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ESTIMATING THE EFFECTS OF GOVERNMENT SPENDING THROUGH THE PRODUCTION NETWORK

Alessandro Barattieri
Matteo Cacciatore
Nora Traum

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ABSTRACT

We estimate the effects of government spending along the supply chain using disaggregated U.S. government procurement data. We first identify sectoral public spending shocks and combine them with input-output tables to measure upstream and downstream exposure through the production network. We then estimate panel local projections and find that sector-specific government purchases have sizable effects both in industries that receive procurement contracts and industries across the supply chain. Employment increases significantly in recipient industries and in sectors supplying intermediate inputs to these industries, while employment decreases downstream. The response of prices and wages suggest higher intermediate-input demand by recipient industries translates into higher intermediate-input prices across the network, accounting for the crowding out of downstream employment. We then estimate the aggregate implications of sectoral shocks and the influence of sectoral heterogeneity using a granular instrumental variable approach. Consistent with existing models, we find that aggregate effects are higher when recipient sectors are more downstream, have stickier prices, and when the government accounts for most of the recipient's total sales.

Alessandro Barattieri
World Bank
1818 H st. NW
Washington, DC 20433
United States
abarattieri@worldbank.org

Matteo Cacciatore
HEC Montreal
Institute of Applied Economics
3000 Côte-Sainte-Catherine
Montreal, QC H3T 2A7
and NBER
matteo.cacciatore@hec.ca

Nora Traum
HEC Montreal
Institute of Applied Economics
3000, chemin de la Cote-Sainte-Catherine
Montreal, Quebec H3T 2A7
Canada
nora.traum@hec.ca

1 Introduction

In the last decade, a vast research program has documented the importance of input-output linkages and the production network for the transmission of shocks and policies.[1] Spurred by the observation that public purchases of goods and services from the private sector are highly granular (Cox et al., 2022), i.e., concentrated in a few industries, a rapidly expanding theoretical literature examines how sectoral characteristics of recipient industries influence the aggregate spending multiplier (e.g., Bouakez et al., 2022; Cox et al., 2022; Proebsting, 2022). To date, however, there is very limited empirical evidence on how production linkages propagate sector-specific government spending.

How do changes in granular spending affect employment, output, and prices in the recipient industries? How do they transmit through the production network? And ultimately, what are the implications for aggregate outcomes? Addressing these questions has first-order implications for policy design, as the composition of public spending changes over time when the government's needs and preferences vary.[2] In addition, studying the supply-chain transmission of sectoral spending shocks has implications for the design of production network models, as it provides a sharp example of the propagation of granular demand shocks.

To estimate the industry and aggregate effects of public spending, we use the universe of U.S. federal purchases accessible through *USASpending.gov*. The database provides detailed information on individual U.S. procurement contracts for goods and services. It includes both defense and non-defense contracts, and recipient industries encompass both manufacturing and services sectors.

Our first contribution is to identify sectoral changes that are plausibly unanticipated and uncorrelated with macroeconomic outcomes. Using the universe of contracts awarded from 2001 to 2019, we construct quarterly spending data for a panel of NAICS 6-digit industries, the finest possible sectoral disaggregation. We then purge sectoral government spending of movements representing an endogenous response to economic conditions or variation that is likely anticipated. Our approach builds on a consolidated strategy in the monetary and

[1] For an excellent review of this literature, see Carvalho and Tahbaz-Salehi (2019).

[2] The targeted fiscal policy interventions during the COVID-19 pandemic and the recent build-up of military spending provide clear examples of how public spending can change across sectors over time.

fiscal policy literature (e.g., Romer and Romer, 2004; Auerbach and Gorodnichenko, 2013), although implemented at a much finer aggregation level and exploiting the panel dimension of the data. Since implementation lags can make spending changes forecastable, particularly following the enactment of fiscal-year budgets, we employ two industry-specific controls that address potential anticipation. The first control is the market-to-book ratio, a benchmark measure of expected profitability derived from firm-level data. The second control consists of industry-specific fixed effects for each fiscal year, capturing expectations regarding within-year allocations of spending. We further consider a specification that exploits contract-level information by restricting the analysis to competitively bid contracts, which are also less likely to be anticipated. In addition, aggregate time fixed effects control for macroeconomic shocks and policies, while other industry-specific controls capture pre-existing sector-specific business cycle conditions.

To gain a better understanding of the origins of the estimated sectoral shocks, we delve into the contract details during the episodes that exhibit the largest unexplained spending variation. We gather firm and contract-level information that helps us contextualize the largest identified shocks. While the median number of firms and contracts per episode is large—648 and 1,710, respectively—the data is highly granular. This is evident as the median share of total spending attributed to the top three recipient firms amounts to 48%. For these top firms, several contracts received media coverage around the signing date, as documented on Factiva. Moreover, many contracts were awarded through competitive processes. Taken together, this evidence suggests that the biggest contracts underlying the largest identified shocks were unlikely to be anticipated by market participants and recipient firms. Furthermore, the timing of several contracts overlaps with events such as military expenditures for conflicts in Iraq and Afghanistan, as well as relief efforts for natural disasters like Hurricane Katrina.

We use the identified industry-level shocks and input-output tables to construct upstream and downstream spending measures capturing the exposure of the suppliers and customers of the recipient industries (i.e., the industries that receive procurement contracts).[3] We then

[3]We aggregate the identified shocks to the NAICS 4-digit level—the most detailed level at which comprehensive data for employment, producer prices, and input-output relationships are available at a consistent level of aggregation.

estimate panel local projections to trace the dynamic response of employment in recipient industries, as well as along the supply chain (i.e., in industries that supply to or buy from recipient industries). We find that employment increases significantly in recipient industries and in sectors supplying intermediate inputs to the recipient industries. In contrast, employment is crowded out downstream. The responses peak several quarters after the initial shock, showing the importance of estimating dynamic responses, hitherto unexplored in the literature. These results survive a battery of sensitivity analyses along several dimensions, including using different measures of government spending and industrial production as an alternative measure of economic activity.[4]

Our second contribution is to provide evidence on the economic mechanism that can explain the estimated network effects, particularly the downstream transmission. We find that prices and wages increase significantly in recipient industries and suppliers to recipients. Thus, both quantity and price responses in the recipient industries and their suppliers are consistent with the textbook transmission of a positive demand shock. Furthermore, price and wage increases in recipient and upstream industries can explain the negative effects on downstream sectors, as higher input prices result in lower input demand and production downstream. We provide additional evidence for this mechanism by showing that intermediate input prices for downstream sectors increase significantly after a sectoral spending shock.

The industry-level analysis demonstrates that sector-specific changes in public demand have heterogeneous effects along the supply chain. This result begs the question of how production linkages and recipient-industry characteristics shape the aggregate effects of sectoral spending. Recent theoretical work yields testable predictions about the aggregate public spending multiplier in production network models. Specifically, theory predicts that the aggregate multiplier is larger when sector-specific spending occurs in industries that (i) are relatively more downstream (Bouakez et al., 2023), (ii) have stickier prices (Bouakez et al., 2023 and Cox et al., 2022), and (iii) sell most of their output directly to the government

[4] We do not consider industrial production in our main specification as it is only available for manufacturing sectors. While output data is available from the BEA at a disaggregated level, it is only consistently available at an annual frequency, precluding its use.

(Cox et al., 2022, and Proebsting, 2022). Our third and last contribution is to quantify the aggregate implications of sectoral shocks and examine how industry characteristics shape the GDP multiplier.

Since the industry-level estimates identify local (relative) effects (e.g., Chodorow-Reich, 2020), they cannot be used to infer aggregate outcomes. For this reason, to estimate the GDP multiplier from aggregate procurement contracts, we construct an aggregate instrumental variable that addresses the potential endogeneity of public spending. Specifically, we implement the granular instrumental variable (GIV) approach proposed by Gabaix and Koijen (2020). Our context represents an ideal setting for this approach since a few large industries account for a large share of total spending. As idiosyncratic shocks from sectors that have exceptionally large weight in total government spending affect aggregate outcomes, they are valid and powerful instruments for total spending.[5] We first show that estimating cumulative GDP multipliers with local projections-IV (Ramey and Zubairy, 2018)—using the GIV as an instrument for the aggregate of procurement contracts—yields estimates in line with the literature that uses aggregate spending data. The GDP multiplier is significantly positive, less than one, and persistent. This result suggests that the positive output effects in recipient and upstream industries are larger than the downstream crowding in general equilibrium.

We then turn to the role of sectoral heterogeneity. In this case, we adapt the GIV approach by creating separate instruments for sectors classified as above or below the median industry, based on a specific sectoral characteristic. We find that when government demand falls on sectors that are relatively more downstream, the GDP multiplier is significantly larger and well above one. The multiplier is also larger when spending is allocated to sectors with higher price rigidities, albeit this effect is estimated less precisely. Finally, the multiplier is significantly higher when government spending represents a larger share of total demand of recipient sectors. Overall, these results provide empirical support to recent theoretical insights and demonstrate the importance of network considerations for the overall impact of granular public spending.

[5] While we can exploit NAICS-4 digit granularity to instrument for aggregate procurement spending, there is not enough idiosyncratic variation at the NAICS-6 digit level to instrument disaggregated industry-level spending.

Related Literature. Our paper breaks new ground by identifying sector-specific fiscal shocks, tracing their dynamic impact on industries via the production network, and quantifying how these effects shape aggregate outcomes. Our work relates to several strands of the literature.

First, previous studies have used the *USASpending.gov* database to analyze defense spending (e.g., Auerbach et al., 2020a and Demyanyk et al., 2019) or contracts awarded to publicly listed firms (Hebous and Zimmermann, 2021). Only Cox et al. (2022) has previously utilized the universe of the database's contracts, without focusing on the production network transmission.

Second, we relate to the literature on the industry-level effects of government spending. A few studies have examined the effects of public spending within recipient industries (e.g., Nekarda and Ramey, 2011; Nakamura and Steinsson, 2014), yet abstracted from input-output linkages. Auerbach et al. (2020a) and Acemoglu et al. (2016) estimate the average upstream effect of government spending shocks. Both studies use yearly data for the manufacturing sector, abstract from price and wage dynamics, and rely on a Bartik approach to instrument sector-specific government spending. However, when studying production network transmissions, the Bartik approach faces some limitations, namely a high cross-industry correlation of the instruments that can result in spurious network effects (e.g., Acemoglu et al., 2016). Motivated by these facts, we develop a new approach that identifies exogenous variation in sector-specific public spending using disaggregated data.

Third, our results relate to the broad literature that studies how the production network propagates shocks and policies. A strand of this literature demonstrates that granular supply and demand shocks that impact large firms or sectors can lead to aggregate fluctuations as they propagate through input-output linkages. Acemoglu et al. (2012), Baqaee and Farhi (2018), and Baqaee and Farhi (2019) characterize theoretically the transmission of shocks along the supply chain.[6] Barrot and Sauvagnat (2016), Boehm et al. (2019), and Carvalho et al. (2021) use natural disasters to study the role of firm-level linkages in propagating shocks. Barrot and Sauvagnat (2016) find downstream propagation of several disaster

[6]See also Atalay (2017);Baqaee and Farhi (2020); Bigio and La'O (2020); Dhyne et al. (2021); and vom Lehn and Winberry (2022).

episodes in the U.S. Boehm et al. (2019) provide evidence that U.S. affiliates of Japanese multinationals suffered large output losses following the 2011 earthquake in Japan. Using the same episode, and exploiting detailed information on the firm-to-firm network of Japanese firms, Carvalho et al. (2021) find both downstream and upstream propagation. While these studies focus on supply-side shocks, our findings on the downstream propagation of public spending shocks offer new empirical insights into the network transmission of granular demand shocks. Our results indicate that relative price adjustment plays a central role in the propagation of demand shocks, a result overlooked in conventional production network models.

Another branch of this literature examines the impact of sector characteristics and input-output linkages on the transmission of macroeconomic policy. While various contributions focus on monetary policy (e.g., Rubbo, Elisa, 2023, and references therein), a growing literature investigates how the allocation of government spending across sectors affects the GDP multiplier. As previously discussed, recent theoretical work highlights the importance of the network position of recipient industries, as well as the extent of their price stickiness and dependence on public demand (Bouakez et al., 2022; Cox et al., 2022; Proebsting, 2022). In addition, Baqaee and Farhi (2018) and Flynn et al. (2021) emphasize the importance of household-firm interactions, as sectors can differ with respect to the distribution of their workers' marginal propensities to consume, which in turn affects the aggregate multiplier. On the empirical front, Bouakez et al. (2023) show the degree of upstreamness is quantitatively important for the local (state-level) multiplier using a Bartik instrument. Cox et al. (2022) use a Blanchard and Perotti (2002) identification in a VAR and find some support for larger output effects when public spending originates in sectors with stronger price rigidities. We contribute to this literature by using for the first time a granular instrumental variable (GIV) approach to identify aggregate effects using highly disaggregated data on public procurement.

