamma}_{0,t}.$$

Notice that the ith element of $\boldsymbol{\gamma}_{1,t}$ is given by:

$$\gamma_{1,i,t} = \underbrace{\frac{\text{SALES}_{i\to G,t}}{\text{SALES}_{i,t}}}_{\text{Direct Sales}} + \underbrace{\sum_{j=1}^{n}\frac{\text{SALES}_{i\to j,t}}{\text{SALES}_{i,t}}\cdot\frac{\text{SALES}_{j\to G,t}}{\text{SALES}_{j,t}}}_{\text{Indirect Sales.}}$$

We report the time-average of $\boldsymbol{\gamma}_{1,t}$ in the fourth column of Table 1.2. Similarly, we construct direct, first and second order indirect sales to the government, shares of total output as:

$$\boldsymbol{\gamma}_{2,t} = \left(I_n + A_t + A_t^2\right)\cdot \boldsymbol{\gamma}_{0,t}.$$

We report the time-average values of $\boldsymbol{\gamma}_{2,t}$ in the fifth column of Table 1.2. Finally, we construct our industry weights θ_i as:

$$\theta_i := \frac{\mathbb{E}\left[\gamma_{2,i,t}\right]}{\max_i \mathbb{E}\left[\gamma_{2,i,t}\right]}$$

We report the weights in the last column of Table 1.2.

Tracking Defense Industrial Production

In Section 1.3 of the first chapter, we use use *Average Hours of Production Workers* of the *Aircraft industry* to keep track of the "*defense production machine*". We now explain the reasons behind that choice. Firstly, we plot the quarterly time series in Figure 1.12.

Table 1.2. INDUSTRY WEIGHTS.

Sector	*Commodity Description*:	$\gamma_{0,i}$	$\gamma_{1,i}$	$\gamma_{2,i}$	θ_i
3364	Other transportation equipment	34.43%	42.00%	43.94%	1.00
334	Computer and electronic products	13.09%	17.04%	18.38%	0.42
323	Printing and related support activities	7.98%	9.35%	9.95%	0.23
332	Fabricated metal products	3.73%	4.78%	5.37%	0.12
3361	Motor vehicles, bodies and trailers, and parts	2.09%	3.70%	4.64%	0.11
339	Miscellaneous manufacturing	2.31%	3.80%	4.49%	0.10
333	Machinery	2.65%	3.84%	4.44%	0.10
335	Electrical equipment, appliances, and components	2.37%	3.66%	4.31%	0.10
325	Chemical products	1.91%	3.50%	4.27%	0.10
324	Petroleum and coal products	2.71%	3.50%	4.17%	0.09
326	Plastics and rubber products	1.13%	2.20%	2.89%	0.07
337	Furniture and related products	0.66%	1.63%	2.19%	0.05
331	Primary metals	0.54%	1.44%	2.06%	0.05
313	Textile mills and textile product mills	0.48%	1.31%	2.01%	0.05
315	Apparel and leather and allied products	0.57%	1.37%	1.98%	0.05
327	Nonmetallic mineral products	0.49%	1.35%	1.91%	0.04
322	Paper products	0.51%	1.25%	1.83%	0.04
311	Food and beverage and tobacco products	0.38%	1.16%	1.77%	0.04
321	Wood products	0.19%	0.91%	1.53%	0.03

Notes: Last column divides $\theta_{2,i}$ by the maximum value (i.e. the one of Other Transportation Equipment Manufacturing). In the first chapter, the weights θ_i that we use are the ones which include second order degree of connections, normalized (last column).

Aircraft Industry:

We choose the Aircraft industry for two reasons: (i) great data availability (monthly data from BLS discontinued series starting from 1939) and (ii) high dependency on government purchases (see Nekarda and Ramey (2011)).

Hours-per-Worker:

In general, there are no direct measures of industrial output. In the case of the aircraft industry, we do not observe the exact number of aircraft produced every month nor their percentage of completion. However, we have three variables which can proxy for industrial production: (i) average weekly hours of production workers, (ii) number of production workers (i.e., employment) and (iii) their product, namely total hours worked. The first one is a measure

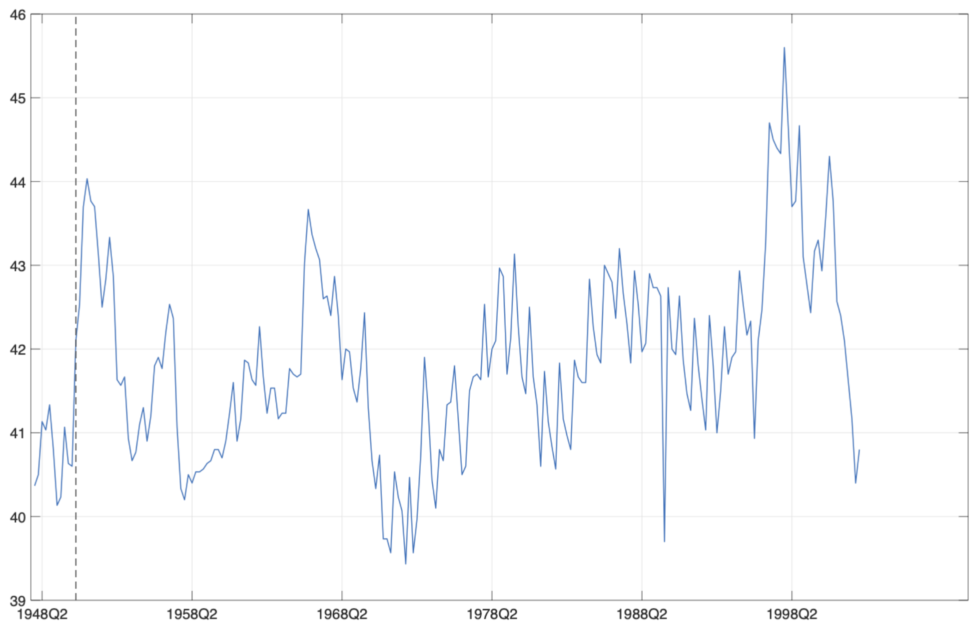


Figure 1.12. AVERAGE HOURS OF PRODUCTION WORKERS IN THE AIRCRAFT INDUSTRY

of intensity of production, while the other two are stock variables measuring the extensive margin of production.

In order to understand which one is more suitable to measure changes in production, we consider as an illustrative example the outbreak of the Korean War. During this period, defense manufacturers foresee a period of high demand of weapons by the government and adjust production accordingly. The first sensible thing is to increase production, given the predetermined level of capital and labor inputs. For instance, increasing production requires extra use of electricity to operate machinery in the assembly lines as well as a higher number of shifts with longer duration for production workers. By consequence, hours per worker increase immediately. Over time, contractors expand production by widening their stock of capital and workers, thus overcoming problems related to capital immobility (see e.g., Ramey and Shapiro (1998)) and labor market frictions. As contractors expand their production facilities and hire new production workers, intensity of production returns back to normal.

This example highlights two facts. Firstly, intensity of production of manufacturing industries is a good indicator of switches in the production regime. Secondly, intensity of production leads employment and other stock variables which tend to move more slowly. This intuition is consistent with Bils and Cho (1994), who find that hours per worker lead employment and the business cycle. Moreover, they emphasize how hours-per-worker co-moves with other relevant but unobserved measures of intensity of production.[33] are strongly related to hours per worker in the US textile industry and (ii) electricity use of manufacturing industries and hours worked per week co-moves. On the contrary, they find that the relationship between their measures of capital utilization and the number of production workers is much weaker. Along these lines, Fernald (2012) suggest to use hours of production workers to proxy other unobserved measures of intensity of production. According to them, a cost-minimizing firm operates on all margins simultaneously, both observed (i.e., hours per worker) and unobserved (i.e., labor effort and workweek of capital).

In what follows, we show that (i) hours-per-worker in the aircraft industry leads employment and (ii) employment drives the dynamics of total hours, overshadowing very informative lumpy changes in hours-per-worker. In light of all this, *hours-per-worker is the most suitable variable to timely measure changes in production*.

Hour per Worker, Employment and Total Hours in the Aircraft Industry:

Figure 1.13 shows in its top-left panel the lead-lag correlation map between changes in average hours of production workers and changes in the number of production workers in the Aircraft industry. Clockwise from the top-right panel we show the time series of average hours of production workers ($\bar{h}_t$), number of production workers (e_t) and total hours of production workers ($\bar{h}_t \cdot e_t$) around the onset of the Korean war for the Aircraft industry (i.e., 1950Q3), respectively.

Firstly, from the lead-lag correlation map, we observe that average hours of production

[33]They find that (i) "looms hours

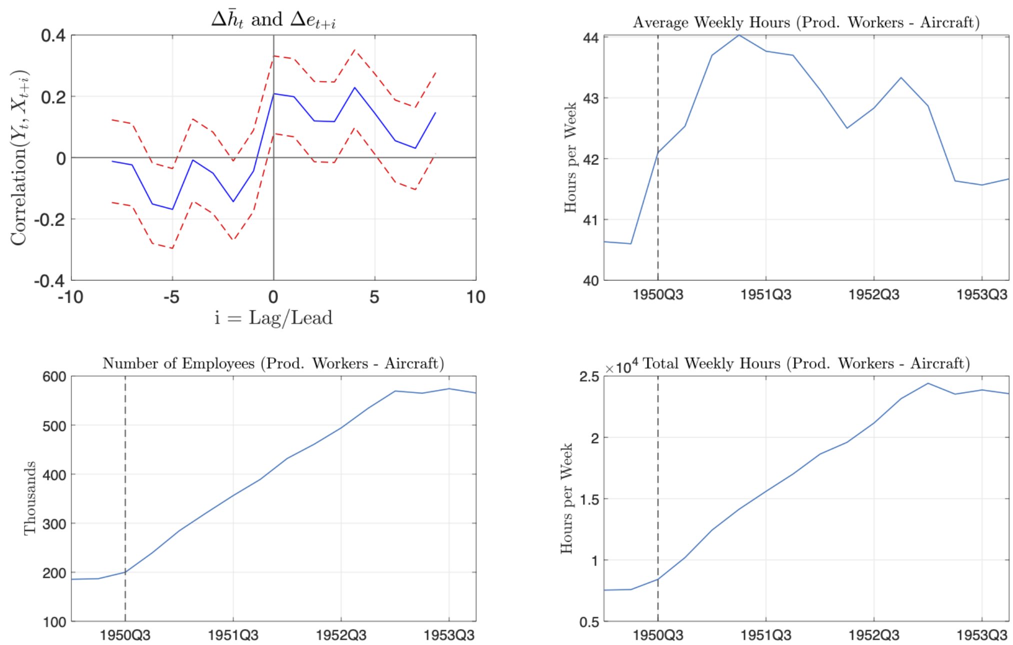


Figure 1.13. AVERAGE HOURS OF PRODUCTION WORKERS VS PRODUCTION WORKERS - AIRCRAFT INDUSTRY

workers lead employment. This is consistent with the findings of Bils and Cho (1994). Secondly, notice that the dynamics of total hours is dominated by employment, and not by average hours per worker. Therefore, if we gauge industrial production by simply looking at the dynamics of total hours, we would conclude that the response of the Aircraft industry at the outbreak of the Korean war was mild and slow. On the contrary, average hours per production worker anticipated the peak response of employment and total hours of production, signaling that defense production had already fired up at the onset of the war.

We further clarify what is happening by breaking down the change in total hours into two components, one which accrues to changes in hours worked (intensive margin) and one which accrues to changes in number of workers (extensive margin):

$$H_t = \bar{h}_t \cdot e_t$$

$$\frac{\partial H_{t+h}}{\partial z_t} = \underbrace{\frac{\partial \bar{h}_{t+h}}{\partial z_t} \cdot e_{t+h}}_{\text{Intensive Margin}} + \underbrace{\frac{\partial e_{t+h}}{\partial z_t} \cdot \bar{h}_{t+h}}_{\text{Extensive Margin}}$$

where z_t is a defense news shock. We break down the dynamic response of total hours to the Korean War using the previous expression:

$$\left(H_{1950Q3+h} - H_{1950Q2}\right) = \underbrace{\left(\bar{h}_{1950Q3+h} - \bar{h}_{1950Q2}\right) \cdot e_{1050Q3+h}}_{\text{Intensive Margin}} + \underbrace{\left(e_{1950Q3+h} - e_{1950Q2}\right) \cdot \bar{h}_{1050Q3+h}}_{\text{Extensive Margin}}$$

with $h = 0, 1, ..., H$. We show this breakdown in Table 1.3:

Table 1.3. BREAKDOWN TOTAL HOURS - KOREAN WAR

Date	$\bar{h}_t$	e_t	H_t	$H_{1950Q3+h} - H_{1950Q2}$	Int. Margin	Ext. Margin	Int. Margin (%)	Ext. Margin (%)
1950Q2	40.60	186.83	7585.43	0.00	0.0	0.0	-	-
1950Q3	42.10	200.00	8420.00	834.57	300.0	554.3	35.9%	66.4%
1950Q4	42.53	239.70	10195.24	2609.81	463.4	2248.6	17.8%	86.2%
1951Q1	43.70	284.57	12435.56	4850.13	882.2	4270.9	18.2%	88.1%
1951Q2	44.03	321.00	14134.70	6549.27	1102.1	5907.8	16.8%	90.2%
1951Q3	43.77	356.37	15596.98	8011.55	1128.5	7419.9	14.1%	92.6%
1951Q4	43.70	389.27	17010.95	9425.52	1206.7	8846.3	12.8%	93.9%
1952Q1	43.13	432.00	18633.60	11048.17	1094.4	10574.9	9.9%	95.7%
1952Q2	42.50	461.07	19595.33	12009.90	876.0	11654.9	7.3%	97.0%
1952Q3	42.83	494.30	21172.52	13587.08	1103.9	13169.8	8.1%	96.9%
1952Q4	43.33	534.37	23155.89	15570.46	1460.6	15059.8	9.4%	96.7%
1953Q1	42.87	569.43	24409.71	16824.28	1290.7	16400.8	7.7%	97.5%

Notice that the dynamic of Total hours, H_t is dominated by the extensive margin. Therefore, using total hours would overshadow the early change in hours-per-worker, which is a clear signal that contractors were already responding to the shock in the third quarter of 1950.

Delay in the FED's Defense Industrial Production Index:

Notice that the Board of Governors of Federal Reserve System constructs a monthly real index of industrial production of manufacturing equipment in defense industries.[34]

The Fed makes clear that such defense production index is *mainly obtained from BLS data on production-hours (i.e., total hours). Hours are then used to infer output.* However, we have just seen that the dynamics of total hours worked are delayed relative to average hours worked. In fact, we now show that hours-per-worker in the Aircraft industry leads defense production as measured by the Fed.

In particular, we study the lead-lag correlation map between each labor margin and defense procurement obligations, production, and spending. Figure 1.14 plots the results.

Firstly, looking at the first row, average hours of production workers in the Aircraft industry (intensive margin) appear to: (i) co-move with obligations, (ii) lead industrial output by 8 months (2 quarters), and (iii) lead payments by 4 quarters.

From the second row, we notice that the number of production workers (extensive margin) appear to: (i) lag behind obligations (the delay is about 3 quarters), (ii) co-move with the production index and (iii) co-move with payments.

Finally, the third row shows that total hours of production workers co-move with industrial production as measured by the Fed. This confirms the fact that the Federal Reserve adopts total hours to construct the defense production variable. Moreover, the maps of total hours and employment are basically identical, confirming our previous finding that the dynamics of employment drive movements in total hours.

To summarize, we show that the Fed measures defense production using total hours of production workers. However, the dynamics of total hours is dominated by employment, which is a delayed measure of production and overlooks the ability of producers to ramp-up

[34]Data is available from 1947 to present at monthly and quarterly frequency, both seasonally adjusted and not. It can be downloaded at this link. Detailed information on the Real Index of Industrial Production of Manufacturing Equipment in Defense sector is available at this link. In particular, the underlying industries used for the construction of the series are discussed in these two tables: (i) market structure (Equipment); (ii) Industry Group (defense and space).

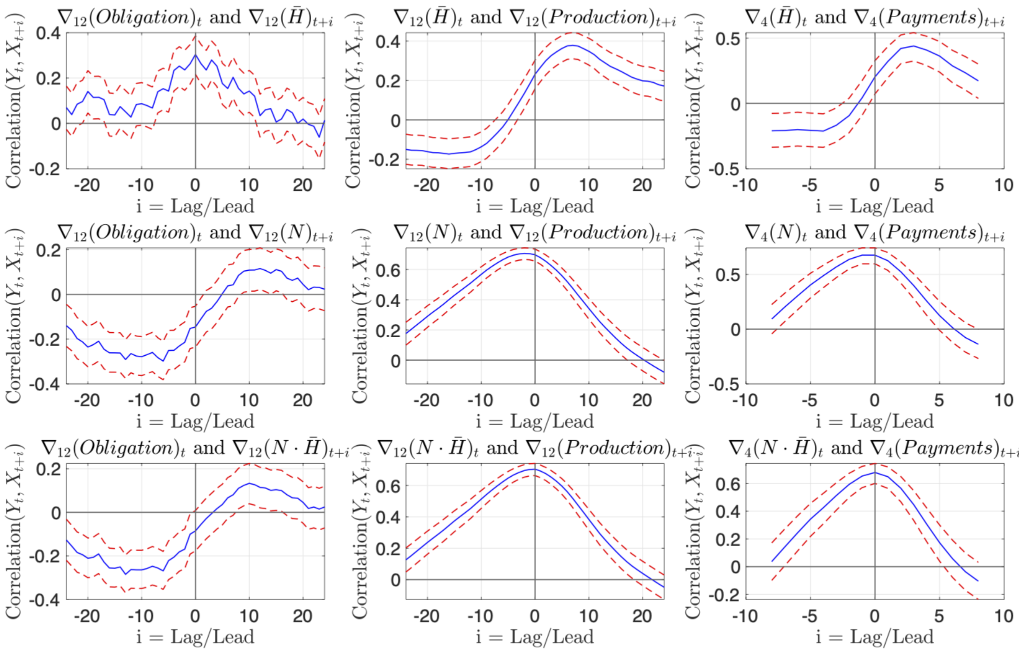


Figure 1.14. LEAD-LAG CORRELATION GRAPH - DEFENSE INDUSTRIAL PRODUCTION

Notes: Defense procurement spending is constructed as discussed in the first chapter and therefore tracks payments to contractors (sample from 1947Q1). Defense procurement obligations come from the original series from Business Condition Digest, discussed in Appendix 1.7.4 and track new contract awards (monthly data from 1951M1 to 1988M11). Defense Production is the monthly seasonally adjusted index constructed by the Fed (data available from 1947M1). Hours and employment data come from the BLS discontinued data series on production workers data (available from 1939M1 to 2003M12).

production by using more intensively their input of production (i.e., capital utilization and average hours worked). Specifically, the Fed's measure lags behind defense procurement obligations but co-moves with spending. This confirms that the Fed's production index is subject to the same delays which affects employment. In light of this, we believe that using average hours of production workers in the Aircraft industry is best suited for capturing real-time changes in defense production.

1.7.4 Details on Defense Procurement in the Data

In this section, we outline the details about measurement of defense procurement spending.

Section 1.7.4 clarifies the accounting origin in the NIPA of outlays which refer to the purchase of goods. Section 1.7.4 shows how we calculate the 2 to 3 quarters delay between defense procurement obligations and spending. Section 1.7.4 uses contract level data from the 2000 to rationalize the existence of a time delay and address the issue of partial delivery payments. Section 1.7.4 illustrates how we construct the quarterly time series of defense procurement obligations. Section 1.7.4 uses data from the 2000 on contracts' opportunities (i.e., contract level *solicitations*) to show that it is unlikely for contracts awards to be anticipated by more than one quarter.

Accounting Origin of Procurement in the NIPA

In this section, we provide further details on the accounting origin of public procurement contracts in the NIPA tables. Figure 1.15 summarizes the accounting of G, according to Chapter 9 of BEA (2017), which explains how the NIPA record all the entries of G. It highlights in red the two entries which contain public procurement spending: (i) Intermediate Goods and Services and (ii) Investment in Fixed Assets.

First of all, notice that G is made of two components, consumption and investments:

$$G = \underbrace{\text{Government Consumption Expenditure}}_{G^C} + \underbrace{\text{Government Gross Investments}}_{G^I}$$

Government Consumption Expenditure

Government consumption originates from the gross output of the government after deducting (i) Sales to Other Sectors and (ii) Own-Account Investments:

$$G^C = \underbrace{\text{Compensations} + \text{CFC} + \text{Intermediates and Services Purchased}}_{\text{Gross Output of General Government}} - \ldots$$
$$- \text{Own Account Investments} - \text{Sales to Others}$$

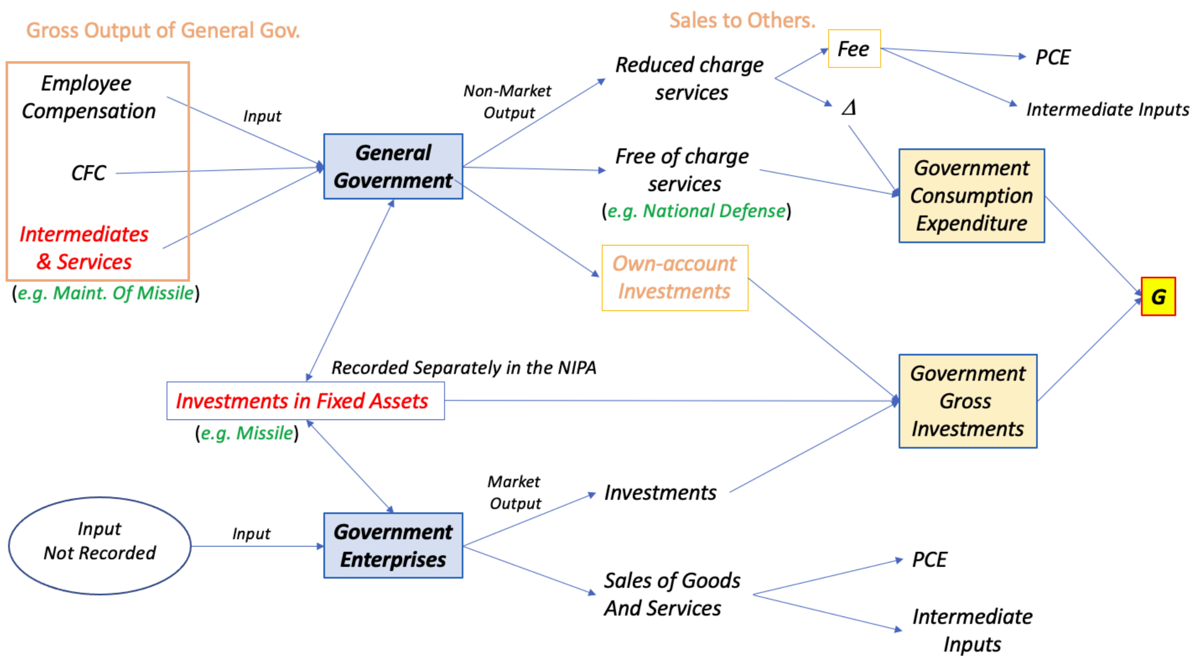


Figure 1.15. ACCOUNTING OF G - SUMMARY

Notes: CFC means "Cost of Fixed Capital" and measures depreciation of government assets. PCE means Personal Consumption Expenditure, the NIPA measure of Consumption which absorbs reduced charge services from the government (e.g. tuition fees from public universities). Own Account Investment is own resources reinvested in the public capital stock.

When a general government entity (e.g., DoD) decides to purchase goods and/or services, they are mainly accounted as Intermediates, which eventually end up in G as government consumption.

Government Gross Investments

The government also makes three types of investments. Firstly, the General Government makes Own-Account-Investments, which are deducted from the gross output of general government, in order to account them as investments. Secondly, both the General Government and Government Enterprises make investments in fixed assets. Investment in Fixed Assets contain other purchases from the private sector.

Example: Purchasing a Missile: To clarify this point, consider the case of the government purchasing a new set of guided missiles:

1. The missile is accounted as Equipment in the Federal Defense category of Change in

Government Fixed Assets and therefore contributes to G as part of Government Gross Investments.

2. Installation, Maintenance, Quality Control and other services related to the Missile are accounted as Intermediate Goods and Services Purchased (input of production).

3. The missiles and the related services are used to produce a non-market output of production, namely, national defense.

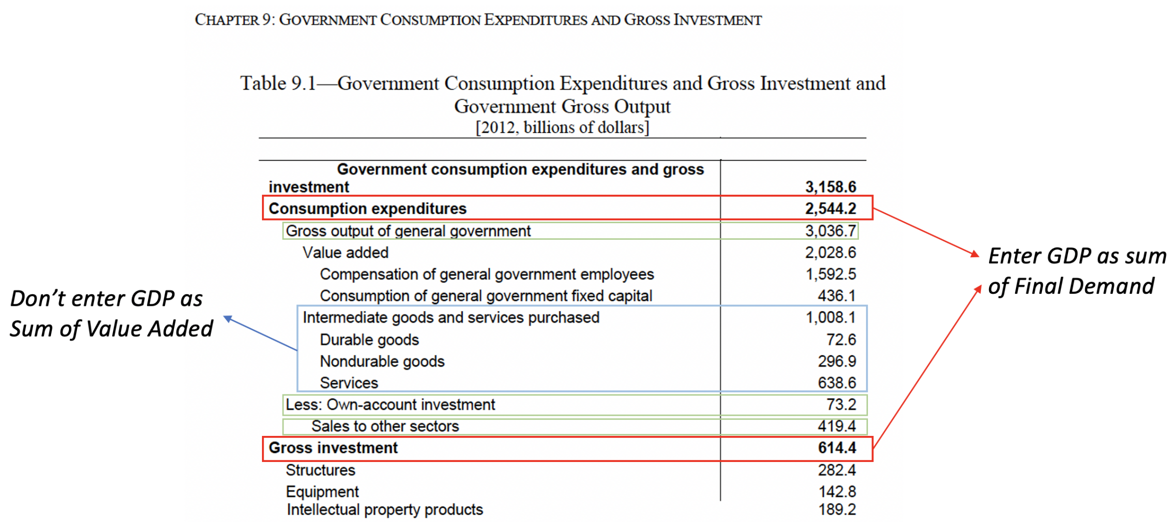
The production of the missile shows up in business inventories as long as the contractor supplying the missile delivers it to the government. Once delivered, inventories decrease and government investment increase. Notice that the reduction in inventories and the corresponding increase in G is a zero-sum game which does not increase GDP (recall that GDP in the US is constructed as the sum of final demand). GDP increases while production takes place and is recorded as inventories. In absence of time-to-build, inventories do not increase and the purchase of the item by the government directly shows up in G. For instance, this is the case of the Installation, Maintenance, Quality Control and other services related to the missile purchased by the Government.

Figure 1.16 provides an example of official accounting table of G, namely NIPA Table 3.10.5A, taken from BEA (2017).

Finally, to clarify the timing, we provide a visual representation of the process in Figure 1.17.

Time Mismatch Between Obligations and Payments

In Section 1.7.4, we show how we construct a proxy for defense procurement spending using data from the NIPA. We now show how we construct the defense procurement obligation proxy. Recall that obligations arise when the DoD awards new contracts while spending reflect government outlays, that is, payment to contractors. We observe obligations through two data sources, discussed below.



CHAPTER 9: GOVERNMENT CONSUMPTION EXPENDITURES AND GROSS INVESTMENT

Table 9.1—Government Consumption Expenditures and Gross Investment and Government Gross Output
[2012, billions of dollars]

Government consumption expenditures and gross investment	**3,158.6**
Consumption expenditures	**2,544.2**
Gross output of general government	3,036.7
Value added	2,028.6
Compensation of general government employees	1,592.5
Consumption of general government fixed capital	436.1
Intermediate goods and services purchased	1,008.1
Durable goods	72.6
Nondurable goods	296.9
Services	638.6
Less: Own-account investment	73.2
Sales to other sectors	419.4
Gross investment	**614.4**
Structures	282.4
Equipment	142.8
Intellectual property products	189.2

Figure 1.16. NIPA TABLE 3.10.5A - EXAMPLE

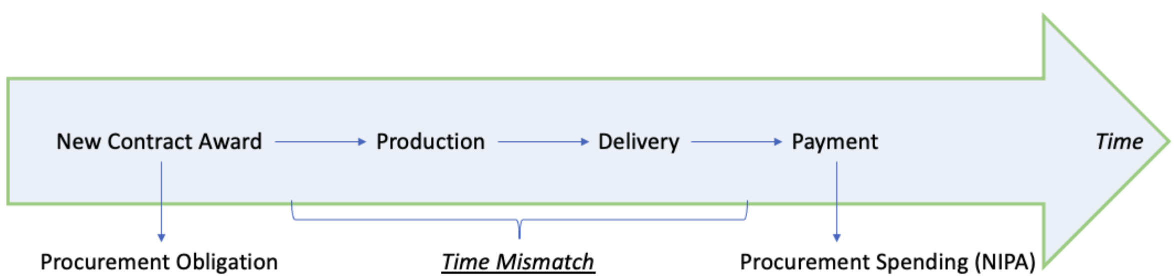


Figure 1.17. TIMELINE OF PROCUREMENT CONTRACTS.

Notes: The procurement timeline follows information from the Federal Acquisition Regulation (FAR) and the BEA's Concepts and Methods of NIPA.

Business Condition Digest:

The periodical *Business Conditions Digest*, available on Fraser at this link, provided Business Cycle Indicators, among which a list of Defense Indicators. The original source of the data was the Department of Defense, Office of the Assistant Secretary of Defense (seasonal adjustment implemented by BEA). In particular, we use Series 525, "*Defense Prime Contracts Awards*. This series was firstly collected by Valerie Ramey for her papers: Ramey (1989) and Ramey (1991). We are grateful to her for providing the data. The periodical was issued monthly from October 1961 until March 1990. However data is available from January 1951 to November

1988.

Business Condition Digest was discontinued in March 1990, and data on prime contracts is no longer recorded starting December 1988 (all year 1989 is missing). Most business indicators on *Business Condition Digest* were moved to another monthly periodical, namely the *Survey of Current Business*. Prime award contracts (series 525) was preserved and moved to Appendix C on *Business Cycle Indicators* (section 2.4: other important economic measures/government activities). Data is available in the form of scanned versions of the *Survey of Current Business* at this link. For some reason, data starting from 1991 does report values of prime contract awards for months in the fourth quarter (Q4) of every year. We believe this is a systematic omission, which results in less reliable data for this time period. Finally, due to reorganization of resources at the BEA, the *Business Cycle Indicators* section was discontinued, and prime award contracts were no longer disclosed to public, following the joint November-December 1995 issue. Therefore data is not available after this date.

To summarize, we obtain reliable monthly data on prime contract awards from January 1951 to November 1988. Notice that in order to match the quarterly frequency of procurement spending, obligation data is aggregated by quarters. Moreover, since NIPA data are annualized (their quarterly averages return their yearly values), we do the same for obligation data to allow for a closer comparison between the two series.

We observe from the graph that obligations lead spending. Notice that obligation data tends to be more noisy than spending data. The main reason for this is that large contracts are often awarded and then terminated a few months later for convenience, or due to litigation with a losing offeror (this is also highlighted in Auerbach, Gorodnichenko, and Murphy (2020)). Moreover, obligations are more lumpy than payments which get smoothed over the duration of a contract. In order to account for this, we use a simple MA smoother (red line in the graph). We then provide a quantitative assessment of the delay by looking at the lead-lag correlation map between the growth rates of smoothed obligations and the growth rates of spending (see top-right panel).[35]

Overall, we find a positive correlation between the two series which increases when obligations are delayed (top-right quadrant of the lead-lag correlation map). In particular, correlation spikes when obligations are delayed by 2, 5 and 8 quarters. Results are robust to a different approach which looks at the lead-lag correlation between year-to-year quarterly changes ($\nabla_4\, x_t = (1-L^4)x_t = x_t - x_{t-4}$) of original -i.e., not smoothed - obligations and spending. In this case, the spikes happen at 2 and 5 quarters.

Federal Procurement Data System Next Generation:

On September 26th 2006, the Federal Funding and Accountability Act is passed by congress as a first step towards a more transparent procurement system, which allows full disclosure of information involving federal contracts. The transparency effort by FFATA culminates in 2019 with the opening of a public website, USASpending.gov, which discloses information on all federal procurement contracts.[36] Data from USASPending.gov is pulled from FPDS-NG, the Federal Procurement Data System Next Generation, which actually includes the whole universe of procurement contracts. FPDS is the system used by government contracting officers to officially input data on awarded contracts in the government-wide system. Data from FPDS can be downloaded from USASpending.gov. The data spans 2000Q4 to the present with a caveat: contract data awarded before the beginning of the construction of the database could have been lost or not recorded. We collect data on all defense procurement contracts on FPDS between 2000Q4-2020Q3.

We again compare obligations and spending in Figure 1.18. The top-right panel plots again the lead-lag correlation between the growth rates of (smoothed) obligations and the growth rates of spending. The highest correlation is recorded when obligations are delayed by 1 quarter. Once again, the results are robust to looking at the lead-lag correlation of year-to-year quarterly changes between original obligations and spending. In this case, the peak occurs from 0 to 2

[35]We look at growth rates ($\Delta_1\, x_t = (1-L)^1 x_t = x_t - x_{t-1}$) to cope with the non-stationarity of the series.

[36]More information on the history of USASpending.gov can be found here.

quarters.

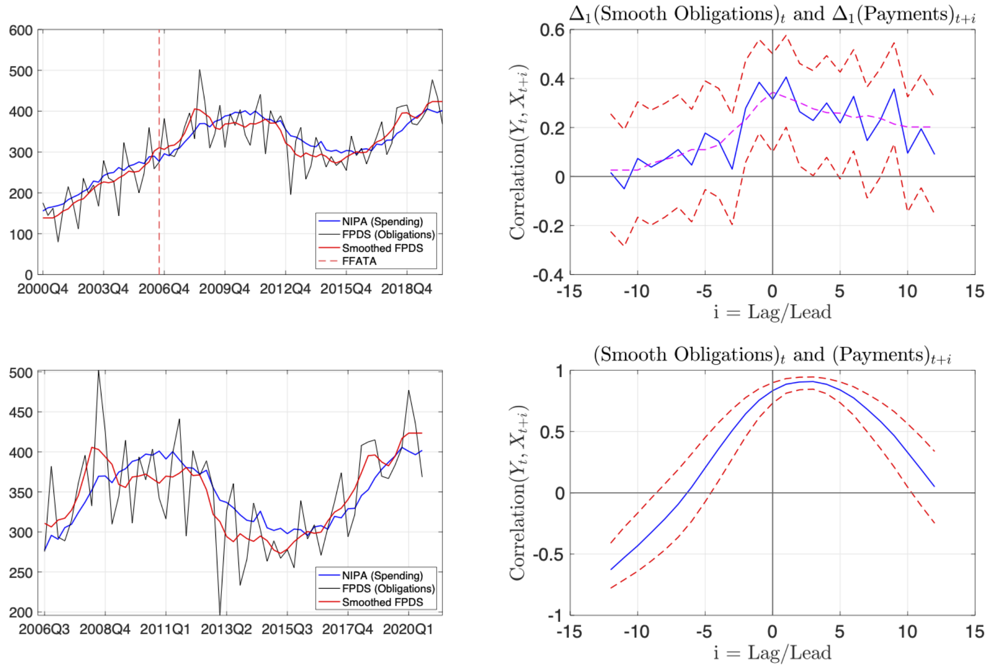


Figure 1.18. ACCOUNTING MISMATCH - JANUARY 2000 ONWARD

Figure 1.18's notes: the FPDS measure of obligation (blue line) is constructed by: (i) summing the daily data to obtain quarterly data; (ii) annualizing the data as done by NIPA; (iii) de-seasonalize data using Brockwell and Davis (1991)'s method (the Matlab code can be found here).

Before the signing of the FFATA, 2006, obligations seem under-reported relative to spending, thus inducing a downward bias in estimates of the accounting time-mismatch. We have two possible explanations for this counter-intuitive result, either this is a consequence of missing contract modifications awarded before the introduction of FPDS, or those modifications could have been classified before FFATA made most of contracts available to the public. In fact, FPDS-obligation data catches up and starts leading spending after the signing of the FFATA. Moreover, we show in Figure 1.19 that the share of large contracts (top 1%, 5% and 10%) out of all procurement spending stabilizes after 2006, indicating that large classified contracts are not showing up in FPDS.

We take this into account and we repeat the analysis only on those quarters following the signing of the FFATA (bottom panel of Figure 1.18). We observe a single clear spike in the lead-lag correlation, which indicates that obligations are delayed by 3 quarters relative to payments.[37]

Summary of Time Mismatch:

We summarize the time delay between obligations and spending in Table 1.4

Table 1.4. SUMMARY OF TIME MISMATCH BETWEEN SPENDING AND OBLIGATIONS

Period	*Data Source*	*Correlation Spike Delay (Quarters)* Δ_1	∇_4
1951M1 to 1988M11	BCD	2-5	2-5
2000M10 to 2020M9	FPDS	1	2
2006M1 to 2020M9	FPDS	3	-

These results suggest that the accounting delay between beginning of production (award date) and the first payment (outlay) is on average between 2 to 3 quarters. Notice also that the time delay seems to shorten over time, when we use FPDS data.

Overall, our results are consistent with anecdotal evidence that government payments happen once every 180 days.[38]

Rationalizing the Time Mismatch:

In this section, we rationalize the existence of an aggregate time-mismatch between defense procurement obligations and spending. In particular, we provide both theoretical and empirical micro-level evidence of the time mismatch.

Duration of Defense Procurement Contracts

Firstly, a necessary condition for the existence of an accounting mismatch is the long duration of contracts. If contracts were less than 90 days in duration, then payments would be

[37]The peculiar non-trending sinusoidal-wave shape of the data referring this period allows us to directly look at the correlation between the two series in levels. The super-positioning of waves which happen when we shift one series back and forth in time, allows to observe a single clear spike which refers to the exact period when the two series overlap. The correlation spikes when obligations are delayed by 3 quarters.

[38]We confirm this timeline in discussions with several federal procurement contractors.

processed in the same quarter as the award date.

We use FPDS data pulled from USASpending.gov from 2000Q4 to 2020Q3 to construct the distribution of duration of defense government contracts. In this context, contracts have two main types: (i) single transaction and (ii) multiple transaction.[39] We calculate the duration of a single transaction contract from the award date to the end of work. The award date almost always indicates the start of work associated with a contract. To calculate the duration of multiple transaction contracts, we take the oldest contract modification end date and subtract from it the "new-action award date".[40] Table 1.5 shows contract durations without distinguishing between single and multiple transaction contracts.

Table 1.5. (LOG)DURATION OF DEFENSE CONTRACTS

Stats		*Unweighted*		*Weighted (by Obligation)*	
		Duration (days)	*Log-Duration*	*Duration (days)*	*Log-Duration*
Percentiles	1%	0	0	0	0
	5%	0	0	46	3.85
	10%	0	0	193	5.27
	25%	3	1.39	514	6.24
	50%	20	3.04	1519	7.33
	75%	126	4.84	2962	7.99
	90%	377	5.93	4844	8.49
	95%	794	6.68	5464	8.61
	99%	2584	7.86	6887	8.84
Mean		173.03	3.09	1988.02	6.94
Std.		485.32	2.14	1746.81	1.57
Min.		0.00	0	0.00	0
Max.		7300.00	8.89	7300.00	8.89

Notes: defense contracts are identified by reporting DoD as funding/awarding agency. Data is taken from FPDS, all defense contracts from 2000Q1 to 2020Q1. Sample is restricted to those contracts for which the entire history of transactions (from the first new contract to the last modification) are available. Number of contracts in the sample is about 17 millions. Almost 5 thousands contracts with duration more than 20 years (7,300 days) are eliminated from the sample.

[39] Transactions which refer to the same contracts are pooled together through a unique contract identifier field in FPDS: `contract_unique_key_identifier`.

[40] This is possible because FPDS reports both the beginning and the end of the PoP (Period of Performance).

The median contract duration is 20 days and 90% of contracts have duration less than one year. These results are in line with the findings of Cox et al. (2023) and suggest that contracts have a short duration.[41] However, this measure does not take into account the size of contracts, as larger contracts might have longer duration. The right columns of Table 1.5 report the distribution of the contracts' (log)duration, weighted by the total obligation amount. The weighted distribution can be interpreted as the duration distribution of a $1 of spending in defense procurement. The following remark characterizes the mean and median of this distribution.

Remark 1.7.1 (Median/Mean Duration of $1) *The median duration of $1 of defense procurement spending is 4.16 years. The mean duration of $1 of defense procurement spending is 5.44 years.*

Notice that after weighting, the shape of the distribution drastically changes. This suggests that procurement spending is characterized by a small number of large and long-duration contracts. We confirm this in Figure 1.19, which plots the share of total spending of the largest 1%, 5% and 10% of contracts. We find that the largest 10% of contracts account for 95% of total spending, on average. Similarly, the top 1% of contracts accounts for roughly 80% of total spending on average.

To summarize the results of this section: (i) large contracts make the bulk of defense spending and (ii) large contracts have long duration.

Partial Delivery Payments:

Now, we want to rationalize the observed aggregate time delay. We do so by assuming there exists a representative large contract which follows a specific delayed payment schedule consistent with partial delivery payments.

Firstly, consider an example of a top 5% defense contract from FPDS. For instance, on December 22nd, 2015, the Department of Defense (DoD) awards a new multi-transactions

[41] They use a sample from 2001 to 2018 and find a median duration of defense contracts of 26 days and 90% of them have duration less than a year.

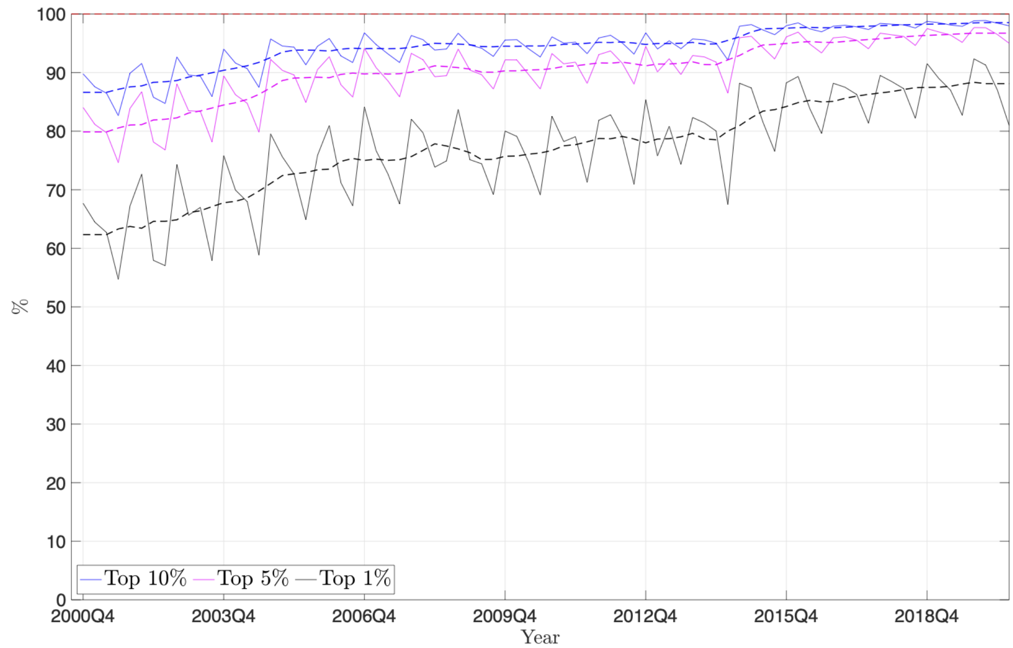


Figure 1.19. LARGE CONTRACTS SHARE OF TOTAL PROCUREMENT SPENDING

contract to L-3 Communications Corporation.[42] The contract has a duration of two years and involves the reparation and maintenance of some aircraft components and accessories.[43] At the time of obligation, this contract has several components, denoted child contracts, and 24 contract modifications. Each modification represents a new child contract with its own duration.[44]

In the top panel of Figure 1.20, we show on the left axis the amount of dollars obligated every quarter by this contract, and on the right axis the number of (child) contracts signed every quarter. The bottom panel shows the corresponding payment schedule which assumes that payments are disbursed once every 180 days, by uniformly spreading the initial amount of obligated funds over a contract duration.[45]

For instance, the first new child contract, signed in December 2015, lasts 375 days and

[42]See contract here.

[43]Duration is measured as the number of days between the Period of Performance (PoP) end date and the PoP start date.

[44]Modifications can have two types: (i) uni-lateral (e.g., administrative actions which obligate new funds for the specific contract) or (ii) bi-lateral (e.g., change to the original orders or additional work).

[45]This assumption is also made in Auerbach, Gorodnichenko, and Murphy (2020).

obligates almost $3 million by the DoD. The payment schedule assumes that the contractors start producing the parts to be replaced immediately with partial delivery and partial reimbursement after 180 days, Therefore, the contractor is paid $1.5 million in June 2016. Finally, in December 2016, the period of performance ends and the DoD pays to the contractor the remaining half of obligated funds.

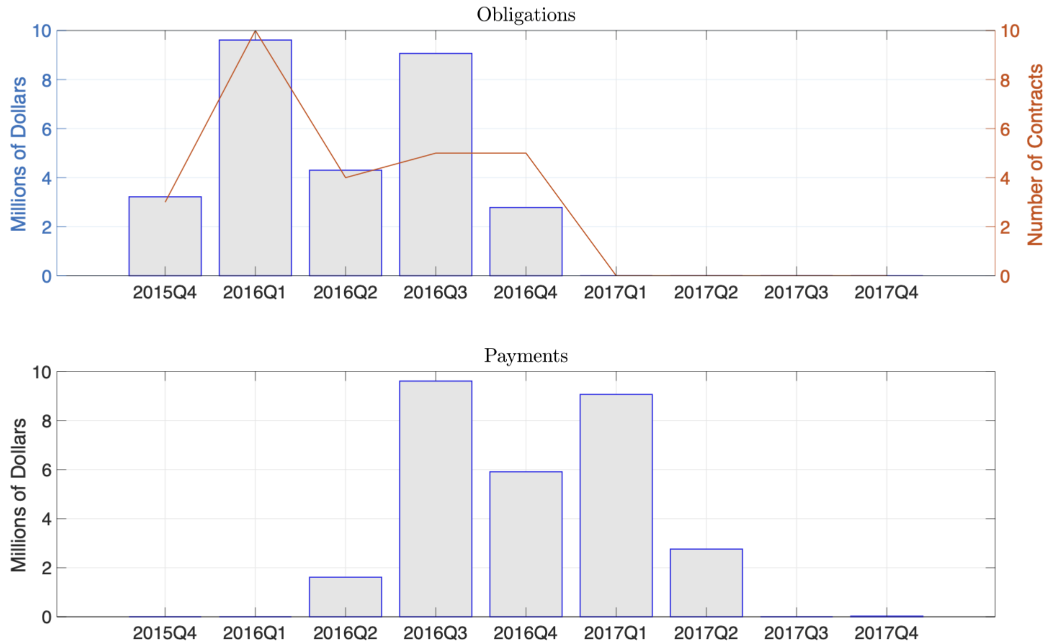


Figure 1.20. EXAMPLE OF A CONTRACT'S OBLIGATION AND PAYMENT SCHEDULE

Notice that payments look like a delayed version of obligations for this particular contract. The choice of 180 days delay between payments is consistent with our estimates for the average time mismatch between defense obligations and payments found earlier. The assumption of uniform production and payments is standard and consistent with the work of Auerbach, Gorodnichenko, and Murphy (2020). In general, contractors are often incentivized to distribute production associated with an obligation throughout the whole duration of the contract.[46] In the data, cost-overruns and delays are common (see e.g., Gonzalez-Lira, Carril, and M. S. Walker

[46]Consider a simple firm optimization problem with convex adjustment costs.

(2021)).

Therefore, consider a representative contract with a structure similar to the one just analyzed: few new child contracts followed by several modifications. Overall, the contract lasts 48 months - consistent with the median weighted duration of defense contracts (see Table 1.5) and is characterized by payments disbursed once every 6 months (for a total of 8 payments). If we denote by P_t the total payments to contractors at time t and by O_t the amount of obligations, it is easy to show that the mapping between spending and obligations is given by the following equation:

$$P_t = \frac{1}{8} \cdot \sum_{j=1}^{8} O_{t-6\cdot j}. \tag{1.4}$$

We take the obligation data from BCD and feed it into Equation (1.4) to construct a time series of simulated payments. The left panel of Figure 1.21 plots BCD defense obligations data and the so constructed payments.

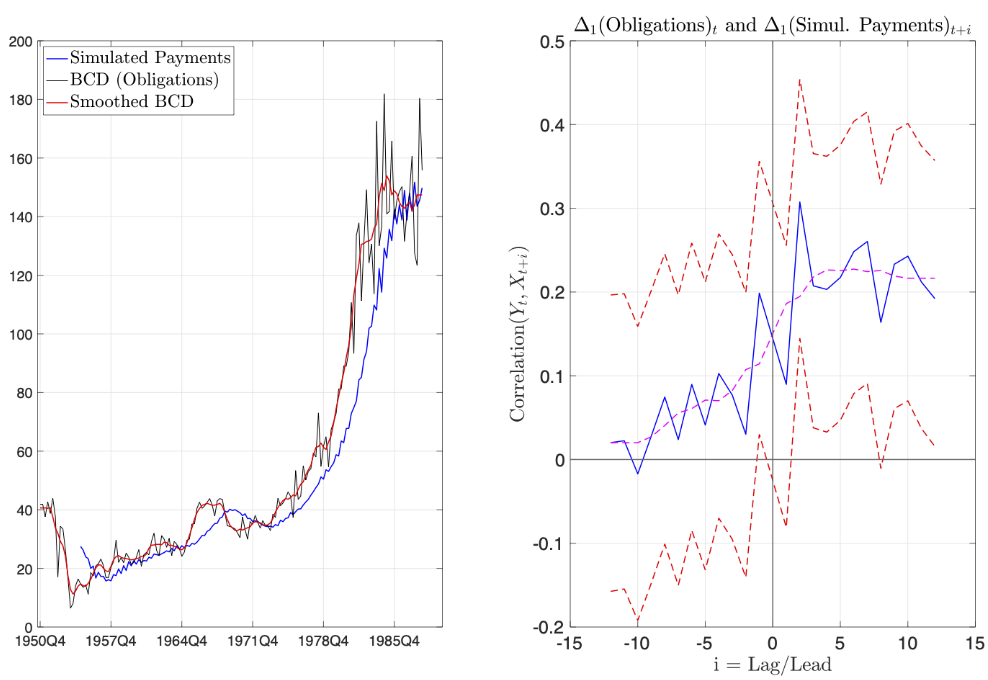


Figure 1.21. BCD Obligations and Simulated Payments

Despite the simplicity of the payments data generating process given by Equation (1.4), the simulated payments data approximate quite well the actual ones. Similarly, the right panel shows the lead-lag correlation map between the growth rates of (smoothed) obligations and simulated payments. Notice that the results are very similar to the ones obtained using real spending data.[47]

Construction of Quarterly Defense Obligation

We show here how we construct the time series of defense procurement obligations.

We face two main challenges: (i) we have obligations data only from 1951 to 1989 and from 2000 onward; (ii) obligations are very lumpy because contracts also get cancelled and we want to focus on obligations which turn into actual production.

i. We turn BCD and FPDS monthly data into quarterly annualized data (sum monthly observations within a quarter and multiply by 4).

ii. We apply the standard Brockwell and Davis (1991) filter to deaseasonalize the data.

iii. We construct a time trend which takes value of 1 in 1947Q1. Denote it by t.

iv. We predict obligations using 4 leads and lags and contemporaneous defense procurement spending, as well as time trends t and t^2.

v. We construct obligations from 1951Q1 to 1988Q4 using the predicted values from the previous regression. We use the estimated coefficients and the values of defense procurement spending from 1947 to 1951 to extrapolate obligations for those years.

vi. We predict obligations from year 2006 onward (FFATA introduction) in the same way. We use the predicted values to be our new series of obligations for those years. Since defense procurement (smoothed) obligations and spending overlap from 2000 to 2006, we use actual defense procurement spending for those years.

[47] We highlight that by allowing time varying number of payments (here 8) and payments delays (here 6 months), we can improve by far the approximation to the actual data. Here, we preferred to keep things simple in the interest of brevity and clarity.

vii. From 1989 to 2000 we use defense procurement spending to proxy obligations which turn into actual production.

Figure 1.22 plots the so constructed defense procurement obligations variable (pink dash line) along with defense procurement spending (blue line) and original defense procurement obligations (dark solid line).

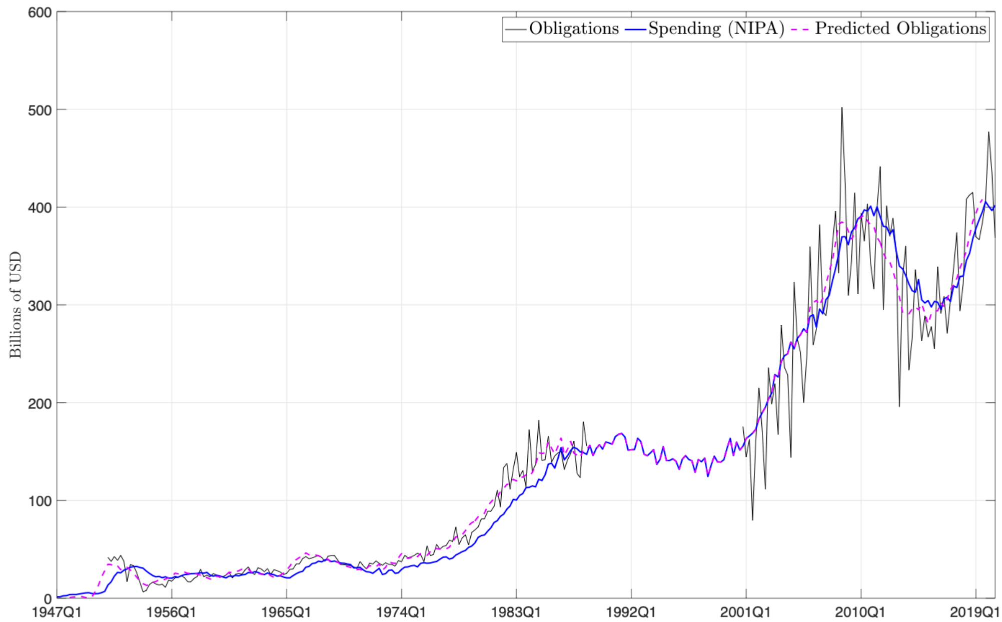


Figure 1.22. QUARTERLY DEFENSE OBLIGATION AND SPENDING

Notes: Variables: (i) $\bar{H}_t$ average hours of production workers; (ii) N_t number of production workers; (iii) $\bar{H}_t \cdot N_t$ total hours of production workers; (iv) *obligation* is defense prime contract awards from BCD (divided by potential output); (v) *output* is industrial production of manufacturing equipment in defense industries (divided by potential output); (vi) *payments* is defense procurement spending (divided by potential output).

What Goes On Before Contract Awards?

Although there is still uncertainty about the contract award when a pre-award notice is posted, firms might still take action in anticipation of the award. This might occur if a firm wants to become more competitive in the bidding process or predicts a contract win with a high probability. In addition, some pre-award notices justify the lack of competition in a sole-sourced contract proposal. In this case, the contractor might even predict a contract award with full certainty.

We argue from the data that any anticipatory behavior is likely to occur at a frequency higher than the frequency of aggregate analysis in this work. In other words, almost all information about contract opportunities is revealed to contractors within the quarter of the contract award. We summarize this finding by notice type in Table 1.6 and plot the distribution of pre-award notice lags in Figure 1.23.

Table 1.6. AVERAGE LAG BETWEEN PRE-AWARD NOTICES AND AWARD DATE

Notice Type	*Avg Lag in Days*	*Proportion of Notices*
Justification / Fair Opportunity	87	1.2%
Other	54	62.5%
Special Notice	41	2.1%
Pre-Solicitation	28	14.6%
Sources Sought	21	4.1%
Solicitation/Contract Solicitation	16	15.5%
TOTAL	43	

Notes: Based on matched notices between FPDS and Contract Opportunities.

Detailed Description of Solicitation Process:

Although public procurement contracts are awarded at a highly decentralized level (i.e., by over 69 federal agencies, 209 sub-agencies), all contracting officers are required to abide by the guidelines proposed in the Federal Acquisition Regulation (FAR). The FAR is a set of principles and procedures intended to organize and guide the procurement process across all federal agencies. In this section, we focus on the publicizing requirements associated with procurement contracts, depicted in Figure 1.24.

In particular, FAR Part 5 (*Publicizing Contract Actions*) requires that contractors publicize contract opportunities with the goal of increasing competition, broadening industry participation, and assisting small businesses in obtaining contracts. Since October 1, 2001, contract actions with an expected value of over $25,000 must be publicized in an online and easy-to-access

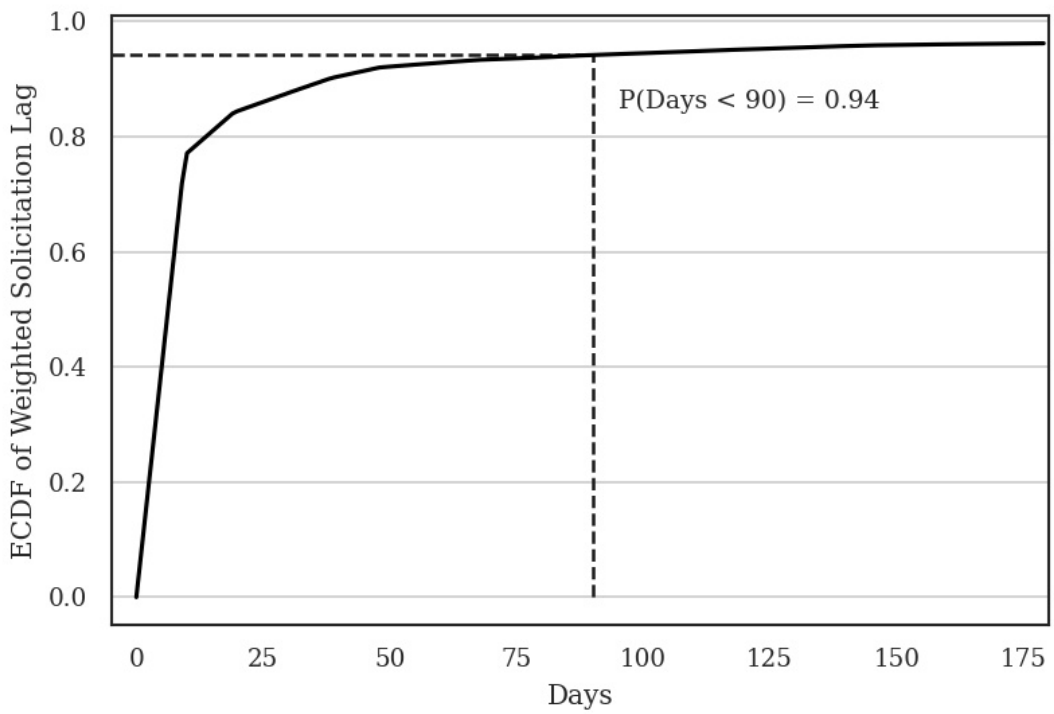


Figure 1.23. EMPIRICAL CDF OF (WEIGHTED) SOLICITATION LAG

Notes: Weighted duration between Contract Solicitation and Award dates measured in days. Dark dashed line represents 1 quarter (90 days). The Empirical CDF is estimated using Gaussian Kernel Density.

government platform, which we refer to as *Contract Opportunities*. Contract actions below the threshold might still be posted to increase visibility. On the other hand, FAR allows for exemptions to the requirement above the threshold when the posting might "compromise national security" or when the posting is "not in the government's interest". The result is that many contracts which are awarded are never solicited. When the regulation applies, Contract Opportunity notices are posted publicly at beta.sam.gov and include award notices such as solicitations, pre-solicitations, or other pre-award and post-award actions.

We describe the types of contract notices below.[48]

[48] Gonzalez-Lira, Carril, and M. S. Walker (2021) also provides a useful description and analysis of the publicizing requirements for Federal Procurement and the effects of information diffusion via public notices. We thank Andres Gonzales-Lira for directing us to the General Services Administration Technical Documentation for the FedBizOpps

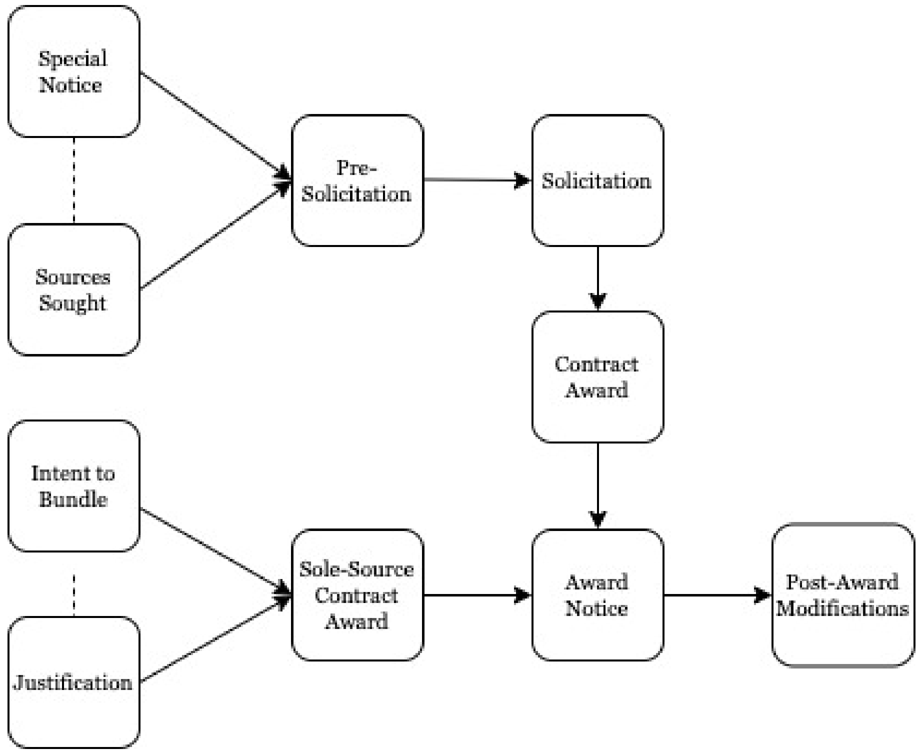


Figure 1.24. TIMELINE OF THE PROCUREMENT PROCESS

Notes: Notice prior to contract award step occur on average within the quarter. Source: beta.sam.gov daily files.

Special Notice

Agencies use Special Notices to announce important pre-award events such as business fairs, long-run procurement forecasts, or pre-award conferences and meetings. Special Notices might also refer to "Requests for Information" (RFI) or draft solicitations.

Sources Sought

Agencies post Sources Sought Notices in order to seek possible sources for a project. As discussed in FAR 7.3, the Sources Sought notice is not a solicitation for work or a request for proposal. Agencies typically use Sources Sought notices to collect industry feedback on key contracting strategy decisions and to perform market research on firm capabilities.

(FBO) website, whose information is now migrated to Contract Opportunities.

Pre-Solicitation

Agencies post a pre-solicitation to notify vendors that a solicitation may follow. Potential vendors might then express interest in the contract by adding themselves to the Interested Vendors List. Government agencies use pre-solicitations to determine the number of qualified vendors to perform the desired work. Contracting officers can also use pre-solicitations to gather information on interested suppliers and determine if a set-aside for a small business might be applicable.

Intent to Bundle Requirements

Agencies post "Intent to Bundle Requirements (DoD-Funded)" (ITB) whenever awarding actions are funded solely by the DoD. ITB supports the requirements in Section 820 of the Fiscal Year (FY) 2010 National Defense Authorization Act (NDAA) for contracting officers to post a notice of intent to use contract bundling procedures 30 days prior to releasing a solicitation or placing an order - if a solicitation is not required.

Solicitation

Agencies post a solicitation to clearly define government requirements for a potential contract so that businesses can submit competitive bids. A "Request for Proposal" (RFP) is the most common type of solicitation used by federal agencies. The solicitation also sets conditions and requirements for contractor proposals and includes the government's plan for evaluating submissions for potential award.

Combined Synopsis/Solicitation

Agencies post a combined synopsis/solicitation when a contract is open for bids from eligible vendors. The Synopsis/Solicitation includes specifications for the product or service requested and a due date for the proposal, as well as the bidding procedures associated with the solicitation.

Award Notice

Agencies post an award notice when they award a contract in response to a solicitation. Federal agencies may choose to upload a notice of the award to make aware other interested vendors of the winning bid. Note that the requirement guidelines for posting the award notice vary based on the agency and the solicitation.

Justification

Agencies are required to post a justification in order to obtain approval to award a contract without posting a solicitation as required by FAR 41 U.S.C. 253(c) and 10 U.S.C. 2304(c). Under certain conditions, agencies are authorized for contracting without full and open competition. The Department of Defense, Coast Guard, and National Aeronautics and Space Administration are subject to 10 U.S.C. 2304(c). Other executive agencies are subject to 41 U.S.C. 253(c). Contracting without providing for full and open competition or full and open competition after exclusion of sources is a violation, unless permitted by one of the exceptions in FAR 6.302.

Sale of Surplus Property

Agencies post a sale of surplus property notice when they wish to sell federal real estate properties for public use. These properties are typically made available for public use to state and local governments, regional agencies, or nonprofit organizations to state and local governments. Public uses for properties are those that are accessible to and can be shared by all members of a community, and include community centers, schools and colleges, parks, municipal buildings and many more.

1.7.5 Time-to-build or Production Smoothing?

We decompose the early response of inventories to a defense news shock into time-to-build and production smoothing. We already have contract level evidence of a long time-to-build, but at the onset of a military build-up, contractors should also presumably change their expectations about future government demand. Even if contractors lack resources to forecast government demand, federal agencies are required by the FAR to provide procurement forecasts each quarter.[49] If contractors anticipate winning future contracts, they might decide to increase production today to smooth convex adjustment costs or reduce future delivery times. We do not take a stance on the exact mechanism here. We consider a recent example of this type of behavior.

Example 1.7.1 (Lockheed Martin in 2022) *In the context of an ongoing military conflict between Russia and Ukraine, new military tests in North Korea, and escalating tension in relationship between China and Taiwan, US-based contractors have modified expectations about future defense spending. In particular, the largest American defense contractor, Lockheed Martin, decided in October 2022 to increase production of HIMARS (High Mobility Artillery Rocket System). When asked about this decision, CEO Jim Taiclet responded as follows:*[50]

> *"The company has met with its long lead supply chain and spent $65 million — which will eventually be paid back by the US government — to fund parts in advance, shortening the time needed to manufacture the rocket system. That was without a contract or any other memo or whatnot back from the government. We just went ahead and did that because we expected it to happen. So those parts are already being manufactured now".*

In order to measure production smoothing, we first provide a formal definition.

Definition (Production Smoothing of Defense Industries): We define production smoothing $\Delta(h)$ as the effect of a defense news shock on inventories, orthogonal to shocks to newly awarded contracts (i.e., defense procurement obligations). In particular, production smoothing is the

[49] See e.g., Agency Recurring Procurement Forecasts.

[50] Find the associated article on *Breaking Defense*. here.

impulse response of inventories to a defense news shock conditional on zero shocks to defense procurement obligations (i.e. orthogonalized IRF):

$$\Delta(h) = \mathbb{E}_t[\text{Invt}_{t+h}|Z_t = 1, \varepsilon_t^O = 0] - \mathbb{E}_t[\text{Invt}_{t+h}|Z_t = 0, \varepsilon_t^O = 0], \tag{1.5}$$

where Invt_t is changes in aggregate inventories as from the NIPA, Z_t is a defense news shock, and ε_t^O is a shock to defense procurement obligations.

We estimate production smoothing using the following tri-variate VAR using quarterly data from 1948Q1 to 2015Q4:

$$\begin{bmatrix} 1 & 0 & 0 \\ -\alpha & 1 & 0 \\ -\beta_{\text{News}} & -\beta_{\text{Oblg}} & 1 \end{bmatrix} \cdot \underbrace{\begin{bmatrix} Z_t \\ O_t \\ \text{Invt}_t \end{bmatrix}}_{\boldsymbol{X}_t^3} = \underset{3\times 3}{\boldsymbol{B}_3(L)} \cdot \boldsymbol{X}_t^3 + \boldsymbol{\varepsilon}_{3,t}$$

where $\mathbf{B}_3(L)$ is a polynomial in the lag operator. The parameter α captures the contemporaneous effect of a defense news shock on obligations, while β_{News} and β_{Oblg} capture the contemporaneous effect of shocks to news and obligations on inventories.

By including our aggregate series for defense procurement obligations O_t, we are able to calculate the effect of defense news shocks on inventories which is independent of the effect of shocks to newly awarded contracts. Figure 1.25 shows the impulse response function to a defense news shock estimated using the above tri-variate VAR as well as the total response of inventories estimated in a bi-variate VAR without obligations.

The top-left panel of Figure 1.25 shows the positive response of defense procurement obligations to a defense news shock. This indicates that new contracts start being awarded as soon as a defense news shock occurs. This confounds the effects of news (i.e., anticipation) with the effects of newly awarded contracts which show up in G with delay. In the bottom-left panel

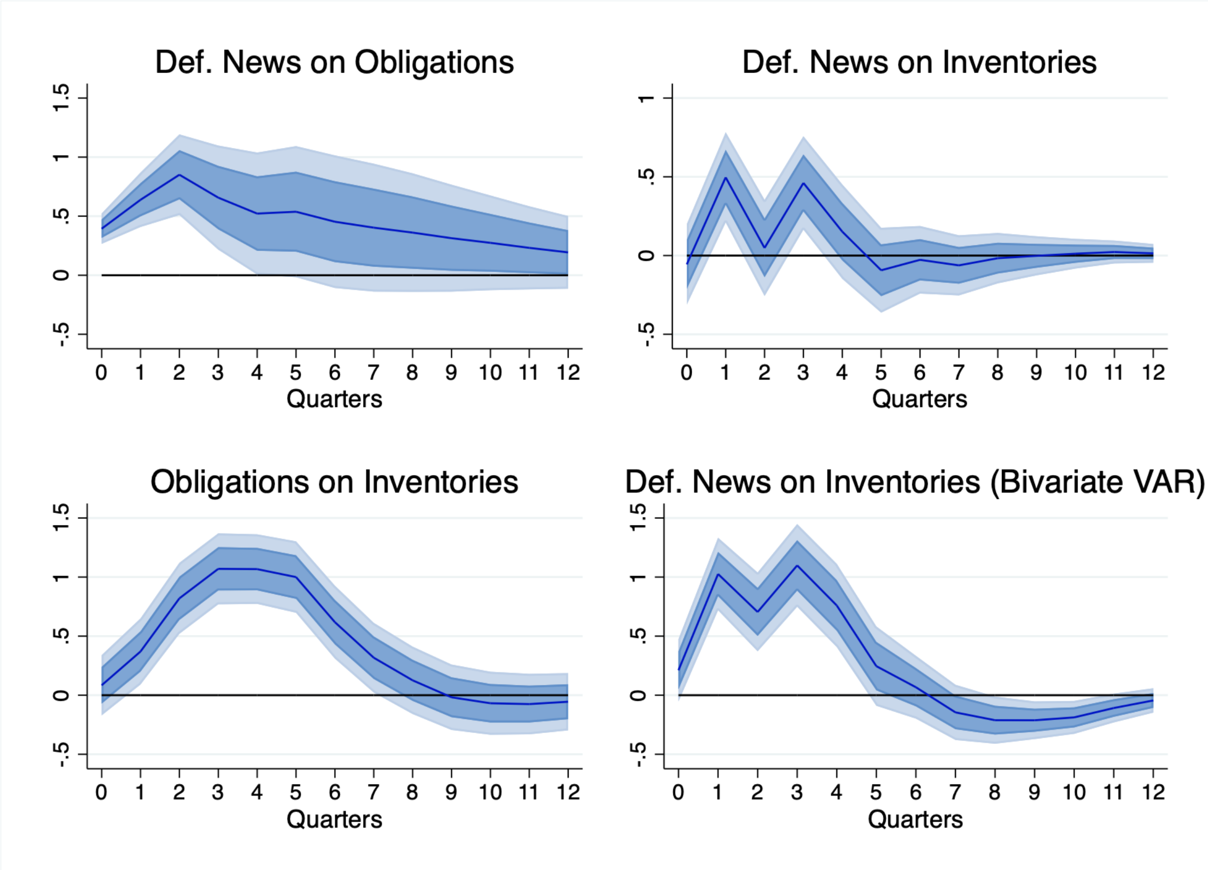


Figure 1.25. (ORTHOGONALIZED) IRFS FROM TRI/BI-VARIATE VARS

Notes: Variables are divided by potential GDP and include a linear time trend. Sample goes from 1948Q1 to 2015Q4. Confidence Bands are 68% and 90%. Values are rescaled by the peak response of Inventories to a defense news shock from the bivariate VAR which excludes defense procurement obligations.

of the figure, we show the effect of shock to obligations ε_t^O, on inventories, orthogonal to defense news. The effect is positive and significant. Additionally, the top-right panel reports production smoothing, or the response of inventories to a defense news shock which is orthogonal to newly awarded contracts. The positive and significant estimates of $\Delta_(h)$ at horizons 1 and 3 suggest that production smoothing plays a role in the response of inventories. The bottom-right panel shows the IRF of inventories to a defense news shock without including obligations in the VAR, i.e. bivariate VAR.

For interpretability, we rescale the IRFs by the peak response of inventories to a defense news shock in the bivariate VAR occurring at horizon 1. Since the horizon 1 response of inventories to a defense news shock in the tri-variate VAR is slightly more than 0.4 it means that roughly 40% of the response of inventories at horizon 1 comes from production smoothing, while the residual part (gap between bottom-right and top-right responses) originates from the effects of newly awarded contracts, i.e. time-to-build production. Intuitively, this can be seen by shrinking the tri-variate VAR into a bivariate one by plugging obligations into the equation of inventories:

$$\begin{bmatrix} 1 & 0 \\ -\left(\beta_{\text{News}} + \alpha \cdot \beta_{\text{Oblg}}\right) & 1 \end{bmatrix} \cdot \underbrace{\begin{bmatrix} Z_t \\ \text{Invt}_t \end{bmatrix}}_{\boldsymbol{X}_t^2} = \underset{2\times 2}{\boldsymbol{B}_2(L)} \cdot \boldsymbol{X}_t^2 + \boldsymbol{\varepsilon}_{2,t}$$

Notice that the impact effect of a defense news shock on inventories is the combination of production smoothing (β_{News}) and the effect of a shock to new contracts on inventories triggered by the news ($\alpha \cdot \beta_{\text{Oblg}}$). Basically, without controlling for new contracts, defense news shock capture both production smoothing and the time-to-build, while augmenting the VAR with new contracts allows us to tell-apart the two effects.

1.7.6 Robustness - Section 1.5

Firstly, we construct an index of cumulative excess returns similar to the Top3 index constructed in Fisher and Peters (2010). The variable is shown in Figure 1.26 along with red lines denoting the Ramey-Shapiro episodes.

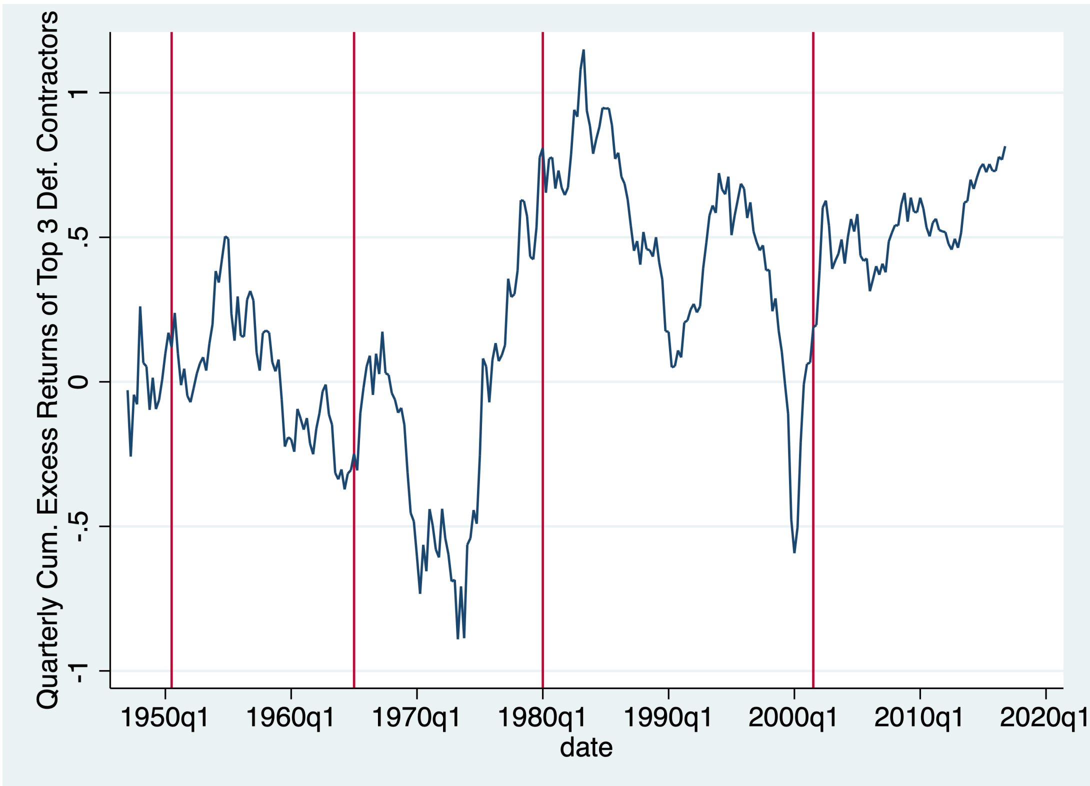


Figure 1.26. TOP3 DEFENSE CONTRACTORS STOCK PRICE INDEX

Notes: Red solid lines are the Ramey-Shapiro episodes. Index is constructed using cumulative excess returns

Similarly to Fisher and Peters (2010), the Top3 index onlr responds to the Vietnam war and 9/11, but not the Carter-Reagan military build-up nor the Korean war.

