Estimating the Effects of Government Spending Through the Production Network

Preliminary Draft

Alessandro Barattieri
ESG UQAM

Matteo Cacciatore
HEC Montréal,
Bank of Canada, and NBER

Nora Traum
HEC Montréal

February 27, 2023

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 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 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. Using a granular instrumental variable approach, we then estimate the aggregate implications of sectoral shocks and the influence of sectoral heterogeneity. We find that aggregate effects are higher when recipient sectors are more downstream, have stickier prices, and when the government accounts for most of their total sales.

JEL Codes: E62; E32

Keywords: Government spending; Input-Output Linkages; Local Projections; Granular IV.

1 Introduction

In the last decade, a vibrant research program has documented the importance of the production network for the transmission of shocks and policies.[1] Recently, researchers' attention has turned to the transmission of public spending along the supply chain. In particular, a fast-growing theoretical literature addresses how sectoral interconnectedness and heterogeneity affect the aggregate transmission of public spending (e.g., Bouakez et al., 2022; Cox et al., 2022; Flynn et al., 2021; Proebsting, 2022). This work is motivated by the observation that public purchases of goods and services from the private sector are highly concentrated in a few industries (Cox et al., 2022), and the composition of government spending can change over time, as a government's needs and preferences vary.[2]

To date, there is little empirical evidence on the importance of the production network in propagating sector-specific government spending. How do changes in granular spending affect the recipient industries? How do they transmit through the production network? And ultimately, what are the implications for aggregate outcomes? This paper addresses these questions.

Since identifying exogenous sectoral government spending variation is necessary for our analysis, our first contribution is to identify sectoral changes that are unanticipated and uncorrelated with macroeconomic outcomes. To do so, we use the public U.S. database *USASpending.gov*, which provides detailed information on individual U.S. procurement contracts for goods and services. We consider the entire universe of both defense and non-defense contracts, implying that recipient industries include both manufacturing and services.

Using the universe of contracts awarded from 2001 to 2019, we purge sectoral government spending of movements representing an endogenous response to economic conditions or variation that is likely anticipated.[3] We aggregate spending data for a panel of NACIS 6-digit industries, the finest possible sectoral disaggregation. We then obtain sectoral shocks by identifying the variation in spending that cannot be explained by quarterly time fixed effects (capturing aggregate business cycle conditions), industry-specific fiscal-year fixed effects (capturing possible budgetary anticipation), and industry-specific controls, including a benchmark measure of expected profitability from

[1] See for instance, Acemoglu et al. (2016); Acemoglu et al. (2012); Acemoglu et al. (2015); Atalay (2017); Baqaee and Farhi (2018); Baqaee and Farhi (2019); Baqaee and Farhi (2020); Barrot and Sauvagnat (2016); Bigio and La'O (2020); Carvalho et al. (2021); Dhyne et al. (2021); Elisa Rubbo (2023); vom Lehn and Winberry (2022).

[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.

[3] In spirit, our approach builds on a consolidated strategy in the monetary and fiscal policy literature (e.g., Romer and Romer, 2004; Auerbach and Gorodnichenko, 2013).

the finance literature (the market-to-book ratio). We further conisder a specification that exploits contract-level information by restricting the analysis to competitively bid contracts, which are also less likely to be anticipated.

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. We combine the identified industry-level shocks with input-output tables to construct upstream and downstream fiscal measures capturing the exposure of the suppliers and customers of the recipient industries. We then estimate panel local projections to trace the dynamic response of employment in recipient industries (i.e., the industries that receive procurement contracts), 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 significantly crowded-out downstream. Importantly, 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 recipients and suppliers industries 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. 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

[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.

production network models. First, the more downstream the industry is, the larger the stimulative effect (Bouakez et al., 2023). Second, the multiplier should be larger for recipient industries with stickier prices (Bouakez et al., 2023 and Cox et al., 2022). Third, the effects of sectoral government shocks are more stimulative when recipient industries sell most of their output directly to the government (Cox et al., 2022, and Proebsting, 2022). Our third and final contribution is to quantify the aggregate implications of sectoral shocks and examine how industry characteristics shape the aggregate GDP multiplier.

To estimate the aggregate effects, we implement the granular instrumental variable (GIV) approach of Gabaix and Koijen (2020).[5] Our context represents an ideal setting for this approach since a few large industries account for a large share of total spending. GIV seeks to isolate the idiosyncratic part of sectoral government spending by focusing on the behavior of the few sectors that have exceptionally large weight in total government spending. We first show that estimating cumulative GDP multipliers with a traditional local projections-IV (Ramey and Zubairy, 2018)—using the GIV as an instrument—yields estimates in line with the literature. The estimated GDP muliplier is significantly positive, less than one, and persistent. Moreover, it is only slightly lower than the value implied by a conventional Blanchard and Perotti (2002) identification.

We then turn to the role of sectoral heterogeneity. We find that when government demand falls on sectors that are relatively more downstream industries, multipliers are significantly larger, well above one. The aggregate multiplier is also larger when spending is allocated to sectors with higher price rigidities, albeit this effect is estimated less precisely. Finally, multipliers are 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.

Related Literature. Our paper is the first to identify fiscal shocks at a sectoral level and to trace their effects through the production network. Few studies have examined the effects of government 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 using yearly data.[6] All these studies rely on a Bartik approach to instrument sector-specific government spending with

[5] Since our estimation approach identifies local effects (Chodorow-Reich, 2020), it cannot be used to quantify the aggregate implications of sectoral shocks.

[6] Other recent studies address how production networks propagate sector-specific shocks (e.g., Horvath, 2000; Carvalho, 2007; Foerster et al., 2011) without considering fiscal policy.

a measure of aggregate government spending weighted by each sector's spending share. While this approach can detect changes in sectoral public spending common to aggregate spending's variation, it is less suited to deal with granular idiosyncratic shocks. Additionally, spending shares may not be exogenous to sectoral output and employment dynamics. For instance, Nekarda and Ramey (2011) suggest that industry-specific technological developments could affect both production and government demand simultaneously. Moreover, Moro and Rachedi, 2022 show government spending has experienced structural change in the past decades, relying more on private-sector goods than its own production of value added. Motivated by these facts, we develop a new approach that identifies exogenous variation in sector-specific public spending using highly disaggregated data.

There is little empirical evidence on the importance of sectoral characteristics following government spending shocks, but our results are consistent with the few current studies. Bouakez et al. (2023) use a Bartik instrument to determine how the average local multiplier depends on sectoral characteristics. They also find the degree of upstreamness is quantitatively important, but their local multiplier has little sensitivity to heterogeneity in price stickiness. Cox et al. (2022) uses a Blanchard and Perotti (2002) identification in a VAR for two separate public spending series: one with recipients in sectors with relatively flexible prices and one with recipients with relatively sticky prices. They find some support for larger effects from government spending shocks originating in sectors with stronger price rigidities.

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 of the results. 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

This section describes the aggregation of contract-level federal procurement spending to the industry-quarter level. 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.[7] 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 Produce 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 contracts 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 and NAICS-6 digit industry to which the contract work is assigned. 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; aggregating contracts to the NAICS-4 digit, the top 25 recipient industries account for 70% of total procurement spending (see Table 1). Notably, the top 25 recipient industries are split roughly in half between manufacturing (NAICS-3xxx digit codes) and some services (NAICS-4xxx and -5xxx digit codes). Incorporating information 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-25 recipient industries over our sample. 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

[7] Other studies have used the database to analyze defense spending (e.g., Auerbach et al., 2020a and Demyanyk et al., 2019) or contracts awarded to listed firms (Hebous and Zimmermann, 2021). Only Cox et al. (2022) has previously utilized the universe of the database's contracts.

Table 1:

TABLE 1: Top 25 recipients (of 351 industries)

NAICS	Industry	% of G
3364	Aerospace Product and Parts Manufacturing	13.52
5417	Scientific Research and Development Services	8.54
5413	Architectural, Engineering, and Related Services	7.2
5415	Computer Systems Design and Related Services	6.77
5612	Facilities Support Services	5.79
5416	Management, Scientific, and Technical Consulting Services	3.67
3366	Ship and Boat Building	2.9
3345	Navigational, Measuring, Medical & Control Inst. Man.	2.68
3241	Petroleum and Coal Products Manufacturing	2.22
5241	Insurance Carriers	2.1
5419	Other Professional, Scientific, and Technical Services	2.03
3342	Communications Equipment Manufacturing	1.67
3254	Pharmaceutical and Medicine Manufacturing	1.44
3369	Other Transportation Equipment Manufacturing	1.41
3329	Other Fabricated Metal Product Manufacturing	1.33
5616	Investigation and Security Services	1.00
3341	Computer and Peripheral Equipment Manufacturing	0.95
4242	Drugs and Druggists' Sundries Merchant Wholesalers	0.95
4244	Grocery and Related Product Merchant Wholesalers	0.90
5171	Wired Telecommunications Carriers	0.75
3362	Motor Vehicle Body and Trailer Manufacturing	0.56
3344	Semiconductor and Other Electronic Component Manufacturing	0.56
3361	Motor Vehicle Manufacturing	0.53
4234	Professional & Commercial Equip. & Supplies Merchant Wholesalers	0.51
3391	Medical Equip. & Supplies Manufacturing	0.45
	TOTAL	**70.43**

Table 2: Table 2. Exposure of suppliers and customers of the top-25 recipient industries.