Outline. The rest of the paper is organized as follows. Section 2 describes the government spending data, while Section 3 discusses our identification strategy of exogenous sectoral public spending changes. Section 4 presents the baseline results of our panel local projections and sensitivity analysis. Section 5 provides an empirical examination of the economic mechanisms that can explain the results. Section 6 presents estimates for the aggregate implications and how they depend on sectoral heterogeneity. Section 7 concludes.

2 Data

To construct industry measures of government spending, we use the public U.S. database *USASpending.gov*. Created out of the Federal Funding Accountability and Transparency Act (FFATA), this database maintains information on individual private contracts awarded from all federal agencies since the fiscal year 2001. Each observation in the database traces a contract from its origin (government agency) to its recipient (individual firm), recording detailed information on the awarded amount, duration, location, NAICS code, and manner in which the contract is executed. These federal procurement contracts encompass public purchases of intermediate goods and services, as well as investment in structures, equipment, and software. According to the National Income and Product Accounts, these expenditures represent roughly 45% of total federal government spending.

To create outflow spending measures from the individual contracts, we first compute average monthly spending per contract by dividing the contract's total obligation value by the monthly duration of the contract. We then equally allocate this value to each month of the contract's lifetime. This method is widely adopted in the literature and the resulting measure closely tracks relevant defense and non-defense spending components in the National Income and Product Accounts (see Auerbach et al., 2020a and Cox et al., 2022).

For our empirical analysis, we use quarterly industry measures over the period 2001-2019. To do so, we aggregate the individual contract outflows by the quarter at the NAICS-6 digit level. The mean of the industry-quarter measure is roughly 70 million dollars, and the distribution is right-skewed with the median being slightly less than 1 million dollars. As documented by Cox et al. (2022), the data is highly granular, with a few industries accounting for a very large share of total spending. For example, Table 1 shows that, at the NAICS 4-digit level (which encompasses a total of 324 industry groups), the top 30 recipient industries account for almost 80% of total procurement spending. Notably, the top 30 recipient industries are split roughly in half between manufacturing (NAICS-3xxx digit codes) and services (NAICS-4xxx and -5xxx digit codes). Using data from both manufacturing and services is therefore important for characterizing how government spending propagates across the production network.

Although the top recipient industries remain stable over time, there are significant movements in the industry shares of public spending. To see this, the blue solid lines of Figure 1 plot the percent of procurement spending allocated to each of the top recipient industries over our sample.[7] In some industries, for instance aerospace product manufacturing and scientific research & development services (NAICS codes 3364 and 5417), the share fluctuates as much as 4% over our sample. This variation is roughly 20 times larger than the fluctuations in their respective industry output shares (see the red solid lines of Figure 1).[8] The figure also shows that various industries exhibit strongly correlated trends across spending and output shares (for example, industries 3341, computer and peripheral equipment manufacturing, and 3344, semiconductor and other electronic component manufacturing). Such trends suggest that some spending changes may be driven by shocks common to both production and government demand. For instance, Nekarda and Ramey (2011) suggest that industry-specific technological developments fueling new generations of weapon systems or computing machinery could affect sectoral output and spending simultaneously.[9] Additionally, since government spending has experienced structural change in the past decades—relying more on private-sector goods than its own production of value added (Moro and Rachedi, 2022)—spending shares may not be exogenous to growth rates of sectoral output and employment.

Given our focus on the propagation of public spending changes through the production network, it is also useful to examine the network structure of the industries receiving government demand. Towards this end, we measure the suppliers' and customers' exposure from

[7]We consider industries for which we have corresponding output data.

[8]Industry output is measured as gross output from the U.S. Bureau of Economic Analysis.

[9]Such trends could also be driven solely by the government if trends in government demand cause trends in production. As shown in Figure A.1 of the Appendix, this is unlikely as the share of government spending to industry output is small —less than 10% — for most of these industries.

Table 1: Top 30 recipients industries, NAICS 4-digit classification

NAICS	Industry	% of G
3364	Aerospace Product and Parts Manufacturing	14.57
5417	Scientific Research and Development Services	9.22
5413	Architectural, Engineering, and Related Services	7.52
5415	Computer Systems Design and Related Services	7.23
5612	Facilities Support Services	4.89
2362	Nonresidential Building Construction	3.53
5416	Management, Scientific, and Technical Consulting Services	3.33
3366	Ship and Boat Building	3.11
3345	Navigational, Measuring, Electromedical, and Control Inst Manuf	2.85
5241	Insurance Carriers	2.29
5419	Other Professional, Scientific, and Technical Services	1.84
3342	Communications Equipment Manufacturing	1.78
3254	Pharmaceutical and Medicine Manufacturing	1.54
3369	Other Transportation Equipment Manufacturing	1.49
3241	Petroleum and Coal Products Manufacturing	1.46
3329	Other Fabricated Metal Product Manufacturing	1.36
4242	Drugs and Druggists' Sundries Merchant Wholesalers	1.05
3341	Computer and Peripheral Equipment Manufacturing	1.01
2379	Other Heavy and Civil Engineering Construction	0.96
5629	Remediation and Other Waste Management Services	0.92
5616	Investigation and Security Services	0.81
4881	Support Activities for Air Transportation	0.81
5171	Wired Telecommunications Carriers	0.75
4812	Nonscheduled Air Transportation	0.67
3362	Motor Vehicle Body and Trailer Manufacturing	0.61
4244	Grocery and Related Product Merchant Wholesalers	0.61
3344	Semiconductor and Other Electronic Component Manufacturing	0.60
4431	Electronics and Appliance Stores	0.59
3361	Motor Vehicle Manufacturing	0.56
6113	Colleges, Universities, and Professional Schools	0.55
	TOTAL	**78.54**

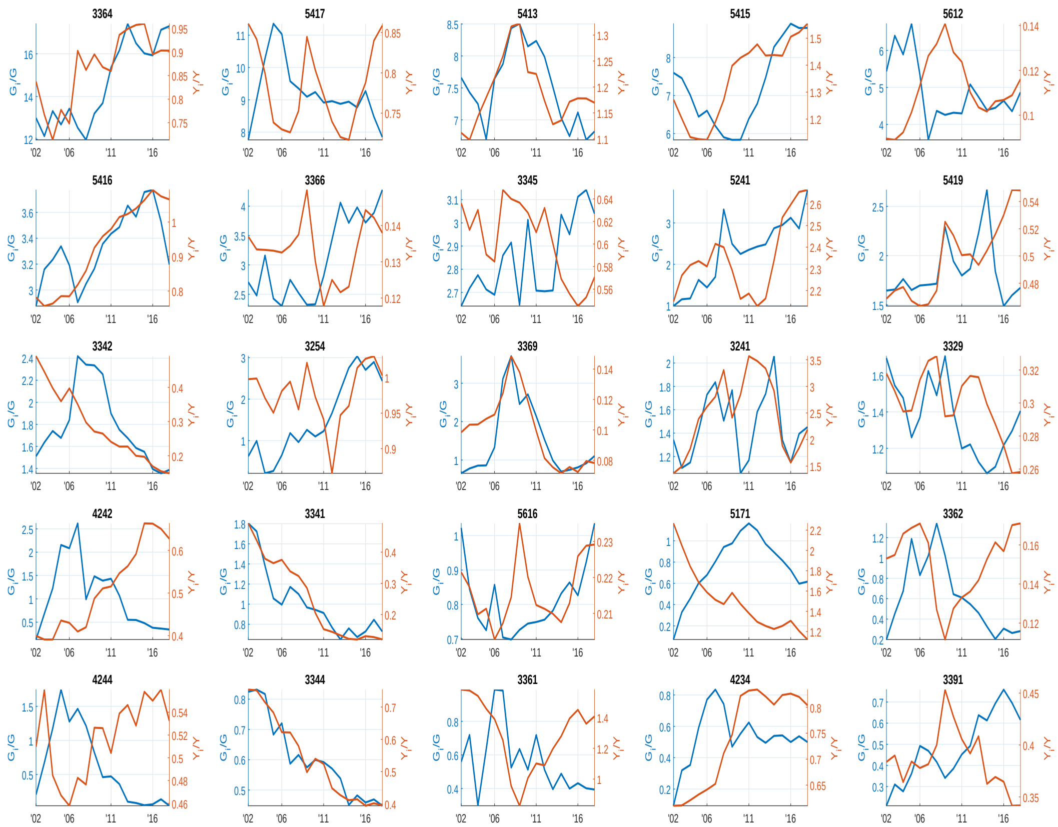

Figure 1: Shares of industry government spending to total public spending (left-scale) and industry output to total output (right-scale) for top recipient industries of government procurement contracts.

Table 2: Exposure of suppliers and customers of the top-30 recipient industries.

	Top suppliers of the top 30 recipients	
NAICS	*Industry*	% of Y_i
3363	Motor Vehicle Parts Manufacturing	67.22
3336	Engine, Turbine, and Power Transmission Equipment Manufacturing	35.69
3344	Semiconductor and Other Electronic Component Manufacturing	34.01
5152	Cable and Other Subscription Programming	30.84
3325	Hardware Manufacturing	28.74
	Top customers of the top 30 recipients	
NAICS	*Industry*	% of Y_i
3341	Computer and Peripheral Equipment Manufacturing	26.42
5172	Wireless Telecommunications Carriers (except Satellite)	24.18
5174	Satellite Telecommunications	17.29
3343	Audio and Video Equipment Manufacturing	17.13
3333	Commercial and Service Industry Machinery Manufacturing	13.58

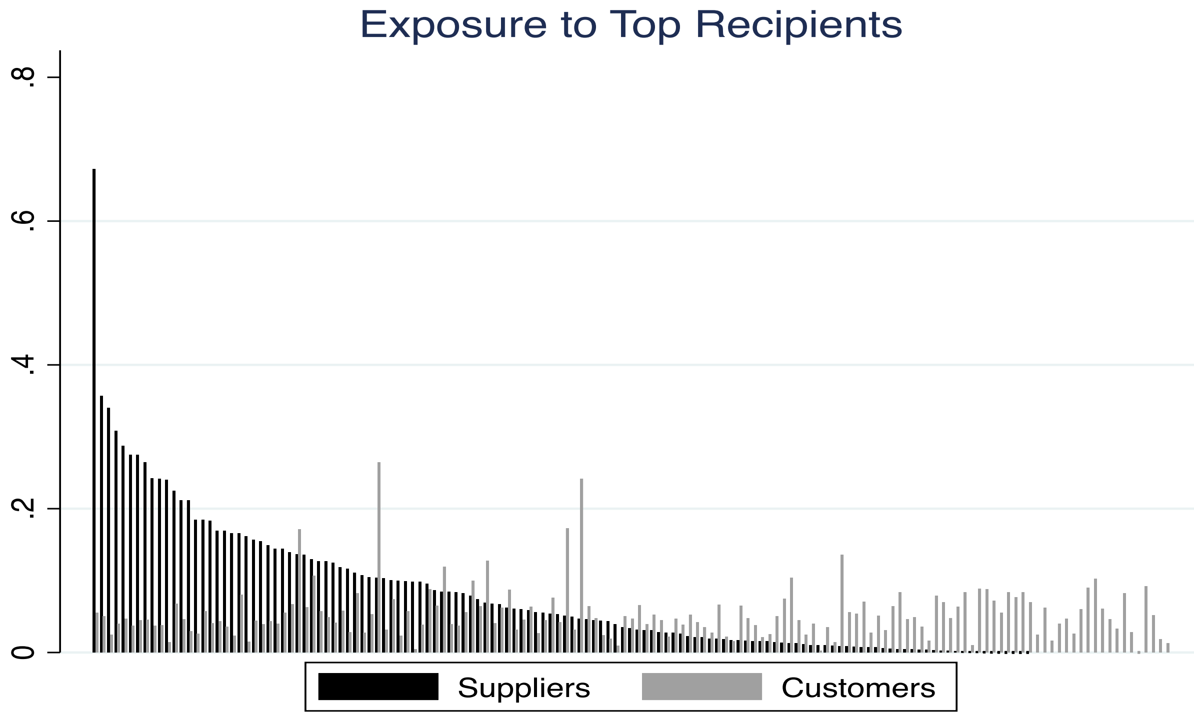

Figure 2: Supplier and customer exposure to top-30 recipients.

the top-30 recipient industries. To do so, we use the detailed use table for 2007 from the U.S. Bureau of Economic Analysis. In the table, each (i, j) cell reports the purchases of the commodity in row i as an intermediate input for the industry in column j. We aggregate the table to the NAICS 4-digit level. To measure suppliers' exposure, for each industry X, we sum the amount of X's output purchased by the top-30 public procurement recipients and divide the total by X's final output. Similarly, we construct a measure of customers' exposure from the top-30 recipients by summing, for each industry X, the total intermediate purchases from the top-30 recipients and dividing the total by X's final output.