We construct shocks to this variable by ordering it first in the same VAR used in Section 1.2 of the first chapter. Furthermore, we complement the Granger Causality test in the first chapter by using these new shocks. Results are shown in table below.

It is clear from Table 1.7 that we find no significant predictability in either direction for the Top3 index.

Table 1.7. PREDICTABILITY OF RECURSIVE SHOCKS VIA OBLIGATIONS

Predicted	Predictor	F	Pvalue	Korea
Recursive Shocks	Top3	0.26	97.84%	Yes
Obligation Shocks	Top3	1.25	26.81%	Yes
Defense News Shocks	Top3	0.42	90.67%	Yes
Recursive Shocks	Top3	0.63	74.93%	No
Obligation Shocks	Top3	0.88	53.53%	No
Defense News Shocks	Top3	0.62	76.22%	No
Top3	Recursive Shocks	1.00	43.57%	Yes
Top3	Obligation Shocks	0.49	86.54%	Yes
Top3	Defense News Shocks	0.89	52.84%	Yes
Top3	Recursive Shocks	0.94	48.09%	No
Top3	Obligation Shocks	0.39	92.70%	No
Top3	Defense News Shocks	0.46	88.44%	No

Notes: Granger Causality test is a Wald test on the 8 lags of the predictor while controlling for 4 lags of the predicted variable.

Secondly, we exclude the Korean war from the sample. Results are shown in Figure 1.27.

1.8 Acknowledgments

Chapter 1, in full, is a reprint of the version submitted to the *American Economic Review*, which was granted a Reject&Resubmit. The original paper is co-authored with Victor Sellemi. The dissertation author was the primary investigator and author of this paper.

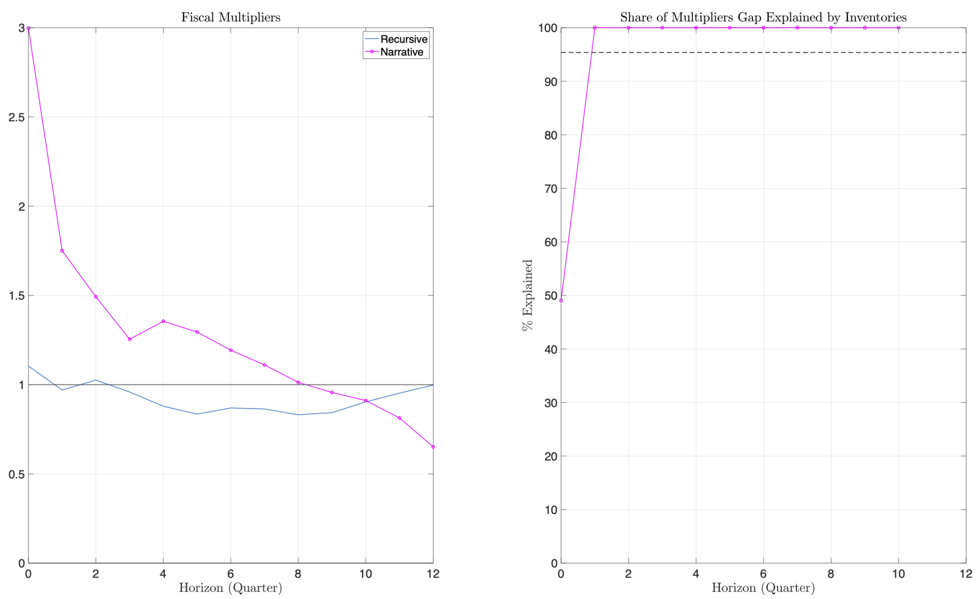


Figure 1.27. FISCAL MULTIPLIERS AND MULTIPLIER-GAP (ROBUSTNESS)

Notes: Sample goes from 1954Q1 to 2015Q4.

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Chapter 2

On The Effects of Government Purchases and Their Transmission Mechanism

2.1 Introduction

What is the impact of government spending (G) on consumption and GDP? Despite this being one of the classic questions in macroeconomics, there is still no consensus on the answer, with the debate centered on the assumptions and methods used to identify government spending shocks.

In this second chapter, I propose to identify government spending shocks using a newly constructed instrument for government spending: "defense contracts," a quarterly time series available from 1947:1, accounting for the dollar value of all US military prime contracts. I find that if government spending increases by 1$, non-durable-plus-service consumption increases by 0.12$.

Previous work in the fiscal policy literature can be divided into two main camps: the Blanchard and Perotti (2002)'s approach, or "SVAR Approach," which identifies government spending shocks by ordering G first in a VAR (henceforth, BP shocks); and (ii) the instrument approach, which (i) relies on instruments for G which measure expected defense spending and (ii) places them first in a VAR.

The first line of research, the SVAR approach, has faced criticism due to its failure to account for the anticipatory effect of government spending (Ramey (2011)). As a response, Ramey proposed the use of “defense news shocks” as an instrument for G. Simultaneously, the second line of research, the instrument approach, has been criticized for reasons such as weak instrument problems.

In this second chapter, my measure aims to address both of these shortcomings. Specifically, I demonstrate that defense contracts accurately measure the timing of the shocks, without missing out on any early and relevant GDP response. Furthermore, defense contracts preserve statistical power and alleviate concerns about weak instrument problems.

The literature has found positive responses of consumption in response to BP shocks but concerns arise from their timing and their potential endogeneity. In fact, G might endogenously respond to GDP within the same quarter, violating the VAR’s recursive assumption (i.e., Cholesky identification). In contrast, defense contracts reflect variation in defense spending that is primarily driven by exogenous military events. Moreover, changes in government spending are anticipated, and BP shocks, constructed using government spending, are anticipated too (Ramey (2011)). In contrast, defense contracts reflect the future value of defense procurement spending, which is part of the National Income and Product Accounts (NIPA)’s measure of G, and they accurately measure the timing of the fiscal shocks. In fact, NIPA follows the accounting practice to record most defense contracts into G only after payment-on-delivery, which, in the case of several complex items such as aircraft and missiles, occurs several quarters after the beginning of production (see Brunet (2022) and Briganti and Sellemi (2023)). Therefore, G lags behind the placement of new defense orders, as measured by defense contracts. Simultaneously, NIPA keeps track of ongoing production in response to new orders using inventories. In fact, I find positive responses of inventories, displaying a faster response than G.

Considering the endogeneity and anticipation of government spending, the literature has constructed instruments which measure future changes in military spending. For example, Ramey (2011) and Ramey and Zubairy (2018) narratively construct defense news shocks, which measure future changes in military spending deemed exogenous to output variations; Fisher and

Peters (2010) constructs Top 5, an index of cumulative excess returns of defense contractors; Ben Zeev and Pappa (2017) identifies defense news shocks using medium-run restrictions. A shared limitation of all these instruments is that they suffer from low statistical power in samples after the Korean War, that is, after 1953 (Ramey (2016)). In fact, results can be quite sensitive to the exclusion of the Korean War (Perotti (2014)). Even if I argue that the Korean War must be included in the baseline sample, as the US economy never turned into a war-economy and its size is dwarfed by the scale of WWII (Hickman (1955), Dupor and Guerrero (2017)), defense contracts provide results robust to the exclusion of the Korean War from the sample. Furthermore, defense contracts preserve statistical power in samples after the Korean War.

Given that defense contracts effectively address the main critiques of the literature regarding the timing of shocks and the statistical power of the instruments, my results remain resilient against these fundamental concerns and aim to provide a more conclusive answer to the longstanding questions on the effects of government purchases.

In the second part of the chapter, I find that a shock to defense contracts causes an increase in labor productivity, which can, in theory, rationalize the observed rise in consumption (Devereux, Head, and Lapham (1996)). Using balance-sheet data from publicly traded defense contractors from Compustat and contract data from the Top100 companies report from the Department of Defense (DoD), I also find that lagged contracts are associated with higher labor productivity of defense contractors around the years of the Vietnam war. Christiansen and Goudie (2007) find similar results using a panel VAR from 1969 to 1996. I offer a comprehensive examination of how learning-by-doing in manufacturing and military production enhances productivity with rising production rates, offering a plausible explanation for the observed rise in labor productivity in response to contracts. To provide context, here are two interesting anecdotes: (i) the concept of learning-by-doing itself was introduced to economics through the analysis of military aircraft production data (Arrow (1962)), and (ii) even the official BEA's Government Transaction Methodology Paper acknowledges the effects of learning in generating rapid price declines for military items due to increased productivity.

Therefore, I use a two-sector RBC model with manufacturing and non-manufacturing to rationalize the empirical evidence. In the model, government purchases increase only in manufacturing, to mimic the well-known sectoral bias of procurement spending (Ramey and Shapiro (1998), Perotti (2007), Nekarda and Ramey (2011), Cox et al. (2023)). Additionally, only manufacturing production is characterized by learning-by-doing, allowing for an increase in labor productivity when production rates rise. The use of learning-by-doing is motivated by the aforementioned thorough discussion of its vast empirical evidence, found almost exclusively in manufacturing and defense production. In the model, learning can induce an increase in consumption of a magnitude similar to that empirically observed, thereby rationalizing the VAR evidence.

Related Literature

My work directly speaks to the vast literature which studies the aggregate effects of government spending. The literature can be segmented into two groups: those finding positive consumption responses with the "*SVAR approach*" and those generally finding negative responses via the "*instrument approach*."

Firstly, the SVAR approach identifies government spending shocks by ordering the NIPA measure of G first in a VAR (Fatas and Mihov (2001), Blanchard and Perotti (2002), Galí, López-Salido, and Vallés (2007), Monacelli and Perotti (2008) and Perotti (2014)). This method is based on the notion that policymakers and legislatures require more than a quarter to learn about a GDP shock, determine the appropriate fiscal response, pass these measures through the legislature, and implement them.

Secondly, the instrument approach identifies government spending shocks by constructing instruments for G using different measures of expected military spending. The instruments use (i) military spending instead of total spending to ensure that the variation is driven by exogenous military events and (ii) expected changes instead of current changes, as government spending is often anticipated several quarters in advance (Ramey (2011)). Notable examples using this approach are Ramey (1989), Ramey (1991), Ramey and Shapiro (1998), Burnside, Eichenbaum, and Fisher (2004), Eichenbaum and Fisher (2005), Fisher and Peters (2010), Ramey (2011), Barro and Redlick (2011), Ben Zeev and Pappa (2017) and Ramey and Zubairy (2018).

Advocates of the instrument approach criticize the SVAR approach, contending that because government spending is anticipated, the shocks they identify are predictable (Ramey (2011)). Proponents of the SVAR approach counter by claiming that the instruments for G often lack statistical power and are overly sensitive to the sample choice (Perotti (2014)).

I contribute to the literature by constructing a new instrument for government spending, "*defense contracts*", which addresses the central critiques from both sides of the literature. Namely, defense contracts measure expected defense (procurement) spending in line with the instrument approach, while avoiding the pitfall of low statistical power and sample choice sensitivity, thus addressing the criticism raised by proponents of the SVAR approach.

The idea of using defense contracts to identify government spending shocks builds on the recent work of Brunet (2022) and Briganti and Sellemi (2023), who propose an alternative empirical explanation for why GDP moves before G in response to a defense news shock (Ramey (2011)). They highlight the NIPA's accounting practice of recording military contracts for complex military items, such as aircraft or missiles, at the time of the payment, which occurs after delivery. NIPA keeps track of the ongoing contractors' production by recording a positive change in inventories. In fact, they find positive responses of inventories in response to fiscal shocks. *The change in inventories creates a semblance of fiscal foresight as GDP mechanically moves before G due to accounting reasons.* If the limitation of the SVAR approach is its oversight of GDP's early response, but this effect primarily reflects contractors' production in response to new contracts not yet recorded by NIPA in G, then defense contracts can account for this, as their timing is aligned with the beginning of production. This distinction clarifies why defense contracts accurately reflects the timing of the shocks and offers a significant advantage over the SVAR approach, which instead relies on the NIPA measure of G, which records military contracts with a delay.

Concerning the effects of new contracts on contractors labor productivity, my work directly relates to Christiansen and Goudie (2007), who find a positive response of labor productivity of defense contractors in response to newly awarded contracts, using a sample which starts from 1969. Since I have been able to gather all available Top 100 companies report from the Directorate for Information Operations and Reports (DIOR), I extend the analysis from 1960 to 1969, the years around the outbreak of the Vietnam war.

I also relate to the vast literature on learning-by-doing developed around manufacturing and, in particular, military programs. Notable examples are: Wright (1936), Asher (1956), Alchian (1963), Smith (1976), Gulledge and Womer (1986), Bourgoine and Collins (1982), Argote and Epple (1990), Argote, Beckman, and Epple (1990), Benkard (2000). Other relevant works which discuss labor productivity gains due to learning effects during WWII are: McGrattan and Ohanian (2010) and Ilzetzki (2023) (i.e. "*Learning-by-Necessity*").

Lastly, on the empirical side, my contribution relates to other works studying the effects of government spending in the US economy. Notable examples are classified as follows: Mountford and Uhlig (2009) (sign restrictions); Leeper, Traum, and Walker (2017) (Bayesian prior and posterior analysis of DSGE model); state/sign dependency: Auerbach and Gorodnichenko (2012), Ramey and Zubairy (2018) and Barnichon, Debortoli, and Matthes (2022); state/city level analysis: Nakamura and Steinsson (2014), Dupor and Guerrero (2017) and Auerbach, Gorodnichenko, and Murphy (2020); consumer level analysis: Giavazzi and McMahon (2012) and Coibion, Gorodnichenko, and Weber (2020); industry level analysis: Acemoglu, Akcigit, and Kerr (2016), Bouakez, Rachedi, and Santoro (2023) and Barattieri, Cacciatore, and Traum (2023).

Although my model is inspired by an empirical question — whether enhancements in labor productivity for manufacturers or contractors due to learning effects can boost aggregate labor productivity and increase consumption — it implicitly relates to the theoretical literature that develops models resulting in consumption increases following a positive government spending shock.

To the best of my knowledge, the models that yield a consumption increase in response to a positive government spending shock are limited to a few examples: Devereux, Head, and Lapham (1996) employs an RBC model with increasing returns to specialization as per Krugman (1979); Galí, López-Salido, and Vallés (2007) uses a New Keynesian (NK) model with rule-of-thumb consumers; both Monacelli and Perotti (2008) and Bilbiie (2011) apply a NK model with non-separable preferences and consumption-hours complementarities; and Jørgensen and Ravn (2022) adopts a medium-scale NK model with variable technology utilization. However, none of these models are well-suited to answer my question, as they do not feature a two-sector framework with manufacturing characterized by learning-by-doing. D'Alessandro, Fella, and Melosi (2019) integrate the learning-by-doing mechanism from Chang, Gomes, and Schorfheide (2002) into a one-sector medium-scale NK model, resulting in increased consumption. Nevertheless, there are two crucial distinctions between our models. First, my model is driven by the observation that learning-by-doing predominantly occurs in manufacturing data and military programs. Consequently, I adopt a two-sector model aligned with this observation, calibrating the learning parameters using empirical findings from military data. Second, my approach to modeling learning differs slightly from Chang, Gomes, and Schorfheide (2002). While they rely on past deviations of hours worked, I use current deviations of manufacturing output, consistent with empirical literature examining learning curves in manufacturing and military programs.

The second chapter is organized as follows: Section 2.2 delineates the construction of the new instrument for G, namely defense contracts, and discusses its benefits. Section 2.3 presents the empirical results. Section 2.4 offers a theoretical rationalization of the empirical findings.

Section 2.5 concludes.

2.2 A New Instrument for G

2.2.1 From VAR Shocks to Contracts

Measuring the aggregate effects of government spending requires the identification of government spending shocks. The conditions that ensure a valid identification of government spending shocks are (i) exogeneity to output changes and (ii) unpredictability (Ramey (2016)).

The SVAR approach identifies government spending shocks using the principle that changes in government spending at quarterly frequency are predetermined (Blanchard and Perotti (2002)). This is achieved by ordering the NIPA measure of government spending, G, first in a VAR (i.e. Cholesky identification). I will refer to these shocks, as the BP shocks.

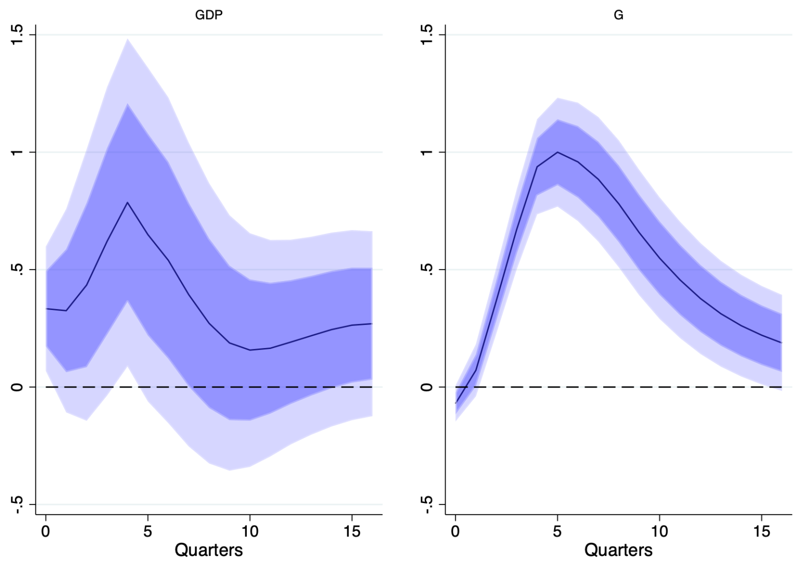
One main concern with BP shocks is that most variation in government spending can be anticipated by economic agents. To better illustrate the point that GDP and its components can move even before any actual visible change in G, I replicate in the top-panel of Figure 2.1 the impulse response functions (IRFs) of GDP and G to a defense news shock, found in Ramey (2011). Firstly, defense news shock is a narratively constructed instrument for government spending, G, which measures the present discounted value of expected changes in military spending associated by exogenous military events, as predicted by the periodical *Business Week*:[1]

$$(\text{Defense News Shocks})_t = \sum_{h=0}^{H} \mathbb{E}\left(\frac{G_{t+h}^{\text{Defense}}}{(1+i_t)^h}\middle|\Omega_t^{\text{News}} \cap \Omega_t^{\text{Exogenous}}\right), \tag{2.1}$$

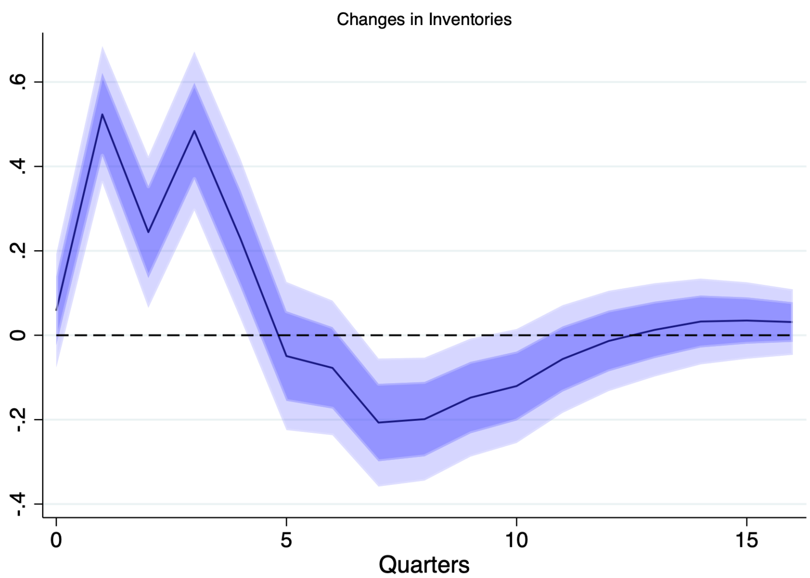
where i_t is the interest rate and Ω denotes an information set.

After a defense news shock, the IRF of G increases starting from quarter 2, while the GDP surge is immediate. The literature attributes the earlier GDP response to the Ricardian behavior of economic agents who supply more hours in anticipation of expected higher taxes

[1] See Figure notes for VAR details.



(a) ANTICIPATION EFFECT OF G



(b) RESPONSE OF INVENTORIES

Figure 2.1. RESPONSE TO A DEFENSE NEWS SHOCK

Notes: IRFs of GDP, G and Inventories with respect to a defense news shock (updated series of Ramey and Zubairy (2018)). Sample: 1947:1 to 2015:4. Values normalized by the peak response of G. IRFs are obtained from a VAR with defense news shocks, G, GDP, tax receipts, business sector hours worked, and the 3-month T-Bill rate, inventories and a quadratic trend. Real variables are divided by real potential GDP, estimated with a sixth degree polynomial fit to log-real GDP (see Ramey (2016)).

needed to fund the additional expenditure (i.e. *negative income effect*).

An alternative explanation is presented by Brunet (2022) and Briganti and Sellemi (2023).

Brunet suggests that the NIPA measure for G is time delayed, as NIPA logs government contracts only upon delivery of the purchased items. In particular, when the government commissions new aircraft, multiple contracts are secured for various components like the airframe, engine, and communication systems. These components are manufactured for multiple aircraft, assembled, and only then delivered to the government. The entire process spans several quarters, with contractors compensated after-delivery. As NIPA logs these payments, a timing disparity arises between the beginning of production and the recording of contracts into G by NIPA.[2] Both Brunet (2022) and Briganti and Sellemi (2023) document empirically the time lag. Furthermore, Brunet posits that NIPA accounts for ongoing production using inventories, a claim for which Briganti and Sellemi (2023) provide corroborative evidence. The bottom-panel of Figure 2.1 exhibits the IRF of inventories following a defense news shock, mirroring the findings of Briganti and Sellemi (2023).

Notice that inventories exhibit a positive response to a defense news shock, peaking at horizon 1 — prior to the initial response of G. Briganti and Sellemi (2023) conclude that the detected anticipation effect with defense news shocks can be attributed to inventory responses, which mirror the deferred production of defense items in G, stemming from two primary factors: (i) the convention of compensating contractors after-delivery and (ii) the duration required to fabricate complex defense items, like military aircraft.

2.2.2 Construction and Benefits of Defense Contracts

In this section I detail the construction of a new quarterly variable of defense contracts and illustrate its advantages compared to other established instruments for government spending.

Construction of Defense Contracts

First, data on defense contracts is recorded when a firm is awarded a new prime contract award from the DoD. For example, imagine Boeing wins a new contract worth 800 million

[2] See the F-15 example at page II-33 of the Government Transaction Methodology paper and the "timing difference" paragraph at page II-11 of the same.

dollars for new military aircraft in quarter t, then Boeing will commence the airframe production within the quarter following the award date, since this moment denotes the end of any demand-uncertainty for Boeing.[3] Payments are processed as batches of parts are sequentially delivered from Boeing to the DoD. For instance, Auerbach, Gorodnichenko, and Murphy (2020) convert lumpy contract data from FPDS-NG into spending data by evenly distributing the value of a contract over its duration. In this example, if the contract to Boeing has duration of 2 years, NIPA spending will contain 100 million dollars in each subsequent quarter according to their logic.

Hence, defense *contracts* can be perceived as a weighted average of the current and future values of NIPA defense procurement *spending*, which is a component of G:

$$\left(\text{Defense Contracts}\right)_t = \sum_{h=0}^{H} \psi_h \cdot G_{t+h}^{\text{Defense Procurement}} \tag{2.2}$$

As a result, the values of future NIPA defense procurement *spending* are known to firms in advance at time t, since the value of lumpy contracts is incorporated by NIPA into G with a delay. Most importantly, as noted in Brunet (2022) and Briganti and Sellemi (2023), when production-deliveries take longer than one quarter, NIPA keeps track of ongoing production using inventories, not defense procurement spending (i.e. G).

Furthermore, comparing Equations (2.1) and (2.2) reveals the similarities and differences between defense news shocks and defense contracts. First, their sole commonality is that they both measure future military spending. However, defense news shocks measure the expectations of overall future defense spending related to exogenous military events as forecasted by the news. In contrast, defense contracts mirror the present value of awarded contracts, which are recorded in G after a delay due to NIPA's accounting methods. In this regard, the two variables differ significantly in the way the measure future military spending.

In what follows I describe the data sources of defense contracts.

[3] I will address the potential anticipatory behavior of contractors in the subsequent section.

(i) BCD:

The first data source comes from contract data used in Ramey (1989), which is originally from the periodical Business Condition Digest, or "*BCD*".[4] It contains monthly data of prime military contracts from January 1951 until November 1988.[5]

A data limitation arises from the fact that the BCD series starts in 1951, during the Korean War, the largest military shock in the post-WWII sample. Therefore, I use NIPA data on defense procurement spending, constructed as in Cox et al. (2023).[6] Given that NIPA data lags behind defense contracts, I use both contemporaneous and future defense procurement spending to forecast current defense procurement contracts. In particular, I estimate the following equation via OLS, spanning from 1951:1 to 1980:4:

$$\underbrace{\text{BCD}_t}_{\text{Def. Prcm. Contracts}} = \kappa + \sum_{h=0}^{4} \psi_h \cdot \underbrace{\text{NIPA}_{t+h}}_{\text{Def. Prcm. Spending}} + \varepsilon_t .$$

The linear regression yields an R^2 of 80%. Using the OLS estimates and the NIPA data on defense procurement spending from 1947:1 to 1950:4, I predict the defense procurement contracts for that time frame. This data is referred to as "*BCD Extrapolated*"

(ii) FPSR:

The second data source originates from the annual Official Federal Procurement Summary Report ("*FPSR*"), produced by DIOR. It contains data on both annual and quarterly federal procurement contracts, and is available starting from the inception of the Federal Procurement Data System (FPDS) in the first quarter of 1981 and ends in the third quarter of 2003. The annual reports present the value of military prime contract awards by fiscal year. They also feature bar

[4]Military contracts became part of the set of instruments known as the Hall-Ramey Instruments (from Hall (1990) and Ramey (1989)).

[5]The series was then discontinued and migrated on the Survey of Current Business (SCB). However, data on SCB is only available from January 1990 until September 1995 with a systematic omission of the fourth quarter of the year. Data on SCB is very noisy and because of the systematic omission, less reliable. Therefore, I will not use this data source.

[6]Sum of NIPA defense intermediate goods and services purchased plus defense gross investments on structure, equipment and software.

charts illustrating quarterly values of total federal procurement contracts: federal defense plus federal non-defense. To remove the non-defense component from the quarterly values, I adjust the quarterly data so that the average of the quarterly values within each fiscal year is equal to the official annual annual values of military data. This adjustment is innocuous; in Online Appendix A, I demonstrate that the fluctuations in federal procurement largely stem from its defense component. Specifically, I reveal that (i) approximately 80% of the federal procurement during those years is attributable to military procurement, and (ii) the quarterly federal values, when aggregated by fiscal year, correlate strongly with the annual military values.

(iii) FPDS-NG:

After the fourth quarter of 2000, all daily federal procurement transactions are observed from the Next Generation of FPDS (or "*FPDS-NG*"). I aggregate all new defense contracts and defense contracts modifications by quarter. Since the FPDS-NG data is very noisy, and most noise comes from contract modifications, I add the original new defense contracts to "smoothed" defense contracts modifications.[7] Therefore, the high-frequency variation in the FPDS-NG data comes from newly-awarded contracts and not contract modifications.

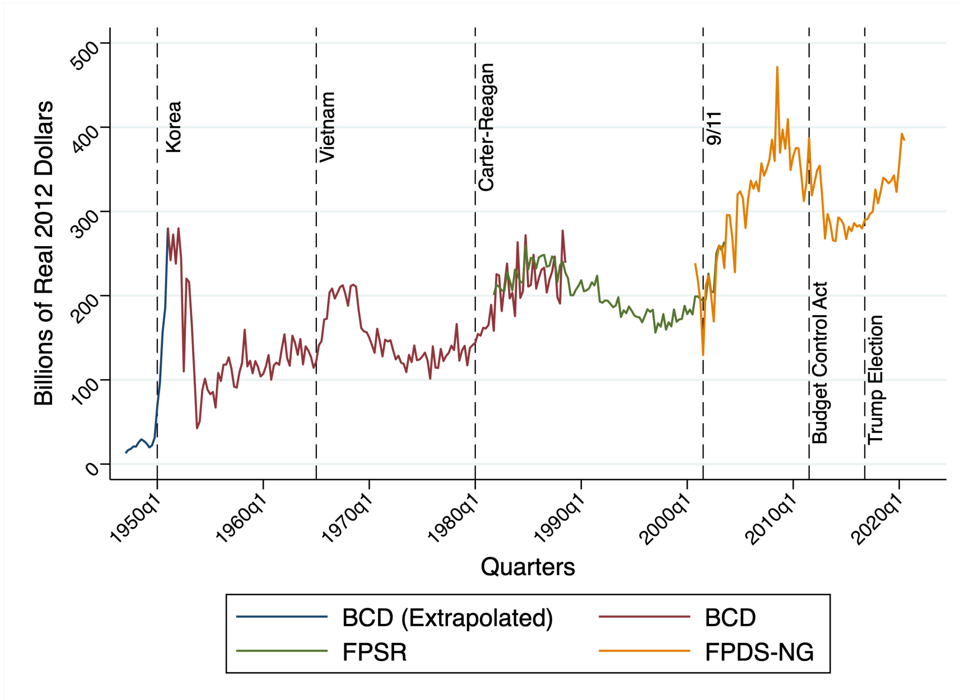
Assembling the Series:

The top panel of Figure 2.2 shows real prime contract measures along with the Ramey and Shapiro (1998)'s war dates augmented with the 9/11, the Budget Control Act of 2011 and the election of President Trump.

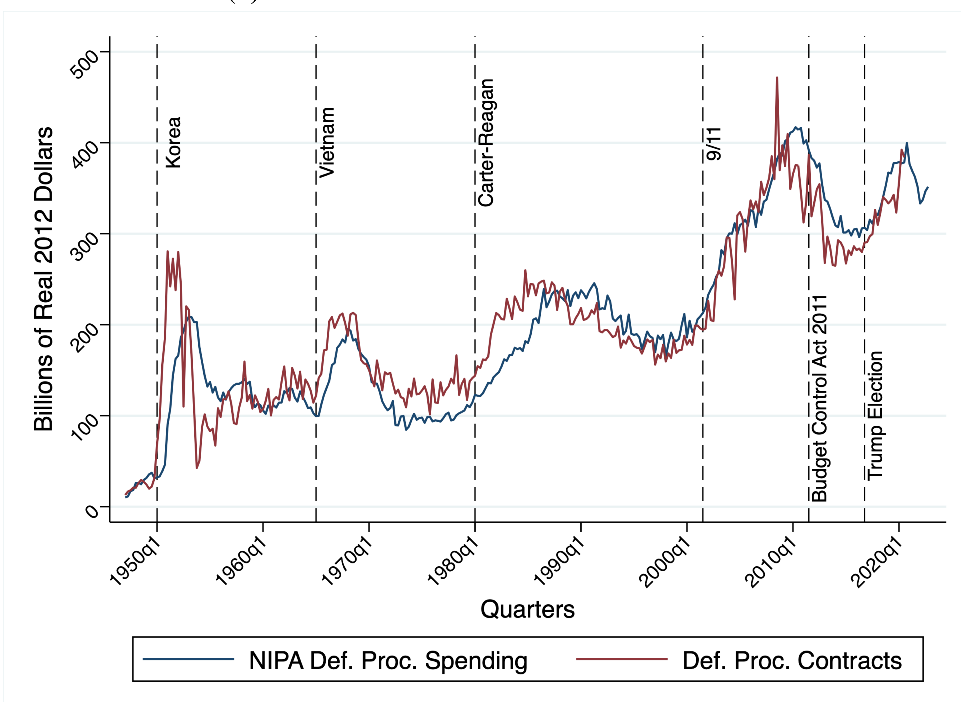
Notice how well the measures overlap in the 80s and at the beginning of the 2000s, indicating a remarkable consistency across the different data sources.

I append all the data from the four sources to construct a new quarterly variable of defense contracts from 1947:1 until 2019:4. In particular, the series is made of data from (i) BCD-extrapolated from 1947:1 until 1950:4, (ii) BCD from 1951:1 until 1980:4, (iii) FPSR from 1981:4 until 2003:3 and (iv) FPDS-NG from 2004:1 onward. Henceforth, I will refer to

[7] Examples of contract modifications are funding only actions, request for extra work, options exercise, cancellations of some work.



(a) Military Prime Contracts Measures



(b) Military Contracts Vs Military Spending

Figure 2.2. Defense Procurement

this variable as simply "*(defense) contracts*". The bottom panel of Figure 2.2 shows the newly constructed (real) defense contracts and (real) defense procurement spending from the NIPA data.[8]

Time Variation:

It is recognized that the primary variations in Government spending (G) are attributed to the military events of the 20th century (Hall (2009) and Ramey (2016)). This is portrayed in Figure 2.3, displaying the newly constructed variable defense contracts as a share of GDP.

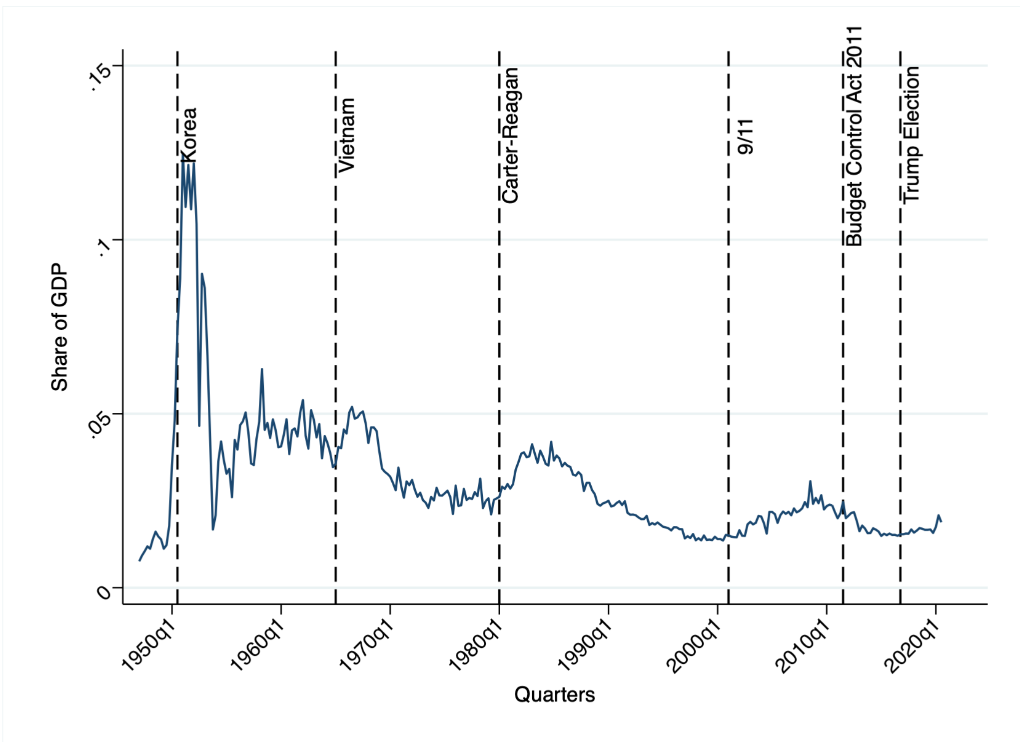


Figure 2.3. DEFENSE CONTRACTS AS SHARE OF GDP

Major shifts in defense expenditure relative to GDP size are mainly linked to war events in the 20th century, with the Korean War standing out as the most substantial shock in the post-WWII era. However, it is worth noting that the Korean War did not transform the US economy into a war-centric one, and its relative size pales when compared to WWII. Consequently, the

[8]Price deflator is an average of price indices for NIPA intermediate goods and services purchased and government gross investments.

Korean War provides a natural experiment to study the impact of government spending and should be part of the baseline sample, since it did not transform the US economy into a war economy (see Hickman (1955) and Dupor and Guerrero (2017)).[9]

The variation of military spending relative to GDP in the early decades of the 21st century is clearly smaller than the variation of the second half of the 20th century. Therefore, I primarily use the 1947:1-2000:4 sample for yielding the most accurate estimates. For robustness, I will also check results with a sample which excludes the Korean War (1954:1 to 2000:4), as sensitivity of results to the exclusion of the Korean war is a well-known fact in the literature (Perotti (2014), Ramey (2016)). Similarly, I will check the robustness of my results over the full-sample (1947:1 - 2019:4). Overall, my results are robust across the three samples.

Advantages of Contracts

In this section, I argue that defense contracts accurately measure the timing of shocks, addressing a limitation of the SVAR approach. Secondly, I maintain that defense contracts can serve as an instrument for G, given that the variable is (i) exogenous and (ii) relevant. Lastly, I highlight that defense contracts do not necessitate a narrative analysis, offering a readily accessible method for estimating the effects of government spending in countries that maintain records of military contracts.

Measurement Delay in NIPA:

The previous section discussed how the early response of GDP relative to G in response to a defense news shock can be reconducted to the early response of inventories. In turn, the response of inventories captures defense production which does not show up in G yet. In fact, G accounts for the dollar value of the contracts only after payments to contractors, which happen after delivery of the item goods. Since it takes time to produce a defense item, such as a guided missile or an aircraft, G will be delayed relative to contracts (see Brunet (2022) and Briganti and

[9] I am aware that price controls were introduced at the end of January 1951, however, their effect was very limited (Hickman (1955)).

Sellemi (2023)).

In fact, the bottom panel of figure 2.2 shows that defense contracts lead defense procurement spending from the NIPA, a component of G. I quantify the delay using a lead-lag correlation map. In particular, Figure 2.4 plots the correlation map between quarterly year-to-year changes of defense procurement contracts and spending.[10]

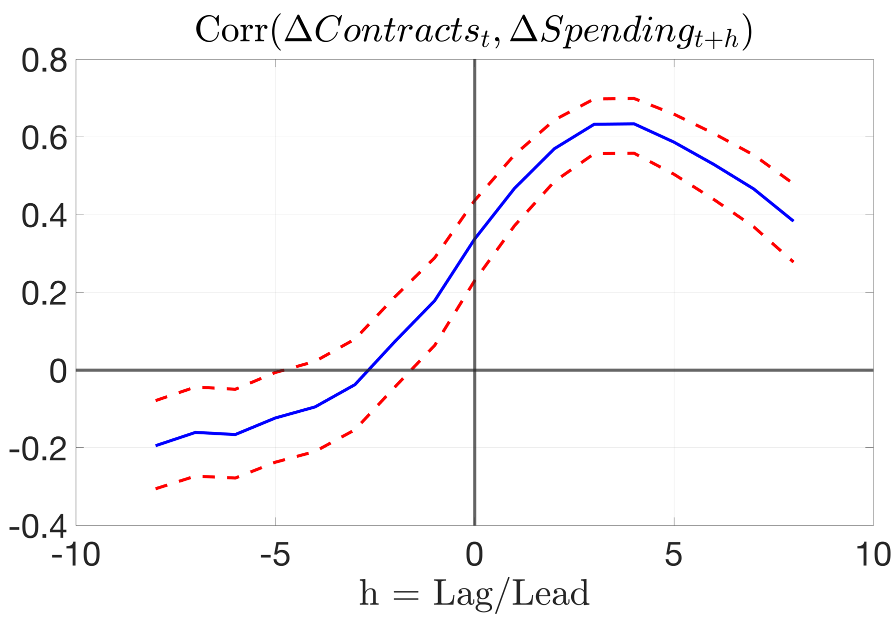


Figure 2.4. LEAD-LAG CORRELATION MAP BETWEEN CONTRACTS/SPENDING

Notes: sample goes from 1948:1 to 2019:4. Here $\Delta_4 x_t$ means $x_t - x_{t-4}$. The price deflator used is the one of Intermediate goods and services purchased by the government, available from NIPA.

Since the correlation map is positive in the North-East quadrant, that is, when spending is delayed, changes in defense procurement contracts anticipate changes in defense procurement spending, as measured by NIPA. In particular, the correlation map spikes at 3 quarters, suggesting a similar average time-delay between contracts and payments. The result replicates if I use first-differences instead of quarterly year-to-year changes and if I look at different time-periods. Robustness checks are reported in Online Appendix A.1.

Another way to formally observe the time delay in G relative to defense contracts is by

[10]Briganti and Sellemi (2023) use lead-lag correlation to study the time mismatch between BCD prime contracts and NIPA spending and find a delay of about 3 quarters between the two.

means of Granger-causality tests. Firstly, I construct BP shocks to government spending by ordering the NIPA measure of G first in a VAR; then, I construct shocks to defense contracts by augmenting the previous VAR with defense contracts ordered first; finally, I conduct Granger Causality tests to see whether one predicts the other and viceversa. Results are reported in Table 2.1.

Table 2.1. DO DEFENSE CONTRACT SHOCKS GRANGER CAUSE BP SHOCKS?

Predicted	*Predictor*	*F*	*Pvalue*	*Sample*
Defense Contract Shocks	BP Shocks	1.34	22.25%	1947:1 - 2019:4
Defense Contract Shocks	BP Shocks	1.13	34.47%	1951:1 -2019:4
BP Shocks	Defense Contract Shocks	7.7	0.00%	1947:1 - 2019:4
BP Shocks	Defense Contract Shocks	3.86	0.00%	1951:1 - 2019:4

Notes: Granger Causality test is a Wald test on the 8 lags of the predictor while controlling for 4 lags of the predicted variable. BP shocks are constructed as OLS residual of a regression of G on four lags of G, GDP, Hours worked in the private sector, 3 Months T-Bill rate. Shocks to defense contracts are obtained as OLS residuals of a regression of defense contracts on four lags of defense contracts, G, GDP, Hours worked in the private sector, 3 Months T-Bill rate. All nominal variables are in logs of real per-capita values while hours are in logs.

The top panel of the table shows that BP shocks fail to predict shocks to defense contracts. On the contrary, shocks to defense contracts do predict the BP shocks., as visible from the bottom panel of the table. Results are robust to the exclusion of the outbreak of the Korean war, 1950:3, which uses extrapolated contract data from NIPA defense procurement spending. I interpret this result as a consequence of the delay in recording military contracts into NIPA measure of government spending, as evident from Figure 2.2 and the lead-lag correlation map.

Defense contracts anticipate NIPA spending, however, I still have to rule out the possibility that contractors systematically anticipate future contracts and begin production even before new contracts awards. Therefore, I carry out two tests.

The first test boils down in augmenting the VAR with Ramey (2011)'s defense news shocks ordered first and investigate the response of contracts and inventories. In fact, if contractors systematically anticipate new contracts, I would expect inventories to significantly respond to a defense news shock even before any significant response of defense contracts. If this is the case, even though contracts predate NIPA spending, they would still miss part of the early response of inventories, which reflects contractors' production.

Therefore, I augment the VAR with the Ramey (2011)'s defense news shocks and inventories. I then look at the IRFs of contracts and inventories to a defense news shock, ordered first. The IRFs are showed in Figure 2.5.

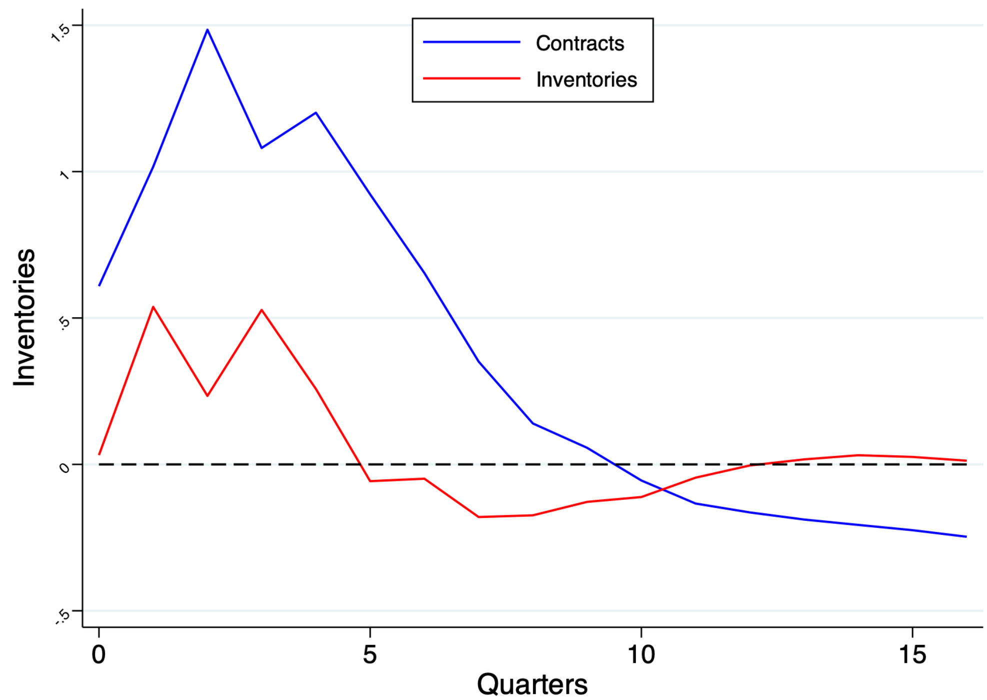


Figure 2.5. Do Contracts Miss Inventories After a Def. News Shock?

Notes: Point estimates of IRFs of defense contracts and inventories to a defense news shock. Sample goes from 1947:1 to 2019:4. IRFs are obtained from the same VAR of Figure 2.1

Notice that the response of contracts (blue line) is largely positive already on impact, indicating that when a defense news shock occurs, newly awarded contracts are disbursed *within the quarter* of the shock's occurrence. In contrast, inventories increase only from quarter 1, that is, *after* the initial positive response of contracts. In other words, concurrently with a positive defense news shock, the Department of Defense promptly awards new prime contracts and contractors appear to increase production, as monitored by inventories, only after the receipt of those newly awarded contracts. Therefore, defense contracts do not miss any part of the response of inventories which occurs before the change in G.

The second test I carry out answers the question: does the stock market anticipate new defense contracts? Therefore, I construct an equally weighted portfolio of stock prices from four major defense contractors: Boeing, Northrop-Grumman, Lockheed-Martin, and Raytheon which goes from 1947:1 till 2001:4.[11] Then, I calculate the cumulative excess quarterly year-to-year returns for this defense sector portfolio, using the S&P500 as a benchmark index; this approach is inspired by the work of Fisher and Peters (2010). I will refer to this variable as the "*Top 4*" index.

I then use a VAR with Top 4 index, defense contracts, G, GDP, hours worked in the private sector, TB3 and total NIPA tax receipts. I look at the IRF of Top 4 index in response to a shock to contracts as well as the IRF of contracts in response to a shock to the Top 4 index. I choose the sample from 1954:1 to 2001:4, which excludes the Korean war as done in Fisher and Peters (2010), who noted that the overall stock-market response at the start of the Korean war was significantly dampened by the profit tax increase.

The top-left panel shows the IRF of the Top 4 index in response to a shock to defense contracts when defense contracts are ordered first in the VAR. The response is precisely estimated and indicates that the portfolio gradually increases its value, peaking 3 quarters after the shock to defense contracts. Conversely, the top-right panel illustrates the IRF of contracts to a shock to the Top 4 excess returns, with defense contracts still ordered first in the VAR. The results suggest that after a positive shock to the Top 4 index, defense contracts do not increase, and the response is imprecisely estimated.

Next, I assume the Top 4 index to be predetermined to contracts by ordering it first in the VAR. A positive shock to defense contracts has a similar effect on the Top 4, although the IRF is

[11]The companies' choice is motivated by their large dependence of their total revenues on government purchases as well as their constant presence in the list of Top 100 defense contractors.

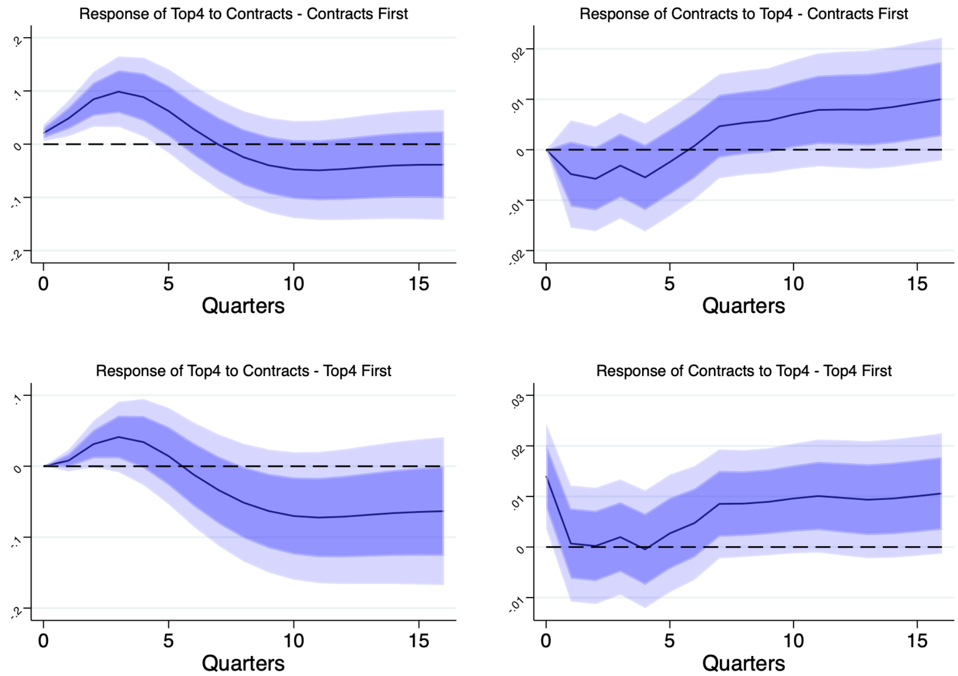


Figure 2.6. ARE CONTRACTS PREDICTED BY THE STOCK MARKET?

Notes: Sample is: 1954:1 to 2000:4. Confidence bands are 68% and 90%. Nominal variables are in logs of real per capita values, while hours are in logs. The deflator is the GDP price deflator. *Top 4* accounts for the cumulative excess returns of an equally weighted portfolio of the stocks of Lockheed-Martin, Raytheon (now RTX), Northrop-Grumman and the Boeing Company; I use the S&P500 as a benchmark.

now less precisely estimated (as seen in the bottom-left panel). The response of defense contracts to a shock to the Top 4 index, when ordered first (bottom-right panel), is also not precisely estimated. However, by design, defense contracts respond positively on impact, aligning with the positive response of the Top 4 index to a shock to defense contracts (as shown in the top-right panel).

Given the absence of a significant delayed response of contracts to a shock to the Top 4 index, and considering the contrasting observation, that the Top 4 has a precisely estimated delayed response to contracts, I conclude that defense contracts are not anticipated by the stock market, or else, the stock market responds to shocks to defense contracts.

In summary, defense contracts provide an accurate measurement of the timing of fiscal shocks, in contrast to the delayed measure of G constructed by NIPA. Defense contracts indeed anticipate spending by three to four quarters, a result of NIPA's accounting practice of recording contracts after-payment-on-delivery for most complex defense items. It is therefore unsurprising that shocks to defense contracts Granger-cause BP shocks but not viceversa. Moreover, production appears to begin following the award of new contracts, as evidenced by the quicker response of contracts compared to inventories in response to defense news shocks. Further supporting the argument that contracts are not anticipated at a quarterly frequency, the stock prices of major defense contractors exhibit a delayed response to a shock to defense contracts, while the contracts themselves do not respond to shocks to stock prices.

Having established that defense contracts accurately measure the timing of shocks, I will now focus on their exogeneity and statistical power as an instrument for G.

Exogeneity:

The first condition for a valid instrument is exogeneity. Defense contracts capture variations in future military procurement spending; in turn, military spending is primarily influenced by exogenous events. However, new contracts might have been awarded in response to a recession. Similarly, higher-than-usual deficits, resulting from slower economic growth, could have prompted endogenous reductions in defense procurement spending. To address these concerns, I conduct two Granger Causality Tests.

I construct shocks to defense contracts as OLS residuals from a regression of defense contracts on four lags of defense contracts, G, GDP, hours worked in the private sector, and TB3. Essentially, this is a VAR with contracts, GDP, G, hours, and TB3, and contracts are ordered first. All nominal variables are expressed as logs of real per capita values, with hours in logs.

Table 2.2 shows the results of the Granger causality tests.

The results indicate that neither a recession nor deficit have predictive power on a shock to defense contracts. Results are also shown for the sample starting from 1951:1, which misses

Table 2.2. GRANGER CAUSALITY TEST

Predicted	*Predictor*	*F*	*Pvalue*	*Sample*
Defense Contract Shocks	NBER Recessions	1.16	32.06%	1947:1 - 2019:4
Defense Contract Shocks	NBER Recessions	0.59	78.32%	1951:1 - 2019:4
Defense Contract Shocks	Deficit	0.51	84.69%	1947:1 - 2019:4
Defense Contract Shocks	Deficit	0.99	44.19%	1951:1 - 2019:4

Notes: Granger Causality test is a Wald test on the 8 lags of the predictor while controlling for 4 lags of the predicted variable. I construct deficit as the difference between government total expenditures less government total receipts (NIPA Table 3.1, Line 43); I use the NBER based recession indicator to identify a recession in a quarter.

the beginning of the Korean war, as data from 1947:1 to 1950:4 is extrapolated.

Furthermore, notice that these results complement the ones of Cox et al. (2023), who show that federal procurement spending was not affected by endogenous counter-cyclical policies like the American Recovery and Reinvestment Act of 2009 and the COVID relief packages.

Statistical Power:

I now turn attention to the statistical power of defense contracts. I do so by estimating a quarterly VAR which includes defense contracts, G, GDP, total hours worked in the private business sector and the 3 months T-Bill rate. I order defense contracts first in the VAR and look at the IRFs of the NIPA measure of G to a shock to defense contracts, using different samples. Results are reported in Figure 2.7.

Observing the left panels, it is clear that when the sample incorporates the Korean War, defense contracts capture a considerable proportion of the variation in G. Following the critique of Perotti (2014), I also ensure that once the Korean War is removed from the sample, the instrument preserves its statistical power. In the right panels, where the sample starts from 1954, defense contracts still capture a considerable variation in G. This represents a great advantage compared to the other instruments for G, like defense news shocks (Ramey (2011), Fisher and

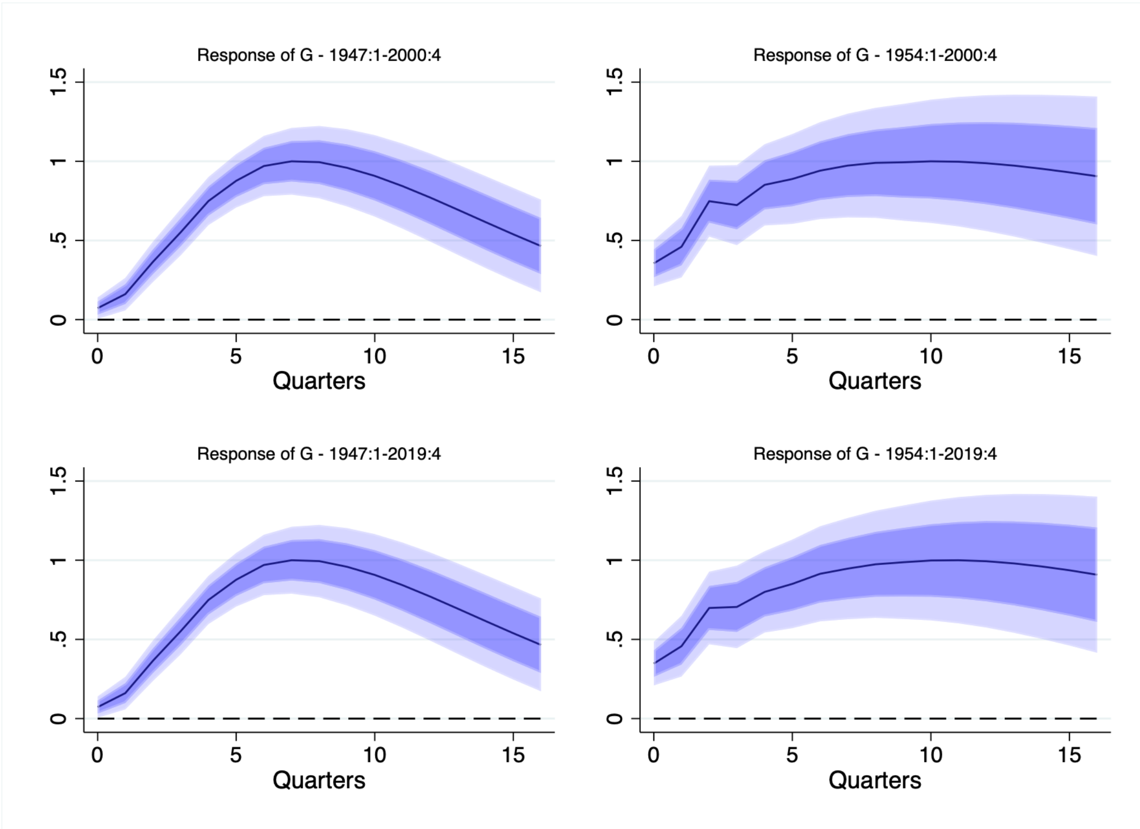


Figure 2.7. RESPONSE OF G TO FISCAL SHOCKS (INSTRUMENT'S POWER)

Notes: Confidence bands are 68% and 90%. Deflator is the GDP price deflator.

Peters (2010)'s shocks of cumulative excess returns of top defense contractors and Ben Zeev and Pappa (2017)'s shocks of expected defense spending obtained via medium horizon restrictions.

Avoiding Narrative Analysis:

Finally, an advantage of defense contracts is that it does not require a narrative analysis. Even though narrative analysis are extremely useful to increase the stock of institutional knowledge about specific aspects of the economy, they are the result of subjective judgment of the researcher. On the contrary, defense contracts come from official government data.

Moreover, data on procurement contracts is becoming more and more available in most OECD countries, thus extending the applicability of this methodology to a panel of countries.[12]

[12] For example: Brazil (see Ferraz, Finan, and Szerman (2015)), South Korea (see Lee (2017)), Austria (see Gugler, Weichselbaumer, and Zulehner (2020)), France (see Pinardon-Touati (2022)), Portugal (see Gabriel (2022)),

2.3 Empirical Results

In this section, I explore the effects of shocks to defense contracts, identified by ordering defense contracts first in a VAR.

GDP Breakdown:

First, I break down the response of GDP in Fixed Investments, Inventories, Durable Consumption, Non-Durable-plus-Service Consumption and G.[13] The VAR always includes defense contracts, G, GDP, hours worked in the private sector and the TB3, then rotates in and out a variable of interest. Nominal variables are in logs of real GDP per capita, while hours are in logs. Figure 2.8 displays the IRFs thus calculated for the components of GDP in response to a shock to defense contracts for the sample spanning from 1947:1 to 2000:4.

The top-left panel shows that GDP increases on impact and spikes at 3 quarters from the shock, then starts falling down to zero. The top-right panel displays how government spending slowly increases, spiking 6-7 quarters after the shock. The middle right panel shows the response of inventories, which increases rapidly, spiking after 2-3 quarters from the shock. Despite being the most volatile component of GDP, I find that inventories respond strongly and significantly. This result complement the findings of Brunet (2022) and Briganti and Sellemi (2023). Note that the unit of inventories is different from the one of the other components of GDP,; in fact, inventories can take on negative values, therefore, I use real changes per capita instead of logs. A VAR specification with the real variables divided by real potential GDP - Gordon and Krenn (2010) transformation - leaves the result unaffected.

The bottom-right panel shows the response of *non-durables-plus-service consumption*, which is positive and significant. The positive response of (non-durable-plus-service) consumption, is an important result. In fact, proponents of the instrument approach, have consistently

Spain (see Gugler, Weichselbaumer, and Zulehner (2020)).

[13]The response of net-export and import is analyzed in the Online Appendix B.3 and it is non significant at any horizons and any sample.

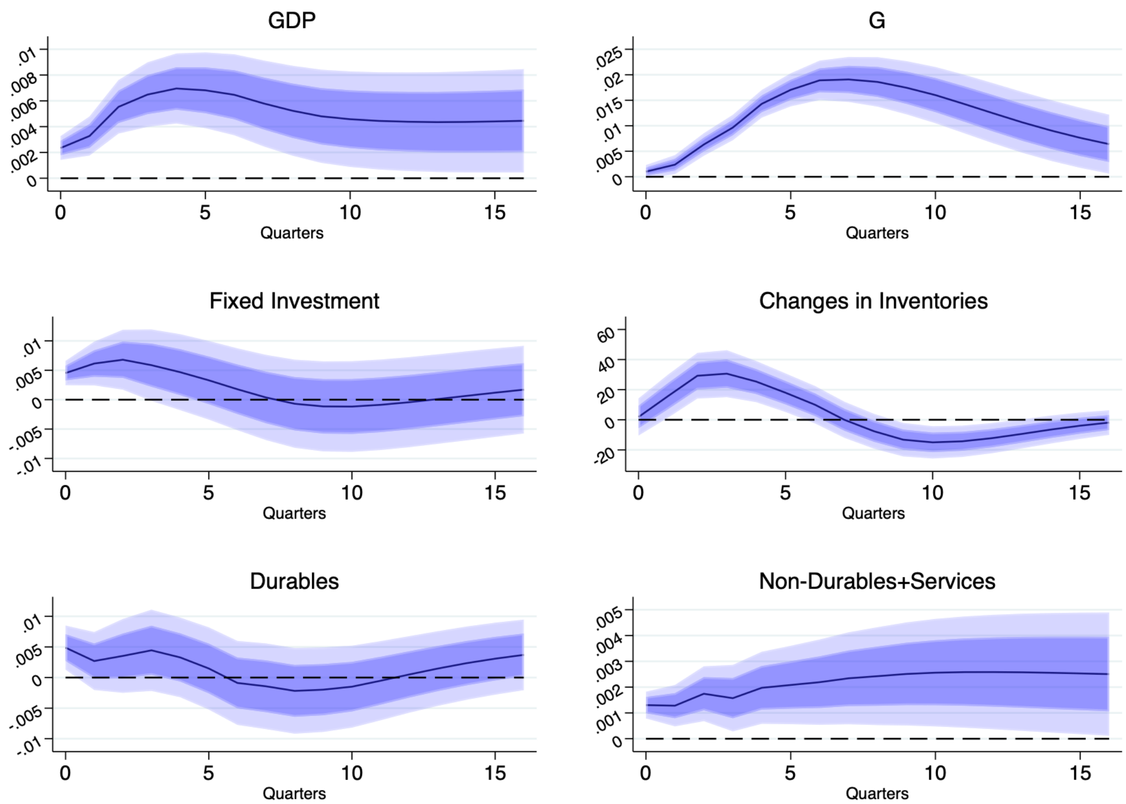


Figure 2.8. IRFs of GDP Components to Defense Contracts

Notes: Sample goes from 1947:1 to 2000:4. Confidence bands are 68% and 90%. Nominal variables are in logs of real GDP per capita, while hours are in logs. Price deflator is the GDP price deflator.

found negative responses of consumption.[14] At the same time, proponents of the SVAR approach, who employ BP shocks, consistently find positive responses of consumption, even if almost all works report 68% confidence bands. However, proponents of the instrument approach are not convinced by these findings since the timing of BP shocks is delayed (Ramey (2011)). Similarly, proponents of the SVAR approach, highlight that the results obtained with the military instruments are sensitive to the exclusion of the Korean war from the sample (Perotti (2014)) and lack statistical power in samples after the Korean war (Ramey (2016)). Therefore, the literature

[14]A notable exception is Fisher and Peters (2010) who find positive responses of consumption in sample which excludes the Korean war. However, their instrument lacks statistical power (Ramey (2016)) and the reported IRF of consumption is barely significant at 68% confidence level.

has not reached an agreement about the effects of fiscal shocks on consumption.

However, defense contracts accurately measure the timing of the shocks, addressing the limitation of the SVAR approach, and preserve statistical power after the Korean War, addressing the limitation of the instrument approach. Additionally, the response of non-durable-plus-service consumption, which accounts for 83% of aggregate consumption on average, is robust to the exclusion of the Korean War. Since defense contracts successfully address the major concerns of the most widely employed methods to study the effects of government spending, I argue that my results provide a more conclusive answer to the long-debated question of the effect of government spending on consumption.

Fixed Investments and Durables:

The response of fixed investments and durables deserves a separate discussion. First, the middle-left panel of Figure 2.8 shows the response of fixed investments. The response is positive on impact and then falls to zero. Second, the bottom left panel portrays the response of durable consumption, which accounts for 17% of total consumption, on average. The response is positive and significant only on impact.

Upon excluding the Korean War from the sample, I observe a noticeable variability in the responses of durables and fixed investments. This phenomenon extends to BP shocks and defense news shocks, which demonstrate an even more pronounced sensitivity in their results. The response of fixed investments and durable consumption for the sample 1954:1 to 2000:4 is showed in Figure 2.9.

The left panel of Figure 2.9 shows a persistent increase in fixed investments after a positive shock to defense contracts, but significant only at 68%. The right panel shows that the response of durable consumption also increases and becomes significant even at 90% confidence.

The sensitivity of these two GDP components to the exclusion of the Korean War from the sample has been underscored in Perotti (2014) and Ramey (2016). Specifically, during the onset of the Korean War in the last two quarters of 1950, consumers, with the fresh memory of

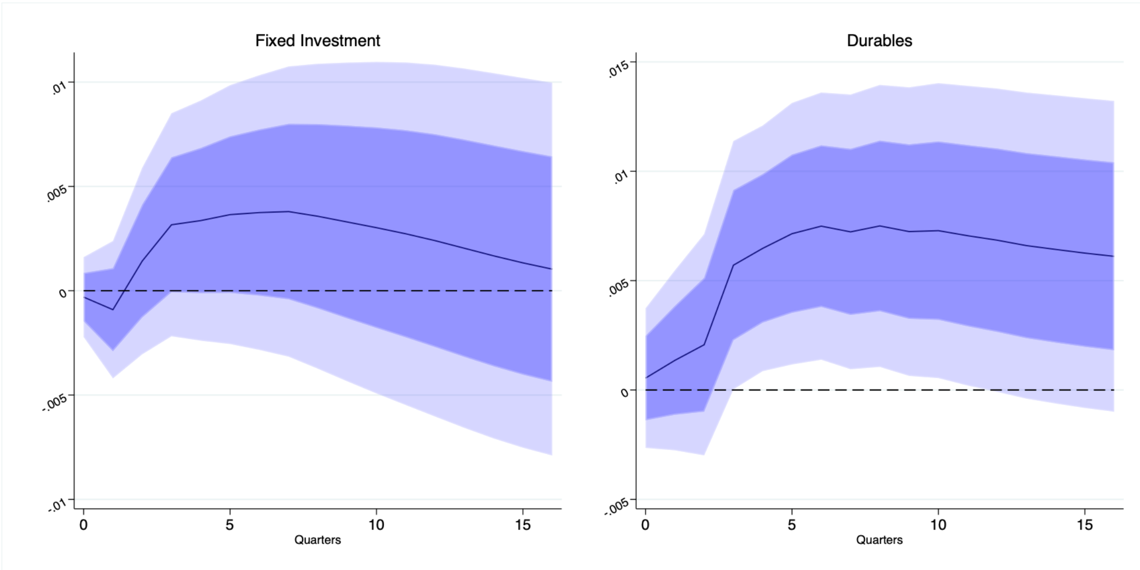


Figure 2.9. Fixed Investments and Durables after Korea

Notes: Sample goes from 1954:1 to 2000:4. Confidence bands are 68% and 90%. Nominal variables are in logs of real GDP per capita, while hours are in logs. Price deflator is the GDP price deflator.

WWII rationing, rushed to purchase durable goods in large quantities (refer to Ginsburg (1952), Hickman (1955), and Ramey (2016) for more details).[15] The introduction of Regulations X and W aimed to mitigate the inflationary pressure resulting from the buying wave, adversely impacting the medium-term response of residential investments and home-building, as well as the consumption of durable goods like furniture and household equipment. Consequently, the responses of fixed investments and durable goods are sensitive to the exclusion of the Korean War from the analysis.

To summarize, in response to a positive shock to defense contracts, GDP, G, inventories and non-durables-plus-service consumption increase significantly, while the response of fixed investments and durables also exhibit positive responses after the Korean war.

Robustness: The results for GDP, G, inventories and non-durables-plus-service consumption are robust to using the samples 1954:1-2000:4 (without Korean war) and 1947:1-2019:4

[15]This mechanism of intertemporal shift of consumption of durable goods is explored also in McKay and Wieland (2021) in the context of raising interest rates.

(full sample). Moreover, the inclusion of a tax control or a quadratic time-trend also do not affect the baseline results reported here.

Lastly, given that the direct estimation of fiscal multipliers requires real variables to be transformed using the Gordon and Krenn (2010)'s transformation (Ramey (2016)), I check the results using a VAR where the real variables are divided by real potential GDP.[16] The estimated multipliers has the interpretation of the ratio of the area under the IRF of GDP and the area under the IRF of G. Results are robust to using this specification.

All these robustness checks are reported in Appendix A.2.

Fiscal Multiplier: In the Online Appendix B.1, I illustrate and derive my estimate of the cumulative fiscal multiplier, obtained with LP-IV (see Ramey (2016)). My baseline estimate for the 4-years GDP multiplier is 0.92, while the non-durable-plus-service consumption multiplier is 0.12. This means that if government spending increases by 1$, non-durable-plus service consumption increase by 0.12$. Results and discussions on fiscal multipliers are remanded to the Online Appendix B.

2.3.1 Wages, Hours, Employment, Production Earning and Income

In this section I explore the effect of a shock to defense contracts on the product wage, hours, employment, production earnings and income.

Product Wage

The fiscal policy literature has paid significant attention to the response of the product wage to fiscal shocks. According to economic theory a fiscal shock is associated with higher taxes, which trigger a negative wealth effect, shifting the labor supply curve to the right. As long as labor demand remains constant, the product wage is expected to decrease, resulting in a

[16] In particular, the VAR includes defense contracts, GDP, G, Hours worked in the private sector, 3 months T-Bill rate. Nominal variables are deflated by the GDP price deflator and divided by potential GDP. Potential GDP is estimated with a 6-degree polynomial fit to log of real GDP.

reduction in consumption within standard DSGE models.[17] Conversely, if labor demand also shifts to the right, it creates the possibility for the product wage to increase, fulfilling a necessary condition for a rise in consumption within DSGE models.

However, the literature has not reached a consensus on the effects of fiscal shocks on the product wage. For example, Ben Zeev and Pappa (2017) find negative responses of the manufacturing product wage using the instrument approach, while Monacelli and Perotti (2008) find positive responses using the SVAR approach.

In light of the low statistical power of the instruments for G and the delayed timing of BP shocks, I add to the literature by also exploring the response of product wages, at different aggregation levels, using shocks to defense contracts, which preserve power across samples and accurately measure the timing of the shocks. In particular, I look at four measures of product wage. First, I use the average hourly wage of aircraft manufacturing from the discontinued BLS data, divided by the Producer Price Index (PPI) of durable manufacturing. Secondly, I construct two measures of manufacturing hourly product wage. Specifically, I use the hourly earnings of production workers in manufacturing from the BLS, divided by the PPI of manufacturing. Additionally, I use the NIPA total wages and salaries in manufacturing divided by total hours of manufacturing production workers from the BLS, divided by the manufacturing PPI. Lastly, I construct the product hourly wage in the private economy by dividing the NIPA wages and salaries in the private sector by the total hours worked in the private sector, then deflated with the GDP price deflator.

As in previous sections, I rotate in and out the log of the four measures of product wages in the baseline VAR augmented with the tax control. Figure 2.10 illustrates the IRFs to a positive shock to defense contracts for the sample 1947:1-2000:4.

[17]The product wage is preferred over the consumption wage based on the theoretical results presented by Ramey and Shapiro (1998). In their two-sector model, an increase in defense purchases increase the relative price of manufacturing goods, subsequently lowering the manufacturing product wage while increasing the overall consumption wage. As a result, the product wage is the appropriate metric to determine whether labor demand or labor supply experiences a more pronounced shift following a government spending shock.

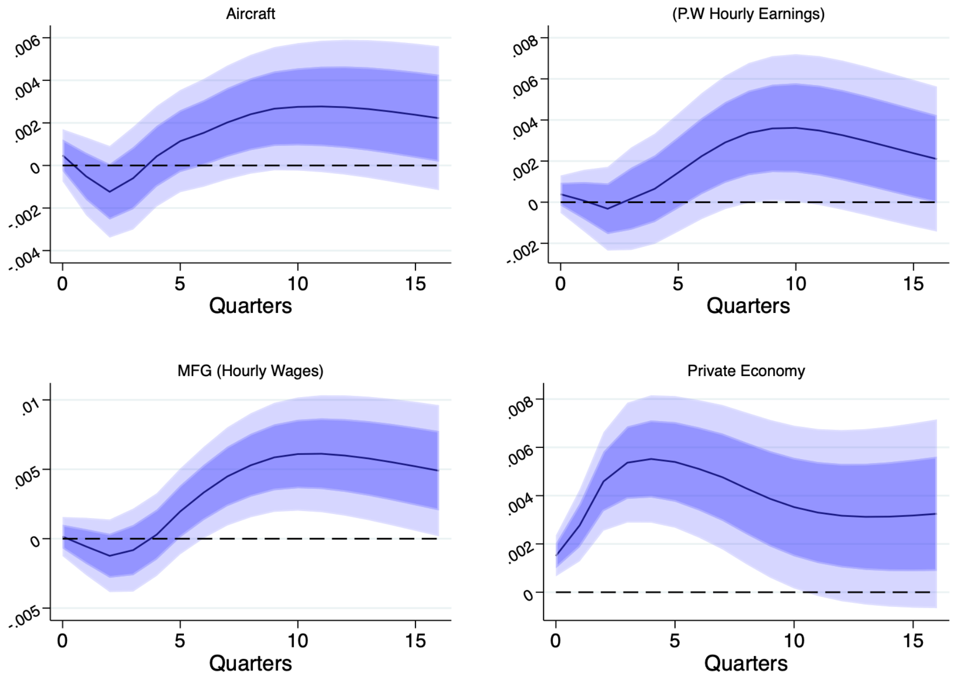


Figure 2.10. RESPONSE OF (PRODUCT) WAGE TO CONTRACTS

Notes: Sample goes from 1947:1 to 2000:4. Confidence bands are 68% and 90%. The VAR contains defense contracts, G, GDP, hours worked in the private sector, the TB3, total tax receipts and a sixth rotating variable of interest. Nominal variables are in logs of real per capita GDP. Deflator is the GDP price deflator. Hourly product wages are in logs, as well as hours.

The real product wage reveals a near-zero response in the short horizons, gradually rising in medium to long horizons.

Robustness:

Similar outcomes are apparent in other samples. Most importantly, the results without the tax control look qualitatively identical but it is estimated with less precision: the IRFs are not statistically significant, except for the private economy case. I also replicate the VAR not in logs but with the variables Gordon-Krenn transformed, with and without taxes. The results are very similar and also indicate to a delayed positive response. All robustness checks are detailed in the Online Appendix D.2.

Hours, Employment, Earnings and Income

I now turn my attention to the responses of hours, employment, production earnings, and disposable income. To this end, I augment the baseline VAR from the previous section with various outcomes of interest: the log of average weekly hours worked, the log of employment, the log of total hours worked, and the log of real total earnings per capita. I study their response at three different levels of aggregation: (i) aircraft manufacturing, (ii) total manufacturing, and (iii) the total private economy. I focus on the responses in aircraft manufacturing and total manufacturing due to the pronounced sectoral bias of defense purchases toward these industries (see Ramey and Shapiro (1998), Perotti (2007), Nekarda and Ramey (2011), and Cox et al. (2023)). At the same time, examining the response in the total private economy is crucial, because sectoral reallocation of workers and crowding-out effects might negate, in the aggregate, the positive effects observed in directly affected industries.

Figure 2.11 shows the IRFs of these variables with respect to contracts: first column is aircraft manufacturing, followed by manufacturing and private economy respectively.

Aircraft Manufacturing: data from aircraft manufacturing is available from 1939 at monthly frequency from the BLS' discontinued database.

