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Industry Evidence on the Effects of Government Spending†

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This paper investigates the effects of government purchases at the industry level in order to shed light on the transmission mechanism for government spending on the aggregate economy. We create a new panel dataset that matches output and labor variables to industry-specific shifts in government demand. An increase in government demand raises output and hours, lowers real product wages and labor productivity, and has no effect on the markup. The estimates also imply approximately constant returns to scale. The findings are more consistent with the effects of government spending in the neoclassical model than the textbook New Keynesian model. (*JEL* E12, E23, E62, H50)

The recent debate over the government stimulus package has highlighted the lack of consensus concerning the effects of government spending. While most approaches agree that increases in government spending lead to rises in output and hours, they differ in their predictions concerning other key variables. For example, both the neoclassical and the standard New Keynesian models predict that an increase in government spending raises labor supply through a negative wealth effect.[1] Under the neoclassical assumption of perfect competition and diminishing returns to labor, the rise in hours should be accompanied by a short-run fall in real wages and labor productivity. In contrast, the textbook New Keynesian approach assumes imperfect competition, sticky prices or price wars during booms, and increasing returns to scale. This model predicts that a rise in government spending lowers the markup of price over marginal cost. Thus, an increase in government spending can lead to a rise in both real wages and hours. In addition, it can lead to a rise in average labor productivity if returns to scale are sufficiently great.[2]

In this paper, we seek to shed light on the transmission mechanism by studying the effects of industry-specific government spending on hours, real wages, and

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[1] For example, Marianne Baxter and Robert G. King (1993) or Julio J. Rotemberg and Michael Woodford (1992).

[2] Michael B. Devereux, Allen C. Head, and Beverly J. Lapham (1996).

labor productivity in a panel of industries. As Valerie A. Ramey and Matthew D. Shapiro (1998) point out, an increase in government spending is typically focused on a subset of industries. Thus, there is substantial heterogeneity in the experiences of different industries after a change in government spending. This heterogeneity allows us to study the partial-equilibrium effects of government spending in isolation since our panel data structure allows us to net out the aggregate effects. Since the partial-equilibrium effects are crucial to the overall transmission mechanism, it is instructive to study them separately.

Building on the ideas of John Shea (1993), Roberto Perotti (2008), and Min Ouyang (2009), we use information from input-output (IO) tables to create industry-specific government demand variables. We then merge these variables with the National Bureau of Economic Research–Center for Economic Studies (NBER-CES) Manufacturing Industry Database (MID) to create a panel dataset containing information on government demand, hours, output, and wages by industry.

The empirical results indicate that increases in industry-specific government demand raise output and hours significantly. On the other hand, real product wages and average labor productivity fall slightly. Markups are unchanged. We show that real product wages and labor productivity do not fall much because other inputs also rise. Our estimates also imply roughly constant returns to scale in production. Our results are generally consistent with the neoclassical model, but are at odds with the textbook New Keynesian model.

I. Existing Evidence on Real Wages and Productivity

The empirical evidence on the effects of government spending on real wages is mixed. Rotemberg and Woodford (1992) were perhaps the first to conduct a detailed study of the effects of government spending on hours and real wages. Using a vector autoregression (VAR) to identify shocks, they found that increases in military purchases led to increases in private hours worked and in real wages.

Ramey and Shapiro (1998), however, questioned the finding on real wages in two ways. First, analyzing a two-sector theoretical model with costly capital mobility and overtime premia, they showed that an increase in government spending in one sector could easily lead to a rise in the aggregate consumption wage but a fall in the product wage in the expanding sector. Rotemberg and Woodford's (1992) measure of the real wage was the manufacturing nominal wage divided by the deflator for private value added, a consumption wage. Ramey and Shapiro (1998) showed that the real product wage in manufacturing, defined as the nominal wage divided by the producer price index in manufacturing, in fact, fell after rises in military spending. Second, Ramey and Shapiro (1998) argued that the standard types of VARs employed by Rotemberg and Woodford (1992) might not properly identify unanticipated shocks to government spending because most government spending is anticipated at least several quarters before it occurs. Using a new variable that reflected the news about future government spending, they found that all measures of product wages fell after a rise in military spending, whereas consumption wages were essentially unchanged. Subsequent research that has used standard VAR techniques to identify the effects of shocks on aggregate real consumption wages tend to find increases in real wages.[3] Research that has used the Ramey-Shapiro methodology has tended to find decreases in real wages.[4]

Marvin J. Barth and Ramey (2002) and Perotti (2008) are two of the few papers that have studied the effect of government spending on real wages in industry data. Barth and Ramey (2002) used monthly data to show that the rise and fall in government spending on aerospace goods during the 1980s Carter-Reagan defense buildup led to a concurrent rise and fall in hours, but to the inverse pattern in the real product wage in that industry. That is, as hours increased, real product wages decreased, and vice versa. Perotti (2008) used IO tables to identify the industries that received most of the increase in government spending during the Vietnam War and during the first part of the Carter-Reagan buildup from 1977–82. Based on a heuristic comparison of real wage changes in his ranking of industries, he concluded that real wages increased when hours increased. In the companion discussion, Ramey (2008) questioned several aspects of the implementation, including Perotti's assumption that there had been no changes in capital stock and technology during each five year period. A second concern was the fact that the semiconductor and computer industries were influential observations that were driving his findings.