	Top suppliers of the top 25 recipients	
NAICS	*Industry*	% of Y_i
3363	Motor Vehicle Parts Manufacturing	67.27
3336	Engine, Turbine, and Power Transmission Equipment Manuf.	35.64
3344	Semiconductor and Other Electronic Component Manufacturing	34.44
5152	Cable and Other Subscription Programming	30.84
5418	Advertising, Public Relations, and Related Services	30.61
	Top customers of the top 25 recipients	
NAICS	*Industry*	% of Y_i
3341	Computer and Peripheral Equipment Manufacturing	28.02
5172	Wireless Telecommunications Carriers (except Satellite)	24.21
3343	Audio and Video Equipment Manufacturing	18.14
5174	Satellite Telecommunications	17.28
3333	Commercial and Service Industry Machinery Manufacturing	14.52

output shares (see the red solid lines of Figure 1).[8] The figure also shows that several industries exhibit strongly correlated trends across spending and output shares (for example, industries 3341, computer and peripheral equipment manufacturing, and 3344, seminconductor 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 both production and government demand 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 the top-25 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

[8] Industry output is measured as gross output from the U.S. Bureau of Economic Analysis. A consistent measure across industries is only available at an annual frequency.

[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 these industries.

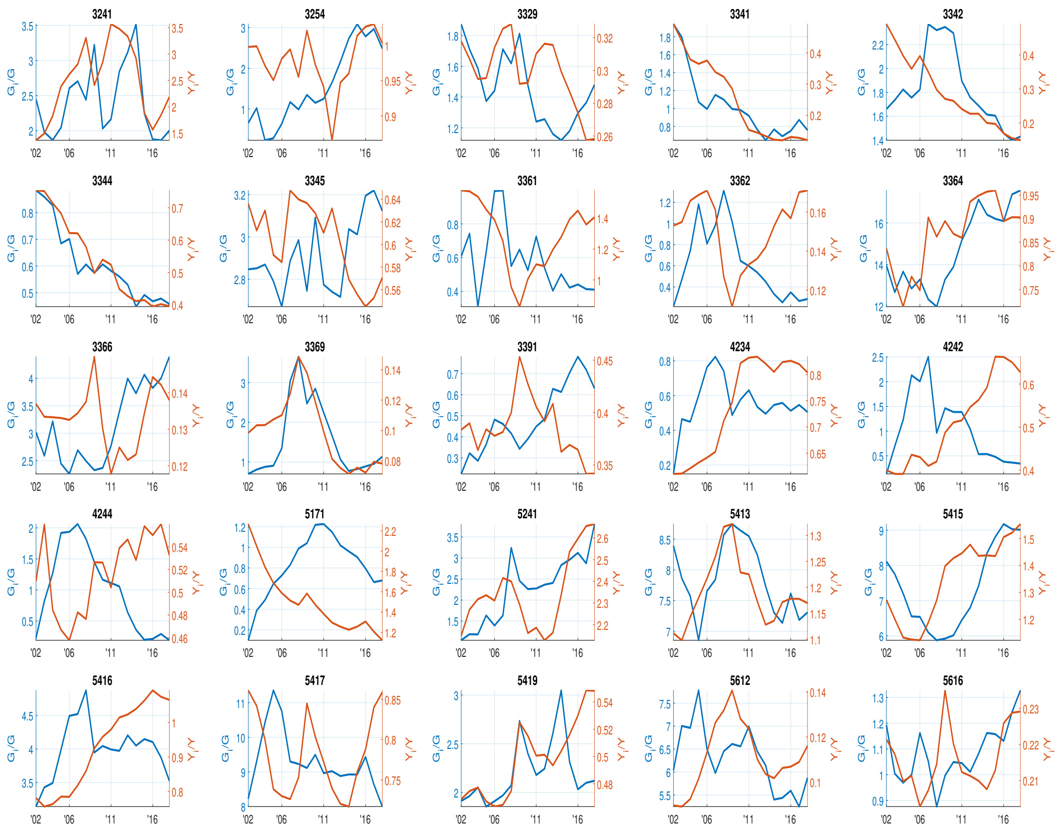

Figure 1: Figure 1. Shares of industry government spending to total public spending (left-scale) and industry output to total output (right-scale) for top-25 recipient industries of government procurement contracts.

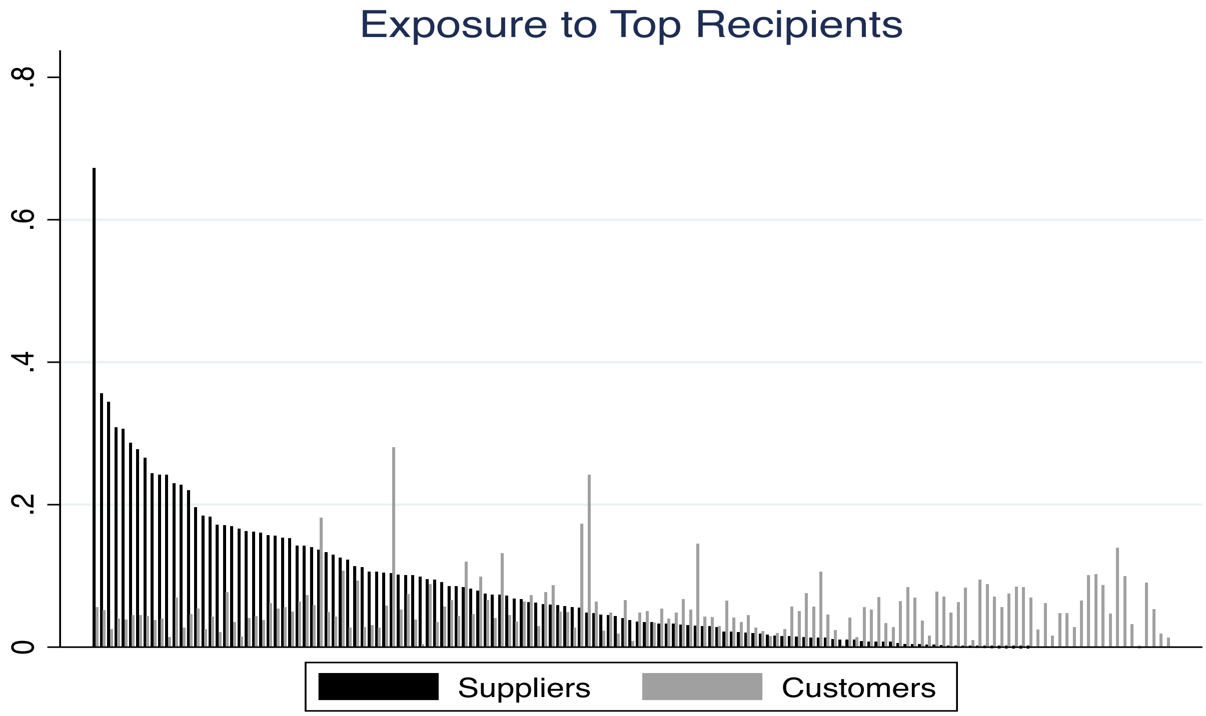

Figure 2: Figure 2.

purchased by the top-25 public procurement recipients and divide the total by X's final output. Similarly, we construct a measure of customers' exposure from the top-25 recipients by summing the total intermediate purchases of X from the top-25 recipients and dividing the total by X's final output.

Table 2 lists the top-5 suppliers and customers of the top-25 recipient industries [10]. The main suppliers and customers of the top-25 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-25 recipients. In contrast, the intermediate inputs purchased by the top customer — computer manufacturing (NAICS code 3341) — from the top-25 recipients are worth 28% 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-25 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

[10] Tables 1 and 2 provide a more complete picture by listing the top-25 respective industries

is no systematic relation across these two measures.

3 Identifying Sectoral Government Spending Shocks

Our first goal is to estimate the effects of exogenous sectoral government spending changes on industry-level economic activity. To do so, we first must address two well-known challenges in identifying public spending shocks: 1) accounting for potential endogeneity and 2) accounting for anticipation effects.

To address potential endogeneity when employing disaggregated data, the previous literature utilized a Bartik-style instrument with aggregate defense spending. In this case, 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. Examples of disaggregation include the geographic level (Nakamura and Steinsson, 2014 and Dupor and Guerrero, 2017) or industry level (Acemoglu et al., 2016 and Auerbach et al., 2020a). The rational for using aggregate defense spending is that defense dynamics are thought to be exogenous with respect to the economic environment (Ramey, 2011). However, when studying production network transmissions, the Bartik approach faces some limitations. As demonstrated in the previous section, some industry-level public-spending shares exhibit trends that are correlated 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.

Motivated by these concerns, we depart from this literature and 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 is similar to past strategies to identify monetary policy shocks (Romer and Romer, 2004), aggregate fiscal policy shocks (Auerbach and Gorodnichenko, 2013), and trade barrier shocks (Barattieri and Cacciatore, 2020). Specifically, we consider a two-step estimation procedure, where in the first stage we regress the sectoral government spending series on specific industry-level controls to identify exogenous variation. In the second stage, we use the identified sectoral shocks as instruments to estimate the effects of public spending changes throughout the supply chain.