Firstly, weekly hours are measured by weekly hours of production workers, and respond positively to a shock to government contracts. As noted by Bils and Cho (1994) and Fernald (2012), average weekly hours worked is an excellent proxy for the intensity of capital utilization. Therefore, its immediate response indicates a rapidly increased production after a shock to defense contracts. Secondly, employment is thousands of production workers and also responds positively, with a delayed response, probably reflecting labor market frictions. Thirdly, total hours worked is the product of weekly hours worked and number of production workers, and responds positively. Lastly, I calculate total earnings, derived from multiplying the hourly wage

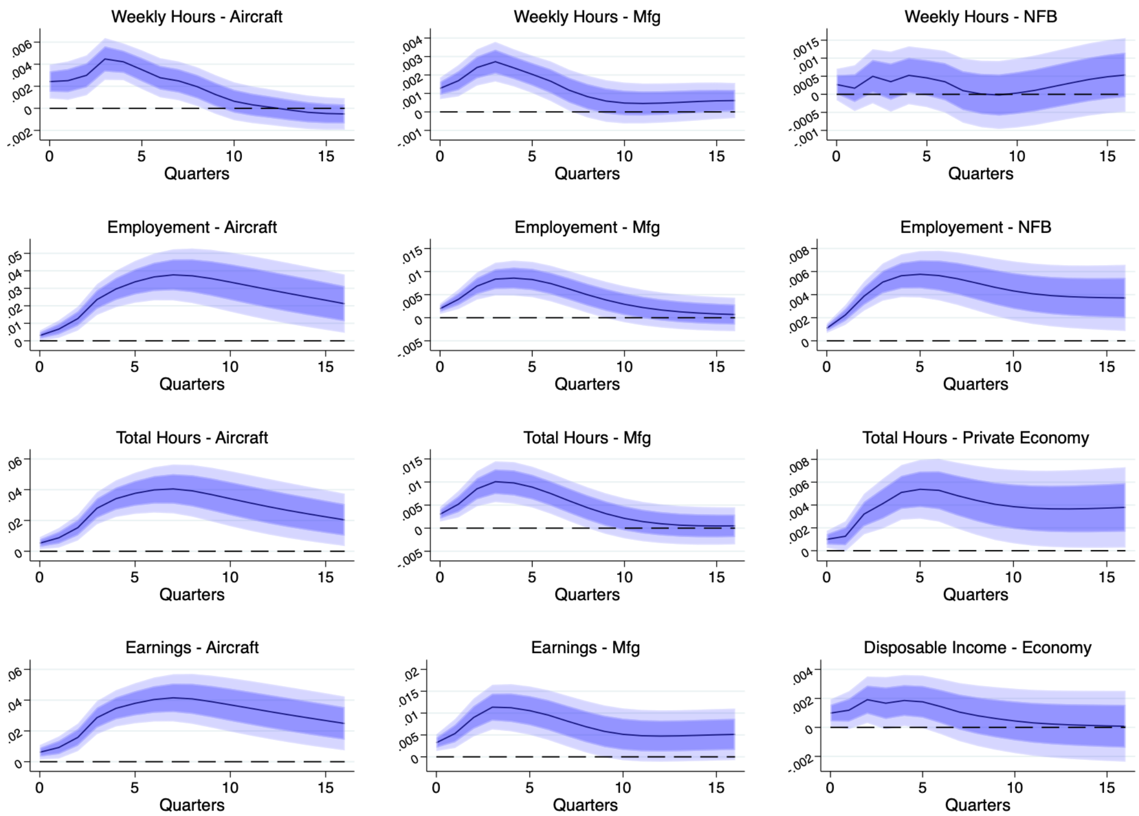


Figure 2.11. RESPONSE OF HOURS, EMPLOYMENT AND INCOME TO CONTRACTS

Notes: Sample goes from 1947:1 to 2000:4. Confidence bands are 68% and 90%. The VAR contains defense contracts, G, GDP, hours worked in the private sector, the TB3 and a sixth rotating variable of interest. Nominal variables are in logs of real per capita values, while hours is in logs. Price deflator is the GDP price deflator. The rotating variables weekly hours, hours and employment are expressed in logs (when aggregate hours are analyzed, the VAR only has 5 variables). Total production earnings and disposable income are in logs of real per capita values.

of production workers with the total hours worked. The response of this variable is positive.[18]

Manufacturing: Similar to the aircraft sector, the total manufacturing data is obtained from the BLS's discontinued monthly data. Like the aircraft data, all variables show a positive response to an increase in defense contracts.

This pronounced positive reaction in the manufacturing sector indicates that government funds positively impact industries outside of just aircraft manufacturing, for at least three reasons.

[18]Total earnings of production workers in aircraft manufacturing account for 0.5% of potential GDP, on average.

First, the government's demand extends to a range of products including motor and space vehicles, ships, IT equipment, ammunition, and clothing (Ramey and Shapiro (1998), Perotti (2007), Nekarda and Ramey (2011) and Cox et al. (2023)). Second, as highlighted by Gulledge and Womer (1986) and the Top 100 companies reports, subcontracting was common, meaning that prime military contractors often delegate work to smaller, specialized firms, thereby distributing the initial increase in demand to various other players in the industry. Lastly, the input-output relationships in the manufacturing network amplify the effects of a spike in defense contract demands, causing a ripple effect upstream in the production network (Acemoglu, Akcigit, and Kerr (2016)). For example, the production of the F-4 Phantom II during the Vietnam war, involved General Electric, which manufactured engines, while other firms such as Alcoa, provided crucial materials like aluminum and titanium.

Aggregate: The last column presents the results for the entire private economy. First, average weekly hours worked in the non-farm business (NFB) sector is constructed by dividing total hours worked of all employees by the total number of employees. The IRF of this variable portrays positive, albeit non-significant, point estimates. Second, the data exhibits a consistent positive response in the total number of NFB employees across different samples, dispelling the concerns of potential crowding-out effects on employment. Third, I examine the total hours worked within the private sector, which serves as a baseline variable in my VAR analysis. Although the response indicates a positive trend, it is significant only on impact. Other samples echo this finding, pointing to a generally mild positive reaction in total hours worked. Lastly, production workers data for the economy is available only from 1964, therefore, I use NIPA's disposable income, given also my interest in the response of consumption. Disposable income has a robust positive response, which is consistent with the rise in aggregate consumption.

Robustness:

All results are robust to the exclusion of the Korean war, sample 1954:1 to 2000:4 and the inclusion of the most recent years, sample from 1947:1 to 2019:4. I also control for a quadratic trend as well as taxes and the results are unaffected. Furthermore, I carry out the analysis for all three samples using a VAR with the nominal variables Gordon-Krenn transformed, the results are also the same. All the robustness checks are illustrated in the Online Appendix D.1.

In summary, the response of product wages, hours, employment, earnings and disposable income to an increase in defense contracts is positive and consistent with the observed rise in non-durable-plus-service consumption. The positive response of total hours and employment is not new, since similar responses have been consistently found in the literature. However, here I analyze these variables at different aggregate levels; notice that the magnitude of the response decreases with the aggregation level, indicating that the effects of a shock to defense contracts are more concentrated in the sectors directly affected by the shock. The response of weekly average hours of production is - to the best of my knowledge - new in the context of time series regressions.[19] and serves as a proxy for capital utilization/production rates. Production earnings and disposable income are studied to substantiate the observed positive response of consumption. I am not aware of other time series studies which analyzed the response of production earnings in aircraft and total manufacturing; on the contrary, the response of disposable income is analyzed in Galí and Monacelli (2008). They find a positive and significant response of both disposable income and consumption; however, they use BP shocks and display IRFs with 68% confidence bands.

2.3.2 Markup and Labor Productivity

In the previous section the observed joint rise in hours worked and the product wage in response to a shock to defense contracts indicate that labor demand shifts to the right. According

[19]Nekarda and Ramey (2011) study weekly hours in a cross-sectional industry-level framework.

to economic theory, labor demand can increase due to sticky prices and/or an increase in labor productivity.

To better illustrate this point, consider the standard textbook New Keynesian model (Chapter 3 of Galí (2015)). Here, the aggregate real marginal cost (MC_t^r) is equal to the real product wage (W_t^r) over the marginal product of labor (MPN_t):

$$\mathrm{MC}_t^r = \frac{W_t^r}{\mathrm{MPN}_t} \implies \hat{mc}_t^r = \hat{w}_t^r - m\hat{p}n_t$$

where the ˆ notation denotes percent deviations from the steady state. By definition, the price-cost markup is the ratio of prices over marginal cost, therefore, using the hat notation, the markup, $\hat{\mu}_t$ is the negative of the real marginal cost: $\hat{\mu}_t = -\hat{mc}_t^r$. Using the two expressions allows me to write the real product wage as a function of the marginal product of labor and the price-cost markup:

$$\text{Labor Demand: } \hat{w}_t^r = m\hat{p}n_t - \hat{\mu}_t.$$

Now, from the household problem, the labor-leisure intratemporal condition is:

$$\underbrace{-u_N(C_t, N_t)}_{\psi \cdot N_t^{\varphi}} = \underbrace{u_C(C_t, N_t)}_{C_t^{-\sigma}} \cdot W_t^r \implies \text{Labor Supply: } \hat{w}_t^r = \varphi \cdot \hat{n}_t + \sigma \cdot \hat{c}_t$$

where the parametric form of the marginal disutility of labor, $-u_N$, and the one of the marginal utility of consumption, u_C, follows, for the sake of the illustration, by assuming a simple isoelastic and separable utility function.[20]

Putting everything together yields:

$$\varphi \cdot \hat{n}_t \uparrow + \sigma \cdot \hat{c}_t \uparrow = m\hat{p}n_t - \hat{\mu}_t.$$

When G rises above its steady state level, hours increase due to a negative wealth effect

[20]For example: $U(C_t, N_t) = (C_t^{1-\sigma}/(1-\sigma) - \psi \cdot N_t^{1+\varphi}/(1+\varphi)$.

resulting from heightened lump-sum taxes.[21] In this context, consumption will increase if any of the following scenarios occur: (i) labor productivity rises, (ii) the price-cost markup decreases, (iii) both labor productivity rises and the price-cost markup decreases, or (iv) the price-cost markup increases but at a slower rate than the rise in labor productivity.

This simple theoretical example aims to highlight the importance of examining the responses of both the price-cost markup and labor productivity in order to rationalize the observed increase in consumption.

Price-Cost Markup:

I investigate the response of the price-cost markup by rotating in and out four measures of the markup in a VAR. Firstly, I construct the markup in the manufacturing sector as in Monacelli and Perotti (2008).[22] Secondly, I use the negative of the log share of labor income in the non-financial-corporate-business (NFCB) sector, also analyzed by Monacelli and Perotti (2008). The third and fourth measures are the negative of the log-share of labor income in the economy and in the non-farm-business (NFB) sector, taken from Nekarda and Ramey (2020)'s online database.[23]

Figure 2.12 shows the responses of these four measures of the markup to a positive shock to defense contracts for sample 1947:1 to 2001:4. The VAR employed here mimics the one of Nekarda and Ramey (2020), it contains defense contracts, G and GDP in logs of real per capital values, the log of the GDP price deflator and the TB3.

The markup exhibits a positive response at short horizons, then diminishes and turns negative across all measures. The positive response of the markup is consistent with the findings of Nekarda and Ramey (2020) who use defense news shocks on a sample from 1947:1 to 2017:4. I extend their results to samples without the Korean war and for the manufacturing price-cost

[21] I acknowledge that in the presence of dividends, the representative household experiences a substantial additional negative income effect through the decrease in profits, which is caused by the conditionally counter-cyclical markup, as noted by Broer and Krusell (2021).

[22] I follow the indications in the appendix of their paper and construct the markup by taking the log of the ratio of manufacturing national income less capital consumption adjustment and manufacturing wages.

[23] I am aware of the recent criticisms moved towards mark-up measures based on the log-shares of variable input of production (see Bond et al. (2021)). However, in the absence of better measures of the price-cost markup, I comply with what the fiscal policy literature has used so far.

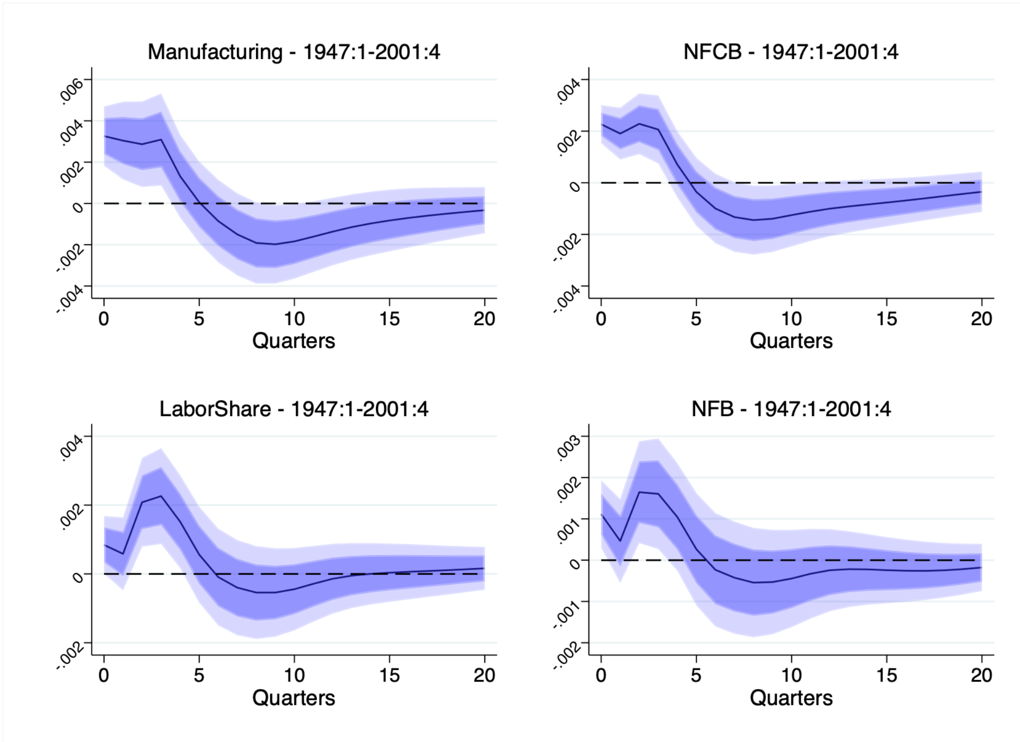


Figure 2.12. RESPONSE OF MARKUPS TO CONTRACTS

Notes: Sample goes from 1947:1 to 2000:4. Confidence bands are 68% and 90%. Price deflator is the GDP price deflator.

markup measure. On the contrary, Monacelli and Perotti (2008) find negative responses of the markup using BP shocks. Therefore, in Online Appendix C I look at the response of the four measures of the markup in response to a BP shock, mimicking the approach of Monacelli and Perotti. I find that the response of the markup in NFCB and manufacturing aligns with those found in their paper, with the markup declining. Yet, these findings are not robust when the Korean war is excluded from the sample; in this case, the markup does not show a significant response. Furthermore, when the markup is quantified as the negative of the log share of labor income in the economy and the NFB, BP shocks lead to positive responses of the markup.

Robustness:

I also look at the response of the mark-up in other samples (1954:1-2000:4 and 1947:1-2019:4) and find similar results. All robustness checks as well as the results with bP shocks are reported in Online Appendix C.

Overall, since defense contracts accurately measure the timing of the shocks and provide results robust to the exclusion of the Korean war, I argue that the price-cost markup increases after a positive fiscal shock.

Labor Productivity:

I now turn attention to the response of labor productivity. More specifically, I look at the response of the the log of output-per-hour (OpH) in the private business sector, a measure of labor productivity, and Total Factor Productivity (TFP), as measured by Fernald (2012). I rotate in and out those variables in my baseline VAR, with the log of real per capita values of defense contracts, GDP and G, the log of hours in the private sector and the TB3.

Figure 2.13 shows the response of OpH and TFP to a positive shock to defense contracts using the baseline sample 1947:1 to 2000:4.

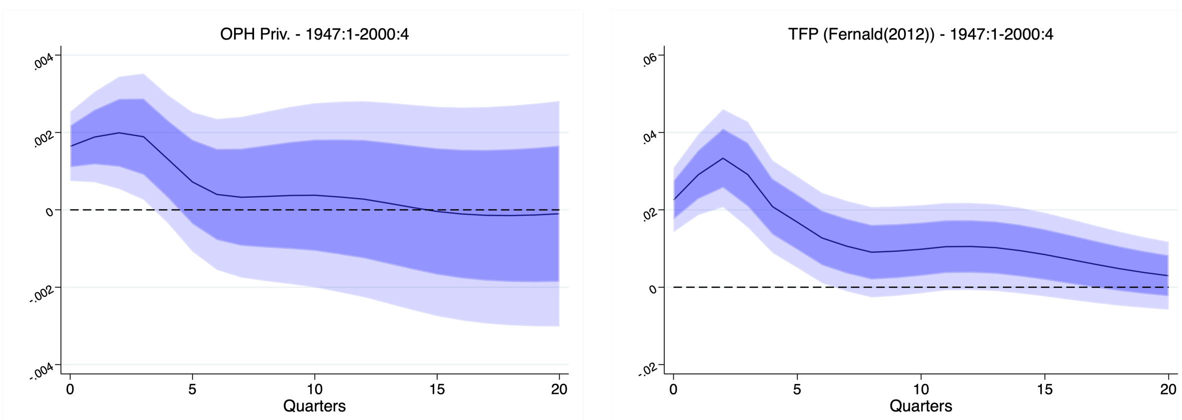


Figure 2.13. Response of Productivity to Contracts

Notes: Left panel is the response of the log of output-per-hour (OpH) in the private sector, a measure of labor productivity. Right panel shows the response of TFP as measured by the cumulative quarterly growth rates of TFP as measured by Fernald (2012). Sample goes from 1947:1 to 2000:4. Confidence bands are 68% and 90%. Price deflator is the GDP price deflator.

Both variables display a significant positive response.

Robustness:

In the Online Appendix D.3 I also study the response of OpH in the NFB and the NFCB. The results indicate a positive response at short horizons.

I also replicate the analysis using the other samples for TFP and OpH in NFB, NFCB and the private sector, finding very similar results. The major discrepancy is when the Korean war is removed from the sample: all three measures of OpH as well as TFP display a slower and hump-shaped response, which preserves statistical significance. I also find that the inclusion of a tax control (log of real total tax receipts per capita) does not affect the results, or else, it makes the responses even more significant and positive.

All these robustness checks are documented in the Online Appendix D.3.

Overall, the findings presented in this section suggest a boost in productivity following a positive shock to defense contracts. Notice that the rise in productivity is not necessarily evidence of increasing return to scale. In fact, Basu and Fernald (1997) propose that government spending shocks prompt a reallocation of resources, particularly labor, toward manufacturing. If the manufacturing sector is more productive than other sectors, this shift could lead to an apparent increase in overall productivity, creating the illusion of increasing returns to scale.[24]

While sectoral reallocation might explain increases in productivity at the aggregate level, it does not align with the findings of Christiansen and Goudie (2007). They merge contract data from the Top 100 companies' annual Department of Defense reports with balance sheet information from Compustat, constructing an annual panel database of publicly traded defense contractors. By estimating a panel VAR from 1969 to 1996, they observe positive effects of new contract awards on sales, employment, and sales-per-employee, a proxy for labor productivity. Their results suggest that defense contracts do, in fact, stimulate productivity gains at the firm level.

[24] It is noteworthy that their research specifically identifies durable manufacturing, the main beneficiary of defense spending, as the sole sector exhibiting increasing returns to scale, even when accounting for sectoral reallocation effects.

In the subsequent section, I propose that a significant source of these productivity gains for manufacturers and contractors is attributable to learning-by-doing.

2.3.3 Showcase: The Vietnam War

I now briefly discuss the empirical evidence during the Vietnam war in order to conceptualize the VAR findings in the context of a major exogenous shock to defense spending in the post WWII sample.

The February attack of 1965 marked the beginning of the US military's escalation in the Vietnam war (Ramey and Shapiro (1998)). Figure 2.2 illustrates in blue the quarterly year-to-year growth rates of defense contracts. A substantial increase was witnessed in the second quarter of 1965, reaching its peak in the final quarter of that year. The top-left panel shows the growth rates of non-durable-plus-service consumption while the top-right panel illustrates output-per-hour growth rates in the private sector. Both variables exhibit a surge concurrent with the increase in defense contracts.[25]

Analysis of the Survey of Current Business (SCB) during the Vietnam War era highlights that the uptick in defense production was a substantial economic stimulus at that time. From the SCB of January 1967:

"*Heavy defense purchases last year accounted for most of the rise in Federal outlays from 1965 to 1966 and were the dominant stimulus to rising activity in the second half of the year. [...] As in the summer months, government purchases continued to be a major stimulus to the rise in production*".

Simultaneously, a surge in personal income, largely attributed to escalated production,

[25]Real service and non-durable consumption per capita during the Korean and Vietnam wars display consistent above-trend values (trend estimated with either Hamilton (2018)'s filter or a polynomial filter). Additional details are available in the Online Appendix A.3.

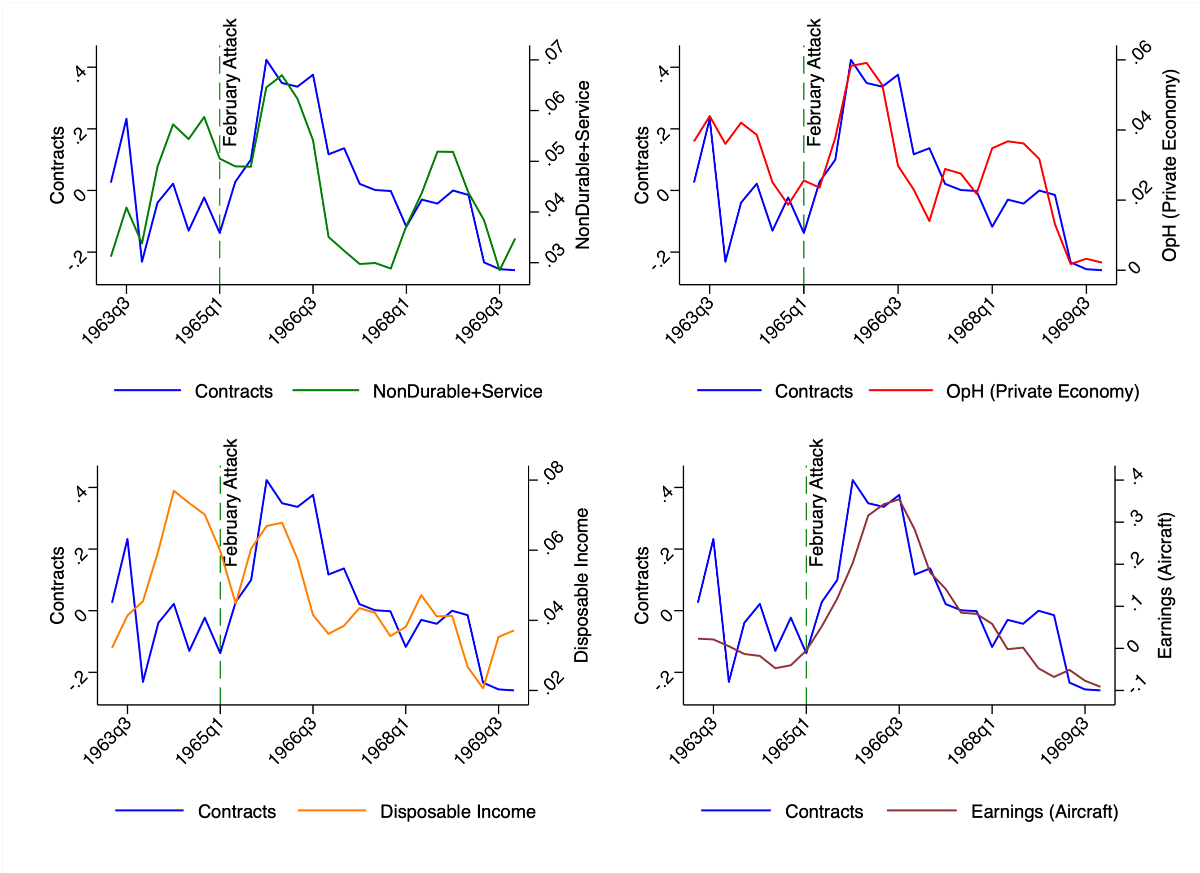


Figure 2.14. GROWTH RATES OF MACRO AGGREGATES DURING VIETNAM

Notes: The GDP price deflator is used to deflate nominal variables. Quarterly year-to-year growth rates are calculated as $(x_t - x_{t-4})/x_{t-4}$.

seemingly fostered the observed growth in consumption during those periods, as reported in the SCB January 1967:

"*Another large increase in personal income accompanied the continued strong advance in economic activity in 1966. The flow of income reflected essentially the large rise in earnings from current production...*".

The bottom-left panel delineates NIPA's disposable income growth rates, illustrating a notable increase concurrent with the heightened contracts in 1965 and 1966, consistently with the SCB narrative.

In the same period, the Top100 companies reports show that major Vietnam war contractors were predominantly aircraft and parts manufacturers.[26] Consequently, the bottom-right panel showcases the earnings growth rates in the aircraft manufacturing sector, indicating a steep ascent beginning in the first quarter of 1965, stemming from increased production. Owing to their substantial engagement with government acquisitions, examining the aircraft manufacturing dynamics can offer critical insights into the direct effects of government purchases. This aspect is further explored in Figure 2.15, which shows labor market variables within aircraft manufacturing during the Vietnam war.

Following the February attack, the industry witnessed an uptick in hiring, as evidenced in the top-left panel of the graph.[27] Between January 1965 and January 1968, the sector's workforce expanded by over 150,000 individuals, representing substantial portions of the *total* production workforce in the private and manufacturing sectors.[28] The escalation in production necessitated increased working hours, including overtime, as indicated in the top-right panel. This period also saw a modest rise in real average hourly earnings (highlighted in the bottom-left panel). Consequently, real average weekly earnings soared, exhibiting an 11.4% year-on-year increase in the first quarter of 1966, significantly exceeding the 3% annual growth observed from 1960 to 1965.

In summary, this evidence corroborates the broader narrative presented in the SCB's January 1967 edition and confirms the expansionary direct effects of government purchases. The events of the Vietnam war are also consistent with the VAR evidence and help conceptualize those findings.

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[26]In FY1967, the top 7 contractors were McDonnell-Douglas Aircraft, General Dynamics, Lockheed Aircraft, General Electric, United Aircraft, Boeing and North American Aviation, collectively accounting for 25% of total defense contracts. General Dynamics was primarily selling aircraft, such as the F-111. While General Electric was producing aircraft engines.

[27]Production workers represent approximately 82% of total employment.

[28]More precisely, those *changes* represented about 0.4% and 1.1% of *total* production workers of January 1965 of the private and the manufacturing sector, respectively.

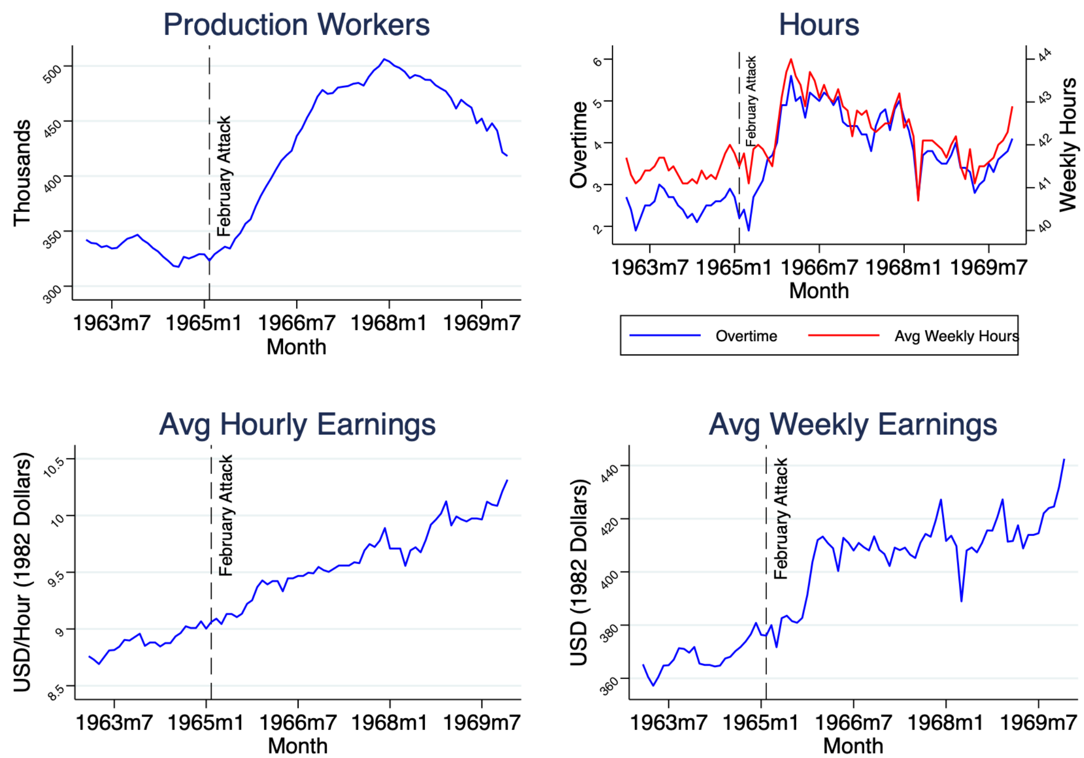


Figure 2.15. AIRCRAFT MANUFACTURING IN THE VIETNAM WAR

Notes: The data, obtained from the BLS's discontinued database, originates from the Current Employment Statistics survey. Price deflator of average hourly and weekly earnings is the PPI of durable goods (1982=100).

Labor Productivity and Manufacturing:

The top-right panel of Figure 2.14 shows a contemporaneous rise in defense contracts and labor productivity, in line with the VAR evidence portrayed in Figure 2.13.

Why did labor productivity increase during the Vietnam War? If labor productivity was directly affected by increased military contracts, I would expect to observe productivity gains within the sector most affected by those contracts: the manufacturing sector. How much of an increase in labor productivity in the manufacturing sector is required to explain the rise in output per hour for the entire private sector experienced in those years?

To answer this question, consider the following back-of-the-envelope calculation. Think of an economy divided into two sectors: manufacturing (mfg) and non-manufacturing (non-mfg). The percentage increase in aggregate output-per-hour can be represented by the following equation:[29]

$$\Delta\%\text{OpH}_t = \frac{Y_t^{\text{non-mfg}}}{Y_t} \cdot \Delta\%\text{OpH}_t^{\text{non-mfg}} + \frac{Y_t^{\text{mfg}}}{Y_t} \cdot \Delta\%\text{OpH}_t^{\text{mfg}} + \frac{\text{OpH}_t^{\text{mfg}} - \text{OpH}_t^{\text{non-mfg}}}{\text{OpH}_t} \cdot d\left(\frac{N_t^{\text{mfg}}}{N_t}\right)$$

where Y denotes output, N employment and OpH, output-per-hour. Using average data from 1960 to 1965 (Pre-Vietnam) and the change around the outbreak of the Vietnam war, I have:

$$\underbrace{\Delta\%\text{OpH}_{\text{Vietnam}}}_{\approx 6\%} = \underbrace{\left(1 - \frac{Y_{\text{Vietnam}}^{\text{mfg}}}{Y_{\text{Vietnam}}}\right)}_{\approx 1-40.9\%} \cdot \underbrace{\Delta\%\text{OpH}_{\text{Vietnam}}^{\text{non-mfg}}}_{\approx 3.5\%(\text{Pre-Vietnam Avg})} + \underbrace{\frac{Y_{\text{Vietnam}}^{\text{mfg}}}{Y_{\text{Vietnam}}}}_{\approx 40.9\%(\text{1965 Use Tab.})} \cdot \underbrace{\Delta\%\text{OpH}_{\text{Vietnam}}^{\text{mfg}}}_{\Longrightarrow \approx 9.0\%} +$$

$$\ldots + \underbrace{\left(\frac{\text{OpH}_t^{\text{mfg}} - \text{OpH}_t^{\text{non-mfg}}}{\text{OpH}_t}\right)}_{\approx \frac{30-22}{24.7} \text{ Compustat Sales-per-Employee}} \cdot \underbrace{d\left(\frac{N_t^{\text{mfg}}}{N_t}\right)}_{\approx 0.8\% \text{ Reallocation}}$$

In 1965, manufacturing output contributed 40.9% to the total private industry output.[30] The share of manufacturing employees grew by 0.8% during the Vietnam war. OpH before the Vietnam war is approximated with the average of sales of employee of all publicly traded firms from Compustat over 1960 through 1965. The same approximation is adopted for the manufacturing and non-manufacturing output-per-hour values.[31] OpH surged by approximately 6% in the Vietnam war's initial phase. Lastly, assuming that OpH in the non-manufacturing sector was growing at the same pace of the pre-Vietnam average of OpH in the private sector, i.e. 3.5%, the above formula suggests that a 9.0% boost in manufacturing output-per-hour was

[29] This follows from the definition of OpH and a log-linearization of the equation: $\text{OpH}_t = \frac{N^{\text{non-mfg}}}{N} \cdot \text{OpH}_t^{\text{non-mfg}} + \frac{N^{\text{mfg}}}{N} \cdot \text{OpH}_t^{\text{mfg}}$.

[30] Refer to the last row of NIPA's Use table Before Redefinitions of 1965.

[31] Average sales-per-employee over the years 1960 through 1965 were 30,000$ in manufacturing, 22,000$ in non-manufacturing and 24,700$ for all private firms covered by Compustat.

necessary to generate the observed 6% increase in aggregate OpH in the initial phase of the Vietnam war. Therefore, productivity increases in manufacturing are quantitatively capable of explaining aggregate fluctuations in total labor productivity.

Labor Productivity and Defense Contractors:

If the rise in total labor productivity was driven by productivity gains in the manufacturing sector triggered by the effects of defense contracts, I would also expect to observe a rise in labor productivity of defense contractors. Therefore, similarly to what done in Christiansen and Goudie (2007), I combine balance-sheet data from the Annual Fundamental segment of Compustat with contract data from the Top 100 companies report for the period spanning from 1960 to 1971. I construct changes in sales per employee, a proxy for labor productivity, denoted as $\Delta \text{SpE}_{i,t}$, and changes in government contracts, expressed as $\Delta G_{i,t}$, where i represents a firm and t a year. I use OLS to estimate the following equation:

$$\Delta \text{SpE}_{i,t} = \lambda_i + \rho \cdot \Delta \text{SpE}_{i,t-1} + \sum_{h=-1}^{1} \beta_h \cdot \Delta G_{i,t-h} + \varepsilon_{i,t}, \quad t = 1960, ..., 1971$$

where λ_i represents a firm fixed effect, with sales per employee measured in \$ per employee, and government contracts quantified in millions of dollars. Estimation results are reported in Table 2.3.

Table 2.3. DOES CONTRACTORS PRODUCTIVITY INCREASE WHEN CONTRACTS INCREASE?

	Dependent: ΔSpE_t															
Regressor	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
$\Delta G_{i,t}$	-1.49			0.11	-1.34			0.65	-0.31			1.18	-0.61			1.16
	(2.04)			(2.01)	(1.56)			(1.40)	(1.35)			(1.55)	(1.05)			(1.17)
$\Delta G_{i,t+1}$		-1.96		-1.07		-1.67		-0.61		-0.59		1.18		-1.19		-0.02
		(1.73)		(1.91)		(1.24)		(1.30)		(1.33)		(1.55)		(1.00)		(1.11)
$\Delta G_{i,t-1}$			3.38*	4.44**			3.23**	4.61***			2.05	3.85**			2.55**	4.32***
			(2.01)	(2.15)			(1.51)	(1.52)			(1.42)	(1.67)			(1.08)	(1.27)
Aircraft Only	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No
Reliance Weighted	No	No	No	No	Yes	Yes	Yes	Yes	No	No	No	No	Yes	Yes	Yes	Yes
N (Contractors)	9	9	9	9	9	9	9	9	55	55	55	55	55	55	55	55
T (Years)	11	10	10	9	11	10	10	9	11	10	10	9	11	10	10	9
Observations	99	90	90	81	99	90	90	81	605	550	550	495	605	550	550	495

Notes: *** denotes 1% significance level. ** denotes 5% significance level. * denotes 10% significance level. All regressions include firm fixed effects. The first eight columns of the table show the results for firms operating in NAICS 3364, Aircraft Manufacturing and Parts. The last eight columns present results for all publicly traded defense contractors. The results shown in columns four to eight and thirteen to sixteen are weighted based on a firm's reliance on government contracts. The reliance of contractor i is $\text{Reliance}_i = \sum_t \text{Sales}_{i,t} / \sum_t \text{G}_{i,t}$. The median reliance is 20%, with a maximum of 100% of sales to the government. This weighting is made to acknowledge that companies more involved with government contracts might experience a greater impact from government purchases.

Notice that future and contemporaneous changes in contracts are not associated with changes in sales-per-employee. On the contrary, lagged changes in government contracts are strongly positively correlated with changes of sales-per-employee. Overall, the results are robust across different specifications: I check for aircraft manufacturers only and/or weigh observations by their average reliance of sales on government purchases (see Table 2.3 notes).

My estimates indicate that if in year t the change in government contracts increases by one million \$, in year $t+1$ the change in output-per-employee should increase by 4.32\$ per employee, on average (see column (16) of Table 2.3). To give a perspective on the size of this effect, Lockheed experienced an increase in government contracts between FY1964 and FY1968 of 415 million dollars. A fluctuation of this size would predict, on average, an increase in sales per employee by 1,792 dollars, which is equal to about 7.7% of Lockheed's average sales per employee during this period.[32]

Additionally, Figure 2.16 depicts the distribution of total defense procurement contracts across firms, showcasing the percentages allocated to the top 5, 25, and 100 companies over time. The top 50 firms account for about half of the total. Consequently, the 55 publicly traded top 100 defense contractors analyzed in Table 2.3 accounted for more than half of all defense procurement contracts. This demonstrates that the productivity gains observed were not confined within the smaller entities in the military procurement sector.

The Phantom F-4 II Case and Learning-by-Doing:

A potential micro-origin of the labor productivity boost experienced in war-times is learning-by-doing (McGrattan and Ohanian (2010)). A case in point is the production of the McDonnell-Douglas F-4 Phantom II, the defining aircraft of the Cold War period. Smith (1976) studied the production of this aircraft; his analysis spans 4665 airframes produced across 57 lots between 1958 and 1975. Delivery rates reached their peak during the Vietnam war with 71 airframes delivered monthly. This surge propelled McDonnell Douglas Aircraft to the premier

[32] Values of Lockheed contracts come from the Top 100 companies report; sales-per-employee data is from the Annual Fundamental segment of Compustat, for the fiscal years 1960 through 1970.

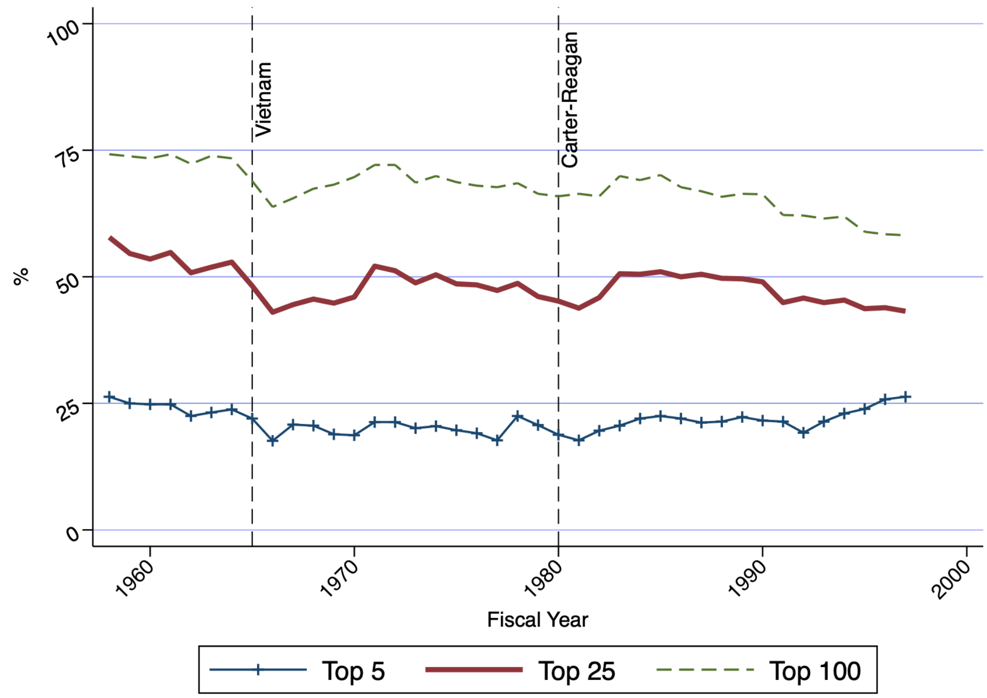


Figure 2.16. GRANULARITY OF DEFENSE PROCUREMENT CONTRACTS

Notes: Fiscal years goes from the 1st of July of year t until 30th of June of year $t+1$, until FY1976. Afterwards, the definition of fiscal year changed: the FY starts on the 1st of October of year t and ends on the 30th of September of year $t+1$.

position among the Top 100 companies.

Smith findings reveal that labor requirements decreased with both cumulative past production - a typical learning curve effect — but also with production rates, via reinforcement of labor routines. Specifically, a 1% uptick in production rates corresponded to roughly a 0.18% reduction in direct labor hours, according to his estimates (see Table 3 and Table 6 in his paper). Given that delivery rates increased by almost 300% from lot 18 to lot 30, Vietnam war build-up, labor requirement to produce the F-4 should have fallen by about 54%, and this is without accounting for the effect from cumulative past production.[33] In essence, as McDonnell Douglas ramped up production during the Vietnam war, labor productivity saw a significant rise due to learning effects.

[33]Notice that this is an extrapolation. Smith (1976) provides all data he used in his analysis, except for labor requirement and the estimated intercepts, which were considered proprietary and they have been masked.

Learning-by-Doing in Manufacturing and Military Production:

It turns out that learning-by-doing is a widely observed phenomenon in the manufacturing and defense production (see Alchian (1963), Gulledge and Womer (1986), Argote and Epple (1990) and Benkard (2000)).[34] In fact, as noted by Arrow (1962), the concept of learning-by-doing originates in the context of (military) aircraft production (see Wright (1936) and Asher (1956)). Formally, it refers to an empirical regularity wherein unit costs decrease by a constant percentage as total production doubles. This decline in unit cost is attributed to the effects of learning.[35]

Learning-by-doing has been widely employed in the macroeconomic literature focused on long-run economic growth.[36] Nevertheless, learning can be rapid and its effects can have short-run implications too, as noted in Chang, Gomes, and Schorfheide (2002). For instance, the official BEA's government transaction methodology paper discusses rapidly falling prices in the context of military aircraft purchases due to learning effects (page II-66):

"*The learning curve may show steeply falling prices in the beginning years of production because of low initial labor productivity and the subsequent rapid price decline as productivity increases.*"

Learning can be fast for two reasons. First, the empirical regularity found in (military) production data, defined as "*learning curve*" is not a time-dependent concept: "*for every doubling of past production, labor requirements decrease by 20%*". Therefore, rapid learning can occur over short periods, provided production rates remain high. Evidence of a negative correlation between production rates and labor requirements has been found in many defense programs

[34] Evidence of learning in other manufacturing sectors: aircraft engines, machine tools, metal products, shipbuilding, semiconductors, refined petroleum products, power plants, chemical processing, and trucks.

[35] Specifically, they referenced: (i) job familiarization, (ii) better tool coordination, shop organization, and engineering coordination, (iii) development of efficient sub-assemblies, (iv) improved parts-supply systems, and (v) creation of more effective tools.

[36] Notable examples: Arrow (1962), P. M. Romer (1986), Lucas (1988) and Young (1991).

(see Smith (1976) and Bourgoine and Collins (1982) for literature review). Second, the stock of experience within a firm is subject to rapid depreciation, due to "*organizational forgetting*", see Argote and Epple (1990), Argote, Beckman, and Epple (1990), and Benkard (2000). These works have found evidence that when production halts or slows, there is a notable surge in labor hours needed per item, indicating the impact of forgetting.[37] According to Argote, Beckman, and Epple (1990), the stock of knowledge depreciates rapidly. Using data from the Liberty Ships program of WWII from 16 shipyards and 2708 ships, they estimate that only 3.2% of the initial yearly stock of knowledge persisted a year later. Less extreme depreciation rates are found in Benkard (2000) using data from the Lockheed's L-1011 commercial aircraft production, estimating a 61% yearly depreciation rate.

Finally, Ilzetzki (2023) provides evidence suggesting that military contractors during WWII experienced learning-by-doing, especially in situations where plants faced significant capacity constraints, a phenomenon referred to as "*learning-by-necessity*." In periods of military buildup, contractors encounter substantial increases in demand, placing considerable pressure on their production capacities. For instance, Figure 2.16 demonstrates a reduction in the share of defense procurement contracts awarded to the top 5, 25, and 100 defense contractors during both the Vietnam War and the Carter-Reagan military buildup. This pattern indirectly suggests that the leading contractors were unable to fulfill the government's entire demand during these times, necessitating that the Department of Defense seek military supplies from a broader array of firms. Should the top contractors have been operating near full capacity, the findings from Ilzetzki (2023) indicate that learning effects might have been particularly pronounced.

2.4 Rationalization: Two Sector RBC with Learning

In this section I show that the empirical evidence brought forward by ordering defense contracts first in a VAR can be rationalized with a model where manufacturers feature learning-

[37] In this sense, it is remarkable the anecdote reported in Benkard (2000) at page 1049: "*In discussions with industry executives they have expressed the belief that disruptions in production, even those designed to improve efficiency, may lead to setbacks in productivity since they upset workers' routines.*"

by-doing, a simple, yet empirically relevant, endogenous mechanism which rises productivity in response to extra demand from the government.

Consumption and Government Spending in Theory:

The first paper to recognize that an endogenous increase in labor productivity could lead to a rise in consumption following a positive government spending shock was Devereux, Head, and Lapham (1996). In their model, productivity increases endogenously when demand rises due to increasing returns to specialization, as described by Krugman (1979). As long as the price-cost markup exceeds 50%, an increase in government purchases leads to an uptick in consumption.

Subsequent modeling efforts to generate an increase in consumption after government spending shocks were motivated by the empirical evidence presented through the SVAR approach. A notable example is Galí, López-Salido, and Vallés (2007), which incorporates sticky prices and rule-of-thumb consumers. Both Monacelli and Perotti (2008) and Bilbiie (2011) employ sticky prices and non-separable preferences, with consumption and leisure acting as substitutes, to produce an increase in consumption.[38] Nonetheless, this class of models necessitates a countercyclical response of the markup to achieve a consumption increase, which contrasts with the evidence presented in Figure 2.12.

Recent studies have employed one-sector NK models with different endogenous mechanisms to boost labor productivity to achieve a positive consumption multiplier, as in Devereux, Head, and Lapham (1996). For instance, D'Alessandro, Fella, and Melosi (2019) leveraged the learning-by-doing mechanism introduced by Chang, Gomes, and Schorfheide (2002), while Jørgensen and Ravn (2022) focused on variable technology utilization.

Motivated by the abundant empirical evidence on learning-by-doing, I formulate a two-sector RBC model replicating the proportions of the manufacturing and non-manufacturing sectors. In this model, the manufacturing sector is characterized by learning-by-doing while

[38] In these models, following a positive government spending shock, hours worked rise for a given level of consumption. As a result, individuals tend to replace some of their leisure time with more consumption, prompting a leftward shift in labor supply.

the non-manufacturing sector is not. Unlike Chang, Gomes, and Schorfheide (2002) and D'Alessandro, Fella, and Melosi (2019), learning applies only to manufacturing, since government purchases are concentrated in manufacturing and evidence of learning is found almost exclusively in manufacturing and military production.

2.4.1 The Model

Households:

Preferences are separable and households solve the following problem:

$$\max_{(N_t,C_{1,t},C_{2,t},u_{1,t},u_{2,t},K_{1,t},K_{2,t},I_{1,t},I_{2,t})}\sum_{t=0}\beta^t\cdot\left(\frac{\left(\tilde{C}_t-b\cdot\tilde{C}_{t-1}\right)^{1-\sigma}}{1-\sigma}-\psi\cdot\frac{N_t^{1+\varphi}}{1+\varphi}\right)$$

subject to:

$$\begin{aligned}C_{1,t}+P_t\cdot C_{2,t}+I_{1,t}+P_t\cdot I_{2,t}=W_t\cdot N_t+\left(r^k_{1,t}\cdot u_{1,t}\;K_{1,t-1}+r^k_{2,t}\cdot u_{2,t}\;K_{2,t-1})\right)-T_t\\ K_{i,t}=(1-a(u_{i,t}))\cdot K_{i,t-1}+I_{i,t}\cdot\left(1-S(\frac{I_{i,t}}{I_{i,t-1}})\right)\quad i=1,2\end{aligned}$$

with $\tilde{C}_t:=C_{1,t}^{1-\phi}\cdot C_{2,t}^{\phi}$.

$C_{1,t}$ is produced by sector 1 which mimics the non-manufacturing sector of the economy. $C_{2,t}$ is the manufacturing good, produced by the manufacturing sector. The price of $C_{1,t}$ is the numeraire of the economy and P_t is the price of $C_{2,t}$ (relative to good 1). Since capital good of sector 2 has a different value of that one of sector 1, there are two rental rates of capital. Since capital goods is sector specific and cannot be shifted from one sector to another, households optimize either type of capital assets. T_t is a lump-sum tax.

Finally, households decide how much to invest in each period as well as how much to utilize capital. In particular, I have that:

- Capital utilization increases the depreciation rate of the capital stock:

$$a(u_{i,t}) = \delta + \delta_1 \cdot (u_{i,t} - 1) + \frac{\delta_2}{2} \cdot (u_{i,t} - 1)^2 \quad i = 1,2$$

with $\delta_1 = \frac{1-\beta}{\beta} + \delta$ to ensure that the steady state value of $u_{i,t}$ is 1 in both sectors.

- Investment adjustment costs are:

$$S(\frac{I_{i,t}}{I_{i,t-1}}) = \frac{\kappa}{2} \cdot \left(\frac{I_{i,t}}{I_{i,-1}} - 1 \right)^2 \quad i = 1,2$$

Therefore, $S(1) = 0$ and $S'(1) = 0$. Moreover, if $\kappa = 0$, there are no adjustment costs.

Production:

Production in the non-manufacturing sector occurs via a simple Cobb-Douglas technology with constant return to scale:

$$Y_{1,t} = N_{1,t}^{\alpha_1} \cdot \left(K_{1,t}^*\right)^{1-\alpha_1} \quad \text{with } K_{1,t}^* := u_{1,t} \cdot K_{1,t-1},$$

Firms maximize profits under perfect competition (take prices as given). The FOCs are:

$$[N_{1,t}]: \quad W_t = \alpha_1 \cdot \frac{Y_{1,t}}{N_{1,t}} := \text{MPN}_{1,t}$$
$$[K_{1,t}^*]: \quad r_{1,t}^k = (1 - \alpha_1) \cdot \frac{Y_{1,t}}{K_{1,t}^*} := \frac{\text{MPK}_{1,t}}{u_{1,t}}$$

The same production technology applies to the manufacturing sector:

$$Y_{2,t} = \left(E_t^{\theta} \cdot N_{2,t}\right)^{\alpha_2} \cdot \left(K_{2,t}^*\right)^{1-\alpha_2} \quad \text{with } K_{2,t}^* := u_{2,t} \cdot K_{2,t-1},$$

Here, E_t represents the stock of experience and θ is the learning parameter. The dynamics of experience is inspired by learning models with organizational forgetting (Argote and Epple (1990), Argote, Beckman, and Epple (1990) and Benkard (2000)). Organizational forgetting refers to the fact that the stock of experience depreciates over time due to (i) falling production rates, since typically such times are accompanied by layoffs or even (ii) normal rates, as employee turnover also lead to experience depreciation during periods of constant production.

Therefore, the dynamics of experience is equal to:

$$E_t = (1-\delta_E)\cdot E + \underbrace{\delta_E \cdot E_{t-1}}_{\text{“Forgetting”}} + \underbrace{(Y_{2,t} - Y_2)}_{\text{“Learning”}},$$

where E is the steady state value of the stock of experience and Y_2 is the steady state value of production of manufacturing good.[39] On the contrary, Chang, Gomes, and Schorfheide (2002) uses past deviations of hours worked from steady state.

When $Y_{2,t}$ is above its steady-state level, experience accumulates, enhancing output-per-hour. This suggests that during economic booms, elevated production rates foster (i) greater reinforcement of routines among production workers and (ii) faster descent along the learning curve, thereby increasing labor productivity. Once production is back to its steady-state level, experience geometrically decays at rate δ_E. This reduction is due to organizational forgetting characterized by a slowdown in production rates, which leads to knowledge loss.

Conversely, when $Y_{2,t}$ is below the steady-state, the loss of experience triggers a decline in productivity. This can be likened to a recession period where turnover exceeds the normal rate, production is diminished, and experience is eroded due to layoffs and reduced reinforcement of routines, consequently exacerbating the recession (see Benkard (2000)).

Firms maximize profits under perfect competition (take prices as given). The FOCs are:

$$\begin{aligned}
[N_{2,t}]: &\quad W_t = P_t \cdot \alpha_2 \cdot \frac{Y_{2,t}}{N_{2,t}} := P_t \cdot \mathrm{MPN}_{2,t} \\
[K^*_{2,t}]: &\quad r^k_{2,t} = P_t \cdot (1-\alpha_2) \cdot \frac{Y_{2,t}}{K^*_{2,t}} := P_t \cdot \frac{\mathrm{MPK}_{2,t}}{u_{2,t}}
\end{aligned}$$

[39] For comparison, see Equation (2) in Argote and Epple (1990) and equation (6) in Benkard (2000).

Note that the firms do not internalize future productivity gains resulting from learning. This assumption aligns with Chang, Gomes, and Schorfheide (2002) and captures the firms' inability to foresee efficiency improvements.[40]

Markets Clearing, Aggregation and Fiscal Policy:

Resources are sector specific:

$$Y_{i,t} = C_{i,t} + I_{i,t} + G_{i,t}, \quad i = 1,2.$$

The sector specific capital accumulation equations are internalized in the household problem.[41]

The labor market clears ($N_t = N_{1,t} + N_{2,t}$), and real quantities are obtained using the price level at the beginning of the simulation, that is, the steady state value, P.[42]

Government spending is financed via lump-sum taxes. The government budget constraint is given by:

$$T_t = G_{1,t} + P_t \cdot G_{2,t}$$

Since I am interested in the effects of military purchases, which are primarily concentrated in manufacturing, I assume that government spending in non-manufacturing sector, sector 1, is constant: $G_{1,t} := G_1 = \gamma_1 \cdot Y_1$, where γ_1 is the fraction of output of sector 1 purchased by the government in steady state. On the contrary, government spending in the manufacturing sector, sector 2, is pinned down from the value of government spending in sector 1 and total (real)

[40] I attempted to incorporate this mechanism into the firm's problem, but it led to the product wage becoming a weighted average of current and future productivity values. Consequently, in times of expanding demand and rising productivity, the firms would incur losses, as the product wages paid today would exceed that of the present value of labor productivity.

[41] Notice that in this setup it is not possible to shift capital from one sector to another as in Ramey and Shapiro (1998). This is equivalent to a situation where the cost of shifting capital is high enough to make it always sub-optimal to shift capital from one sector to another. In a model like the one of Ramey and Shapiro (1998), a cost of shifting capital of 0.50, like the one suggested in their paper, would be enough to make shifting capital always sub-optimal. Therefore, this setup can be interpreted like one in which the cost of shifting capital is simply very high.

[42] This is consistent with what done in Ramey and Shapiro (1998) (see page 163 of their paper).

government spending, which is exogenous:[43]

$$G_t = (1 + \text{IRF}_t^G) \cdot G$$
$$G_{2,t} = \frac{G_t - G_{1,t}}{P}$$

where P and G are the steady state values of the relative price and total government spending. IRF_t^G is an exogenous process for government spending estimated from the data: it is the estimated impulse response function of real government spending per-capita to a 1% structural shock to defense contracts.

2.4.2 Model Simulation

Table 2.4 shows the calibrated values of all parameters in the model, with their source.

Table 2.4. CALIBRATION SUMMARY

Parameter	*Description*	*Value*	*Source*
φ	Inverse Frisch	1 or 0.20	Standard Calibration or Galí, López-Salido, and Vallés (2007)
β	Discount Factor	0.985	Quarterly Calibration
δ	Capital Depreciation	0.015	Quarterly Calibration
r	Net Interest Rate	$\frac{1}{\beta} - 1$	Follows from SS
κ	Inv. Adj. Cost	5.2	Ramey (2020)
δ_1	Capital Util. (Linear)	$r + \delta$	Standard to ensure $u = 1$
δ_2	Capital Util. (Quadratic)	$2 \cdot \delta_1$	Ramey (2020): $2 \cdot \delta_1$
σ	Inverse IES	1	Jaimovich and Rebelo (2009)
b	Consumption Habit	0.71	Burnside, Eichenbaum, and Fisher (2004)
α_1	Labor Income Share of GDP	0.63	Allows aggregate labor share to be 2/3
α_2	Labor Income Share of GDP	0.75	Ramey and Shapiro (1998)
γ_2	G_2/Y_2	16.2	(Gov. Purchases of MFG Commod.)/(MFG's VA) (from 1963 Use Table)
γ_1	G_1/Y_1	0.2134	Calibrated such that $G/Y = 0.20$
ϕ	Expenditure Share of MFG consumption	0.275	Match $C_{1963}^{MFG}/C_{1963}^{PrivateNon-MFG}$ (from 1963 Use Table)
ρ_E	Forgetting	0.75^3	Argote, Beckman, and Epple (1990)
θ	Learning	0.65	Benkard (2000)
ρ_A	Persistence of Contracts	0.84	Estimated from VAR's IRF
ψ	Weight of Labor	1	-

Organizational Forgetting: according to Benkard (2000) the range of estimates of monthly depreciation rates of the stock of knowledge is between 0.75 and 0.95. For instance Argote, Beckman, and Epple (1990) estimate a monthly depreciation rate of the stock of knowledge of 75% in the Liberty Ships program of WWII. Benkard (2000) finds higher estimates for

[43] Real here means measured at constant, i.e. steady state, price levels.

the Lockheed TriStar program and finds a monthly deprecation rate of 95%. I set a value of $\delta_E = 0.75$, consistent with the estimates of Argote, Beckman, and Epple (1990).

Learning Rate: Parameter θ determines the speed of learning: the learning rate is calculated as $1 - 2^{-\theta}$ and represents how much labor requirement would fall if cumulative past output doubled. A negative relationship between labor requirements and experience is found by log-linearizing the production function, while leaving the capital stock and output unchanged:

$$\hat{N}_{2,t} = -\theta \cdot \hat{E}_t.$$

Simple learning models regressed the log of labor-requirement per unit of output on the log of experience and the log of production rates, where experience was proxied by either the stock of cumulative past output (e.g. Smith (1976)) or the stock of discounted cumulative past production (e.g. models of organizational forgetting like Argote and Epple (1990), Darr, Argote, and Epple (1995) and Benkard (2000)).

Table 2.5 summarizes different estimates for the learning parameters for different military products.

The first column of Table 2.5 report estimates of θ: percent changes in labor requirement on percent changes in experience.

Models with organizational forgetting (OF) obtain higher estimates of θ: Benkard (2000) finds values around 0.64 (model with/without knowledge spillover), while Argote and Epple (1990) find a value of 0.65.[44]

Since Benkard (2000) estimates are obtained from a model which features organizational forgetting and the parameters of his model are estimated via GMM, using several instruments to rule out endogeneity problems like reverse causality (see Ilzetzki (2023)), I prefer to set the value of θ to match the learning rate estimated by Benkard (2000): $\theta = 0.65$.

[44] Argote and Epple (1990) estimate a production function, rather than a production frontier, and that's why their estimate are not reported in Table 2.5.

Table 2.5. ESTIMATES OF LEARNING MODELS

Dependent Variable: Labor Requirement		Experience (-θ)	Production Rate	Learning Rate $1-2^{-\theta}$
Smith (1976):	Aircraft (F-4)	-0.26	-0.17	16.5%
Benkard (2000):	Aircraft (without OF)	-0.35	-0.05	21.5%
	Aircraft (with OF)	-0.65	-0.86	36.3%
	Aircraft (with OF and Spillover)	-0.63	-0.89	35.4%
Gulledge and Womer (1986):				
	Aircraft A	-0.45	-0.04	26.9%
	Aircraft C	-0.37	-0.33	22.8%
	Aircraft D	-0.18	-0.56	11.8%
	Aircraft E	-0.14	-0.57	9.5%
	Aircraft F	-0.21	-0.80	13.4%
	Aircraft G	-0.25	-0.30	16.0%
	Aircraft H	-0.43	-0.13	25.6%
	Helicopter	-0.25	-0.16	16.2%
	Jet Engine A	-0.42	-0.12	25.0%
	Jet Engine B	-0.49	-0.16	28.6%
	Missile G&C	-0.12	-0.75	8.1%
	Ordnance Item	-0.18	-0.04	11.9%
	RadarSet A	-0.10	-0.17	6.9%
	Radar Set B	-0.02	-0.13	1.1%
Mean		-0.31	-0.35	18.5%
St.Dev		0.18	0.31	9.9%

Notes: Results from Gulledge and Womer (1986) are taken from Table 7.1 at page 124. They present estimates of two parameters: γ and δ, which map into the parameters of a regression of unit labor cost/requirement on cumulative past output, β_1, and production rates, β_2. The mapping between parameters is presented at page 120, after Equation 7.4: $\beta_1 = -\gamma \cdot \delta$ and $\beta_2 = \gamma - 1$. Here θ corresponds to their β_1 and estimates of the production rates corresponds to their β_2. Value of Smith (1976) are taken from Table 3 at page 66. Values from Benkard (2000) are taken from regressions (3) and (9); the production rates parameters correspond to his γ_0 estimates minus 1, like in Gulledge and Womer (1986). OF means "Organizational Forgetting" model.

Additionally, the second column of the Table shows the estimates of the coefficient in front of the log of production rates. The estimate is negative, suggesting increasing return to scale: higher production rates lead to lower labor requirements. Finally, the last column shows the implied estimates of the learning ratio, which are consistent with a 20% learning curve, on average. The bottom line of Table 2.5 is that evidence of learning-by-doing and increasing returns to scale has been documented in the production of several military programs.

Results:

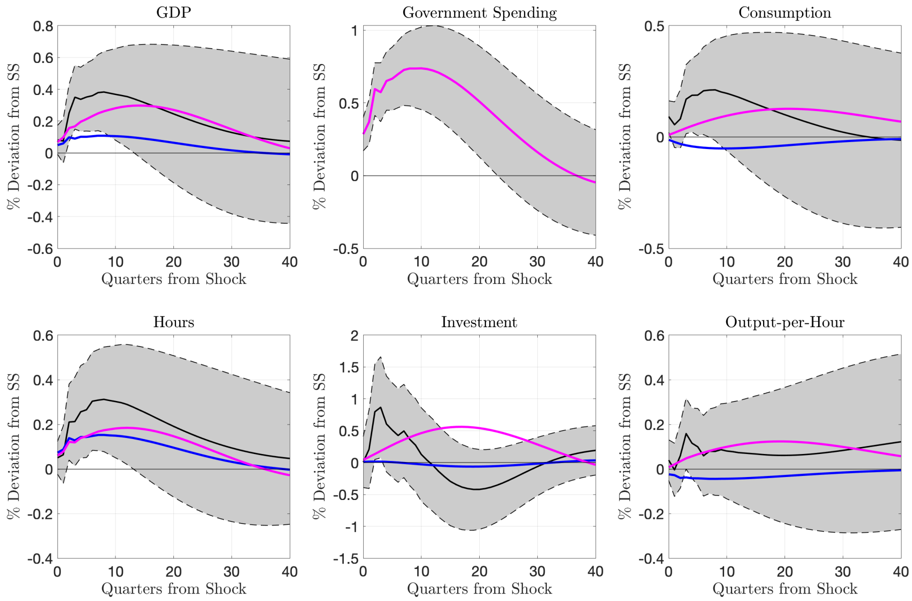
I simulate the effect of an increase in government spending by feeding the estimated impulse response function of government spending to a 1% structural shock to defense contracts into the model.

The top panel of Figure 2.17 shows the results of a perfect foresight simulation for different values of θ. The blue solid line assumes no learning, $\theta = 0$; the magenta solid line assumes that manufacturing production is characterized by learning, with $\theta = 0.65$. Both cases assume a high Frisch elasticity of labor supply: $1/\varphi = 1/0.20$, consistent with that used in Galí, López-Salido, and Vallés (2007). Finally, the dark line presents the estimated impulse response function of several variables to a shock to defense contracts, along with the 90% confidence bands.

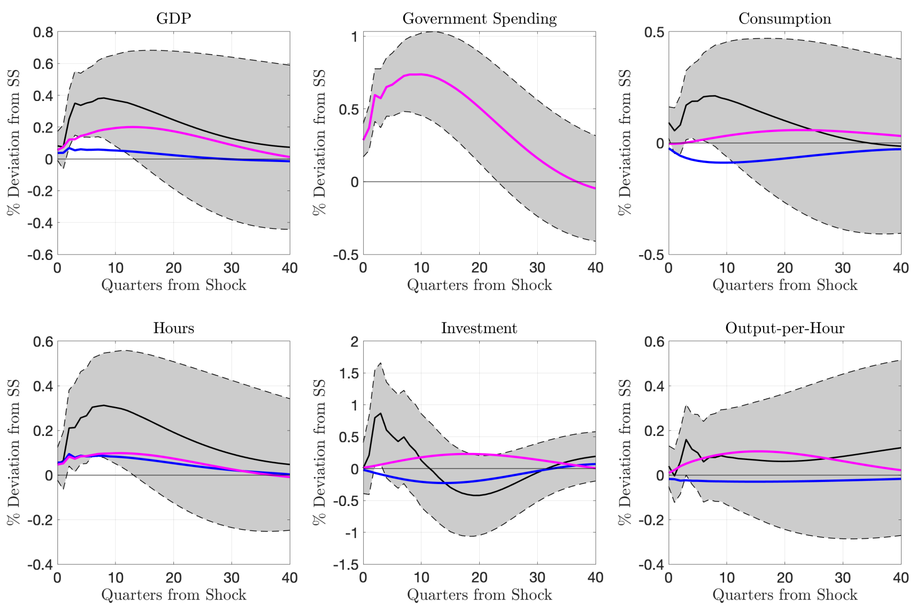
Since the model does not distinguish between durable and non-durable-plus-service consumption, I compare the model's and the empirical impulse response functions using the post-Korean War sample from 1954:Q1 to 2000:Q4. This approach helps to avoid the problem of underestimating the response of total consumption, due to the peculiar response of durable consumption during the Korean War, as discussed earlier.

The top-left panel illustrates the response of real GDP, which rises in all scenarios due to the increase in G, depicted in the top-middle panel. The bottom-left panel indicates that hours worked increase across all cases, a typical outcome stemming from the negative income effect of government spending: the necessity of higher lump-sum taxes to fund government purchases induces households to supply more labor. Even if I set a high value of the Frisch elasticity of labor supply, the response of hours in the model fall short of the observed empirical one. The bottom-middle figure displays the response of investment, which increases when learning is active, as households capitalize on the sustained productivity boost by augmenting the capital stock. In contrast, in the absence of learning, investment declines, mirroring the typical response in RBC models (refer to Baxter and King (1993) and Ramey and Shapiro (1998)). The bottom-right figure showcases the response of output-per-hour, or labor productivity, which decreases in the absence of learning due to increased hours worked and diminishing marginal returns. Conversely, output-per-hour rises when learning is operative.

Concluding, the top-right figure presents the response of consumption. In absence of



(a) HIGH ELASTICITY (GALÍ, LÓPEZ-SALIDO, AND VALLÉS (2007): $\varphi = 0.20$)



(b) LOW ELASTICITY ($\varphi = 1$)

Figure 2.17. EMPIRICAL VS MODEL RESPONSES

Notes: Blue line: no learning ($\theta = 0$). Magenta line: learning ($\theta = 0.65$). Dark line: empirical IRF with 90% confidence bands (sample is 1954:1 to 2000:4). Real variables in the model are obtained by summing sectoral values at constant prices.

learning, consumption declines as government purchases increase. This behavior is typical in standard RBC models with government spending, where consumption multipliers are negative without increasing returns to scale (see Proposition 2 in Bilbiie (2011)). In contrast, when the model incorporates learning, consumption increases by a magnitude similar to the empirical one. As long as production remains above the steady state, accumulated experience enhances labor productivity and real wages (as seen in the bottom-right panel), resulting in a net positive effect on consumption when the increase in labor earnings compensates for the adverse effects of higher taxes.

Lastly, the bottom panel of Figure 2.17 reports the results of a simulation when the Frisch elasticity is equal to one. The results are qualitatively identical to the high-elasticity case, however, the magnitude of the responses are now smaller due to the lower response of hours worked (bottom-left panel).

2.5 Conclusion

In this third chapter, I introduce a new quarterly time series, defense contracts, that measures the dollar value of all prime contract awards from the Department of Defense. I use it as an instrument for G to establish stylized facts of government spending.

Defense contracts overcome the major limitations of current methods to estimate the effects of government purchases. First, they accurately measure the timing of the shocks. In fact, since NIPA records military contracts into G with a delay, contracts lead G. This property of defense contracts represents a great advantage relative to the SVAR approach, which uses BP shocks. Second, defense contracts mainly capture fluctuations in military spending, which are driven by exogenous military events. Third, defense contracts retain statistical power as an instrument for G, even when data related to the Korean War is omitted from the sample. This addresses a major concern associated with the currently available instruments for measuring government spending, as noted by Perotti (2014) and Ramey (2016). Lastly, using data on defense contracts eliminates the necessity for narrative analysis. This methodology can be readily adopted for studies in various other countries that keep records of military contracts.

I find that a shock to defense contracts triggers a positive response in GDP, G, inventories, non-durable-plus-service consumption, hours worked, employment, production earnings, disposable income, the product wage, the price-cost markup, and labor productivity. Employing firm-level data, I demonstrate that lagged values of defense contracts correlate with increases in labor productivity among major defense contractors. Extensive evidence of productivity gains is found in both manufacturing and military production data, generally linked to learning effects. Consequently, I use a two-sector RBC model that simulates the proportions of the manufacturing and non-manufacturing sectors, with the former exhibiting learning-by-doing. In this model, a shock to defense contracts leads to an increase in government purchases from the manufacturing sector. This, in turn, boosts manufacturing production, enhancing labor productivity through learning-by-doing. As a result, the product wage increases, paving the way for a positive response in aggregate consumption, rationalizing the findings from the VAR analysis.

It should be noted that while learning-by-doing is a distinguishing feature of manufacturing, and particularly of defense production, it is not yet clear whether this transmission mechanism is characteristic of fiscal shocks exclusively or if it can influence other types of demand shocks. For instance, Christiano, Eichenbaum, and Evans (2005) observe a positive impact on labor productivity following an expansionary monetary policy shock. Learning-by-doing could potentially contribute to this increase in labor productivity, provided that the monetary expansion spurs manufacturing production, the sector most affected by learning. A potential propagation channel might be the automobile industry: lower interest rates encourage consumers to augment their current demand for vehicles, albeit to the detriment of future demand, thereby boosting present-day automobile consumption and production (see McKay and Wieland (2021)). While this exploration goes beyond the scope of the chapter, it remains the subject of future research.

2.6 Appendix

2.6.1 Output Effects of Defense Contracts - Extra and Robustness

Lead-Lag Correlation - Robustness

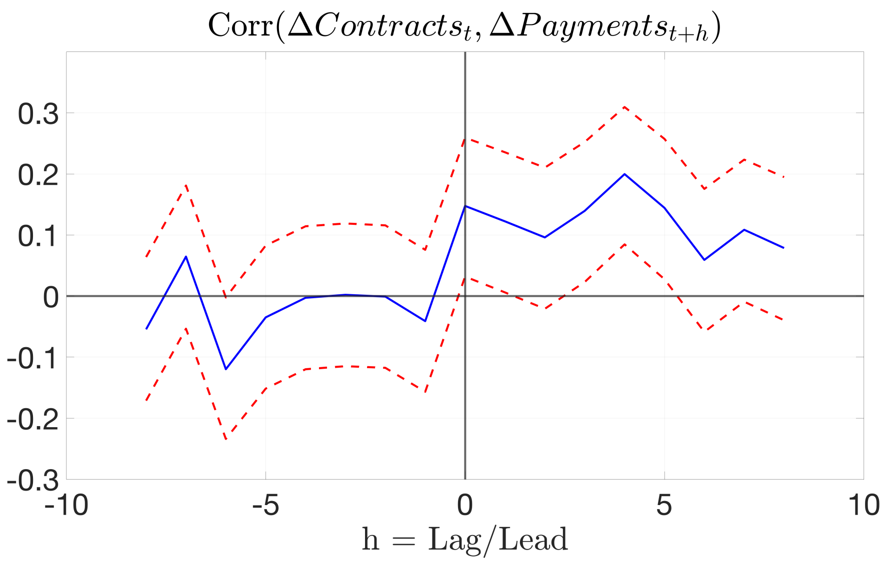


Figure 2.18. LEAD-LAG CORRELATION MAP BETWEEN CONTRACTS/SPENDING

Notes: sample goes from 1947:1 to 2019:4. Here Δx_t means $x_t - x_{t-1}$. The price deflator used is the one of Intermediate goods and services purchased by the government, available from NIPA.

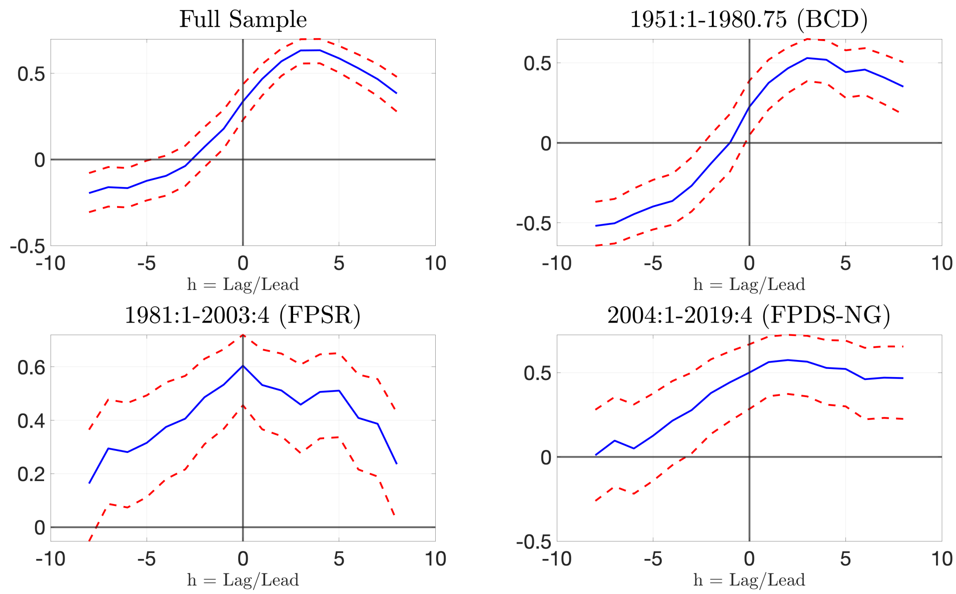


Figure 2.19. LEAD-LAG CORRELATION MAP BETWEEN CONTRACTS/SPENDING

Notes: sample goes from 1947:1 to 2019:4. Here $\Delta_4 x_t$ means $x_t - x_{t-4}$. The price deflator used is the one of Intermediate goods and services purchased by the government, available from NIPA.

IRFs of GDP Components - Robustness

In this section I carry out robustness analysis for the IRFs of GDP's components:

- Figure 2.20: baseline VAR from 1947:1 to 2019:4.
- Figure 2.21: baseline VAR from 1954:1 to 2000:4.
- Figure 2.23: baseline VAR with quadratic trend from 1947:1 to 2000:4.
- Figure 2.22: baseline VAR with tax receipts from 1947:1 to 2000:4.
- Figures 2.24 and 2.25: mimic Ramey (2011)'s VAR:
  - *Purpose*: in this chapter I follow Ramey (2016) and use the Gordon and Krenn (2010)'s transformation. Unlike her, I prefer using VAR over local projections since they deliver slightly more efficient results (see Li, Plagborg-Møller, and C. Wolf (2021)). The conclusion should not be affected, given that local projections and VAR

estimate the same IRFs in population (see Plagborg-Møller and C. K. Wolf (2021)). Nonetheless, I provide a more standard VAR with the usual "log-real-percapita" specification as a further robustness check.