On the other hand, most research has typically found an increase in labor productivity at the aggregate level, although it is not often highlighted. For example, even though their different identification methods lead to fundamentally different results for consumption and real wages, the impulse response functions of both Galí, López-Salido and Vallés (2007) and Ramey (forthcoming) imply that aggregate labor productivity rises after an increase in government spending.

In sum, the evidence for real wages is quite mixed, while the evidence for productivity is less mixed, but often ignored. Therefore, it is useful to study the behavior of the key variables in the labor demand equation in more detail.

II. Theoretical Predictions for Industry Labor Markets

In this section, we review the differences between textbook neoclassical and New Keynesian models with respect to their predictions about labor markets. These models usually assume one sector with representative firms. However, the specific assumptions about production functions and labor demand should also apply to the industry level. We thus use the assumptions these models make about the representative firm to derive predictions for the variables of interest.

To begin, consider the production function for output in industry i in year t:

$$Y_{it} = A_{it} F(H_{it}, \mathbf{Z}_{it}) - \Phi_i, \tag{1}$$

where Y is output, A is technology, H is hours, $\mathbf{Z}$ is a vector of other inputs (including capital), and Φ is a fixed cost. Both the neoclassical and standard New Keynesian

[3] See, for example, Antonio Fatás and Ilian Mihov (2001); Perotti (2004); Evi Pappa (2005); and Jordi Galí, J. David López-Salido, and Javier Vallés (2007).

[4] See, for example, Craig Burnside, Martin Eichenbaum, and Jonas D. M. Fisher (2004); Michele Cavallo (2005); and Ramey (forthcoming).

models assume diminishing marginal product of labor, so that F is increasing in its inputs, and $F_{HH} < 0$. The first-order condition describing the demand for labor in industry i in year t is

$$A_{it}F_H\left(H_{it}, \mathbf{Z}_{it}\right) = \mathcal{M}_{it}\,\frac{W_{it}}{P_{it}}, \tag{2}$$

where W is the nominal wage and P_i is the price of industry i's output. The left-hand side is the marginal product of labor. The right-hand side is the markup, $\mathcal{M}$, times the real product wage.

The two models differ in their assumptions about fixed costs and the markup. The neoclassical model assumes that $\Phi = 0$, so that there are constant returns to scale, and $\mathcal{M} = 1$, so that markups are constant. The New Keynesian model assumes fixed costs of production, so that there are increasing returns to scale. It also assumes that because of sticky prices or oligopolistic behavior, the markup moves countercyclically in response to demand shocks.

In both models, an increase in government purchases from industry i leads to an outward shift of the demand curve for output, resulting in higher equilibrium output and hours in the industry. The models diverge in their predictions for relative prices, real product wages, and labor productivity. If other factors are slow to adjust, the neoclassical models imply a short-run increase in the relative price of industry output and decreases in the real product wage, marginal product of labor, and average product of labor. In contrast, the New Keynesian production and labor demand functions imply a decrease in the markup, an increase in the real product wage, and an ambiguous effect on average labor productivity (because of fixed costs).

The behavior of industry relative wages depends on assumptions about labor supply that are independent of the other distinguishing features of neoclassical and New Keynesian models. In the most standard model with Cobb-Douglas production and perfect mobility of homogenous labor, nominal wages should be equalized across sectors.

Even with perfect mobility of labor and homogenous labor, however, wages can differ across sectors. Ramey and Shapiro (1998) demonstrate this possibility in a two-sector dynamic stochastic general equilibrium model with costly capital mobility and perfect labor mobility, but where firms must pay an overtime premium to workers if they want to increase the workweek of capital. They show that with this type of model, an increase in government spending on a particular industry raises that industry's relative price and relative nominal wage. Costly labor reallocation models can also lead to different wages across industries, such as in the costly search model of Robert E. Lucas Jr. and Edward C. Prescott (1974). Patrick Kline (2008) estimates a generalized version of this model using data from the oil and gas field services industry. He finds that labor adjusts quickly across sectors in response to price shocks, but that industries must pay substantial wage premia to induce reallocation. Thus, his model also implies that a sectoral shift can raise the relative wage in an industry.

Heterogeneity of labor can affect relative industry wages in a different way. If the marginal worker in an expanding industry is less productive, then the relative wage of an expanding industry could actually fall. Thus, how relative nominal wages change in response to industry-specific changes in government spending depends on the nature of sectoral adjustment costs rather than on the specifics of neoclassical or New Keynesian models.