Table 2 lists the top-5 suppliers and customers of the top-30 recipient industries.[10] The main suppliers and customers of the top-30 recipient industries include both manufacturing and service industries. For the top suppliers, the exposure is stronger than for the top customers. For instance, 67% of the output of the motor vehicle parts industry (NAICS code 3363) is purchased by the top-30 recipients. In contrast, the intermediate inputs purchased

[10]Tables A.1 and A.2 in the Appendix provide a more complete picture by listing the top-30 respective industries.

by computer manufacturing (NAICS code 3341)—the industry that relies the most on output produced by the top-30 recipients—are worth 26% of its output.

Table 2 also shows there is no systematic overlap across the top suppliers and customers. Figure 2 provides further evidence by plotting all industries ranked in terms of their exposure as suppliers to the top-30 recipients of government spending (dark grey bars). For each industry, the figure also shows the industry's exposure as customers (light grey bars). As is evidenced by the graph, there is no systematic relation across these two measures.

3 Identifying Sectoral Government Spending Shocks

Our first goal is to estimate the industry-level effects of sectoral government spending. Towards this end, we first identify suitable exogenous variation in sectoral spending. This requires addressing two well-known challenges: 1) accounting for potential endogeneity of public spending and 2) accounting for anticipation effects.

To address potential endogeneity when employing disaggregated data, e.g., state-level variation (Nakamura and Steinsson, 2014 and Dupor and Guerrero, 2017) or industry-level variation (Acemoglu et al., 2016 and Auerbach et al., 2020a), the previous literature used a Bartik-style instrument with aggregate defense spending.[11] However, when studying production network transmissions, the Bartik approach faces some limitations. As demonstrated in the previous section, some industry-level public-spending shares correlate with industry-level output shares, suggesting technological shocks may drive changes in both industry production and government demand. Such trends could invalidate the Bartik's exogeneity assumption of the spending shares (see Goldsmith-Pinkham et al., 2020). In addition, as discussed in Acemoglu et al. (2016), since the Bartik instrument proxies each industry-level spending with the same aggregate measure, the instrument by design induces high between-industry correlation of the proxied industry-level public spending. This can create spurious network effects in the presence of an omitted higher-order impact of shocks to recipient industries.

[11] A disaggregated spending measure is instrumented by multiplying aggregate defense by the average share of the disaggregated level of government spending to total defense spending. The rational for using aggregate defense spending is that defense dynamics are thought to be exogenous with respect to the economic environment (Ramey, 2011).

Motivated by these concerns, we develop an alternative empirical strategy to simultaneously rid our industry-level public spending data of movements that represent endogenous responses to past, current, and expected dynamics of a given variable of interest (i.e., employment). Our approach builds on a consolidated strategy in the monetary and fiscal policy literature (e.g., Romer and Romer, 2004; Auerbach and Gorodnichenko, 2013), although implemented at a much finer aggregation level and exploiting the panel dimension of the data.[12]

Identification Strategy

Let G_{it} denote the annualized NAICS-6 digit public spending, the most disaggregated sectoral level possible. Given that industry-level government contracts exhibit seasonal trends, we follow Auerbach et al. (2020b) and consider differences over four quarters, rather than over a single quarter. Our measure of sectoral spending is thus the annualized quarter-to-quarter difference divided by industry output, $\Delta G_{it} \equiv 4(G_{it} - G_{it-4})/Y^a_{js-1}$. Given that output data are not available at the NAICS-6 digit level nor at quarterly frequency, we use annual output at the relevant NAICS-4 digit, Y^a_{js-1}, in this measure.

In our first-stage estimation, we exploit the panel dimension of the data to deal with both endogeneity and anticipatory effects. Since implementation lags can in principle make sectoral spending changes forecastable, particularly following the enactment of fiscal-year budgets, we employ two industry-specific controls that address potential anticipation. The first control is the market-to-book ratio, a benchmark measure of expected profitability derived from firm-level data. The second control consists of industry-specific fixed effects for each fiscal year, capturing expectations regarding within-year allocations of spending. While the literature typically assumes that public spending does not react within a quarter to the business cycle (e.g., Blanchard and Perotti (2002)), we include time fixed effects that further control for contemporaneous macroeconomic shocks and policies. Finally, we include additional industry-specific controls to capture the potential impact of sector-specific business cycle conditions.

[12] Barattieri and Cacciatore (2023) adopted a similar strategy to identify trade policy shocks.

Concretely, we estimate the following regression:

$$\begin{aligned}\Delta G_{it} = \alpha_i + \gamma_t + (\psi_{FY} \times \alpha_j) + \sum_{k=1}^{p} \left(\frac{G_{t-k}}{Y_{t-k}} \times \eta_j \right) \\ + \sum_{k=1}^{p} \beta_{i,k} \Delta G_{it-k} + \sum_{k=1}^{p} \phi_{j,k} \Delta L_{jt-k} + \nu_{it}\end{aligned} \tag{1}$$

where i indexes a NAICS 6-digit industry, j indexes the corresponding NAICS 4-digit industry, and t indexes time at quarterly frequency. Our interest is the estimated residual ν_{it}, which serves as our measure of exogenous sectoral spending variation in the second-stage estimation.

The term α_i represents the NAICS 6-digit industry fixed effect, which controls for time-invariant, unobserved heterogeneity. γ_t is a quarterly time fixed effect. $(\psi_{FY} \times \alpha_j)$ is the industry-specific fixed effect for the fiscal year, controlling for anticipation of spending outlays within a fiscal-year budget cycle. This fixed effect captures the notion that during the fiscal year, the average spending within an industry could already be anticipated—at the start of the fiscal year, a detailed federal budget is made publicly available and includes breakdowns of spending allocations across federal departments for various goods and services.

The term ΔMB_{jt} denotes the year-on-year growth rate of the median market-to-book ratio at the NAICS 4-digit. Following Barattieri and Cacciatore (2023), we construct this variable to control for changes in the industry's future expected profitability, including the possible anticipation of future contracts. We start by taking the ratio between the market and book values of equity at the firm-level for firms from Compustat/CRSP. The market value corresponds to the total number of outstanding shares multiplied by the current share price. The book value is the accounting value calculated from the firm's balance sheet. A market-to-book ratio above one suggests strong future profit expectations, as investors are willing to pay more for a firm than its net assets are worth. To construct an industry-level market-to-book ratio, we take the median of the market-to-book measures across firms within each NAICS 4-digit code. To show that this measure contains information about future industry-specific economic conditions, Table 3 reports the results of a Granger causality test using employment growth as the dependent variable. We use data for all NAICS 4-digit industries, regressing employment growth on lags of itself and MB_{jt}. An F-test of the joint significance of the market-to-book ratio coefficient shows the market-to-book ratio has forecasting power for employment growth, as the test rejects the null hypothesis of zero significance at the 1-percent level.

Table 3: Market-to-book ratio explanatory power.

Dep Variable: Empl. Growth	(1)	(2)	(3)
ΔMTB_{t-1}	0.00706***	0.00715***	0.00188***
	(0.00052)	(0.00052)	(0.00055)
ΔMTB_{t-2}	0.00597***	0.00633***	0.00234***
	(0.00053)	(0.00053)	(0.00057)
ΔMTB_{t-3}	0.00322***	0.00391***	0.00104*
	(0.00053)	(0.00053)	(0.00057)
Constant	0.00014	0.00154	-0.00006
	(0.00011)	(0.00165)	(0.00183)
Joint F-test	102.5	112.4	8.7
P-value	0.000	0.000	0.000
Lagged Empl. Growth	Yes	Yes	Yes
NAICS4 FE	No	Yes	Yes
Time FE	No	No	Yes
R-squared	0.273	0.296	0.365
N	13598	13598	13598

To control for industry specific business-cycle conditions, we include lags of the government spending measure, ΔG_{it}, the year-on-year growth rate of employment at the NAICS 4-digit, ΔL_{jt}, and the lagged spending-to-output ratio, G_t/Y_t, interacted with a NAICS 4-digit fixed effect. Lagged employment growth and sectoral government spending account for persistent changes to past economic conditions and industry-level government spending. The term $(G_{t-k}/Y_{t-k}) \times \eta_j$ captures potential industry-specific effects of aggregate spending changes not subsumed in the time fixed effects.[13]

There are 126 industries classified at the NAICS 4-digit for which there are output, employment, and procurement contract data. To ensure that our estimates are not driven by outliers, when estimating equation (1), we exclude industries that exhibit episodes where spending is considerably in excess of output, following Auerbach et al. (2020a). Specifically,

[13]We do not consider the interaction at the NAICS 6-digit level to avoid an excessive proliferation of regressors.

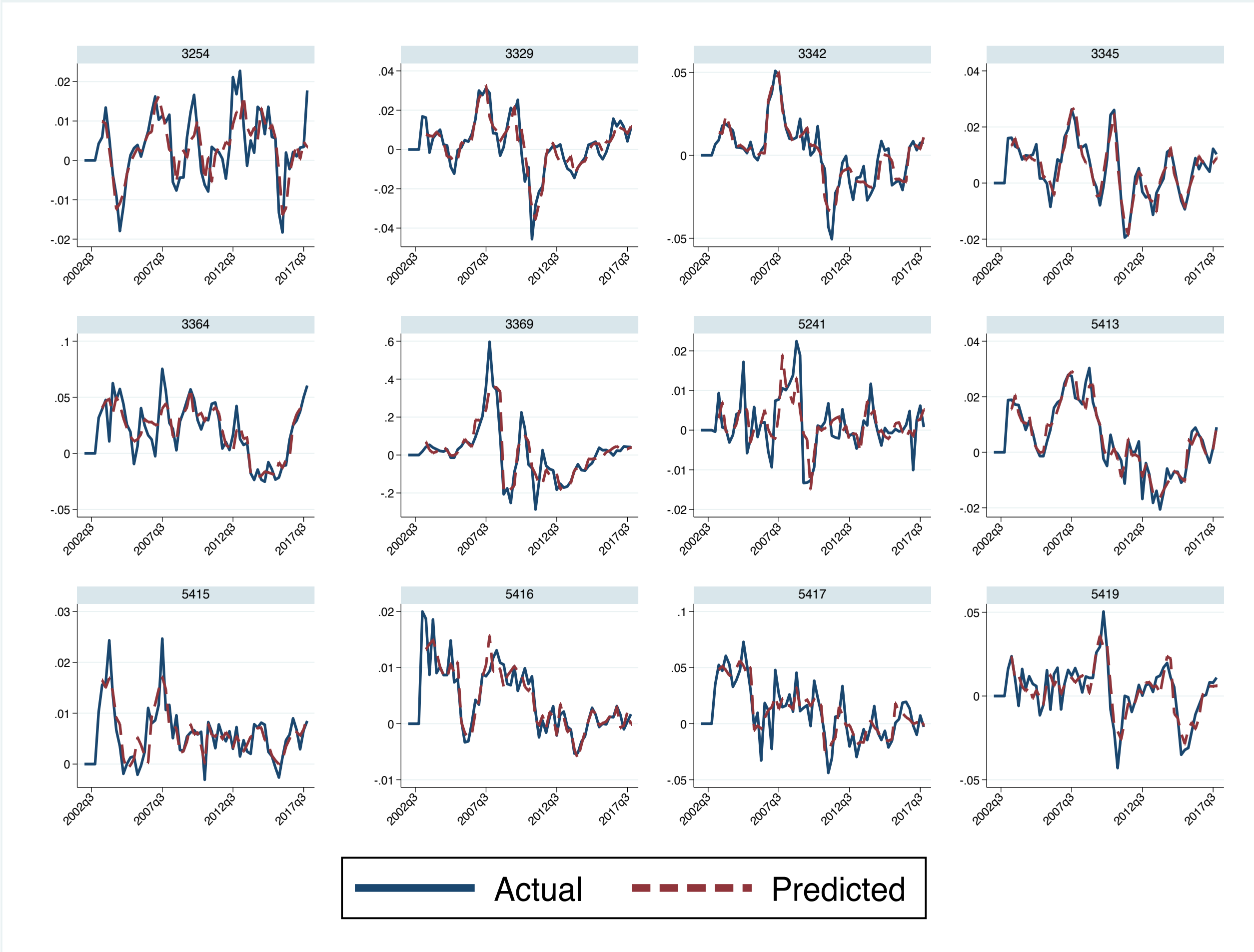

Figure 3: Predicted (red dashed lines) and actual (blue solid) government spending for the top NAICS 4-digit recipients of government contracts.

we exclude industries where ΔG_{jt} takes values greater than 50% and less than -50%.[14]

Estimated Sectoral Shocks

The most detailed level at which comprehensive data for employment, prices, and input-output relationships are available at a consistent level of aggregation is at the NAICS 4-digit. Since the NAICS 6-digit shocks, $\hat{\nu}_{it}$, are expressed in terms of the same NAICS 4-digit output, we can construct 4-digit level sectoral, $\hat{\nu}_{jt}$, shocks by summing the identified shocks

[14]We consider outliers at the NAICS 4-digit level, as that is the level of analysis in our second-stage estimation. In order to maximize the degrees of freedom when estimating equation 1, we exclude NAICS 4-digit industries for which there are only one or two NAICS 6-digit sub-industries.