- *Variables*: defense contracts, GDP, G, Hours worked in the private sector, 3 months T-Bill rate, Barro and Redlick (2011)'s average marginal tax rate and a quadratic trend. Nominal variables are deflated by the GDP price deflator and are expressed as logs of per capita values. Hours are in logs. Inventories are only in real per capita values - no logs - since they take on negative values and, they are not trending.
- *Identification*: order log of real per capita defense contracts first in the VAR.
- *Sample*: (i) 1947:1 - 2008:4 and (ii) 1954:1 - 2000:4 (sample capped by availability of Barro-Redlick's average marginal tax rate).

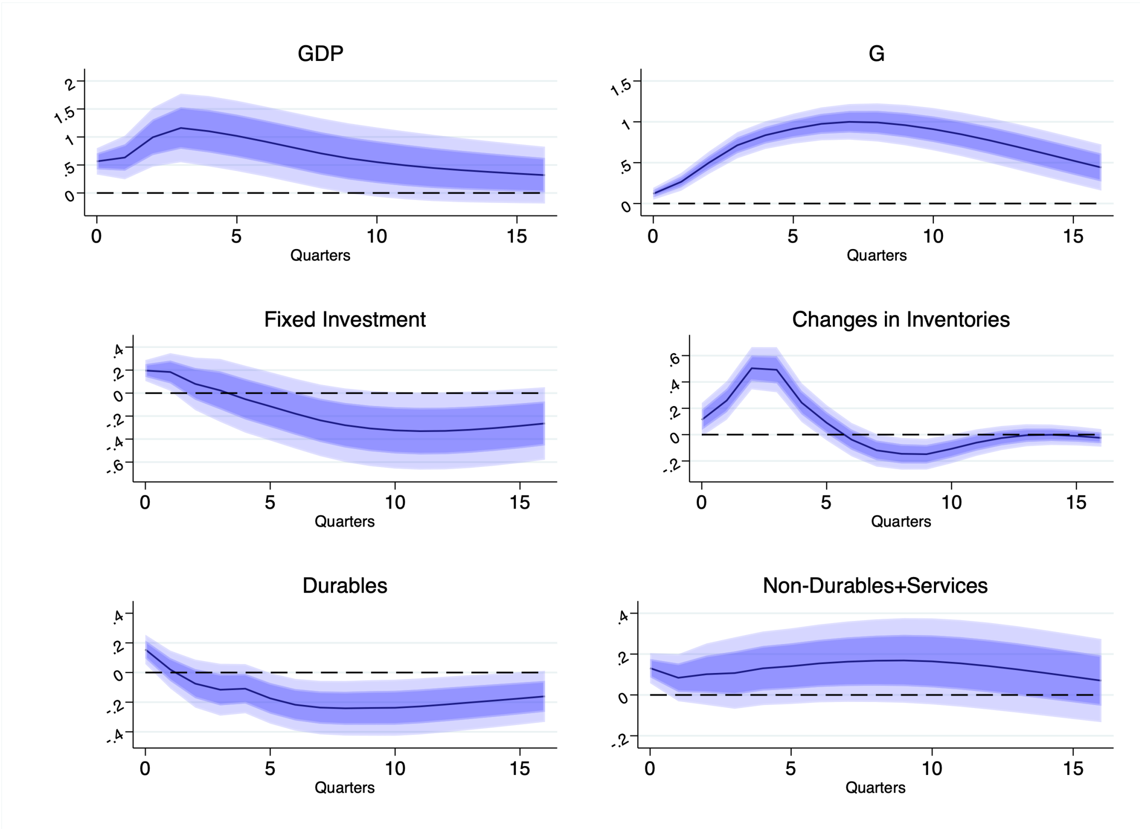


Figure 2.20. BASELINE VAR - 1947:1 TO 2019:4

Notes: Confidence bands are 68% and 90%. Values of the IRFs are normalized by the peak response of G.

On the Response of Consumption - Extra

The fiscal policy literature has been very divided on the response of consumption to a fiscal shock. Proponents of the identification via recursive assumption (i.e. Cholesky shocks) have consistently found positive responses of consumption. On the contrary, empirical work which used either war dates or defense news shock has found more negative responses of consumption, with some exception and caveats.[45] Table 2.6 summarizes the previous findings of the literature about the effects of fiscal shocks on different measures of consumption.

The literature review confirms the lack of a consenus around the effects of fiscal shocks

[45]For instance, service consumption increase after a defense news shock (see Ramey (2011)). Moreover, the initial positive response of durable consumption followed by its fall is primarily driven by the forwards buying at the onset of the Korean war (see Ramey (2016)). I summarize in detail the empirical evidence on the response of consumption in the Online Appendix A.3.

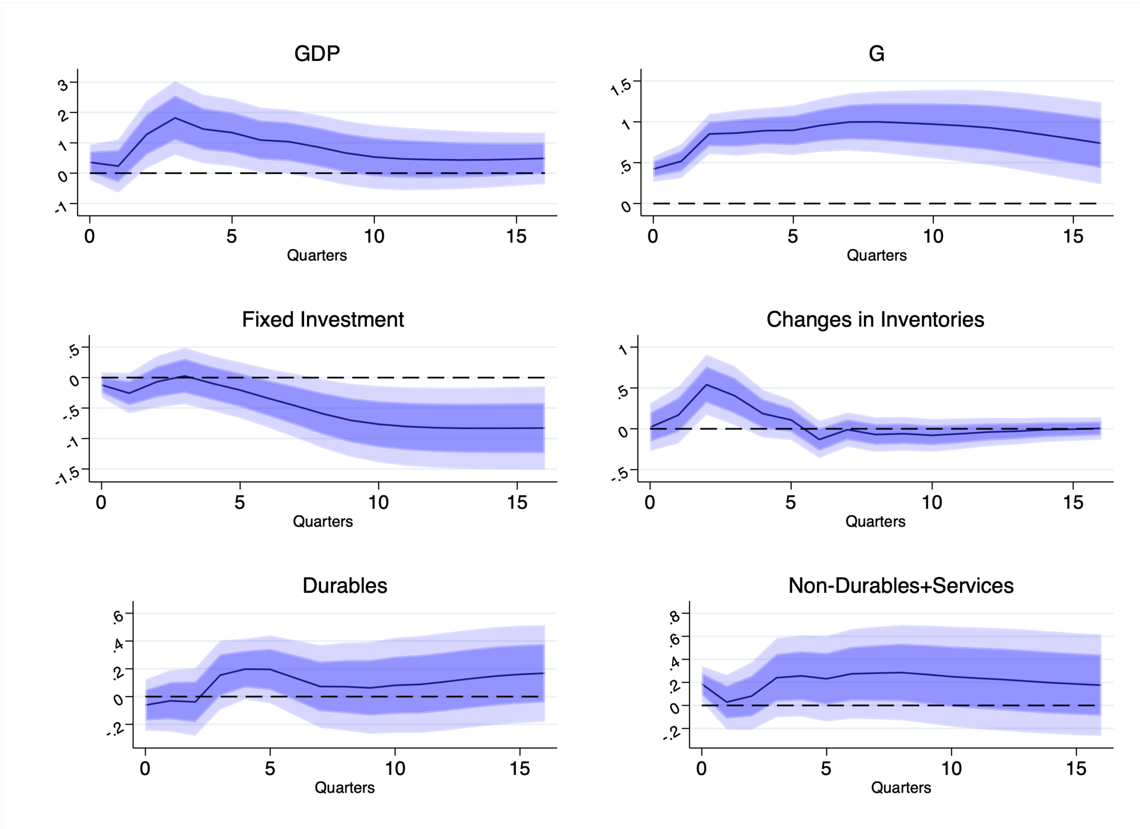


Figure 2.21. BASELINE VAR - 1954:1 TO 2000:4

Notes: Confidence bands are 68% and 90%. Values of the IRFs are normalized by the peak response of G.

Table 2.6. LITERATURE REVIEW: CONSUMPTION RESPONSE TO FISCAL SHOCKS

Paper	Shock	Method	Sample	Bands	C	$C^{\text{Dur.}}$	$C^{\text{NonDur.}}$	$C^{\text{Serv.}}$	$C^{\text{NonDur. + Serv.}}$
Ramey and Shapiro (1998)	War Dates	Distributed Lags	1947:1-1996:4	80%	NA	↑↓	↔	NA	NA
Edelberg, Eichenbaum, and Fisher (1999)	War Dates	VAR	1947:1-1996:4	68%	↔	↑↓	NA	NA	↔
Burnside, Eichenbaum, and Fisher (2004)	Weighted War Dates	Distributed Lags	1947:1-1995:4	95%	↔	NA	NA	NA	NA
Fisher and Peters (2010)	Top3 Excess Returns	VAR	1958:1-2008:4	68%	↓↑	NA	NA	NA	NA
Ramey (2011)	Defense News	VAR	1947:1-2008:4	95%	NA	↓	↓	↑	NA
Nekarda and Ramey (2011)	Bartik	CrossSectional	1960-2005	95%	NA	NA	NA	NA	NA
Ramey (2016)	Defense News	LP	1947:1-2008:4	90%	NA	↑↓	NA	NA	↓
Ben Zeev and Pappa (2017)	Defense News	VAR(MediumHorizon)	1947:1-2007:4	95%	↑↓	NA	NA	NA	NA
Fatas and Mihov (2001)	Cholesky	VAR	1960:1-1996:4	68%	↑	↑	↑	↑	NA
Galí, López-Salido, and Vallés (2007)	Cholesky	VAR	1954:1-2003:4	68%	↑	NA	NA	NA	NA
Monacelli and Perotti (2008)	Cholesky	VAR	1947:1-2003:4	68%	↑	NA	NA	NA	NA

Notes: NA means “Not Available” because researchers did not look into it. “0” means “response is not statistically significant”. ↓↑ means the variable initially falls and then increases.

on consumption. This is why I turn attention to the actual data during the two major military build-ups after WWII: the Korean and the Vietnam wars. Data on real service and non-durable consumption per capita during the Korean and Vietnam war suggest that consumption was almost never below trend, estimated either with a polynomial or Hamilton (2018)’s filter. First, Figure

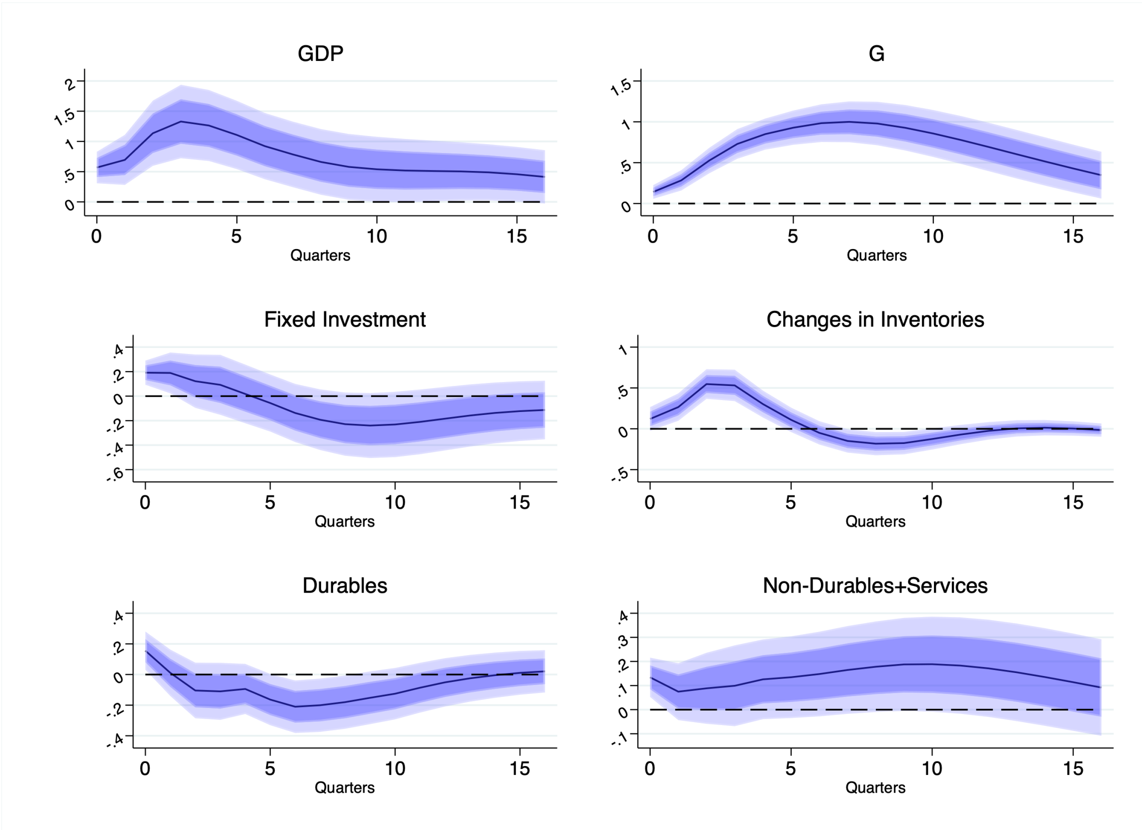


Figure 2.22. BASELINE VAR - TAX CONTROL

Notes: Sample goes from 1947:1 to 2000:4. The var also includes total tax receipts divided by potential output. Confidence bands are 68% and 90%. Values of the IRFs are normalized by the peak response of G.

2.26 shows the path of real service and non-durable consumption per capita during the Vietnam war, along with their long run trend. The dashed vertical line indicates the Tonkin incident on 1965:1, which marked the beginning of the military build-up.

The figure shows the path of real (i) service consumption per capita (left panel) and (ii) non-durable consumption per capita (right panel), during the Korean war and Vietnam war respectively. The thicker solid red line shows the data as they come from the NIPA tables. The blue line is a polynomial trend while the green dashed line shows the trend estimated via Hamilton (1994)'s filter.

Notice that in both cases, consumption tends to be above trend. In those years, the share of defense contracts relative to potential GDP increased right after the Tonkin incident and

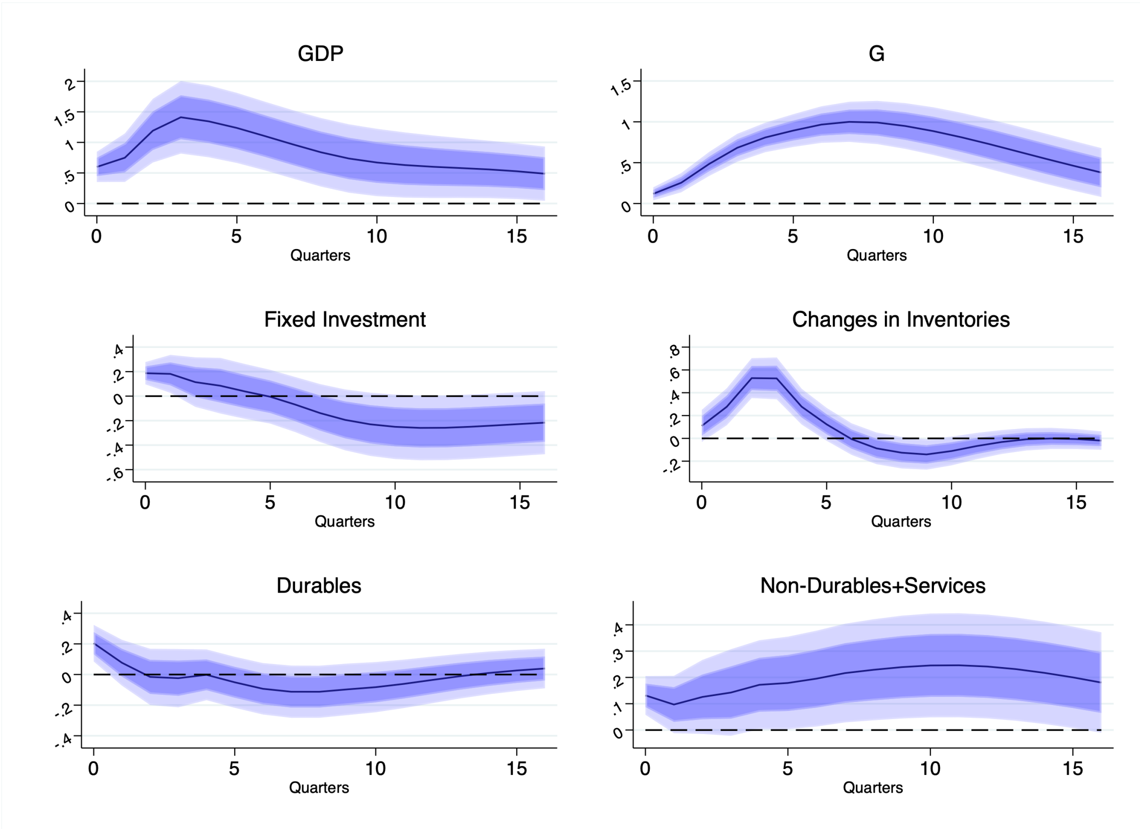


Figure 2.23. BASELINE VAR - QUADRATIC TREND

Notes: Sample goes from 1947:1 to 2000:4. The var also includes total tax receipts divided by potential output. Confidence bands are 68% and 90%. Values of the IRFs are normalized by the peak response of G.

peaked in 1966:3. The apparent decrease in consumption occurring from 1967 to 1968 was due to increased taxes. In March of 1966 the Tax Adjustment Act increased taxation by almost one billion of dollars and in November of the same year Public Law 89-800 increased taxation by another 1.5 billion dollars in order to finance the military operations in Vietnam (see C. D. Romer and D. H. Romer (2010)). Nevertheless, consumption never fell below trend.

Second, Figure 2.27 shows the path of real service and non-durable consumption per capita during the Korean war, along with their long run trend. The dashed vertical line emphasizes 1950:3, when the Korean war began following the North Korean surprise invasion of South Korea, which marked the beginning of the military build-up.

Notice that the service consumption was never below trend during the war. On the

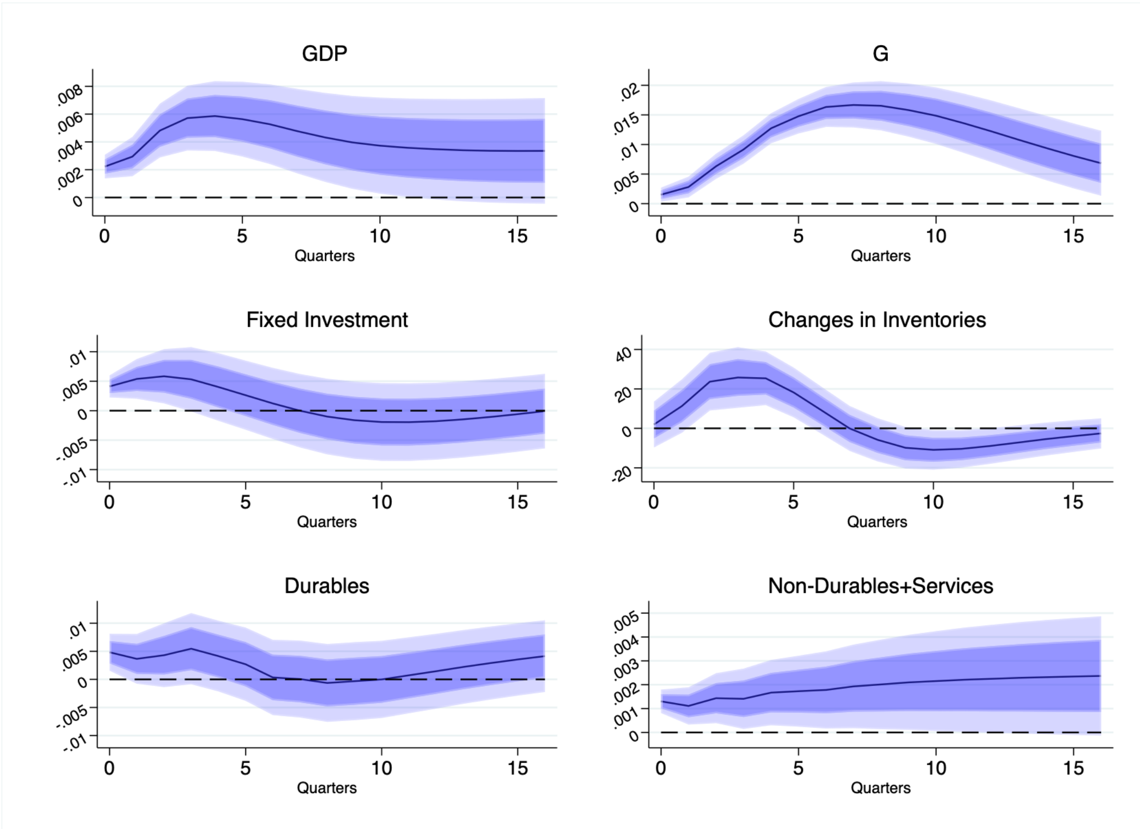


Figure 2.24. RAMEY(2011)-TYPE VAR - 1947:1 TO 2008:4

Notes: Confidence bands are 68% and 90%.

contrary, non-durable consumption was subject, as well as durable, to the buying wave driven by fear of rationing. Basically, individuals had fresh in their mind the rationing occurred during WWII and they rushed to buy all those goods which used to be in short supply: durables (like cars and kitchen appliance) and non-durables (like coffee and food). This is well known in the literature (see Ginsburg (1952), Hickman (1955), Ramey (2016) and Binder and Brunet (2021)). The forward buying wave caused non-durables to spike in 1950:3 (first wave) and in 1951:1 (second wave). Afterwards, individuals realized that the scale of the Korean war was minimal relative to WWII and the shelves in the grocery stores were promptly re-stocked. Therefore, non-durable consumption - as well as durable - fell since individuals had stockpiled enough items which could suffice for several months (intertemporal substitution).

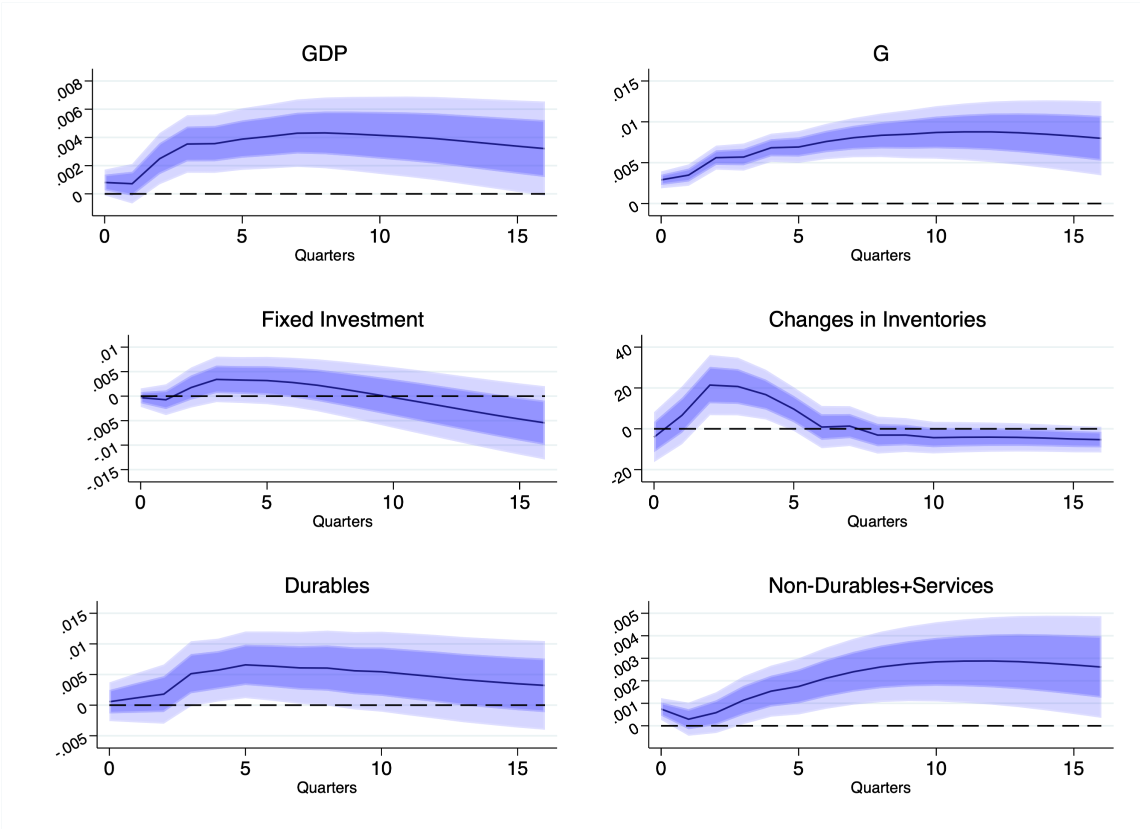


Figure 2.25. RAMEY(2011)-TYPE VAR - 1954:1 TO 2000:4

Notes: Confidence bands are 68% and 90%.

Augmenting the VAR with Defense News Shocks:

As a further robustness check, I estimate the baseline VAR by ordering the updated series of defense news shocks of Ramey and Zubairy (2018) first. I then look at the shocks to defense contracts, ordered second. This is done in the spirit of netting out the effects of news from the effects of contracts. The results are qualitatively identical to the one reported in the second chapter, obtained without defense news shocks ordered first. However, the response of consumption is now stronger relative to the previous one. Figure 2.28 shows the IRFs of non-durables-plus-service consumption in the two cases in response to a shock to contracts.

Notice that the response of consumption at early horizons is stronger when defense news shocks are ordered first in the VAR. The difference is never statistically significant, though. This evidence is consistent with a theory which see defense news shocks as a stronger shifter of labor

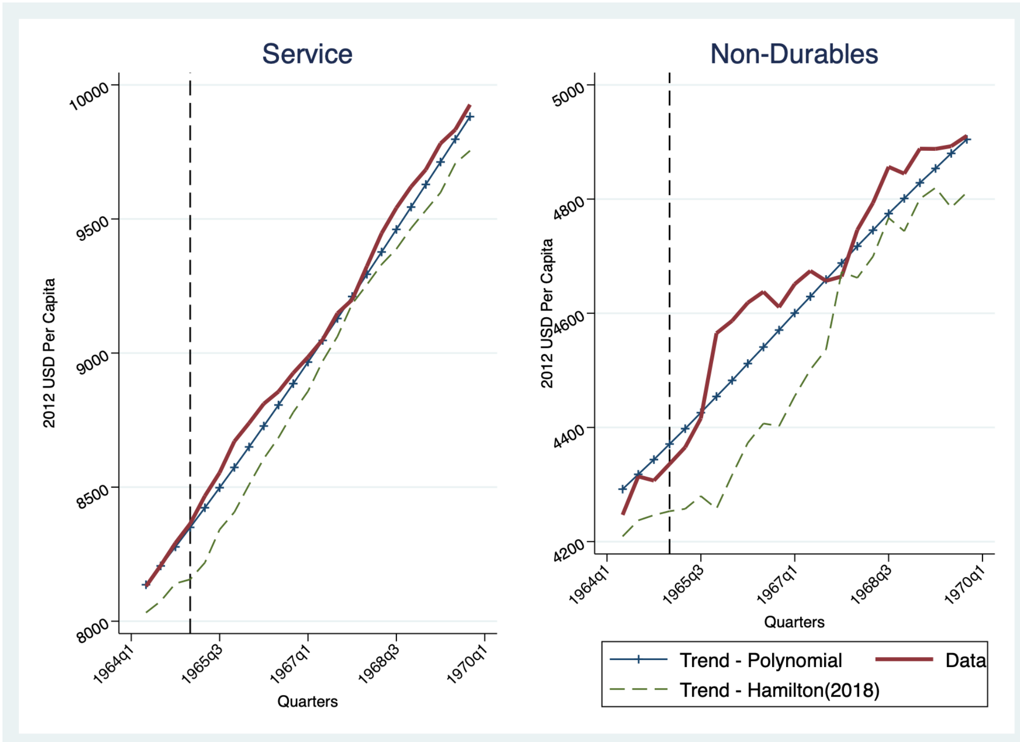


Figure 2.26. CONSUMPTION PATH - VIETNAM WAR

Notes: trends are calculated in the 30 years around the Vietnam war.

supply than labor demand and contracts as a shifter of labor demand.

2.6.2 Fiscal Multipliers

In this section I estimate the fiscal multiplier implied by defense contract shocks. Secondly, I compare my estimates to the estimates of "*obligation-multipliers*" obtained by Dupor and Guerrero (2017) and Brunet (2020). Here, obligation-multipliers indicates a multiplier defined by the effects of a 1$ increase in federal obligations, rather than government spending, on GDP. Finally, I provide evidence that the multiplier estimated in this manner aligns with the characterization of an approximately closed-economy/no-monetary-policy-response/tax-financed national multiplier. The "closed economy" characterization follows since no international spillover is systematically detected in response to shocks to defense contracts.

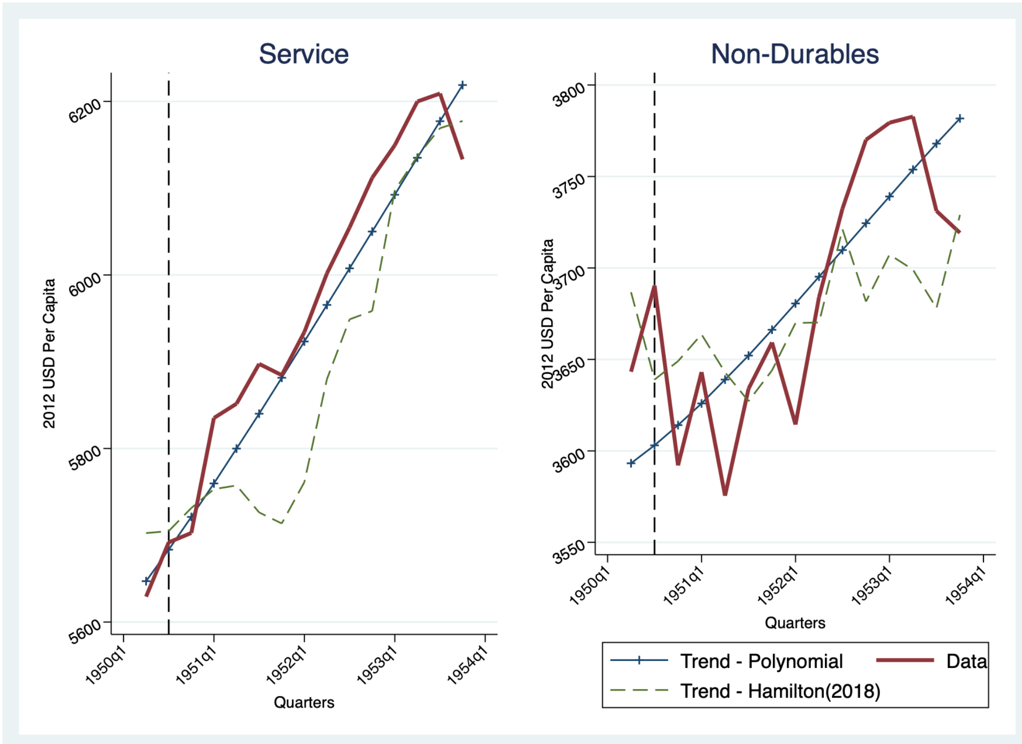


Figure 2.27. Real Consumption per Capita - Korea War

Multiplier Estimates

My starting point is Ramey (2016), which suggests to calculate the multiplier using the one-step LP-IV method (see also Stock and Watson (2018)). The method consists in regressing the cumulative change in GDP on the cumulative change in G, instrumented by the shocks and incorporating relevant (lagged) variables as controls.

$$\sum_{h=0}^{H} y_{t+h} = \mathscr{M}_H \cdot \underbrace{\sum_{h=0}^{H} g_{t+h}}_{\text{Instrumented with Shock}_t} + \text{Lags \& Controls} + \varepsilon_{t+h} \tag{2.3}$$

where y_t is GDP divided by potential output, g_t is NIPA measure of G divided by potential output, Lags&Controls include 4 lags of y_t and g_t plus four lags of the Shock$_t$ as well as four lags of hours worked in the private business sector, the 3 months T-Bill rate plus four lags of

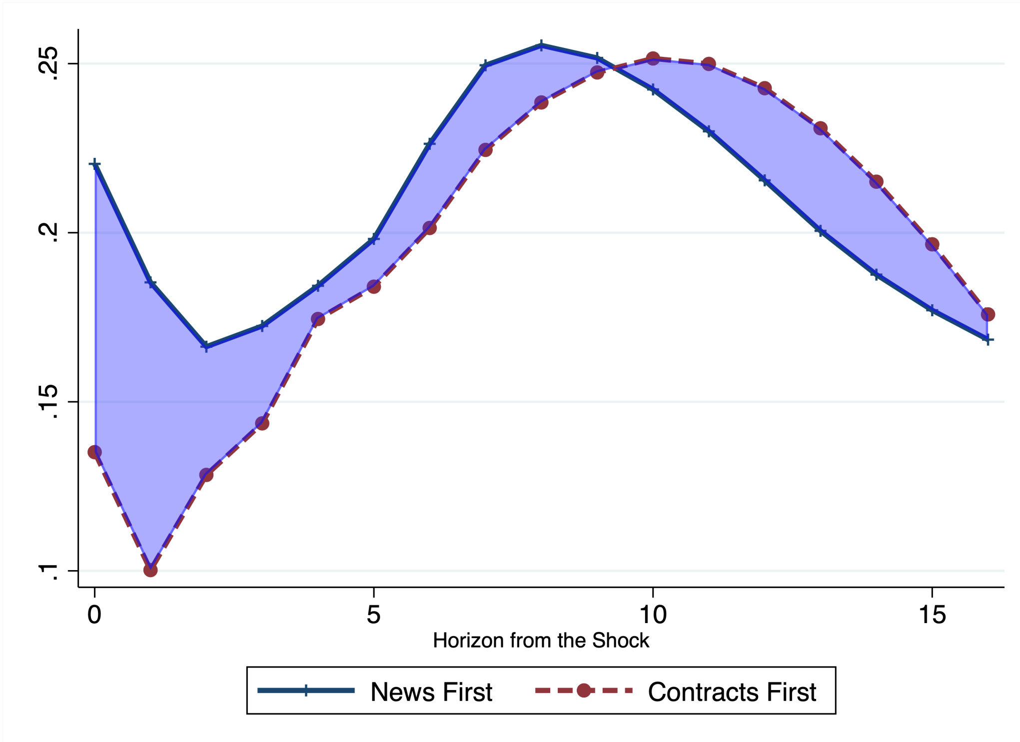


Figure 2.28. IRFs of Non-Durable-plus-Service Consumption to Contracts

Notes: Sample goes from 1947:1 to 2000:4. Values of the IRFs are normalized by the peak response of G. "*News First*" refers to the IRF of consumption in a VAR which orders defense news shocks first and contracts second. "*Contracts First*" reports the IRF showed in the second chapter.

consumption and investment also divided by potential output.[46] Shock$_t$ can be either defense news shocks (i.e. narrative method), NIPA government spending (i.e. Cholesky decomposition) or defense contracts, depending on what identification method the researcher decides to use.

This method is equivalent to a two steps procedure where the cumulative change in GDP is regressed on the shock via local projections and the estimated OLS coefficient is divided by the OLS coefficient of a regression of the cumulative change in G on the shock. The benefit of the one-step procedure is that it allows to obtain the standard errors of the multiplier as the TSLS' standard errors of $\hat{\mathscr{M}}_H$. Finally, notice that since local projections and VAR estimate the same IRFs in population (see Plagborg-Møller and C. K. Wolf (2021)), this method is asymptotically equivalent to calculating multipliers by dividing the area under the IRF of GDP by the area under

[46]I have noticed that the inclusion of consumption and investment helps estimating multipliers more precisely, no matter the instrument used (i.e. defense news shocks, Cholesky shocks or defense contracts).

the IRF of G.

Figure 2.29 shows the estimates of the fiscal multiplier by horizon obtained with defense contracts.[47]

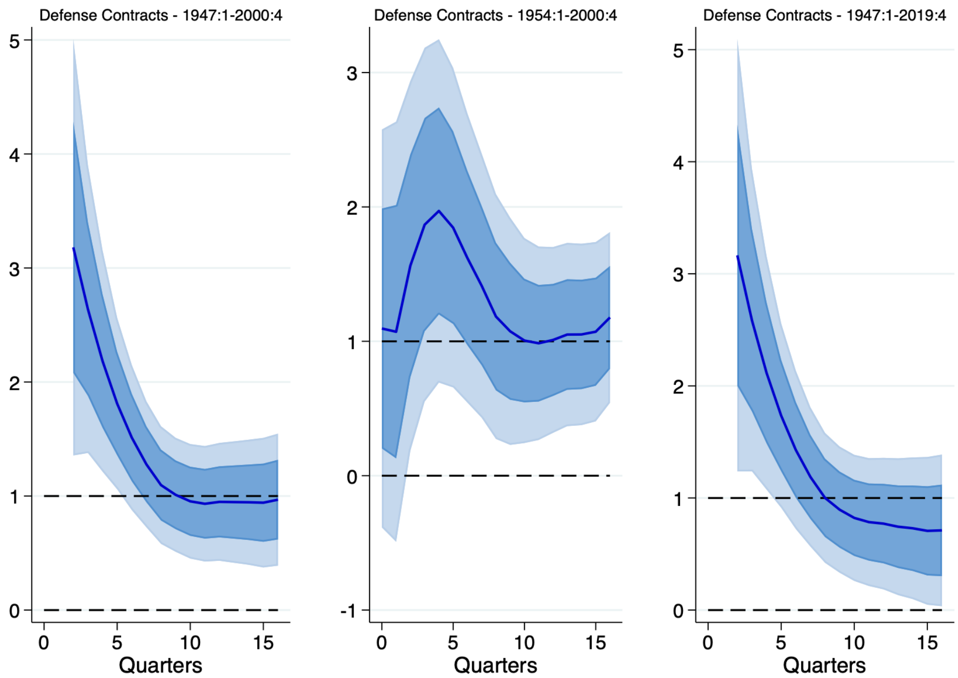


Figure 2.29. CUMULATIVE FISCAL MULTIPLIERS - DEFENSE CONTRACTS

Notes: Multipliers are obtained using the same method outlined in the second chapter in Equation (2.3). Confidence bands are 68% and 90%.

For the initial two quarters, the estimates are infinite and thus omitted when the sample includes the Korean war. This infinite size of the multiplier is a typical occurrence due to the anticipation effect, where GDP components surge before G does. Given that the multiplier is asymptotically akin to the ratio of the area under GDP's IRF to that of G, the multiplier skyrockets when the denominator is near zero. Eventually, the multiplier gradually decreases, settling at a value of one in the long-run (i.e., 4-year multiplier).

[47] This boils down in setting "Shock$_t$" equal to real defense contracts divided by real potential output in Equation (2.3).

Inclusion of taxes and/or a quadratic trend leads to slightly higher estimates than the baseline. Using the sample from 1954:1-2000:4, which excludes the Korean War, results in slightly larger multipliers compared to the baseline sample (middle panel). Although these estimates are less precise, they still hold statistical significance. Lastly, estimates from the full sample are smaller and less precise in comparison to the baseline, with a long-run multiplier estimated at 0.71 (right panel).

Long-run Multiplier Distribution:

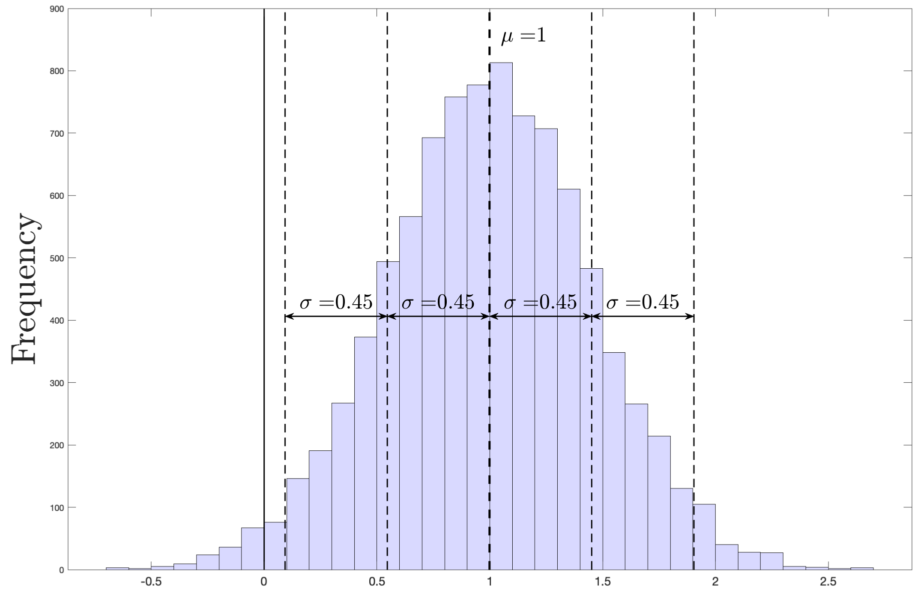
In order to account for this variability, I also construct a distribution of the long-run (i.e., 4 years) multiplier via Monte Carlo experiment. This involves pooling estimates of the multiplier's asymptotic distributions for each specification and sample to gain insight into the most probable size of the fiscal multiplier across different specifications and samples. The distribution, when all samples are considered, is centered around one with a standard deviation of 0.45; see top panel of Figure 2.30. When specifications with the full sample are excluded from the simulation, the distribution narrows, displaying a standard deviation of 0.40 and centering around 1.14; see bottom panel of Figure 2.30.

Varying specifications using defense contracts yield a distribution of the 4-year multiplier that aligns with the reasonable range of estimates found in Ramey (2016) meta-analysis: between 0.6 and 1.5.

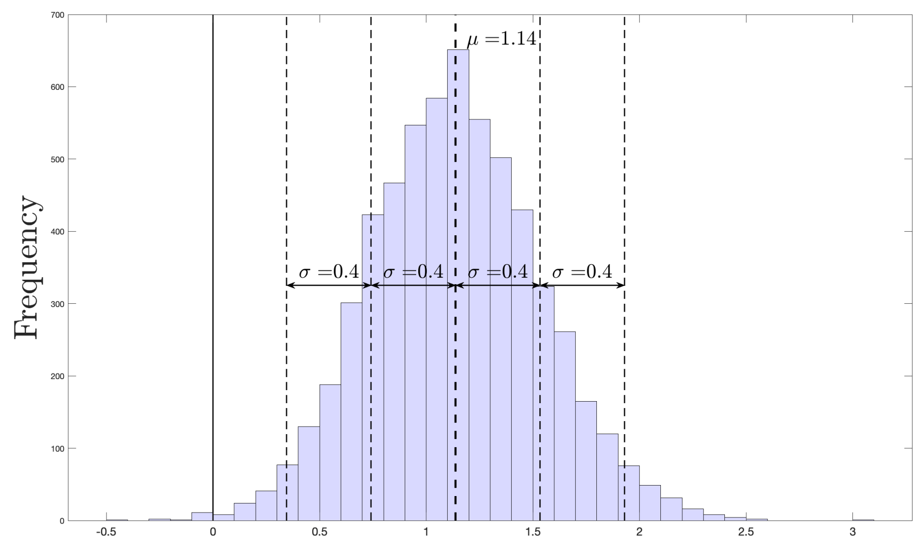
Comparison of National Multiplier Estimates:

Finally, I compare my estimates to those ones obtained with those ones obtained with (i) defense news shocks and (ii) Cholesky shocks.

I plot in Figure 2.31 the estimates of the fiscal multipliers obtained with (i) shocks to defense contracts (first column), (ii) defense news shocks (second column) and (iii) Cholesky shocks (third column). I consider three samples: (a) 1947:1 to 2000:4 (first row), (b) 1954:1 to 2000:4 (second row), (c) 1947:1 to 2019 (third row) and (d) 1954:1 to 2019:4 (fourth row).



(a) All Samples



(b) Excluding Sample 1947:1-2019:4

Figure 2.30. DISTRIBUTION OF 4 YEARS MULTIPLIER ACROSS SPECIFICATIONS

Notes: distribution of multipliers constructed in the same way as the one reported in the second chapter but omitting the full-sample. Notice that the distribution has a smaller standard deviation and a larger mean: multipliers are larger and estimated more precisely.

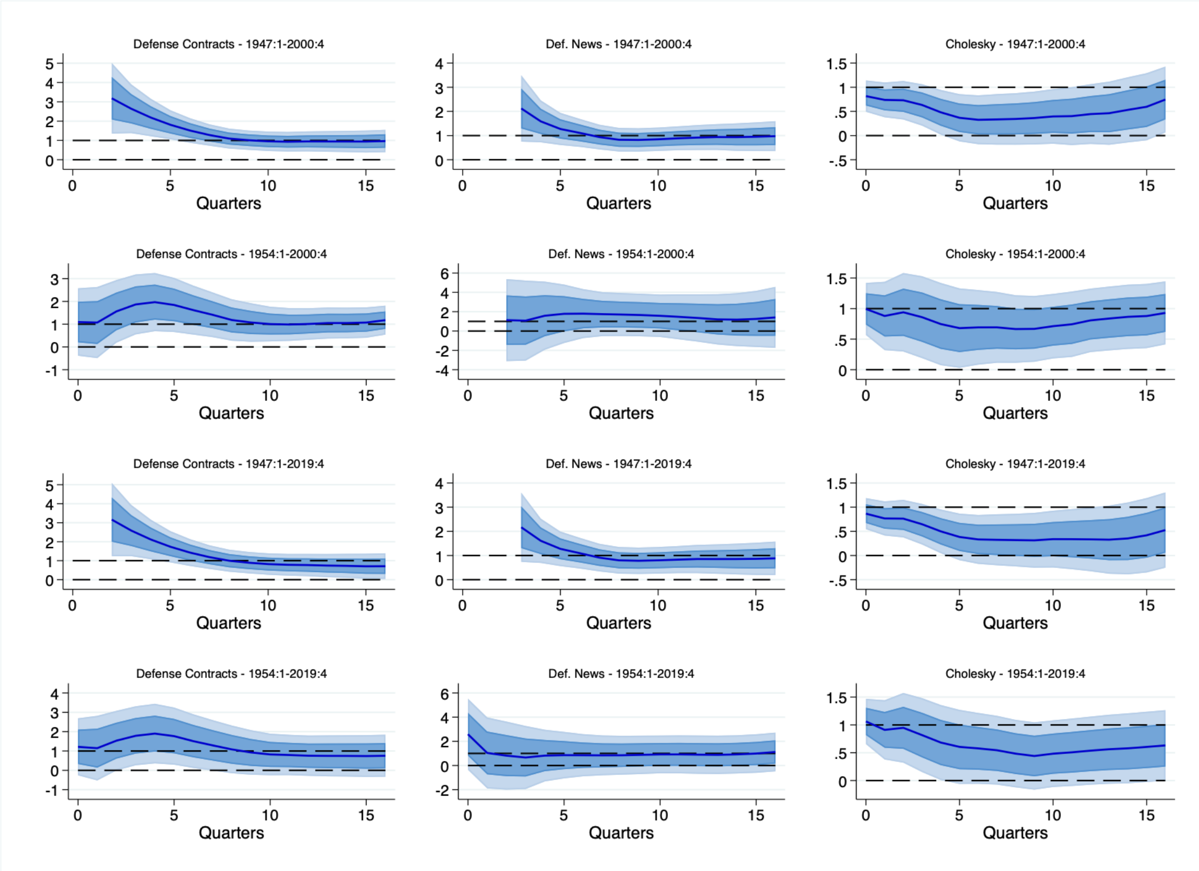


Figure 2.31. CUMULATIVE FISCAL MULTIPLIERS

Notes: Multipliers are obtained by estimating Equation (2.3). Set Shock$_t$ equal to either (i) defense contracts, (ii) defense news shocks or (iii) G as measured by NIPA.

There are two main take-away from this figure. First, defense contracts allow for precise multiplier estimates and yield slightly larger multiplier point estimates compared to defense news shocks. Gains in efficiency are more evident in samples which exclude the Korean war (row 2 and 4). Second, multipliers derived from Cholesky shocks are smaller than those ones obtained with either defense news shocks or defense contracts due to a downward bias originating from their delay (as detailed in Briganti and Sellemi (2023)). Basically, Cholesky shocks miss the early-stage production of defense contractors, monitored by NIPA as inventories. This problem originates from using the delayed NIPA measure of G ordered first in the VAR to identify government spending shocks.

Comparison with Obligations Multipliers

In this section, I aim to reconcile my multiplier estimates with those of Dupor and Guerrero (2017) and Brunet (2020), who used a measure of defense obligations, rather than spending, to estimate national multipliers. As defense contracts are a type of federal obligation, it's crucial to align these different yet related measures to establish a comprehensive view of fiscal policy impacts.[48]

Firstly, Dupor and Guerrero (2017) utilize Department of Defense (DoD) documents pertaining to state-level defense contracts, dating back to the fiscal year of 1951. They assemble an annual panel of defense contracts at the state level, spanning from the fiscal year 1951 to 2014. After aggregating spending across states, they employ the following equation for their estimation:

$$\sum_{h=0}^{H} \frac{Y_{t+h}-Y_{t-1}}{Y_{t-1}} = \mathscr{M}_H \cdot \underbrace{\sum_{h=0}^{H} \frac{G_{t+h}-G_{t-1}}{Y_{t-1}}}_{\text{Instrumented}} + \text{Controls} + \varepsilon_{t+H}$$

where Y_t is national real GDP per capita in calendar year t, G_t is the aggregated real per-capita value of military contracts across state by fiscal year t, $\mathscr{M}_H$ is the cumulative fiscal multiplier at horizon H.[49] The instrument for the cumulative sum of contracts at horizon H is: $\frac{G_t - G_{t-1}}{Y_{t-1}}$.

Brunet (2020) uses a similar specification but without instrumenting the cumulative sum of G_t. Moreover, her measure of G_t is a new variable called Budget Authority, which measures defense spending when it is authorized and before funds are dispersed from the Treasury, in a given fiscal year.

Firstly, notice that both works do not provide estimates of the fiscal multiplier, defined as the effect of 1$ of spending on GDP. In fact, they estimate the effect of 1$ of defense contracts

[48]Nakamura and Steinsson (2014) and Auerbach, Gorodnichenko, and Murphy (2020) also estimate local multipliers using a measure of defense contracts. However they do not provide empirical estimates of the national multiplier.

[49]They use CPI inflation to deflate variables and the total US population to obtain per-capita values. Their set of controls includes four variables: the price of oil, the real interest rate and their lags.

and 1$ of Budget Authority on GDP. The advantage of using quarterly defense contracts as an instrument for the NIPA measure of G, is to preserve the traditional definition of multiplier and to account for potential different effects of fiscal shocks on other components of G, different from defense contracts and defense spending.

Secondly, both works provide estimates of the "multiplier" using measures of spending recorded by fiscal year on an annual measure of output recorded on a calendar year basis. In this sense, my measure of quarterly defense contracts is more precise.

Table 2.7 reports the estimates of the national multiplier calculated using my method (top panel), Dupor and Guerrero (2017)'s method (middle panel) and Brunet (2020)'s method (bottom panel).

Table 2.7. COMPARISON OF FISCAL MULTIPLIERS

Instrument	Multiplier Interpretation	Frequency	Sample	1 Year	2 Year	3 Year	4 Year
Defense Contracts	Spending Multiplier	Quarterly	1947:1-2000:4	2.184***	1.096***	0.949***	0.968***
				(0.586)	(.311)	(0.312)	(0.350)
Defense Contracts	Spending Multiplier	Quarterly	1955:1-2000:4	1.970***	1.184**	1.010**	1.178***
				(0.772)	(0.550)	(0.417)	(0.383)
Defense Contracts	Spending Multiplier	Quarterly	1955:1-2014:4	1.761*	0.982	0.724	0.716
				(0.918)	(0.746)	(0.620)	(0.631)
Defense Contracts	Spending Multiplier	Quarterly	1951:1-2014:4	1.225	0.312	0.105	0.033
				(0.793)	(0.588)	(0.556)	(0.575)
Dupor and Guerrero (2017):							
Defense Contracts	Obligation Multiplier	Fiscal Year	1951-2014	-	0.33***	-	0.07
					(0.12)		(0.24)
Defense Contracts	Obligation Multiplier	Fiscal Year	1955-2014	-	1.00	-	-
					(0.64)		
Brunet (2020):							
(Defense) Budget Authority	Obligation Multiplier	Fiscal Year	1946-2007	1.291***	1.375***	1.512***	-
				(0.180)	(0.280)	(0.415)	
(Defense) Budget Authority	Obligation Multiplier	Fiscal Year	1954-2007	1.650***	1.420	1.291	-
				(0.774)	(1.137)	(1.385)	

Notes: symbol "-" means the estimate is not reported in the second chapter. SEs are reported in parenthes and they are heteroskedasticity robust for my estimates. $*$ means $p < 0.1$, $**$ means $p < 0.05$, $***$ means $p < 0.01$.

Comparing with Brunet (2020):

Starting from the bottom panel, Brunet (2020) produces precise estimates exceeding 1.3 when the sample includes the Korean War. However, when she excludes the Korean War from the sample, the estimates lose statistical significance and their magnitude diminishes. In contrast, estimates obtained using quarterly defense contracts as an instrument for G yield stable and robust results across these two samples, as illustrated in the first two rows of the top panel. In general, Brunet's estimates exceed mine and, in turn, are larger than those previously obtained via other methods such as Cholesky shocks and defense news shocks.

As a potential explanation for these results, she suggests that her new measure precedes the initiation of production by defense contractors, as monitored by inventories. This theory, confirmed in Briganti and Sellemi (2023), suggests that this only applies to Cholesky shocks, since defense news shocks also predate the start of production. Furthermore, as defense contracts are recorded at the time a new contract is awarded — which marks the onset of production — defense contracts do not omit any inventory response related to defense production. Thus, the larger size of Brunet's estimated multipliers could be attributable to her distinct estimation method and the annual aggregation.

Comparing with Dupor and Guerrero (2017):

In examining the estimates of Dupor and Guerrero (2017), it's evident from the middle panel that they obtain very small point estimates: 0.33 for the 2-year multiplier and essentially zero for the 4-year multiplier. The authors note that this small magnitude is due to the inclusion of the years 1953 and 1954 in the sample, which are associated with the large drop in defense contracts following the end of the Korean War.[50] Thus, they adjust their sample to start from 1955 and find a multiplier of 1.00, which is slightly non-significant (p-value of about 12%). They conclude that the inclusion of the Korean War years is the primary reason for their small multiplier estimate.

I will now reconcile my estimates with theirs. I extend my estimation sample to cover the period from 1955:1 to 2014:4 and the multipliers become smaller and insignificant, except for the horizon 1. The 2-year multiplier is approximately 1, identical to theirs when they employ the same sample. However, my point estimate for the 4-year multiplier is 0.7, which is ten

[50] Actually, the total value of defense contracts stops falling in the 4th quarter of 1953, according to BCD. However, since Dupor and Guerrero (2017)'s measure of defense contracts is recorded by fiscal year, 1953Q4 already belongs to fiscal year 1954 and this is likely the reason why they observe a fall of defense contracts in that year.

times higher than theirs when the sample starts in 1951. Consequently, I extend the sample back to 1951 to match theirs, and I find that the estimates suddenly decrease to 0.3 and 0 for the 2-year and 4-year multipliers, matching theirs. There are two reasons for this outcome. Firstly, extending the sample beyond 2000 adds minimal variation in G relative to GDP, which seems to make estimates less precise (see Figure 2.3). Secondly, the most significant drop in my estimates occurs when I extend the sample back to 1951, that is, right in the middle of the Korean War. In fact, initiating the sample from 1951 misses out on the outbreak of the Korean War, whose primary output effect occurred in the last quarter of 1950 with the large response of inventories, primarily capturing defense production. Starting the sample in the middle of the war can therefore bias the estimates of the multiplier downwards by missing out that initial response. Dupor and Guerrero (2017)'s sample choice simply omits the robust initial output effect of defense contracts at the onset of the Korean War, which did not have a zero multiplier, as indicated in my baseline estimate of a unity multiplier.

Characterizing the Nature of the National Multiplier

In this section, I examine the response of taxes, monetary policy, and imports to a positive shock to defense contracts. My findings suggest that an increase in government spending, triggered by this type of fiscal shock, is funded by distortionary taxation. It doesn't prompt any significant reaction from monetary policy and doesn't instigate any "expenditure switches" through the rise in imports. Therefore, I argue that my estimated multiplier aligns with the definition of a tax-financed, no-monetary-policy-response, close-economy national multiplier. It's essential to note that designating the multiplier as a "close-economy" one doesn't imply that the US economy is a closed economy, which, in reality, isn't the case. Instead, it indicates that the operative transmission channels don't exhibit the characteristics of an open economy, meaning no significant international spillover is detected in reaction to a shock.

The characterization of the multiplier is crucial for at least three reasons. Firstly, it helps unravel some primary transmission channels at play. For instance, as shocks to defense contracts are financed via distortionary taxation, work incentives are affected, subsequently impacting the multiplier's magnitude, as it is well known in theoretical literature (see Baxter and King (1993), Ohanian (1997) and Burnside, Eichenbaum, and Fisher (2004)). Likewise, the role of the monetary policy response in determining the multiplier's size is well-recognized in theoretical models (see Woodford (2011), Christiano, Eichenbaum, and Rebelo (2011) and Nakamura and Steinsson (2014)).[51] However, my study shows that monetary policy was either extremely weak - as suggested in Clarida, Galí, and Gertler (2000) - or non-responsive given these shocks' limited inflationary effect. Grasping these transmission channels' significance for the propagation of fiscal shocks is essential for formulating the simplest yet empirically consistent model to (i) simulate the effects of fiscal policy and then (ii) create policy counterfactuals.

Secondly, the multiplier's characterization enables me to compare my estimate to those derived from model-simulated data, facilitating discrimination between models. For example, Nakamura and Steinsson (2014) develop a regional New Keynesian model to produce a cross-sectional multiplier and a tax-financed, non-monetary-policy-response, close-economy national multiplier. With my multiplier characterization, I can compare my estimate with those generated by different versions of their model and draw conclusions about which version approximates the empirical one I obtain and which transmission mechanism allows that.

Finally, this national multiplier characterization notably narrows the gap between regional and national estimates. It is well known in the literature that national and regional estimates are significantly different. Specifically, Chodorow-Reich (2019) shows that a regional multiplier is a lower-bound for a deficit-financed, non-monetary-policy-response, close-economy national multiplier. This is because regional spillovers reduce the regional multiplier's size, unlike the national one, which fully encompasses all potential cross-regional effects. Incorporating government deficits into a structural model calibrated to match my estimates, would allow me to transform my tax-financed, non-monetary-policy-response, close-economy national multiplier

[51] In particular, an accommodating policy discourages intertemporal substitution and reduces the crowding out of consumption by boosting the multiplier, while "*leaning against the wind*" has the opposite effect and dampens the multiplier.

into a deficit-financed one. This would enable comparison with available cross-sectional estimates derived from more recent regional databases, allowing me to test empirically the lower-bound result's validity.

Given the importance of the multiplier's characterization, I will first analyze the response of taxes to a positive shock to defense contracts in the following paragraph. Then, I will examine the response of monetary policy, and finally, I will study the import response.

The Response of Taxes.

The fiscal policy literature commonly acknowledges that military expansions were primarily financed through distortionary taxation up until the 2000s.[52] For instance, during the onset of the Korean war, both personal income and production taxes saw significant increases, with President Truman firmly advocating for fiscal equilibrium despite the considerable military expenditure. Although the fiscal response to the Vietnam war was less immediate compared to that of the Korean war, President Johnson had been recommending tax hikes from as early as 1967. By June of 1968, the Revenue and Expenditure Control Act was enacted to curb an overheating economy, primarily brought about by the military stimulus required for the operations in Vietnam, as per the Survey of Current Business.[53] This increased taxation predominantly impacted excise taxes, as well as personal income and corporate taxes.

To substantiate this historical evidence, I expand the baseline VAR from the second chapter by rotating in and out the average labor income tax rate, the average capital income tax rate, and the average total tax rate. The average labor tax rate was determined by dividing personal income tax receipts by total wages, as per NIPA data. Similarly, I obtain a proxy for the average capital income tax rate by dividing the sum of taxes on corporate income and production by nominal GDP. Lastly, as with Ramey (2016), the average total tax rate is constructed by dividing total tax receipts by nominal GDP. Figure 2.32 depicts the IRFs of these

[52] See Ohanian (1997), Edelberg, Eichenbaum, and Fisher (1999), Burnside, Eichenbaum, and Fisher (2004), Eichenbaum and Fisher (2005) and Ramey (2016).

[53] The other major reason was a tax credit on business investments on new plant and equipment, introduced before the outbreak of the Vietnam war.

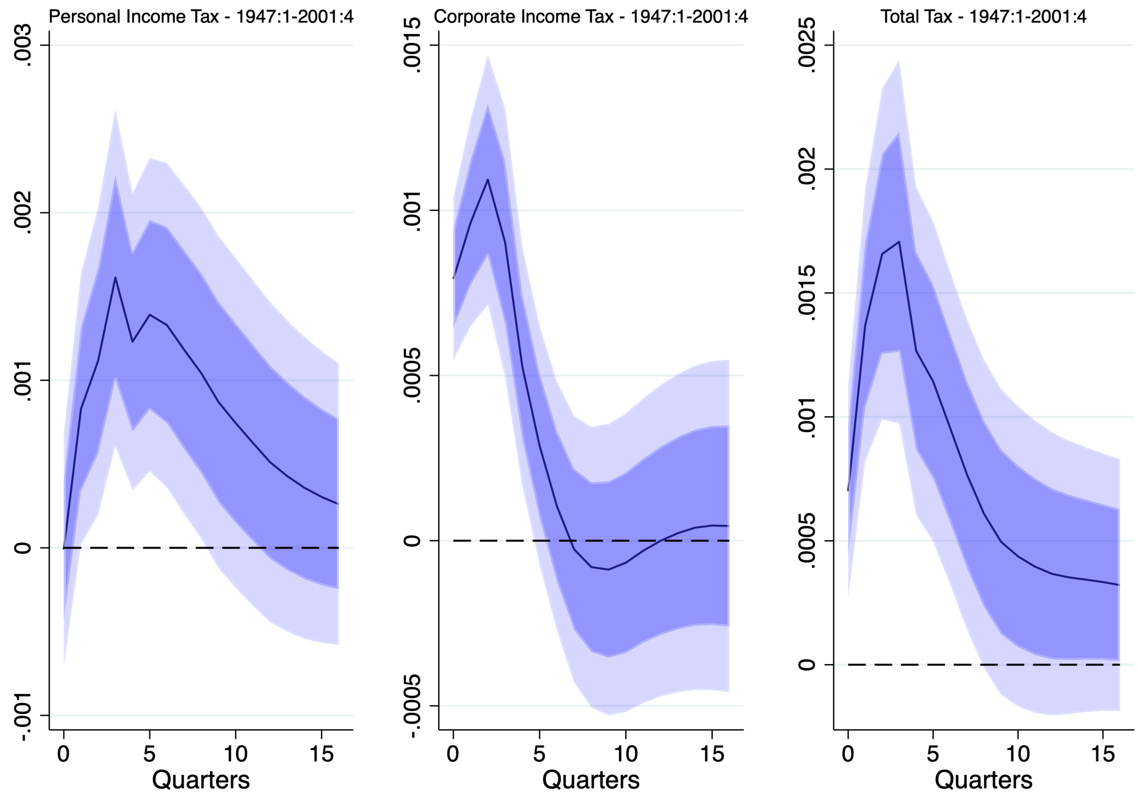


Figure 2.32. TAX RESPONSE

three variables in reaction to defense contracts for the baseline sample period of 1947:1 to 2001:4.

All average tax rates rise, reinforcing that variations in G triggered by defense contracts shocks are financed through taxation. Consequently, the estimated fiscal multiplier can be interpreted as a tax-financed multiplier.

Interest Rates, Inflation and the Monetary Policy Response.

Several compelling reasons suggest that both real and nominal interest rates should rise following a positive government spending shock.

First, viewed through the lens of the standard Real Business Cycle (RBC) model, an increase in government spending implies additional taxation, which escalates competition for resources, subsequently crowding out investment and consumption. To counteract this negative income effect, households expand their labor supply, which boosts capital productivity due to labor-capital complementarity, thereby increasing the real interest rate. Formally:

$$R_t\uparrow - 1 = f_k\left(\underset{(-)}{K_t}, \underset{(+)}{N_t\uparrow}, \underset{(+)}{u_t}\right) - \delta$$

where R_t is the gross real interest rate, f_K is the marginal product of capital, which, in turn, is a negative function of the level of capital K_t and a positive function of hours worked N_t and capital utilization, u_t. Second, from a Neo-Keynesian perspective, an increase in government spending triggers inflation, and according to a Taylor-type monetary policy rule, this would cause a surge in nominal interest rates (e.g. see Galí, López-Salido, and Vallés (2007), Woodford (2011) and Christiano, Eichenbaum, and Rebelo (2011)). Lastly, a more intuitive explanation is that military build-ups, even when tax-financed, might be viewed by financial markets as a potential precursor to a larger deficit. This perception would then trigger an increase in government bond interest rates.

Given these reasons, one would anticipate an uptick in both nominal and real interest rates following a positive shock to defense contracts. I examine this assumption by augmenting my baseline VAR with some outcome of interests. Specifically, I observe the reactions of the 3-month T-Bill rate, the CPI inflation, and the real interest rate, derived from the difference between the two. The IRFs to a shock to defense contracts are presented in Figure 2.33.

Firstly, it is clear from the middle panel that the nominal interest rate, represented by the 3-month T-Bill rate, remains unaffected by defense contracts. This finding holds true even when various other interest rate measures are used. For example, I look at the response of the Aaa corporate bond yields (Figure 2.34), the Baa corporate bond yields (Figure 2.35) and the federal funds effective rate (Figure 2.36).

The lack of movement in the nominal interest rate could be viewed as an indication of

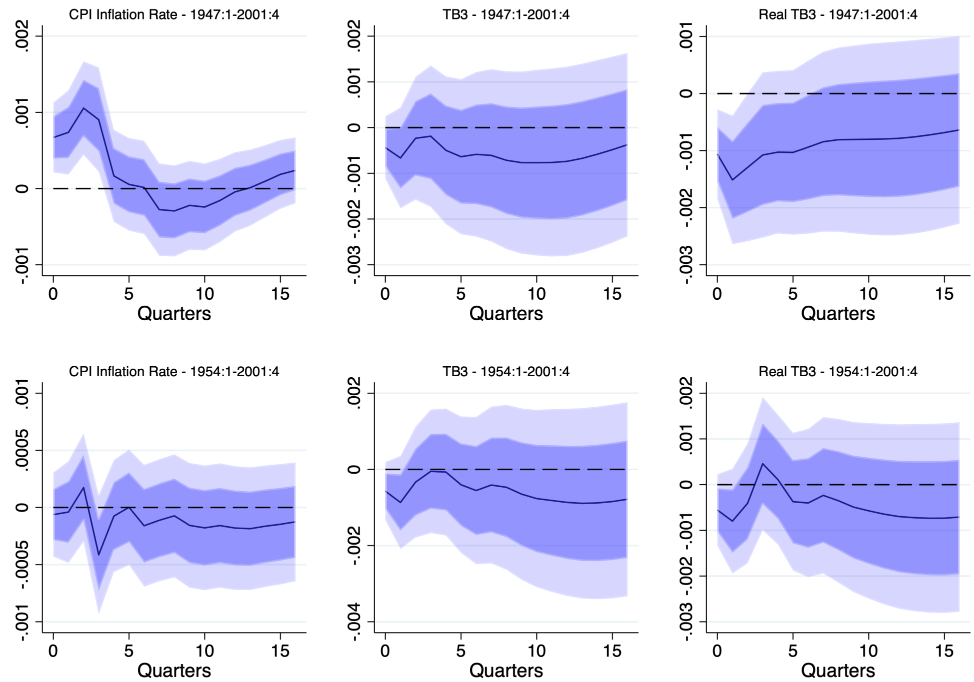


Figure 2.33. IRFs of Inflation and Interest Rates to Contracts

Notes: in the top panel the sample goes from 1947:1 to 2000:4. In the bottom panel the sample goes from 1954:1 to 2000:4.

a strongly accommodating monetary policy, where nominal rates are kept fixed while strong inflation dampens the real interest rate. This experiment is analyzed in Nakamura and Steinsson (2014), and their model produces either infinite or very large national multipliers. At a superficial analysis, this story is consistent with the empirical evidence showed in the left and right graphs panels of Figure 2.33: the real interest rate declines in the right panel, a result entirely driven by increased inflation, showed in the left panel. However, the positive response of inflation and the consequent fall in the real interest rate, is not robust to the exclusion of the Korean war. This finding remains consistent when the GDP price deflator inflation measure is used in place of the CPI inflation measure.

The lack of movement in the real interest rate might again be viewed as evidence of accommodating monetary policy as it was analyzed in Woodford (2011) and Nakamura and

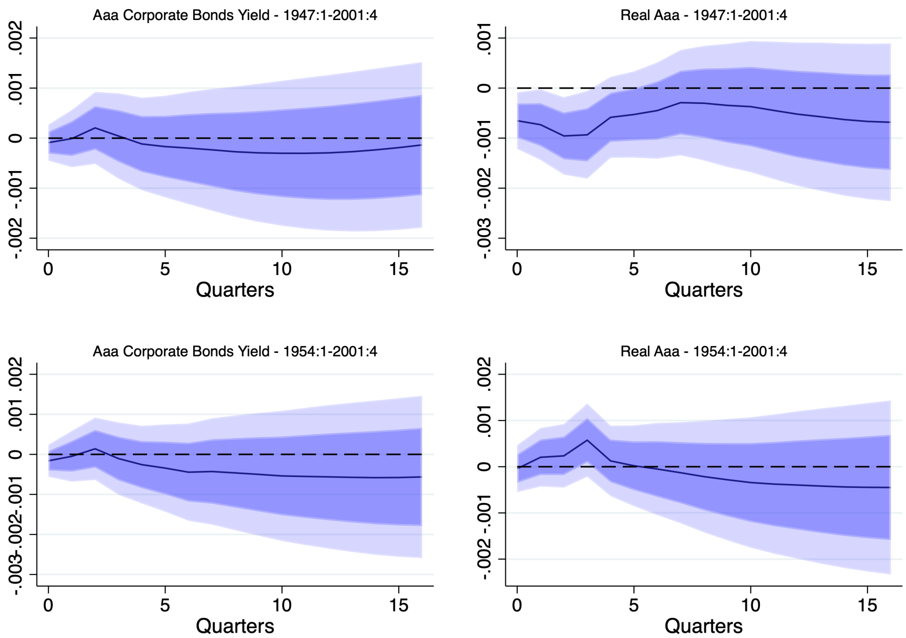


Figure 2.34. IRF to Defense Contracts - AAA Corporate Bonds Yield

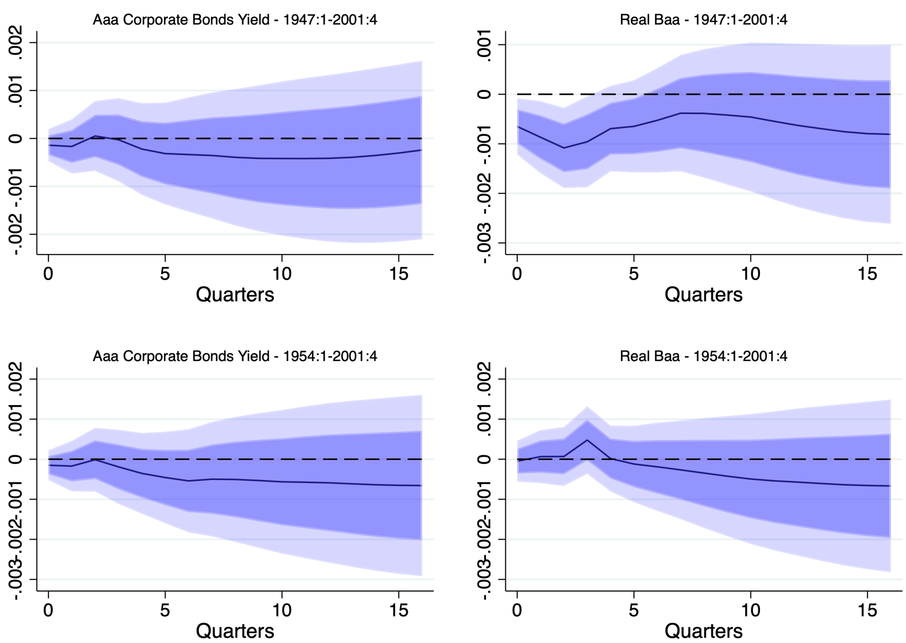


Figure 2.35. IRF to Defense Contracts - Baa Corporate Bonds Yield

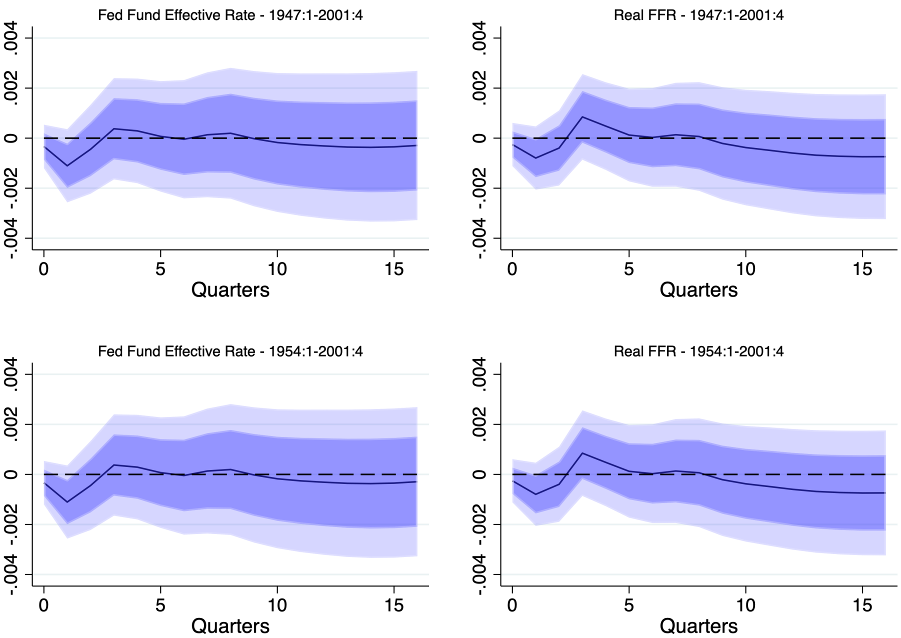


Figure 2.36. IRF to Defense Contracts - Effective FFR

Steinsson (2014). However, even in this limiting scenario, the nominal interest rate should rise in response to current and future increases in government spending to keep the real interest rate constant.[54] However, this is at odds with null response of nominal rates.

Moreover, note that neither the nominal nor the real interest rates move significantly when using either defense news shocks or Cholesky shocks. If there is movement, it is in a negative direction, which motivated the work of Murphy and Walsh (2022) and Bredemeier, Juessen, and Schabert (2022) on accommodating monetary policy in response to a fiscal shock.[55] However, I find that also these responses are not robust to the exclusion of the Korean war: Figure 2.37 shows the response of nominal and real TB3 and CPI inflation to a defense news

[54] See end of Section IIIA in Woodford (2011). Plug his Equation (14) into his Equation (24), use the definition of $\hat{G}_t$, a first-order Taylor approximation and the Fisher equation to obtain this result.

[55] Murphy and Walsh (2022) find that Cholesky shocks to NIPA measures of government spending have negative effects on the Treasury General Account at the Fed, suggesting a money creation process in response to positive shocks, which decrease nominal rates. Bredemeier, Juessen, and Schabert (2022) find that several measures of liquidity spreads increase in response to a shock to government spending forecast errors by the Survey of Professional Forecasters. They construct a model where the interest rate set by the Fed is different from the one on corporate bonds. When the government increases its demand of goods, the liquidity spread increases even if the FFR does not.

shock.

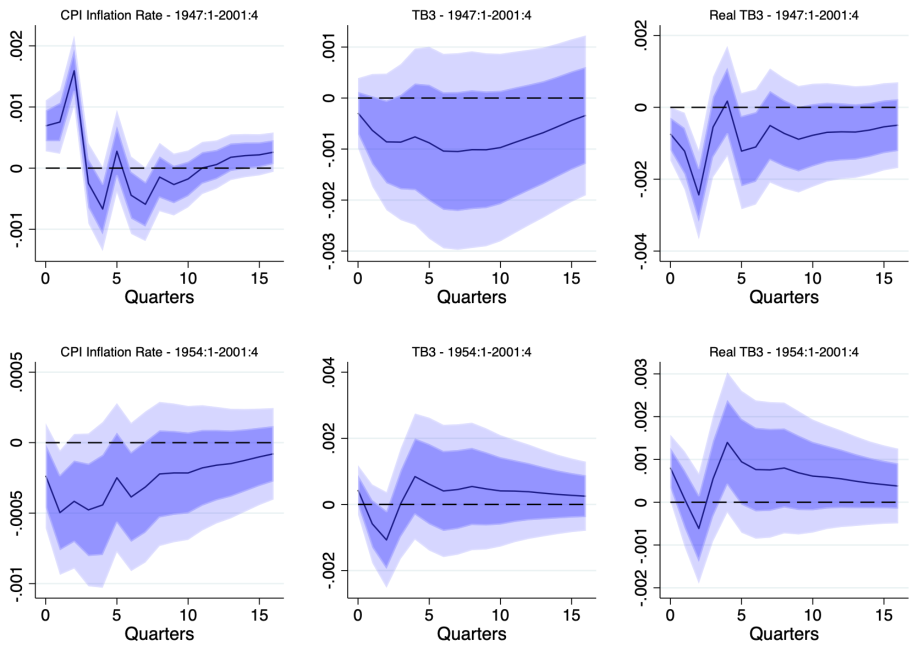


Figure 2.37. IRFs to Defense News Shocks - Inflation and TB3

Overall, in samples which exclude the Korean war, monetary policy was not reacting since the inflationary effect of fiscal shocks was very small. This is plausible for two reasons. First, I defense purchases are highly concentrated in few firms, for example, during the Vietnam war, the top 5 defense contractors accounted for one fourth of total defense purchases. Second, positive shocks to defense contracts increase labor productivity which decrease the price of products, dampening the upward pressure on prices due to scarce resources (in fact, in my model, the relative price of manufacturing goods fall after an increase in government purchases).