Identification Strategy

Let G_{it} denotes 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 quarter-to-quarter difference divided by industry output, $\Delta G_{it} \equiv G_{it} - G_{it-4}/Y^a_{js-1}$. 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 our measures to deal with both endogeneity and anticipatory effects. Concerning the former, we use aggregate time fixed effects to control for aggregate shocks and policies, as well as lagged employment growth and sectoral government spending to account for persistent changes to industry-level government spending and past economic conditions. We also construct a benchmark measure of industry-specific expected profitability (the market-to-book ratio) to control for industry-level expectations. Since implementation lags can make spending changes forecastable — particularly following the enactment of fiscal-year budgets — we further include industry-specific fixed effects for each fiscal year that capture expectations of within-year allocations of spending.

Concretely, we estimate the following regression:

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

where i, j, and t index industries i (NAICS 6-digit) and j (NAICS 4-digit) and time t (quarters). 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. $(\psi_{FY} \times \eta_i)$ is an 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 be already 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.

To control for past industry specific business-cycle conditions, we include lags of government spending (ΔG_{it}) and year-on-year growth rates of employment at the NAICS 4-digit (ΔL_{jt}). While aggregate effects are subsumed in the time fixed effects, one could imagine that aggregate changes impact certain industries differently. To control for this, we include the lagged spending-to-output ratio (G/Y) interacted with a NAICS 4-digit fixed effect.[11]

Finally, the term ΔMB_{jt} denotes the year-on-year growth rates of the median market-to-book ratio at the NAICS 4-digit. Following Barattieri and Cacciatore (2020), we construct this variable to control for anticipated changes in the industry's future profitability. 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 employment growth, Table 3 reports the results of a Granger causality test. 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.

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, we exclude industries where ΔG_{jt} has values both greater than 50% and less than -50%.[12]

[11] We do not consider the interaction at the NAICS 6-digit level to avoid an excessive proliferation of regressors.
[12] We consider outliers at the NAICS 4-digit level, as that is the level of analysis in our second-stage estimation.

Table 3: 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

Estimated Sectoral Shocks

We aggregate the identified NAICS 6-digit shocks ν_{it} to the NAICS 4-digit level—the most detailed level at which comprehensive data for employment, prices, and input-output relationships are available at a consistent level of aggregation. Let ν_{jt} be the NAICS 4-digit aggregation, constructed as:

$$\nu_{jt} = \sum_{i=1}^{N_j} \nu_{it}, \tag{2}$$

where N_j is the number of NAICS 6-digit industries within a 4-digit classification. Notice this aggregation exploits the fact that within a NAICS 4-digit code, the NAICS 6-digit shocks are all expressed in terms of the same NAICS 4-digit output.

These 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 suggesting no correlation across industries.[13]

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

[13] 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.

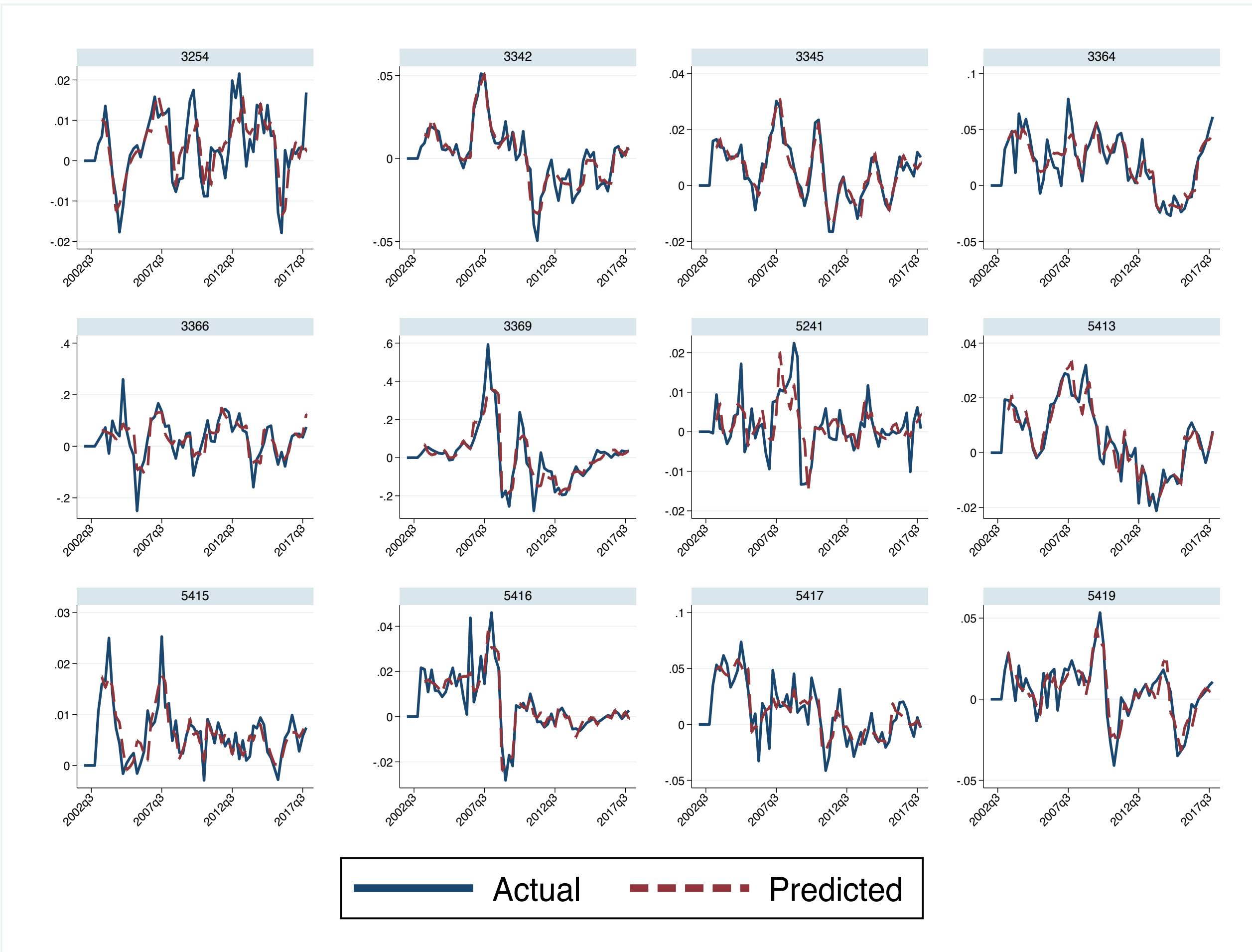

Figure 3: Figure 3. Predicted (red dashed lines) and actual (blue solid) government spending for the top NAICS 4-digit recipients of government contracts.

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, according to our model, the large swing in spending around 2007 in industry 3369 (transportation equipment manufacturing) is only partly anticipated. Digging into this episode, the bulk of the variation came from one 6-digit industry: 336992 (i.e., military armored vehicle, tank, and tank component manufacturing). More specifically, in the fourth quarter of 2007, several large contracts were awarded to different firms to provide military vehicles aimed at sustaining the U.S. war efforts in Iraq and Afghanistan.[14] Some of these contracts were part of longstanding programs, which were also reported in the business press several months before.[15] Other contracts, instead, were far less likely to be anticipated, as they aimed to limit U.S. troop casualties and were implemented quite quickly during 2007.[16]

In summary, Figure 3 demonstrates that 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.[17]

Upstream and Downstream Shocks

We now discuss our 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

[14] On November 29th 2007, BAE System Land and Armaments was awarded a contract worth $812 million and on December 12th, 2007, BAE System Land and Armaments, NAVISTAR Defence LLP, and General Dynamics Land Systems were awarded contracts worth respectively $1.1, $1.4 and $0.8 billion.

[15] An example of such long lasting programs is the Bradley reset process, for which the Department of Defense awarded several multi-million contracts in the period 2005-2009. See for instance: `https://defense-update.com/20070122_bradley-reset.html`.

[16] In February 2007, the Assistant Secretary of the Navy (ASN) for Research, Development, and Acquisition (RDA) approved the Rapid Acquisition of Mine Resistant Ambush Protected Vehicles (MRAP) program's entry into production as a rapid acquisition capability. This program was aimed at limiting the casualties that the U.S. troops were sustaining from Improvised Explosive Devices (IED). In September 2007, the Under Secretary of Defense for Acquisition, Technology, and Logistics designated MRAP as a major defense acquisition program with the Navy as the Executive Agent and the Marine Corps Systems Command as the Joint Program Executive Officer. See U.S. Government Accountability Office (2018) for further details.

[17] In practice we consider recipient industries with an average sectoral public spending to output ratio above 0.5%.

spending shocks (i.e., supplier shocks).

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:

$$\nu_{jt}^{up} = \sum_k (\tilde{\omega}_{jk} - \mathbf{1}_{k=j})\nu_{kt}, \tag{3}$$

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.[18] 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:

$$\nu_{jt}^{down} = \sum_k (\omega_{kj} - \mathbf{1}_{k=j})\nu_{kt}, \tag{4}$$

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 (3) and (4).