In sum, the behavior of relative nominal wages depends on how industry labor supply responds. Irrespective of labor supply features, though, the textbook neoclassical model predicts that an increase in government spending raises an industry's output and hours, but lowers its real product wage and average labor productivity if other factors are slow to adjust. The markup does not change. The textbook New Keynesian model predicts an increase in output, hours, and the real product wage, but a decrease in the markup and an ambiguous effect on average labor productivity.

III. Data Description

In order to link industry-specific government spending with industry behavior of output, hours, prices, and wages, we match data from benchmark IO accounts to the NBER-CES Manufacturing Industry Database (MID). Benchmark IO tables based on Standard Industrial Classification (SIC) codes are available for 1963, 1967, 1972, 1977, 1982, 1987, and 1992. Merging manufacturing SIC industry codes and IO industry codes yields 274 industries. The online Appendix details how we merged the two datasets.

We consider both direct government spending and its downstream linkages. This comprehensive measure captures the fact that an increase in government purchases of finished airplanes can also have an indirect effect on the aircraft parts industries who supply parts to the aircraft industries. Because it is difficult to distinguish nondefense from defense spending when calculating indirect effects, we use total federal government spending. Figure 1 shows real federal spending and real federal defense spending from 1960 to 2005. The figure makes clear that almost all fluctuations in federal government purchases are due to defense spending. Robert E. Hall (1980), Robert J. Barro (1981), and Ramey (2009) have all argued that movements in defense spending are induced by political events rather than by economic events.

Most of the remaining variables are constructed from the MID. This database contains annual 4-digit industry-level data from 1958 to 2005 on gross shipments, employment, production worker hours, payroll, price indices, as well as information on other factors such as materials, energy, inventories, and capital stock. We construct wages by dividing payroll data by hours and construct gross output from data on shipments and inventories. For one measure of the markup, we convert average wages to marginal wages using Nekarda and Ramey's (2010) implementation of Mark Bils's (1987) framework. We augment the MID with data on the four-firm concentration ratio from the US Census Bureau and with data on the percent of workers who are unionized from John M. Abowd (1990). The online Appendix provides details of the data sources and variable construction.

Table 1 shows the 20 industries with the largest share of shipments to the federal government, along with other key characteristics. The shares are calculated by averaging over the 1963, 1967, 1972, 1977, 1982, 1987, and 1992 IO tables. Not surprisingly, most are defense industries. Guided missiles and space vehicles send 92 percent of their shipments to the government, either directly or indirectly. The

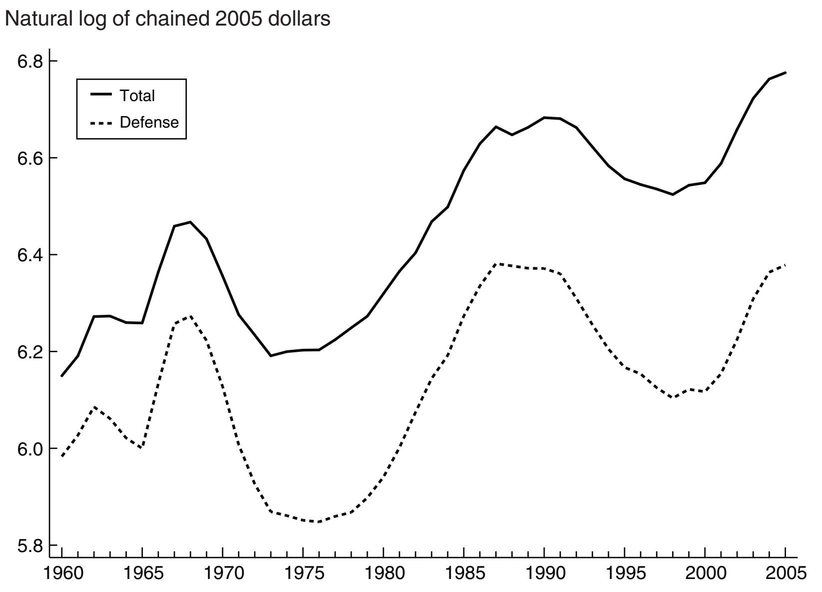

FIGURE 1. US FEDERAL GOVERNMENT SPENDING, 1960–2005

Source: BEA.

average for all manufacturing industries over this time period is 9 percent. The capital-labor ratios for these industries tend to be lower than the average capital-labor ratio in manufacturing. On the other hand, nominal wages, four-firm concentration ratios, and unionization rates tend to be higher in these industries than the average in manufacturing.

IV. Constructing Government Demand Instruments

Our analysis builds on Perotti's (2008) clever idea of using IO tables to construct an instrument for government demand. We show, however, that his particular formulation of the instrument is likely correlated with technological change. We suggest alternative formulations that isolate the demand component.