Furthermore, my readings of the Survey of Current Business indicated the willingness of the Federal Reserve to follow a "lean against the wind"-type of policy during war-times, which is against the constant-rate/accommodating policy view. Nonetheless, recall that Clarida, Galí, and Gertler (2000) have shown how in the pre-Volcker era, the estimated reaction parameter to expected inflation of a Taylor-type monetary policy rule was much smaller than those during the

Volcker disinflation and subsequent periods. As most of the variation in defense contracts comes from periods when monetary policy was weak, and the inflationary effects of these shocks was small, it is quite safe to assume that monetary policy did not play a significant role in explaining the aggregate effects of these shocks.

Concerning the fall in the real rate and the inflationary response in samples with the Korean war, the response appears to be driven by this specific event and the quantitative evidence needs to be complemented with historical evidence from that period.

Korean War and Monetary Policy. At the onset of the Korean war, despite initial inflationary concerns, the Fed did not respond until March 1951 due to a disagreement with the Treasury, which aimed to keep borrowing costs low. The Fed, on the other hand, sought to increase the long-term bond ceiling above 2.5%, a move opposed by the Treasury.[56] However, by the time the Fed regained control of monetary policy, other policies had already begun to put downward pressures on prices.[57] Consequently, the rise in the 3-month T-Bill rate in March was very small.

One might think that the constraint on the yield of long-term government bonds could have stimulated consumption by lowering the real interest rate, a scenario discussed in Nakamura and Steinsson (2014) where the nominal interest rate is held constant, or in Christiano, Eichenbaum, and Rebelo (2011) when they examine the impacts of fiscal policy at the zero lower bound. However, this is very unlikely for two reasons. First, the 2.50% constraint on the 10-year yield on Treasuries was not binding and the short term interest rate, TB3, had been increasing since the outbreak of the war.[58] Second, the surge in durable and non-durable goods consumption only

[56]The Fed only introduced in September and October of 1950 Regulation W and X, which limited financing abilities of individuals to (i) purchase durable goods (appliances and motor vehicles) and (ii) get a mortgage (see Perotti (2014)). These measures however did not affect nominal interest rates in those quarters.

[57]For instance, the Revenue Act of September 23, 1950 and the Excess Profits Tax Act signed on January 3, 1951, which increased labor income tax and business profit tax respectively; additionally, price controls were implemented in January, and the rush to purchase durable goods and food supplies had already subsided, driving durable and non-durable consumption below trend because households had previously stockpiled supplies through intertemporal demand substitution (see Ginsburg (1952)).

[58]This can be easily checked by looking at the discontinued series of composite yield on U.S. Treasury bonds with maturity over 10 years on Fred.

affected those items which were in short supply during WWII, such as coffee, sugar, clothing, refrigerators and cars (see Hickman (1955)). Therefore, this buying wave was not driven by a decrease in the real interest rate (i.e., crowding-in), but by fears of rationing and inflation; indeed, this buying wave subsided when households realized product availability was not significantly affected by the military effort and despite inflation expectations were still high (see Ginsburg (1952) and the Survey of Consumer Finances of 1951). Therefore, monetary policy played a minor role during the Korean War.

In summary, the lack of response from nominal interest rates, the non-robust response of the real interest rate, the findings of Clarida, Galí, and Gertler (2000), and anecdotal evidence from the Korean War all suggest that monetary policy did not play a significant role in explaining the aggregate effects of defense contracts. Consequently, the multiplier I've calculated can be interpreted as a no-monetary-policy-response multiplier.

The Response of Import and Net-Export:

The final distinction Chodorow-Reich (2019) highlights between national and local multipliers pertains to the open versus closed economy condition. Suppose the world consists of two regions, home and foreign, and government spending only increases in the home region. In such a case, firms operating in the home region might face increased competition for inputs required by contractors to produce government-purchased items. Increased demand could lead to higher prices, forcing producers to rely on foreign imports. This phenomenon, known as "expenditure switching", is discussed in the context of the Vietnam War in the Survey of Current Business, where a scarcity of production inputs led producers to increase imports. However, this circumstance may be specific to the Vietnam War, given the already high economic activity levels. Nakamura and Steinsson (2014), for example, found no evidence of local consumer price increases following a rise in local government spending, suggesting that the inflationary effects of defense contracts might not be as pronounced, thus reducing the likelihood of a systematic increase in imports following a defense contract shock.

Another potential driver of imports could be increased labor earnings following a military build-up. As income increases in response to a positive shock to contracts, import levels, being a positive function of home income, might rise as well. For instance, higher labor earnings might induce individuals to increase their demand for foreign-produced goods. Both "expenditure switching" and this "income effect" should diminish the size of the national multipliers relative to a closed economy, where all production is domestic.

Lastly, he suggests that migration flows, or "factor mobility", from the foreign region —stimulated by higher labor demand and wages— should increase the open economy multiplier compared to the closed one. However, Nakamura and Steinsson (2014) estimated the cross-state population response to local government spending and found no response. Given that migration costs are much lower between U.S. states than between countries, it is doubtful whether increased defense contracts should significantly boost immigrant inflow.

In light of these discussions, I test whether shocks to defense contracts significantly impact import and net-export levels. I do this by augmenting the baseline VAR, first rotating import in and out, then doing the same with net-export. The bottom panel of Figure 2.38 shows the Impulse Response Functions (IRFs) of these two variables in response to a positive shock to defense contract.

My findings show that neither import nor net-export levels change in response to a positive shock to defense contracts. This result suggests that there is no systematic "expenditure switch" or "income effect" from abroad when defense contracts increase.

Since there isn't a systematic response of imports to defense contracts, the estimates of the multiplier aren't subject to economic spillovers towards foreign regions, which would otherwise diminish the size of the multiplier. Theoretically, expenditure-switches and income effects, reflected in the import response, are the primary channels that should render the closed economy multiplier a lower bound to the open economy multiplier. Given that these channels

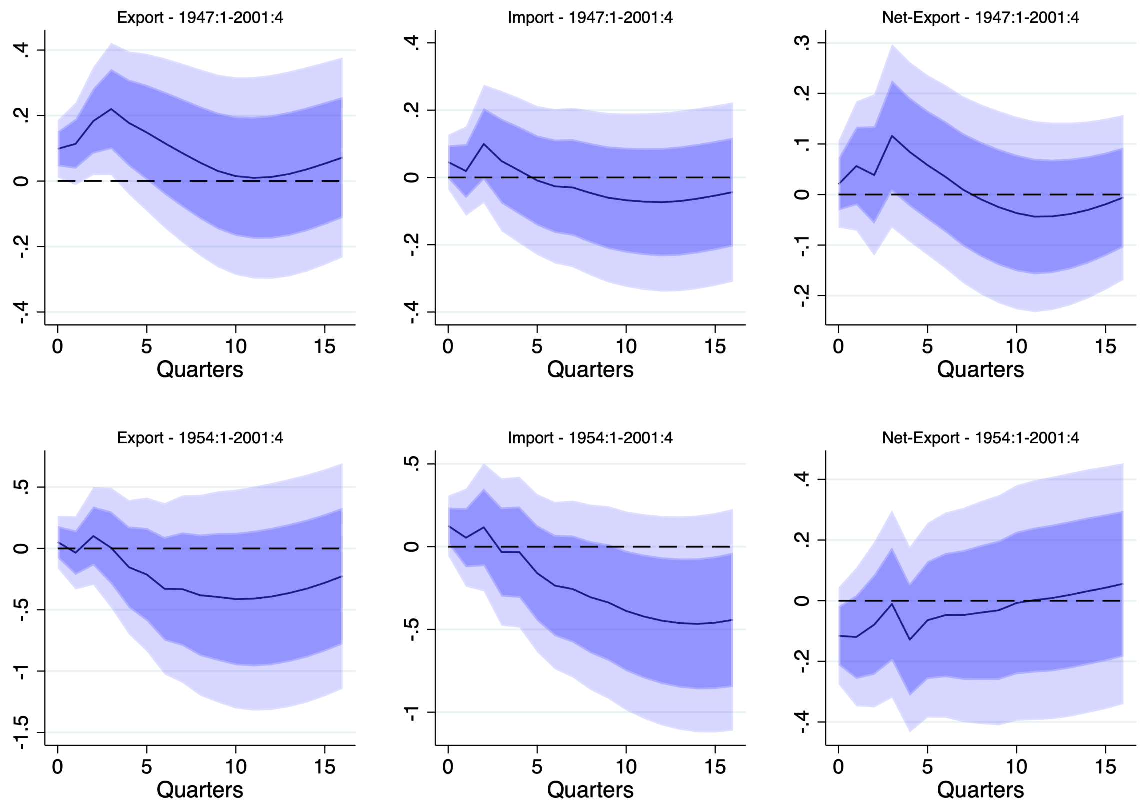


Figure 2.38. IRFs of EX/IM/NX to Contracts

Notes: the sample goes from 1947:1 to 2000:4. Values are normalized by the peak response of government spending to a positive shock to defense contracts in the same VAR.

don't appear to be operative, I can deduce that the multiplier estimated via defense contracts approximates a closed-economy multiplier.

I also find a positive response of export. However, this response is not robust to the exclusion of the Korean war from the sample. My readings of the SCB during the Korean war, unveiled that export boomed in that period for very extraordinary circumstances.[59]

[59]The reasons listed in the SCB are: UK's blockade of Iranian's petroleum due to the nationalization of the Anglo-Iranian-Oil-Company (then BP); contraction of the grain crops in India, Canada, Argentina and other producing countries; the revived need of American coal by Europe; finally, military aid due to the Mutual Defense Assistance Act after the outbreak of the first Indochina war between the French and Vietnam, backed by the Soviet Union.

Conclusion (Multipliers):

In summary, in this section, I have provided estimates of the fiscal multiplier obtained using defense contracts as an instrument for G. Pooling estimates from the all samples and different specifications deliver an average multiplier of 1.0, while samples ending in 2000:4 provide more precise estimates, centered around 1.14. Secondly, I reconciled my estimates with those found in similar works, emphasizing the benefits of my approach: my estimates offer greater precision and are more easily interpretable as a traditional fiscal multiplier. Lastly, I demonstrated that shocks to defense contracts are financed with distortionary taxes, aligning with previous research. I argued that the central bank did not accommodate shocks to defense contracts, or if it did, the response was a weak "leaning against the wind" that did not significantly affect the overall impact: nominal and real interest rates never have robust responses. Furthermore, the lack of import responses indicates that expenditure switches and income effects, as defined in Chodorow-Reich (2019), were, at best, very weak or non-existent. Hence, my estimates of the national multiplier adhere to the definition of an approximate tax-financed/closed economy/no-monetary-policy-response national multiplier.

2.6.3 Evidence on Markup

I investigate the response of the price-cost markup by rotating in and out four measures of the markup in the baseline VAR. Firstly, I construct the markup in the manufacturing sector as in Monacelli and Perotti (2008).[60] Secondly, I use the negative of the log share of labor income in the non-finacial-corporate-business (NFCB) sector, also analyzed by Monacelli and Perotti (2008). The third and fourth measures are the negative of the log-share of labor income in the economy and in the non-farm-business (NFB) sector, taken from Nekarda and Ramey (2020)'s online database.

Figure 2.39 shows the IRFs of these four measures of the markup to a positive shock to defense contracts. In particular, the first row shows results for sample 1947:1 to 2001:4; the second row shows sample 1954:1 to 2000:4; and the third row shows sample 1947:1 to 2019:4. Concerning the markup-measures: first column shows the response of the markup in manufacturing industries; the second column shows the response of the markup of the non-financial-corporate-business sector; the third column shows the response of the markup of the non-farm business sector; and the fourth column shows the response of the markup in the economy. All measures are based on the Cobb-Douglas production function: negative log-shares of labor income.

The markup exhibits a positive response at short horizons, then diminishes and turns negative across all measures. This initial positive and significant response of the markup is consistent across all sample periods.

For robustness, I also study the response of the price-cost markup to a shocks to defense contracts by also adopting a VAR model similar to the one used by Nekarda and Ramey (2020). In this case the VAR includes the log of real GDP and G per capita, the log of GDP price deflator,

[60] I follow the indications in the appendix of their paper and construct the markup by taking the log of the ratio of manufacturing national income less capital consumption adjustment and manufacturing wages.

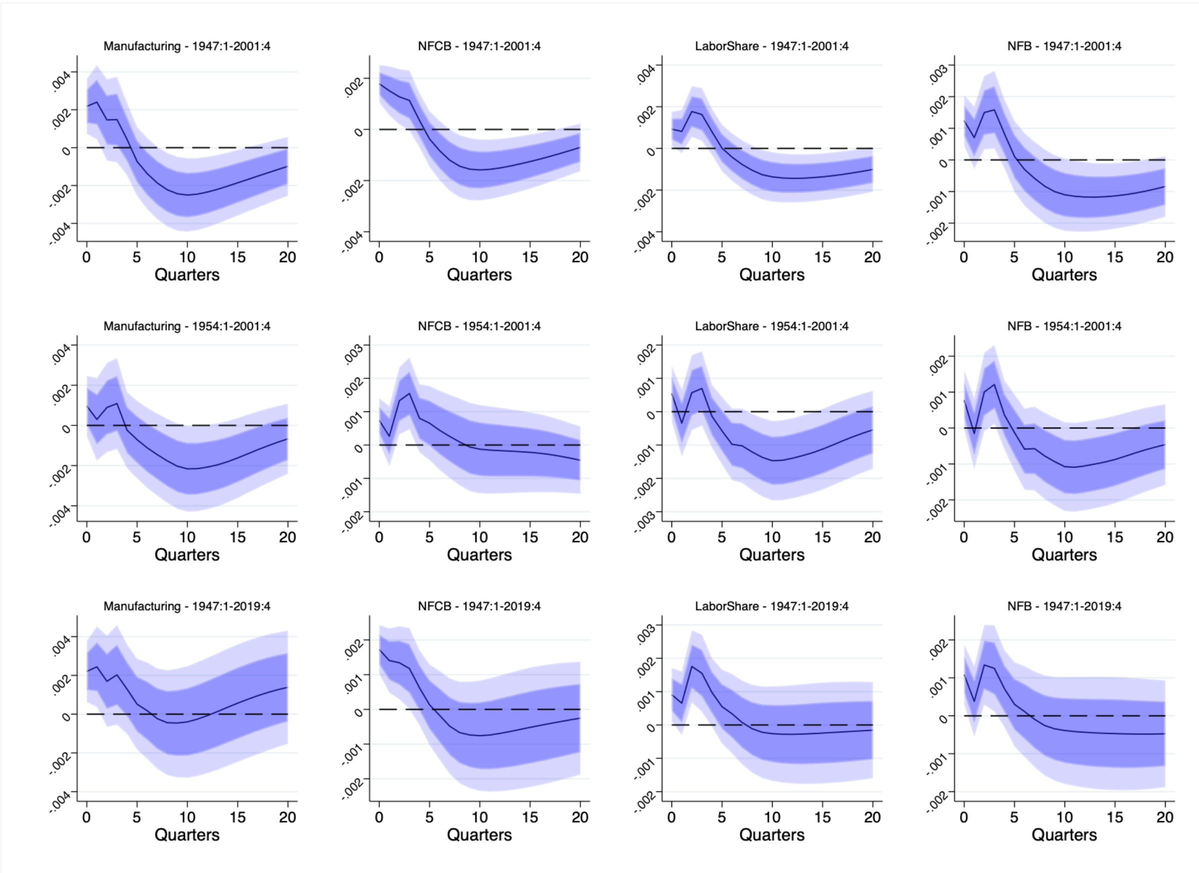


Figure 2.39. IRFS OF MARKUPS TO CONTRACTS - BASELINE VAR

the 3 months TB3 rate. I order the log of real per capita defense contracts first in the VAR and obtain qualitatively the same results for all three samples. Results are shown in Figure 2.40.

It is evident that the initial positive response intensifies, while the subsequent decrease in the markup is less pronounced, thereby reinforcing the conclusion drawn from the baseline analysis.

I also look at the IRFs of the four markup measures to a positive defense news shock using the same VAR of Nekarda and Ramey (2020): log of real per capita GDP, the log of the GDP price deflator, the 3 months T-Bill rate and defense news shocks divided by output ordered first. The specification also includes a quadratic time trend. Results are shown in Figure 2.41.

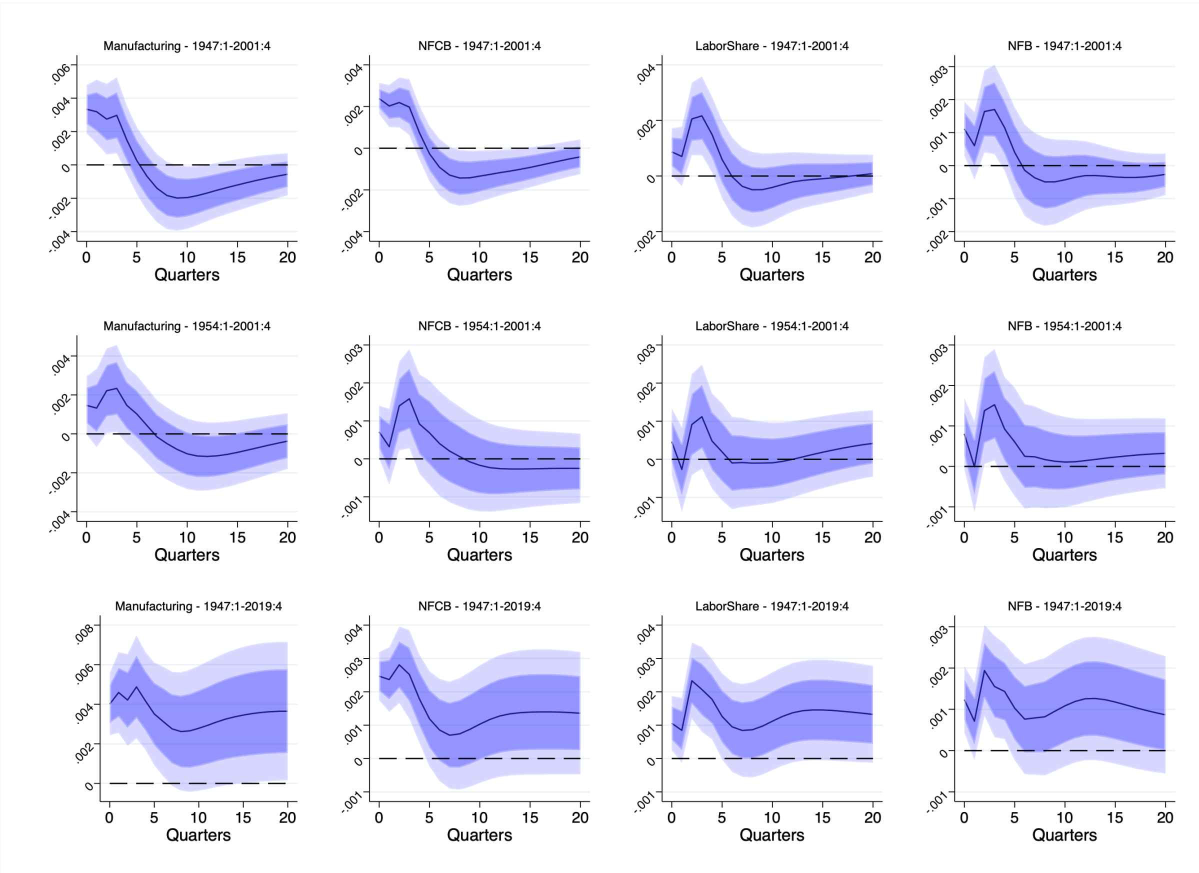


Figure 2.40. IRFs of Markups to Contracts - Nekarda and Ramey (2020)'s VAR

Notes: Rows and columns shows the same graphs as in Figure 2.39.

Similar to the previous observations, ordering defense news shocks first also generates positive responses at short horizons, complementing the results of Nekarda and Ramey (2020) who did not use the manufacturing markup measure used here and only looked at the full sample.

Lastly, I look at the IRFs of the four measures of the markup in response to a positive Cholesky shock. In this case the VAR includes the log of real per capita GDP and G, the log of the GDP price deflator, the 3 months T-Bill rate, the Barro and Redlick (2011)'s marginal tax rate. Identification is achieved by ordering G first in the VAR. Consistently with Monacelli and Perotti (2008), I include a linear time trend. Results are shown in Figure 2.42.

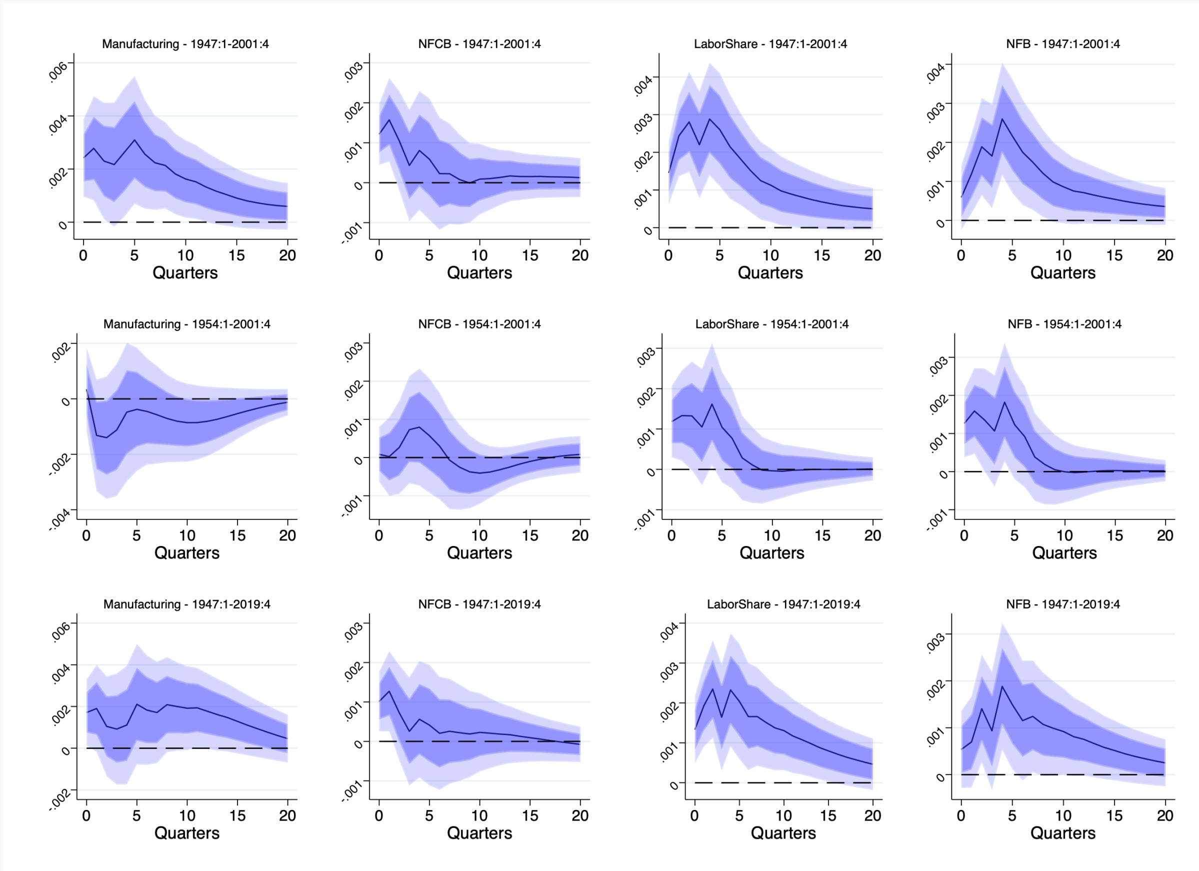


Figure 2.41. IRFs of Markups to Defense News - Nekarda and Ramey (2020)'s VAR

Notes: Rows and columns shows the same graphs as in Figure 2.39.

Notice that when I employ the Cholesky shocks to government spending, the results align with those found in Monacelli and Perotti (2008), with the markup declining. Yet, these findings are not robust when the Korean war is excluded from the sample; in this case, the markup seems to increase. Furthermore, when the markup is quantified as the negative of the log share of labor income in the economy and the non-farm business sector, Cholesky shocks lead to positive markup responses.

In conclusion, my results indicate that a fiscal shock typically triggers a positive response

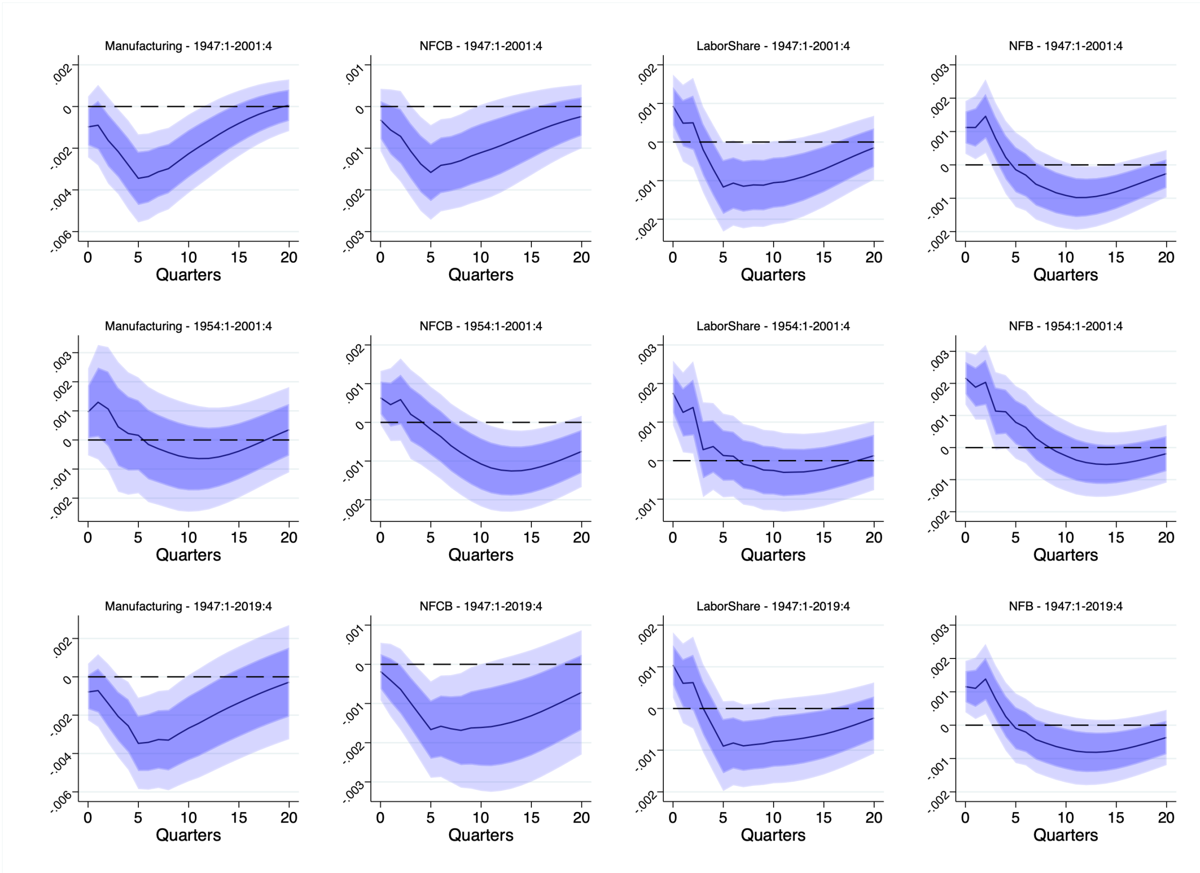


Figure 2.42. IRFS OF MARKUPS TO CHOLESKY SHOCKS - NEKARDA AND RAMEY (2020)'S VAR

Notes: Rows and columns shows the same graphs as in Figure 2.39.

of the markup. This finding implies that the observed positive reaction of consumption is unlikely to be driven by price stickiness, as in Galí, López-Salido, and Vallés (2007), Monacelli and Perotti (2008) and Bilbiie (2011).

2.6.4 In Search of the Transmission Mechanism - Robustness

Labor Market Outcomes - Robustness

In this section I robustify the results for the baseline VAR. First, I replicate those results using the samples (i) 1954:1 to 2000:4 and (ii) 1947:1-2019:4.

Figure 2.43 shows the IRFs of hours, employment and earnings/income for the baseline VAR for the sample without the Korean war: 1954:1-2000:4.

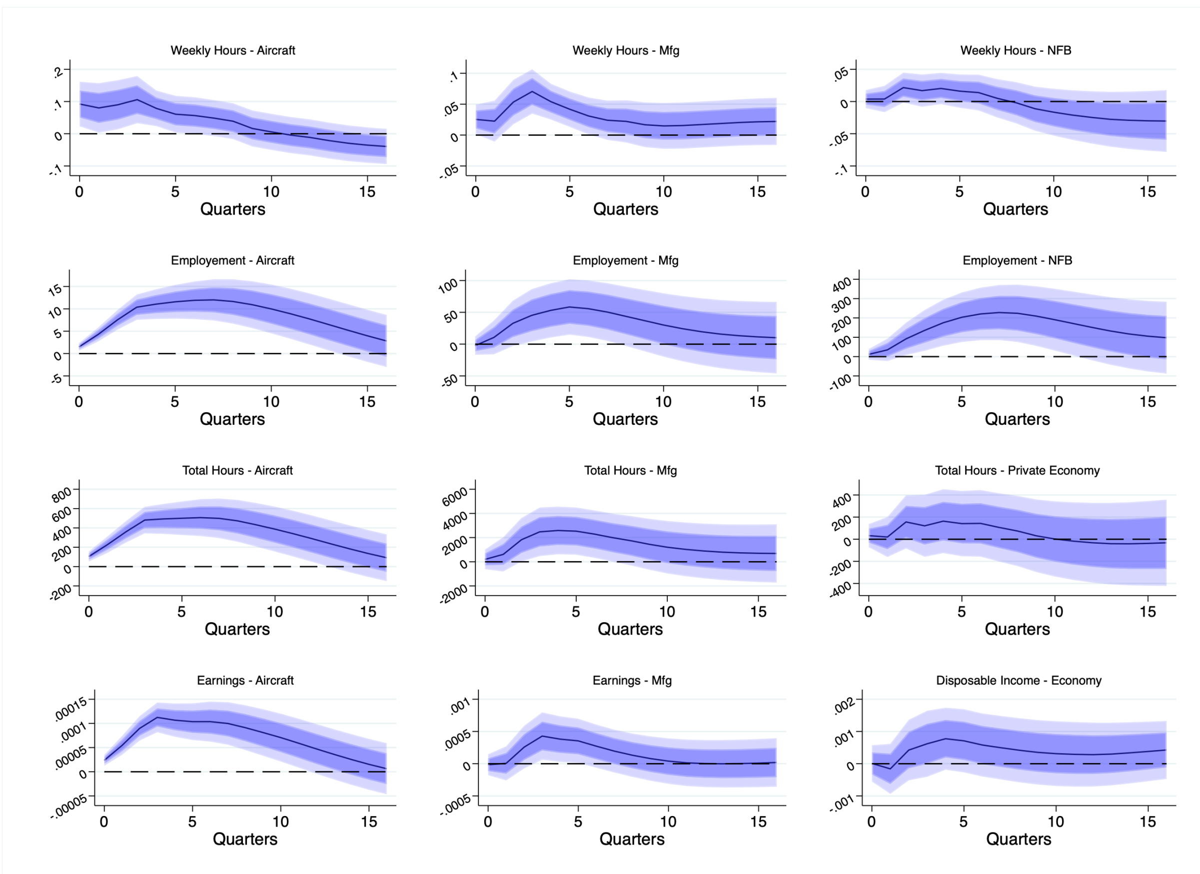


Figure 2.43. IRFs of Hours, Employment and Income - 1954:1-2000:4

Figure 2.44 shows the IRFs of hours, employment and earnings/income for baseline VAR using the full sample: 1947:1-2019:4.

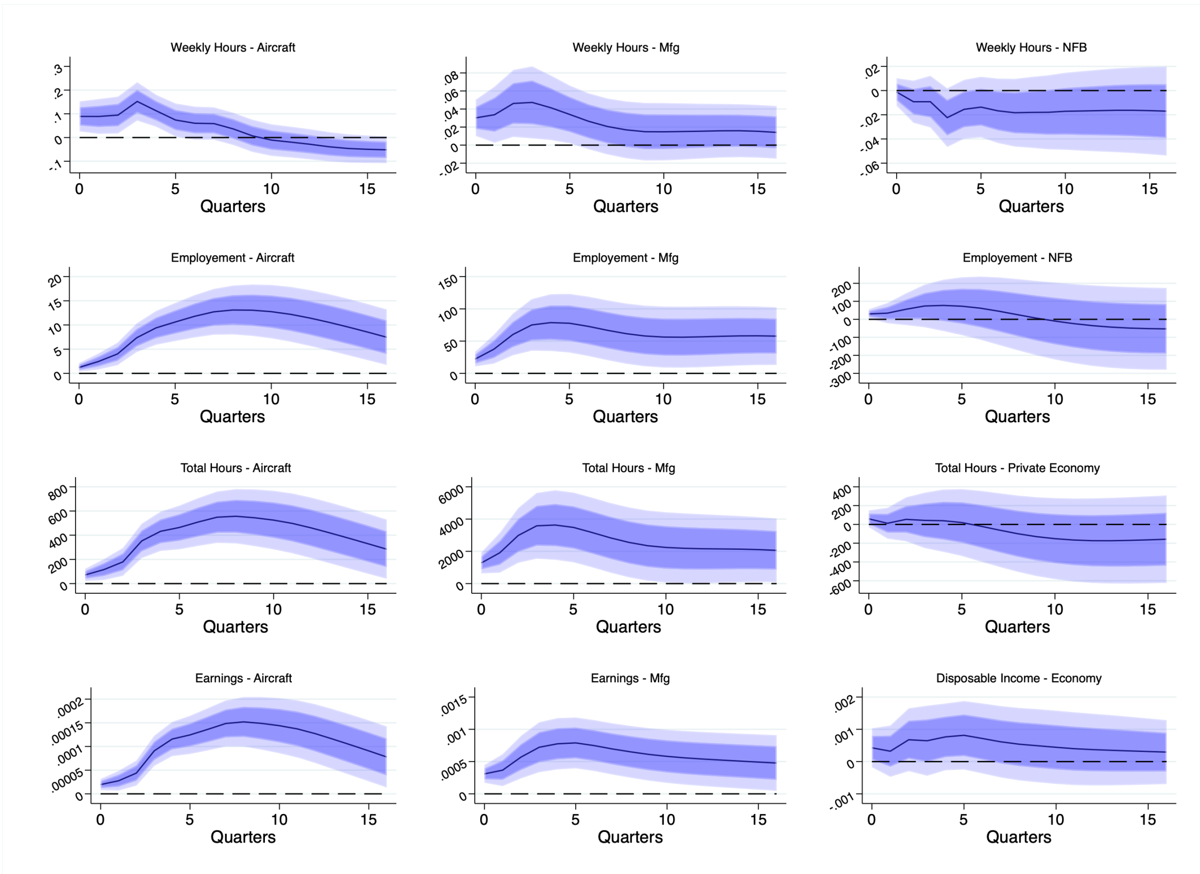


Figure 2.44. IRFs of Hours, Employment and Income - 1947:1-2019:4

Secondly, I mimic the approach of Ramey (2012) to study labor market outcomes, using a VAR specification in logs of real per capita values. In particular, the VAR includes defense contracts, GDP, G and total tax receipts in log of real per capita values, the log of hours in the private sector and the 3 months T-Bill rate. Concerning the outcome variables, weekly hours worked, employment, and real product wages are in logs. Earnings and disposable income are in log of real per capita values. In all cases the deflator is the GDP price deflator.

Figure 2.45 shows the results for the baseline sample 1947:1 to 2000:4.

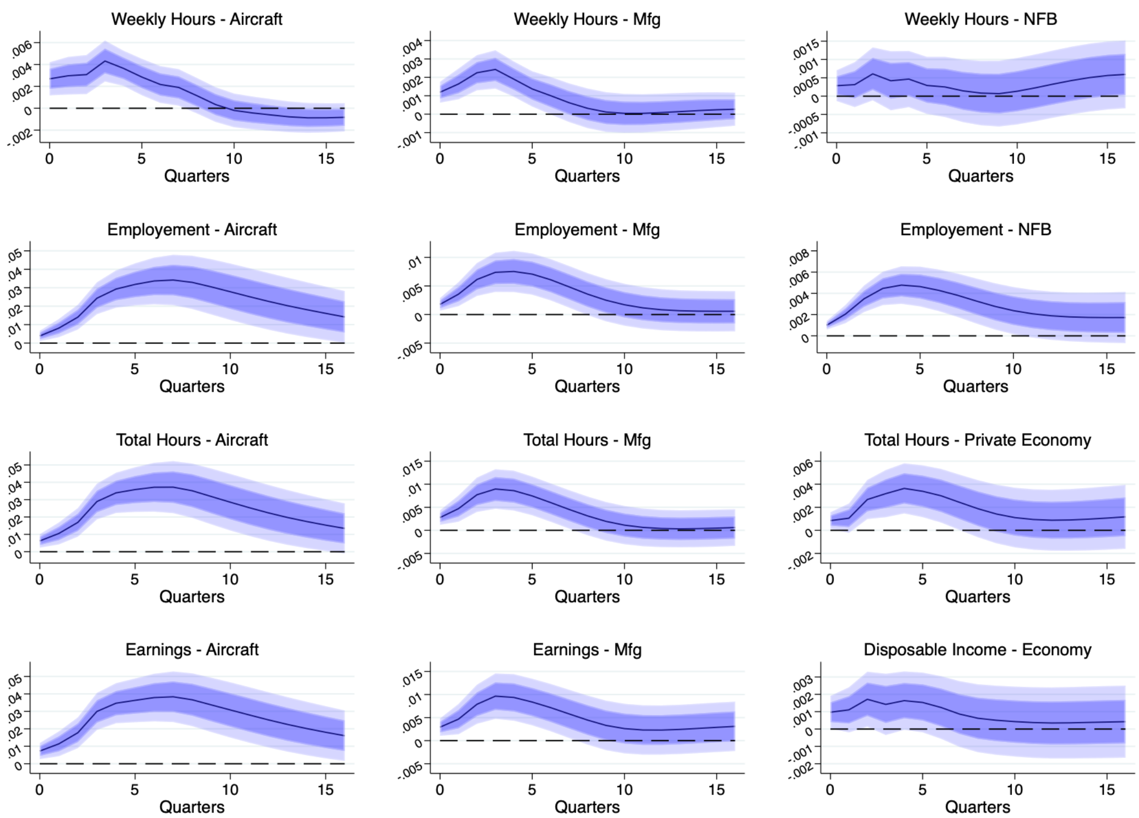


Figure 2.45. IRFs of Hours, Employment and Income - Log-VAR - 1947:1-2000:4

Figure 2.46 shows the results for the baseline sample without the Korean war: 1954:1 to 2000:4.

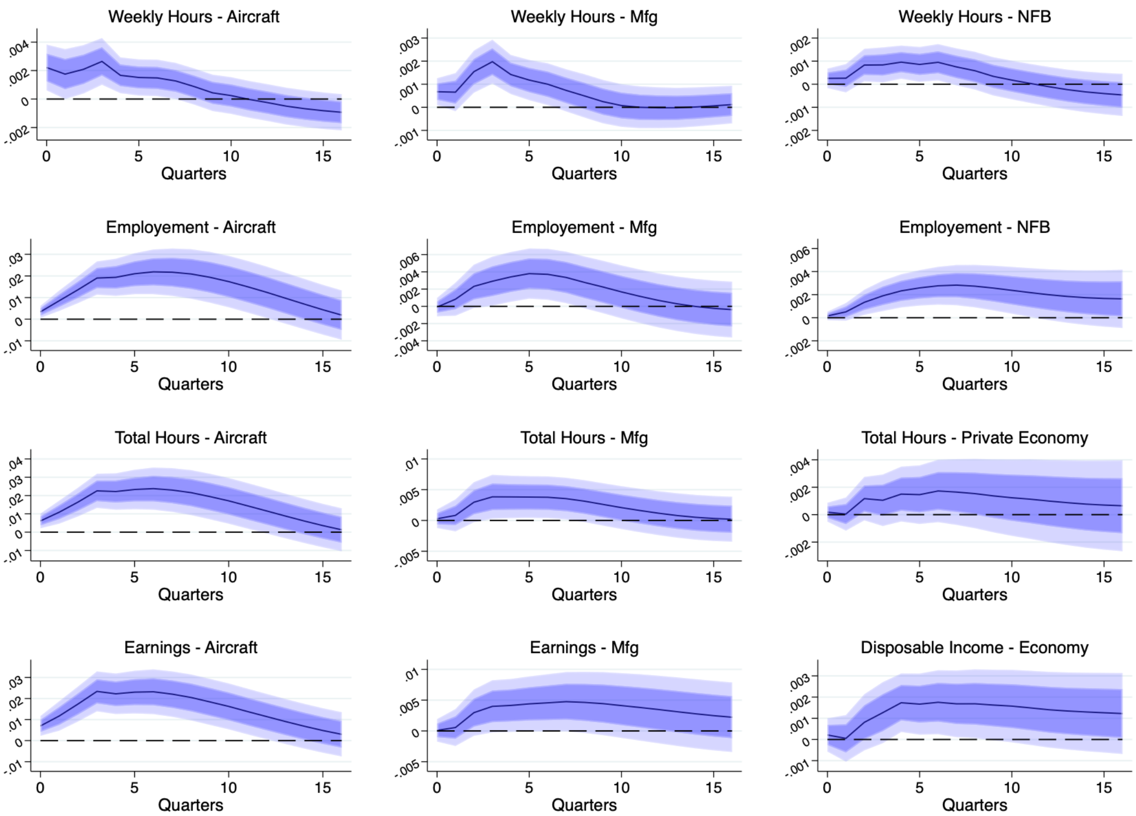


Figure 2.46. IRFs of Hours, Employment and Income - Log-VAR - 1954:1-2000:4

Figure 2.47 shows the results for the baseline sample without the Korean war: 1954:1 to 2000:4.

Summary: To conclude, the results showed here, indicate that the baseline results showed in the second chapter are robust across different samples and specifications. The response of aircraft manufacturing increases as well as total manufacturing. Responses of the total private economy are generally weaker but still positive and significant in most of the cases.

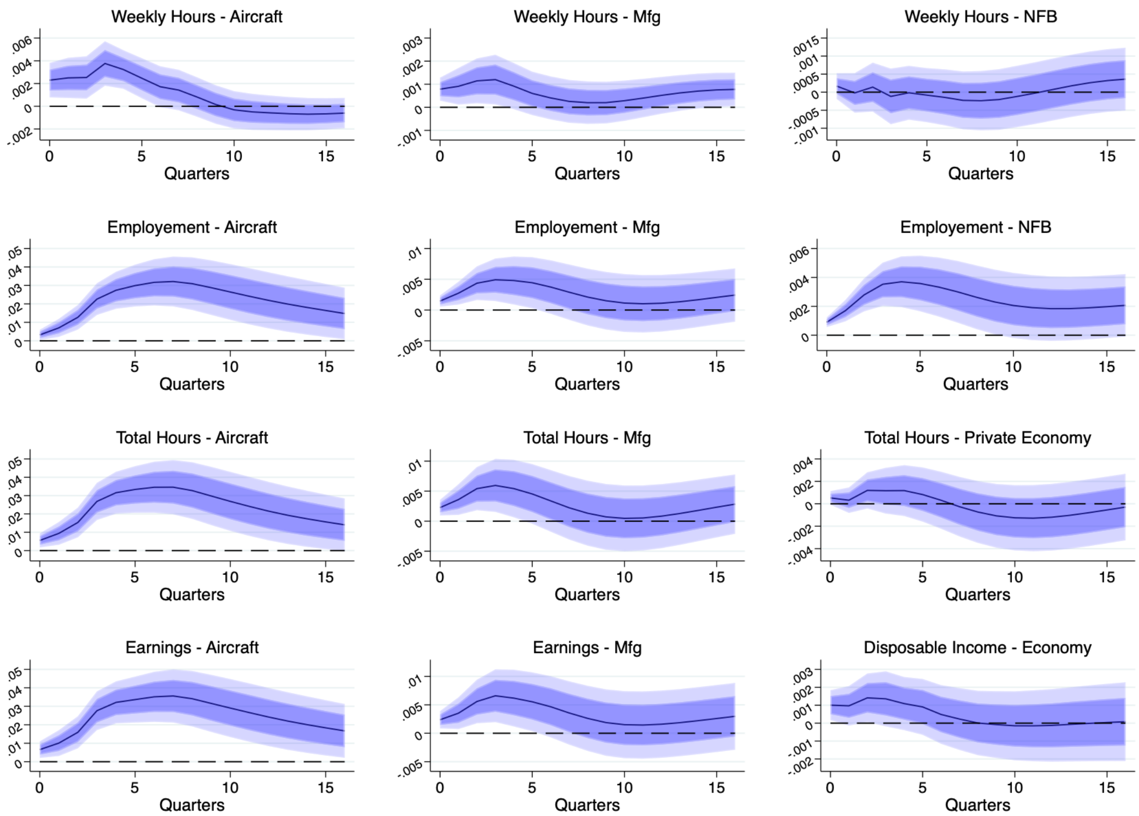


Figure 2.47. IRFs of Hours, Employment and Income - Log-VAR - 1947:1-2019:4

Real Product Wage - Robustness

For the hourly product wage I also check the results for (i) the baseline VAR showed in the second chapter but using the other two samples and (ii) the log-VAR for all samples.

Figure 2.48 shows the IRFs of the four measures of real product wage in response to a shock to defense contracts, for the baseline sample without the Korean war: 1954:1 to 2000:4.

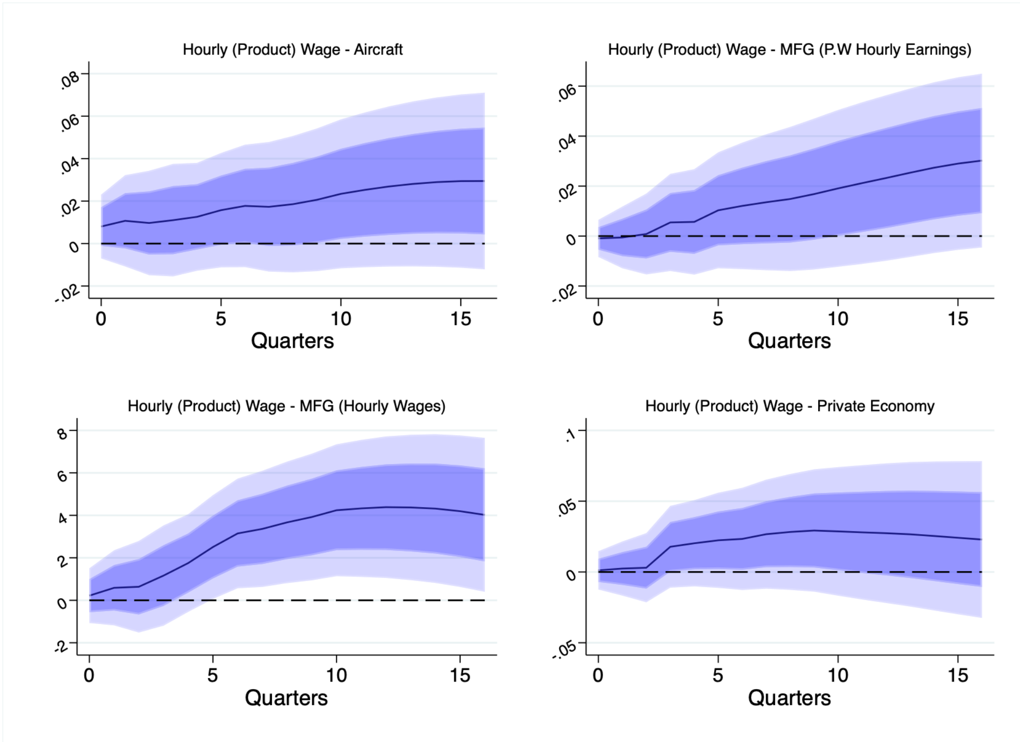


Figure 2.48. IRFs of Real (Product) Wage to Contracts - Baseline VAR - 1954:1-2000:4

Figure 2.49 shows the IRFs of the four measures of real product wage in response to a shock to defense contracts, for the full sample: 1947:1 to 2019:4.

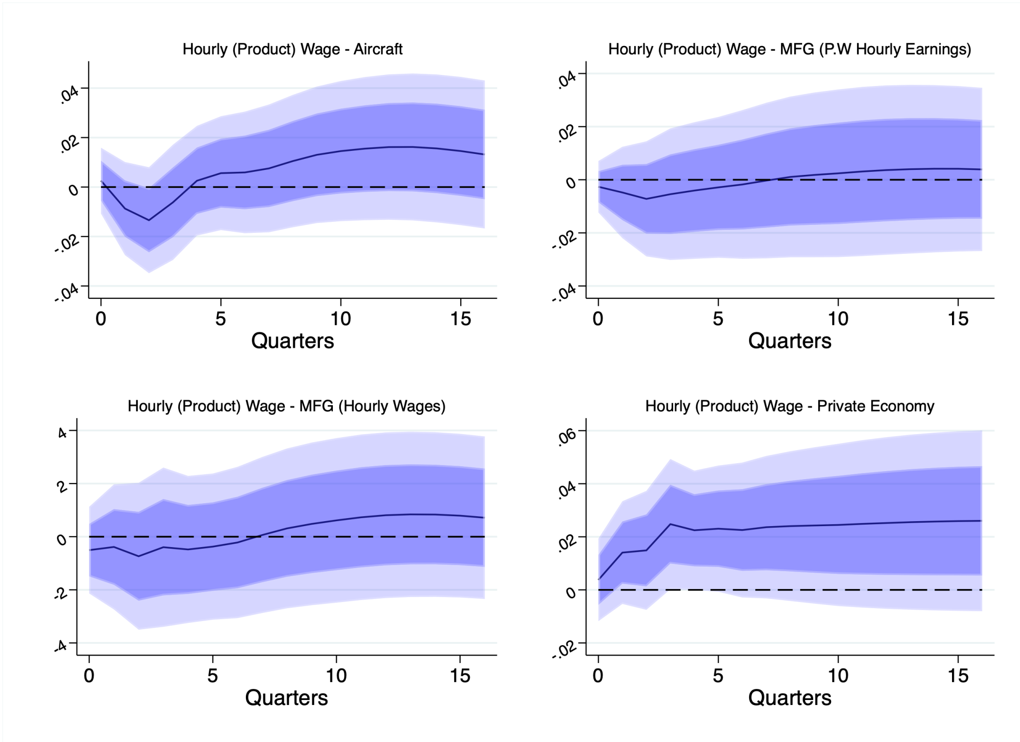


Figure 2.49. IRFs of Real (Product) Wage to Contracts - Baseline VAR - 1947:1-2019:4

I then use again the VAR in log of real per capita values. In particular, the VAR includes defense contracts, GDP, G and total tax receipts in log of real per capita values, the log of hours in the private sector and the 3 months T-Bill rate. The deflator is, as usual the GDP price deflator.

Concerning the outcome variables, I simply take the logs of the hourly (product) wage measures used in the baseline VAR.

Figure 2.50 shows the IRFs of the four measures of real product wage in response to a shock to defense contracts, for the sample: 1947:1 to 2000:4.

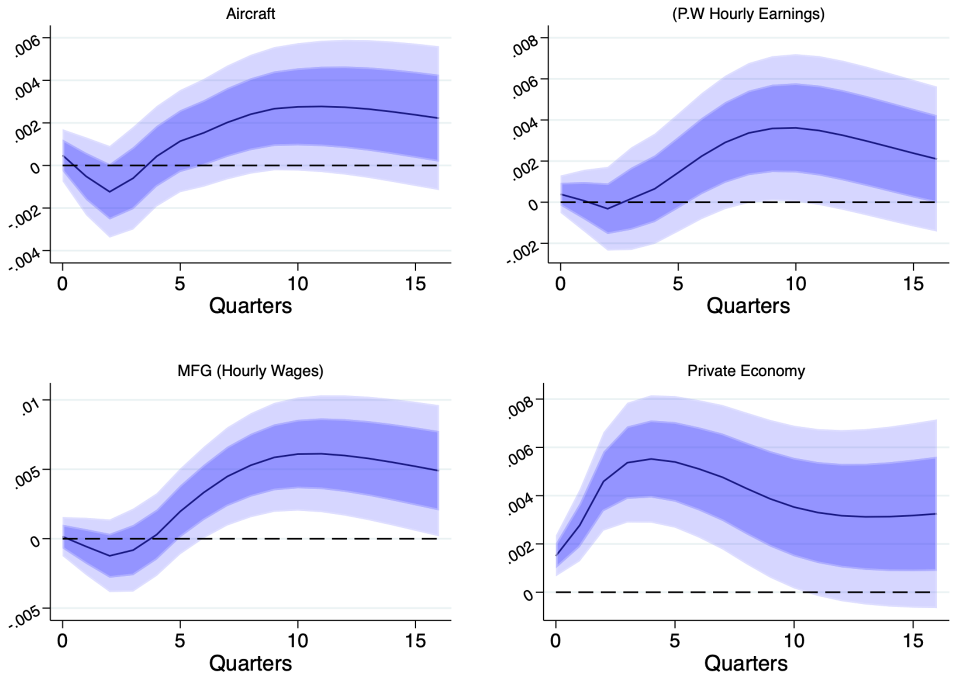


Figure 2.50. IRFs of Real Wage to Contracts - log-VAR - 1947:1-2000:4

Figure 2.51 shows the IRFs of the four measures of real product wage in response to a shock to defense contracts, for the sample: 1954:1 to 2000:4.

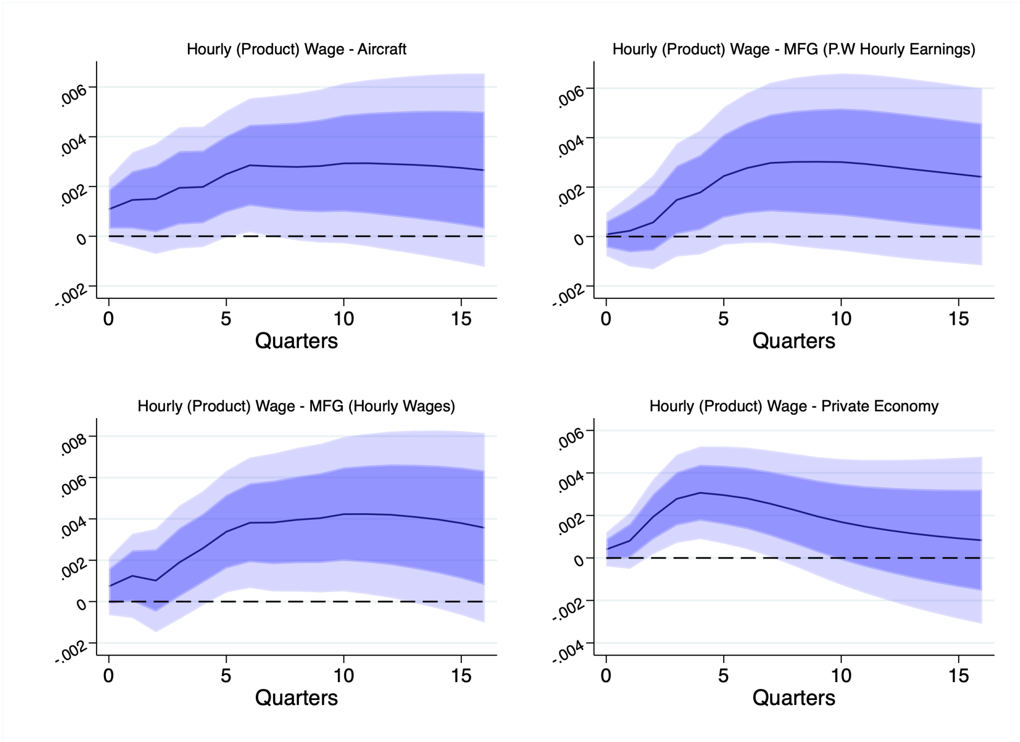


Figure 2.51. IRFs of Real Wage to Contracts - log-VAR - 1954:1-2000:4

Figure 2.52 shows the IRFs of the four measures of real product wage in response to a shock to defense contracts, for the full sample: 1947:1 to 2019:4.

Summary: To conclude, the results showed for the baseline VAR and sample reported in the second chapter are confirmed by all these robustness checks. Actually, the produce wage in manufacturing, as measured by the NIPA wages, is positive and significant. Furthermore, almost all results for the log-VAR indicate a more positive and statistically significant response of the hourly product wage.

In all cases, samples with the Korean war exhibit a slower response of the real wage, probably due to the high PPI inflation in durables experienced at the onset of the Korean war because of the buying waves caused by the fear of rationing.

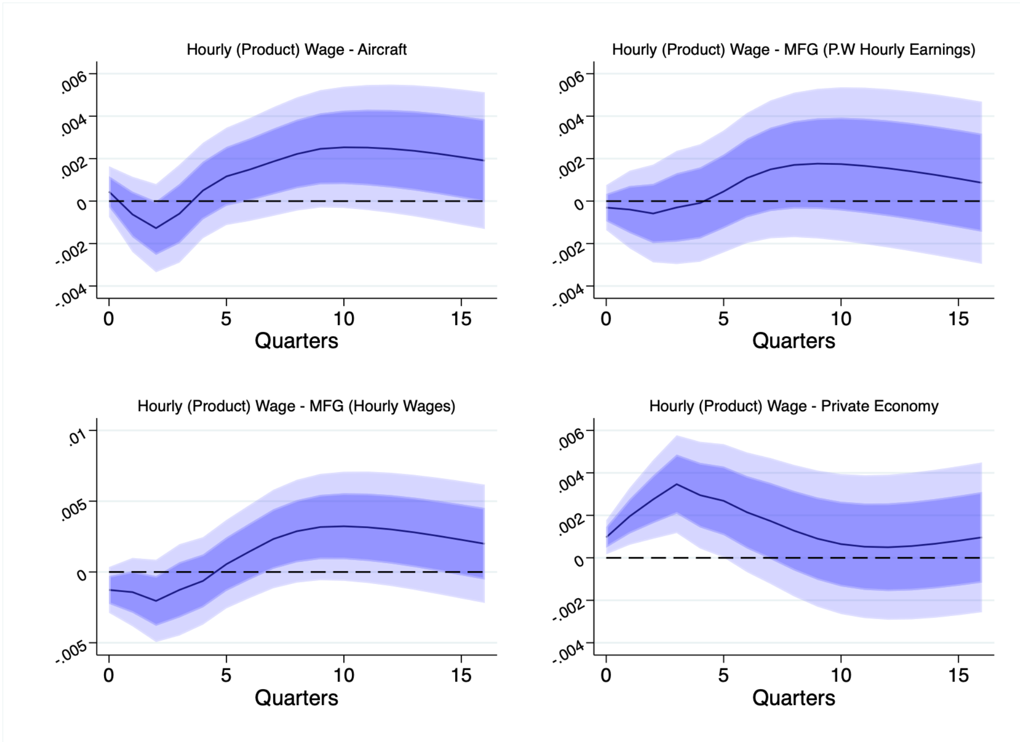


Figure 2.52. IRFs of Real Wage to Contracts - log-VAR - 1947:1-2019:4

Output per Hour - Robustness

The robustness analysis on Output-per-Hour (OpH) is carried out for three different sectors: total private, non-farm business and non-financial-corporate-business. I check the IRFs of these three measures of labor productivity in all three samples: 1947:1 to 2000:4 (baseline), 1954:1 to 2000:4 (baseline less Korea) and 1947:1 to 2019:4 (full sample).

I use two VAR models: (i) the baseline with potential output and (ii) the log-VAR with log-real per capita values. Furthermore, I check results with and without taxes.

Figure 2.53 shows the IRFs to a positive shock to defense contracts for OpH in the private sector (left column), in the NFB sector (middle column) and in the NFCB sector (right column). The VAR employed is the baseline used in the second chapter. The first row shows results for the baseline sample, the second row shows results for the baseline less Korea sample, and the last row exhibits the results for the full sample. Notice that this pattern of the figure with sectors by column and samples by rows is maintained throughout the remaining of the section.

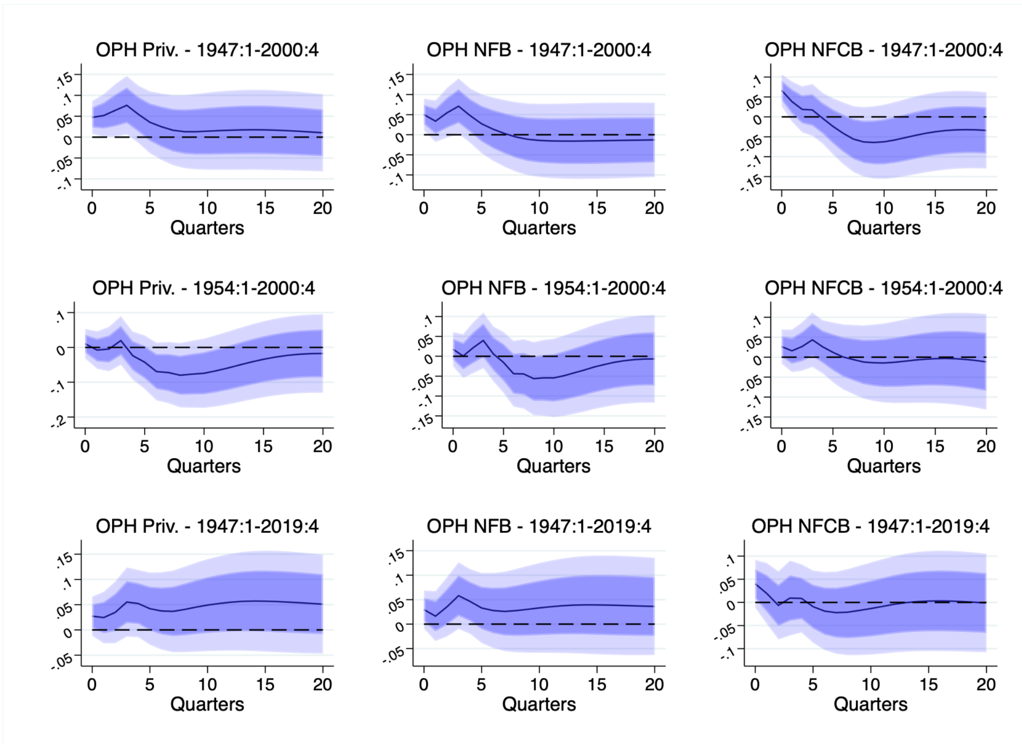


Figure 2.53. IRFs of OPH to Contracts - Baseline VAR - No Taxes

Figure 2.53 shows the results for the same VAR but augmented with total tax receipts divided by potential output.

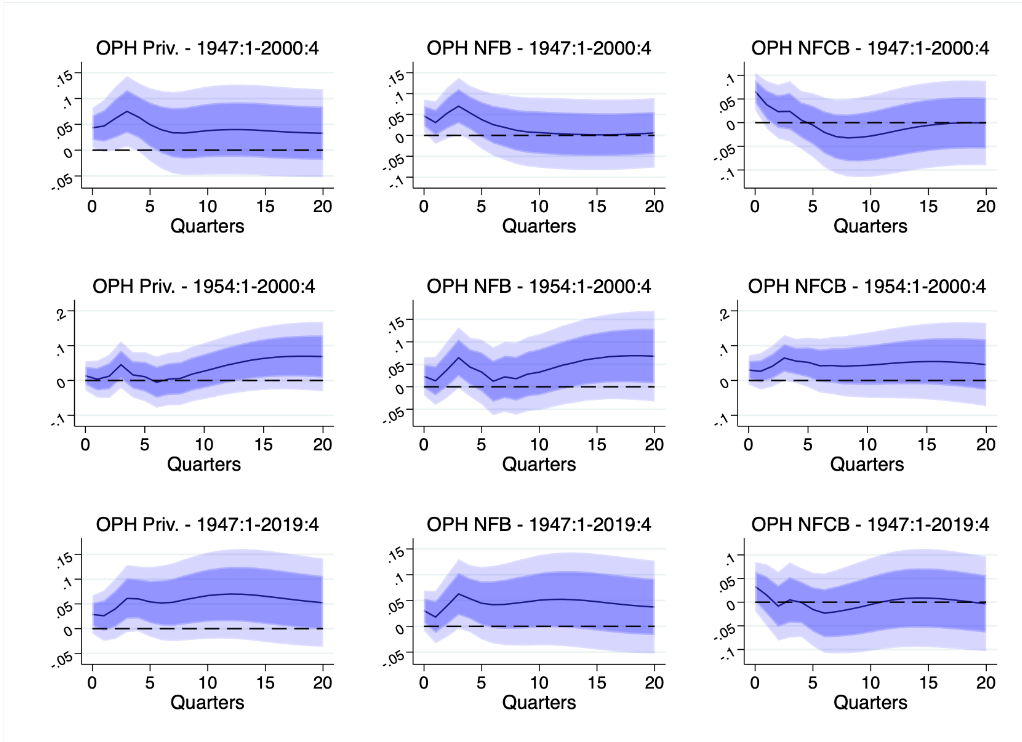


Figure 2.54. IRFs of OPH to Contracts - Baseline VAR - With Taxes

Figure 2.55 shows the results for the Log VAR. It includes defense contracts, GDP and G in log of real per capita values, the log of hours in the private sector and the 3 months T-Bill rate. The deflator is, as usual the GDP price deflator.

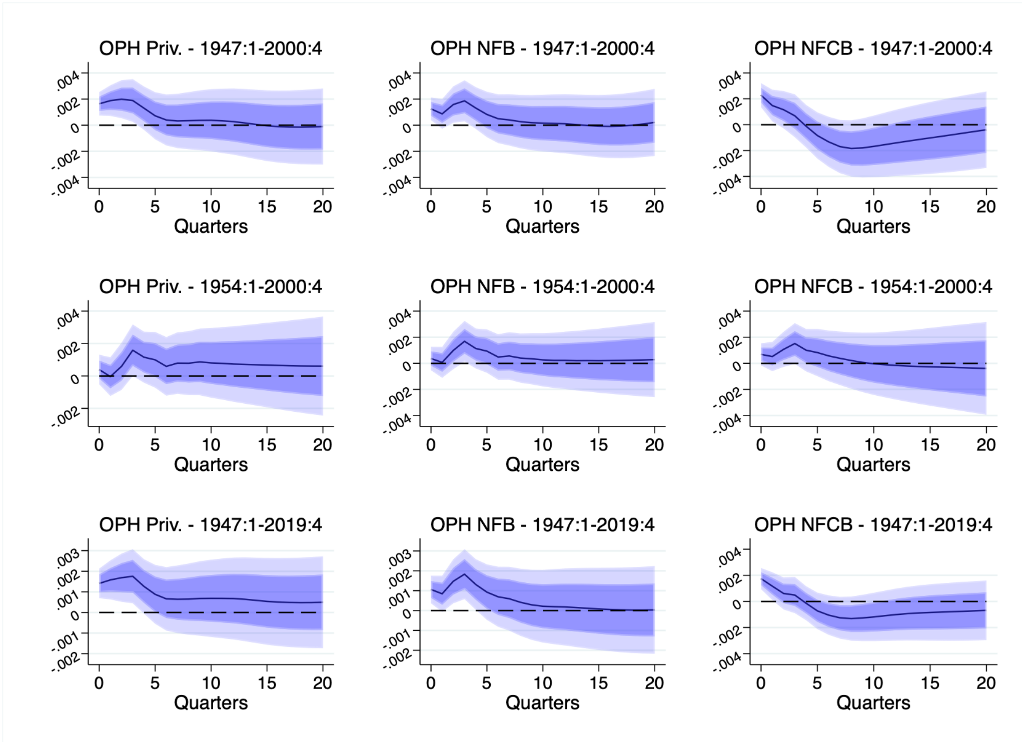


Figure 2.55. IRFs of OpH to Contracts - Log-VAR - No Taxes

Lastly, Figure 2.56 shows the results for the same Log-VAR but augmented with the log of real total tax receipts per capita.

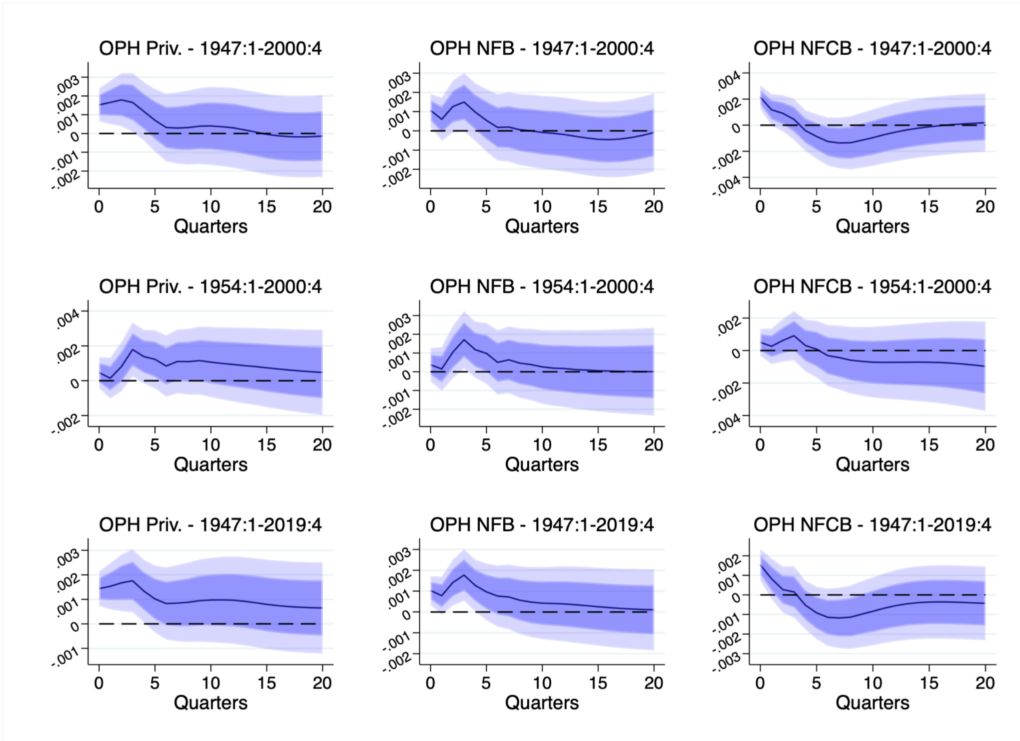


Figure 2.56. IRFs of OpH to Contracts - Log-VAR - With Taxes

Summary: To conclude, all IRFs of OpH exhibit a spike at horizon 3 with more positive results at short horizons. NFCB is the only sector which exhibits a U-shape pattern, but only for samples with the Korean war. For the samples wouthout the Korean war also NFCB assumes the common pattern with a peak at horizon 3. Taxes help estimating the effects more precisely and, the log-model, also delivers more precise estimates.

Overall, the results point to a rapid increase in labor productivity observed in all three measures.

2.6.5 Theory

In this section I provide more details on the model.

Households' Problem:

The Lagrangean of the problem is:

$$\begin{aligned}
\mathscr{L} := \sum_{t=0} \beta^t \cdot \left(\frac{\tilde{C}_t^{1-\sigma}}{1-\sigma} - \psi \cdot \frac{N_t^{1+\varphi}}{1+\varphi} \right) + \ldots \\
\ldots + \beta^t \cdot \lambda_t \cdot \Big[W_t \, N_t + \Big(r^k_{1,t} \; u_{1,t} \; K_{1,t-1} + r^k_{2,t} \; u_{2,t} \; K_{2,t-1}) \Big) - T_t - \ldots \\
\ldots (C_{1,t} + P_t \cdot C_{2,t} + I_{1,t} + P_t \cdot I_{2,t}) \Big] + \ldots \\
\ldots + \beta^t \cdot \lambda_t \cdot q_{1,t} \cdot \left[(1 - a(u_{1,t})) \cdot K_{1,t-1} + I_{1,t} \cdot \left(1 - S(\frac{I_{1,t}}{I_{1,t-1}}) \right) - K_{1,t} \right] + \ldots \\
\ldots + \beta^t \cdot P_t \cdot \lambda_t \cdot q_{2,t} \cdot \left[(1 - a(u_{2,t})) \cdot K_{2,t-1} + I_{2,t} \cdot \left(1 - S(\frac{I_{2,t}}{I_{2,t-1}}) \right) - K_{2,t} \right]
\end{aligned}$$

The Kuhn-Tucker's FOCs of the problem are:

$$\begin{aligned}
[C_{1,t}]: &\quad \lambda_t = (1-\phi) \cdot \frac{\tilde{C}_t}{C_{1,t}} \\
[C_{2,t}]: &\quad \lambda_t \cdot P_t = \phi \cdot \frac{\tilde{C}_t}{C_{2,t}} \\
[N_t]: &\quad \psi \; N_t^{\varphi} = \lambda_t W_t \\
[K_{1,t}]: &\quad q_{1,t} = \mathrm{SDF}_t \cdot \Big[r^k_{1,t+1} \; u_{1,t+1} + q_{1,t+1} \cdot (1 - a(u_{1,t+1})) \Big], \quad \mathrm{SDF}_t := \beta \cdot \frac{\lambda_{t+1}}{\lambda_t} \\
[K_{2,t}]: &\quad q_{2,t} = \frac{P_{t+1}}{P_t} \cdot \mathrm{SDF}_t \cdot \Big[\frac{r^k_{2,t+1} \; u_{2,t+1}}{P_{t+1}} + q_{2,t+1} \cdot (1 - a(u_{2,t+1})) \Big] \\
[I_{1,t}]: &\quad 1 = q_{1,t} \cdot \Big[1 - S(x_{1,t}) - x_{1,t} \cdot S'(x_{1,t}) \Big] + \mathrm{SDF}_t \cdot q_{1,t+1} \cdot x^2_{1,t+1} \cdot S'(x_{1,t+1}), \quad x_{i,t} := \frac{I_{i,t}}{I_{i,t-1}} \\
[I_{2,t}]: &\quad 1 = q_{2,t} \cdot \Big[1 - S(x_{2,t}) - x_{2,t} \cdot S'(x_{2,t}) \Big] + \frac{P_{t+1}}{P_t} \cdot \mathrm{SDF}_t \cdot q_{2,t+1} \cdot x^2_{2,t+1} \cdot S'(x_{2,t+1}) \\
[u_{1,t}]: &\quad r^k_{1,t} = a'(u_{1,t}) \cdot q_{1,t} \\
[u_{2,t}]: &\quad \frac{r^k_{2,t}}{P_t} = a'(u_{2,t}) \cdot q_{2,t}
\end{aligned}$$

Equilibrium

The equilibrium is characterized by the following equations.