$\hat{\nu}_{it}$:

$$\hat{\nu}_{jt} = \sum_{i=1}^{N_j} \hat{\nu}_{it},$$

where N_j is the number of NAICS 6-digit industries within a 4-digit classification.

The NAICS 4-digit shocks have plausible statistical properties: they are serially uncorrelated and not correlated across industries. For instance, the median pairwise correlation of two given shock series is 0.002, suggesting no correlation across industries.[15]

Figure 3 plots the predicted spending series at the NAICS 4-digit (i.e., actual spending minus $\hat{\nu}_{jt}$) against the data for the top recipients of government contracts. For certain industries, the NAICS 4-digit predicted values account for almost all the industries' variation in government spending (for instance, industries 3345 and 5415, which represent respectively navigational, measuring, medical & control instrument manufacturing and computer systems design & related services). In other industries, there remains unexplained variation. For instance, the large swing in spending around 2007 in industry 3369 (transportation equipment manufacturing) is only partly anticipated.

To better understand the origin of our estimated shocks, we examined contract details underlying the largest identified shocks. To do so, for each industry-quarter pairing, we selected the episodes where both the shocks ($\hat{\nu}_{jt}$) and the measure ΔG_{jt} were larger than their respective standard deviations.[16] For these episodes, we gathered firm and contract level details that help understand the context of the shocks, which we report in Tables 4 and 5. The tables summarize the number of firms and contracts per episode. They also provide information related to the contracts accruing to the top recipient firms—the firms that receive the largest share of contracts within each specific episode. The median number of firms and contracts per episode is quite large —648 and 1,710 respectively—precluding a systematic analysis of the institutional details of the contracts. Nevertheless, the data is highly granular, as the median share of total spending accruing to the top three firms in

[15] Alternatively, one could calculate the median of the absolute value of the pairwise correlations, to ensure negative and positive numbers do not imply a zero median result. In this case, the median pairwise correlation is still only 0.14.

[16] ΔG_{jt} signifies the annualized quarter-to-quarter difference in NAICS 4-digit public spending divided by industry output, i.e. the spending measure corresponding to ν_{jt}.

each episode is 48%. To assess whether the largest contracts were plausibly unanticipated, we report two additional contract-level pieces of information for these top firms. First, we verify whether the largest contracts received media coverage (as documented on Factiva) around their signature date. Second, we check whether the largest contracts were awarded competitively (i.e., in a full and open competition with at least two bidders). As shown in the last column of Tables 4 and 5, several contracts feature media coverage around the signing date, and many contracts were awarded competitively. Taken together, this suggests that these contracts were unlikely to be anticipated by market participants and recipient firms. Moreover, the timing of various contracts overlaps with exogenous events such as military expenditures for conflicts in Iraq and Afghanistan and relief for natural disasters such as Hurricane Katrina.

Returning to Figure 3, our identified industry-level shocks can be sizeable or fairly small, depending on the industry and episode. In the following analysis, we exploit this residual variation to identify the direct effects of sectoral government spending shocks and their impact through the supply chain. In what follows, we restrict the analysis to industries that receive economically meaningful demand from the government. In practice, we consider recipient industries with an average sectoral public spending to output ratio above 0.5%.

Upstream and Downstream Effects

We now discuss the measurement of suppliers' and customers' exposure to the identified sectoral government spending shocks. We follow Acemoglu et al. (2016)'s measurement and terminology for describing upstream and downstream effects. We refer to upstream effects as those arising to suppliers of industries receiving government spending shocks (i.e., customer shocks). At the same time, we label downstream effects as those arising to customers of industries receiving public spending shocks (i.e., supplier shocks).

Table 4: **Largest Episodes**

Industry	Date	# of Firms	# of Contracts	Top Recipient	Recipient's Share	
3369	2007q4	354	858	BAE Systems Land & Armaments Int. Military & Gov. LLC (Navistar) Force Protection Industries	0.67 0.19 0.07	Main purchases include mine-resistant ambush-protected vehicles, Bradley fighting vehicles, self-propellant howitzers, and velocity weapons. Largest contract (1.2 bn) awarded competitively. Media coverage on November 22 and December 19.
3369	2010q1	281	1210	Oshkosh Corp. Int. Military & Gov. LLC (Navistar) BAE Systems Land & Armaments	0.53 0.13 0.10	Main purchases include mine-resistant ambush-protected vehicles. Largest contract (709 million) awarded competitively. Media coverage on February 23rd.
3369	2007q3	484	1734	Int. Military & Gov. LLC (Navistar) Stewart & Stevenson General Dynamics Land Systems	0.16 0.16 0.14	Main purchases awarded under the Mine Resistant Ambush Protected vehicle program. Contracts were competitively awarded and featured media coverage on July 13, 2007 (Stewart and Stevenson) and on July 23, 2007 (Navistar 's subsidiary International Military and Government LLC and Stewart). The news on July 23 also reported an increase in the Navistar stock price following the contract award.
3362	2005q3	813	1254	Bourget's of the South Stream Coach Inc. Morgan Building Transport	0.15 0.08 0.08	Purchases were by the Department of Homeland Security and FEMA for Hurricane Katrina relief (e.g., new trailers). Largest contract (98 million) awarded competitively.
3362	2005q4	455	901	Dixie Motors Inc. Berryland Motors LLC Stewart Park LLC	0.14 0.12 0.09	Purchases were by the Department of Homeland Security and FEMA for Hurricane Katrina relief. These purchases do not appear in the media in Factiva, but the largest contracts do appear in FEMA's list of all contracts awarded in Support of Hurricane Katrina Recovery Efforts.
3369	2010q2	328	1687	Navistar Defense LLC General Dynamics Land Systems Oshkosh Corp.	0.10 0.10 0.09	Medium tactical vehicles and enhancements to mine resistant ambush protected vehicles, tanks, rocket-propelled grenades protection kits. Largest contracts awarded competitively, with media coverage on April 7 and 28, May 4 and 20.
3364	2007q3	2817	19377	McDonnell Douglas Corp. (Boeing) Lockheed Martin Corp. General Electric	0.12 0.11 0.04	Largest contracts include purchases for aircraft including F/A-18Fs, E/A-18Gs, and F-22 raptors, as well as parts for aircraft. Contracts featured media coverage on multiple dates including July 11, July 31, and Sept. 1.
3341	2016q3	1394	12521	CDW Government LLC World Wide Technology HPI Federal LLC	0.17 0.12 0.10	Main purchases include commercial firewall hardware and incidental services, Dell laptops and docking stations. Largest contract (16 million) awarded competitively awarded. Media coverage on Sept. 5th.
3362	2008q2	340	1366	BAE System Tactical Vehicle Systems Navistar Defense LLC Freightliner LLC	0.33 0.31 0.11	Main purchases include medium tactical vehicles. Largest contracts awarded competitively. Media coverage on May 5th (Navistar) and June 3rd (BAE System) .
3369	2003q3	261	762	Goodyear Tire & Rubber General Dynamics Land Systems Freightliner LLC	0.28 0.28 0.04	Main purchases include combat vehicle tracks to be used for the Bradley Fighting Vehicle and the M113, M578, M109, M60, Paladin and M9 Ace armored combat earthmover. Largest contract awarded competitively. Press Coverage on August 27th .

Table 5: **Largest Episodes (Continued)**

Industry	Date	# of Firms	# of Contracts	Top Recipient	Recipient's Share	
3364	2004q1	1541	7408	Lockheed Martin Corp. McDonnell Douglas Corp. (Boeing) Northrop Grumman Space & Missile	0.29 0.11 0.07	Largest contracts include purchases for PAC-3 missiles, munitions, and ground support equipment. Lockheed Martin's largest contract (214 million) received wide news coverage, e.g. on Feb. 12. Several other contracts (over 100 million) also were featured in the news the day or day after the contract signing.
5417	2007q2	3228	10213	Lockheed Martin Corp. Raytheon Comp. Science Applications Int.	0.08 0.04 0.03	Lockheed Martin provided litigation support services to seven of the Justice Department's litigation divisions. Press coverage on June 13th. Rayethon was awarded a contract for the purchase of an expanded TCN software licence and featured press coverage on May 30th.
3364	2006q1	2471	13577	Lockheed Martin Corp. TRW Inc. Boeing	0.45 0.13 0.07	Main purchases include backbone network for Transformational Satellite Communications System (TSAT). The largest contract (1.6bn) was awarded competitively. Press coverage on Feb. 8th.
3362	2008q4	239	574	Freightliner LLC Oshkosh Corp. BAE System Survivability Systems	0.32 0.16 0.07	Main purchases include trailers. Largest contract (128mn) awarded competitively. Mentioned in the press on Dec 13th .
3364	2012q4	1761	12626	Lockheed Martin Corp. Boeing General Electric	0.21 0.11 0.07	Main purchases: F-35 fighter jets. Largest contract (1.9 bn) awarded non-competitively. Press coverage on December 29th.
5419	2009q4	1636	4896	Brookhaven Science Associates Global Linguist Solutions LLC MIT	0.62 0.06 0.05	The Office of Science in the Department of Energy is the primary funder of Brookhaven Science, which manages and operates Brookhaven National Laboratory. All largest contracts were modifications to increase spending for this ongoing long-term research relationship. Contracts to Global Linguist were competitively awarded for translation services.
5417	2005q1	2983	9633	UC Berkeley Stanford University West Valley Nuclear Services	0.33 0.14 0.03	The Department of Energy competitively awarded a contract to the University of California to manage and operate the Lawrence Berkeley National Laboratory. Media coverage on April 19.
3369	2017q2	359	1250	General Dynamics Land Systems AM General LLC Honeywell International	0.22 0.21 0.07	Largest contracts awarded for Humvees and upgrading engine hardware in M1 Abrams tanks. Media coverage featured on April 6, April 28, and April 29.

To measure upstream effects, we construct "customer shocks" as in Acemoglu et al. (2016). Specifically, we construct a weighted-average measure of sector j's exposure to customer-k shocks:

$$\nu_{jt}^{up} = \sum_k (\tilde{\omega}_{jk} - \mathbf{1}_{k=j})\nu_{kt}, \tag{2}$$

where $\tilde{\omega}_{jk}$ represents the fraction of j's output demanded by the k-th sector in its Leontief Inverse form, and $\mathbf{1}_{k=j}$ is an indicator function for $k = j$. We compute these values using the 2007 total-requirements input-output table.[17] Similarly, to measure downstream effects, we construct "supplier shocks" following Acemoglu et al. (2016). We construct a weighted-average measure of sector j's exposure to supplier-k shocks:

$$\nu_{jt}^{down} = \sum_k (\omega_{kj} - \mathbf{1}_{k=j})\nu_{kt}, \tag{3}$$

where ω_{kj} represents the fraction of j's output from the k-th intermediate in its Leontief Inverse form.

4 Industry-Level Effects of Sectoral Spending Changes

We now estimate the effects of sector-specific shocks on recipient industries and across the supply chain. To do so, we use Jordà (2005)'s local projection method, which amounts to running a sequence of predictive regressions of an outcome variable on our government spending shocks for different prediction horizons. To account for uncertainty in the first-stage estimates, we do not directly use the identified shocks as regressors in the local projections. Instead, we use them as an instrument, paralleling the fiscal policy literature that rely on local projection-IV to estimate aggregate fiscal multipliers (e.g., Ramey and Zubairy, 2018). Specifically, we use $\hat{\nu}_{jt}$, $\hat{\nu}_{jt}^{up}$, and $\hat{\nu}_{jt}^{down}$ to instrument for ΔG_{jt}—the annualized quarter-to-quarter difference in NAICS 4-digit public spending divided by industry output—and ΔG_{jt}^{up} and ΔG_{jt}^{down}, where the latter two are calculated directly using public spending in equations (2) and (3).

[17] The use of fixed weights has the advantage of addressing endogeneity concerns (at the cost of potentially introducing measurement error). This choice is also consistent with Acemoglu et al. (2012), who suggest the stability of the production network over time.