A. *Conceptual Framework*

Perotti (2008) defined his government demand variable as the change in an industry's shipments to the government between two IO benchmark years, divided by the initial value of total shipments of the industry

$$\frac{G_{it} - G_{i(t-5)}}{S_{i(t-5)}},$$

where G_{it} is real shipments to the government by industry i in year t, and S_{it} is total real shipments by industry i in year t. Perotti's measure makes the implicit assumption that the distribution of government spending across industries is uncorrelated

Table 1—Industries with Largest Share of Shipments to the Government

Rank	SIC	Industry	θ	Relative[a] Capital[b]	Relative[a] Wages[c]	C4	Unionization rate Production workers	Unionization rate All workers
1	3761	Guided missiles and space vehicles	0.920	164	163	65	31	60
2	3483	Ammunition, except for small arms, n.e.c.	0.807	80	105	50	43	61
3	3489	Ordnance and accessories, n.e.c.	0.769	130	133	64	39	61
4	3728	Aircraft and missile equipment, n.e.c.	0.628	81	133	42	42	60
5	3731	Ship building and repairing	0.626	47	118	45	44	49
6	3724	Aircraft and missile engines and engine parts	0.610	97	135	74	40	60
7	3663	Communication equipment	0.496	73	102	38	29	50
8	3721	Aircraft	0.491	83	146	66	40	60
9	3795	Sighting and fire control equipment	0.489	83	137	89	43	59
10	3812	Engineering and scientific instruments	0.435	82	135	28	29	48
11	3463	Nonferrous forgings	0.419	131	128	70	50	63
12	3482	Small arms ammunition	0.384	65	113	87	45	61
13	3339	Primary nonferrous metals, n.e.c.	0.321	231	121	42	49	61
14	3672	Other electronic components	0.294	48	81	17	28	39
15	3674	Semiconductors and related devices	0.282	198	102	46	27	39
16	3484	Small arms	0.278	46	104	52	45	61
17	3364	Nonferrous castings, n.e.c.	0.231	55	96	21	51	60
18	3471	Coating, engraving and allied services	0.208	47	84	11	43	52
19	3671	Electron tubes	0.207	122	107	56	33	39
20	3592	Machine shop products	0.207	53	103	10	34	42
Memorandum: All manufacturing								
Weighted by output			0.089	162	112	36	50	39
Weighted by θ			0.319	161	123	41	53	38

Notes: Calculated from a panel of 274 industries in 1963, 1967, 1972, 1977, 1982, 1987, and 1992. θ is the average fraction of industry's total nominal shipments that go to the federal government. C4 is four-firm concentration ratio.
[a] Relative to average value in each year; reports average over all years.
[b] Real capital per production worker hour.
[c] Production worker wage.

Source: Author's calculations using data from BEA benchmark IO tables; US Census Bureau; and Abowd (1990).

with industry technological change. As we now demonstrate, we believe that this assumption does not hold.

To see this, first define an industry's share of all shipments to the government as $\phi_{it} = G_{it}/G_t$, where G_t is aggregate real shipments to the government. Rearranging this expression relates an industry's shipments to the government to total government spending:

$$G_{it} = \phi_{it} G_t. \tag{3}$$

Differentiating this expression with respect to time yields

$$\dot{G}_{it} = \phi_{it}\dot{G}_t + G_t\dot{\phi}_{it}, \tag{4}$$

where a dot over a variable indicates its time derivative. Using equation (4), we can decompose the numerator of Perotti's (2008) measure as

$$\Delta_5 G_{it} \simeq \overline{\phi}_i \times \Delta_5 G_t + \overline{G} \times \Delta_5 \phi_{it}, \tag{5}$$

where Δ_5 denotes the five-year difference and $\overline{\phi}_i$ and $\overline{G}$ indicate averages over time.

Consider using $\Delta_5 G_{it}$ as an instrument in a panel data estimation. Including industry and year fixed effects captures any long-run differences in technology across industries and any aggregate changes in technology. The first term in equation (5) weights the aggregate change in government spending by a time-invariant industry-specific weight. Thus, this term cannot be correlated with industry-specific changes in technology. The second term includes the change in the industry's share of total shipments to the government. This share could change for several reasons. For example, if the United States shifted from military engagements that involved no armed combat to ones that involved armed combat, then the share of small arms ammunition in government shipments would rise for reasons unrelated to technology. On the other hand, the share could also rise because of technological change in the industry. New generations of weapon systems made possible by technological innovation and the incorporation of computing technology are just a few examples of how industry-specific technology can change the industry's share of total government spending.[5]

Perotti's instrument also includes lagged industry total shipments in the denominator. Thus, even if one used only the first term of the numerator, there is still a possibility of correlation with technology. Therefore, our measure purges the demand instrument further. To derive our instrument, we divide both sides of equation (4) by S_{it} to obtain

$$\frac{\dot{G}_{it}}{S_{it}} = \frac{\phi_{it}\dot{G}_t}{S_{it}} + \frac{G_t\dot{\phi}_{it}}{S_{it}}. \tag{6}$$