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

$$\Delta L_{jt+h} = \alpha_{hj} + \beta_h^{own}\Delta G_{jt} + \beta_h^{up}\Delta G_{jt}^{up} + \beta_h^{down}\Delta G_{jt}^{down} + \varphi_h(L)C_{t-1} + \gamma_{ht} + \epsilon_{jt+h}. \tag{5}$$

[18] Acemoglu et al. (2012) suggest the stability of the production network over time.

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.[19] 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.

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 effect 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 and 2 of Figure 4). On average, a 1% increase in ΔG_{it} implies a peak increase of employment in sector i of roughly 0.55%, 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 0.45%. Importantly, all the responses peak several quarters after the initial shock, suggesting 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 0.4%. This result may seem surprising in light of benchmark models of network transmission following demand shocks, e.g. Acemoglu et al. (2016). The conventional view is that demand shocks only propagate upstream. In section 5, we provide evidence that price dynamics across the production network can rationalize our estimates.

Given the novelty of our results — particularly in terms of a significant downstream economic

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

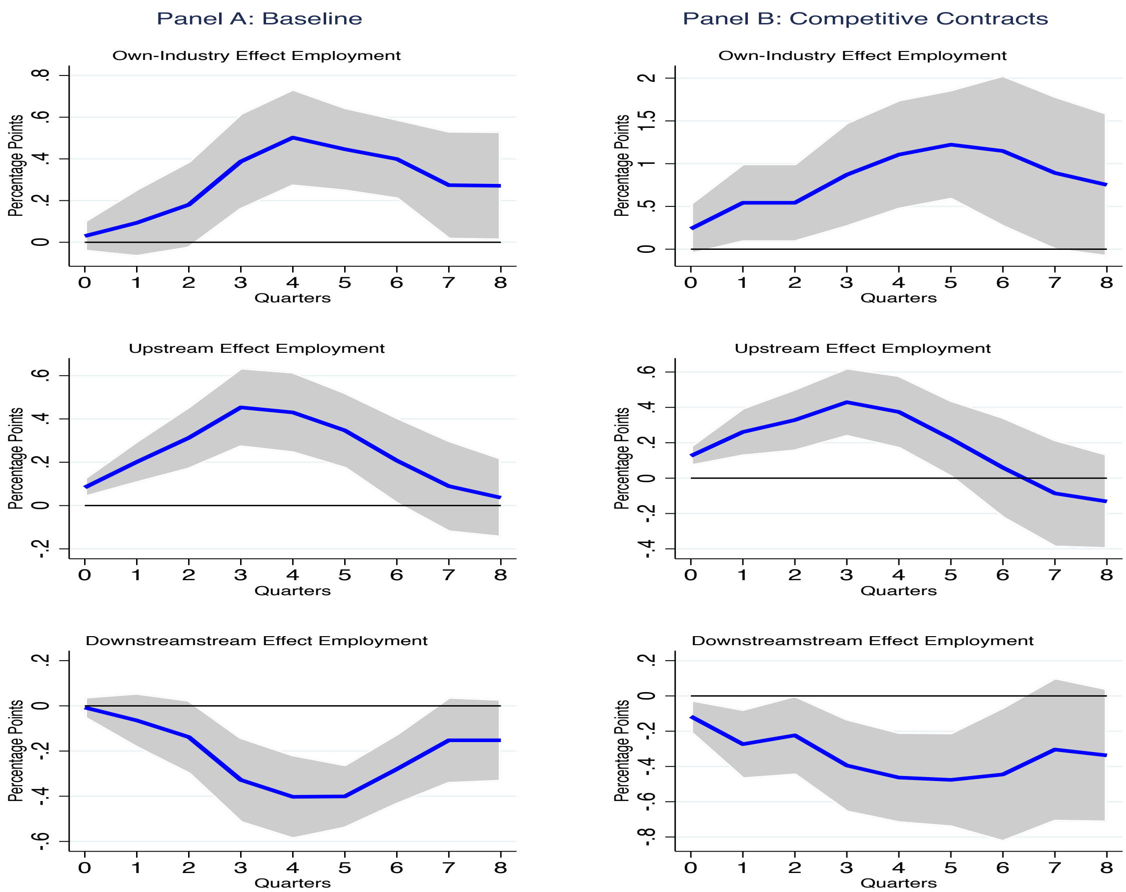

Figure 4: Figure 4. Impulse responses from local projections. Top row displays effects in recipient industry; middle row shows effects from shocks to an industry's consumers; bottom row displays effects from shocks to an industry's suppliers.

effect — we now provide further evidence that these results hold when considering several robustness checks. 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 far less likely to have been anticipated.[20] This lowers the coverage of the value of contracts considered, as only 51% 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 network, as both the upstream and downstream effects are of similar magnitudes as the direct effect.

In the next subsection, we provide a variety of sensitivity analysis further documenting the robustness of these results.

Sensitivity Analysis

In this section, we explore the sensitivity of our results to the specification and measurement. We first consider an alternative outcome variable as well as alternative specifications to estimate government spending shocks, i.e., our first-stage regression. We then consider the results using alternative measurements 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

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

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

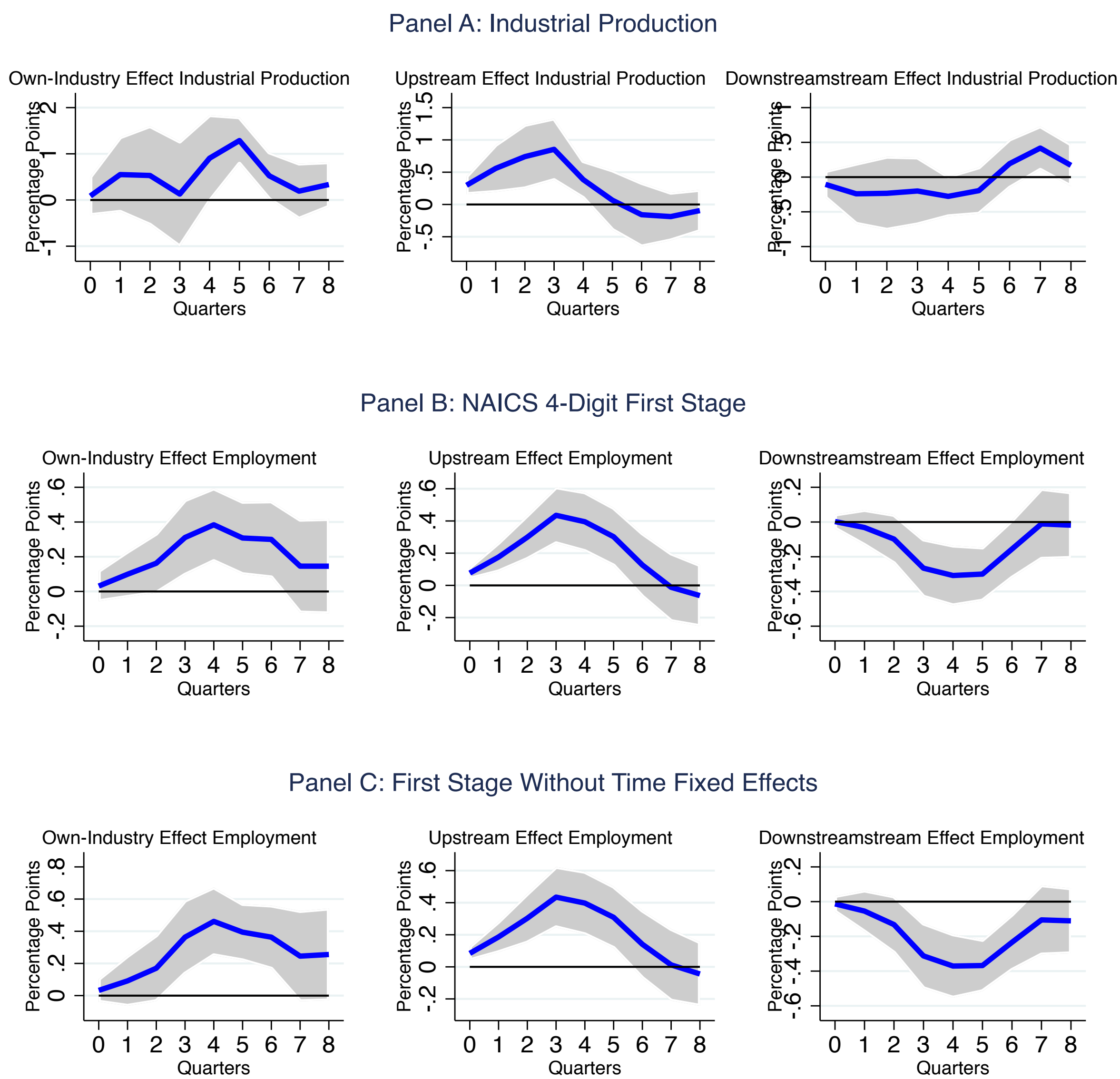

Figure 5: Figure 5. Sensitivity analysis of impulse responses from local projections. Top row: using Industrial Production in place of employment as the outcome variable. Middle row: Using only NAICS 4-digit analysis at the first stage. Bottom row: excluding time fixed effects in the first-stage estimation.

on recipient industries (first column), the upstream effects of customer shocks (middle column), and the downstream effects of supplier shocks (last column). The results look 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 identified 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, which instead is measured at the NAICS 4-digit level. To the extent that the 6-digit price deflator differs within a NAICS 4-digit industry, dynamics in ΔG_{it} could also reflect relative price movements. Given this mismatch, we directly construct ΔG_{it} at the NAICS 4-digit level and use it in all subsequent analysis. The middle row of Figure 5 plots the responses for employment in this case. The results show that relative price effects do not have first-order effects on the estimates.