Households:

$$\lambda_t = (1-\phi) \cdot \frac{\tilde{C}_t}{C_{1,t}} \quad \text{(MUC 1)} \tag{E1}$$

where $\tilde{C}_t = \left(C_{1,t}^{1-\phi} \cdot C_{2,t}^{\phi}\right)^{1-\sigma}$

$$\lambda_t \cdot P_t = \phi \cdot \frac{\tilde{C}_t}{C_{2,t}} \quad \text{(MUC 2)} \tag{E2}$$

$$\psi\, N_t^{\varphi} = \lambda_t\, W_t \quad \text{(Labor-Leisure)} \tag{E3}$$

$$q_{1,t} = \text{SDF}_t \cdot \left[r_{1,t+1}^k\, u_{1,t+1} + q_{1,t+1} \cdot (1 - a(u_{1,t+1}))\right] \quad \text{(Euler 1)} \tag{E4}$$

with $\text{SDF}_t := \beta \cdot \frac{\lambda_{t+1}}{\lambda_t}$.

$$q_{2,t} = \frac{P_{t+1}}{P_t} \cdot \text{SDF}_t \cdot \left[\frac{r_{2,t+1}^k\, u_{2,t+1}}{P_{t+1}} + q_{2,t+1} \cdot (1 - a(u_{2,t+1}))\right] \quad \text{(Euler 2)} \tag{E5}$$

$$1 = q_{1,t} \cdot \left[1 - S(x_{1,t}) - x_{1,t} \cdot S'(x_{1,t})\right] + \text{SDF}_t \cdot q_{1,t+1} \cdot x_{1,t+1}^2 \cdot S'(x_{1,t+1}) \quad \text{(Optimal Investment 1)} \tag{E6}$$

with $x_{i,t} := I_{i,t}/I_{i,t-1}$.

$$1 = q_{2,t} \cdot \left[1 - S(x_{2,t}) - x_{2,t} \cdot S'(x_{2,t})\right] + \frac{P_{t+1}}{P_t} \cdot \mathrm{SDF}_t \cdot q_{2,t+1} \cdot x_{2,t+1}^2 \cdot S'(x_{2,t+1}) \tag{E7}$$

(Optimal Investment 2)

$$r_{1,t}^k = a'(u_{1,t}) \cdot q_{1,t} \quad \text{(Optimal Capital Utilization 1)} \tag{E8}$$

$$\frac{r_{2,t}^k}{P_t} = a'(u_{2,t}) \cdot q_{2,t} \quad \text{(Optimal Capital Utilization 1)} \tag{E9}$$

Production:

$$Y_{1,t} = N_{1,t}^{\alpha_1} \cdot \left(K_{1,t}^*\right)^{1-\alpha_1} \quad \text{(Production Technology 1)} \tag{E10}$$

where $K_{i,t}^* := u_{i,t} \cdot K_{i,t-1}$

$$W_t = \alpha_1 \cdot \frac{Y_{1,t}}{N_{1,t}} := \mathrm{MPN}_{1,t} \quad \text{(Labor Demand 1)} \tag{E11}$$

$$r_{1,t}^k = (1-\alpha_1) \cdot \frac{Y_{1,t}}{K_{1,t}^*} := \frac{\mathrm{MPK}_{1,t}}{u_{1,t}} \quad \text{(Capital Demand)} \tag{E12}$$

$$Y_{2,t} = (E_t \cdot N_{2,t})^{\alpha_2} \cdot \left(K_{2,t}^*\right)^{1-\alpha_2} \quad \text{(Production Technology 2)} \tag{E13}$$

$$E_t = (1-\delta_E) \cdot E + \delta_E \cdot E_{t-1} + \theta \cdot (Y_{2,t-1} - Y_2) \quad \text{(Experience)} \tag{E14}$$

$$W_t = P_t \cdot \alpha_2 \cdot \frac{Y_{2,t}}{N_{2,t}} := P_t \cdot \mathrm{MPN}_{2,t} \quad \text{(Labor Demand 2)} \tag{E15}$$

$$r^k_{2,t} = P_t \cdot (1-\alpha_2) \cdot \frac{Y_{2,t}}{K^*_{2,t}} := P_t \cdot \frac{\text{MPK}_{2,t}}{u_{2,t}} \quad \text{(Capital Demand)} \tag{E16}$$

Markets Clearing:

$$Y_{1,t} = C_{1,t} + I_{1,t} + G_{1,t} \quad \text{(Resources 1)} \tag{E17}$$

$$Y_{2,t} = C_{2,t} + I_{2,t} + G_{2,t} \quad \text{(Resources 2)} \tag{E18}$$

$$K_{1,t} = (1 - a(u_{1,t})) \cdot K_{1,t-1} + I_{1,t} \cdot (1 - S(x_{1,t})) \quad \text{(Capital Accumulation 1)} \tag{E19}$$

$$K_{2,t} = (1 - a(u_{2,t})) \cdot K_{2,t-1} + I_{2,t} \cdot (1 - S(x_{2,t})) \quad \text{(Capital Accumulation 2)} \tag{E20}$$

Fiscal Policy:

$$T_t = G_{1,t} + P_t \cdot G_{2,t} \quad \text{(Government Budget)} \tag{E21}$$

$$A_t = (1-\rho_A)\, A + \rho_A \cdot A_{t-1} + \varepsilon^A_t \quad \text{(New Military Contracts)} \tag{E22}$$

$$G_{1,t} = G_1 \quad \text{(Government Spending 1)} \tag{E23}$$

$$G_{2,t} = \frac{\sum_{h=1}^{H} A_{t-h}}{H} \quad \text{(Government Spending 2)} \tag{E24}$$

There are 24 equations for 24 variables:

$$\text{Sector 1: } C_{1,t}\ I_{1,t}\ Y_{1,t}\ u_{1,t}\ K_{1,t}\ N_{1,t}$$

$$\text{Sector 2: } C_{2,t}\ I_{2,t}\ Y_{2,t}\ u_{2,t}\ K_{2,t}\ N_{2,t}\ E_t$$

$$\text{Fiscal Policy: } A_t\ T_t\ G_{1,t}\ G_{2,t}$$

$$\text{Prices: } \lambda_t\ P_t\ W_t\ r^k_{1,t}\ r^k_{2,t}\ q_{1,t}\ q_{2,t}$$

Steady State

From the Optimal Investment Equations, the Tobin's Qs are equal to one in steady state. Since $\delta_1 = r + \delta$, where $r = 1/\beta - 1$, combining the optimal capital utilization equations and the Euler equations, allows to find that the steady state capital utilization is also equal to one. Therefore, I have

$$q_1 = u_1 = q_2 = u_2 = 1.$$

From the Euler equation I find the value of the rental rate of capital:

$$r_1^k = r + \delta$$
$$r_2^k = P \cdot r_1^k$$

Non-Mfg Production: Using the capital FOC of sector 1, I find the capital output ratio:

$$\frac{K_1}{Y_1} = \frac{1-\alpha_1}{r_1^k} \Longleftrightarrow \text{MPK}_1 := (1-\alpha_1) \cdot \frac{Y_1}{K_1} = r_1^k.$$

Using the production function, I can express the output-per-hour of sector 1 as a function of its capital-output ratio:

$$\frac{Y_1}{N_1} = \left(\frac{K_1}{Y_1}\right)^{\frac{1-\alpha_1}{\alpha_1}}.$$

Using the firm's FOC for optimal labor demand we can find the steady stae value of the wage:

$$W = \text{MPN}_1 = \alpha_1 \cdot \frac{Y_1}{N_1}$$

Mfg Production: Using the sector 2's FOC for capital demand and the link between rental rates of capital, I find the capital output ratio:

$$\frac{K_2}{Y_2} = \frac{1-\alpha_2}{r_1^k} \Longleftrightarrow \text{MPK}_2 := (1-\alpha_2) \cdot \frac{Y_2}{K_2} = \text{MPK}_1.$$

Analogously to what done for sector 1, I find output-per-hour in sector 2:

$$\frac{Y_2}{N_2} = E \cdot \left(\frac{K_2}{Y_2}\right)^{\frac{1-\alpha_2}{\alpha_2}},$$

which allows me to find the marginal product of labor:

$$\text{MPN}_2 = \alpha_2 \cdot \frac{Y_2}{N_2}.$$

Using sector 2's FOC for optimal labor demand, I can find the steady state price level:

$$P = \frac{\text{MPN}_1}{\text{MPN}_2}$$

and notice that as long as $\alpha_1 = \alpha_2$, I have $P = 1/E$. Therefore, if $E = 1$ and labor shares are equal, the relative price is one, as in Ramey and Shapiro (1998)'s model. In turn, the steady state price level allows to find the rental rate of capital in sector 2: $r_2^k = P \cdot r_1^k$.

Households' FOC: combining the two households' FOC for optimal consumption demand, I have:

$$\frac{C_2}{C_1} = \frac{\phi}{1-\phi} \cdot \frac{1}{P}.$$

Resources: From the capital accumulation equation of sector 1, $I_1 = \delta\, K_1$. Using this in the resource constraint, I can find the consumption-hours ratio:

$$\frac{C_1}{N_1} = \left(1 - \delta \cdot \frac{K_1}{Y_1} - \gamma_1\right) \cdot \frac{Y_1}{N_1}.$$

Similarly, from sector 2:

$$\frac{C_2}{N_2} = \left(1 - \delta \cdot \frac{K_2}{Y_2} - \gamma_2\right) \cdot \frac{Y_2}{N_2}.$$

Labor Ratio: Given all the values found so far, I can find the sectoral labor ratio:

$$\frac{N_2}{N_1} = \frac{C_2}{C_1} \cdot \frac{\frac{C_1}{N_1}}{\frac{C_2}{N_2}}$$

Sector 1 Hours: Using the labor-leisure condition and all the expressions derived so far, I can derive hours in sector 1:

$$N_1 = \left[\left(1 + \frac{N_2}{N_1}\right)^{-\varphi} \cdot \frac{W \cdot (1-\phi)}{\psi} \left(\frac{C_1}{N_1}\right)^{-\sigma} \right]^{\frac{1}{\varphi+\sigma}} \cdot \left(\frac{C_2}{C_1}\right)^{\phi \varepsilon^M}$$

where $\varepsilon_M = (1-\sigma)/(\varphi+\sigma)$ is the Marshallian elasticity of labor supply.

Finding all remaining steady-state values is trivial.

Response of Wages, Prices and Productivity

Figure 2.57 shows the response of experience, E_t, and output-per-hour, Y_t/N_t, where Y_t is real output (output measured at baseline prices).

The left panel shows that experience starts increasing from period 2, as a result of increased production, experience keeps increasing and stays above steady-state level as long as $Y_{2,t} > Y_2$. It then decays geometrically at rate δ_E. The right panel shows the response of output-per-hour, which increases slowly as experience builds-up.

Figure 2.58 shows the dynamics of several prices and wages.

Firstly, the bottom-right figure shows the dynamics of P_t, the price of good 2 relative to the price of good 1. In the case of no-learning, the price increases as sector 1 becomes more productive than sector 2 (i.e. recall that $P_t = \text{MPN}_{1,t}/\text{MPN}_{2,t}$), since labor reallocation increases $\text{MPN}_{1,t}$ and decreases $\text{MPN}_{2,t}$. When there is learning in the model, the effect of experience overcomes the one of sectoral reallocation, making $\text{MPN}_{2,t}$ increases more than $\text{MPN}_{1,t}$ does. Therefore, the price falls.

The top-left figure shows the product wage of sector 1, which is identical to the nominal

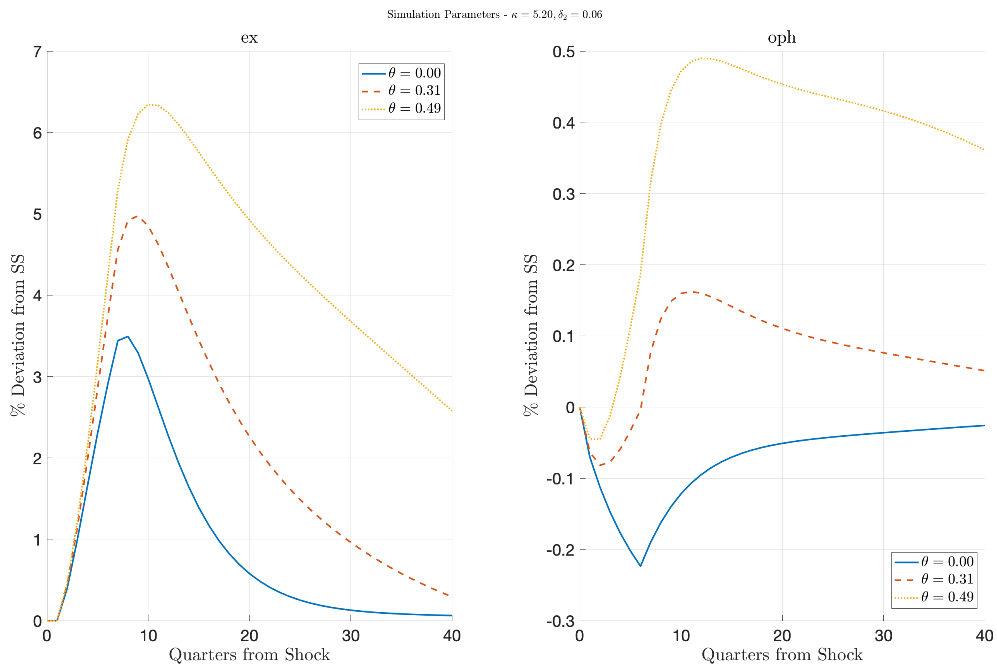


Figure 2.57. EXPERIENCE AND OUTPUT-PER-HOUR

Notes: The simulation is obtained with Dynare. The blue line sets $\theta = 0$ and assumes no-learning. The dashed orange line sets $\theta = E/(4 \cdot Y_2)$ and assumes learning-by-doing. The model sets $\kappa = 5.2$ (investment adjustment costs) and $\delta_2 = 2 \cdot \delta_1$ (capital utilization). Output-per-Hour is obtained diving real GDP by total hours.

wage W_t in the model, given that the price of good 1 is the numeraire of the economy. The bottom-left panel shows the response of the rental rate of capital of sector 1, which coincides with the marginal product of capital of sector 1. Given that sector 1 is not much affected by the build-up, the magnitude of their response is very limited compared to the dynamics of sector 2 and the aggregate one.

The top-middle panel shows the product wage of sector 2, obtained as W_t/P_t. Notice that the product wage increases when there is learning and falls when there is not learning, a result driven by the dynamics of relative prices (bottom-right figure). The bottom-middle panel shows the rental rate of capital of sector 2 (recall that $r^k_{2,t} = P_t \cdot \text{MPK}_{2,t}/u_{2,t}$). The rental rate initially increases, boosted by extra hours worked in sector 2, as well as extra TFP coming from learning-by-doing. As hours fall and experience achieves its peak, the fall in the price drives

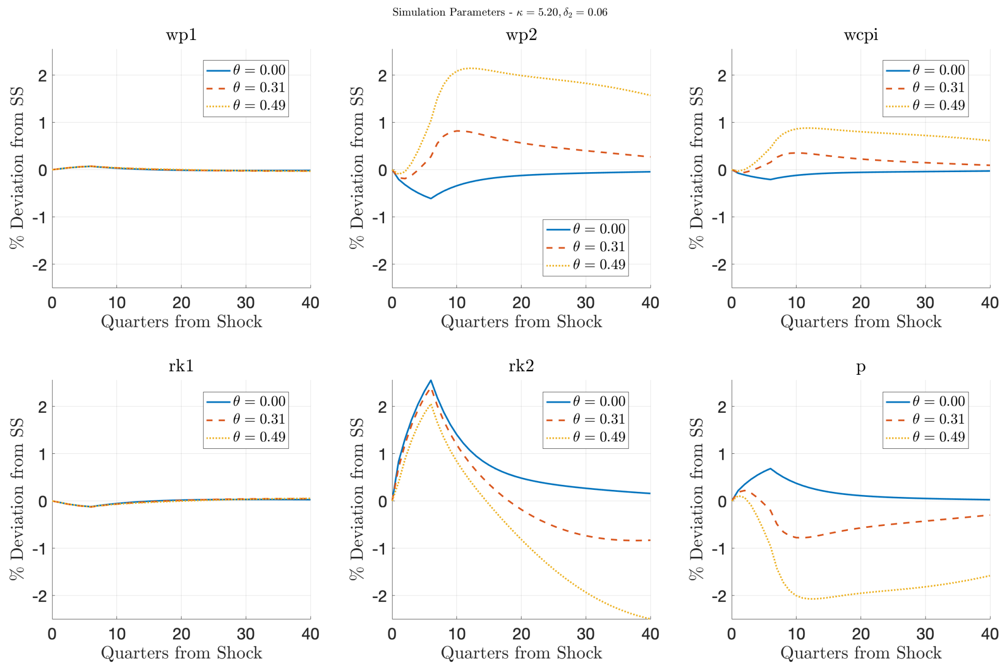


Figure 2.58. PRICES AND WAGES

Notes: The simulation is obtained with Dynare. The blue line sets $\theta = 0$ and assumes no-learning. The dashed orange line sets $\theta = E/(4 \cdot Y_2)$ and assumes learning-by-doing. The model sets $\kappa = 5.2$ (investment adjustment costs) and $\delta_2 = 2 \cdot \delta_1$ (capital utilization).

down the rental rate of capital.

Finally, the top-right panel shows the response of the consumption wage, which is constructed as the ratio between the nominal wage W_t and the CPI. I construct the CPI as follows:

$$\begin{aligned}
\text{CPI}_t &= \frac{C_1}{C} \cdot 1 + \frac{P \cdot C_2}{C} \cdot P_t \\
&= \frac{C_1}{C_1\left(1 + \frac{P \cdot C_2}{C_1}\right)} + \frac{P \cdot C_2}{C_1\left(1 + \frac{P \cdot C_2}{C_1}\right)} \cdot P_t \\
&= \frac{1}{1 + \frac{\phi}{1-\phi}} + \frac{\frac{\phi}{1-\phi}}{1 + \frac{\phi}{1-\phi}} \cdot P_t \\
&= (1-\phi) + \phi \cdot P_t.
\end{aligned}$$

Therefore, the consumption wage is:

$$W_t^{\text{CPI}} = \frac{W_t}{(1-\phi)+\phi \cdot P_t}.$$

The consumption wage increases in a way similar to the one of the product wage of sector 2, driven up by the fall in the relative price.

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Chapter 3

The Network Effect of Fiscal Adjustment Plans

3.1 Introduction

The interconnectedness of countries, financial systems, and industries is crucial for understanding the transmission of policy shocks. This chapter investigates the propagation mechanisms of fiscal consolidations through the industrial production network with a particular focus on the differential impacts of tax-based (TB) and expenditure-based (EB) adjustments. We explore how fiscal shocks when filtered through the production network, lead to varied macroeconomic outcomes.

Economic principles and best practices advocate for deficit spending during economic downturns and surplus budgeting in times of prosperity, aiming for overall fiscal balance. In accordance with this principle, the fiscal stimuli implemented in response to the COVID-19 pandemic have led to a deterioration in public finances, increasing the likelihood of austerity measures in several countries.[1] In this context, gaining a comprehensive understanding of the mechanisms through which fiscal consolidations are transmitted is essential for their efficient implementation.

Our analysis is situated within the broader literature on fiscal policy and its effects on

[1]On April 25, 2020, in an article entitled "After the disease, the debt", The Economist wrote:"... governments should prepare for the grim business of balancing budgets later in the decade."

economic output. It is well-documented that consolidations achieved through spending cuts generally have a less detrimental impact on economic growth than those achieved through increased taxation (Ramey (2019)). This distinction is crucial for policymakers charged with designing and implementing fiscal strategies that minimize loss to economic output while ensuring fiscal stability.

Despite the importance of this finding, the literature has devoted little attention to the reasons behind this asymmetrical effect on the economy. In this chapter, we propose production networks as a potential explanation for the asymmetric output responses to tax-based (TB) versus expenditure-based (EB) fiscal consolidations. In particular, we investigate the effects of fiscal consolidations in the United States from 1978 to 2014 at an industry level, covering 62 interconnected industries. Our findings indicate that TB fiscal adjustments result in a significant recessionary output multiplier over two years (about 1.4%), while the effects of EB fiscal plans are not statistically different from zero. These results align with existing literature (see Guajardo, Leigh, and Pescatori (2014), Alesina et al. (2015)) but extend the analysis by incorporating the network dimension.

We employ a spatial autoregressive (SAR) model (J. LeSage and Pace, 2009), with spatial distance defined by the input-output production network.[2] Specifically, we utilize a panel version of the SAR model, which not only considers the spatial-industry dimension but also the time dimension. To accommodate the varying volatility in growth rates across sectors, we allow for heteroskedasticity by employing both the maximum likelihood method, as suggested by Aquaro, Bailey, and Pesaran (2021), and Bayesian MCMC, as described in J. LeSage and Pace (2009).

We decompose the aggregate effects of fiscal consolidations into direct and network effects. The direct effect measures the impact of the fiscal shock on each industry, while the network effect considers the spillover effects from other industries within the same production network. Our findings show that approximately 27% of the total effect of TB fiscal consolidations

[2]Given that input-output (IO) coefficients typically remain stable over time, we use a static IO matrix. This approach assumes that market participants respond based on the existing intensity of production network connections. As mentioned in Giovanni et al. (2023), this assumption is particularly suitable at the industry level.

is due to network spillovers, in contrast to a more modest 11% for EB plans. This variance in network effects contributes to about one-fourth of the difference in the total effects of TB and EB plans, underscoring the importance of production networks in explaining the asymmetric output response to fiscal consolidations.

Furthermore, our analysis highlights the role of key suppliers in the economy in propagating tax shocks through the network.[3] This finding is consistent with research on the upstream propagation of monetary policy shocks by Ozdagli and Weber (2020) and Giovanni et al. (2023), emphasizing the significance of incorporating production networks into fiscal policy analysis.

In summary, this chapter enhances the understanding of how fiscal adjustment plans are transmitted by spotlighting the role of production networks in amplifying and disseminating fiscal shocks. Through an examination of the direct and network effects of fiscal consolidations, we offer insights into the mechanisms that contribute to the asymmetric output response to TB and EB plans.

Related Literature

First, our work relates to the literature on fiscal consolidations, including works by Guajardo, Leigh, and Pescatori (2014), Alesina et al. (2015), Pappa, Sajedi, and Vella (2015), Alesina et al. (2017), Born, Müller, and Pfeifer (2020), Beetsma et al. (2021), Carrière-Swallow, David, and Leigh (2021), Chang et al. (2021), Gabriel, Klein, and Pessoa (2023). Unlike these studies, which primarily focus on country-level analyses, we investigate the network effects of fiscal consolidations within a panel of U.S. industries.

Alesina et al. (2017) provide a theoretical framework for understanding the stronger impact of tax-based (TB) fiscal consolidations. Other studies, such as Brinca et al. (2021), explore various channels through which fiscal consolidations affect the economy. Our work adds to this literature by offering a network-based perspective on the asymmetric effects of TB and

[3]Key suppliers in the network include: Fabricated Metal Products, Primary Metals, Wholesale Trade, Plastic and Rubber Products, Chemical Products, Real Estate, Administrative Services, and Miscellaneous Professional, Scientific, and Technical Services.

EB fiscal consolidations.

Second, our research is related to the literature on production networks, exemplified by the seminal works of Gabaix (2011) and Acemoglu, Carvalho, et al. (2012). These studies highlight the role of networks in amplifying economic shocks. Recent contributions in this area have explored various aspects of network dynamics, including the asymmetric propagation of shocks (Acemoglu, Akcigit, and Kerr, 2016, the impact of fiscal spending multipliers (Flynn, Patterson, and Sturm (2021), Barattieri, Cacciatore, and Traum (2023) and Bouakez, Rachedi, and Santoro (2023)). Our work extends this analysis by adopting a spatial framework to examine the network transmission of fiscal adjustment plans, drawing on approaches used by Ozdagli and Weber (2020) and Di Giovanni and Hale (2022) in the context of monetary policy.

Third, we contribute to the literature on the industry-level effects of fiscal policy. Studies by Ramey and Shapiro (1998), Perotti (2007), and Nekarda and Ramey (2011) have examined the impact of government spending on specific sectors. Cox et al. (2023) explore public procurement contracts and uncover a significant sectoral bias in government spending. Auerbach, Gorodnichenko, and Murphy (2020) analyze city-level data on local defense public procurement, discovering substantial fiscal spillovers among industries. These findings underscore the importance of considering sectoral heterogeneity in fiscal policy effects. We build on this work by analyzing the transmission of fiscal adjustment plans across a comprehensive set of industries within a production network framework.

In summary, our work provides new insights into the propagation mechanisms of fiscal adjustment plans, highlighting the significance of production networks in determining their effects.

The chapter is organized as follows: Section 3.2 outlines how fiscal adjustment plans indicate exogenous fiscal consolidation policies and examines their aggregate effects, offering a theoretical rationale for the transmission mechanism. Section 3.3 details our findings. Section 3.4 addresses robustness checks, and Section 3.5 concludes.

3.2 Fiscal Adjustments Plans in the US

Measuring the propagation of fiscal adjustments requires the identification of an exogenous demand and supply shocks. Our identification strategy thus relies on the narrative analysis of fiscal adjustment plans. This strategy is a recent innovation in the fiscal policy literature and employs narrative exogenous shocks as a proxy for fiscal consolidation policies. This strategy was introduced in Alesina et al. (2015) to take into account the fact that fiscal adjustments are implemented through multi-year plans with both an intertemporal and an intratemporal dimension.

The intratemporal dimension refers to the fact that fiscal consolidations are implemented with a mix of tax increases and spending cuts. Tax and the expenditure components of the adjustments are correlated since governments decide first on the size of the adjustment, and then on its composition in terms of expenditures and revenues. The intertemporal dimension is important since fiscal adjustments are implemented via multi-year plans with measures upon announcement (the unanticipated component of the plan) and measures announced for subsequent years (the anticipated component of the plan). In particular, each country has a specific "recipe" to implement fiscal consolidations: some countries prefer to unexpectedly raise taxes without cutting expenditures, while others announce large future cuts in spending and only marginally increase taxes. Alesina et al. (2015) refer to this as the country-specific "style of the plan".

These complications make identifying pure and isolated tax hikes and spending cuts during years of fiscal consolidation a difficult, if not impossible, task. Fiscal plans provide an effective tool to circumvent these difficulties when studying austerity policies.

3.2.1 Modeling Fiscal Plans:

From a mathematical standpoint, plans are sequences of fiscal corrections, announced at time t and implemented between t and $t+K$, where K is the anticipation horizon. In each year t, two types of fiscal corrections are possible:

1. The *<u>unanticipated fiscal shock</u>*, that is, the surprise change in the primary surplus at time t, which we denote by:

$$f_t^u := tax_t^u + exp_t^u,$$

where tax_t^u is the surprise increase in taxes announced and implemented at time t, while exp_t^u is the surprise reduction in government expenditure also announced and implemented at time t.

2. The *<u>anticipated fiscal shock</u>*: the change in the primary surplus at time t, which had already been announced in the previous years and is either implemented in year t or scheduled to happen within K years. In particular, we denote as $tax_{t,j}^a$ and $exp_{t,j}^a$ the tax and expenditure changes announced by the fiscal authorities at date t with an anticipation horizon of j years (*i.e.,* to be implemented in year $t+j$). Therefore, we further distinguish between:

   (a) The *<u>anticipated implemented shock</u>*: scheduled in the past and implemented in year t:

   $$f_t^a := \ tax_{t,0}^a + exp_{t,0}^a$$

   (b) The *<u>anticipated future shocks</u>*: sum of scheduled tax and government spending changes which have to be implemented within K years from their announcement:

   $$f_t^f := \sum_{j=1}^{K} tax_{t,j}^a + \sum_{j=1}^{K} exp_{t,j}^a.$$

   In a fiscal adjustment database, as long as no policy revision takes place, the anticipated shocks roll over year-by-year. In formulae:

   $$tax_{t,j}^a = \underbrace{tax_{t-1,j+1}^a}_{\textit{Old shock, rolled over}} \qquad exp_{t,j}^a = \underbrace{exp_{t-1,j+1}^a}_{\textit{Old shock, rolled over}} .$$

   However, if from one year to another, a policy revision takes place, then, the new anticipated future shock will embed such change:[4]

$$tax^a_{t,j} = \underbrace{tax^a_{t-1,j+1}}_{\textit{Old shock, rolled over}} + \underbrace{\left(tax^a_{t,j} - tax^a_{t-1,j+1}\right)}_{\textit{Policy Revision}}, \quad \text{with } j \geq 1$$

$$exp^a_{t,j} = \underbrace{exp^a_{t-1,j+1}}_{\textit{Old shock, rolled over}} + \underbrace{\left(exp^a_{t,j} - exp^a_{t-1,j+1}\right)}_{\textit{Policy Revision}}, \quad \text{with } j \geq 1$$

We adopt the annual database on fiscal adjustment plans constructed by Alesina et al. (2015) and consider only fiscal consolidations that occurred in the US from 1978 to 2014. They identify fiscal adjustments exogenous with respect to output fluctuations using a narrative identification method. This approach is similar to C. D. Romer and D. H. Romer (2010), who identify exogenous tax shocks from presidential speeches, congressional debates, budget documents, and congressional reports. From these documents, they identify the size, timing, and principal motivation for all major postwar tax policy actions. Legislated changes are then classified into two categories: 1) endogenous, if induced by short-run counter-cyclical concerns; 2) exogenous, if taken in response to the state of government debt (deficit-driven).[5]

As mentioned earlier, fiscal adjustment plans allow us to control for the intertemporal and intratemporal correlation, which we report in Table 3.1:

Notice from Table 3.1 that the intra-temporal correlation between unanticipated tax and unanticipated expenditure adjustments is 60% (blue figures in Table 3.1). Similarly, the (inter-temporal) correlation between future and anticipated components of expenditure is 78% (green figures in Table 3.1). As both the inter-temporal and the intra-temporal dimension matter, it is worth considering multi-year fiscal plans instead of individual measures of tax and government spending shocks.

Since this source of correlation confounds the effects of taxes and expenditures, we need to

[4] In the above expression $j \geq 1$ since any policy revision introduced upon implementation ($j = 0$) is no longer a part of an anticipated shock; in fact, it is a new unanticipated component.

[5] Concerning expenditure shocks, we emphasize that Alesina et al., 2017 disentangle transfers from taxes and government spending. They show that the difference in output responses is not driven by the inclusion of transfers among other public spending measures.

Table 3.1. Correlation matrix of Fiscal Adjustments Plans in the US

	tax_t^u	$tax_{t,0}^a$	tax_t^f	exp_t^u	$exp_{t,0}^a$	exp_t^f
tax_t^u	1	0.041	0.570	0.596	-0.126	0.105
$tax_{t,0}^a$		1	0.038	0.098	0.361	0.310
tax_t^f			1	-0.047	0.019	0.180
exp_t^u				1	-0.050	0.014
$exp_{t,0}^a$					1	0.782
exp_t^f						1

Notes: Linear correlation matrix of legislated changes in taxes and expenditure identified by the narrative analysis. Sample: annual data from 1978 to 2014 of US fiscal adjustment plans from Alesina et al. (2015). In blue is reported the intra-temporal correlation (between each component of taxes and expenditures. In green is the inter-temporal correlation (within tax or expenditure component, but between components with different timing). In black we have a mix of the two: correlation between tax and expenditure components with different timing.

classify plans into mutually exclusive categories which can be simulated independently. We can then take into account the inter-temporal correlation within each category. To this end, we exploit the fact that not all the plans are the same. Some fiscal plans are designed to increase taxes more than cut expenditures and are labeled as TB (tax-based). On the contrary, those plans which rely more on expenditure cuts rather than tax hikes are labeled as EB (expenditure-based). For instance, the criterion which determines whether a fiscal consolidation is labeled as TB can be written:

$$\underbrace{\left(tax_t^u + tax_{t,0}^a + \sum_{j=1}^{K} tax_{t,j}^a\right)}_{\text{overall tax hike in } t} > \underbrace{\left(exp_t^u + exp_{t,0}^a + \sum_{j=1}^{K} exp_{t,j}^a\right)}_{\text{overall expenditure cut in } t}. \tag{3.1}$$

Criterion (3.1) is saying that if the overall tax hike in year t exceeds the overall spending cut, then we label year t as a year of TB fiscal consolidation. We keep track of these years by constructing two dummy variables, TB_t and EB_t, which are equal to one if year t is labeled as TB or EB, respectively. By construction, TB and EB plans are mutually exclusive. That is, EB and TB plans cannot occur simultaneously. This lets us simulate separately the effect of TB and EB plans while preserving, within each type of plan, the observed intra-temporal correlation between adjustments on government's revenues and expenditure.

Figure 3.1 plots our fiscal adjustment plans database. This contains all of the nominal changes in taxes and expenditure, scaled by GDP of the year before the consolidation occurs to avoid potential endogeneity issues. Moreover, the future component of the fiscal adjustment plan has a maximum anticipation horizon of three years (K). This is in line with the small numbers of occurrences of policy shifts anticipated four and five years ahead, and is consistent with the database in Guajardo, Leigh, and Pescatori (2014). The top row of Figure 3.1 illustrates the three components of fiscal adjustments interacted with the dummy TB_t to identify the components of tax-based fiscal consolidations. The bottom row does the same for expenditure-based fiscal consolidations.

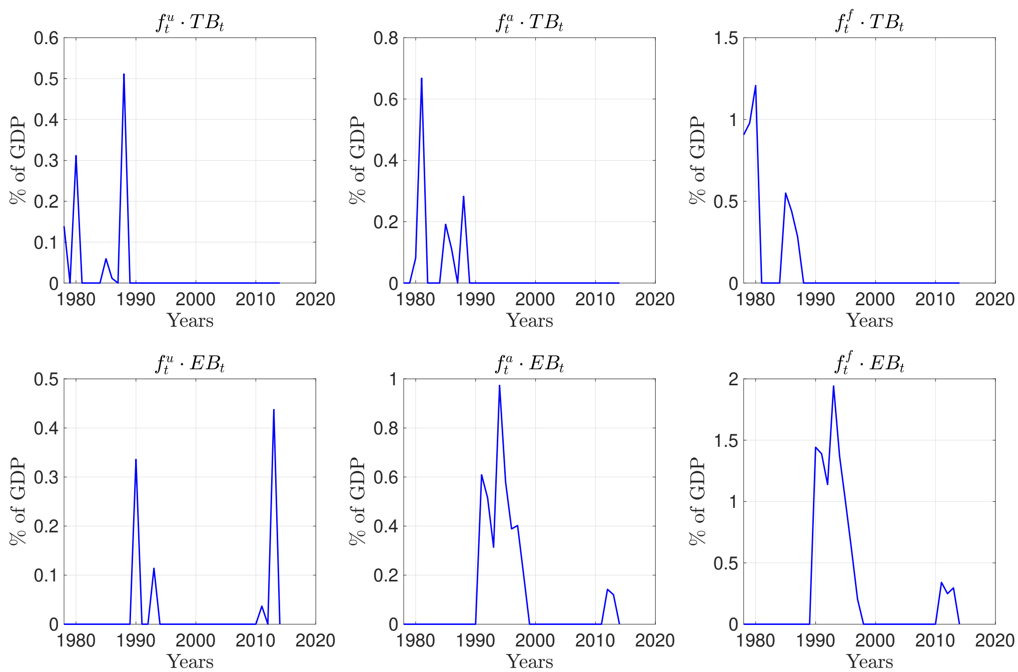

Figure 3.1. FISCAL ADJUSTMENTS PLANS - UNITED STATES 1978-2014

We assess the goodness of our orthogonalization criterion (3.1), by showing in Figure 3.2 the share of tax increases and spending cuts of each total fiscal adjustment, $f_t^u + f_t^a + f_t^f$.

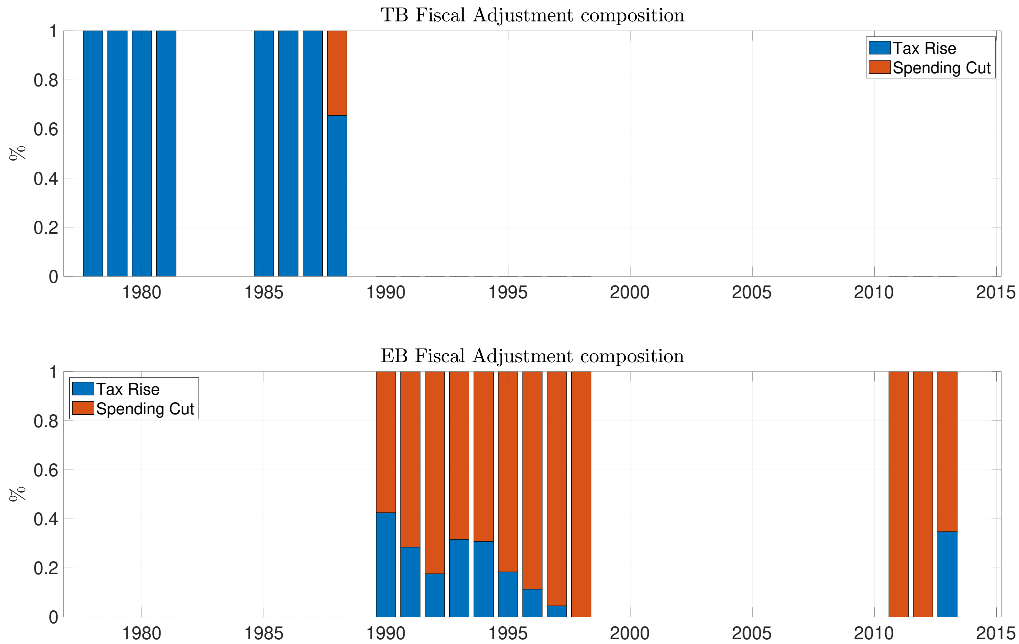

Figure 3.2. FISCAL ADJUSTMENT PLANS - COMPOSITION

Figure 3.2 shows that the labeling of fiscal adjustment into EB or TB plans, by means of criterion (3.1), is never marginal: i. TB plans are all pure tax hikes except for the year 1988, which is the result of a hybrid fiscal plan with only 30% in spending cuts; ii. EB plans are mainly made up of spending cuts with only 20% of policy changes coming from a tax increase, on average. Figure 3.2 also illustrates the timing of fiscal consolidations in the US: i. there are two periods of TB fiscal adjustments ($TB_t = 1$) between 1978-1981 and 1985-1988; ii. there are three periods of EB fiscal adjustments ($EB_t = 1$) between 1990-1992, 1993-1998 and 2011-2013.

To summarize, we classify fiscal consolidations into TB and EB fiscal adjustment plans to account for the observed correlation between tax and expenditure adjustments. This correlation comes from the fact that policy makers implement fiscal consolidations by adopting multi-year fiscal plans with both tax hikes and spending cuts.

Finally, we highlight that fiscal consolidations censor changes in G and T above and below 0, respectively, by construction.[6] Therefore, estimates of their economic effects are valid for this type of fiscal policy only. Simply put, we do not estimate tax and government spending multipliers. However, if the United States plans to undertake either a TB or an EB fiscal consolidation, our estimates are externally valid and can be used as a benchmark for policy-makers.

3.2.2 Aggregate Effects of Fiscal Consolidations in the US

The first step of our analysis is to study the aggregate effects of fiscal consolidations in the US. We estimate the impulse response functions of EB and TB plans using a truncated moving average (MA) representation as in C. D. Romer and D. H. Romer (2010) but where the shocks are given by the fiscal consolidations as in Alesina et al. (2015). So we simulate the response to an unanticipated component taking into account that it is accompanied by the announcement of future changes. Following Alesina et al. (2015) we compute impulse response functions as a difference between the forecast obtained conditionally on a fiscal adjustment plan and the forecast with no plan.[7] Figure 3.3 shows the estimated cumulative impulse response function of output and employment growth rates using quarterly data from 1978Q1 to 2014Q4.

The left panel of Figure 3.3 shows that TB plans trigger a cumulative drop of output and employment by 4% and 2% respectively. On the contrary, EB plans do not seem to be recessionary. This result is in line with the findings of the fiscal policy literature.

We repeat the analysis on each component of GDP and report the estimated cumulative impulse response functions in Figure 3.4.

We find that TB fiscal plans are associated with lower than average consumption growth while the other components of GDP do not respond. On the contrary, EB fiscal consolidations exhibit increases in each component of private GDP which are not statistically significant while

[6]We thank Valerie Ramey for bringing up this point.

[7]See Appendix 3.6.1 for details on the data and the regression equation.

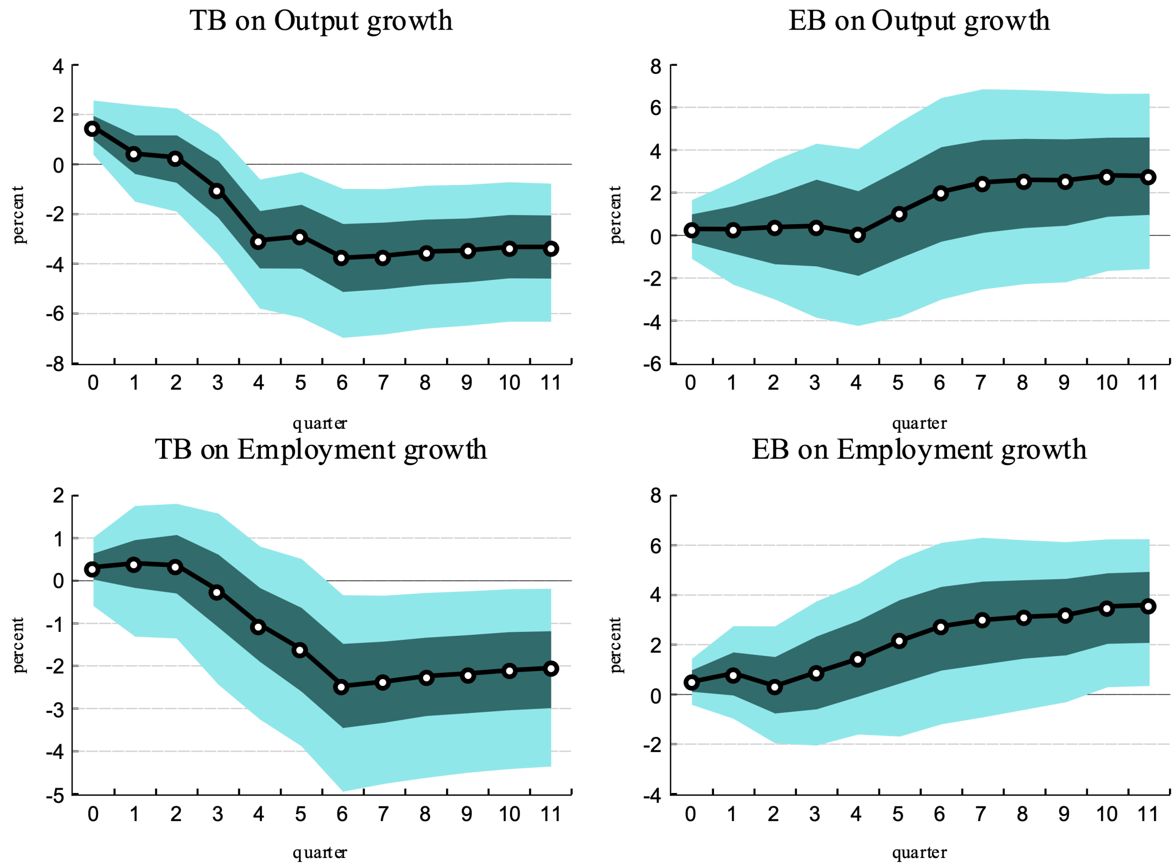

Figure 3.3. OUTPUT AND EMPLOYMENT RESPONSE TO AUSTERITY

Notes: Cumulative IRFs of Output and Employment growth. The darker region refers to the 68% confidence level while the lighter region represents the 95% confidence level, obtained via residual block-bootstrap. Quarterly data. Sample goes from 1978Q1 to 2014Q4. See Appendix 3.6.1 for further details on estimation equation.

government spending falls significantly.

Having illustrated what happens to all components of output we turn our attention on the type of fiscal policy change implemented during years of austerity. Firstly, we estimate the effects of fiscal plans on the growth rates of government receipts shares of output using again a truncated moving average. Figure 3.5 shows the cumulative response of government receipts shares of output coming from excise/production taxes and payroll taxes. Other types of government receipts such as corporate tax, income tax, estate/gift tax and custom duties are not affected (see Appendix 3.6.1).

Looking at the top-left panel, we find that excise/production taxes are the main component

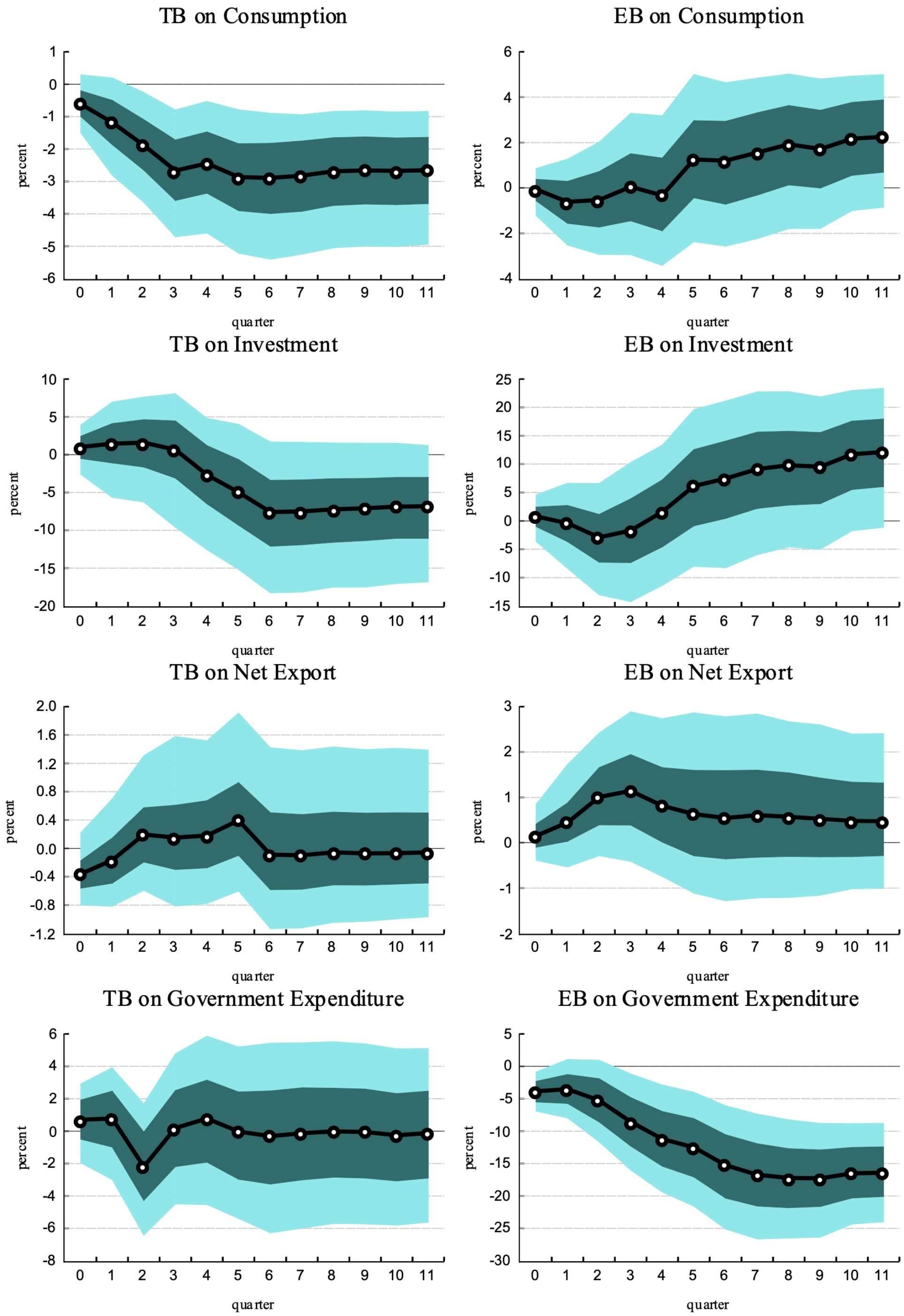

Figure 3.4. GDP BY AUSTERITY

Notes: Variables are in real dollars (source NIPA). The darker region refers to the 68% confidence level while the lighter region represents the 95% confidence level obtained via block-bootstrap. Quarterly data. Sample goes from 1978Q1 to 2014Q4.

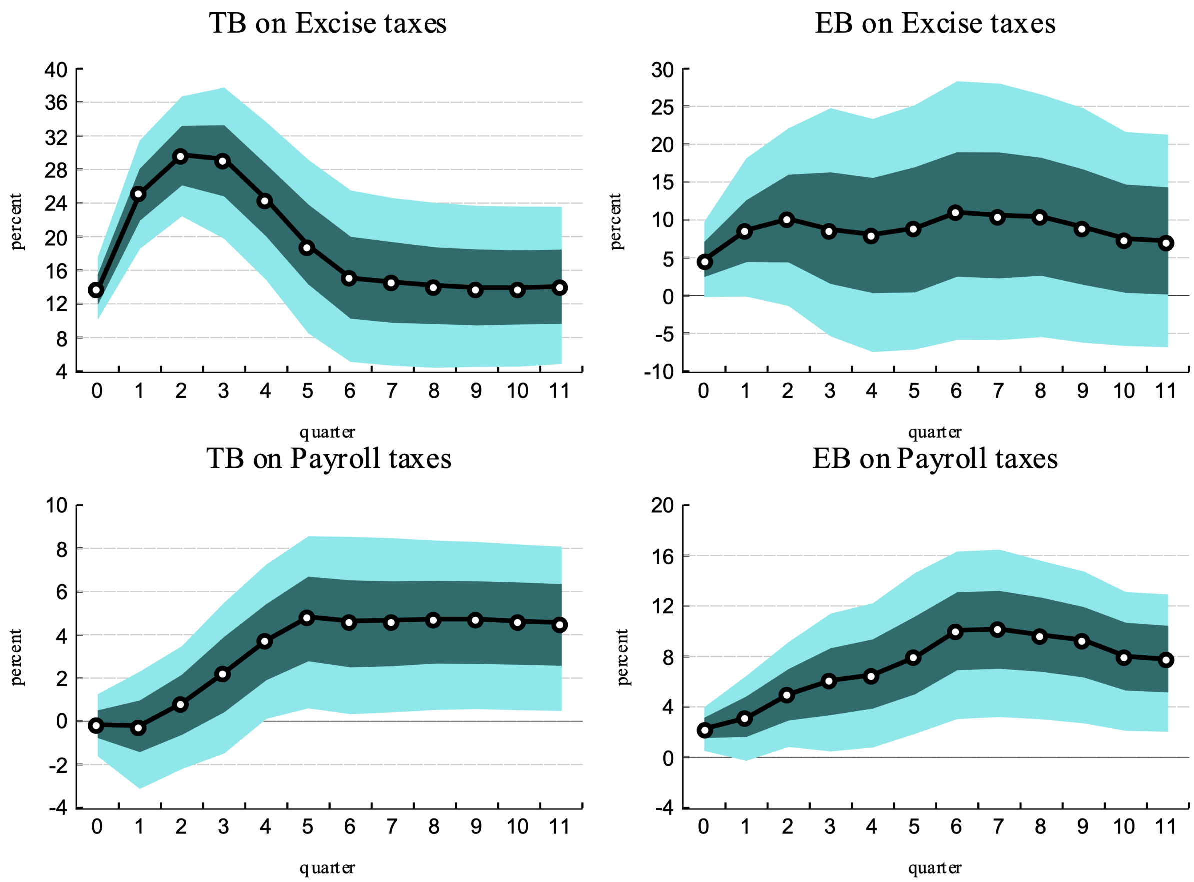

Figure 3.5. Government Revenues Affected by Austerity

Notes: Cumulative IRFs of government receipts share of GDP. The darker region refers to the 68% confidence level while the lighter region represents the 95% confidence level, obtained via residual block-bootstrap as suggested in Jentsch and Lunsford (2019a). Quarterly data. Sample goes from 1978Q1 to 2014Q4.

of government receipt affected by TB fiscal consolidations, increasing its share of GDP by 12% over a three-year horizon. On the contrary, the change in excise taxes share of output during EB fiscal plans is not statistically different from zero (see top-right panel). This goes in line with Dabla-Norris and Lima (2023) who by investigating the macroeconomic consequences of tax changes during fiscal consolidation periods-distinguished by changes in tax rates and tax base modifications-reveals that base broadening measures lead to less severe declines in output and employment than rate increases. Interestingly, they show that consolidations heavily rely on increases in indirect taxes (both VAT and excises) which both lean towards an emphasis on increasing tax rates and not base changes. Looking at the bottom panels, government receipts share of output coming from payroll taxes appears to increase during both TB and EB fiscal consolidations. This is not surprising if we look back at Figure 3.2: EB plans also have a small fraction of tax increases in their style (i.e. intra-temporal correlation).

Secondly, we study what happens to government expenditures during years of fiscal consolidations. In particular, we break down government spending, G, into two components: procurement spending and the residual part of G, non-procurement spending.[8] Figure 3.6 shows the cumulative impulse response function of the two components of G as share of GDP. Notice from the right column that only EB plans affect government expenditures. In fact, recall from Figure 3.2 that TB plans are pure tax hikes.

Overall, the aggregate results show that tax-based austerity plans (i) were recessionary, (ii) hit especially consumption and (iii) were implemented by increasing payroll and excise taxes. The expenditure side was unaffected. On the contrary, spending-cuts austerity was characterized by mild and statistically insignificant increases in output and was mainly done via equal cuts in procurement spending and the rest of government consumption expenditure.[9]

3.2.3 Fiscal Plans and Production Networks

In the previous section we highlight an important difference between TB and EB plans: positive changes in excise/production taxes are unique to TB plans while procurement spending cuts are unique to EB fiscal consolidations.

In this section we use Acemoglu, Akcigit, and Kerr (2016)'s framework to convey intuition and illustrate different propagation mechanisms of taxes and government purchases in a standard static multi-sector Neoclassical model. In this framework a change in government purchases behaves as a demand shock which propagates upstream in a production network: an industry affected by a demand shock propagates the shock to all its suppliers of input. On the contrary, excise/production taxes behave as supply shocks which propagate downstream: an

[8] We measure procurement spending as done in Chapter 1 and 2 of this dissertation.

[9] EB plans also increase payroll taxes, however, they account for a minor part of the total EB plan (see again Figure 3.2).

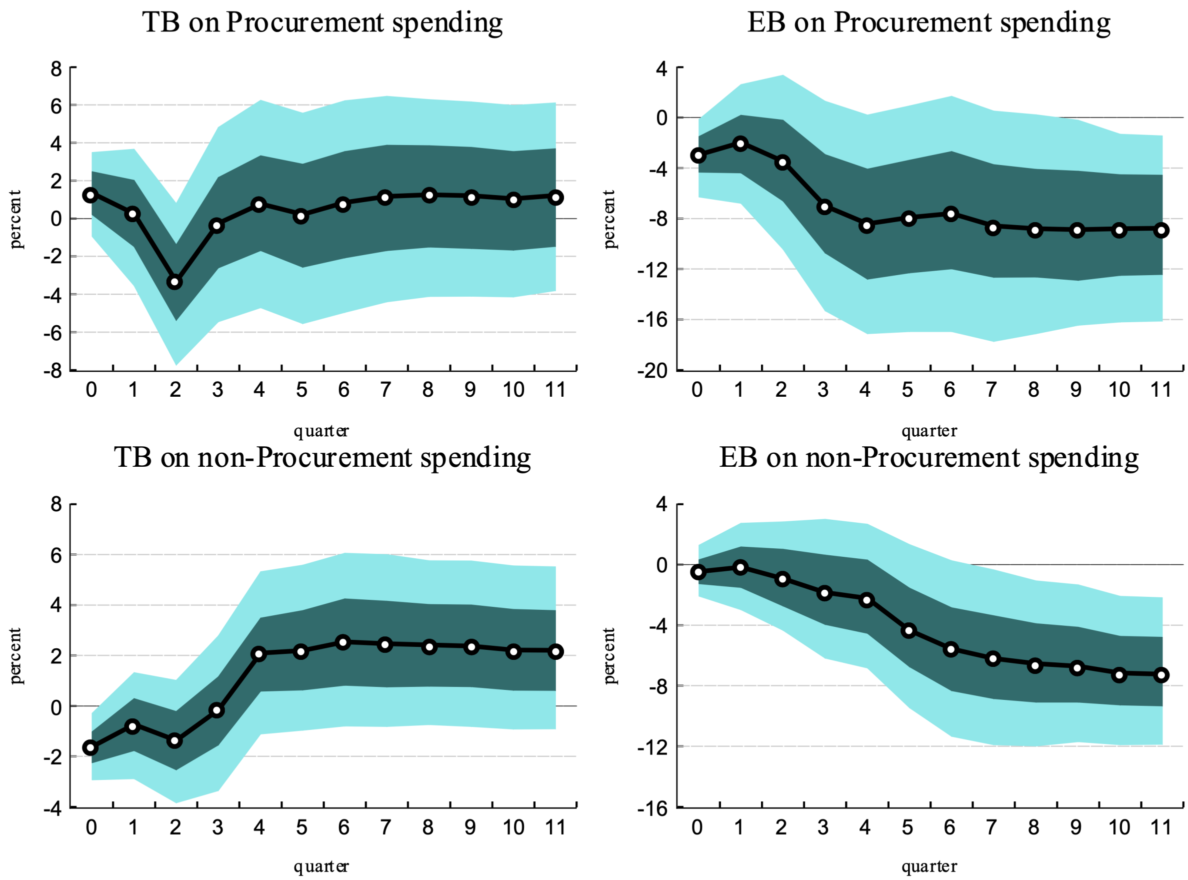

Figure 3.6. GOVERNMENT EXPENDITURES AFFECTED BY AUSTERITY

Notes: Cumulative IRFs of government expenditure two components shares of GDP. The darker region refers to the 68% confidence level while the lighter region represents the 95% confidence level, obtained via residual block-bootstrap as suggested in Jentsch and Lunsford (2019a). Quarterly data. Sample goes from 1978Q1 to 2014Q4.

industry affected by a supply shock passes the shock to all its customers. Step by step, the shock trickles down to consumers. Notice that this asymmetric transmission mechanism of taxes and government purchases is consistent with the asymmetric response of consumption during years of TB and EB fiscal consolidations.

In this section we explore the theoretical propagation of these types of fiscal policy through the lens of a simple static model with production network, which is a slightly modified version of Acemoglu, Akcigit, and Kerr (2016).[10]

[10]The modifications come from the inclusion of a production tax and an extra parameter in the production function. We remand to the Appendix 3.6.5 for the detailed derivations.

In this model the economy is inhabited by a representative agent with Cobb-Douglas utility over n-goods. On the production side, the representative sector i maximizes profits:

$$\max_{l_i,\{x_{ij}\}_{j=1}^n} (1-\tau)\cdot p_i \cdot \underbrace{\left(l_i^{\alpha_i^l} \cdot \big(\prod_{j=1}^n x_{ij}^{a_{ij}}\big)^{\rho} \right)}_{:=y_i} - wl_i - \sum_{j=1}^n p_j x_{ij}$$

where τ is the excise/production tax, p_i is the price of output i, l_i is the labor input of sector i, $x_{i,j}$ is the quantity of intermediate good j purchased by sector i as input of production, w is the wage and y_i is output of producer of good i.[11] The resource constraint of the economy is:

$$y_i = c_i + \sum_{j=1}^n x_{ji} + G_i$$

where c_i and G_i are consumption and government purchases of good i respectively, while x_{ji} is the quantity of good i used as input of production by sector j.

EB Plans

In this static economy a change in government purchases has the following output effect:[12]

$$d\log y_i = \rho \cdot \sum_{j=1}^n \underbrace{a_{ji} \cdot \frac{p_j \cdot y_j}{p_i \cdot y_i}}_{:=\hat{a}_{ji}} \cdot d\log y_j + \frac{G_i}{y_i} \cdot d\log G_i, \tag{3.2}$$

which in matrix form becomes:

$$\underset{n\times 1}{d\log \mathbf{y}} = \rho \cdot \hat{A}^T \cdot d\log \mathbf{y} + \Lambda \cdot d\log \boldsymbol{G}$$

[11] Because of constant return to scale we have $\alpha_i^l + \rho \cdot \sum_{j=1}^n a_{i,j} = 1$ for all sectors.

[12] See Appendix 3.6.5.

where $\Lambda = diag(G_1/y_1,..,G_n/y_n)$ and $\hat{A} = [a_{ji} \cdot (p_j \cdot y_j)/(p_i \cdot y_i)]_{i,j=1,...,n}$. Moreover, in equilibrium, we also have:

$$\underset{n \times n}{\hat{A}^T} \propto \left[\frac{p_i \cdot x_{ji}}{p_i \cdot y_i}\right]_{i,j=1,...,n} = \left[\frac{\text{SALES}_{i \to j}}{\text{OUTPUT}_i}\right]_{i,j=1,...,n}$$

The $i-j$ element of $\hat{A}^T$ is proportional to the sales of sector i to sector j, relative to its output, y_i. Therefore, the transmission of government purchases works from customers (sector j) to suppliers (sector i). Finally, to understand the transmission mechanism of government purchases, it is convenient to solve the above expression and then expand it using the definition of geometric sum:

$$\begin{aligned} \underset{n \times 1}{d \log \mathbf{y}} &= \left(I_n - \rho \cdot \hat{A}^T\right)^{-1} \cdot \Lambda \cdot d \log \boldsymbol{G} \\ &= \left(I_n + \rho \cdot \hat{A}^T + \rho^2 \cdot (\hat{A}^T)^2 + ...\right) \cdot \Lambda \cdot d \log \boldsymbol{G} \end{aligned} \tag{3.3}$$

Equation (3.3) is saying that spending cuts propagate upstream in the production network. For example, consider a spending cut on good j (i.e. $d \log G_j < 0$). Firstly, output is directly reduced and this first order effect is represented by matrix I_n in the geometric sum expansion. Secondly, sector j reduces the amount of input it needs. Therefore, for each sector i, supplier of j, we have that $x_{ji} = \text{SALES}_{i \to j}$ decreases. This is a second order effect working via $\rho \cdot \hat{A}^T$. Thirdly, suppliers of suppliers of producer of good j also face an indirect effect and so on and so forth. Since the propagation of the spending cut happens from customers to suppliers, we refer to this type of transmission mechanism as *upstream propagation*.

Example: 3 Sectors Economy.

We further clarify this type of propagation using a simple numerical example illustrated in Figure 3.7.

In the example we have an economy with three sectors which are vertically integrated:

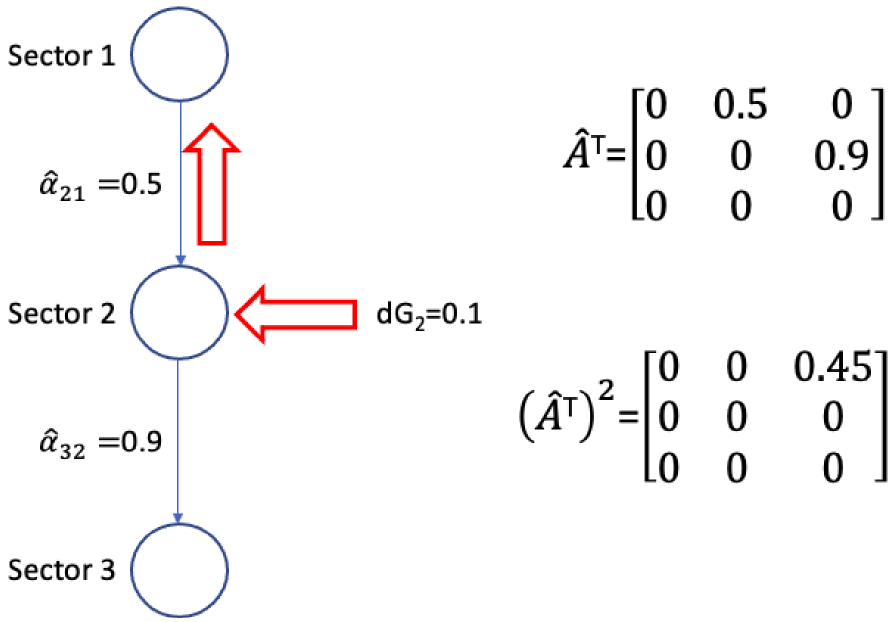

Figure 3.7. EXAMPLE OF SPENDING CUT

Notes: Vertically integrated 3 sectors economy. $\hat{a}_{21} = 0.5$ means that sector 1 sells 50% of its output to sector 2. $\hat{a}_{32} = 0.9$ means that sector 2 sells 90% of its output to sector 3. $\hat{a}^2_{31} := \hat{a}_{21} \cdot \hat{a}_{32} = 0.45$, it means that 45% of sector's 1 output is indirectly purchased by sector 3 via sector 2.

sector 1 supplies sector 2 which supplies sector 3. The *upstream* input-output matrix is given by $\hat{A}^T$, which is sparse everywhere but in positions 1-2 and 2-3, which reflect the fact that sector 1 supplies sector 2 and sector 2 supplies sector 3. Moreover, $(\hat{A}^T)^2$ represents the second order connection, that is, the suppliers of the suppliers. This production network is characterized by a single second order connection: sector 1 indirectly supplies sector 3 via sector 2. In fact, $(\hat{A}^T)^2$ is sparse everywhere but in position 1-3.

Suppose the government cuts by 0.1 the demand from sector 2. Suppose also that government spending shares of sectoral output are all the same before the policy change, then, the output effect implied by Equation (3.3) is:

$$d\log \boldsymbol{y} = \left(\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} + \rho \begin{bmatrix} 0 & 0.5 & 0 \\ 0 & 0 & 0.9 \\ 0 & 0 & 0 \end{bmatrix} + \rho^2 \begin{bmatrix} 0 & 0 & 0.45 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \right) \cdot \begin{bmatrix} 0 \\ -0.1 \\ 0 \end{bmatrix} = - \begin{bmatrix} 0.05 \cdot \rho \\ 0.1 \\ 0 \end{bmatrix}$$

Notice that sector 2 is hit directly by the shock and its output shrinks exactly by 0.1. Afterwards, the shock travels upstream in the production network, hitting sector 1 because it is the input-supplier of sector 2. On the contrary sectors located downstream in the network are not affected. Finally, the aggregate output effect is given by the average of the sectoral output changes: $d\log y = 1/3 \cdot (0.1 + \rho \cdot 0.05)$. Notice that the stronger the intensity of the input-output connections, represented by ρ, the stronger the aggregate output effect.

Therefore, the model suggests that during years of EB fiscal consolidations sectors located upstream in the production network should be negatively affected by input-output spillovers coming from those cuts in government purchases which we documented in the previous section. Moreover, the total output effect and the network-effect are proportional to the intensity of the upstream propagation during those years, represented in the model by ρ.

TB Plans

When the government increases the production/excise tax, the model returns the following output change:

$$d\log y_i = \rho \cdot \sum_{j=1}^{n} a_{ij} \cdot d\log y_j - \psi_i \cdot d\log \tau_i, \tag{3.4}$$

where $\psi_i > 0$.[13] In matrix form the above expression becomes:

$$\underset{n\times 1}{d\log \mathbf{y}} = \rho \cdot A \cdot d\log \mathbf{y} - \Psi \cdot d\log \boldsymbol{\tau}$$

[13]See Appendix 3.6.5 for derivation.

where $\Psi = diag(\psi_1, ..., \psi_n)$ and $A = [a_{ij}]_{i,j=1,...,n}$. The economic interpretation of A is the opposite of the one of $\hat{A}^T$. In fact, in equilibrium we have:

$$\underset{n\times n}{A} \propto \left[\frac{p_j \cdot x_{ij}}{p_i \cdot y_i}\right]_{i,j=1,...,n} = \left[\frac{\text{SALES}_{j\to i}}{\text{OUTPUT}_i}\right]_{i,j=1,...,n}$$

that is, the $i-j$ element is proportional to the purchase of good j by sector i relative to its output, y_i. In this case, the transmission mechanism works from suppliers (sector j) to customers (sector i).

Once again, we solve the above expression and then expand it using the definition of geometric sum:

$$\underset{n\times 1}{d\log \mathbf{y}} = -\left(I_n + \rho \cdot A + \rho^2 \cdot A^2 + ...\right) \cdot \Psi \cdot d\log \boldsymbol{\tau} \tag{3.5}$$

In this case, the shock propagates in the production network from suppliers to customers via matrix A. In particular, the underlying transmission of the shock works through price increases. In fact, in equilibrium we have:

$$d\log p_i = \rho \cdot \sum_{j=1}^{n} a_{ij} \cdot d\log p_j + \frac{\tau_i}{1-\tau_i} \cdot d\log \tau_i.$$

When taxes increase, production becomes more costly and prices go up. A price increase impact the direct customers of the taxed producer, which react by increasing their price too. Eventually, the price-increase trickles down to consumers who respond by decreasing consumption:

$$d\log c_i = -d\log p_i.$$

Therefore, we refer to this type of transmission mechanism as *downstream propagation*.

Consider the example of the vertically integrated 3-sectors economy of Figure 3.7. In this case, a tax specific shock to sector 2, would have a direct effect on sector 2. Secondly, the shock would travel downstream in the production network via matrix A and would hit sector 3. The tax increase hits the supplier (sector 2), which increases prices, thus damaging its customer (sector 3). On the contrary, sector 1, located upstream in the supply chain, would not be affected by the tax shock.

Therefore, the model suggests that during years of TB fiscal consolidations, when excise/production taxes were increased, sectors located downstream, as well as consumers, are hit by negative spillovers from sectors located upstream in the production network.

3.3 The Network Effect of Fiscal Plans: Results

In the previous section we illustrated that fiscal policy changes implemented during years of fiscal consolidations, namely excise/production tax increases and procurement spending cuts, propagate downstream and upstream in the production network. In particular, expression (3.2) suggests that changes in sectoral output, $d\log\boldsymbol{y}$, during years of EB fiscal adjustment plans, should be proportional to an *upstream spatial lag*, $\rho\cdot\hat{A}^T\cdot d\log\boldsymbol{y}$ and the spending shock, that is, the EB fiscal adjustment plan. Similarly, expression (3.4) suggests that changes in sectoral output during years of TB fiscal adjustment plans, should be proportional to a *downstream spatial lag*, $\rho\cdot A\cdot d\log\boldsymbol{y}$ and the tax shock, that is, the TB fiscal adjustment plan.

Therefore, the most natural regression equation to test the intensity of the propagation of fiscal consolidations in the production network is:[14]

$$\Delta \log y_{i,t} = a_i + \left(\rho^{down} \cdot \underbrace{\sum_{j=1}^{n} a_{ij} \cdot \Delta \log y_{j,t}}_{\Delta y_{i,t}^{down}} + \psi_i \cdot (\underbrace{\tau_u \cdot f_t^u + \tau_a \cdot f_t^a + \tau^f \cdot f_t^f}_{\text{Tax Increases}}) \right) \cdot TB_t +$$
$$+ \left(\rho^{up} \cdot \underbrace{\sum_{j=1}^{n} \hat{a}_{ji} \cdot \Delta \log y_{j,t}}_{\Delta y_{i,t}^{up}} + \lambda_i \cdot (\underbrace{\gamma_u \cdot f_t^u + \gamma_a \cdot f_t^a + \gamma^f \cdot f_t^f}_{\text{Spending Cuts}}) \right) \cdot EB_t + \nu_{i,t} \tag{3.6}$$

Firstly, Equation (3.6) includes industry fixed effects, a_i, industry weights ψ_i and λ_i for TB and EB fiscal consolidations respectively and $\nu_{i,t}$, a serially uncorrelated, heteroskedastic error term. We allow for heteroskedasticity since sectors exhibit different volatility in growth rates in the data. Secondly, the first line of Equation (3.6) contains the downstream spatial variable which captures the downstream spillovers of the unanticipated, announced and future tax increases. Both are interacted with TB_t, the dummy variable which is one during years of TB fiscal consolidations. Similarly, the second line of Equation (3.6) captures the effects of EB fiscal consolidations as well as its upstream spillovers.

Our econometric specification relates to Alesina et al. (2015), who regress country-level output growth on the 3 components of TB and EB country-specific fiscal plans. Unlike them, we focus on a single country, the United States, by breaking down its economy into $n = 62$ industries. Furthermore, we enrich their specification with two *spatial variables* to take into account the input-output connections among sectors and break down the output effect into a direct and a network effects. This is similar to the empirical approach in Acemoglu, Akcigit, and Kerr (2016) and Ozdagli and Weber (2020).

[14]We denote the parameters that we estimate in blue.

3.3.1 Model Estimation

We focus on a partition of the US economy made by 62 industries, observed from 1978 to 2014 at a yearly frequency. Details on the data construction are reported in Appendix 3.6.2.

We report results based on the static spatial panel autoregressive models specified by Equation (3.6). The spatial models allow us to track the effect of EB and TB fiscal adjustment plans on industry output growth, while controlling for downstream and upstream spillovers. When estimating the corresponding parameters, standard OLS delivers inconsistent results since the spatial variables are endogenous. We overcome this problem using spatial econometric techniques. In particular, we use a modified version of the Bayesian Markov Chain Monte Carlo (MCMC) illustrated in J. LeSage and Pace (2009) to estimate the parameters of equation (3.6). We also report Maximum Likelihood Estimates (MLE) for two main reasons: (i) if all priors are non-informative, then the Bayesian MCMC should exactly return the MLE, (ii) MLE properties of spatial panel autoregressive models with fixed effects are well known (see Yu, De Jong, and L.-f. Lee (2008)).[15] The derivation of the Bayesian MCMC and of the MLE as well as other technical details are remanded to Appendix 3.6.3.

Table 3.2 reports descriptive statistics of the estimated parameters of interest of model (3.6):

Firstly, looking at Table 3.2, we notice that the maximum likelihood estimates are very close to the expected value and standard deviation of the posterior distributions estimated by MCMC. This is a consequence of using mainly non-informative priors. Secondly, we notice that during years of TB fiscal consolidations, the downstream spatial correlation is much stronger than the upstream spatial correlation during EB fiscal consolidations. In fact, looking at the quantiles of the posterior distribution of ρ^{up}, it is clear that it is much more skewed towards zero than then one of ρ^{down}, and with a posterior average of 0.25 against 0.57 of ρ^{down}

Concerning the fiscal coefficients, we find that announced tax rises, τ_a, and future

[15]Bayesian MCMC is also more appealing than MLE for some quite technical reasons. However, we save these details for Appendix 3.6.3.

Table 3.2. Estimation Results

Baseline Model - Equation (3.6)												
Parameters	MLE		Bayesian MCMC - Posterior Distributions:									
	$\hat{\theta}_i^{\mathrm{ML}}$	MLE Std.	$\mathbb{E}(\theta_i)$	$\sqrt{\mathbb{V}(\theta_i)}$	$Pr(\theta_i < 0)$	5%	10%	16%	50%	84%	90%	95%
ρ^{down} (TB)	0.603	0.125	0.569	0.117	0.000	0.374	0.419	0.453	0.569	0.687	0.720	0.761
τ_u	0.411	1.278	0.555	1.196	0.322	-1.411	-0.971	-0.629	0.551	1.743	2.095	2.533
τ_a	-1.259	0.990	-1.294	0.930	0.917	-2.820	-2.488	-2.218	-1.295	-0.366	-0.100	0.237
τ_f	-0.192	0.432	-0.219	0.404	0.708	-0.887	-0.735	-0.621	-0.220	0.182	0.300	0.447
ρ^{up} (EB)	0.271	0.092	0.247	0.096	0.000	0.088	0.121	0.148	0.246	0.343	0.372	0.407
γ_u	-0.167	1.129	-0.132	1.046	0.551	-1.855	-1.460	-1.166	-0.130	0.907	1.207	1.582
γ_a	0.942	0.616	1.037	0.582	0.038	0.077	0.292	0.461	1.039	1.610	1.779	1.997
γ_f	-0.477	0.283	-0.482	0.261	0.968	-0.908	-0.817	-0.742	-0.481	-0.224	-0.148	-0.053
D2008	-2.941	0.671	-2.903	0.633	1.000	-3.946	-3.714	-3.532	-2.902	-2.274	-2.092	-1.861
D2009	-5.664	0.671	-5.326	0.658	1.000	-6.416	-6.173	-5.981	-5.321	-4.672	-4.488	-4.248

Notes: θ_i denotes a generic parameter that we estimate. The columns report the following: $\hat{\theta}_i^{ML}$ is the ML point estimate; "MLE Std." is the standard deviation of the ML estimate, calculated using the analytical Fisher Information Matrix derived in Appendix 3.6.3: $\sqrt{\mathscr{I}(\hat{\theta}^{ML})_{ii}^{-1}}$; $\mathbb{E}(\theta_i)$ is the expected value of the posterior distribution; $\sqrt{\mathbb{V}(\theta_i)}$ is the standard deviation of the posterior distribution; $Pr(\theta < 0)$ is the probability that a parameter is negative, calculated by integrating the posterior distribution; p% is the p-th percentile of the posterior distribution. For brevity we don't report here the Industry Fixed Effects and the Industry specific variances. We also include year dummies for 2008 and 2009 to improve the precision of our estimates by capturing the industry-wide dip caused by the Great Recession. In the first columns, the spatial parameters also report the type of fiscal plan they are interacted with (in blue).

spending cuts, γ_f, exhibit a statistical significant recessionary effect, while the other shocks do not. Their posterior probability of being negative is 92% and 97% respectively. Interestingly, the effect of announced spending cuts,γ_a, is statistically significant and expansionary, or positive. Nevertheless, the single coefficients of the three components of fiscal adjustment plans are not very informative: we are interested in the convex combination of all three components in a fiscal plan. Similarly, the mere size of the spatial coefficients is not enough to quantify the aggregate direct and network effect. We address these issues in the following section.

3.3.2 Aggregate Output Effect of Fiscal Consolidations

We are interested in estimating the average aggregate output effect of fiscal consolidations and then breaking it down into its direct and network effect. Our spatial econometric methodology conveniently provides such a decomposition.