We estimate the following set of h-steps ahead predictive panel-IV regressions for $h = \{0, .., H\}$:

$$\Delta L_{jt+h} = \alpha_{hj} + \beta_h^{own} \Delta G_{jt} + \beta_h^{up} \Delta G_{jt}^{up} + \beta_h^{down} \Delta G_{jt}^{down} + \varphi_h(L) C_{t-1} + \gamma_{ht} + \epsilon_{jt+h}. \quad (4)$$

where $\Delta L_{jt+h} = (L_{jt+h} - L_{jt-1})/L_{jt-1}$ represents the growth in industry j's employment, α_{hj} is an industry fixed effect, and γ_{ht} is a quarterly time-fixed effect. The coefficient β_h^{own} measures the direct effect on economic activity in the recipient industry at horizon h. The coefficients β_h^{down} and β_h^{up} measure the industry's reaction to shocks from its suppliers and customers, respectively.

We use employment as the outcome variable as there is broad coverage of employment data at the quarterly, NAICS 4-digit level across many industries, including both manufacturing and service sectors. In the sensitivity analysis below, we also consider the effects on industrial production, which is only available for the manufacturing sector.[18] The term C_{t-1} includes a vector of control variables, and $\varphi_h(L)$ is a polynomial in the lag operator. We consider four lags of employment growth and four lags of the relevant shock ($\hat{\nu}_{jt}$, $\hat{\nu}_{jt}^{up}$, or $\hat{\nu}_{jt}^{down}$).[19]

Results

Panel A in Figure 4 displays the impulse responses of employment following recipient industry shocks, i.e., the estimated β_h^{own} coefficients (top row); for the upstream effects of customer shocks, i.e., the estimated β_h^{up} coefficients (middle row); and for the downstream effects of supplier shocks, i.e., the estimated β_h^{down} coefficients (bottom row). We compute 90% confidence intervals for each impulse response estimate by clustering at the NAICS 4-digit industry.

Following a government spending increase, employment rises significantly in recipient industries and in sectors supplying intermediate inputs to the recipient industries (see rows 1

[18] We do not directly consider output data as it is only available annually at the industry level.

[19] Thus, in practice, we estimate three separate versions of equation (4). We do so to include a parsimonious set of controls given the relatively short sample. Notice that when identifying upstream and downstream effects, we directly include $\hat{\nu}_{jt}$ (rather than instrumenting ΔG_{jt}) to avoid excluding industries for which we have no industry-level shocks.

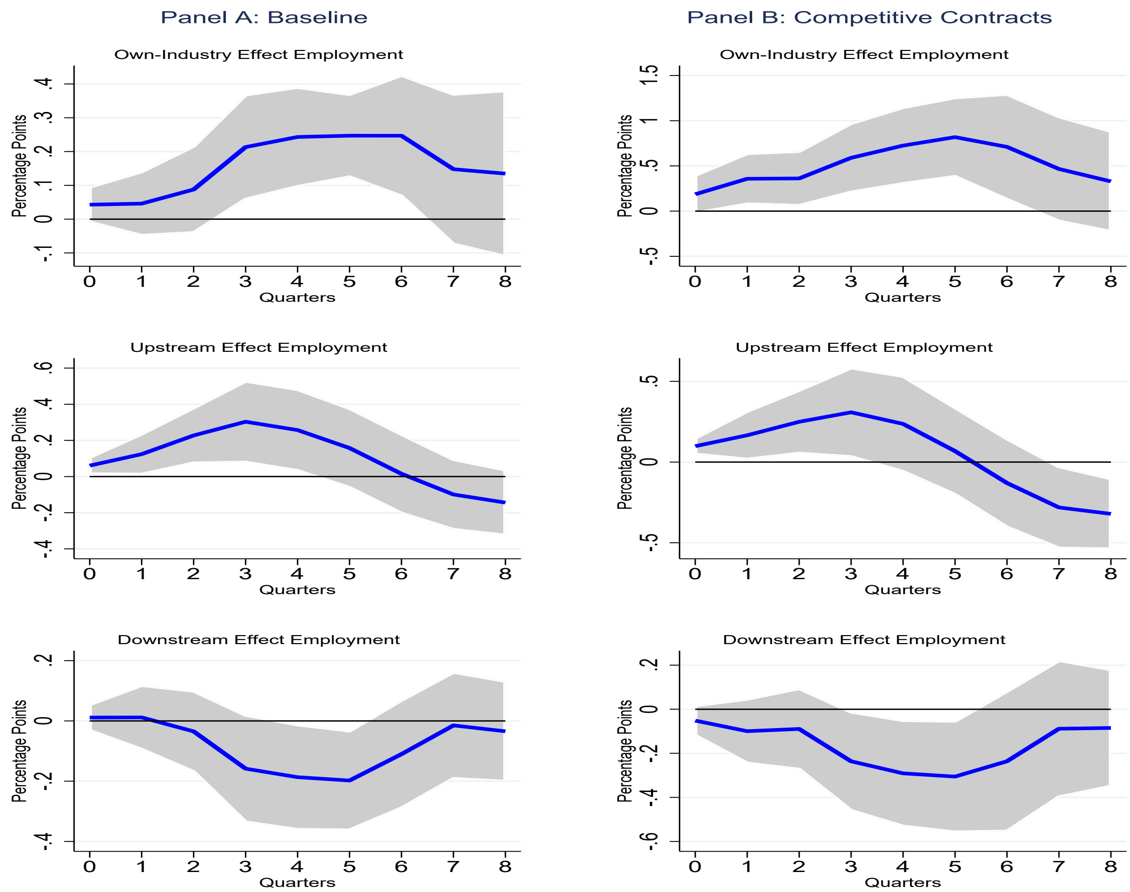

Figure 4: Impulse responses from local projections. Top row displays effects in recipient industry; middle row shows effects from shocks to an industry's consumers; bottom row displays effects from shocks to an industry's suppliers.

and 2 of Figure 4). On average, a 1% increase in ΔG_{it} implies a peak increase of employment in sector i of roughly 0.25%, which occurs four quarters after the shock. A uniform 1% increase in ΔG_{it} in all recipient industries implies, on average, a peak increase in upstream employment of similar magnitude to the own-industry effect. Importantly, all the responses peak several quarters after the initial shock, showing the importance of estimating the dynamic effect, which has not been previously estimated.

In contrast, employment is significantly crowded-out downstream (see row 3). A uniform 1% increase in ΔG_{it} in all recipient industries implies, on average, a peak decrease in downstream employment of 0.2%. This result may seem surprising in light of the predictions of benchmark production-network models following a demand shock (e.g., Acemoglu et al., 2016) which imply that demand shocks only propagate upstream. In section 5, we provide evidence that price dynamics across the production network can rationalize the estimated downstream effects.

The results hold when considering several robustness checks. First and foremost, while our first-stage estimation already addresses potential anticipation of government contracts, we consider a refinement exploiting contract-level characteristics. Specifically, *USAspending.gov* provides information on whether a given contract was awarded competitively (i.e., in a full and open competition with at least two bidders). We restrict the sample to these contracts, as they are even less likely to have been anticipated.[20] This lowers the coverage of the value of contracts considered, as only 50% of total government spending is accounted for by these contracts over the entire sample. We re-estimate the first- and second-stage equations using only this subset of contracts.

Panel B in Figure 4 displays the impulse responses of employment using this subset of contracts. Qualitatively, the results are similar to the baseline specification. Quantitatively, the direct and downstream effects are estimated to be larger, although their confidence intervals encompass the baseline point estimates. The upstream effects are more similar quantitatively, whereas the baseline results are significant over a longer horizon. Altogether, the estimated responses stress the importance of the propagation through the input-output

[20]This measure has been used by Hebous and Zimmermann (2021) to study the effects of firm-level investment following public spending shocks.

network, as both the upstream and downstream effects are of similar magnitudes as the direct effect.

In the next subsection, we present additional sensitivity analysis further documenting the robustness of the results.

Sensitivity Analysis

To provide additional robustness, we consider an alternative outcome variable, alternative specifications of the first-stage regression, and alternative measures of government spending. In all cases, the results are robust and inline with the baseline estimates of Figure 4.

First, since our interest is in measuring the effects of government spending shocks on sectoral economic activity, we consider an alternative measure to employment, namely industrial production. Industrial production provides a direct measure of output, but is only available for manufacturing sectors, limiting the sample relative to the baseline.[21] The first row of Figure 5 displays the effect on recipient industries (first column), the upstream effects of customer shocks (middle column), and the downstream effects of supplier shocks (last column). The results are similar qualitatively to the baseline employment responses, with recipient and upstream sectors increasing industrial production while sectors downstream decrease it.

We next consider an alternative specification for the first-stage estimation of public spending shocks. In the baseline case, we identify shocks at the NAICS 6-digit level to control for potential anticipation at the most disaggregated level. However, our measure of government spending, ΔG_{it}, is the difference in sectoral public spending at the NAICS 6-digit level relative to output measured at the NAICS 4-digit level. To the extent that the 6-digit price deflators differ from the NAICS 4-digit price deflator, dynamics in ΔG_{it} could also reflect relative price movements. Given this mismatch, we construct ΔG_{it} at the NAICS 4-digit level and directly use it in the first- stage estimation. While this approach effectively addresses potential relative price effects, it also substantially reduces the degrees of freedom available for estimation due to the inclusion of NAICS 4-digit specific coefficients for multiple con-

[21]While output data is available from the BEA at the NAICS 4-digit level, it is only consistently available at an annual frequency.

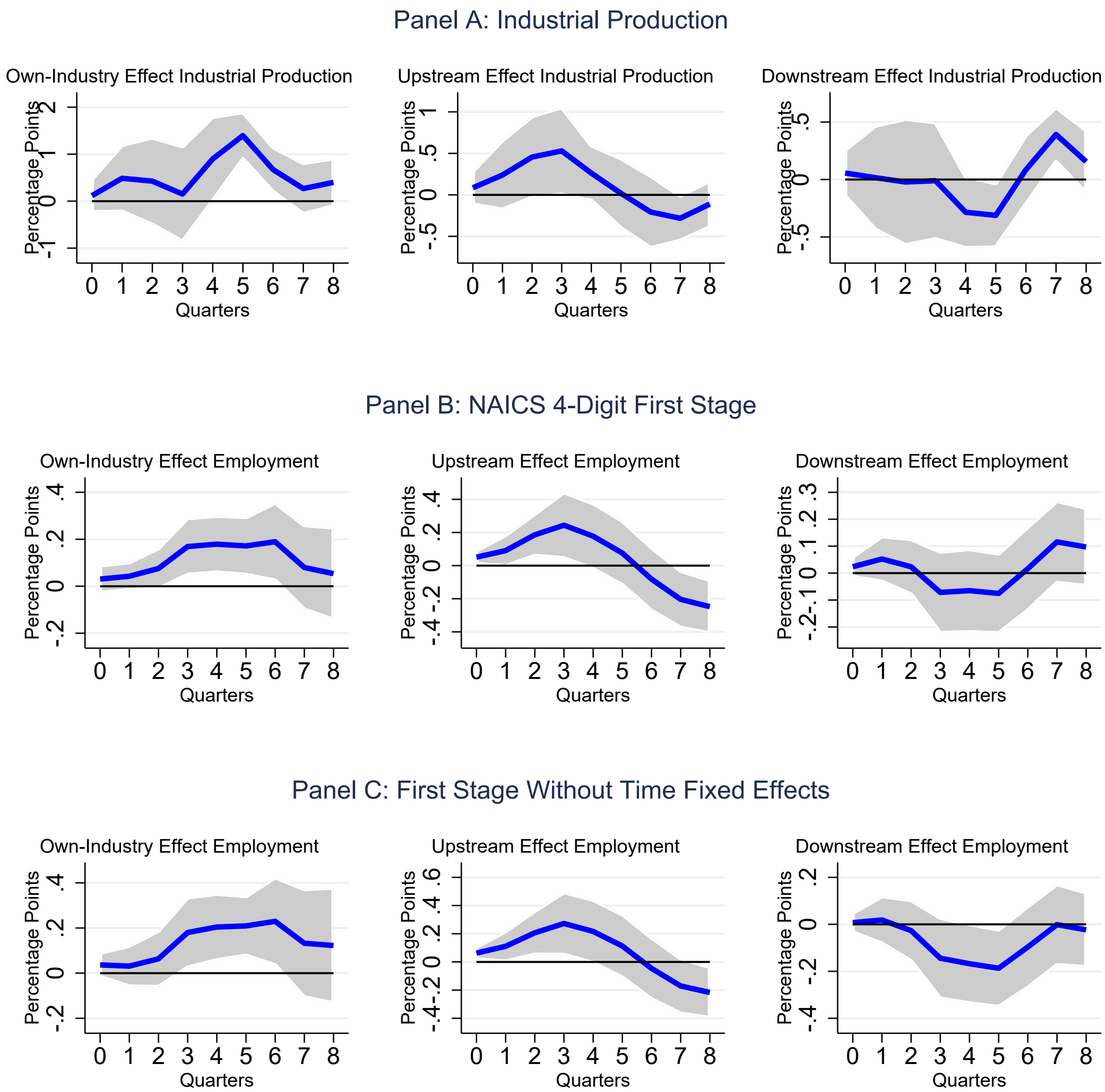

Figure 5: Sensitivity analysis of impulse responses from local projections. Top row: using Industrial Production in place of employment as the outcome variable. Middle row: Using only NAICS 4-digit analysis at the first stage. Bottom row: excluding time fixed effects in the first-stage estimation.

trols. The middle row of Figure 5 illustrates the responses for employment in this scenario. Own industry and upstream effects continue to show statistically significant positive results, and their magnitudes are comparable to the baseline. The estimates for downstream effects, while still negative, are less precise in this case.