The first term on the right-hand side can be rewritten as

$$\frac{\phi_{it}\dot{G}_t}{S_{it}} = \frac{G_{it}}{S_{it}}\frac{\dot{G}_t}{G_t} = \theta_{it}\frac{\dot{G}_t}{G_t}, \tag{7}$$

where $\theta_{it} \equiv G_{it}/S_{it}$ is the fraction of an industry's total shipments that are sent to the government. Approximating the time derivative, we define our government demand instrument as

$$\Delta g_{it} = \overline{\theta}_i \times \Delta \ln G_t, \tag{8}$$

where $\overline{\theta}_i$ is the time average of θ_{it}. In order to construct our instrument at an annual frequency to match the MID, we use aggregate real federal purchases from the national income and product accounts (NIPA).

Because we have substituted the long-run average of θ_{it}, this measure should be uncorrelated with industry-specific technological change for the same reasons given above. It also has intuitive appeal: It weights the percent change in aggregate government spending by the long-run importance of government spending to the industry. We do not include the second term on the right-hand side of equation (6) in our instrument because it is likely to be correlated with technology. As we show next, our instrument remains highly relevant despite discarding this source of variation in G_{it}.

[5] As another example, the computer industry's share of total shipments to the government rose from 2.3 percent in 1987 to 6.8 percent in 1992, an increase that was no doubt linked to technological progress in this industry.

B. *Comparison of Government Demand Instruments*

We now assess the relevance and exogeneity of the government demand measures discussed above. Because Perotti's (2008) measure can only be constructed for years the benchmark IO tables are available, we compare all instruments using data at quinquennial frequency over the period 1963–1992. We also show several permutations of the Nekarda-Ramey instrument for comparison purposes.

For each instrument, we explore two relationships. First, as a test for relevance, we show the coefficient from a reduced-form regression of the log change in industry shipments on the instrument. Second, as an indicator of possible correlation with technological change, we show the coefficient from a reduced-form regression of average labor productivity on the instrument. All regressions include industry and year fixed effects.

Table 2 reports our comparison of government demand instruments. All instruments are standardized to have unit standard deviation so that the coefficients are comparable. The upper panel reports results using five-year changes. Perotti's instrument (row 1) is highly relevant, with an implied first-stage F-statistic of output growth on the instrument of over 100.[6] The last column shows that the instrument has a statistically significant positive effect on labor productivity, suggesting either increasing returns to scale or a correlation between the instrument and technological change.

To explore whether Perotti's instrument is correlated with technology, we consider two variants of it. The first variant (row 2) purges the change in the share of industry i's shipments to the government from the numerator of Perotti's instrument: $\overline{\phi}_i \times \Delta_5 G_t / S_{i(t-5)}$, where $\overline{\phi}_i$ is the average of ϕ_{it} over time. The purged-numerator instrument is still relevant for output growth, with an implied F-statistic of 50. However, it implies no effect on the five-year growth rate of labor productivity.[7] The second variant (row 3) takes the first variant and purges the change in total shipments from the denominator: $\overline{\phi}_i \times \Delta_5 G_t / \overline{S}_i$, where $\overline{S}_i$ is the average over time. This instrument has a first-stage F-statistic of 145, and continues to imply no change in labor productivity.

To summarize, the two variants of Perotti's instrument continue to be highly relevant for output growth, but show no correlation with productivity growth. We take this as evidence that Perotti's instrument may be correlated with industry-specific technological change. In addition, because the purged instruments remain highly relevant, we believe the sacrifice in variation of G_{it} is necessary to minimize concerns about the instrument's validity.

Rows 4 and 5 of Table 2 report results using our government demand instrument (equation (8) using five-year changes estimated over Perotti's sample period. In the first case (row 4), we use real total shipments to the federal government from the IO tables. In the second case (row 5), we use real federal purchases from the NIPA.

[6] This is calculated as the square of the t-statistic: $(1.294/0.122)^2 = 112$.

[7] As we will show in Section VC, this result is consistent with constant returns to scale because the other inputs rise as well.