Firstly, fiscal consolidations are made of three components: unanticipated, anticipated, and future. Therefore, we cannot define the impulse response in the standard way as the the partial derivative of a dependent variable with respect to a single shock. Rather, we construct the impulse response as a convex combination of the individual derivatives of $\Delta \log \boldsymbol{y}_t$ with respect to each of the three components of fiscal consolidations. The weights on each component are determined by the "style" of the plan, defined analytically as:

$$\underbrace{\boldsymbol{s}_{TB}}_{3\times 1} := \left[s^u_{TB}\ s^a_{TB}\ s^f_{TB} \right]^T \qquad \underbrace{\boldsymbol{s}_{EB}}_{3\times 1} := \left[s^u_{EB}\ s^a_{EB}\ s^f_{EB} \right]^T.$$

For instance, if we want to simulate the effects of a TB fiscal plan which is 30% unanticipated, 0% anticipated, and 70% future, then we would set: $s^u_{TB} = .3$, $s^a_{TB} = 0$, $s^f_{TB} = .7$ and the vector of the "style" would be: $\boldsymbol{s}_{TB} = [.3\ 0\ .7]^T$.

Secondly, given: *i*. the above definition of impulse response, *ii*. the vector representation of Equation (3.6), *iii*. the vectors of fiscal parameters $\boldsymbol{\tau}^T = \left[\tau_u\ \tau_a\ \tau_f\right]$ and $\boldsymbol{\gamma}^T = \left[\gamma_u\ \gamma_a\ \gamma_f\right]$ and iv. industry weights for TB plans $\boldsymbol{\Psi}^T = [\psi_1 \ldots \psi_n]$ and EB plans $\boldsymbol{\Lambda}^T = [\lambda_1 \ldots \lambda_n]$; then, the $n \times 1$ vector of industry specific Total Effect of a TB plan ($TB_t = 1$ and $EB_t = 0$) is defined as:

$$TE_{TB} := s^u_{TB} \cdot \frac{\partial \Delta \log \boldsymbol{y}_t}{\partial f^u_t}\Big|_{TB_t=1} + s^a_{TB} \cdot \frac{\partial \Delta \log \boldsymbol{y}_t}{\partial f^a_t}\Big|_{TB_t=1} + s^f_{TB} \cdot \frac{\partial \Delta \log \boldsymbol{y}_t}{\partial f^f_t}\Big|_{TB_t=1}$$

$$= \underbrace{\left(I_n - \rho^{down} \cdot A\right)^{-1}}_{:=\boldsymbol{H}^{TB}} \cdot \boldsymbol{\Psi} \cdot \boldsymbol{\tau}^T \cdot \boldsymbol{s}_{TB} = \underbrace{\mathbf{H}^{TB} \cdot \boldsymbol{\Psi}}_{n\times 1} \cdot \underbrace{\boldsymbol{\tau}^T \cdot \boldsymbol{s}_{TB}}_{1\times 1}$$

Analogously, for an EB plan we have:

$$TE_{EB} := \underbrace{(I_n - \rho^{up} \cdot \hat{A}^T_0)^{-1}}_{:=\boldsymbol{H}^{EB}} \cdot \boldsymbol{\Lambda} \cdot \boldsymbol{\gamma}^T \cdot \boldsymbol{s}_{EB} = \underbrace{\mathbf{H}^{EB} \cdot \boldsymbol{\Lambda}}_{n\times 1} \cdot \underbrace{\boldsymbol{\gamma}^T \cdot \boldsymbol{s}_{EB}}_{1\times 1}.$$

Using the spatial framework, we can break down the TE into a Direct and Network Effect, as in Acemoglu, Akcigit, and Kerr (2016) and Ozdagli and Weber (2020). The former represents the direct impact of the fiscal plan and the latter represents the network spillovers:

$$DE_{TB} = \boldsymbol{\Psi} \cdot \boldsymbol{\tau}^T \cdot \boldsymbol{s}_{TB} \qquad NE_{TB} = (\boldsymbol{H}^{TB} - I_n) \cdot \boldsymbol{\Psi} \cdot \boldsymbol{\tau}^T \cdot \boldsymbol{s}_{TB}$$

$$DE_{EB} = \boldsymbol{\Lambda} \cdot \boldsymbol{\gamma}^T \cdot \boldsymbol{s}_{EB} \qquad NE_{EB} = (\boldsymbol{H}^{EB} - I_n) \cdot \boldsymbol{\Lambda} \cdot \boldsymbol{\gamma}^T \cdot \boldsymbol{s}_{EB}.$$

The TE, DE and NE are $n \times 1$ vectors of industry specific effects of fiscal adjustment plans. However, we are interested in their aggregate effect. Therefore, we take a weighted average across industries with weights given by each industry's output share.[16] By doing so we obtain the Average Total Effect, ATE, of a fiscal consolidation. We similarly construct the Average Direct Effect, ADE, and the Average Network Effect, ANE. Notice that given the linearity of the weighted average operation, we have that $ATE = ADE + ANE$, which therefore summarizes the breakdown of the total effect into its two components.

Table 3.3 reports descriptive statistics of the posterior distributions of the ATE and its decomposition into ADE and ANE for 2-year fiscal adjustment plans in the United States. This is our main contribution to the literature on fiscal consolidations. We obtain these results via Monte-Carlo, by drawing the parameters of equation (3.6) from their estimated posterior distributions.[17] The style of the simulated plans, $\boldsymbol{s}_{TB}$ and $\boldsymbol{s}_{EB}$ - which determines the composition of a fiscal plan in terms of unanticipated, anticipated, and future components - is randomly drawn at each iteration from a distribution which mimics the in-sample data and satisfies three conditions: 1) the overall size of a plan is 1%; 2) the anticipated component is zero; 3) the horizon of the plan is two years.[18] This procedure ensures that our results are robust to different styles of fiscal plans and are not driven by a style redistribution of the 1% fiscal shock.

In Table 3.3, we document two main facts. First of all, consistent with existing work,

[16] We use average output shares in years of TB fiscal consolidation for aggregating TB effects. We use average output shares in years of EB fiscal consolidation for aggregating EB effects

[17] In doing so we draw all the parameters jointly from each step of the Markov Chain to take into account the potential correlation among the parameters' distributions.

[18] See Appendix, section 3.6.3, for further information on the empirical distribution of the style of US fiscal plans.

Table 3.3. AVERAGE TOTAL, DIRECT AND NETWORK EFFECTS OF FISCAL CONSOLIDATIONS IN THE UNITED STATES

Baseline Model - Equation (3.6)											
	$\mathbb{E}(\theta)$	%	$\sqrt{\mathbb{V}(\theta)}$	$Pr(\theta < 0)$	5%	10%	16%	50%	84%	90%	95%
ATE_{TB}	-1.397	100%	1.109	0.904	-3.297	-2.835	-2.487	-1.346	-0.308	-0.027	0.328
ADE_{TB}	-1.017	73%	0.789	0.904	-2.327	-2.031	-1.798	-1.006	-0.238	-0.021	0.258
ANE_{TB}	-0.380	27%	0.337	0.904	-1.014	-0.825	-0.694	-0.328	-0.066	-0.006	0.065
ATE_{EB}	0.370	100%	0.371	0.152	-0.265	-0.103	0.014	0.386	0.727	0.825	0.950
ADE_{EB}	0.326	88%	0.327	0.152	-0.225	-0.088	0.012	0.336	0.643	0.732	0.845
ANE_{EB}	0.043	12%	0.052	0.152	-0.038	-0.014	0.001	0.041	0.090	0.106	0.130

Table 3.3: *descriptive statistics of posterior distributions of Average Effects of a 2 years, 1% magnitude fiscal adjustment plan. 2 years means that results are calculated by cumulating the effect of the first year of the plan and then the second one. The style of the plan is simulated from a distribution which mimics the observed one; see Appendix 3.6.3 for technical details. Columns:* $\mathbb{E}(\theta)$ *is the expected value of the posterior distribution; % is the share of ATE represented by ADE and ANE.* $\sqrt{\mathbb{V}(\theta)}$ *is the standard deviations of the posterior distribution;* $Pr(\theta < 0)$ *is the probability of negative values, calculated by integrating the posterior distribution; "p% is the* p-th percentile of the posterior distribution."

TB fiscal consolidations imply larger output losses than EB fiscal consolidations. The expected value of ATE_{TB} is -1.397 against a positive and insignificant ATE_{EB} of 0.370. This implies that a 2 years TB fiscal consolidation of 1% causes a cumulative average contraction of -1.397% over two years. On the other hand, the effects of EB fiscal consolidations are mildly positive and not statistically significant.

Secondly, around 27% of ATE_{TB} comes from network spillovers, confirming the relevance of the industrial network in the transmission of the TB fiscal adjustments. On the contrary, the network propagation of an EB fiscal plan is much smaller, accounting for only 12% of ATE_{EB}. We calculate the average extent to which differences in the network effects of EB and TB plans account for differences in their total effects: $|\mathbb{E}(ANE_{TB}) - \mathbb{E}(ANE_{EB})| \,/\, |\mathbb{E}(ATE_{TB}) - \mathbb{E}(ATE_{EB})|$. We find a value of approximately 25%.[19] Therefore, we conclude that at least 25% of the difference between EB and TB output effects can be explained by differences in production network spillovers.

We summarize our findings so far. TB fiscal consolidations have stronger effects in the United States than EB fiscal consolidations, with an average two years contraction of around

[19]From Table 3.3, we have: $|-0.380-0.043|\,/\,|-1.397-0.370| \approx 25\%$ in the baseline model and $|-0.300-0.031|\,/\,|-1.148-0.522| \approx 20\%$ in the inverted model.

-1.4%. EB fiscal consolidations in the United States have effects which are either not statistically different from zero, or mildly expansionary after two years. Network effects of TB consolidations explain 27% of the overall contraction. On average, 25% of the differences in the ATE of TB and EB plans can be attributed to the stronger network propagation of TB fiscal consolidations.

3.4 Robustness

3.4.1 Spatial Model and Orders of Propagation

An alternative to spatial lags in our econometric model is a standard panel data model with several "cross-terms" representing the first-order, second-order, and higher-order degrees of connection, as in Hale, Kapan, and Minoiu (2020). However, this methodology requires a large number of parameters to be estimated, especially when the network is persistent, and when higher-order propagation effects are relevant. On the contrary, a spatial variable is capable of capturing the entire feedback effect with an infinite number of orders of connection whose impact decays geometrically.

In order to assess whether the US industrial network with $n = 62$ sectors generates relevant high-order spillovers, we perform the partitioning of the effect, similar to what suggested by J. LeSage and Pace (2009). For instance, for the downstream propagation, we have:

$$\underbrace{(I_n - A)^{-1} \cdot \mathbf{1}_n}_{\textit{Total Effect}} = \underbrace{\mathbf{1}_n}_{\textit{Direct}} + \underbrace{A \cdot \mathbf{1}_n}_{\textit{1st order In-degree}} + \underbrace{A^2 \cdot \mathbf{1}_n}_{\textit{2nd order In-degree}} + \quad \dots$$

where the term in-degree refers to the fact that the row-sum of the elements of A represents the weighted in-degree of the network (total share of input purchased by a sector). For the upstream propagation, we have:

$$\underbrace{(I_n - \hat{A}^T)^{-1} \cdot \mathbf{1}_n}_{\textit{Total Effect}} = \underbrace{\mathbf{1}_n}_{\textit{Direct}} + \underbrace{\hat{A}^T \cdot \mathbf{1}_n}_{\textit{1st order Out-degree}} + \underbrace{(\hat{A}^T)^2 \cdot \mathbf{1}_n}_{\textit{2nd order Out-degree}} + \quad \dots$$

where the term out-degree refers to the fact that the row-sum of $\hat{A}^T$ represents the weighted out-degree of the network (total share of output sold to other sectors).[20] By averaging across the 62 industries the above expressions, we can calculate how much of the average total effect (left hand side of the expressions) can be attributed to each order of propagation (addends of the right hand side of the expressions). The results are reported in Table 3.4 Notice that, consistent

Table 3.4. PARTITIONING OF THE NETWORK

Order	*Downstream Network*		*Upstream Network*	
	%	*Cumulative*	%	*Cumulative*
0 (*Direct*)	53.36%	53.36%	54.53%	54.53%
1^{st}	24.53%	77.89%	23.34%	77.86%
2^{nd}	11.49%	89.39%	11.33%	89.20%
3^{rd}	5.48%	94.87%	5.52%	94.72%
4^{th}	2.64%	97.51%	2.70%	97.42%
5^{th}	1.28%	98.79%	1.32%	98.74%
⋮	⋮	⋮	⋮	⋮

with Acemoglu, Carvalho, et al. (2012), the first two orders of the in-degrees and out-degrees are enough to capture most of the spillovers, roughly 89% of the overall effects. However, to capture the whole scope of network effects we should add terms up to the 5th order, which account for almost 99% of the total effect. Since we have 6 "core regressors" (TB and EB unanticipated, announced, and future components), the adoption of cross terms which capture the order of propagation, would require us to include 6 times 5 orders plus one (the Direct effect) for a total of 36 core regressors. Considering this unfeasible econometric specification, we opt for the more parsimonious spatial lag.

3.4.2 Dynamics and Delayed Network Effects

The baseline model specified by Equation (3.6) does not include any time lag. We adopt a fully static specification because annual industry value-added growth rates are not very persistent,

[20] For more on in-degrees and out-degrees of the industrial network see Acemoglu, Carvalho, et al. (2012) and Carvalho and Tahbaz-Salehi (2019).

in particular at the fine disaggregation level of 62 sectors. Nevertheless, few sectors still show a non-negligible degree of autocorrelation. Therefore, we check whether our results are robust to the inclusion of a lagged dependent variable and we augment Equation (3.6) with a time lag: $\phi_i \cdot \Delta \log y_{i,t-1}$ The results are summarized by cumulative dynamic ATE, ADE and ANE, which now take the form of cumulative impulse response functions, reported in Figure 3.8. The values of the median of the dynamic ATE, ADE and ANE (blue solid lines in Figure 3.8) are reported in Table 3.5.

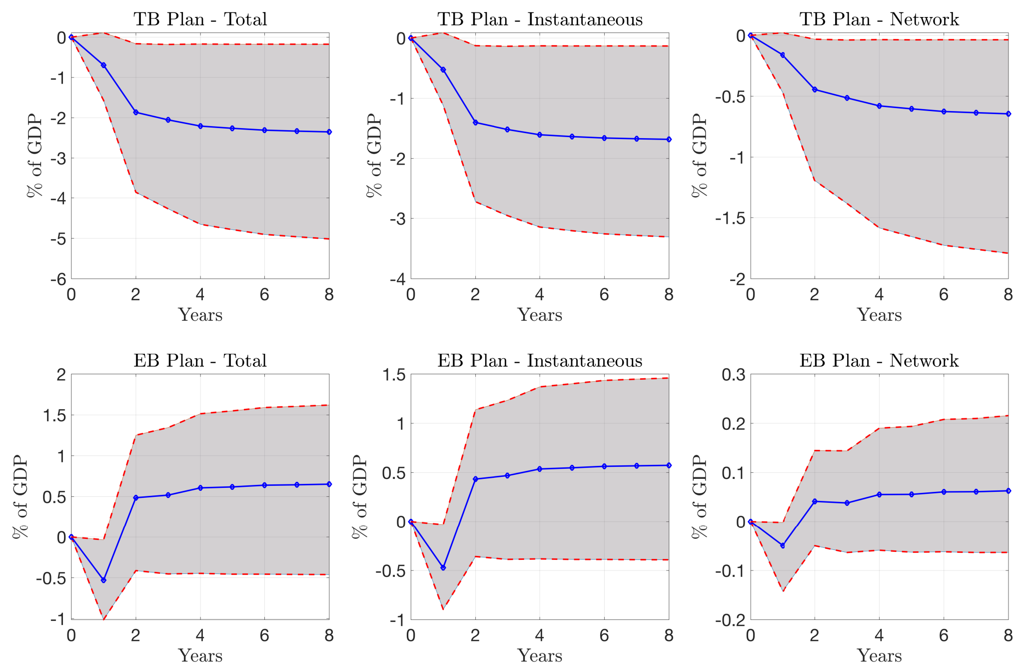

Figure 3.8. Cumulative Impulse Response Functions

Notes: Blue solid lines are the median cumulative impulse response functions (median of the posterior distributions). Red dashed lines are the 5^{th} and 95^{th} percentile of their posterior distributions, which represent our confidence bands. The "shock" is constructed by simulating a two years fiscal adjustment plan of 1% of GDP, exactly as done earlier to derive our static baseline results.

Notice that after year 2, the end of the fiscal consolidation, the dynamic response is minimal, which corroborates our static analysis. In general, the effects are slightly larger in year

Table 3.5. MEDIAN CUMULATIVE IMPULSE RESPONSE FUNCTIONS

	1 year	%	*2 years*	%	···	*Long Run*	%
ATE_{TB}	-0.695	100%	-1.865	100%	···	-2.351	100%
ADE_{TB}	-0.526	76.7%	-1.403	75.2%	···	-1.683	71.6%
ANE_{TB}	-0.162	23.3%	-0.445	24.8%	···	-0.644	28.4%
ATE_{EB}	-0.523	100%	0.486	100%	···	0.628	100%
ADE_{EB}	-0.472	90.2%	0.433	89.1%	···	0.573	91.2%
ANE_{EB}	-0.049	9.8%	0.041	10.9%	···	0.063	8.8%

2 compared to the ones estimated in the static model and reported in Table 3.3. Except for this, the results are comparable: 1) TB fiscal consolidations are recessionary and statistically different from zero; 2) the network effect is around one-fourth of the total effect of a TB plan; 3) EB fiscal consolidations have a minor network effect in the order of 10% of the total effect; 4) EB fiscal consolidations seem to be expansionary, but nothing can be concluded since they are not statistically different from zero.

We conclude this section by highlighting one fact: from Table 3.5 we notice that the relevance of ANE_{TB} increases over time, from 23.3% to 28.4% in the long-run. This could be indicative of *delayed network effects*. Suppose a price shock takes longer than a year to travel from one sector to another, then the relevance of the network effect will increase over time since the spillover takes time to kick-in. For instance, Smets, Tielens, and Van Hove (2019) show that the autocorrelation between inflation in crude oil's price and synthetic rubber's price spikes after three months. Then the autocorrelation between inflation in synthetic rubber's price and tires' price also spikes after three months, but the autocorrelation between inflation in tires' price and transport costs spikes after 16 months. Therefore, downstream propagation of price changes does seem to have delayed effects consistent with the increasing relevance over time of the network effect of TB fiscal adjustments. We leave the issue of timing of the network effect for future research.

3.4.3 Inverted Propagation Mechanism

The baseline regression equation, Equation (3.6), implicitly assumes that TB fiscal consolidations exclusively propagate downstream, from suppliers to customers while the opposite is true for EB fiscal consolidations. This is done by interacting TB_t with $\Delta y_{i,t}^{\text{down}}$ and EB_t with $\Delta y_{i,t}^{\text{up}}$. This assumption is consistent with the theoretical propagation suggested by the model.

We now relax the assumption above and we switch the interaction of our dummies with the spatial variables. Therefore, we estimate the following equation:

$$\begin{aligned}\Delta \log y_{i,t} = \tilde{\alpha}_i + \left(\tilde{\rho}^{down} \cdot \Delta y_{i,t}^{up} + \psi_i \cdot (\underbrace{\tilde{\tau}_u \cdot f_t^u + \tilde{\tau}_a \cdot f_t^a + \tilde{\tau}^f \cdot f_t^f}_{\text{Tax Increases}})\right) \cdot TB_t + \\ + \left(\tilde{\rho}^{up} \cdot \Delta y_{i,t}^{down} + \gamma_i \cdot (\underbrace{\tilde{\gamma}_u \cdot f_t^u + \tilde{\gamma}_a \cdot f_t^a + \tilde{\gamma}^f \cdot f_t^f}_{\text{Spending Cuts}})\right) \cdot EB_t + \tilde{\nu}_{i,t}. \qquad (3.7)\end{aligned}$$

Another option is to consider all propagation channels at once by estimating a single larger model which nests both Equation (3.6) (baseline model) and (3.7) (inverted model). However, this option is intractable due to the large number of parameters relative to the sample size, and due to collinearity between the spatial variables. We therefore estimate two separate models and then we apply a Vuong test for non-nested models to see which one fits the data better (see Vuong (1989) and Wooldridge (2010)). We find that the theoretically consistent model of Equation (3.6), where TB shocks propagate downstream and EB shocks upstream, provides a better fit to the data but not enough to reject the null hypothesis of the Vuong test, which assumes that the two model describe the data equally well.[21]

Secondly, we use the new estimates from the inverted model of Equation (3.7) to calculate the total, direct and network effect.[22] We find the network effect of EB plans accounts for only 6% of their total effect, against the 12% of the baseline model. On the contrary, the relevance

[21]Derivation and details of the Vuong test are outlined in Appendix 3.6.4.
[22]Tables of results are reported in Appendix 3.6.4.

of network effects of TB plans is basically unaffected, diminishing only by 1% relative to the baseline model (from 27% to 26%). Moreover, its statistical significance declines, since the posterior distribution shrinks towards zero.

Overall, the results indicate that the baseline model, which is consistent with the theoretical transmission channel illustrated in Section 3.2.3, delivers slightly stronger network effects and a slightly better fit.

3.4.4 Spurious Correlation and Placebo Experiments

One result of the chapter is to record significant network effects of TB fiscal consolidations, accounting for 27% of the total effect, and capable of explaining up to one fourth of the differences between the total output effect of TB and EB fiscal consolidations. What feature of the network is at basis of such strong spillovers? Are we measuring spurious correlation between sectors? or are we capturing some deep structural feature of the industrial network?

First of all, we plot in Figure 3.9 the downstream network A associated with the downstream propagation of TB fiscal consolidations. Recall that the generic element of A, denoted by a_{ij}, is given by the reliance of sector i (row) on industrial input j (column): $SALES_{j \to i}/SALES_i$. Figure 3.9 is a "threshold heat-map" which reports a blue cell if $a_{ij} < 0.0001$, an orange cell if $a_{ij} > 0.03$ and a white cell otherwise.[23] Two facts are salient from this "X-ray" of the downstream network. Firstly, the columns of A tend to contain either only very small or only very large values. Secondly, the rows of A do not exhibit such a pattern. In other words, some sectors, such as "Social Assistance" or "Motion Picture and Sound Recording Industries", produce an output that is either not employed at all as an intermediate by other sectors, or it is employed only in minor quantity. Unlike them, some other sectors, such as "Wholesale" and "Miscellaneous Professional, Scientific and Technical Services", produce an output which is a key input of production for many sectors. The bottom line is that the US downstream network is characterized

[23] The choice of 0.0001 is motivated by the presence of several values of A which are close to zero but not exactly zero. The choice of 0.03 is motivated by the presence of only a few values above this threshold. In general, tweaking these numbers still allows observing such a visual pattern of matrix A.

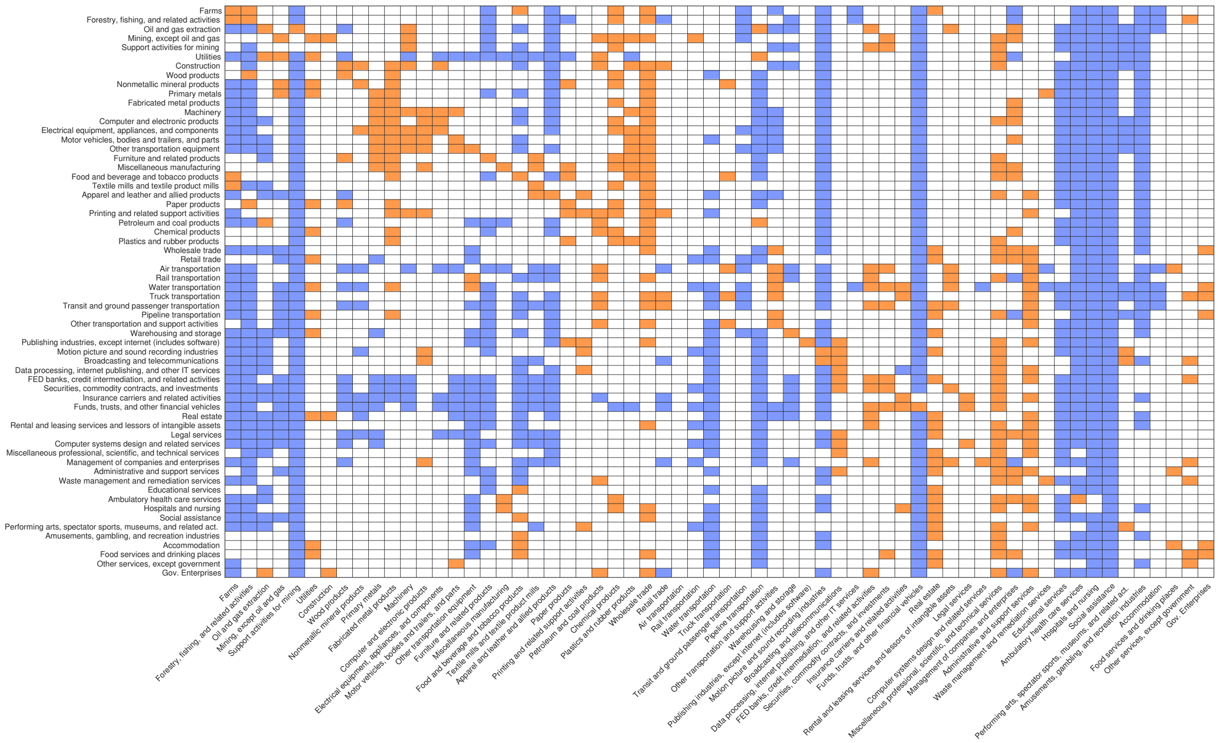

Figure 3.9. SMALL, MEDIUM AND LARGE ELEMENTS OF DOWNSTREAM NETWORK A

by the presence of key suppliers and the lack of key customers. This asymmetric nature of the I-O connections is a well-known feature in the production network literature (see Acemoglu, Carvalho, et al. (2012)).

An interesting robustness exercise is to see what happens to our estimates if we employ simulated network matrices that break this pattern. We estimate Equation (3.6) (baseline) several times by employing simulated downstream matrices ("placebo") and compare the results with the original estimates. We carry out two experiments:

i. *Column-Shuffling*: we randomly shuffle the order of the columns of A and create 100 simulated downstream matrices. This random permutation of the columns allows us to break that natural equilibrium in which some sectors behave as key suppliers and others are marginalized. In fact, in this first simulation, some real-world key supplier might be forced to behave as a peripheral sector and vice-versa. Therefore we expect less statistically significant results.

ii. *Row-Shuffling*: we randomly shuffle the order of the rows of A. Unlike the first experiment, reshuffling the elements within a column (shuffle the order of the rows) does not break the aforementioned characterizing pattern of the US downstream network. Sectors that originally were key suppliers will still behave in the same way. The same is true for peripheral sectors. We are reshuffling elements with similar magnitude along a column of A. Therefore, we expect to record both stronger and weaker results in terms of statistical significance.

Notice that in a Bayesian framework it is not fully correct to talk about statistical significance, however, with a little abuse of terminology we state that the ANE_{TB} is more statistically significant if the values of $\mathbb{E}(ATE_{TB})/\sqrt{\mathbb{V}(ATE_{TB})}$ and $Pr(ATE_{TB} > 0)$ are both smaller. The first measure represents how many standard deviations we need, to obtain the average ANE_{TB}: the smaller it is, the more likely is to obtain sizable negative spillovers. The second measure is simply the probability of obtaining a non-negative network effect: the smaller it is, the higher the chances of getting recessionary spillovers.

Figure 3.10 plots on the horizontal axis the first measure and on the vertical axis the second one. The red dot represents the values obtained by employing the original matrix A (see Table 3.3). The left panel of Figure 3.10 reports the results of the experiment of shuffling the order of

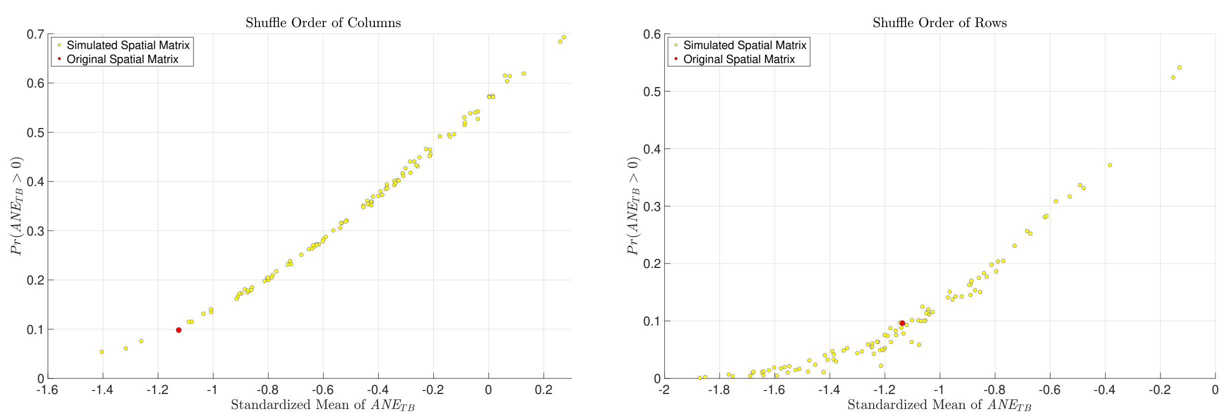

Figure 3.10. PLACEBO EXPERIMENT ON ANE_{TB}

the columns: the red-dot is located in the South-West region of the graph, indicative of more significant spillover effects, as expected. The right panel reports the results of the "row-shuffling" experiment: the red-dot is located almost in the middle of the cloud of simulations' results, also in line with what expected.[24]

We highlight that these three steps procedure (simulation of network matrices, re-estimation, and comparison with the original values) is analogous to Ozdagli and Weber (2020). Unlike them, our "placebo" matrices are simulated in a simpler way by simply reshuffling the orders of the columns and rows.

Our procedure has the benefit of preserving the original elements of the network matrices, thus matching one to one both the distribution of the original elements a_{ij}, as well as its sparsity (number of zero entries). Unlike the original network A, the placebo matrices do not have large entries on the main diagonal in either simulations ("dense main diagonal").

Concerning the first order weighted in-degrees ($A \cdot \mathbf{1}_n$) we have that the placebo matrices will exactly match it in the first simulation (shuffling the columns) while in the second one (shuffling the rows), the values are the same but they are assigned to different industries.

The second-order weighted in-degrees ($A^2 \cdot \mathbf{1}_n$) are not matched in either simulation, but the shape of their distribution is similar to the original one. Table 3.6 summarizes the results.

Table 3.6. PLACEBO EXPERIMENT RESULTS

Network Features:	*Shuffling the Columns*	*Shuffling the Rows*
Sparsity	*same*	*same*
Distribution of a_{ij}	*same*	*same*
Dense Main Diagonal	*no*	*no*
1^{st} *Weighted In-degree*	*same values*	*same distribution*
2^{nd} *Weighted In-degree*	*similar distribution*	*similar distribution*
Key Suppliers	*same*	*different*
Peripheral Suppliers	*same*	*different*
Is original ANE_{TB} stronger?	*yes*	*no*

[24]Actually, slightly more dots are located more South-West than the original simulation; this is not surprising if we think that we are moving the large elements of the main diagonal (see heat-map 3.9) outside of it, thus mechanically inflating the indirect spillover of the sector receiving the main diagonal entry.

Ozdagli and Weber (2020) conclude that matching the first and second order out-degree is not sufficient to justify the strong upstream propagation of monetary policy shocks. In fact, they say, matching the properties of the network industry by industry is necessary to obtain a strong network effect. We achieve the same conclusion in the context of downstream propagation of TB fiscal consolidations, measured by ANE_{TB}, by means of an easier experiment, namely shuffling the order of rows and columns.

Finally, we answer the initial two questions: the significant downstream network effect of TB fiscal consolidation that we find, is not capturing a spurious relationship between the sectors, otherwise its effects should not be stronger than the placebo ones when we shuffle the columns. In fact, the downstream propagation hinges on the presence of key suppliers of input of production in the industrial network, as witnessed by the lack of superior results when employing the original downstream matrix and we break this pattern (row shuffling).

3.5 Conclusions

This chapter investigates the effects of fiscal consolidations and their propagation in the industrial network in the US from 1978-2014. We find that TB fiscal consolidations are associated with slower consumption growth and are implemented with excise/production tax increases which are supposed to propagate downstream in the production network, via price increases. EB fiscal consolidations have no recessionary effects and are implemented mainly with procurement spending cuts which propagate upstream in the production network via changes in input-demand. Using a panel of 62 industries, we find evidence of network effects of fiscal consolidations. In particular, we apply spatial econometric techniques to break down the total aggregate effect of fiscal consolidations into a direct component and a network component.

Firstly, we find stronger effects of tax-based fiscal adjustments. In particular, an adjustment of one percent of GDP leads to an average contraction over two years of about -1.4% of value-added. Secondly, 27% of this effect can be attributed to spillovers from a supplying industry to a customer one. Thirdly, we find no evidence for a statistically significant recessionary impact of fiscal consolidations achieved by means of spending cuts. Rather, our evidence indicates mild expansionary effects. Fourthly, only 11% of EB effects originate from an upstream network transmission. Fifthly, we find that almost one-fourth of the different average total effects of TB and EB fiscal consolidations can be explained by stronger network spillovers of the former. Moreover, placebo experiments find that such a network effect of TB fiscal plans originates from the presence of key suppliers in the economy and does not depend on the particular shape of the distribution of first and second-order in-degrees of the network. When those key suppliers are forced to behave as peripheral suppliers the downstream propagation of TB plans vanishes or becomes significantly weaker.

In terms of policy implications, we provide further evidence that a fiscal consolidation based on spending cuts should be preferred to one based on tax hikes. The rationale is that smaller negative spillovers associated with spending cuts reduce the overall output cost. Also, the placebo experiments stress the importance of key suppliers of input in the industrial network. However, we do not comment on the possibility of designing optimal policies which take into account the special role of key suppliers in the propagation of shocks. We plan to address these issues in further research.

3.6 Appendix

3.6.1 Details on Aggregate Level Analysis

Impulse response functions are computed following the algorithm. Step 1 - solve dynamically forward the estimated equation putting all shocks to zero; step 2 - simulate the equation setting the fiscal adjustment plan to 1% of GDP; step 3 - compute impulse response as a difference between step 2 and step 1; step 4 - compute confidence intervals using the block bootstrap to take into account serial correlation.

In Section 3.2.2 we build impulse response functions using truncated moving average model. In particular we estimate the following specification:

$$\begin{aligned}\Delta y_t = \alpha + B_1(L)\cdot f_t^u \cdot EB_t + B_2(L) f_t^u \cdot TB_t + ...\\ ... + C_1(L)\cdot f_t^a \cdot EB_t + C_2(L)\cdot f_t^a \cdot TB_t + ...\\ ... + \sum_{j=1}^{H} D_j \cdot f_{t,t+j}^a \cdot EB_t + \sum_{j=1}^{H} E_j \cdot f_{t,t+j}^a \cdot TB_t + \varepsilon_t\end{aligned}$$

with:

$$f_{t,t+j}^a = \delta_j^{TB}\cdot f_t^u \cdot TB_t + \varepsilon_{t+j}^1, \text{ for } j = \overline{1,H}$$

$$f_{t,t+j}^a = \delta_j^{EB}\cdot f_t^u \cdot EB_t + \varepsilon_{t+j}^2, \text{ for } j = \overline{1,H}$$

where B(L) and C(L) are polynomials of the length six, H - is the anticipation horizon and also equal to six. We follow Mertens and Ravn (2012) on this and six is the median implementation lag.

Figure 3.11 and 3.12 show the estimated impulse response functions of several other tax receipts shares of GDP to TB and EB fiscal adjustment plans. Those impulse responses are obtained using truncated moving average model.

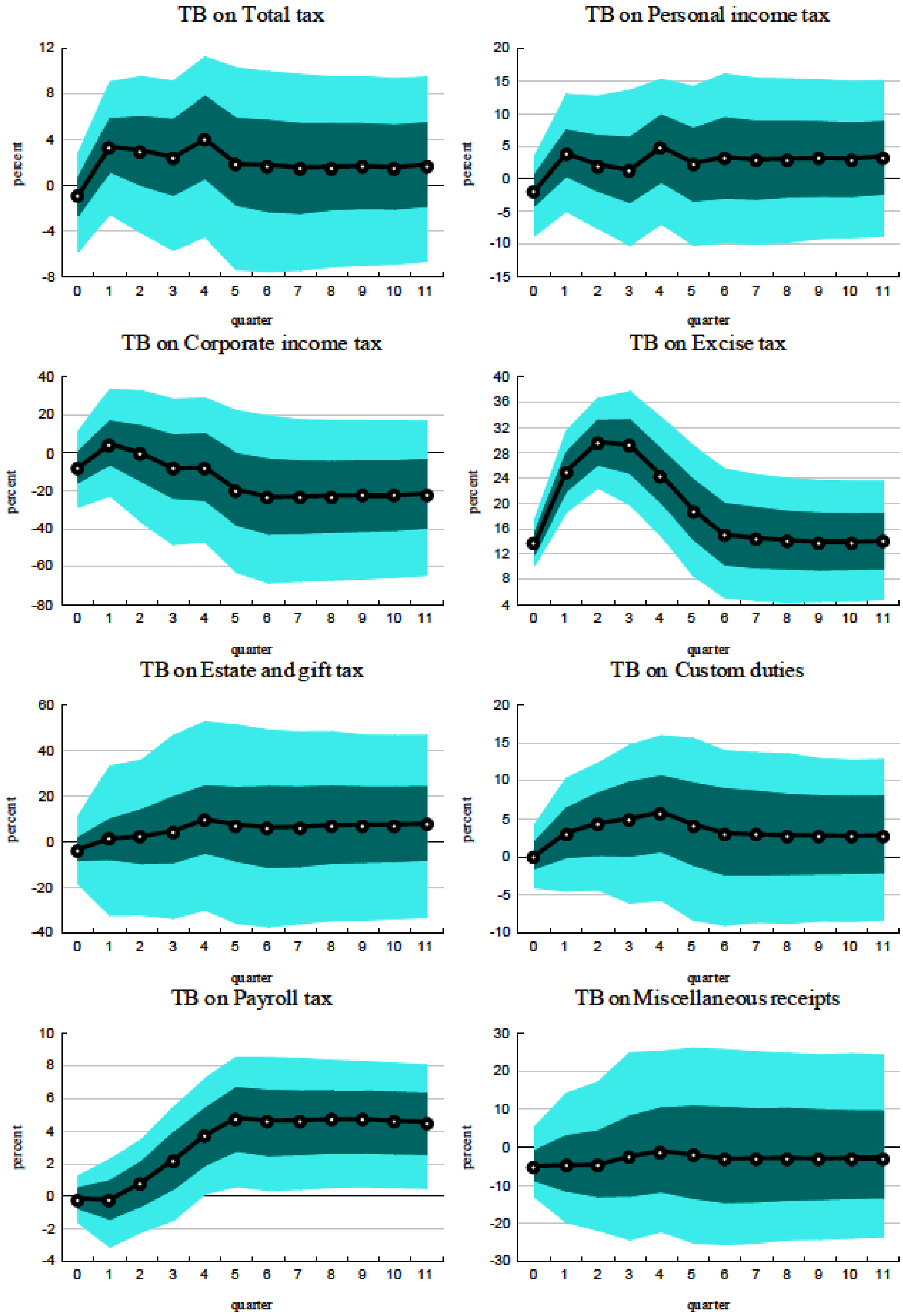

Figure 3.11. TAX RECEIPTS RESPONSE TO TB PLANS

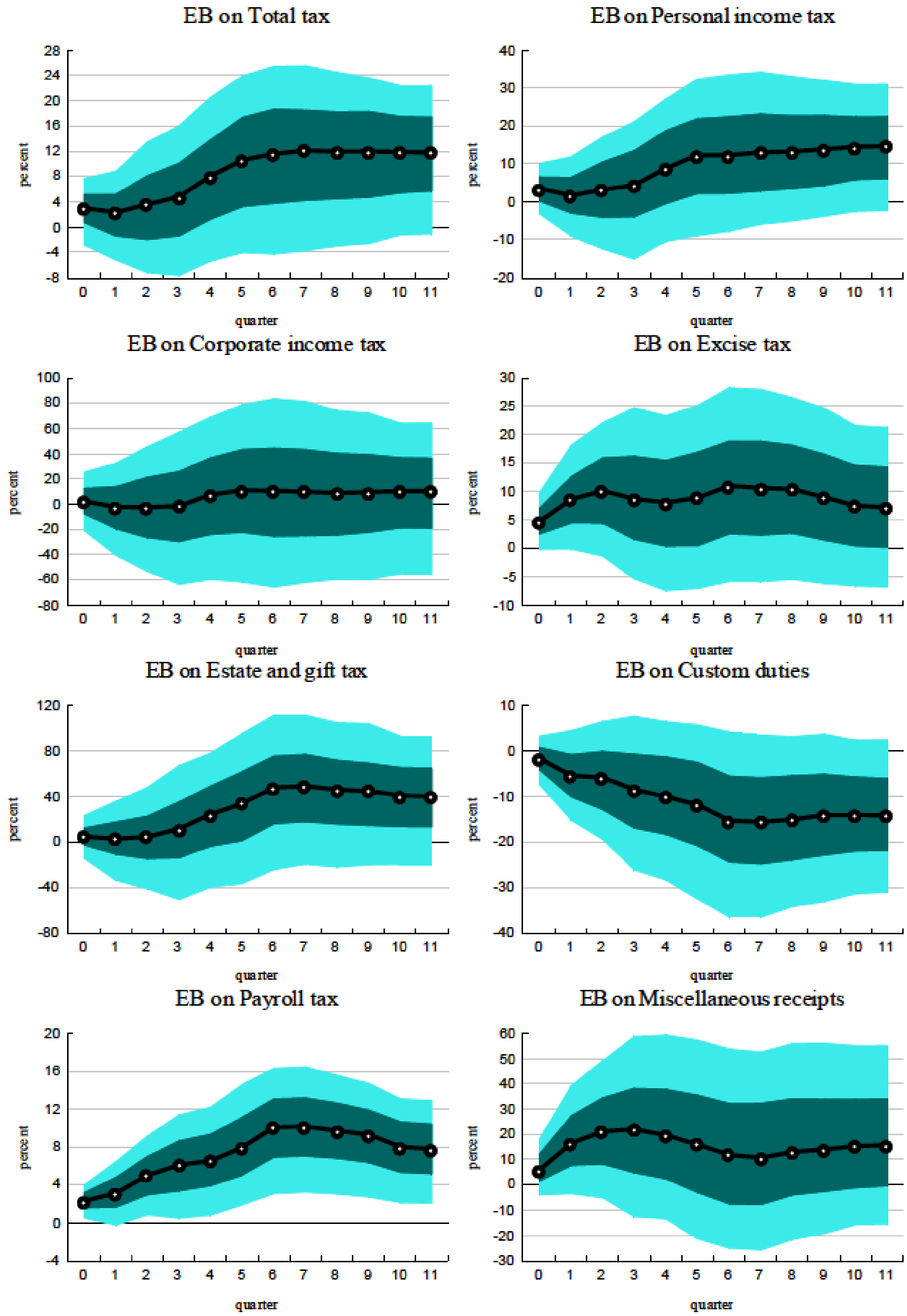

Figure 3.12. TAX RECEIPTS RESPONSE TO EB PLANS

3.6.2 Industry Data

In this section we describe the data we use in our analysis.

Firstly, the disaggregation level, $n = 62$, is determined by starting from the finest decomposition available on the Bureau of Economic Analysis (BEA) at a yearly frequency, namely 71 sectors, and then aggregating those sectors whose data are not available for older years. We exclude the Government sector and consider only Government Enterprises as the only public, but politically independent, sector. The Government sector needs to be excluded since its outcome variable is G, government spending, which mechanically falls when a fiscal adjustment occurs.

Value Added

We use real industry value-added as the dependent variable, Δy_{it}. Value-added equals gross output minus intermediate inputs. It consists of compensation of employees, taxes on production and imports less subsidies (formerly indirect business taxes and non-tax payments), and gross operating surplus (formerly "other value added"). We prefer it over gross output to be consistent with Acemoglu, Akcigit, and Kerr (2016).[25]

Industry Specific Shares:

Following Acemoglu, Akcigit, and Kerr (2016), we construct the vector of industry-specific weights by exploiting information from the input-output tables, namely: $\omega_i^{EB} = \frac{Sales_{i \to G}}{Sales_i}$; where "G" stands for Government.[26] By doing so, we take into account the fact that the government purchases goods and services in different quantities from each sector.[27] Lastly, the vector of weights for the EB plan, denoted by $\boldsymbol{\omega}^{EB}$, is then normalized to one.

On the contrary, we assume that aggregate TB fiscal plans impact each sector in the same fashion, therefore, we set $\omega_i^{TB} = 1/n$ for all i and the $n \times 1$ vector will be: $\boldsymbol{\omega}^{TB} = 1/n \cdot \mathbf{1}_n$.

[25] Their decision is justified by the fact that value-added is adjusted for energy costs, non-manufacturing input, and inventory changes which are all outside of the general equilibrium model which provides the theoretical underpinning to their empirical strategy.

[26] Our definition of Government encompasses both Federal and State&Local government spending. We therefore exclude here Government Enterprises, which instead are considered as part of the industrial network.

[27] We thank Roberto Perotti for this point.

Input-Output Network

The BEA provides I-O tables that report the amount of commodity used (Use Table) and made (Make Table) by each industry. Horowitz and Planting (2009) outline the procedure to construct an industry-by-industry direct requirement matrix, with elements given by $SALES_{j \to i}/SALES_i$ for each sector. Let's denote this matrix by A and note that its elements coincide one to one with the weights of $\Delta y_{i,t}^{\text{down}}$ in Equation 3.6. Therefore, the downstream spatial variable can be written in vector notation as: $\Delta \boldsymbol{y}_t^{\text{down}} = A \cdot \Delta \log \boldsymbol{y}_t$ and matrix A can be constructed from the Make and Use Tables of the BEA.[28] Henceforth we will refer to matrix A as the "downstream matrix".

Finally, we construct a new matrix starting from A and using BEA's industry specific gross output, such that its $(ij)_{th}$ element is represented by $SALES_{i \to j}/SALES_i$, which coincides one to one with the weights of $\Delta y_{i,t}^{\text{up}}$ in Equation 3.6. We denote this new matrix by $\hat{A}^T$, and refer to it as the "upstream matrix". The upstream spatial variable can now be written in vector notation as: $\Delta \boldsymbol{y}_t^{\text{up}} = \hat{A}^T \cdot \Delta \log \boldsymbol{y}_t$.

The construction of matrices A and $\hat{A}^T$ starts from the analysis of the Make and Use tables illustrated in chapter 12 of Horowitz and Planting (2009). We outline here the details of the construction and the precise mapping between the theory and the data.

The Use Table

The Use table is a commodity-by-industry table which illustrates the uses of commodities by intermediate and final users. The rows of the Use Table represent the commodities (or products) and the sum of the entries in a row is the total output of that commodity. On the contrary, the columns display the industries that employ them and the final users. Horowitz and Planting (2009) provides a useful numerical example with 3 industries: What is of our interest is

[28] We use the Make and Use tables of year 1997, which is the closest to the occurrence of fiscal plans. Nevertheless, notice that I-O matrices are fairly stable over time.

Example of Use Table - 3 Industries					
Commodity/Industry	1	2	3	Final demand	Total Commodity Output
1	50	120	120	40	330
2	180	30	60	130	400
3	50	150	50	20	270
Scrap	1	3	1	0	5
VA	47	109	34	/	190
Total Industry Output	328	412	265	190	/

clearly the $n \times n$ commodity-by-industry part of the Table, whose values can be denoted with the following notation:

$$(Use)_{ij} = \mathrm{INP}_{i\to j} := \text{Commodity } i \text{ used as input by Industry } j$$

Therefore, the $n \times n$ part of the Use Table we are going to use is:

$$U = \begin{bmatrix} \mathrm{INP}_{1\to 1} & \mathrm{INP}_{1\to 2} & \mathrm{INP}_{1\to 3} \\ \mathrm{INP}_{2\to 1} & \mathrm{INP}_{2\to 2} & \mathrm{INP}_{2\to 3} \\ \mathrm{INP}_{3\to 1} & \mathrm{INP}_{3\to 2} & \mathrm{INP}_{3\to 3} \end{bmatrix} = \begin{bmatrix} 50 & 120 & 120 \\ 180 & 30 & 60 \\ 50 & 150 & 50 \end{bmatrix}$$

In practice, the above matrix U is a "symmetric" commodity-by-industry Use Table.

Next step boils down in constructing a *commodity-by-industry direct requirement table* by dividing each industry's input, $\mathrm{INP}_{j\to i}$, by its corresponding total industry output, y_i. We denote such a matrix with letter B:

$$
\mathrm{B} = \begin{bmatrix} \frac{\mathrm{INP}_{1\to1}}{y_1} & \frac{\mathrm{INP}_{1\to2}}{y_2} & \frac{\mathrm{INP}_{1\to3}}{y_3} \\ \\ \frac{\mathrm{INP}_{2\to1}}{y_1} & \frac{\mathrm{INP}_{2\to2}}{y_2} & \frac{\mathrm{INP}_{2\to3}}{y_3} \\ \\ \frac{\mathrm{INP}_{3\to1}}{y_1} & \frac{\mathrm{INP}_{3\to1}}{y_2} & \frac{\mathrm{INP}_{3\to3}}{y_3} \end{bmatrix} = \begin{bmatrix} \frac{50}{328} & \frac{120}{412} & \frac{120}{265} \\ \\ \frac{180}{328} & \frac{30}{412} & \frac{60}{265} \\ \\ \frac{50}{328} & \frac{150}{412} & \frac{50}{265} \end{bmatrix} = \begin{bmatrix} 0.152 & 0.291 & 0.453 \\ \\ 0.549 & 0.073 & 0.226 \\ \\ 0.152 & 0.364 & 0.189 \end{bmatrix}.
$$

Notice one important thing: matrix B is different from matrix A, since $x_{i\to j} \neq \mathrm{INP}_{i\to j}$: the former is an industry output flow, while the second measures a commodity flow to an industry.

The Make Table

The Make table is an industry-by-commodity table which shows the production of commodities by industries. Row i represents an industry and its summation delivers the total industry output, y_i. Column j represents a commodity and its summation delivers the total commodity output.

Borrowing again Horowitz and Planting, 2009's 3 industries example, we have:

Example of Make Table - 3 Industries

Industry/Commodity	1	2	3	Scrap	Total Industry Output
1	300	25	0	3	328
2	30	360	20	2	412
3	0	15	250	0	265
Total Commodity Output	330	400	270	5	/

Similarly to what done for the Use Table, we are interested in the central $n \times n$ elements of the table, which we can denote by V. The generic element of the "heart" of the Make table is:

$$
(Make)_{ij} = \mathrm{OUT}_{i\to j} := \text{Commodity } j \text{ produced by Industry } i
$$

Therefore, the $n \times n$ part of the Make Table we are going to employ is:

$$V = \begin{bmatrix} \mathrm{OUT}_{1\to1} & \mathrm{OUT}_{1\to2} & \mathrm{OUT}_{1\to3} \\ \\ \mathrm{OUT}_{2\to1} & \mathrm{OUT}_{2\to2} & \mathrm{OUT}_{2\to3} \\ \\ \mathrm{OUT}_{3\to1} & \mathrm{OUT}_{3\to2} & \mathrm{OUT}_{3\to3} \end{bmatrix} = \begin{bmatrix} 300 & 25 & 0 \\ 30 & 360 & 20 \\ 0 & 15 & 250 \end{bmatrix}$$

In practice, the above matrix V is a "symmetric" industry-by-commodity Make Table.

Analogously to what done before, we now take ratios; in particular, we divide each element of V by the total production of commodity j. The resulting matrix is denoted by D, and its generic element is:

$$(D)_{ij} = \frac{OUT_{i\to j}}{\sum_{k=1}^{n} OUT_{k\to j}} = \frac{OUT_{i\to j}}{C_j}$$

where $C_j := \sum_{k=1}^{n} OUT_{k\to j}$ is the total production of commodity j. D represents the share of industry i in the total production of commodity j; not surprisingly, Horowitz and Planting (2009) refer to this matrix as the "market share matrix". In the 3 industries/commodities example we have:

$$D = \begin{bmatrix} \frac{OUT_{1\to1}}{C_1} & \frac{OUT_{1\to2}}{C_2} & \frac{OUT_{1\to3}}{C_3} \\ \\ \frac{OUT_{2\to1}}{C_1} & \frac{OUT_{2\to2}}{C_2} & \frac{OUT_{1\to3}}{C_3} \\ \\ \frac{OUT_{3\to1}}{C_1} & \frac{OUT_{3\to2}}{C_2} & \frac{OUT_{3\to3}}{C_3} \end{bmatrix} = \begin{bmatrix} \frac{300}{330} & \frac{25}{400} & \frac{0}{270} \\ \\ \frac{30}{330} & \frac{360}{400} & \frac{20}{270} \\ \\ \frac{0}{330} & \frac{15}{400} & \frac{250}{270} \end{bmatrix} = \begin{bmatrix} 0.909 & 0.063 & 0 \\ 0.091 & 0.900 & 0.074 \\ 0 & 0.038 & 0.926 \end{bmatrix}$$

Adjustment for Scrap Products

The I-O accounts include a commodity for scrap, which is a byproduct of industry production. No industry produces scrap on demand; rather, it is the result of production to meet other demands. In order to make the I-O model work correctly, we have to eliminate scrap as a secondary product. At the same time, we must also keep industry output at the same level.

This adjustment is accomplished by calculating the ratio of non-scrap output to industry output for each industry and then applying these ratios to the market shares matrix in order to account for total industry output. More precisely, the non-scrap ratio, which I denote by θ_i, is defined as follows:

$$\theta_i = \frac{y_i - (\text{scrap})_i}{y_i}$$

and represents the share of total industry output i made of commodity different from "scrap". In the 3 industries example we have:

Industry	Tot.Ind.Out.	Scrap	Δ	θ_i
1	328	3	325	0.991
2	412	2	410	0.995
3	265	0	265	1

The market shares matrix, D, is adjusted for scrap by dividing each row by the non-scrap ratio for that industry. In the resulting transformation matrix, called W, the implicit commodity output of each industry has been increased. In other words, we are increasing each market share to take into account that to produce each unit of each commodity, industry i will produce $1/\theta_i$ units of output. In essence, we are spreading the production of commodity "scrap" over the production of all the other commodities:

$$W = \begin{bmatrix} \frac{OUT_{1\to1}}{C_1}\cdot\frac{1}{\theta_1} & \frac{OUT_{1\to2}}{C_2}\cdot\frac{1}{\theta_2} & \frac{OUT_{1\to3}}{C_3}\cdot\frac{1}{\theta_3} \\ \\ \frac{OUT_{2\to1}}{C_1}\cdot\frac{1}{\theta_1} & \frac{OUT_{2\to2}}{C_2}\cdot\frac{1}{\theta_2} & \frac{OUT_{1\to3}}{C_3}\cdot\frac{1}{\theta_3} \\ \\ \frac{OUT_{3\to1}}{C_1}\cdot\frac{1}{\theta_1} & \frac{OUT_{3\to2}}{C_2}\cdot\frac{1}{\theta_2} & \frac{OUT_{3\to3}}{C_3}\cdot\frac{1}{\theta_3} \end{bmatrix} = \begin{bmatrix} \frac{0.909}{0.991} & \frac{0.063}{0.991} & \frac{0}{0.991} \\ \\ \frac{0.091}{0.995} & \frac{0.900}{0.995} & \frac{0.074}{0.995} \\ \\ \frac{0}{1} & \frac{0.038}{1} & \frac{0.926}{1} \end{bmatrix} = \begin{bmatrix} 0.917 & 0.063 & 0 \\ 0.091 & 0.904 & 0.074 \\ 0 & 0.038 & 0.926 \end{bmatrix}$$

The Direct Requirement Table

To summarize:

1. We constructed matrix B, a commodity-by-industry direct requirement table, whose columns tell us how much an industry j needs of commodity i relative to its own total industry production.

2. We constructed matrix W, an industry-by-commodity matrix which represent the market share - adjusted for scrap - of each industry i in the production of a commodity j.

By combining these two matrices we can obtain an industry-by-industry direct requirement matrix:

$$\underbrace{P}_{\text{industry}\times\text{industry}} := \underbrace{W}_{\text{industry}\times\text{commodity}} \cdot \underbrace{B}_{\text{commodity}\times\text{industry}}$$

In order to understand the meaning of each element of matrix P, it is important to derive it analytically:

$$P = \underbrace{\begin{bmatrix} \frac{OUT_{1\to 1}}{C_1 \cdot \theta_1} & \frac{OUT_{1\to 2}}{C_2 \cdot \theta_2} & \frac{OUT_{1\to 3}}{C_3 \cdot \theta_3} \\ \\ \frac{OUT_{2\to 1}}{C_1 \cdot \theta_1} & \frac{OUT_{2\to 2}}{C_2 \cdot \theta_2} & \frac{OUT_{1\to 3}}{C_3 \cdot \theta_3} \\ \\ \frac{OUT_{3\to 1}}{C_1 \cdot \theta_1} & \frac{OUT_{3\to 2}}{C_2 \cdot \theta_2} & \frac{OUT_{3\to 3}}{C_3 \cdot \theta_3} \end{bmatrix}}_{W} \cdot \underbrace{\begin{bmatrix} \frac{\mathrm{INP}_{1\to 1}}{y_1} & \frac{\mathrm{INP}_{1\to 2}}{y_2} & \frac{\mathrm{INP}_{1\to 3}}{y_3} \\ \\ \frac{\mathrm{INP}_{2\to 1}}{y_1} & \frac{\mathrm{INP}_{2\to 2}}{y_2} & \frac{\mathrm{INP}_{2\to 3}}{y_3} \\ \\ \frac{\mathrm{INP}_{3\to 1}}{y_1} & \frac{\mathrm{INP}_{3\to 2}}{y_2} & \frac{\mathrm{INP}_{3\to 3}}{y_3} \end{bmatrix}}_{B}$$

Denoting by p_{ij} the generic element of P, we have:

$$p_{ij} = \frac{\frac{OUT_{i\to 1}}{C_1 \cdot \theta_1} \cdot \mathrm{INP}_{1\to j} + \frac{OUT_{i\to 2}}{C_2 \cdot \theta_2} \cdot \mathrm{INP}_{2\to j} + \frac{OUT_{i\to 3}}{C_3 \cdot \theta_3} \cdot \mathrm{INP}_{3\to j}}{y_j} \approx \frac{\mathrm{SALES}_{i\to j}}{SALES_j}$$

In other words, p_{ij} represents how much industry j depends on inputs form industry i relative to its own total industry output y_j.[29]

Notice that the transposed of matrix P is approximately equal to matrix A in the third chapter:

$$P \approx \begin{bmatrix} \frac{\mathrm{SALES}_{1\to 1}}{\mathrm{SALES}_1} & \frac{\mathrm{SALES}_{1\to 2}}{\mathrm{SALES}_2} & \frac{\mathrm{SALES}_{1\to 3}}{\mathrm{SALES}_3} \\ \\ \frac{\mathrm{SALES}_{2\to 1}}{\mathrm{SALES}_1} & \frac{\mathrm{SALES}_{2\to 2}}{\mathrm{SALES}_2} & \frac{\mathrm{SALES}_{2\to 3}}{\mathrm{SALES}_3} \\ \\ \frac{\mathrm{SALES}_{3\to 1}}{\mathrm{SALES}_1} & \frac{\mathrm{SALES}_{3\to 2}}{\mathrm{SALES}_2} & \frac{\mathrm{SALES}_{3\to 3}}{\mathrm{SALES}_3} \end{bmatrix} \implies \boxed{A \approx P^T}$$

Matrix P can be either constructed from the Make and Use table or downloaded from the BEA,

[29] Notice that a big assumption is made in the construction of this matrix: if industry i has adjusted market share of production of commodity K, $OUT_{i\to K}/(C_K \cdot \theta_K)$ equal to, say 10%, then it is assumed that if industry j purchases $z := \mathrm{INP}_{K\to j}$ dollars of commodity K, then 10% of z\$ come from industry i. This must be true on average but it might not be exactly true case by case.

as an industry-by-industry direct requirement table. Its transposed value identifies the matrix A in Equation (3.6).

The construction of matrix $\hat{A}^T$, in equation (3.7), is trivial once we have matrix A as well as a vector of average industry output.

3.6.3 Spatial Econometric Estimation

We believe that our empirical methodology presents some results of independent interest. Although we do not want to divert attention from the macroeconomic focus of the third chapter, we believe certain econometric facts are worth mentioning here in the Appendix. We provide this discussion in the spirit of promoting the usage of these new techniques in macroeconomic analysis.

Firstly, the adoption of spatial econometric methods allows us to disentangle the direct and network effect of aggregate shocks. This is a novel and recent innovation in macroeconomics, as noted in Ozdagli and Weber (2020). Secondly, spatial models are traditionally estimated by row-normalizing and removing the main diagonal from the weighting matrix. Another common assumption is homoskedasticity of the error term. In a recent paper, Aquaro, Bailey, and Pesaran (2021) develop a new estimator which relaxes homoskedasticity and allow for different spatial coefficients, thus indirectly relaxing the row-normalization assumption. They refer to it as Heterogenous Spatial Autoregressive model (HSAR). They also point out that not assuming zero entries on the main diagonal of the weighting matrix is simply a re-parameterization of the model, which does not harm the statistical properties of the MLE, but does change the interpretation of the parameters.[30] Their econometric model, adopted by Ozdagli and Weber (2020), is very convenient for macroeconomic applications which use non-row-normalized, dense main diagonal weighting matrices and in a setting where units are subject to heteroskedastic idiosyncratic shocks.

[30] We are grateful to Hashem Pesaran for making us aware of this.

However, we highlight that even the standard dynamic spatial panel autoregressive model of Yu, De Jong, and L.-f. Lee (2008) can easily be relaxed to accommodate for non-zero entries on the main diagonal and non-row-normalized weighting matrix with heteroskedastic errors.[31] Our construction of a Bayesian MCMC, similar to the one in J. LeSage and Pace (2009), is thus an easy and natural extension to the more general version of the spatial panel autoregressive model of Yu, De Jong, and L.-f. Lee (2008). Moreover, the Bayesian MCMC method provides an easy way to recover the posterior distributions of the aggregate effects of the shocks, as illustrated earlier.

We encourage macroeconomists to adopt spatial econometric tools to study the propagation of aggregate shocks into a network of sub-units (countries, industries, regions...) but in doing so we also recommend them to follow three good practices:

1. Firstly, always allow for heteroskedasticity, since sub-units in general have different volatilities.

2. Secondly, never remove the main diagonal from the empirically observed weighting matrices, in our case A and $\hat{A}^T$. In fact, zero-entries in the main diagonal imposes a lack of spillovers within the same observed unit ("intra-unit feedback"). This is a reasonable assumption when units are individuals - like in standard spatial econometric applications - but it is not sensible when units are aggregates, such as industries. Notice, that the empirically observed A and $\hat{A}^T$ weighting matrices from our analysis exhibit very dense main diagonals (see Figure 3.9).

3. Thirdly, never row-normalize the weighting matrices. Row-normalization flattens the differences in the degree of connection of each unit. For instance, in our application with the industrial network, A and $\hat{A}^T$ exhibit very different row-sums, indicative of different degrees of exposure to customer and supplying industries.

[31] We thank Lung-Fei Lee for pointing this out.

We recommend using either the Bayesian MCMC methodology developed here and detailed in Appendix 3.6.3 or the HSAR model of Aquaro, Bailey, and Pesaran (2021), whenever the application requires heterogeneous spatial coefficients. The relationship between the two models is left for future research.

In what follows we outline the details of the spatial econometric estimator that we employ.

Log-likelihood

The standard way to estimate the parameters of Equations (3.6) and (3.7) is via maximum likelihood (see J. LeSage and Pace (2009) for an introduction to spatial econometrics). The asymptotic and small sample properties of the MLE have been studied in L.-F. Lee (2004) for cross-sectional data, and in Yu, De Jong, and L.-f. Lee (2008), for dynamic panel data models with fixed effects.

We provide here the derivation of the log-likelihood of the baseline model (3.6), necessary for the calculation of both the MLE and the conditional posterior distributions of the Bayesian MCMC.[32] Collecting fiscal adjustment plans, industry fixed effects and other controls into matrix X_t, from Equation (3.6):

$$\begin{aligned}
&H_t^{-1} \cdot \underset{n\times 1}{\Delta y_t} = \underset{n\times k}{X_t} \cdot \beta + \varepsilon_t \\
&H_t = \left(I_n - \rho^{down} \cdot A \cdot TB_t - \rho^{up} \cdot \hat{A}^T \cdot EB_t\right)^{-1} \\
&\varepsilon_t \sim \mathcal{N}(0, \Omega), \forall t \in \{1, ..., T\} \\
&\Omega = diag(\sigma_1^2, ..., \sigma_n^2) \\
&\varepsilon_t \perp \varepsilon_{t+i}, \quad \forall t \in \{1, ..., T\}, \forall i \in \mathscr{Z}
\end{aligned}$$

where k is the number of regressors.[33] We now make a convenient change in the notation: 1.

[32]Results for the inverted model, Equation (3.7)) are symmetric to the baseline case.

[33]k in our baseline is n fixed effects plus 6 fiscal adjustment components (unexpected, announced and future for

we now use $'$ as a symbol for transposition instead of ^{T}; 2. we now set $\rho_1 = \rho^{down}$, $\rho_2 = \rho^{up}$, $A = W_1$ and $\hat{A}' = W_2$. We have:

$$Z_t := H_t^{-1} \cdot \Delta y_t \sim \mathcal{N}(X_t\beta, \Omega) \implies \Delta y_t \sim \mathcal{N}(H_t X_t \beta, H_t \Omega H_t')$$

The density function of the random vector Δy_t is:

$$\underset{n\times 1}{f(\Delta y_t}|X_t,\rho,\beta,\Omega) = \frac{1}{\sqrt{(2\pi)^n \cdot |H_t\Omega H_t'|}} \exp\left\{ -\frac{1}{2} \cdot (\Delta y_t - H_t X_t \beta)' \cdot (H_t \Omega H_t')^{-1} \cdot (\Delta y_t - H_t X_t \beta) \right\},$$

with $\rho = \left[\rho^{down}, \rho^{up}\right]$.

Given that $(H_t\Omega H_t')^{-1} = (H_t')^{-1} \cdot \Omega^{-1} \cdot H_t^{-1}$ and $|H_t \Omega H_t'| = |H_t|^2 \cdot |\Omega|$, we have:

$$\begin{aligned}
f(\Delta y_t|\cdot) = (2\pi)^{-n/2} \cdot |H_t|^{-1} \cdot |\Omega|^{-1/2} \cdot \ldots \\
\ldots \cdot \exp\left\{ -\frac{1}{2}(Z_t - X_t\beta)' \cdot H_t' \cdot (H_t')^{-1} \cdot \Omega^{-1} \cdot H_t^{-1} \cdot H_t \cdot (Z_t - X_t\beta) \right\} \\
= (2\pi)^{-n/2} \cdot |(I_n - \rho_1 W1TB_t - \rho_2 W_2 EB_t)^{-1}|^{-1} \cdot |\Omega|^{-1/2} \exp\left\{ -\frac{1}{2}\varepsilon_t'\Omega^{-1}\varepsilon_t \right\} \\
= (2\pi)^{-n/2} \cdot |I_n - \rho_1 \cdot W_1 \cdot TB_t - \rho_2 \cdot W_2 \cdot EB_t| \cdot |\Omega|^{-1/2} \exp\left\{ -\frac{1}{2}\varepsilon_t'\Omega^{-1}\varepsilon_t \right\},
\end{aligned}$$

At this point we need to find the likelihood of the random vector $\Delta y = \begin{bmatrix} \Delta y_1' & \ldots & \Delta y_T' \end{bmatrix}$. Since the model is static and we have assumed $cov(\varepsilon_t, \varepsilon_{t-k}) = \underset{n\times n}{\rho^0}$, then Δy_t is *iid* over time. By consequence, the following holds:

$$\begin{aligned}
f(\underset{nT\times 1}{\Delta y}|X_1,\ldots,X_T,\rho,\beta,\Omega) = \prod_{t=1}^{T} f(\underset{n\times 1}{\Delta y_t}|X_t,\rho,\beta,\Omega) = \left((2\pi)^n|\Omega|\right)^{-T/2} \cdot \\
\cdot \prod_{t=1}^{T} |I_n - \rho_1 \cdot W_1 \cdot TB_t - \rho_2 \cdot W_2 \cdot EB_t| \exp\left\{ -\frac{1}{2} \cdot \sum_{t=1}^{T} \varepsilon_t'\Omega^{-1}\varepsilon_t \right\}.
\end{aligned}$$

Now we divide the time series of length T in three different sub-periods. In doing so, consider

both TB and EB plans) plus 2 year dummies for 2008 and 2009.

the following new parameters:

- t_1: set of years when a tax based fiscal adjustment occurs.

  Formally $t_1 := \{1,...,t,...,T_1 |\, t$ such that $TB_t = 1\}$. We set: $H_t |\, t \in t_1 = (I_n - \rho_1 \cdot W_1)^{-1} = H_\tau$.

- t_2: set of years when an expenditure tax based fiscal adjustment occurs.

  Formally: $t_2 := \{1,...,t,...,T_2 |\, t$ such that $EB_t = 1\}$. We set $H_t |\, t \in t_2 = (I_n - \rho_2 \cdot W_2)^{-1} = H_\gamma$.

- t_3: set of years when neither a tax based fiscal adjustment nor an expenditure based fiscal adjustment occurs.

  Formally $t_3 := \{1,...,t,...,T_3 |\, t$ such that $TB_t = 0 \wedge EB_t = 0\}$. We set $H_t |\, t \in t_3 = (I_n)^{-1} = I_n$.

Therefore, we have that t_1, t_2 and t_3 account for a partition of the whole time series and $T = T_1 + T_2 + T_3$. By consequence we have:

$$\begin{aligned}
\prod_{t=1}^{T} |I_n - \rho_1 W_1 TB_t - \rho_2 W_2 EB_t| &= \prod_{t=1}^{T} |H_t^{-1}| \\
&= \prod_{t=1}^{T} \frac{1}{|H_t|} \\
&= \prod_{t\in t_1}^{T_1} \frac{1}{|H_t|} \cdot \prod_{t\in t_2}^{T_2} \frac{1}{|H_t|} \cdot \prod_{t\in t_3}^{T_3} \frac{1}{|H_t|} \\
&= |H_\tau|^{-T_1} \cdot |H_\gamma|^{-T_2} \cdot |I_n|^{-T_3} \\
&= |I_n - \rho_1 \cdot W_1|^{T_1} \cdot |I_n - \rho_2 W_2|^{T_2}
\end{aligned}$$

At this point, we rewrite the probability density function of our dependent variable as:

$$f(\Delta y_t|X_1,\dots,X_T,\rho,\beta,\Omega) = (2\pi)^{-nT/2}\cdot|\Omega|^{-T/2}\cdot$$
$$\cdot|I_n-\rho_1\cdot W_1|^{T_1}\cdot|I_n-\rho_2 W_2|^{T_2}\cdot\exp\left\{-\frac{1}{2}\cdot\sum_{t=1}^{T}\varepsilon_t'\cdot\Omega^{-1}\cdot\varepsilon_t\right\}.$$

Finally, the log-likelihood of our dataset is:

$$\log\mathscr{L}(\rho,\beta,\Omega|\Delta y_1,\dots,\Delta y_T,X_1,\dots,X_T) = -\frac{nT}{2}\ln(2\pi)-\frac{T}{2}\cdot\ln(|\Omega|)+$$
$$+T_1\cdot\ln(|I_n-\rho_1\cdot W_1|)+T_2\cdot\ln(|I_n-\rho_2 W_2|)-\frac{1}{2}\cdot\sum_{t=1}^{T}\varepsilon_t'\cdot\Omega^{-1}\cdot\varepsilon_t.$$

with:

$$\varepsilon_t = Z_t - X_t\cdot\beta = H_t^{-1}\cdot\Delta y_t - X_t\beta = (I_n-\rho_1 W_1 TB_t-\rho_2 W_2 EB_t)\cdot\Delta y_t - X_t\cdot\beta.$$

Furthermore, we impose the condition $\lambda_{\min}^{-1}<\hat{\rho}_1<\lambda_{\max}^{-1}$ and $\mu_{\min}^{-1}<\hat{\rho}_2<\mu_{\max}^{-1}$, where λ and μ are the eigenvalues of the spatial matrices W_1 and W_2 respectively. This condition guarantees that the estimated model will have positive definite covariance matrix (see Ord (1975)).
Notice that in the inverted model of Equation (3.7), it is enough to switch the definition of W_1 and W_2 by setting: $A = W_2$ and $\hat{A}' = W_1$.

The Analytical Fisher Information Matrix

In order to derive the Fisher Information Matrix we firstly need to obtain the total gradient of the log-likelihood function. Let's start with the spatial coefficient ρ_1:

$$\frac{\partial\log\mathscr{L}(\theta|\Delta y,X)}{\partial\rho_1} = T_1\frac{1}{|I_n-\rho_1 W_1|}\frac{\partial|I_n-\rho_1 W_1|}{\partial\rho_1}-\frac{1}{2}\sum_{t=1}^{T}\frac{\partial(Z_t'\Omega^{-1}Z_t)}{\partial\rho_1}-2\frac{\partial(Z_t'\Omega^{-1}X_t\beta)}{\partial\rho_1}.$$

By some matrix algebra, it is possible to show that:

$$\frac{\partial(Z_t'\Omega^{-1}Z_t)}{\partial\rho_1} = -TB_t\cdot\Delta y_t'\cdot\Omega^{-1}\cdot W_1\cdot\Delta y_t - TB_t\cdot\Delta y_t'\cdot W_1'\Omega^{-1}\cdot\Delta y_t$$
$$+2\rho_1\cdot TB_t^2\cdot\Delta y_t'\cdot W_1\cdot\Omega^{-1}\cdot W_1\cdot\Delta y_t' + 2\rho_2\cdot TB_t\cdot EB_t\cdot\Delta y_t'\cdot W_1\cdot\Omega^{-1}\cdot W_2\cdot\Delta y_t'$$

Since our fiscal adjustment plans are mutually exclusive, we have that $TB_t\cdot EB_t = 0$ for all t. Moreover, by rearranging the above expression, we get:

$$\frac{\partial(Z_t'\Omega^{-1}Z_t)}{\partial\rho_1} = -2\cdot TB_t\cdot\Delta y_t'\cdot(I_n-\rho_1\cdot W_1')\cdot\Omega^{-1}\cdot W_1\cdot\Delta y_t$$

After other matrix algebra, we get:

$$-2\cdot\frac{\partial(Z_t\cdot\Omega^{-1}X_t\beta)}{\partial\rho_1} = 2\cdot TB_t\cdot\Delta y_t'\cdot W_1'\cdot\Omega^{-1}\cdot X_t\cdot\beta$$

Wrapping up all together, and employing the notation introduced earlier: $(I_n-\rho_1W_1)^{-1} = H_\tau$, we have:

$$\begin{aligned}
\frac{\partial\log\mathscr{L}(\theta|\Delta y, X)}{\partial\rho_1} &= T_1\frac{1}{|I_n-\rho_1W_1|}\frac{\partial|I_n-\rho_1W_1|}{\partial\rho_1}+\\
&+\sum_{t\in t_1}^{T_1}\Big[\Delta y_t'\cdot(I_n-\rho_1\cdot W_1')\cdot\Omega^{-1}\cdot W_1\cdot\Delta y_t - \Delta y_t'\cdot W_1'\cdot\Omega^{-1}\cdot X_t\cdot\beta\Big] =\\
&= T_1\frac{1}{|I_n-\rho_1W_1|}\cdot|I_n-\rho_1W_1|\cdot Tr\Big((I_n-\rho_1W_1)^{-1}\cdot(-W_1)\Big)+\\
&+\sum_{t\in t_1}^{T_1}\Big[\big((I_n-\rho_1\cdot W_1)\cdot\Delta y_t\big)'\cdot\Omega^{-1}\cdot W_1\cdot\Delta y_t - \beta'\cdot X_t'\cdot\Omega^{-1}\cdot W_1\cdot\Delta y_t\Big]\\
&= -T_1\cdot Tr\Big(H_\tau\cdot W_1\Big)+\sum_{t\in t_1}^{T_1}\Big[\big(Z_t-X_t\beta\big)'\cdot\Omega^{-1}\cdot W_1\cdot\Delta y_t\Big]\\
&= \sum_{t\in t_1}^{T_1}\big(\varepsilon_t'\cdot\Omega^{-1}\cdot W_1\cdot\Delta y_t\big) - T_1\cdot Tr\big(H_\tau\cdot W_1\big).
\end{aligned}$$

By simmetry we have that:

$$\frac{\partial \log \mathscr{L}(\theta|\Delta y, X)}{\partial \rho_2} = \sum_{t \in t_2}^{T_2} \left(\varepsilon_t' \cdot \Omega^{-1} \cdot W_2 \cdot \Delta y_t\right) - T_2 \cdot Tr\left(H_\gamma \cdot W_2\right),$$

with $H_\gamma = (I_n - \rho_2 W_2)^{-1}$, from the previous notation.