Our baseline first-stage estimation uses a time fixed effect to control for aggregate business-cycle conditions. However, this specification is potentially too conservative as it removes all variation (including that which is exogenous) common across industries. For this reason, we consider an alternative specification without the time fixed effect. The bottom row of Figure 5 shows that the estimated responses align qualitatively with our baseline results.

Next, we examine a scenario where only competitive contracts are considered in the first-stage estimation, and the resulting shocks are utilized as instruments for total government spending, which encompasses both public spending from competitive and non-competitive contracts, in the second stage. The top panel of Figure 6 displays the results in this case, confirming the presence of significantly positive effects within recipient and upstream industries, as well as significantly negative effects in downstream industries.

Finally, most empirical studies of government spending focus solely on defense expenditures, as changes in defense spending are thought to be less related to economic activity (Ramey, 2011). For comparability, we consider two specifications with government spending originating from contracts only with the Department of Defense. The middle panel of Figure 6 displays the employment response using all defense procurement contracts while the bottom panel considers only defense contracts that were competitively bid. In both cases, the employment responses are qualitatively in line with the baseline results.

5 Inspecting the Economic Mechanism

Having established that government spending shocks significantly affect economic activity in both recipient industries and industries that are upstream and downstream relative to the recipients, we turn to identifying mechanisms to explain the results.

Acemoglu et al., 2016 provide seminal theoretical analysis of the transmission of shocks through the network. They propose a benchmark model of a production network featur-

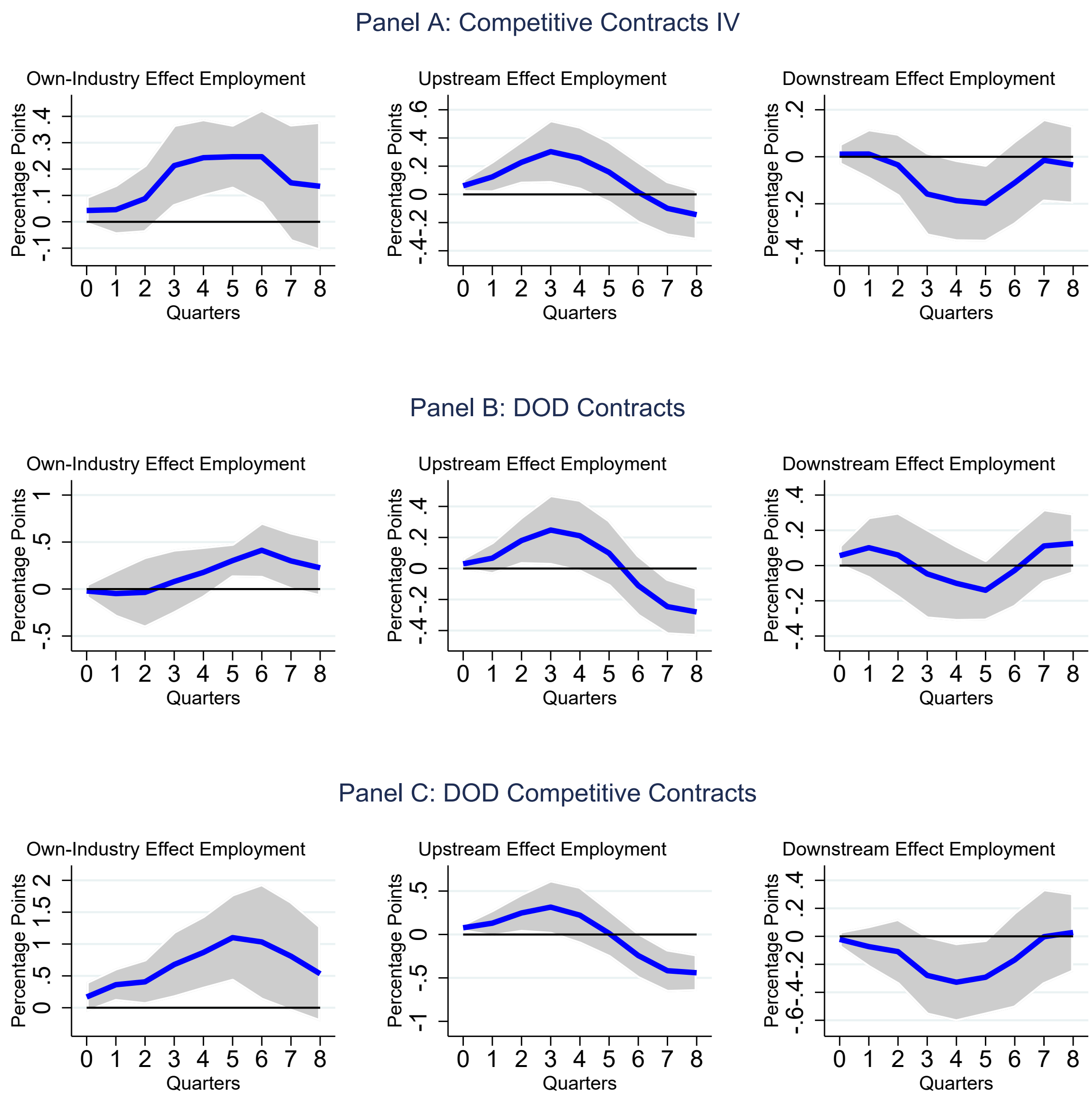

Figure 6: Sensitivity analysis of impulse responses from local projections. Top row: estimation using the public spending in levels. Bottom row: including only government spending data from the Department of Defense.

ing Cobb-Douglas production functions with constant returns to scale. One of their main theoretical results is that demand shocks, such as government spending shocks, increase economic activity in the recipient industries and propagate though the network only upstream. Higher sectoral demand increases production within the sector, leading to higher intermediate input demand, and ultimately raises production in industries upstream of the recipient. The absence of downstream propagation stems from the assumption that all sectors feature constant returns to scale, which implies that relative prices are independent of aggregate demand (Acemoglu et al., 2016). In this particular setting, government spending shocks change quantities but not relative prices, hence explaining the lack of downstream propagation.[22]

This discussion highlights the importance of exploring the transmission of demand shocks (e.g., government spending shocks) through the production network not only to quantities, but also to prices. This motivates us to estimate equation (4) by replacing the dependent variables with measures of industry-level prices and wages.[23] We focus on price and wage dynamics in both the recipient industries and their suppliers upstream, as recipient and upstream price movements are most relevant to explaining the results on downstream propagation.

Figure 7 displays the impulse responses for prices (first column) and wages (second column) of the recipient industries (top row) and their suppliers (bottom row). In all cases, prices and wages increase significantly after a government spending shock. A caveat is that we only have price data for roughly half of the top recipient industries for which we have government spending shocks. Thus, the smaller sample size may lead to less precise estimates of the own-industry effects.

The increases in prices and wages are relevant for two reasons. First, they show that movements in quantities and prices in recipient industries and their suppliers are consistent with the textbook transmission of a demand shock. Second, price and wage increases in recipient and upstream industries provide a natural explanation for the negative employment

[22]Obtaining non-zero downstream effects of sectoral demand shocks would require relaxing the assumption of constant returns to scale or, for instance, introducing imperfect labor mobility as argued by Bouakez et al. (2023).

[23]We use producer price indexes from the U.S. Bureau of Labor Statistics (BLS), which for most industries are only available since 2004. Our measure of wages is average hourly earnings from the BLS. Notice that we re-estimate the first-stage regression including lags of prices and wages as additional controls. Otherwise, the specifications remain the same.

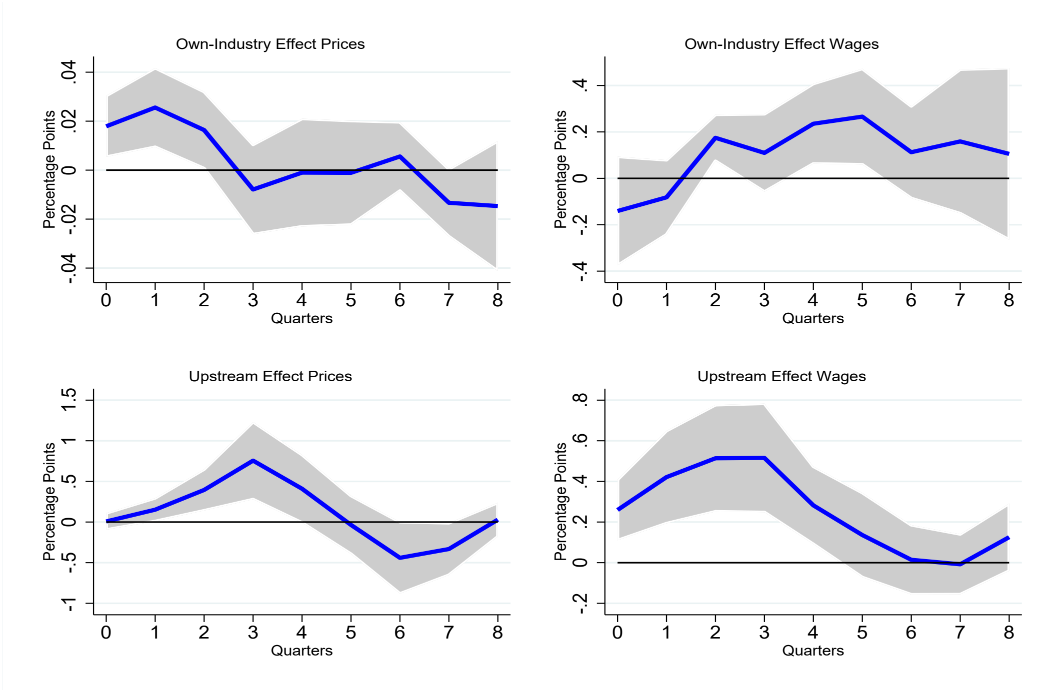

Figure 7: Price and wage impulse responses from local projections.

effects in downstream sectors. Intuitively, higher upstream prices imply higher intermediate-input prices downstream, lowering input demand and production. Higher wages in more upstream sectors may also adversely affect downstream employment if labor is mobile across sectors, as employees may reallocate to industries with higher wages.

To further corroborate the importance of price adjustments for the negative employment effects, we explore an additional indirect channel of downstream transmission. Consider for simplicity an industry A that experiences an increase in government demand that leads to higher intermediate demand for goods produced by industry U, which is upstream relative to A. Higher demand in industry U, in turn, results in higher prices. As a consequence, firms downstream from U—for instance in industry D—lower their demand for the intermediate input produced by U, even if there is no direct link between industries D and A. Our measure ν_{jt}^{down} would not capture such indirect network effects.