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

Finally, we consider the sensitivity of the results using two alternative government spending measures. First, we consider an alternative first-stage estimation where we replace the dependent variable with the level of government spending to output: G_{it}/Y^a_{js-1}, where i represents the NAICS 6-digit industry and j represents the NAICS 4-digit industry. Studies that estimate local projections using aggregate government spending shocks often consider a similar measure, namely the public spending to output ratio (see for instance Ramey and Zubairy, 2018). Thus, we test if our results are sensitive to specifying spending changes in levels or relative to the previous-year quarter (our baseline specification). The top panel of Figure 6 plots the impulse responses and shows the results are qualitatively insensitive to the measurement of public spending.

Next, 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 government spending originating from contracts only with the Department of Defense. The middle panel of Figure 6 displays the employment impulse responses in this case and shows that the qualitative results also hold only for the subset of defense expenditures.

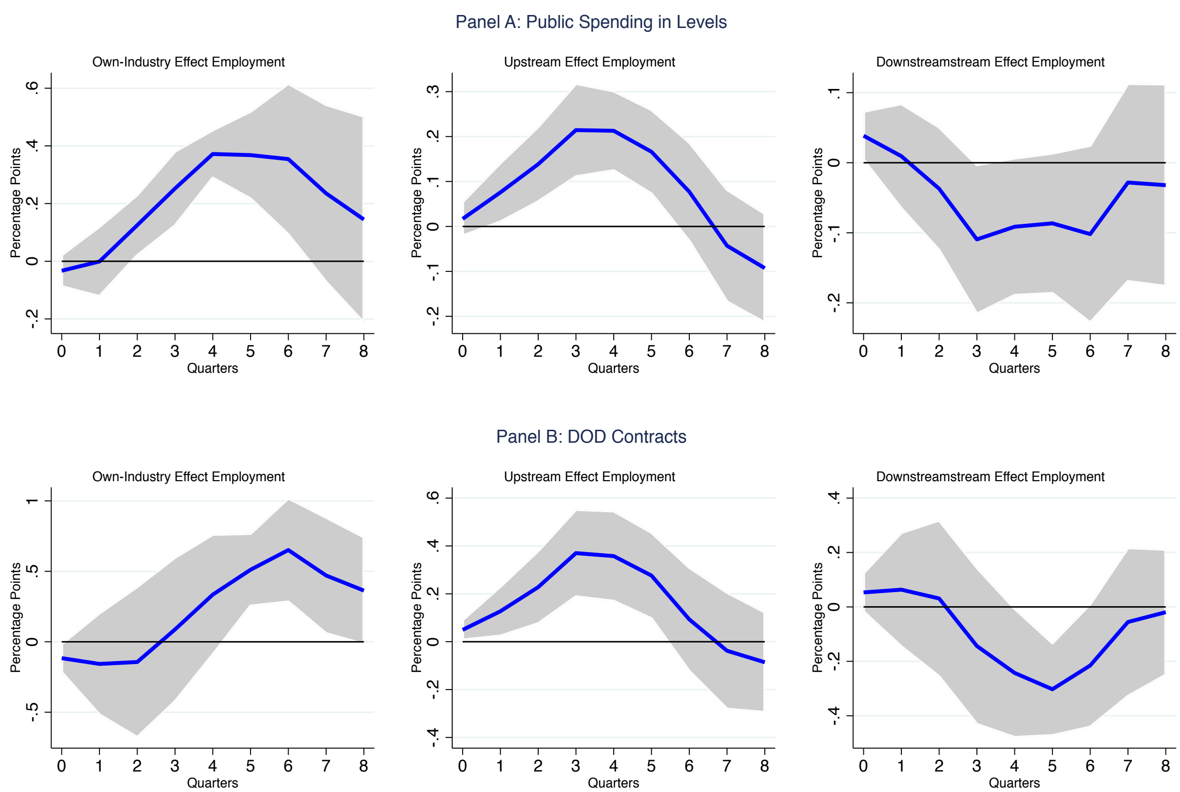

Figure 6: Figure 6. Sensitivity analysis of impulse responses from local projections. Top row: estimation using the public spending in levels. Bottom row: including only government spending data from the Department of Defense.

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 featuring 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. Sectoral demand shocks increase production within an industry, and in order to increase production, the recipient industry raises demand for intermediate inputs, expanding production in industries upstream of the recipient. The absence of downstream propagation stems from a specific modelling assumption: Since all sectors feature constant returns to scale, prices are independent of demand conditions (Acemoglu et al., 2016). In this particular setting, government spending shocks change quantities but not prices, hence explaining the lack of downstream propagation.

This discussion highlights the importance of exploring the transmission of demand shocks (e.g., government spending shocks) through the production networks not only on quantities, but also on prices. This motivates us to estimate equation (5) by replacing the dependent variables with measures of industry prices and wages.[22] 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, both 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. 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 establish that the movements in quantities and prices in the recipients industries and their suppliers are indeed consistent with the textbook transmission of a demand shock. Second, price and wage increases in

[22] 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 remains the same.

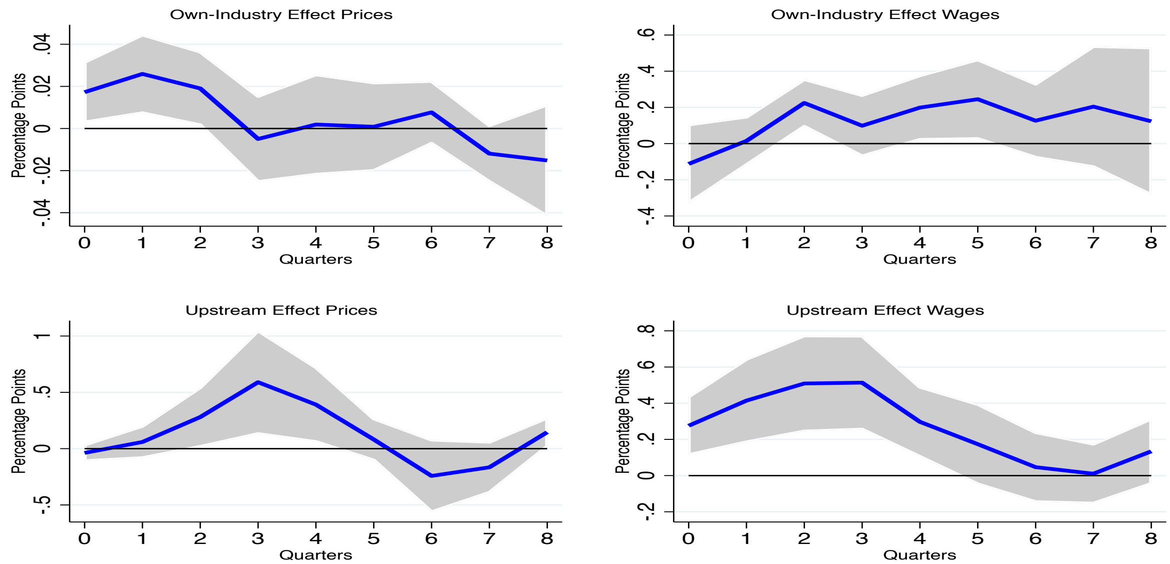

Figure 7: Figure 7. Price and wage impulse responses from local projections.

recipient and upstream industries provide a natural explanation for the negative employment effects in downstream sectors.[23] 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 price effects, we explore an additional indirect channel of downstream transmission. Imagine for simplicity an industry A that experiences an increase in government demand that leads it to increase demand for goods in industry U, which is upstream. Industry U, in turn, raises prices. This price increase may make firms downstream from U, for instance in industry D, lower their demand for intermediate inputs, even if there is no direct link between industry D and industry A. Our measure ν_{jt}^{down} would not capture these indirect network effects.

To explore this possibility, we estimate equation (5) for an alternative measure of the indirect network exposure. For each industry d (in our example industry D), we build a weighted average of the exposure of all its suppliers u (in our example, industry U) to the recipient industries (in our example industry A), weighted by the importance of industry u as supplier to industry d. Specifically, we construct: $\nu_{dt}^{ndown} = \sum_{u \neq d} \tilde{\omega}_{ud} \nu_{ut}^{up}$, where $\tilde{\omega}_{ud}$ represents the fraction of d's output

[23] In the context of Acemoglu et al. (2016), obtaining non-zero downstream effects of sectoral demand shocks would require relaxing the assumption of constant returns to scale.