Table 2—Comparison of Government Demand Instruments

Instrument	Formula	Sample	Coefficient on instrument for indicated dependent variable: Real gross output	Labor productivity
Five-year changes				
1. Perotti (2008)	$\Delta_5 G_{it}/S_{i(t-5)}$	1963–1992, 1,630 obs.	1.294*** (0.122)	0.196*** (0.069)
2. Purged numerator	$\overline{\phi}_i \times \Delta_5 G_{it}/S_{i(t-5)}$	1963–1992, 1,630 obs.	0.897*** (0.121)	−0.001 (0.067)
3. Purged numerator and denominator	$\overline{\phi}_i \times \Delta_5 G_t/\overline{S}_i$	1963–1992, 1,643 obs.	1.541*** (0.128)	0.056 (0.073)
4. NR w/average share	$\overline{\theta}_i \times \Delta_5 G_t$	1963–1992, 1,643 obs.	1.516*** (0.129)	0.067 (0.073)
5. NR w/average share	$\overline{\theta}_i \times \Delta_5 \ln G_t^N$	1963–1992, 1,643 obs.	1.546*** (0.138)	−0.003 (0.078)
6. NR w/1963 share	$\theta_{i1963} \times \Delta_5 \ln G_t^N$	1963–1992, 1,643 obs.	1.490*** (0.139)	−0.017 (0.078)
Annual changes				
7. NR w/average share	$\overline{\theta}_i \times \Delta \ln G_t^N$	1960–2005, 12,536 obs.	1.475*** (0.115)	−0.130 (0.087)
8. NR w/1963 share	$\theta_{i1963} \times \Delta \ln G_t^N$	1960–2005, 12,536 obs.	1.776*** (0.139)	−0.156 (0.104)

Notes: G_{it} is real shipments by industry i to government (IO); S_{it} is real total shipments by industry i; G_t^N is real federal purchases (NIPA). $\phi_i \equiv G_{it}/G_t$ and $\theta_i \equiv G_{it}/S_{it}$. An overbar indicates a time average. Specification is $\Delta\ln(\text{Dependent variable}_{it}) = \alpha_i + \alpha_t + \beta\text{Instrument}_{it} + \omega_{it}$. All instruments are standardized to have unit standard deviation. All regressions include industry (α_i) and year (α_t) fixed effects. Standard errors are reported in parentheses.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Source: Authors' regressions using data from the NBER-CES MID and BEA NIPA and IO tables.

Both instruments are highly relevant for output growth and are uncorrelated with productivity growth. The results are similar when we use the initial share of shipments to the government rather than the long-term average (row 6).

Rows 7 and 8 show estimates using our government demand instrument for annual data over 1960–2005. The first variation uses the long-term average share of shipments to the government, and the second variation uses the initial share (1963). In both cases, the first-stage F-statistics for output growth are well above 100. Also, the effect of the instrument on labor productivity is negative, although it is estimated imprecisely. We will show later that the results are more significant when we allow richer dynamics.

To summarize, all variants of the government demand instrument that we explore are highly relevant for changes in industry output. However, the instrument that includes time variation in industry share of shipments to the government is positively correlated with labor productivity, suggesting that it may be correlated with industry-specific technological change. For the remainder of the paper, we use the instrument from equation (8), which uses the long-term average share of shipments to the government. Our findings are similar if we use the 1963 share instead.

V. Reduced-Form Evidence of the Effects of Changes in Government Demand

We now study the effects of our government demand shifter on output, hours, wages, and prices. We expand our analysis by considering two aspects of potential dynamic effects. First, we allow for the possibility of anticipation effects. Ramey (forthcoming) presents arguments and evidence that most changes in government spending are anticipated. For example, the government awards prime contracts at least several quarters before actual payments are made. This means that firms may begin adjusting inputs and raising output before government spending shows an increase. To account for this possibility, we study whether the change in government spending over the next two or four quarters have an effect on the current year's change in industry variables. In virtually every case, the one-year ahead change has more predictive power than the two-quarter ahead change. We thus use the former. Second, to the extent that there are adjustment costs on some variables, we also include one lag of the dependent variable and the government demand variable.

We estimate variations on the following reduced-form specification in order to study the dynamic effects of government spending:

$$(9)\quad \Delta z_{it} = \alpha_i + \alpha_t + \rho \Delta z_{i(t-1)} + \kappa_1 \Delta g_{i(t-1)} + \kappa_2 \Delta g_{it} + \kappa_3 \Delta g_{i(t+1)} + \varepsilon_{it},$$

where z is the log of the variable interest, Δg is the government demand instrument (equation (8)), α_i and α_t are industry and year fixed effects, and ε_{it} is the error term. We include the lagged endogenous variable to allow for dynamics due to adjustment costs, as well as the lagged, contemporaneous, and future change in the government demand.

A. *Output, Hours, Wages, and Prices*

Table 3 shows the effects of government spending growth on two measures of output growth. The first column shows the effect of the contemporaneous change in the government demand instrument, the second shows the lagged effect alone, the third shows the anticipation effect from the one-year-ahead change, and the fourth shows the results when all three are all included. We did not standardize the government demand variables in this case; they are measured in percentage changes.