To account for this potential indirect transmission, we construct a measure of indirect downstream exposure. Specifically, for each industry d we construct: $\nu_{dt}^{ndown} = \sum_{u \neq d} \lambda_{ud} \nu_{ut}^{up}$, where ν_{ut}^{up} (defined in equation 2) represents "customer shocks" of industry u, and λ_{ud} rep-

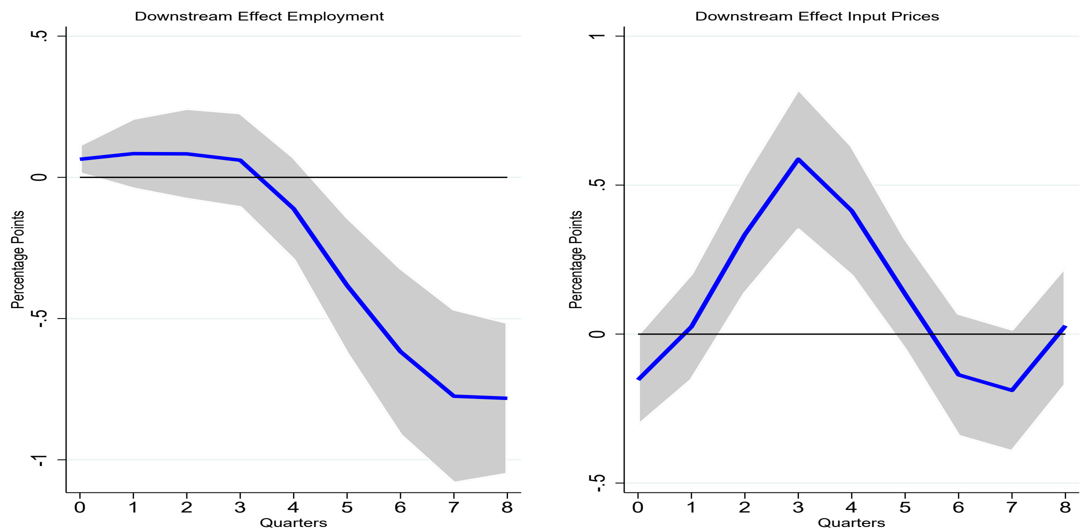

Figure 8: Impulse responses for measures of downstream effects from local projections.

resents the fraction of industry d's output purchased from the supplier u (the direct requirement in the input-output table). We then estimate a version of equation 4 where we replace ΔG_{jt}^{down} with $\Delta G_{jt}^{ndown} = \sum_{u \neq d} \lambda_{ud} \Delta G_{ut}^{up}$. We also estimate an analogous regression for a measure of intermediate-input prices, defined as $P_{dt}^{I} = \sum_{u \neq d} \lambda_{ud} P_{ut}$, where P_{ut} is the producer price index of industry u and λ_{ud} represents the fraction of d's output purchased from the u-th intermediate.

Figure 8 displays the response of downstream employment and intermediate-input prices. Similarly to Figure 4, downstream employment decreases significantly after several quarters (first panel). Notably, the decrease in employment is preceded by a significant increase in intermediate input prices (second panel). Altogether, these results confirm that price movements across the network can explain the change in downstream economic activity following an industry-specific demand shock.

6 Aggregate Effects

So far, our analysis has focused on identifying industry-level effects by regressing sectoral outcomes on sectoral shocks. The analysis demonstrates that sector-specific changes in public demand have heterogeneous effects along the supply chain. This result begs the question of how production linkages and recipient-industry characteristics shape the aggregate effects of granular public spending. Our last contribution is to estimate the GDP multiplier of aggregate procurement contracts, also addressing how the aggregate effects depend on the production network and sectoral characteristics.

By design, the industry-level estimates cannot be used to infer aggregate outcomes. First, aggregate effects reflect general equilibrium across all sectors, which do not necessarily correspond to the sum of direct, upstream, and downstream effects. For example, aggregate outcomes may also reflect changes in variables that occur at the national level, such as monetary policy, that are averaged out with our estimation technique. Second, since the identification approach in section 3 only identifies local (relative) effects (Chodorow-Reich, 2020), we also cannot simply aggregate industry-level shocks. Third, it is also not possible to sum sectoral shocks from equation (1) since they correspond to sectoral public spending changes divided by nominal sectoral output, making each sector's shock in different output units.[24]

For these reasons, to estimate the aggregate procurement contract multiplier, we employ an instrumental variable approach that addresses the potential endogeneity of sectoral spending.

Granular Instrumental Variable and the GDP Multiplier

To estimate aggregate effects, measured by the cumulative GDP multiplier, we exploit the granularity of the *USAspending.gov* procurement contract data. We implement the granular instrumental variable (GIV) approach of Gabaix and Koijen (2020). GIVs are particularly suitable instruments in situations where the data are highly granular, i.e., as in our context, when a few industries or firms account for the majority of government spending. As idiosyncratic shocks from sectors that have exceptionally large weight in total government spending affect aggregate outcomes, the GIV can provide a valid and powerful instrument.

In our context, the application of the GIV method aims to isolate the idiosyncratic part

[24]To aggregate the shocks, one would have to (1) rescale them using constant weights—such as the ratio of sectoral output to total output—which would introduce measurement error or (2) rescale them using time-varying weights, which would introduce endogenous movements in the measures.

of sectoral government spending, which is in turn used to instrument aggregate spending. The granular instrumental variable z_t constructs a proxy for aggregated idiosyncratic shocks from the difference between the size-weighted average of sectoral government spending and its equal-weighted average:

$$z_t = \sum_j \left(\frac{\bar{G}_j}{G} - \frac{1}{N} \right) G_{it}, \tag{5}$$

where $\bar{G_j}/G$ is the average sectoral share over the sample. This type of GIV is frequently employed in the literature now (e.g., Chodorow-Reich et al., 2021; Ma et al., 2022). The GIV creates a new measure of aggregate government spending that gives higher weight on sectors with larger spending shares. It captures pure idiosyncratic changes in sector-specific public spending, as well as unexpected changes in the loading of common shocks (e.g., an aggregate public spending shock that increased spending in sector j inordinately than expected). See Gabaix and Koijen (2020) for more details and examples. We construct the instrument z_t at the NAICS 4-digit level. As shown in section 2, government spending is highly granular at this level of aggregation.[25]

To determine the aggregate effects of spending shocks, we follow the methodology of Ramey and Zubairy (2018) and estimate cumulative GDP multipliers with local projections-IV. We first adapt their framework by using z_t as our instrument for government spending. Specifically, we estimate

$$\sum_{k=0}^{h} y_{t+k} = \alpha_h + \beta_h \sum_{k=0}^{h} g_{t+k} + \varphi_h(L) C_{t-1} + \epsilon_{t+h} \tag{6}$$

using z_t to instrument for $\sum_{\kappa=0}^{h} g_{t+k}$. As shown by Ramey and Zubairy (2018), β_h provides a direct measure of the cumulative GDP multiplier at horizon h. The variables y and g denote real GDP and real federal government spending divided by an estimate of potential output.[26] C_{t-1} represents a vector of control variables, and $\varphi_h(L)$ is a polynomial in the lag operator. To control for potential serial correlation in the instrument, we include two lags of z_t. In addition, the controls include two lags of y, g, the average federal tax rate, the

[25] We do not consider higher levels of aggregation since input-output linkages are measured less precisely.

[26] Following Ramey and Zubairy (2018), we estimate potential output by fitting log real GDP to a quadratic trend.

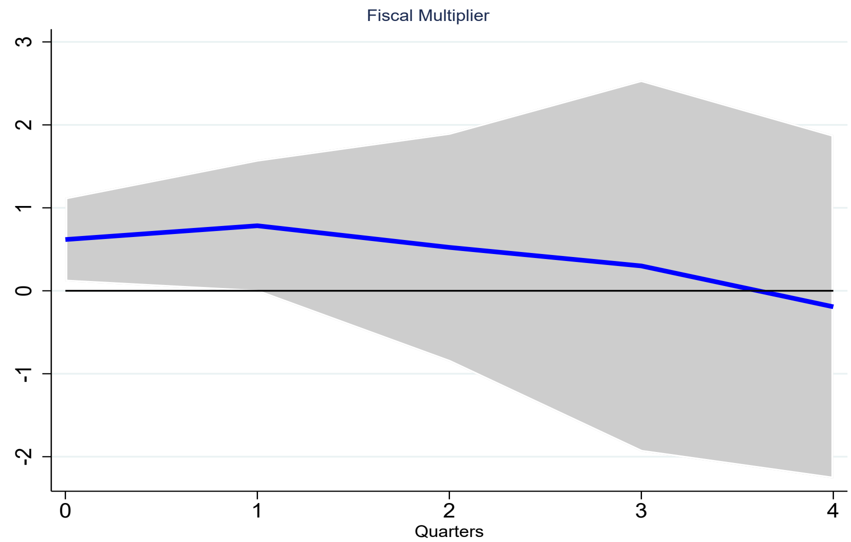

Figure 9: Cumulative GDP multiplier estimated by equation (6).

inflation rate, and the nominal interest rate. The average federal tax rate is constructed by dividing federal current receipts by nominal GDP and controls for tax policy. Both inflation and the interest rate are included to control for monetary policy. Given our sample features an extended period in which the fed funds rate was at the zero lower bound, we use the shadow rate of Wu and Xia (2016) as our measure of the interest rate.

Figure 9 plots the cumulative GDP multiplier along with the 90% confidence bands based on Newey-West corrections of standard errors. The y-axis measures the multiplier effect of a change in government spending, i.e., an increase of \$1 leads to an increase in GDP of 0.6 cents. Theoretical models often predict an output multiplier less than one due to private consumption and/or investment being crowded out by the increase in government demand (e.g., Woodford, 2011, Leeper et al., 2017). The estimated multiplier is persistently positive for several quarters, albeit our short sample implies imprecise estimates over longer time horizons. The multipier estimates and its persistence are within the range of values from the literature (see Ramey, 2016 for a survey).[27]

[27] For robustness, we also considered a standard Blanchard and Perotti (2002) approach to identify government spending shocks, which we then use to instrument public spending in equation (6)—see also Ramey and Zubairy (2018). In this case, the point estimate of the multiplier is 0.61. Results are available upon request.

Production Network, Sectoral Heterogeneity and Aggregate Outcomes

The industry-level analysis demonstrates that sector-specific changes in public demand have heterogeneous effects along the supply chain. This result begs the question of how production linkages and recipient-industry characteristics shape the aggregate effects of sectoral spending. Recent theoretical work yields testable predictions about the aggregate public spending multiplier in production network models. Specifically, theory predicts that the aggregate multiplier is larger when sector-specific spending occurs in industries that (i) are relatively more downstream (Bouakez et al., 2023), (ii) have stickier prices (Bouakez et al., 2023 and Cox et al., 2022), and (iii) sell most of their output directly to the government (Cox et al., 2022, and Proebsting, 2022). As we elaborate on below, theory suggests multipliers are higher in all these cases.

To test these predictions, we modify the GIV approach and create separate instruments that include all sectors above or below the median industry defined along a particular sectoral characteristic:

$$z_t^{\text{above}} = \sum_{j \in \Omega^{\text{above}}} \left(\frac{\bar{G}_j}{G^{\text{above}}} - \frac{1}{N^{\text{above}}} \right) G_{jt}, \tag{7}$$

$$z_t^{\text{below}} = \sum_{j \in \Omega^{\text{below}}} \left(\frac{\bar{G}_j}{G^{\text{below}}} - \frac{1}{N^{\text{below}}} \right) G_{jt}, \tag{8}$$

where $G_j/\bar{G}^{\text{above}}$ represents the average sectoral share over the sample for industries above the median (Ω^{above}) and G_j/G^{below} represents the average sectoral share over the sample for industries below the median (Ω^{below}). We create these instruments using three separate characteristics: (1) upstreamness of the sector, (2) price stickiness of the sector, (3) share of government spending to total sectoral demand. In each case, equations (7) and (8) represent the sum of idiosyncratic shocks in sectors that are above and below the median in terms of a particular characteristic.

To examine the importance of an industry's location in the production network, we use the measure of upstreamness of Antras et al. (2012). The index measures the distance of a production sector from final demand. A relatively upstream sector is one that sells a small share of its output to final consumers, and instead sells disproportionately to other sectors.

Theory predicts that government demand from industries that are less upstream will have larger aggregate effects, as these sectors in turn adjust their own demand for inputs, which has a ripple effect of increasing demand throughout the production network (Bouakez et al., 2023).

To explore the consequence of price rigidities, we use the sectoral frequency of price adjustment measure of Pasten et al. (2021).[28] A larger measure implies a sector with more frequent price adjustments, i.e. a smaller price rigidity. Theory predicts that government demand from industries that have more rigid prices will have larger aggregate effects, as fewer changes in prices—and in turn the interest rate—imply less crowding out of private demand (Cox et al., 2022).

Finally, we investigate how the ratio of government demand to sectoral output shapes the aggregate multiplier. To construct this measure, we use the data described in section 2. Theory predicts that when the government accounts for a larger share of total demand, the aggregate multiplier is larger, as prices respond less in this case, leading to less crowding out of private consumption (Cox et al., 2022, Proebsting, 2022).

To test the importance of these sectoral characteristics, we re-estimate equation (6) using either z_t^{above} or z_t^{below} to instrument for $\sum_{\kappa=0}^{h} g_{t+k}^{\text{above}}$ and $\sum_{\kappa=0}^{h} g_{t+k}^{\text{below}}$, respectively.[29] In each case, we include the same set of controls as before, plus two lags of the instrumented shock series and two lags of each spending measure.