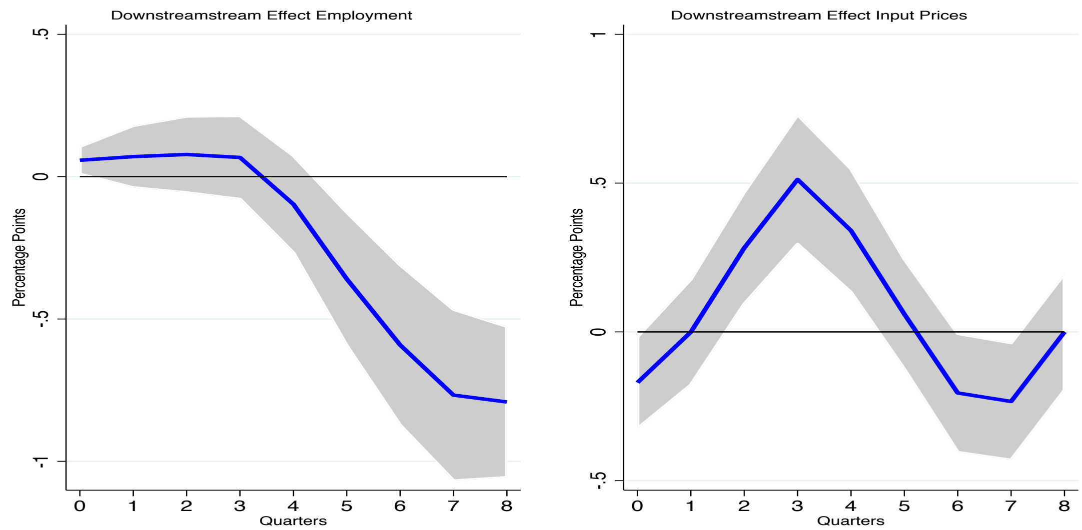

Figure 8: Figure 8. Impulse responses for measures of downstream effects from local projections.

purchased from the intermediate-input supplier u.

Figure 8 displays the results of estimating equation (5) for downstream employment and intermediate input prices for shocks measured by this alternative downstream effect.[24] Similarly to Figure 4, employment downstream 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 suggest that price movements and network connections can account for changes in economic activity across the network following an industry-specific shock.

6 Aggregate Effects

So far, our analysis has focused on identifying relative (industry-level) effects by regressing sectoral outcomes on sectoral shocks. Our last contribution is to estimate the aggregate effects of granular government spending and demonstrate how the overall impact depends on the production network and sectoral characteristics.

By construction, local effects differ from aggregate outcomes in several respects. First, aggregate outcomes reflect general-equilibrium across all sectors, which would include all direct, upstream, and downstream effects. Second, aggregate outcomes may also reflect changes in variables that

[24]We construct the intermediate input price as $P^I_{dt} = \sum_{u \neq d} \tilde{\omega}_{ud} P_{ut}$, where P_{ut} is the producer price index of industry u and $\tilde{\omega}_{ud}$ represents the fraction of d's output purchased from the u-th intermediate.

occur at the national level, such as monetary policy, that are averaged out with our estimation technique. Because of such influences, one cannot construct the aggregate effect by combining the local estimates of direct, upstream, and downstream effect.[25]. Moreover, since the estimation approach in section 3 only identifies local effects (Chodorow-Reich, 2020), we also cannot simply aggregate industry-level shocks.[26]

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. In this case, idiosyncratic shocks to these few industries can account for the aggregate effects. By focusing on the behavior of the few sectors that have exceptionally large weight in total government spending, the GIV method aims to isolate the idiosyncratic part of sectoral government spending.

Our 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:

$$z_t = \sum_j \left(\frac{\bar{G_j}}{G} - \frac{1}{N} \right) G_{it}, \tag{6}$$

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 measure of government spending with a 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.[27]

[25] See Chodorow-Reich, 2020 for more discussion on differences between local and aggregate estimates

[26] 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. Thus, each sector's shock is denoted in different output units. To aggregate the shocks, one would have to (1) rescale using constant weights—such as the ratio of sectoral output to total output—which would introduce measurement error or (2) rescale using time-varying weights, which would introduce endogenous movements in the measures.

[27] We do not consider higher levels of aggregation since input-output linkages are measured less precisely. We also note that while theoretically one could consider estimating industry-level effects (section 4) using the GIV approach, practically this approach is not feasible since several NAICS 4-digit industries consists of only one or two NAICS 6-digit production units.

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

$$\sum_{k=0}^{h} y_{t+k} = \alpha_h + \beta_h \sum_{k=0}^{h} g_{t+k} + \varphi_h(L)C_{t-1} + \epsilon_{t+h} \tag{7}$$

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 a measure of potential output to control for a polynomial trend in real GDP.[28] C represents a vector of control variables, and $\varphi_h(L)$ is a polynomial in the lag operator. To avoid serial correlation in our instrument, we include two lags of z_t. In addition, our controls include two lags of y, g, the average federal tax rate, the 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. Given the extended period of the interest rate at the effective lower bound over our sample, we use the shadow rate of Wu and Xia (2016) as our measure of the interest rate. Both inflation and the interest rate are included to control for monetary policy.

To consider how relevant the GIV is as an instrument, we look at the first-stage F-statistics across estimated horizons. Montiel Olea and Pflueger (2013) construct thresholds for this statistic for cases with serial correlation. For the first-stage of equation (7), the threshold is 16 at the 10% level, and values below this level suggest the instrument may not be valid. For the horizon h ranging from 0 to 5, the F-statistics from equation (7) are 52-72.

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. Consistent with the range of values from the literature (see Ramey, 2016 for a survey), the impact multiplier is estimated to be less than one and statistically significant. 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). Also consistent with the literature, the estimated multiplier is persistently positive for several quarters, albeit our short sample implies imprecise estimates over longer time horizons.

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

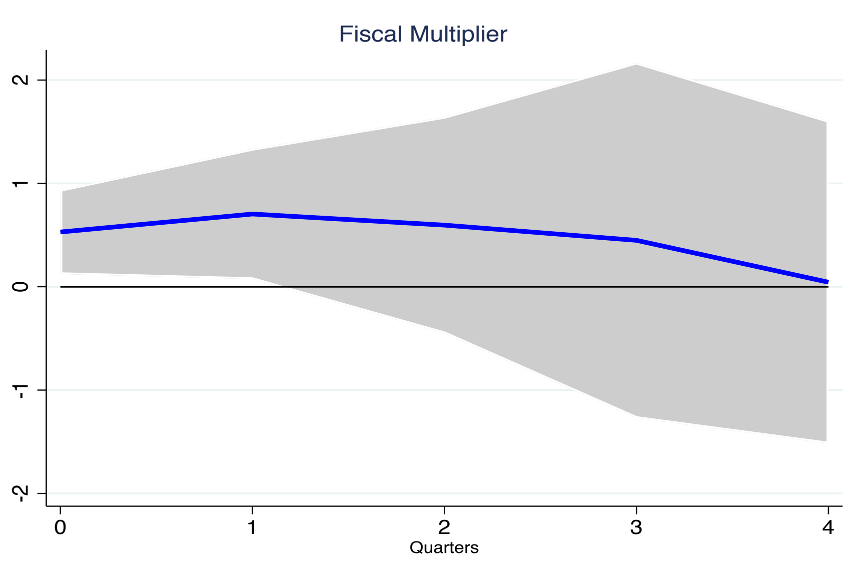

Figure 9: Figure 9. Cumulative GDP multiplier estimated by equation (7).

Given the GDP multiplier is constructed using government spending data from our procurement contracts, which is a slightly different measure and sample period often considered in the literature, we also estimate equation (7) using the standard Blanchard and Perotti (2002) approach to instrument government spending shocks. In this case, a spending shock is identified from a Cholesky decomposition in a VAR with government spending ordered first and including GDP and real federal tax revenue. With the Blanchard-Perotti identification, the point estimate of the multiplier is 0.61, and the estimate is significantly positive (see Figure A.2). This estimate is similar to our point estimate of 0.53 using the GIV approach (Figure 9). However, the advantage of the GIV approach is its flexibility to estimate how the aggregate multiplier depends on sectoral heterogeneity, which is our next focus.

Sectoral Heterogeneity and Aggregate Outcomes

In this section, we test theoretical predictions from the literature about the dependence of government spending multipliers on the structural characteristics of sectors that receive public spending. Specifically, we test whether multipliers are higher when (1) government spending originates downstream in the supply chain; (2) when government spending originates in industries with higher price stickiness; and (3) when government spending is skewed to sectors that contribute less to private final demand. 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:

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

$$z_t^{\text{below}} = \sum_{j \in \Omega^{\text{below}}} \left(\frac{\bar{G}_j}{G^{\text{below}}} - \frac{1}{N^{\text{below}}} \right) G_{jt}, \tag{9}$$

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 (8) and (9) 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). With this measure, larger values are associated with relatively higher levels of upstreamness of the industry's use. Theory predicts that government demand from industries that are more downstream (z_t^{below}) 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).[29] 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 (z_t^{below}) 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, to investigate the importance of sectoral bias of government demand, we construct measures of the government demand for a sector's good relative to its total sectoral output (see section 2 for the data). A larger measure implies a sector with more total demand stemming from the government. Theory predicts that when the government has higher importance in accounting for total demand (z_t^{above}), there are larger aggregate effects, as private consumer prices respond less in this case, leading to less crowding out (Cox et al., 2022, Proebsting, 2022).