The two output measures are real shipments and real gross output, the latter constructed from the shipments and inventory data. The results are quite similar for both measures. In all cases, the government demand instruments enter positively and are statistically significant in all but one case. The results indicate that, even after controlling for contemporaneous changes in government demand, lagged and future changes are also important. Since the average manufacturing industry sends about 10 percent of its output to the government, the coefficient in the first column implies that a 10 percent increase in real federal spending leads to a 2.3 percent increase in real gross output.[8] The coefficient on the lagged endogenous variable is

[8] A 10 percent change in aggregate federal spending and $\theta = 0.1$ implies a change in output of $10 \times 0.1 \times 2.3 = 2.3$ percent.

Table 3—Reduced-Form Regressions of Industry Output on Government Demand

Independent variable	(1)	(2)	(3)	(4)
Dependent variable: Real shipments				
Lagged dependent variable	0.021**	0.023**	0.029***	0.021**
	(0.009)	(0.009)	(0.009)	(0.009)
$\Delta g_{i(t-1)}$		1.591***		0.579***
		(0.166)		(0.218)
Δg_{it}	2.239***			1.125***
	(0.165)			(0.275)
$\Delta g_{i(t+1)}$			2.055***	1.168***
			(0.167)	(0.224)
Observations	12,536	12,536	12,536	12,536
F-statistic on Δg	183.0***	91.8***	152.2***	70.9***
Dependent variable: Real gross output				
Lagged dependent variable	−0.012	−0.007	−0.003	−0.011
	(0.009)	(0.009)	(0.009)	(0.009)
$\Delta g_{i(t-1)}$		1.433***		0.290
		(0.175)		(0.238)
Δg_{it}	2.317***			1.288***
	(0.176)			(0.314)
$\Delta g_{i(t+1)}$			2.191***	1.250***
			(0.176)	(0.249)
Observations	12,262	12,262	12,262	12,262
F-statistic on Δg	173.1***	67.0***	154.8***	66.3***

Notes: Specification is $\Delta z_{it} = \alpha_i + \alpha_t + \rho\Delta z_{i(t-1)} + \kappa_1\Delta g_{i(t-1)} + \kappa_2\Delta g_{it} + \kappa_3\Delta g_{i(t+1)} + \varepsilon_{it}$. Δg_{it} is the industry-specific change in government demand (equation (8). Estimated on a panel of 274 industries over the period 1960–2005; all regressions include industry (α_i) and year (α_t) fixed effects. Standard errors are reported in parentheses.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Source: Authors' regressions using data from the NBER-CES MID and BEA NIPA and IO tables.

positive and statistically significant for shipments, but very small in magnitude. It is essentially zero for output. The other coefficients are little changed if we omit the lagged dependent variable.

Table 4 shows the effects of government demand on total hours of production workers and on output per hour. Lagged, contemporaneous, and future values of the government demand instrument are positive and statistically significant for hours. The contemporaneous change in government spending has the largest effect on hours, although future government spending also leads to increases in hours. Total hours shows evidence of small, but statistically significant, positive autocorrelation. In contrast, the change in government spending has a negative effect on productivity, particularly at the one year lag. The coefficients on future government spending are positive, but never statistically significant from zero.

To investigate the effects on real wages, Table 5 shows the effects of government demand on wages and prices. The top panel shows that an increase in government demand lowers the real product wage. The largest reduction is associated with the lagged change in government spending. The effect on wages is much smaller in

Table 4—Reduced-Form Regressions of Industry Hours and Labor Productivity on Government Demand

Independent variable	(1)	(2)	(3)	(4)
Dependent variable: Production worker hours				
Lagged dependent variable	0.025***	0.027***	0.034***	0.024***
	(0.009)	(0.009)	(0.009)	(0.009)
$\Delta g_{i(t-1)}$		1.609***		0.460***
		(0.151)		(0.197)
Δg_{it}	2.357***			1.403***
	(0.150)			(0.249)
$\Delta g_{i(t+1)}$			2.071***	1.039***
			(0.151)	(0.203)
Observations	12,536	12,536	12,536	12,536
F-statistic on Δg	247.6***	113.8***	188.4***	91.9***
Dependent variable: Labor productivity				
Lagged dependent variable	−0.149***	−0.150***	−0.149***	−0.149***
	(0.009)	(0.009)	(0.009)	(0.009)
$\Delta g_{i(t-1)}$		−0.286**		−0.226
		(0.129)		(0.178)
Δg_{it}	−0.175			−0.198
	(0.130)			(0.234)
$\Delta g_{i(t+1)}$			0.061	0.255
			(0.131)	(0.185)
Observations	12,262	12,262	12,262	12,262
F-statistic on Δg	1.8	4.9**	0.2	2.3*

Note: See notes to table 3.

Source: Authors' regressions using data from the NBER-CES MID and BEA NIPA and IO tables.

magnitude than on hours or output. The middle panel shows that there is essentially no effect on the nominal wage. Finally, as shown in the bottom panel, an increase in government spending leads to an increase in the relative price of output, particularly at the one-year lag. Thus, the decline in the real product wage is mostly due to a rise in the relative product price. We find no evidence that real wages rise in response to an increase in government spending.