Figure 10 displays how the cumulative multipliers vary with the different sectors' characteristics. In all cases, the responses are consistent with theoretical predictions. When government spending originates in sectors that are less upstream, multipliers are significantly larger (top row of Figure 10) with an impact multiplier well above one. When recipient sectors feature stronger price rigidities (middle row of Figure 10), the point estimate of the multiplier is also higher, albeit the effects are not tightly estimated. Finally, multipliers are higher when the government accounts for a larger share of the recipient-industry demand (bottom row of Figure 10). Overall, these results provide empirical support to recent the-

[28]We thank Michael Weber for graciously sharing the data.

[29]The variables g_{t+k}^{above} and g_{t+k}^{below} denote total real federal government spending in industries ranked as above and below median for a particular sectoral characteristic, divided by potential output.

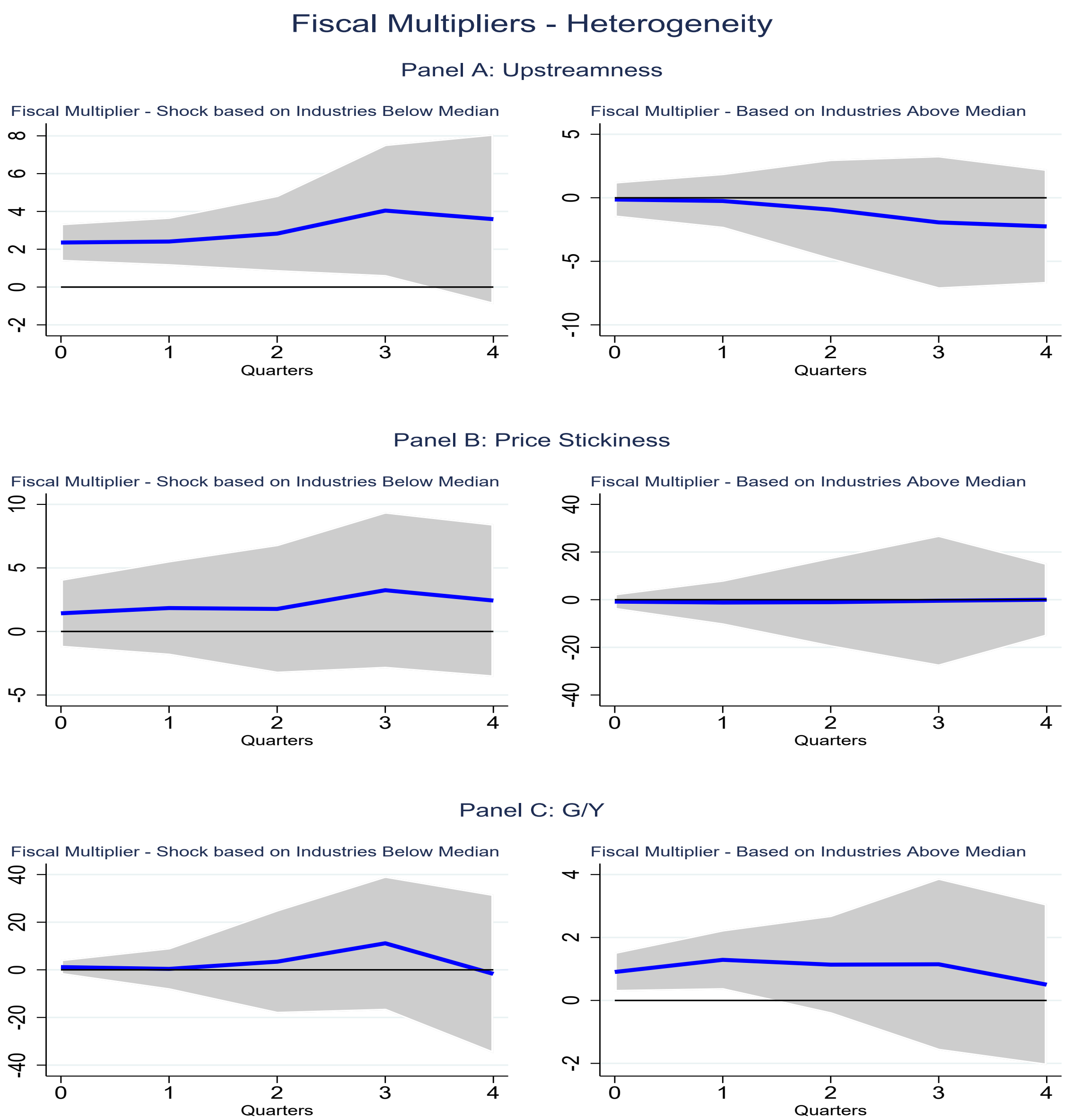

Figure 10: Cumulative GDP multipliers for sectors less upstream than the median (left figure) and more upstream than the median (right figure).

oretical insights and demonstrate the importance of network considerations for the overall impact of granular public spending.

7 Conclusion

Using disaggregated U.S. government procurement data, we estimate the effects of government spending through the production network. Panel local projection estimates document sizable effects both in recipient industries (i.e., industries that receive procurement contracts) and across the supply chain. Employment increases in recipient industries and in sectors supplying intermediate inputs to these industries. In contrast, employment is crowded-out downstream. We then document that prices and wages increase significantly in recipient industries and for their suppliers. Moreover, higher intermediate-input demand by recipient industries translates into higher intermediate-input prices across the network, accounting for the crowding out of downstream employment. We then estimate the aggregate implications of sectoral shocks and the influence of sectoral heterogeneity We find the effects are higher when recipient sectors are more downstream, have stickier prices, and when the government accounts for most of their total sales.

Our research suggests important avenues for future research. First, our empirical results imply that accounting for the sectoral origin of government spending and its transmission through the production network have first-order implications for the design and effectiveness of public purchases. Second, the heterogenous effects along the supply chain may have distributional consequences for firms and workers across sectors. Finally, our results show that accounting for price adjustment across industries is central to understand the aggregate implications of granular demand shocks, a dimension thus far overlooked by the theoretical production network literature.

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Online Appendix to:
"Estimating the Effects of Government Spending Through the Production Network"

Authors: A. Barattieri, M. Cacciatore, and N. Traum

A Additional Details of Government Spending

Figure A.1 plots the percent of procurement spending allocated to each top-25 industry over our sample (blue solid lines) as well as the share of government spending to industry output (red solid lines). The figure demonstrates that trends in the spending shares, and output shares seen in Figure 1 of the main paper, are unlikely to be driven by trends in the government's demand for specific industry goods, as the share of government spending to industry output is small —less than 10% — for these industries.

Tables 1 and 2 list the top-25 suppliers and customers of the top-25 recipient industries in terms of their output exposure. As can be seen from the table, upstream and downstream connections are found in both manufacturing and service industries. Moreover, there is virtually no overlap between the op suppliers and customers.

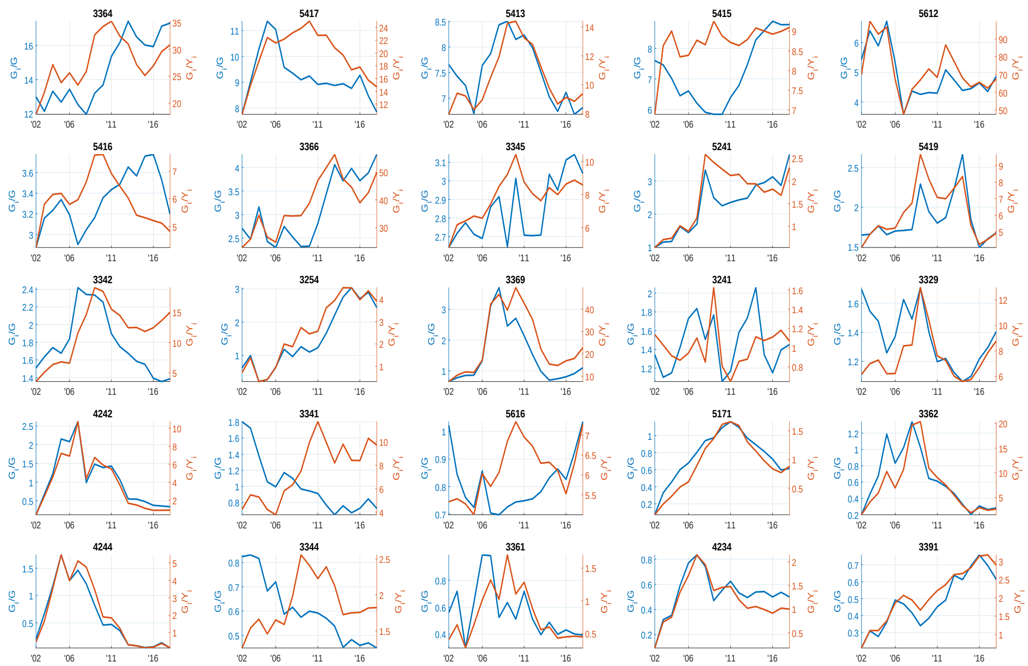

Figure A.1: Shares of industry government spending to total public spending (left-scale) and industry public spending to industry output (right-scale) for top-25 recipient industries of government procurement contracts.

Table 1: Top suppliers of the top 30 recipients

NAICS	Industry	% of Y_i
3363	Motor Vehicle Parts Manufacturing	67.22
3336	Engine, Turbine, and Power Transmission Equipment Manufacturing	35.69
3344	Semiconductor and Other Electronic Component Manufacturing	34.01
5152	Cable and Other Subscription Programming	30.84
3325	Hardware Manufacturing	28.74
5418	Advertising, Public Relations, and Related Services	27.51
3272	Glass and Glass Product Manufacturing	27.50
3326	Spring and Wire Product Manufacturing	26.47
4231	Motor Vehicle and Motor Vehicle Parts and Supplies Merchant Wholesalers	24.19
3262	Rubber Product Manufacturing	24.18
7115	Independent Artists, Writers, and Performers	23.98
3359	Other Electrical Equipment and Component Manufacturing	22.48
5416	Management, Scientific, and Technical Consulting Services	21.18
3321	Forging and Stamping	21.17
5121	Motion Picture and Video Industries	18.47
3346	Manufacturing and Reproducing Magnetic and Optical Media	18.45
5414	Specialized Design Services	18.34
3327	Machine Shops; Turned Product; and Screw, Nut, and Bolt Manufacturing	16.94
3313	Alumina and Aluminum Production and Processing	16.92
5613	Employment Services	16.61
5612	Facilities Support Services	16.58
3314	Nonferrous Metal (except Aluminum) Production and Processing	16.19
3311	Iron and Steel Mills and Ferroalloy Manufacturing	15.70
5611	Office Administrative Services	15.43
4236	Household Appliances and Electrical and Electronic Goods Merchant Wholesalers	14.93
3261	Plastics Product Manufacturing	14.44
5614	Business Support Services	14.39
5419	Other Professional, Scientific, and Technical Services	13.92
3343	Audio and Video Equipment Manufacturing	13.65
3255	Paint, Coating, and Adhesive Manufacturing	13.59

Table 2: Top customers of the top 30 recipients

NAICS	Industry	% of Y_i
3341	Computer and Peripheral Equipment Manufacturing	26.42
5172	Wireless Telecommunications Carriers (except Satellite)	24.18
5174	Satellite Telecommunications	17.29
3343	Audio and Video Equipment Manufacturing	17.13
3333	Commercial and Service Industry Machinery Manufacturing	13.58
3345	Navigational, Measuring, Electromedical, and Control Instr. Manuf.	12.72
3362	Motor Vehicle Body and Trailer Manufacturing	11.94
3342	Communications Equipment Manufacturing	10.67
3332	Industrial Machinery Manufacturing	10.36
6216	Home Health Care Services	10.22
5182	Data Processing, Hosting, and Related Services	10.00
3366	Ship and Boat Building	9.21
6219	Other Ambulatory Health Care Services	8.99
6215	Medical and Diagnostic Laboratories	8.87
5413	Architectural, Engineering, and Related Services	8.82
3117	Seafood Product Preparation and Packaging	8.82
5191	Other Information Services	8.69
3114	Fruit and Vegetable Preserving and Specialty Food Manufacturing	8.39
3113	Sugar and Confectionery Product Manufacturing	8.38
3115	Dairy Product Manufacturing	8.35
5417	Scientific Research and Development Services	8.34
6211	Offices of Physicians	8.21
3259	Other Chemical Product and Preparation Manufacturing	8.20
5612	Facilities Support Services	8.06
5239	Other Financial Investment Activities	7.90
6114	Business Schools and Computer and Management Training	7.68
3231	Printing and Related Support Activities	7.59
3254	Pharmaceutical and Medicine Manufacturing	7.47
3251	Basic Chemical Manufacturing	7.41
3364	Aerospace Product and Parts Manufacturing	7.21