To test the importance of these sectoral characteristics, we re-estimate equation (7) using either

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

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

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.[30] 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' structural characteristics. In all cases, the responses are consistent with theoretical predictions. When government spending arises in sectors that are more downstream, multipliers are significantly larger (top row of Figure 10), with an impact multiplier well above one. While the point estimate of the multiplier is also higher in recipient sectors with stronger price rigidities (middle row of Figure

[30] 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.

10), the confidence bands encompass zero, suggesting price stickiness may be less important quantitatively. Finally, multipliers are higher in recipient sectors where government spending is a large share of total demand (bottom row of Figure 10). At the same time, the quantitative importance of this channel is weaker relative to the others, consistent with the model-based predictions of Cox et al. (2022).

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. Similar results hold when considering industrial production. We then document that prices and wages increase significantly in recipient industries and 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, using a granular instrumental variable approach. 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.

References

Acemoglu, D., U. Akcigit, and W. Kerr (2016): "Networks and the Macroeconomy: An Empirical Exploration," *NBER Macroeconomics Annual*, 30, 273–335.

Acemoglu, D., V. M. Carvalho, A. Ozdaglar, and A. Tahlbaz-Salehi (2012): "The Network Origins of Aggregate Fluctuations," *Econometrica*, 80, 1977–2016.

Acemoglu, D., A. Ozdaglar, and A. Tahbaz-Salehi (2015): "Systemic Risk and Stability in Financial Networks," *American Economic Review*, 105, 564–608.

Antras, P., D. Chor, T. Fally, and R. Hillberry (2012): "Measuring the Upstreamness of Production and Trade Flows," *American Economic Review*, 102, 412–416.

Atalay, E. (2017): "How Important Are Sectoral Shocks?" *American Economic Journal: Macroeconomics*, 9, 254–280.

Auerbach, A., Y. Gorodnichenko, and D. Murphy (2020a): "Local Fiscal Multipliers and Fiscal Spillovers in the USA," *IMF Economic Review*, 68, 195–229.

Auerbach, A. J. and Y. Gorodnichenko (2013): "Output Spillovers from Fiscal Policy," *American Economic Review*, 103, 141–46.

Auerbach, A. J., Y. Gorodnichenko, and D. Murphy (2020b): "Effects of Fiscal Policy on Credit Markets," *AEA Papers and Proceedings*, 110, 119–124.

Baqaee, D. R. and E. Farhi (2018): "Macroeconomics with Heterogeneous Agents and Input-Output Networks," NBER Working Papers 24684, National Bureau of Economic Research, Inc.

——— (2019): "The Macroeconomic Impact of Microeconomic Shocks: Beyond Hulten's Theorem," *Econometrica*, 87, 1155–1203.

——— (2020): "Productivity and Misallocation in General Equilibrium," *The Quarterly Journal of Economics*, 135, 105–163.

Barattieri, A. and M. Cacciatore (2020): "Self-Harming Trade Policy? Protectionism and Production Networks," NBER Working Papers 27630, National Bureau of Economic Research, Inc.

Barrot, J.-N. and J. Sauvagnat (2016): "Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks," *The Quarterly Journal of Economics*, 131, 1543–1592.

Bigio, S. and J. La'O (2020): "Distortions in Production Networks," *The Quarterly Journal of Economics*, 135, 2187–2253.

Blanchard, O. and R. Perotti (2002): "An Empirical Characterization of the Dynamic Effects of Changes in Government Spending and Taxes on Output," *The Quarterly Journal of Economics*, 117, 1329–1368.

Bouakez, H., O. Rachedi, and E. Santoro (2022): "The sectoral origins of the spending multiplier," *American Economic Journal: Macroeconomics, Forthcoming.*

——— (2023): "The sectoral origins of the spending multiplier," manuscript, HEC Montréal.

Carvalho, V. (2007): "Aggregate fluctuations and the network structure of intersectoral trade," Economics Working Papers 1206, Department of Economics and Business, Universitat Pompeu Fabra.

Carvalho, V. M., M. Nirei, Y. U. Saito, and A. Tahbaz-Salehi (2021): "Supply Chain Disruptions: Evidence from the Great East Japan Earthquake," *The Quarterly Journal of Economics*, 136, 1255–1321.

Chodorow-Reich, G. (2020): "Regional data in macroeconomics: Some advice for practitioners," *Journal of Economic Dynamics and Control*, 115.

Chodorow-Reich, G., A. Ghent, and V. Haddad (2021): "Asset Insulators [Asset pricing and the bid-ask spread]," *Review of Financial Studies*, 34, 1509–1539.

Cox, L., G. MÃijller, E. PastÃĺn, R. Schoenle, and M. Weber (2022): "Big G," NBER Working Papers 27034, National Bureau of Economic Research, Inc.

Demyanyk, Y., E. Loutskina, and D. Murphy (2019): "Fiscal Stimulus and Consumer Debt," *The Review of Economics and Statistics*, 101, 728–741.

Dhyne, E., A. K. Kikkawa, M. Mogstad, and F. Tintelnot (2021): "Trade and Domestic Production Networks," *Review of Economic Studies*, 88, 643–668.

Dupor, B. and R. Guerrero (2017): "Local and aggregate fiscal policy multipliers," *Journal of Monetary Economics*, 92, 16–30.

Elisa Rubbo (2023): "Networks, Phillips Curves, and Monetary Policy," *Econometrica, forthcoming.*

Flynn, J. P., C. Patterson, and J. Sturm (2021): "Fiscal Policy in a Networked Economy," NBER Working Papers 29619, National Bureau of Economic Research, Inc.

Foerster, A. T., P.-D. G. Sarte, and M. W. Watson (2011): "Sectoral versus Aggregate Shocks: A Structural Factor Analysis of Industrial Production," *Journal of Political Economy*, 119, 1–38.

Gabaix, X. and R. S. J. Koijen (2020): "Granular Instrumental Variables," NBER Working Papers 28204, National Bureau of Economic Research, Inc.

Goldsmith-Pinkham, P., I. Sorkin, and H. Swift (2020): "Bartik Instruments: What, When, Why, and How," *American Economic Review*, 110, 2586–2624.

Hebous, S. and T. Zimmermann (2021): "Can government demand stimulate private investment? Evidence from U.S. federal procurement," *Journal of Monetary Economics*, 118, 178–194.

Horvath, M. (2000): "Sectoral shocks and aggregate fluctuations," *Journal of Monetary Economics*, 45, 69–106.

Jordà, s. (2005): "Estimation and Inference of Impulse Responses by Local Projections," *American Economic Review*, 95, 161–182.

Leeper, E. M., N. Traum, and T. B. Walker (2017): "Clearing Up the Fiscal Multiplier Morass," *American Economic Review*, 107, 2409–2454.

Ma, Y., T. Paligorova, and J.-L. Peydro (2022): "Expectations and Bank Lending," manuscript, Chicago Booth.

Montiel Olea, J. L. and C. Pflueger (2013): "A Robust Test for Weak Instruments," *Journal of Business & Economic Statistics*, 31, 358–369.

Moro, A. and O. Rachedi (2022): "The Changing Structure of Government Consumption Spending," *International Economic Review*.

Nakamura, E. and J. Steinsson (2014): "Fiscal Stimulus in a Monetary Union: Evidence from US Regions," *American Economic Review*, 104, 753–92.

Nekarda, C. J. and V. A. Ramey (2011): "Industry Evidence on the Effects of Government Spending," *American Economic Journal: Macroeconomics*, 3, 36–59.

Pasten, E., R. Schoenle, and M. Weber (2021): "Sectoral Heterogeneity in Nominal Price Rigidity and the Origin of Aggregate Fluctuations," Working Paper 2018-54, Becker Friedman Institute for Economics.

Proebsting, C. (2022): "Market segmentation and spending multipliers," *Journal of Monetary Economics*.

Ramey, V. (2016): "Macroeconomic Shocks and Their Propagation," in *Handbook of Macroeconomics*, ed. by J. B. Taylor and H. Uhlig, Elsevier, vol. 2 of *Handbook of Macroeconomics*, chap. 0, 71–162.

Ramey, V. A. (2011): "Identifying Government Spending Shocks: It's all in the Timing," *The Quarterly Journal of Economics*, 126, 1–50.

Ramey, V. A. and S. Zubairy (2018): "Government Spending Multipliers in Good Times and in Bad: Evidence from US Historical Data," *Journal of Political Economy*, 126, 850–901.

Romer, C. D. and D. H. Romer (2004): "A New Measure of Monetary Shocks: Derivation and Implications," *American Economic Review*, 94, 1055–1084.

U.S. Government Accountability Office (2018): "Rapid Acquisition of Mine Resistant Ambush Protected Vehicles," Tech. rep., GAO-08-884R.

vom Lehn, C. and T. Winberry (2022): "The Investment Network, Sectoral Comovement, and the Changing U.S. Business Cycle," *The Quarterly Journal of Economics*, 137, 387–433.