As far as concern the derivative with respect to β, we have already seen when concentrating the log-likelihood that:

$$\begin{aligned}
\frac{\partial \log \mathscr{L}(\theta|\Delta y, X)}{\partial \beta} &= X' \cdot \Sigma^{-1} \cdot Z - X' \cdot \Sigma^{-1} \cdot X \cdot \beta \\
&= X' \cdot \Sigma^{-1} \cdot (Z - X \cdot \beta) = \\
&= X' \cdot \Sigma^{-1} \cdot \varepsilon = \\
&= \sum_{t=1}^{T} X_t' \cdot \Omega^{-1} \cdot \varepsilon_t .
\end{aligned}$$

Concerning the derivatives with respect to σ_i^2, we need firstly to acknowledge that:

$$\sum_{t=1}^{T} \varepsilon_t' \cdot \Omega^{-1} \cdot \varepsilon_t = \sum_{t=1}^{T} \sum_{i=1}^{n} \frac{\varepsilon_{i,t}^2}{\sigma_i^2} = \sum_{i=1}^{n} \frac{1}{\sigma_i^2} \sum_{t=1}^{T} \varepsilon_{i,t}^2,$$

and that:

$$\ln(|\Omega|) = \ln(\prod_{i=1}^{n} \sigma_i^2) = \sum_{i=1}^{n} \ln(\sigma_i^2).$$

Therefore, we have that:

$$\begin{aligned}
\frac{\partial \log \mathscr{L}(\theta|\Delta y, X)}{\partial \sigma_i^2} &= -\frac{T}{2} \frac{\partial \ln(|\Omega|)}{\partial \sigma_i^2} - \frac{1}{2} \cdot \frac{\partial}{\partial \sigma_i^2} \sum_{t=1}^{T} \varepsilon_t' \cdot \Omega^{-1} \cdot \varepsilon_t \\
&= -\frac{T}{2 \cdot \sigma_i^2} + \frac{1}{2 \cdot \sigma_i^4} \cdot \sum_{t=1}^{T} \varepsilon_{i,t}^2 .
\end{aligned}$$

We now have all the elements to write down the gradient of the log-likelihood:

$$\nabla \log \mathscr{L}(\theta|\Delta y, X) = \underbrace{\begin{bmatrix} \dfrac{\partial \log \mathscr{L}(\theta|\Delta y, X)}{\partial \rho_1} \\ \\ \dfrac{\partial \log \mathscr{L}(\theta|\Delta y, X)}{\partial \rho_2} \\ \\ \dfrac{\partial \log \mathscr{L}(\theta|\Delta y, X)}{\partial \beta} \\ \\ \dfrac{\partial \log \mathscr{L}(\theta|\Delta y, X)}{\partial \sigma_1^2} \\ \vdots \\ \dfrac{\partial \log \mathscr{L}(\theta|\Delta y, X)}{\partial \sigma_n^2} \\ \end{bmatrix}}_{38\times 1} = \begin{bmatrix} \sum_{t\in t_1}^{T_1} \left(\varepsilon_t' \cdot \Omega^{-1} \cdot W_1 \cdot \Delta y_t\right) - T_1 \cdot Tr\left(H_\tau \cdot W_1\right) \\ \\ \sum_{t\in t_2}^{T_2} \left(\varepsilon_t' \cdot \Omega^{-1} \cdot W_2 \cdot \Delta y_t\right) - T_2 \cdot Tr\left(H_\gamma \cdot W_2\right) \\ \\ \sum_{t=1}^{T} X_t' \cdot \Omega^{-1} \cdot \varepsilon_t \\ \\ -\dfrac{T}{2\cdot\sigma_1^2} + \dfrac{1}{2\cdot\sigma_1^4} \cdot \sum_{t=1}^{T} \varepsilon_{1,t}^2 \\ \vdots \\ -\dfrac{T}{2\cdot\sigma_n^2} + \dfrac{1}{2\cdot\sigma_n^4} \cdot \sum_{t=1}^{T} \varepsilon_{n,t}^2 \end{bmatrix}$$

Another round of derivation is now needed. Let's start with the first row of the matrix: all the derivatives of $\dfrac{\partial \log \mathscr{L}(\theta|\Delta y, X)}{\partial \rho_1}$ with respect to all the parameters. To simplify notation we will refer with $\mathscr{H}_{ij}$ to the element of row i and column j of the Hessian matrix.

$$\begin{aligned}
\mathscr{H}_{1,1} = \frac{\partial^2 \log \mathscr{L}(\theta|\Delta y, X)}{\partial \rho_1^2} &= \sum_{t \in t_1}^{T_1} \big(\frac{\partial \varepsilon_t'}{\partial \rho_1} \cdot \Omega^{-1} \cdot W_1 \cdot \Delta y_t \big) - T_1 \cdot \frac{\partial Tr\big(H_\tau \cdot W_1\big)}{\partial \rho_1} \\
&= \sum_{t \in t_1}^{T_1} \big((-\Delta y_t' \cdot W_1') \cdot \Omega^{-1} \cdot W_1 \cdot \Delta y_t \big) - T_1 \cdot Tr\big(\frac{\partial H_\tau}{\partial \rho_1} \cdot W_1 \big) = \\
&= -\sum_{t \in t_1}^{T_1} \big(\Delta y_t' \cdot W_1' \cdot \Omega^{-1} \cdot W_1 \cdot \Delta y_t \big) - T_1 \cdot Tr\big((-H_\tau \cdot (-W_1) \cdot H_\tau) \cdot W_1 \big) = \\
&= -T_1 \cdot Tr\big(W_1 \cdot H_\tau \cdot W_1 \cdot H_\tau \big) - \sum_{t \in t_1}^{T_1} \big(\Delta y_t' \cdot W_1' \cdot \Omega^{-1} \cdot W_1 \cdot \Delta y_t \big)
\end{aligned}$$

Symmetrically we have:

$$\begin{aligned}
\mathscr{H}_{2,2} = \frac{\partial^2 \log \mathscr{L}(\theta|\Delta y, X)}{\partial \rho_2^2} &= \\
&= -T_2 \cdot Tr\big(W_2 \cdot H_\gamma \cdot W_2 \cdot H_\gamma \big) - \sum_{t \in t_2}^{T_2} \big(\Delta y_t' \cdot W_2' \cdot \Omega^{-1} \cdot W_2 \cdot \Delta y_t \big)
\end{aligned}$$

Going back to the first row, we now calculate the cross derivative with respect to $\rho 2$. Before doing so, recall that, being the log-likelihood a continuously diffirentiable function, the Schwarz's theorem applies and the Hessian matrix is symmetric.

$$\mathscr{H}_{1,2} = \mathscr{H}_{2,1} = \frac{\partial^2 \log \mathscr{L}(\theta|\Delta y, X)}{\partial \rho_1 \partial \rho_2} = 0.$$

Going on with the calculation we have:

$$\begin{aligned}
\mathscr{H}_{1,3:1,23} = \frac{\partial^2 \log \mathscr{L}(\theta|\Delta y, X)}{\partial \rho_1 \partial \beta} &= \sum_{t \in t_1}^{T_1} \big(\frac{\partial \varepsilon_t'}{\partial \beta} \cdot \Omega^{-1} \cdot W_1 \cdot \Delta y_t \big) \\
&= -\sum_{t \in t_1}^{T_1} X_t' \cdot \Omega^{-1} \cdot W_1 \cdot \Delta y_t \\
&= -X_\tau' \cdot \underbrace{(I_{T_1} \otimes \Omega^{-1})}_{\Sigma_\tau^{-1}} \cdot (I_{T_1} \otimes W_1) \cdot \Delta y_\tau
\end{aligned}$$

where $\mathscr{H}_{1,3:1,23}$ means all the elements of the first row, from column 3 up to column 23. X_τ and Δy_τ represent X and Δy but for the only years when a tax based fiscal adjustment occur:

$$X_\tau = \underset{T_1 n\times k}{\begin{bmatrix} X_1 \\ \vdots \\ X_t \\ \vdots \\ X_{T_1} \end{bmatrix}} \quad \text{and} \quad \Delta y_\tau = \underset{T_1 n\times k}{\begin{bmatrix} \Delta y_1 \\ \vdots \\ \Delta y_t \\ \vdots \\ \Delta y_{T_1} \end{bmatrix}} \quad \text{with } t \in t_1,$$

Symmetrically:

$$\begin{aligned}
\mathscr{H}_{2,3:2,23} = \frac{\partial^2 \log \mathscr{L}(\theta|\Delta y, X)}{\partial \rho_2 \partial \beta} &= \sum_{t\in t_2}^{T_2} \big(\frac{\partial \varepsilon_t'}{\partial \beta} \cdot \Omega^{-1} \cdot W_2 \cdot \Delta y_t\big) \\
&= -\sum_{t\in t_2}^{T_2} X_t' \cdot \Omega^{-1} \cdot W_2 \cdot \Delta y_t \\
&= -X_\gamma' \cdot \underbrace{(I_{T_2} \otimes \Omega^{-1})}_{\Sigma_\gamma^{-1}} \cdot (I_{T_2} \otimes W_2) \cdot \Delta y_\gamma,
\end{aligned}$$

with:

$$X_\gamma = \underset{T_2 n\times k}{\begin{bmatrix} X_1 \\ \vdots \\ X_t \\ \vdots \\ X_{T_2} \end{bmatrix}} \quad \text{and} \quad \Delta y_\gamma = \underset{T_2 n\times k}{\begin{bmatrix} \Delta y_1 \\ \vdots \\ \Delta y_t \\ \vdots \\ \Delta y_{T_2} \end{bmatrix}} \quad \text{with } t \in t_2,$$

$$\begin{aligned}
\mathscr{H}_{3,3:23,23} &= \frac{\partial^2 \log \mathscr{L}(\theta|\Delta y, X)}{\partial \beta^2} = \frac{\partial}{\partial \beta^2}\left(\sum_{t=1}^{T} X_t' \cdot \Omega^{-1} \cdot \varepsilon_t\right) \\
&= \sum_{t=1}^{T} X_t' \cdot \Omega^{-1} \cdot \frac{\partial (Z_t - X_t \cdot \beta)}{\partial \beta^2} \\
&= \sum_{t=1}^{T} X_t' \cdot \Omega^{-1} \cdot X_t \\
&= -X' \cdot \Sigma^{-1} \cdot X.
\end{aligned}$$

$$\mathscr{H}_{3,24:23,38} = \frac{\partial^2 \log \mathscr{L}(\theta|\Delta y, X)}{\partial \beta \partial \sigma^2} = \sum_{t=1}^{T} X_t' \cdot \frac{\partial \Omega^{-1}}{\partial \sigma^2} \cdot \varepsilon_t$$

The generic element of the above matrix is a $k \times 1$ vector:

$$-\sigma_1^{-4} \cdot \sum_{t=1}^{T} X_{1,t}' \cdot \varepsilon_{i,t}.$$

Going on with the calculation:

$$\mathscr{H}_{i,i|i \in [24,38]} = \frac{\partial^2 \log \mathscr{L}(\theta|\Delta y, X)}{\partial (\sigma_i^2)^2} = \frac{T}{2} \cdot \frac{1}{\sigma_i^4} \cdot \left(1 - \frac{2}{T \cdot \sigma_i^2} \cdot \sum_{t=1}^{T} \varepsilon_{i,t}^2\right).$$

$$\mathscr{H}_{23+i,23+j|i,j \in [1,n]} = \frac{\partial^2 \log \mathscr{L}(\theta|\Delta y, X)}{\partial \sigma_i^2 \partial \sigma_j^2} = 0 \quad \forall i \neq j.$$

$$
\begin{aligned}
\mathscr{H}_{1,24:1,38} &= \frac{\partial^2 \log \mathscr{L}(\theta|\Delta y, X)}{\partial \rho_1 \partial \sigma_i^2} = \frac{\partial}{\partial \sigma_i^2}\Big(\sum_{t\in t_1}^{T_1} \varepsilon_t' \cdot \Omega^{-1} \cdot W_1 \cdot \Delta y_t\Big) \\
&= \frac{\partial}{\partial \sigma_i^2}\Big(\sum_{t\in t_1}^{T_1} Tr\big(\varepsilon_t' \cdot \Omega^{-1} \cdot W_1 \cdot \Delta y_t\big)\Big) \\
&= \frac{\partial}{\partial \sigma_i^2}\Big(Tr\big(\big(\sum_{t\in t_1}^{T_1} \Delta y_t \cdot \varepsilon_t'\big) \cdot \Omega^{-1} \cdot W_1\big)\Big) \\
&= Tr\Big(\big(\sum_{t\in t_1}^{T_1} \Delta y_t \cdot \varepsilon_t'\big) \cdot \frac{\partial \Omega^{-1}}{\partial \sigma_i^2} \cdot W_1\Big)
\end{aligned}
$$

Note that

$$
\frac{\partial \Omega^{-1}}{\partial \sigma_i^2} = \begin{bmatrix} 0 & \cdots & 0 & \cdots & 0 \\ \vdots & \ddots & \vdots & & \vdots \\ 0 & \cdots & -\sigma_i^{-4} & \cdots & 0 \\ \vdots & & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & \cdots & 0 \end{bmatrix} = diag(0,\cdots,0,-\sigma_i^{-4},0,\cdots,0)
$$

Symmetrically:

$$
\mathscr{H}_{2,24:2,38} = \frac{\partial^2 \log \mathscr{L}(\theta|\Delta y, X)}{\partial \rho_2 \partial \sigma_i^2} = Tr\Big(\big(\sum_{t\in t_2}^{T_2} \Delta y_t \cdot \varepsilon_t'\big) \cdot \frac{\partial \Omega^{-1}}{\partial \sigma_i^2} \cdot W_2\Big)
$$

At this point we have all the elements to construct the Hessian matrix of the log-likelihood.

To sum up, first row:

- $\mathscr{H}_{1,1} = -T_1 \cdot Tr\big(W_1 \cdot H_\tau \cdot W_1 \cdot H_\tau\big) - \sum_{t\in t_1}^{T_1} \big(\Delta y_t' \cdot W_1' \cdot \Omega^{-1} \cdot W_1 \cdot \Delta y_t\big)$

- $\mathscr{H}_{1,2} = 0$

- $\mathscr{H}_{1,3:1,23} = -\sum_{t\in t_1}^{T_1} X_t' \cdot \Omega^{-1} \cdot W_1 \cdot \Delta y_t$

- $\mathscr{H}_{1,24:1,38} = Tr\Big(\big(\sum_{t\in t_1}^{T_1} \Delta y_t \cdot \varepsilon_t'\big) \cdot \dfrac{\partial \Omega^{-1}}{\partial \sigma_i^2} \cdot W_1\Big).$

Second row:

- $\mathscr{H}_{2,1} = 0$

- $\mathscr{H}_{2,2} = -T_2 \cdot Tr\big(W_2 \cdot H_\gamma \cdot W_2 \cdot H_\gamma\big) - \sum_{t\in t_2}^{T_2} \big(\Delta y_t' \cdot W_2' \cdot \Omega^{-1} \cdot W_2 \cdot \Delta y_t\big)$

- $\mathscr{H}_{2,3:2,23} = -\sum_{t\in t_2}^{T_2} X_t' \cdot \Omega^{-1} \cdot W_2 \cdot \Delta y_t$

- $\mathscr{H}_{2,24:2,38} = Tr\Big(\big(\sum_{t\in t_2}^{T_2} \Delta y_t \cdot \varepsilon_t'\big) \cdot \dfrac{\partial \Omega^{-1}}{\partial \sigma_i^2} \cdot W_2\Big).$

From row 3 to row 23:

- $\mathscr{H}_{3,1:23,1} = \mathscr{H}_{1,3:1,23}'$

- $\mathscr{H}_{3,2:23,2} = \mathscr{H}_{2,3:2,23}'$

- $\mathscr{H}_{3,3:23,23} = \sum_{t=1}^{T} X_t' \cdot \Omega^{-1} \cdot X_t$

- $\mathscr{H}_{3,24:23,38} = \sum_{t=1}^{T} X_t' \cdot \dfrac{\partial \Omega^{-1}}{\partial \sigma^2} \cdot \varepsilon_t$

From row 24 to the last row (number 38):

- $\mathscr{H}_{24,1:38,1} = \mathscr{H}_{1,24:1,38}'$

- $\mathscr{H}_{24,2:38,2} = \mathscr{H}'_{2,24:2,38}$

- $\mathscr{H}_{24,3:38,23} = \mathscr{H}'_{3,24:23,38}$

- $\mathscr{H}_{23+i,23+j|i,j\in[1,n]} = \begin{cases} \frac{T}{2} \cdot \frac{1}{\sigma_i^4} \cdot \left(1 - \frac{2}{T \cdot \sigma_i^2} \cdot \sum_{t=1}^{T} \varepsilon_{i,t}^2\right) & \forall i = j \in [1,n] \\ \\ 0 \quad \forall i \neq j \end{cases}$

The last step we have to make to finally obtain the Fisher Information Matrix is taking expectations of every element.

$$
\begin{aligned}
E[\mathscr{H}_{1,1}] &= -T_1 \cdot Tr\big(W_1 \cdot H_\tau \cdot W_1 \cdot H_\tau\big) - \sum_{t\in t_1}^{T_1} E\big[\Delta y_t' \cdot W_1' \cdot \Omega^{-1} \cdot W_1 \cdot \Delta y_t\big] = \\
&= -T_1 \cdot Tr\big(W_1 \cdot H_\tau \cdot W_1 \cdot H_\tau\big) - \sum_{t\in t_1}^{T_1} E\big[Tr\big(W_1 \cdot \Delta y_t \cdot \Delta y_t' \cdot W_1' \cdot \Omega^{-1}\big)\big] = \\
&= -T_1 \cdot Tr\big(W_1 \cdot H_\tau \cdot W_1 \cdot H_\tau\big) - \sum_{t\in t_1}^{T_1} Tr\big(W_1 \cdot E\big[\Delta y_t \cdot \Delta y_t'\big] \cdot W_1' \cdot \Omega^{-1}\big) = \\
&= -T_1 \cdot Tr\big(W_1 \cdot H_\tau \cdot W_1 \cdot H_\tau\big) - \sum_{t\in t_1}^{T_1} Tr\big(W_1 \cdot E\big[H_\tau \cdot X_t \cdot \beta \cdot \varepsilon_t' \cdot H_\tau' + \\
&+ H_\tau \cdot X_t \cdot \beta \cdot \beta' \cdot X_t' \cdot H_\tau' + H_\tau \cdot \varepsilon_t \cdot \varepsilon_t' \cdot H_\tau' \cdot \varepsilon_t \cdot \beta' \cdot X_t' \cdot H_\tau'\big] \cdot W_1' \cdot \Omega^{-1}\big) = \\
&= -T_1 \cdot Tr\big(W_1 \cdot H_\tau \cdot W_1 \cdot H_\tau\big) - \sum_{t\in t_1}^{T_1} Tr\Big(W_1 \cdot \Big[H_\tau \cdot X_t \cdot \beta \cdot E[\varepsilon_t'] \cdot H_\tau' + \\
&+ H_\tau \cdot X_t \cdot \beta \cdot \beta' \cdot X_t' \cdot H_\tau' + H_\tau \cdot E[\varepsilon_t \cdot \varepsilon_t'] \cdot H_\tau' + E[\varepsilon_t] \cdot \beta' \cdot X_t' \cdot H_\tau'\Big] \cdot W_1' \cdot \Omega^{-1}\Big) = \\
&= -T_1 \cdot Tr\big(W_1 \cdot H_\tau \cdot W_1 \cdot H_\tau\big) - \\
&- \sum_{t\in t_1}^{T_1} Tr\Big(W_1 \cdot \Big[H_\tau \cdot X_t \cdot \beta \cdot \beta' \cdot X_t' \cdot H_\tau' + H_\tau \cdot \Omega \cdot H_\tau'\Big] \cdot W_1' \cdot \Omega^{-1}\Big) = \\
&= -T_1 \cdot Tr\big(W_1 \cdot H_\tau \cdot W_1 \cdot H_\tau\big) - \\
&- \sum_{t\in t_1}^{T_1} Tr\big(W_1 \cdot H_\tau \cdot X_t \cdot \beta \cdot \beta' \cdot X_t' \cdot H_\tau' \cdot W_1' \cdot \Omega^{-1} + W_1 \cdot H_\tau \cdot \Omega \cdot H_\tau' \cdot W_1' \cdot \Omega^{-1}\big) = \\
&= -T_1 \cdot Tr\big(W_1 \cdot H_\tau \cdot W_1 \cdot H_\tau + H_\tau' \cdot W_1' \cdot \Omega^{-1} \cdot W_1 \cdot H_\tau \cdot \Omega\big) - \\
&- \sum_{t\in t_1}^{T_1} Tr\big(\beta' \cdot X_t' \cdot H_\tau' \cdot W_1' \cdot \Omega^{-1} \cdot W_1 \cdot H_\tau \cdot X_t \cdot \beta\big) =
\end{aligned}
$$

Setting $M_1^\tau = H_\tau' \cdot W_1' \cdot \Omega^{-1} \cdot W_1 \cdot H_\tau$ we can rewrite the above identity as:

$$E[\mathscr{H}_{1,1}] = -T_1 \cdot Tr\big(W_1 \cdot H_\tau \cdot W_1 \cdot H_\tau + M_1^\tau \cdot \Omega\big) - \sum_{t \in t_1}^{T_1} \beta' \cdot X_t' \cdot M_1^\tau \cdot X_t \cdot \beta =$$

$$= -T_1 \cdot Tr\big(W_1 \cdot H_\tau \cdot W_1 \cdot H_\tau + M_1^\tau \cdot \Omega\big) - \beta' \cdot X_\tau' \cdot \big(I_{T_1} \otimes M_1^\tau\big) \cdot X_\tau \cdot \beta.$$

Simmetrically:

$$E[\mathscr{H}_{2,2}] = -T_2 \cdot Tr\big(W_2 \cdot H_\gamma \cdot W_2 \cdot H_\gamma + M_1^\gamma \cdot \Omega\big) - \beta' \cdot X_\gamma' \cdot \big(I_{T_2} \otimes M_1^\gamma\big) \cdot X_\gamma \cdot \beta.$$

with $M_1^\gamma = H_\gamma' \cdot W_2' \cdot \Omega^{-1} \cdot W_2 \cdot H_\gamma$.

Going on with the calculation:

$$\begin{aligned}
E[\mathscr{H}_{1,3:1,23}] &= E\Big[-\sum_{t \in t_1}^{T_1} X_t' \cdot \Omega^{-1} \cdot W_1 \cdot \Delta y_t\Big] = \\
&= -\sum_{t \in t_1}^{T_1} X_t' \cdot \Omega^{-1} \cdot W_1 \cdot E\Big[H_\tau \cdot X_t \cdot \beta + H_\tau \cdot \varepsilon_t\Big] = \\
&= -\sum_{t \in t_1}^{T_1} X_t' \cdot \Omega^{-1} \cdot W_1 \cdot H_\tau \cdot X_t \cdot \beta \\
&= X_\tau' \cdot (I_{T_1} \otimes M_2^\tau) \cdot X_\tau \cdot \beta
\end{aligned}$$

with $M_2^\tau = \Omega^{-1} \cdot W_1 \cdot H_\tau$.

Simmetrically:

$$E[\mathscr{H}_{2,3:2,23}] = X_\gamma' \cdot (I_{T_2} \otimes M_2^\gamma) \cdot X_\gamma \cdot \beta$$

with $M_2^\gamma = \Omega^{-1} \cdot W_2 \cdot H_\gamma$.

Next step:

$$\begin{aligned}
E[\mathscr{H}_{1,24:1,38}] &= Tr\Big(\big(\sum_{t\in t_1}^{T_1} E\big[\Delta y_t \cdot \varepsilon_t'\big]\big) \cdot \frac{\partial \Omega^{-1}}{\partial \sigma_i^2} \cdot W_1\Big) = \\
&= Tr\Big(\big(\sum_{t\in t_1}^{T_1} E\big[\Delta y_t \cdot \varepsilon_t'\big]\big) \cdot \frac{\partial \Omega^{-1}}{\partial \sigma_i^2} \cdot W_1\Big) = \\
&= Tr\Big(\big(\sum_{t\in t_1}^{T_1} H_\tau \cdot E\big[\varepsilon_t \cdot \varepsilon_t'\big]\big) \cdot \frac{\partial \Omega^{-1}}{\partial \sigma_i^2} \cdot W_1\Big) = \\
&= T_1 \cdot Tr\Big(H_\tau \cdot \Omega \cdot \frac{\partial \Omega^{-1}}{\partial \sigma_i^2} \cdot W_1\Big) = \\
&= T_1 \cdot Tr\Big(\Omega \cdot \frac{\partial \Omega^{-1}}{\partial \sigma_i^2} \cdot W_1 \cdot H_\tau\Big),
\end{aligned}$$

Notice that

$$\Omega \cdot \frac{\partial \Omega^{-1}}{\partial \sigma_i^{-2}} = -\sigma_i^2 \cdot I_{ii}$$

where the generic element of matrix I_{ii} is given by

$$\omega_{s,t} = \begin{cases} 1 & s = i, j = i \\ 0 & \text{otherwise} \end{cases}$$

Therefore

$$E[\mathscr{H}_{1,23+i}] = T_1 \cdot \sigma_i^{-2} \cdot Tr\Big(I_{ii} \cdot W_1 \cdot H_\tau\Big) =$$
$$= T_1 \cdot \sigma_i^{-2} \cdot \Big(W_1 \cdot H_\tau\Big)_{ii}$$

Finally we have that:

$$E[\mathscr{H}_{1,24:1:38}] = T_1 \cdot diag\Big(\Omega^{-1} \cdot W_1 \cdot H_\tau\Big) = T_1 \cdot diag(M_2^\tau).$$

Simmetrically:

$$E[\mathscr{H}_{2,24:2:38}] = T_2 \cdot diag\Big(\Omega^{-1} \cdot W_2 \cdot H_\gamma\Big) = T_2 \cdot diag(M_2^\gamma).$$

Going on:

$$E[\mathscr{H}_{3,3:23,23}] = E[\sum_{t=1}^{T} X_t' \cdot \Omega^{-1} \cdot X_t] = \sum_{t=1}^{T} X_t' \cdot \Omega^{-1} \cdot X_t = X' \cdot \Sigma^{-1} \cdot X$$

$$\begin{aligned} E[\mathscr{H}_{3,24:23,38}] &= E[\sum_{t=1}^{T} X_t' \cdot \frac{\partial \Omega^{-1}}{\partial \sigma^2} \cdot \varepsilon_t] \\ &= \sum_{t=1}^{T} X_t' \cdot \frac{\partial \Omega^{-1}}{\partial \sigma^2} \cdot E[\varepsilon_t] \\ &= \underset{k \times n}{\mathbf{0}} \end{aligned}$$

$$E[\mathscr{H}_{23+i,23+j|i,j\in[1,n]}] = \begin{cases} \frac{T}{2} \cdot \frac{1}{\sigma_i^4} \cdot \left(1 - \frac{2}{T \cdot \sigma_i^2} \cdot \sum_{t=1}^{T} E[\varepsilon_{i,t}^2]\right) & \forall i = j \in [1,n] \\ \\ 0 & \forall i \neq j \end{cases}$$

$$= \begin{cases} -\frac{T}{2} \cdot \frac{1}{\sigma_i^4} & \forall i = j \in [1,n] \\ 0 & \forall i \neq j \end{cases}$$

$$= -\frac{T}{2} \cdot \begin{bmatrix} \sigma_1^{-4} & 0 & \cdots & 0 \\ 0 & \sigma_2^{-4} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ o & 0 & \cdots & \sigma_n^{-4} \end{bmatrix} = -\frac{T}{2} \cdot V$$

We finally have all the elements of the Fisher Information Matrix for our panel (with dummy variables) spatial model:

$$\mathscr{I} =$$

$$\begin{bmatrix} \begin{array}{c} -T_1 \cdot Tr\left(W_1 \cdot H_\tau \cdot W_1 \cdot H_\tau + M_1^\tau \cdot \Omega\right) - \\ -\beta' \cdot X_\tau' \cdot \left(I_{T_1} \otimes M_1^\tau\right) \cdot X_\tau \cdot \beta \end{array} & 0 & \left(X_\tau' \cdot (I_{T_1} \otimes M_2^\tau) \cdot X_\tau \cdot \beta\right)' & T_1 \cdot diag(M_2^\tau)' \\ 0 & \begin{array}{c} -T_2 \cdot Tr\left(W_2 \cdot H_\gamma \cdot W_2 \cdot H_\gamma + M_1^\gamma \cdot \Omega\right) - \\ -\beta' \cdot X_\gamma' \cdot \left(I_{T_2} \otimes M_1^\gamma\right) \cdot X_\gamma \cdot \beta \end{array} & \left(X_\gamma' \cdot (I_{T_2} \otimes M_2^\gamma) \cdot X_\gamma \cdot \beta\right)' & T_2 \cdot diag(M_2^\gamma)' \\ X_\tau' \cdot (I_{T_1} \otimes M_2^\tau) \cdot X_\tau \cdot \beta & X_\gamma' \cdot (I_{T_2} \otimes M_2^\gamma) \cdot X_\gamma \cdot \beta & X' \cdot \Sigma^{-1} \cdot X & \underset{k \times n}{\mathbf{0}} \\ T_1 \cdot diag(M_2^\tau) & T_2 \cdot diag(M_2^\gamma) & \underset{n \times k}{\mathbf{0}} & -\frac{T}{2} \cdot V \end{bmatrix}$$

Bayesian MCMC - Technical Details

Even if the MLE is a common standard method in spatial econometric applications, we have two valid reasons for not adopting it: 1. non-stationary estimates of aggregate total effects; 2. prior information on the values of the parameters. Let's explore both the issues.

1. Non-Stationary Solutions

We can estimate the parameters by maximizing the concentrated log-likelihood over the compact set which guarantees a positive definite matrix (see Ord (1975)): $C^{down} = \left(\lambda_{\min}^{-1}, \lambda_{\max}^{-1}\right)$ and $C^{up} = \left(\mu_{\min}^{-1}, \mu_{\max}^{-1}\right)$. The standard errors are constructed using the analytical Fisher Information of the model, centered on the point estimates, $\hat{\rho}^{down}$ and $\hat{\rho}^{up}$. The asymptotic results of Yu, De Jong, and L.-f. Lee (2008) guarantees the asymptotic normality of the parameters of equation (3.6) and (3.7) (See Theorem 3 case $n/T \to 0$). For instance, for the estimator of ρ^{down} we have:

$$\sqrt{T \cdot n}\left(\hat{\rho}_{nT}^{down} - \rho^{down}\right) \xrightarrow{d} \mathscr{N}\left(0, \sigma^2\right)$$

where σ^2 is the asymptotic variance of the MLE, obtained by the calculating the analytical Fisher Information matrix of our model. However, we are interested in estimating the aggregate total effect of fiscal consolidations, not the parameters of the model themselves. At page 70, J. LeSage and Pace (2009) suggest to construct the asymptotic distribution of the average total effect (our aggregate total effect) by following these steps: 1. estimate the parameters of the model via MLE; 2. Draw values of the parameters by their approximate asymptotic distribution ($\tilde{\rho}^{down} \approx \mathscr{N}\left(\hat{\rho}_{nT}^{down}, \frac{\hat{\sigma}^2(\hat{\rho}_{nT}^{down})}{nT}\right)$; 3. Calculate at each step the aggregate total effect. After doing so we calculated the standard errors of the ATE_{TB} by calculating the standard deviation of the asymptotic distribution so constructed. We obtained explosive solutions. This is a surprising result, in fact, the asymptotic normality of the average effect is guaranteed by the Δ-method:

$$\sqrt{T \cdot n}\left(ATE_{TB}(\hat{\rho}_{nT}^{down}) - ATE_{TB}(\rho^{down})\right) \xrightarrow{d} \mathscr{N}\left(0, \sigma^2 \cdot \left(\frac{\partial ATE_{TB}(\rho^{down})}{\partial \rho^{down}}\right)^2\right)$$

where $ATE_{TB} : C^{down} \to \mathbb{R}$ and $ATE_{TB}(x) = v' \cdot (I_n - x \cdot A)^{-1} \cdot \omega_{TB}$ and v is a vector of industry output shares of total industrial production (the weights we use to calculate the aggregate effect of fiscal consolidations). What goes wrong in this procedure? The Δ-method is an asymptotic result, which might provide a terrible approximation of a finite sample distribution. It all boils down in finding a distribution which approximates well the small sample one. If $\hat{\rho}_{nT}^{down}$ is very closed to the boundary and its asymptotically normal standard errors are large, that is, they approach the boundary of C^{down} then we end up drawing values of ρ^{down} which deliver unrealistically large values of ATE_{TB}, because matrix $(I_n - \rho^{down} \cdot A)^{-1}$ becomes singular (the boundary is one eigenvalue of A). This situation is described in Figure 3.13.

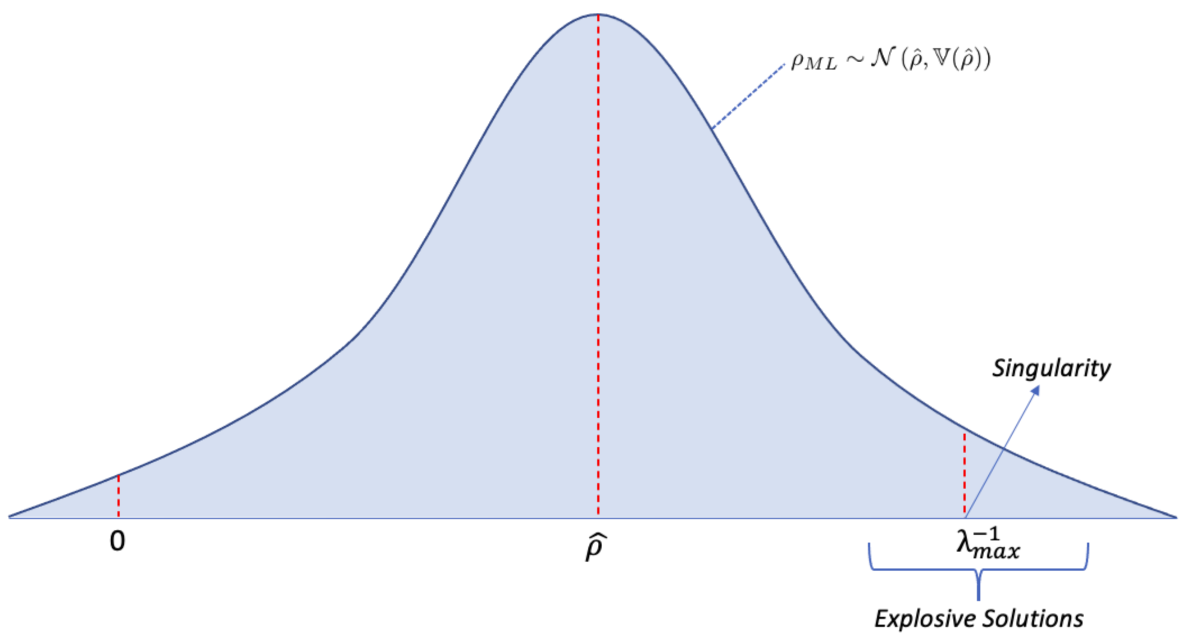

Figure 3.13. EXPLOSIVE SOLUTIONS OF ATE_{TB}

2. Prior Information

We have two extra "prior" pieces of information on the value of the spatial parameters, ρ^{down} and ρ^{up}:

i. Values of ρ^{down} and ρ^{up} close to the boundaries will deliver unrealistically high values of ATE, ADE and ANE, since the determinant of matrices $(I_n - \rho^{down} \cdot A)$ and $(I_n - \rho^{up} \cdot \hat{A}^T)$

will approach zero by definition of eigenvalue. In turn, the elements of their inverse matrices will explode, as illustrated above. Therefore, we should assign less weight to values of ρ^{down} and ρ^{up} close to the boundaries.

ii. We know that industries that are close to each other in the production network will co-move. For instance, if industry X faces increasing prices for its input, it will shrink production and increase prices; in turn, customers of X will also face the same problem and will react similarly, by reducing production and increasing prices. Therefore, the direction of the spatial correlation among industries' output is positive: $\rho^{down} > 0$ and $\rho^{up} > 0$.

Model Estimation

We can integrate such prior information into our estimation and avoid non-stationarity aggregate effects, by adopting a Bayesian MCMC similar to the one introduced by J. P. LeSage and Parent (2007). We illustrate here how we implement the Bayesian MCMC to estimate the parameters of Equation (3.6) (baseline). The log-likelihood of that model is the one outlined above. The priors we employ on the parameters are:

$$\begin{aligned}
&\pi(\beta) \propto constant \\
&\Omega = \sigma^2 \cdot V \quad \text{with } V = diag(v_1, ..., v_n) \\
&\pi(\sigma^2) \propto \frac{1}{\sigma^2} \\
&\pi(v_i) \overset{iid}{\sim} \Gamma^{-1}\left(\frac{r}{2}, \frac{r}{2}\right), \quad i = 1, ..., n \\
&\rho^{down} \sim Gen.Beta(d, d) \\
&\rho^{up} \sim Gen.Beta(d, d).
\end{aligned}$$

We adopt non-informative priors for σ^2 and β to reflect our lack of information around the values of these parameters. Concerning r, a lower value generates more diffusion in the distributions of

v_i, thus regulating our confidence towards heteroskedasticity. Unlike J. LeSage and Pace (2009), who suggest a value of 4, we set r equal to 3 to reflect a strong belief towards heteroskedasticity. For instance, industries in the Agriculture (NAICS 11) as well as Mining (NAICS 21) macro sectors, exhibit much higher volatilities than the rest of the industries.

We impose a "generalized (or non-standardized) $Beta(d,d)$ prior", with support from 0 to λ_{max}^{-1} for ρ^{down} and from 0 to $\hat{\lambda}_{max}^{-1}$ for ρ^{up}. We follow J. LeSage and Pace (2009) and set d equal to 1.1; which has the benefit of letting the generalized Beta prior to resemble a Uniform distribution (diffuse prior), but with low density at the boundaries, as illustrated in Figure 3.14.

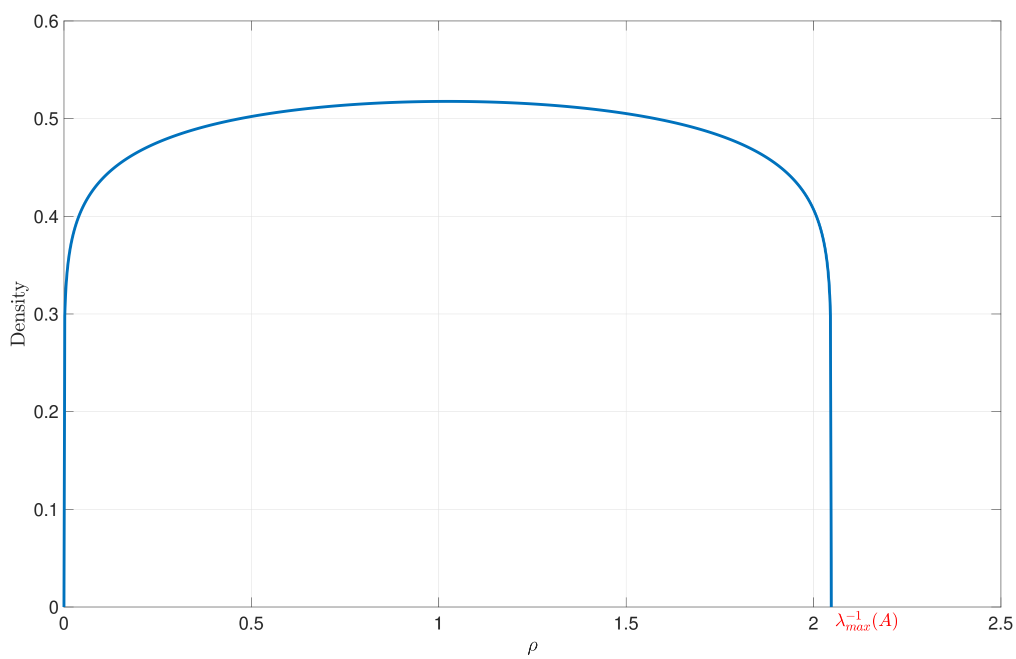

Figure 3.14. GENERALIZED BETA PRIOR

Notes: line-plot of a non-standardized $Beta(1.1, 1.1)$ density function, with support from $(0, \lambda_{max}^{-1}(A) = 2.047)$ which we employ as a prior for the spatial parameter ρ^{down}.

The choice of such a prior allows us to be agnostic about the specific value of the spatial parameters but at the same time it allows to embed the prior information we have into their estimates.

Furthermore, we assume that all the prior distributions are independent from each other. We use the standard "Metropolis within Gibbs" algorithm, and we obtain an approximation of the posterior densities for each parameter of the model.

We now outline the precise steps of the procedure:

1. **Initialization:** Set up initial values for the parameters: $\beta_{(0)}, \sigma^2_{(0)}, V_{(0)}, \rho^{down}_{(0)}, \rho^{up}_{(0)}$, where $V_{(0)} = diag\left(v^2_{1,(0)}, \ldots, v^2_{n,(0)}\right)$.

2. **Gibbs Sampling:**

   a) Draw $\beta_{(1)}$ from the conditional posterior distribution, which is obtained by mixing the likelihood with a normal prior with mean c (a vector of zeros in our simulation) and covariance matrix L. In order to not add any information, we simply set L to be equal to a diagonal matrix whose entries are infinite (1e12 in our simulation):

   $$P(\beta_{(0)}|\mathscr{D}, \sigma^2_{(0)}, V_{(0)}, \rho^{down}_{(0)}, \rho^{up}_{(0)}) = \mathscr{N}(c^*, L^*) \propto \mathscr{L}(\theta|\mathscr{D}) \cdot \mathscr{N}(c, L)$$
   $$c^* = \frac{1}{T} \cdot (\sum_{t=1}^{T} X_t' \cdot V^{-1}_{(0)} \cdot X_t + \frac{\sigma^2_{(0)}}{T} \cdot L^{-1})^{-1} \cdot (\frac{1}{T} \cdot \sum_{t=1}^{T} X_t' \cdot V^{-1}_{(0)} \cdot H_t \cdot \Delta y_t + \frac{\sigma^2_{(0)}}{T} \cdot L^{-1} \cdot c)$$
   $$L^* = \frac{\sigma^2_{(0)}}{T} \cdot (\sum_{t=1}^{T} X_t' \cdot V^{-1}_{(0)} \cdot X_t + \frac{\sigma^2_{(0)}}{T} \cdot L^{-1})^{-1}$$

   b) Draw $\sigma^2_{(1)}$ from the conditional posterior distribution, which is proportional to likelihood times an inverse gamma distribution as a prior:

   $$P(\sigma^2_{(1)}|\mathscr{D}, \beta_{(1)}, V_{(0)}, \rho^{down}_{(0)}, \rho^{up}_{(0)}) = \Gamma^{-1}(\frac{\theta_1}{2}, \frac{\theta_2}{2}) \propto \mathscr{L}(\theta|\mathscr{D}) \cdot \Gamma^{-1}(a, b)$$
   $$\theta_1 = nT + 2a \quad \theta_2 = \sum_{t=1}^{T} \varepsilon_t' \cdot V^{-1}_{(0)} \cdot \varepsilon_t + 2b$$

   In practice we draw $\sigma^2_{(1)}$ from θ_2/χ_{θ_1}.

   Notice that, setting a and b (the prior's parameters) equal to 0, is like putting a Jefferey's prior on σ^2. This is exactly what we do.

c) Draw $v_{i,(1)}$ from the following conditional posterior distribution, proportional to an inverse gamma prior:

$$P(v_{i,(1)}|\mathscr{D},\sigma^2_{(1)},\rho^{down}_{(0)},\rho^{up}_{(0)}) = \Gamma^{-1}(\frac{q_1}{2},\frac{q_2}{2}) \propto \mathscr{L}(\theta|\mathscr{D})\cdot\Gamma^{-1}(\frac{r}{2},\frac{r}{2})$$
$$q_1 = r+T \quad q_2 = \frac{1}{\sigma^2_{(1)}}\cdot\sum_{t=1}^{T}\varepsilon^2_{i,t}+r$$

In practice we draw $v_{i,(1)}$ from q_2/χ_{q_1}.

As anticipated above, since we are confident on the heteroskedastic behavior of industry value added, we set our prior hyperparameter r to be equal to 3 rather than 4, as done in J. LeSage and Pace (2009).

Replicating this procedure n times, we get a first simulation of matrix $V_{(1)}$.

3. **Metropolis-Hastings**: We now need to draw the spatial coefficients. However we cannot apply a simple Gibbs Sampling, since the conditional posterior distribution is not defined for them. J. LeSage and Pace (2009) suggest the adoption of the Metropolis-Hastings algorithm to overcome this problem. To ease notation we set $\rho_1 := \rho^{down}$ and $\rho_2 := \rho^{up}$. The algorithm is the following:

   (a) Draw ρ_1^c (where the c superscript stands for "candidate") from the (random walk) proposal distribution:

   $$\rho_1^c = \rho_{1,(0)} + c_1\cdot\mathscr{N}(0,1)$$

   (b) Run a bernoulli experiment to determine the updated value of ρ_1:

   $$\rho_{1,(1)} = \begin{cases} \rho_1^c & \pi \quad \text{(accept)} \\ \rho_{1,(0)} & 1-\pi \quad \text{(reject)} \end{cases}$$

Where π is equal to $\pi = \min\{1, \psi_{MH_1}\}$ and, setting: $A_\tau(\rho_1) = I_n - \rho_1 \cdot W_1$, we have:

$$\psi_{MH_1} = \frac{|A_\tau(\rho_1^c)|}{|A_\tau(\rho_{1,(0)})|} \cdot \exp\Big\{ - \frac{1}{2\sigma^2_{(1)}} \cdot \sum_{t \in t_1}^{T_1} \Big[\Delta y_t' \cdot \big(A_\tau(\rho_1^c)' \cdot V_{(1)}^{-1} \cdot A_\tau(\rho_1^c) -$$

$$- A_\tau(\rho_{1,(0)})' \cdot V_{(1)}^{-1} \cdot A_\tau(\rho_{1,(0)}) \big) \cdot \Delta y_t -$$

$$- 2\beta' \cdot X_t' \cdot V_{(1)}^{-1} \big(A_\tau(\rho_1^c) - A_\tau(\rho_{1,(0)}) \big) \cdot \Delta y_t \Big] \Big\} \cdot$$

$$\cdot \left[\frac{(\rho_1^c - 0) \cdot (\lambda_{max}^{-1} - \rho_1^c)}{(\rho_{1,(0)} - 0) \cdot (\lambda_{max}^{-1} - \rho_{1,(0)})} \right]^{d-1} \cdot \mathbf{1}\big(0 \leq \rho_1^c \leq \lambda_{max}^{-1}\big)$$

Basically, we compute the probability to accept the candidate value from the proposal distribution, and then we update the value of ρ_1 by running the bernoulli experiment with such a probability of success. Notice that if we draw a value of ρ_1 outside the support of the beta prior, $\psi_{MH_1} = 0$ and then $\pi = 0$ and we clearly reject the candidate value.

We set d equal to 1.1, on both ρ_1 and ρ_2; this is done to resemble a Uniform (0,1) but with less density on its boundary values.

(c) Once updated ρ_1, we replicate the procedure for ρ_2. Setting $A_\gamma(\rho_2) = I_n - \rho_2 \cdot W_2$ we have:

$$\psi_{MH_2} = \frac{|A_\gamma(\rho_2^c)|}{|A_\gamma(\rho_{2,(0)})|} \cdot \exp\Big\{ - \frac{1}{2\sigma^2_{(1)}} \cdot \sum_{t \in t_2}^{T_2} \Big[\Delta y_t' \cdot \big(A_\gamma(\rho_2^c)' \cdot V_{(1)}^{-1} \cdot A_\gamma(\rho_2^c) -$$

$$- A_\gamma(\rho_{2,(0)})' \cdot V_{(1)}^{-1} \cdot A_\gamma(\rho_{2,(0)}) \big) \cdot \Delta y_t -$$

$$- 2\beta' \cdot X_t' \cdot V_{(1)}^{-1} \big(A_\gamma(\rho_2^c) - A_\gamma(\rho_{2,(0)}) \big) \cdot \Delta y_t \Big] \Big\} \cdot$$

$$\cdot \left[\frac{(\rho_2^c - 0) \cdot (\hat{\lambda}_{max}^{-1} - \rho_2^c)}{(\rho_{2,(0)} - 0) \cdot (\hat{\lambda}_{max}^{-1} - \rho_{2,(0)})} \right]^{d-1} \cdot \mathbf{1}\big(0 \leq \rho_2^c \leq \hat{\lambda}_{max}^{-1}\big)$$

(d) At this point we need to update the variance of the proposal distributions: if the acceptance rate (number of acceptances over number of iterations of the Markov Chain) of the first parameter ρ_1 falls below 40% we need to reduce the value of c_1, the so called tuning parameter, which regulates the variance of the proposal distribution. The variance is reduced by rescaling it: $c'_1 = \frac{c_1}{1.1}$. In this way, we are able to draw values closer to the current state of ρ_1, and therefore, we expect to increase the acceptance rate.

On the contrary, if the acceptance rate rises above 60%, we need to increase the tuning parameter, in order to draw values far from the current state, in this way we increase the chance to explore more the low-density parts of the distribution. We increase the variance of the candidate distribution by scaling upward its standar deviation: $c'_1 = 1.1 \cdot c_1$.

Clearly we replicate this procedure also for ρ_2.

4. **Repeat**: Once updated all the values, we replicate steps 2 and 3, 45,000 times to make sure the acceptance rate has converged.

5. **Burn-in**: we drop the first 35,000 iterations of the Markov Chain, thus obtaining a vector of 10,000 observations for each of the parameters, which account for the simulated posterior distributions.

Simulating the ATE, ADE and ANE

We construct via Monte Carlo the distribution of the ATE, ADE and ANE. In particular we follow these steps:

1. **(Parameters)** Draw ρ^{down}, ρ^{up}, $\boldsymbol{\tau}$ and $\boldsymbol{\gamma}$ from their posterior distributions. To take into account the potential correlation among them, draw from the same iteration of the Bayesian MCMC.

2. **(Style of the plan)** Construct both a TB and an EB simulated fiscal plan, by drawing the style from a distribution which mimics the empirical one.

3. **(Average effects)** Construct ATE, ADE and ANE using the parameters drawn in step 1 and the style drawn in step 2.

4. Repeat 100,000 times steps from 1 though 3, to make sure all the possible combination of styles and parameters are simulated.

Step 2 allows us to claim that the baseline results reported in the thrid chapter are robust to different styles of fiscal plans.

Empirical distribution of style of fiscal plans

We are interested in simulating a 2 years fiscal consolidation made of an unexpected part, no announced part and a single year future part to be implemented in the second year of the simulation.

First of all, we want to simulate the unexpected part of the fiscal plan, therefore, we need to look at those years when an unanticipated shock occurs. Define the two sub-samples: $TB^u := \{t : 1,...,T \mid tax_t^u > 0\}$ and $EB^u := \{t : 1,...,T \mid exp_t^u > 0\}$. Then calculate the mean and the standard deviation of the unexpected component conditional on the occurrence of an unexpected shock:

$$\mu_\tau := \mathbb{E}(tax_t^u \mid t \in TB^u) \qquad \sigma_\tau := \sqrt{\mathbb{V}(tax_t^u \mid t \in TB^u)}$$
$$\mu_\gamma := \mathbb{E}(exp_t^u \mid t \in EB^u) \qquad \sigma_\gamma := \sqrt{\mathbb{V}(exp_t^u \mid t \in EB^u)}$$

In order to simulate a plausible unexpected component of the plan, we draw them from the following distributions:

$$t\tilde{a}x^u \sim \mathscr{U}(\mu_\tau - \sigma_\tau, \mu_\tau + \sigma_\tau)$$
$$e\tilde{x}p^u \sim \mathscr{U}(\mu_\gamma - \sigma_\gamma, \mu_\gamma + \sigma_\gamma)$$

where the ˜ denotes a simulated component.

Concerning the future component, we need to predict what is the value of a one year ahead policy change, conditional on the occurrence of an unexpected policy change. Therefore, we run the following regressions:

$$tax^f_{t,1} = a_\tau + b_\tau \cdot tax^u_t \qquad \textit{with: } t \in TB^u$$
$$exp^f_{t,1} = a_\gamma + b_\gamma \cdot exp^u_t \qquad \textit{with: } t \in EB^u$$

The estimates of a_τ, b_τ, a_γ, b_γ will be stored and used to predict values of $tax^f_{t,1}$ and $exp^f_{t,1}$, conditional on the occurrence of an unexpected component.

At this point we have all the ingredients to outline the steps we do in the construction of a simulated style of the plan:

1. Draw unexpected components from their candidate distributions: $t\tilde{a}x^u \sim \mathscr{U}(\mu_\tau - \sigma_\tau, \mu_\tau + \sigma_\tau)$ and $e\tilde{x}p^u \sim \mathscr{U}(\mu_\gamma - \sigma_\gamma, \mu_\gamma + \sigma_\gamma)$.

2. Predict the future component using the estimates of a_τ, b_τ, a_γ, b_γ. We have: $t\tilde{a}x^f = \hat{a}_\tau + \hat{b}_\tau \cdot t\tilde{a}x^u$ and $e\tilde{x}p^f = \hat{a}_\gamma + \hat{b}_\gamma \cdot e\tilde{x}p^u$.

3. Normalize the value to one: $t\tilde{a}x^u + t\tilde{a}x^f = 1$ and $e\tilde{x}p^u + e\tilde{x}p^f = 1$.

For each iteration of the MC simulation used to approximate the posterior distributions of the ATE, ADE and ANE, we repeat steps 1 through 3 to simulate the style of the plan.

In the first year of the simulation we calculate the effects of TB and EB plans with style given by: $\boldsymbol{s}_{TB} = [t\tilde{a}x^u \; 0 \; t\tilde{a}x^f]$ and $\boldsymbol{s}_{EB} = [e\tilde{x}p^u \; 0 \; e\tilde{x}p^f]$ respectively. In the second year of the simulation, the future component of the shock is rolled over and becomes an announced and implemented shock. Therefore we calculate the effects of TB and EB plans with style given by: $\boldsymbol{s}_{TB} = [0 \; t\tilde{a}x^f \; 0]$ and $\boldsymbol{s}_{EB} = [0 \; e\tilde{x}p^f \; 0]$ respectively.

3.6.4 Estimates of Inverted Model

In this section we report the tables of estimates of the inverted model. Firstly, Table 3.7 shows the estimates of Equation (3.7).

Table 3.7. Estimation Results

Inverted Model - Equation (3.7)												
Parameters	MLE		Bayesian MCMC - Posterior Distributions:									
	$\hat{\theta}_i^{\mathrm{ML}}$	MLE Std.	$\mathbb{E}(\theta_i)$	$\sqrt{\mathbb{V}(\theta_i)}$	$Pr(\theta_i < 0)$	5%	10%	16%	50%	84%	90%	95%
ρ^{up} (TB)	0.554	0.103	0.528	0.097	0.000	0.368	0.405	0.432	0.528	0.625	0.653	0.687
τ_u	0.684	1.283	0.815	1.193	0.247	-1.143	-0.712	-0.372	0.814	2.002	2.351	2.778
τ_a	-1.298	0.986	-1.290	0.919	0.920	-2.794	-2.463	-2.202	-1.293	-0.382	-0.112	0.225
τ_f	-0.080	0.426	-0.084	0.391	0.585	-0.726	-0.585	-0.474	-0.082	0.301	0.415	0.562
ρ^{down} (EB)	0.096	0.114	0.125	0.083	0.000	0.014	0.026	0.040	0.112	0.211	0.241	0.281
γ_u	0.073	1.126	0.050	1.034	0.480	-1.650	-1.272	-0.973	0.051	1.073	1.370	1.760
γ_a	1.286	0.617	1.296	0.567	0.011	0.361	0.572	0.732	1.295	1.861	2.023	2.226
γ_f	-0.502	0.282	-0.499	0.259	0.973	-0.923	-0.831	-0.757	-0.499	-0.241	-0.169	-0.075
D2008	-2.984	0.674	-2.934	0.633	1.000	-3.973	-3.744	-3.562	-2.936	-2.307	-2.120	-1.891
D2009	-5.710	0.674	-5.371	0.661	1.000	-6.469	-6.216	-6.025	-5.368	-4.717	-4.529	-4.290

Notes: θ_i denotes a generic parameter that we estimate. The columns report the following: $\hat{\theta}_i^{ML}$ is the ML point estimate; "MLE Std." is the standard deviation of the ML estimate, calculated using the analytical Fisher Information Matrix derived in Appendix 3.6.3: $\sqrt{\mathscr{I}(\hat{\theta}^{ML})_{ii}^{-1}}$; $\mathbb{E}(\theta_i)$ is the expected value of the posterior distribution; $\sqrt{\mathbb{V}(\theta_i)}$ is the standard deviation of the posterior distribution; $Pr(\theta < 0)$ is the probability that a parameter is negative, calculated by integrating the posterior distribution; p% is the p-th percentile of the posterior distribution. For brevity we don't report here the Industry Fixed Effects and the Industry specific variances. In the first columns, the spatial parameters also report the type of fiscal plan they are interacted with (in blue).

Model Selection - Vuong Test for Static Spatial Panel Data

We also provide results for a Vuong test of non-nested models, adapted to our spatial specification, as in Wooldridge (2010).

Firstly, the Vuong test (see Vuong (1989)) is meant to discriminate between two misspecified and non-nested models. Basically, we assume there is a hidden true model and we want to choose one of two competing non-nested models which fit the data equally well. The Vuong test calculates and compares the Kullback-Leibler distance between the two and the true model. In practice, is a t-test on the KL divergence. One problem we encounter is that it was developed for one-dimensional iid data, however, we deal with a panel whose observations are serially uncorrelated but spatially correlated. Wooldridge (2010) shows that the Vuong test can easily be extended to panel data models by accounting for serial correlation in the time series.[34] However, in our problem the $n \times 1$ vector of industry observations is iid over time and our asymptotic keeps the cross-sectional dimension, which is spatially correlated, fixed, and then let the time series to go to infinite $T \to \infty$. Economically speaking this makes sense: we observe those fixed

[34]See Section 13.11.2 - Model Selection Tests.

62 industries over time, however, the cross sectional dimension exceeds the times series one, 37 years. This means that our finite sample distribution will not be a very good approximation of the asymptotic one. However, this is the best we can do, given the data availability.

Let's derive now the Vuong Test. The quasi-log-likelihood of the baseline model, Equation (3.6), is:

$$\ell_{t,B}(\underbrace{\rho,\beta,\Omega}_{\theta_B}) = \log f_B(\Delta y_t|X_t;\theta_B) = -\frac{n}{2}\ln(2\pi) - \frac{1}{2}\cdot\ln(|\Omega|) +$$
$$+\ln(|I_n - \rho^{down}\cdot A\cdot TB_t - \rho^{up}\cdot\hat{A}'\cdot EB_t|) - \frac{1}{2}\cdot\varepsilon_t'\cdot\Omega^{-1}\cdot\varepsilon_t.$$

with:

$$\varepsilon_t = \left(I_n - \rho^{down}\, A\; TB_t - \rho^{up}\,\hat{A}'\; EB_t\right)\cdot\Delta y_t - X_t\cdot\beta.$$

The sum of the quasi-log-likelihood evaluated at the MLE, $\hat{\theta}_B$, for the baseline model is: $\mathscr{L}_B = \sum_{t=1}^{T}\ell_{t,B}(\hat{\theta}_B)$. Analogously, for the inverted model, Equation (3.7), the quasi-log-likelihood is:

$$\ell_{t,I}(\underbrace{\tilde{\rho},\tilde{\beta},\tilde{\Omega}}_{\theta_I}) = \log f_I(\Delta y_t|X_t;\theta_I) = -\frac{n}{2}\ln(2\pi) - \frac{1}{2}\cdot\ln(|\tilde{\Omega}|) +$$
$$+\ln(|I_n - \tilde{\rho}^{down}\cdot A\cdot EB_t - \tilde{\rho}^{up}\cdot\hat{A}'\cdot TB_t|) - \frac{1}{2}\cdot\varepsilon_t'\cdot\tilde{\Omega}^{-1}\cdot\varepsilon_t.$$

with:

$$\varepsilon_t = \left(I_n - \tilde{\rho}^{down}\, A\; EB_t - \tilde{\rho}^{up}\,\hat{A}'\; TB_t\right)\cdot\Delta y_t - X_t\cdot\tilde{\beta}.$$

The sum of the quasi-log-likelihood evaluated at the MLE, $\hat{\theta}_I$, for the inverted model is: $\mathscr{L}_I = \sum_{t=1}^{T}\ell_{t,I}(\hat{\theta}_I)$.

Following Wooldridge (2010), let's define the estimator for the variance of the KL divergence as:

$$\hat{\eta}^2 = \frac{1}{T}\cdot\sum_{t=1}^{T}\left(\ell_{t,B}(\hat{\theta}_B) - \ell_{t,I}(\hat{\theta}_I)\right)^2.$$

Then, the Vuong Model Selection Statistic, VMS, is:

$$
\begin{aligned}
VMS &= T^{-1/2} \cdot \frac{(\mathscr{L}_B - \mathscr{L}_I)}{\hat{\eta}} \\
&= \frac{\frac{1}{T} \cdot \sum_{t=1}^{T} \left(\ell_{t,B}(\hat{\theta}_B) - \ell_{t,I}(\hat{\theta}_I) \right)}{\sqrt{\frac{\frac{1}{T} \cdot \sum_{t=1}^{T} \left(\ell_{t,B}(\hat{\theta}_B) - \ell_{t,I}(\hat{\theta}_I) \right)^2}{T}}} \xrightarrow{d} N(0,1)
\end{aligned}
$$

where the standard normal distribution holds under:

$$H_0 : \mathbb{E}[\ell_{t,B}(\theta_B^*)] = \mathbb{E}[\ell_{t,I}(\theta_I^*)]$$

where θ_B^* and θ_I^* are the pseudo-true values of the parameters. Basically, the null hypothesis is saying that the two potentially misspecified models fit the data equally well. Notice that the test is super easy to implement: 1) define the difference: $\hat{d}_t = \ell_{t,B}(\hat{\theta}_B) - \ell_{t,I}(\hat{\theta}_I)$; 2. Regress $\hat{d}_t$ on unity; 3. Run a t-test to verify that the average of the difference is statistically different from zero.

We reject the null hypothesis in favor of a better fit to the data of the baseline model if $\hat{d}_t$ is statistically greater than zero. Notice that if this happens it does not mean that the baseline model is correctly specified (although it could be), however, we can conclude that the baseline model fits better in terms of expected likelihood.

The value we obtain is VMS = 0.033 which is clearly not statistically different from zero. Even if positive sign of the statistics points at a better fit of the baseline model against the inverted one, there is not enough statistical evidence to claim that the baseline outperforms on average the inverted model.

Output Effect of Fiscal Plans in the Inverted Model

We report here the estimated posterior distributions of the ATE, ADE and ANE for fiscal adjustment plans obtained from the estimates of Equation (3.7) (inverted model).

Table 3.8. AVERAGE TOTAL, DIRECT AND NETWORK EFFECTS OF FISCAL CONSOLIDATIONS IN THE UNITED STATES

Inverted Model - Equation (3.7)											
	$\mathbb{E}(\theta)$	*%*	$\sqrt{\mathbb{V}(\theta)}$	$Pr(\theta < 0)$	*5%*	*10%*	*16%*	*50%*	*84%*	*90%*	*95%*
ATE_{TB}	-1.148	1	1.034	0.872	-2.909	-2.481	-2.162	-1.107	-0.131	0.140	0.480
ADE_{TB}	-0.848	0.74	0.756	0.872	-2.106	-1.819	-1.593	-0.835	-0.101	0.107	0.375
ANE_{TB}	-0.300	0.26	0.290	0.872	-0.828	-0.682	-0.572	-0.263	-0.029	0.030	0.102
ATE_{EB}	0.522	1	0.337	0.064	-0.048	0.096	0.203	0.536	0.847	0.936	1.046
ADE_{EB}	0.491	0.94	0.318	0.064	-0.044	0.089	0.188	0.501	0.799	0.886	0.990
ANE_{EB}	0.031	0.06	0.032	0.064	-0.002	0.002	0.005	0.024	0.059	0.073	0.091

Notes: descriptive statistics of posterior distributions of Average Effects of a 2 years, 1% magnitude fiscal adjustment plan. 2 years means that results are calculated by cumulating the effect of the first year of the plan and then the second one. The style of the plan is simulated from a distribution which mimics the observed one; see Appendix 3.6.3 for technical details. Columns: $\mathbb{E}(\theta)$ is the expected value of the posterior distribution; % is the share of ATE represented by ADE and ANE. $\sqrt{\mathbb{V}(\theta)}$ is the standard deviations of the posterior distribution; $Pr(\theta < 0)$ is the probability of negative values, calculated by integrating the posterior distribution; "p%" is the p-th percentile of the posterior distribution.

The most important thing to notice is that the ANE of EB plans accounts for only 6% of their ATE, against the 12% of the baseline model. The relevance of ANE of TB plans is basically unaffected, diminishing only by 1% relative to the baseline (from 27% of the ATE to 26%). The statistical significance of the ANE of TB plans declines, since the posterior distribution shrinks towards zero.

3.6.5 A Potential Theoretical Framework

We show here the theoretical framework which we have in mind when we refer to the theoretical transmission of demand and supply shocks. The model is a slight modification of Acemoglu, Akcigit, and Kerr (2016), which we adapted to allow for the propagation of a production tax.

The model considers a perfectly competitive economy with n sectors, where the market clearing condition for the generic industry i is:

$$y_i = c_i + \sum_{j=1}^{n} x_{ji} + G_i \tag{3.8}$$

where c_i is household's consumption of good produced by industry i; x_{ij}[35] is the quantity of goods produced in industry j used as inputs by industry i; G_i are government purchases.

$$\sum_{i=1}^{n} p_i G_i = T + \tau \sum_{i=1}^{n} p_i y_i \tag{3.9}$$

Each sector solves the following profit maximization problem:

$$\max_{l_i, \{x_{ij}\}_{j=1}^{n}} (1-\tau) \cdot p_i \cdot \left(\underbrace{l_i^{\alpha_i^l} \cdot (\prod_{j=1}^{n} x_{ij}^{\alpha_{ij}})^{\rho}}_{y_i} \right) - w l_i - \sum_{j=1}^{n} p_j x_{ij}$$

where τ is a sales/production tax which mimics an excise tax.[36] Notice that the production function is similar to the one in Acemoglu, Carvalho, et al. (2012). All alpha's are non negative, and we assume constant return to scale: $\alpha_i^l + \rho \cdot \sum_{j=1}^{n} a_{ij} = 1$. Notice here, that thanks to the Cobb-Douglas specification, ρ can be interpreted as the share of intermediates in production.

The economy is populated by a representative agent, who maximizes utility subject to a budget constraint:

$$\max_{l, \{c_i\}_{i=1}^{n}} (1-l)^{\lambda} \cdot \prod_{i=1}^{n} c_i^{\beta_i} \quad \text{s.t.} \sum_{i=1}^{n} p_i c_i \leq wl$$

with $\sum_{i=1}^{n} \beta_i = 1$.

Firms and households take all prices as given, and the market-clearing conditions are satisfied in the goods market and the labor market. Government actions are taken as given and the wage is chosen as a numeraire $(w = 1)$.

We do not explicitly model a government budget constraints, since during years of

[35] In Equation (3.8) we actually have x_{ji}, that is, the amount of good i used as input by industry j; we then sum over the j-s to obtain the total demand of good i from all the industries.

[36] For example, an excise is a special type of sales tax, which is sector-specific. Excise tax might be of two types: ad valorem (percentage of values of a good) and specific (tax paid per unit). The excise tax may be paid by the producer, retailer, and consumer. Moreover, it might be taken on federal, state, and local levels.

fiscal consolidations, spending cuts are not compensated by tax reductions and viceversa. For simplicity we also do not model government debt and deficit.

Households.

The household problems returns the following equilibrium conditions:

$$\frac{p_i \cdot c_i}{\beta_i} = \frac{p_j \cdot c_j}{\beta_j} \quad \forall i, j$$
$$l = \frac{1}{1+\lambda}$$
$$c_i = \frac{\beta_i}{p_i} \cdot \frac{1}{1+\lambda} \quad \forall i$$
$$\sum_{i=1}^{n} p_i \cdot c_i = \frac{1}{1+\lambda}$$

Therefore, in equilibrium we have:

$$d \log c_i = -d \log p_i \quad \forall i$$

that is, percent changes in consumption of good i only depend on percent changes in the price of the same good (with Cobb-Douglas utility income and substitution effects cancel out).

Firms

Firms maximize profits and in equilibrium the following FOCs hold true:

$$(1-\tau) \cdot p_i \cdot \rho \cdot a_{ij} \cdot \frac{y_i}{x_{ij}} = p_j$$
$$(1-\tau) \cdot p_i \cdot \rho \cdot a_i^l \cdot \frac{y_i}{l_i} = 1$$
$$y_i = l_i^{\alpha_i^l} \cdot \big(\prod_{j=1}^{n} x_{ij}^{\alpha_{ij}}\big)^{\rho}$$

Acemoglu, Akcigit, and Kerr (2016) notes that solving the dual problem (cost minimization) and obtaining the unit cost function is beneficial to the analysis. The unit cost function is equal to:

$$C(p_1,...,p_n) = \underbrace{\left(\frac{1}{a_i^l}\right)^{a_i^l} \cdot \left(\prod_{j=1}^{n}\left(\frac{1}{\rho \cdot a_{ij}}\right)^{a_{ij}}\right)^{\rho}}_{:=B_i} \left(\prod_{j=1}^{n} p_j^{a_{ij}}\right)^{\rho}.$$

Because of perfect competition, price equals marginal cost. Therefore:

$$(1-\tau)\cdot p_i = C(p_1,...,p_n)$$

By log differentiating the above expression, we have:

$$d\log p_i = \rho \cdot \sum_{j=1}^{n} a_{ij} \cdot d\log p_j + \frac{\tau}{1-\tau} d\log\tau$$

The above expression implies that prices are affected only by changes in the production tax τ. Moreover, from profit maximiation we also have:

$$\rho \cdot a_{ij} = \frac{1}{1-\tau} \cdot \frac{p_j \cdot x_{ij}}{p_i \cdot y_i} \propto \frac{\text{SALES}_{j\to i}}{\text{SALES}_i}.$$

In other word, if sector i is affected by a tax shock, the effect is propagated downstream to the customers, via x_{ij}. This should be clear if we substitute the firm's FOC condition into the previous expression:

$$d\log p_i = \frac{1}{1-\tau} \cdot \sum_{j=1}^{n} \frac{p_j \cdot x_{ij}}{p_i \cdot y_i} \cdot d\log p_j + \frac{\tau}{1-\tau} d\log\tau.$$

Network effect of a tax shock

We want to know what is the output effect of a change in the production tax. In order to do so, we need to look at the resource constraint (assuming for simplicity that $G_i = 0$ for all sectors):

$$
\begin{aligned}
y_i &= c_i + \sum_{j=1}^{n} x_{ji} \\
\frac{y_i}{c_i} &= 1 + \sum_{j=1}^{n} \frac{x_{ji}}{c_i} \quad \text{plug in: } x_{ji} = (1-\tau)\cdot p_j \cdot \rho \cdot a_{ji} \cdot \frac{y_j}{p_i} \text{ (Firm FOC)} \\
\frac{y_i}{c_i} &= 1 + (1-\tau)\cdot\rho \sum_{j=1}^{n} a_{ji} \cdot \frac{p_j \cdot y_j}{p_i \cdot c_i} \quad \text{plug in: } c_i = \frac{\beta_i}{\beta_j} \cdot \frac{p_j \cdot c_j}{p_i} \text{ (HH FOC)} \\
\frac{y_i}{c_i} &= 1 + (1-\tau)\cdot\rho \sum_{j=1}^{n} a_{ji} \cdot \frac{\beta_i}{\beta_j} \cdot \frac{y_j}{c_j} \quad \text{Denote by: } \theta_i := y_i/c_i \\
\theta_i &= 1 + (1-\tau)\cdot\rho \sum_{j=1}^{n} \underbrace{a_{ji} \cdot \frac{\beta_i}{\beta_j}}_{m_{ij}} \cdot \theta_j
\end{aligned}
$$

Denote by $M := [m_{ij}]_{i,j=1,\ldots,n}$. Then, in matrix notation the above expression becomes:

$$
\boldsymbol{\theta} = \mathbf{1}_n + (1-\tau)\cdot\rho\cdot M\cdot\boldsymbol{\theta} \implies \boldsymbol{\theta} = (I_n - (1-\tau)\cdot\rho\cdot M)^{-1}\cdot\mathbf{1}_n
$$

Notice that the equilibrium level of the output-to-consumption ratio, θ_i, has a nice analytical form which, however, depends on τ. Therefore, when τ changes, also this ratio changes and we don't have $d\log y_i = d\log c_i$ as in Acemoglu, Akcigit, and Kerr (2016).

Differentiating the above expression yields:

$$
\begin{aligned}
d\boldsymbol{\theta} &= \frac{\partial\left(I_n - (1-\tau)\cdot\rho\cdot M\right)^{-1}}{\partial\tau}\cdot\mathbf{1}_n d\tau \\
&= -\rho\cdot(I_n - (1-\tau)\cdot\rho\cdot M)^{-1}\cdot M\cdot(I_n - (1-\tau)\cdot\rho\cdot M)^{-1}\cdot\mathbf{1}_n d\tau
\end{aligned}
$$

Using the $d\log$ notation:

$$
d\log\boldsymbol{\theta} = -\underbrace{\tau\cdot\rho\cdot\Theta^{-1}\cdot(I_n - (1-\tau)\cdot\rho\cdot M)^{-1}\cdot M\cdot(I_n - (1-\tau)\cdot\rho\cdot M)^{-1}}_{:=F}\cdot\mathbf{1}_n d\log\tau
$$

where $\Theta = diag(\theta_1, ..., \theta_n)$. Recalling the definition of θ_i, we have:

$$d\log \boldsymbol{y} = d\log \boldsymbol{c} - F \cdot \mathbf{1}_n \cdot d\log\tau \implies d\log y_i = d\log c_i - \phi_i \cdot d\log\tau$$

where ϕ_i is the i-th element of vector $F \cdot \mathbf{1}_n$. Notice that if τ were fixed (i.e. $d\log\tau = 0$), percent changes in consumption would be equal to the one of output, as in Acemoglu, Akcigit, and Kerr (2016).

At this point we can find the relationship between output changes and tax shocks. Consider the following three equations we derived earlier:

$$\begin{cases} d\log y_i & = d\log c_i - \phi_i \cdot d\log\tau \\ d\log c_i & = -d\log p_i \\ d\log p_i & = \rho \cdot \sum_{j=1}^{n} a_{ij} \cdot d\log p_j + \dfrac{\tau}{1-\tau} d\log\tau \end{cases}$$

Combining the three equations above yields the following expression:

$$\begin{aligned} d\log y_i &= \rho \cdot \sum_{j=1}^{n} a_{ij} \cdot d\log y_j - \underbrace{\left(\phi_i + \frac{\tau}{1-\tau} - \rho \cdot \sum_{j=1}^{n} \phi_j \cdot a_{ij}\right)}_{=\psi_i > 0} \cdot d\log\tau \\ &= \rho \cdot \sum_{j=1}^{n} a_{ij} \cdot d\log y_j - \psi_i \cdot d\log\tau \end{aligned}$$

which is Equation (3.4) in the third chapter.

Network effect of a spending shock

Suppose now that $\tau = 0$ and that the government reduces its purchases from all sectors (i.e. $d\log G_i < 0$). We want to find the relationship between the percent change in output, $d\log y_i$ and percent changes in government purchases $d\log G_i$.

Consider the resource constraint of the economy:

$$
\begin{aligned}
y_i &= c_i + G_i + \sum_{j=1}^{n} x_{ji} \quad \text{Log-differentiate} \\
d\log y_i &= \frac{c_i}{y_i} \underbrace{d\log c_i}_{=0\ (d\log p_i = 0)} + \frac{G_i}{y_i} d\log G_i + \sum_{j=1}^{n} \frac{x_{ji}}{y_i} \cdot d\log x_{ji} \quad \text{(Firm FOC) } x_{ji} = p_j \rho a_{ji} \frac{y_j}{p_i} \\
d\log y_i &= \frac{G_i}{y_i} d\log G_i + \rho \cdot \sum_{j=1}^{n} \underbrace{a_{ji} \cdot \frac{p_j\, y_j}{p_i\, y_i}}_{:=\hat{a}_{ji}} d\log x_{ji} \\
d\log y_i &= \frac{G_i}{y_i} d\log G_i + \rho \cdot \sum_{j=1}^{n} \hat{a}_{ji} \cdot d\log x_{ji}
\end{aligned}
$$

From the firm's FOC, we have:

$$
d\log y_i = \underbrace{d\log p_j}_{0} + d\log x_{ji} - \underbrace{d\log p_i}_{=0}
$$

therefore we can retrieve Equation (3.2):

$$
d\log y_i = \rho \cdot \sum_{j=1}^{n} \hat{a}_{ji} \cdot d\log y_j + \frac{G_i}{y_i} d\log G_i.
$$

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