Woodford, M. (2011): "Simple Analytics of the Government Expenditure Multiplier," *American Economic Journal: Macroeconomics*, 3, 1–35.

Wu, J. C. and F. D. Xia (2016): "Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound," *Journal of Money, Credit and Banking*, 48, 253–291.

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.

B Alternative Measure of Aggregate Government Spending Multiplier

Figure A.2 shows the cumulative GDP multiplier calculated using the conventional approach of a Blanchard-Perotti identification of spending shocks. The Blanchard-Perotti shocks are used as an instrument in equation (7).

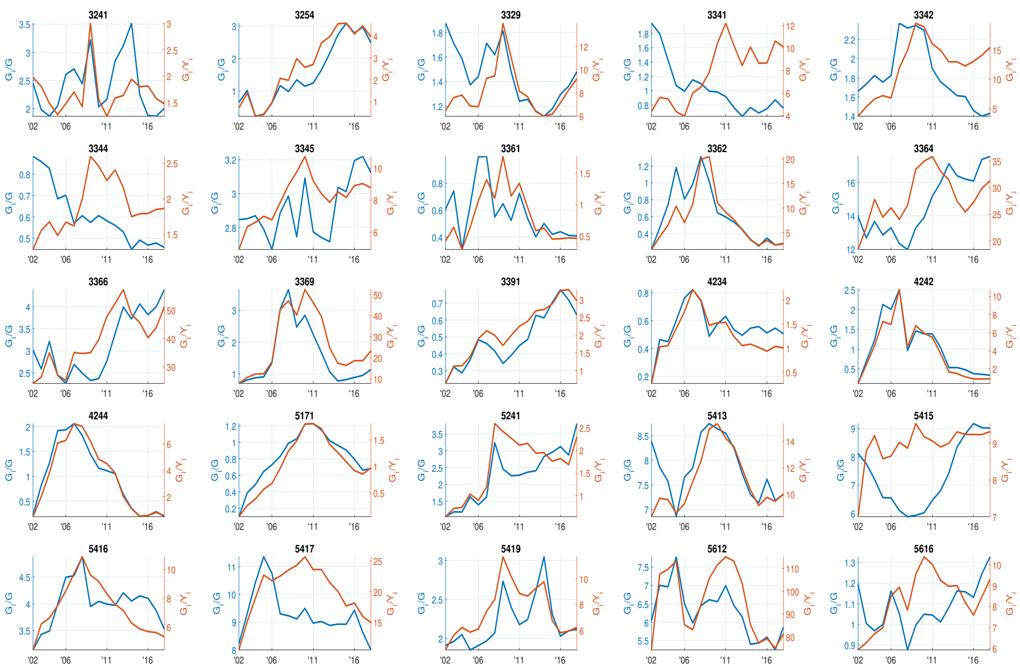

Figure A.1: Figure A.1. Shares of industry government spending to total public spending (left-scale) and industry public spending to industry output (right-scale) for top-25 recipient industries of government procurement contracts.

Table 1:

TABLE 1: Top suppliers of the top 25 recipients

NAICS	Industry	% of Y_i
3363	Motor Vehicle Parts Manufacturing	67.27
3336	Engine, Turbine, and Power Transmission Equipment Manuf.	35.64
3344	Semiconductor and Other Electronic Component Manufacturing	34.44
5152	Cable and Other Subscription Programming	30.84
5418	Advertising, Public Relations, and Related Services	30.61
3325	Hardware Manufacturing	28.70
3272	Glass and Glass Product Manufacturing	27.78
3326	Spring and Wire Product Manufacturing	26.58
3262	Rubber Product Manufacturing	24.39
4231	Motor Vehicle & Motor Vehicle Parts & Supplies Merchant Wholesalers	24.17
7115	Independent Artists, Writers, and Performers	24.17
3359	Other Electrical Equipment and Component Manufacturing	23.00
3321	Forging and Stamping	22.80
5416	Management, Scientific, and Technical Consulting Services	21.98
5414	Specialized Design Services	19.65
5121	Motion Picture and Video Industries	18.47
3327	Machine Shops; Turned Product; and Screw, Nut, and Bolt Manufacturing	18.27
5613	Employment Services	17.16
5612	Facilities Support Services	17.09
3313	Alumina and Aluminum Production and Processing	16.94
3314	Nonferrous Metal (except Aluminum) Production and Processing	16.59
3261	Plastics Product Manufacturing	16.30
3311	Iron and Steel Mills and Ferroalloy Manufacturing	16.18
5611	Office Administrative Services	16.07
3274	Lime & Gypsum Product Manufacturing	15.70

Table 2:

TABLE 2: Top customers of the top 25 recipients

NAICS	Industry	% of Y_i
3341	Computer and Peripheral Equipment Manufacturing	28.02
5172	Wireless Telecommunications Carriers (except Satellite)	24.21
3343	Audio and Video Equipment Manufacturing	18.14
5174	Satellite Telecommunications	17.28
3333	Commercial and Service Industry Machinery Manufacturing	14.52
6212	Offices of Dentists	13.93
3345	Navigational, Measuring, Electrometrical, & Control Inst. Manuf.	13.20
3362	Motor Vehicle Body and Trailer Manufacturing	11.97
3342	Communications Equipment Manufacturing	10.74
3332	Industrial Machinery Manufacturing	10.55
6216	Home Health Care Services	10.25
6219	Other Ambulatory Health Care Services	10.11
6211	Offices of Physicians	9.97
5182	Data Processing, Hosting, and Related Services	9.88
6215	Medical and Diagnostic Laboratories	9.45
3259	Other Chemical Product and Preparation Manufacturing	9.34
3366	Ship and Boat Building	9.05
3117	Seafood Product Preparation and Packaging	8.83
5413	Architectural, Engineering, and Related Services	8.82
6214	Outpatient Care Centers	8.72
5191	Other Information Services	8.67
3113	Sugar and Confectionery Product Manufacturing	8.44
3114	Fruit & Veggie Preserving & Specialty Food	8.43
3115	Dairy Product Manufacturing	8.38
5417	Scientific Research & Development Services	8.35

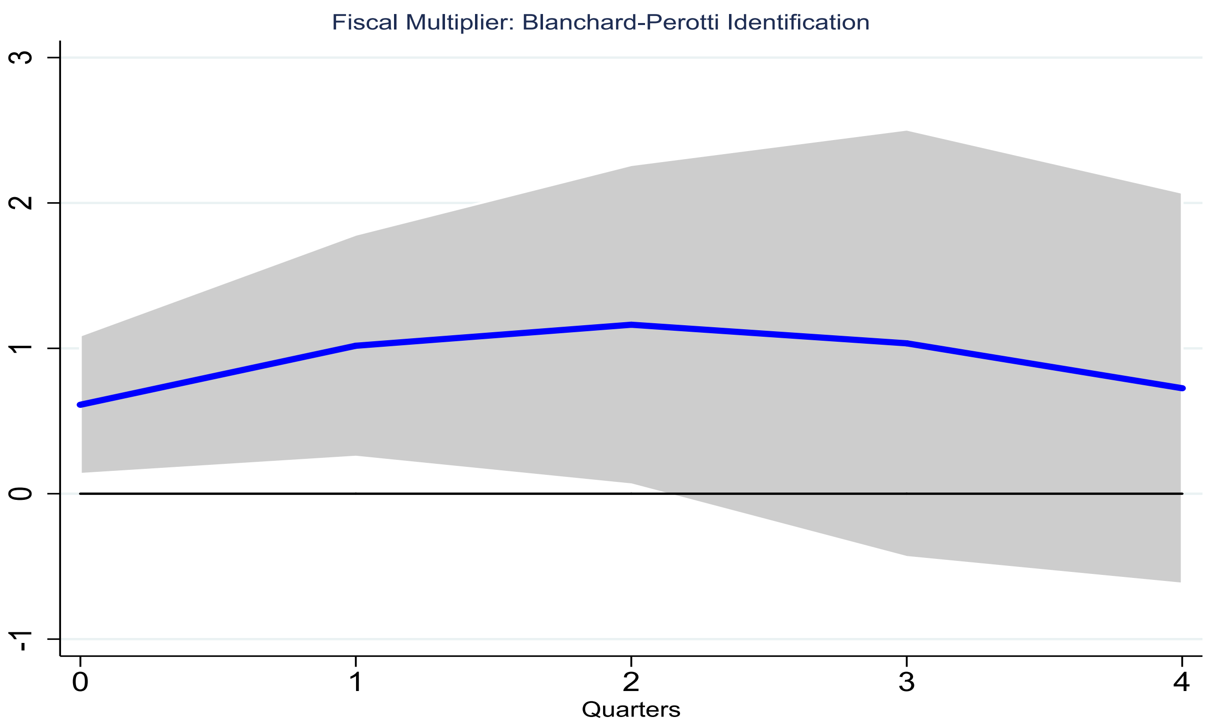

Figure A.2: Figure A.2. Cumulative GDP multiplier estimated by equation (7) using the Blanchard-Perotti shocks as an instrument.