B. *Effects of Concentration and Unionization*

Table 1 showed that the industries with the highest share of government spending also tend to have higher concentration and unionization rates. To determine whether the response of the key variables differs by concentration and unionization, we estimate two sets of equations. In the first, we interact dummy variables indicating whether the industry's concentration ratio is in the upper or lower tercile of the distribution. For the second set of equations, we create the same type of dummy variable for the unionization rate of production workers. Because it is difficult to interpret the interactions with all three timing variations on government spending, we use only the contemporaneous change in government spending when it entered significantly (for real output and total hours); the other regressions use the lagged change.

Table 5—Reduced Form Regressions of Wages and Prices on Government Demand

Independent variable	(1)	(2)	(3)	(4)
Dependent variable: Real production worker wage				
Lagged dependent variable	−0.011	−0.012	−0.011	−0.011
	(0.009)	(0.009)	(0.009)	(0.009)
$\Delta g_{i(t-1)}$		−0.217**		−0.170
		(0.105)		(0.139)
Δg_{it}	−0.177*			−0.082
	(0.105)			(0.176)
$\Delta g_{i(t+1)}$			−0.080	0.020
			(0.106)	(0.144)
Observations	12,536	12,536	12,536	12,536
F-statistic on Δg	2.8*	4.2**	0.6	1.5
Dependent variable: Nominal production worker wage				
Lagged dependent variable	−0.184***	−0.184***	−0.184***	−0.184***
	(0.009)	(0.009)	(0.009)	(0.009)
$\Delta g_{i(t-1)}$		−0.032		0.023
		(0.065)		(0.087)
Δg_{it}	−0.083			−0.071
	(0.066)			(0.110)
$\Delta g_{i(t+1)}$			−0.082	−0.042
			(0.066)	(0.089)
Observations	12,536	12,536	12,536	12,536
F-statistic on Δg	1.6	0.2	1.5	0.7
Dependent variable: Output price				
Lagged dependent variable	0.111***	0.111***	0.111***	0.111***
	(0.009)	(0.009)	(0.009)	(0.009)
$\Delta g_{i(t-1)}$		0.182**		0.167
		(0.082)		(0.109)
Δg_{it}	0.109			0.061
	(0.083)			(0.138)
$\Delta g_{i(t+1)}$			−0.005	−0.090
			(0.083)	(0.113)
Observations	12,536	12,536	12,536	12,536
F-statistic on Δg	1.7	4.9**	0.0	1.9

Note: See notes to table 3.

Source: Authors' regressions using data from the NBER-CES MID and BEA NIPA and IO tables.

Table 6 reports the results. Consider first the regressions with the concentration ratios shown in the upper panel. The results suggest that the effect of the government spending on output is substantially greater for the higher-concentration industries; the coefficient for the high-concentration industries is 2.5, compared to 1.5 for the middle tercile. There is no significant difference between the middle and lower terciles. The results are similar for hours. The industries in the top tercile of concentration respond much more to government demand than those in the lower two terciles. For real product wages, nominal wages, and output prices, none of the interaction terms with concentration is statistically significant. Although some of the coefficients are sizeable, the standard errors are also large.

The lower panel of Table 6 shows the results with the unionization rate. The pattern for unionization is different from that of concentration. For both output and

Table 6—Effect of Industry Concentration and Unionization

Independent variable	Real output	Total hours	Real wage[a]	Output price[a]	Labor productivity[a]
Four-firm concentration ratio[b]					
Lagged dependent variable	−0.012	0.025***	−0.012	0.111***	−0.150***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Δg_{it}	1.554***	1.507***	−0.150	0.156	−0.290*
	(0.338)	(0.288)	(0.125)	(0.098)	(0.155)
$\Delta g_{it} \times \overline{\mathrm{C4}}_i$	0.991***	1.111***	−0.153	0.054	−0.002
	(0.366)	(0.311)	(0.136)	(0.107)	(0.170)
$\Delta g_{it} \times \underline{\mathrm{C4}}_i$	0.207	0.062	0.290	0.021	0.184
	(0.598)	(0.509)	(0.335)	(0.263)	(0.415)
Unionization rate[c]					
Lagged dependent variable	−0.013	0.024***	−0.011	0.111***	−0.150***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Δg_{it}	1.058***	1.228***	−0.320	0.335**	−0.260
	(0.329)	(0.280)	(0.198)	(0.155)	(0.242)
$\Delta g_{it} \times \overline{\mathrm{UR}}_i$	1.617***	1.445***	0.130	−0.191	−0.031
	(0.353)	(0.300)	(0.212)	(0.166)	(0.261)
$\Delta g_{it} \times \underline{\mathrm{UR}}_i$	2.926***	2.137***	0.059	0.361	0.274
	(0.885)	(0.752)	(0.532)	(0.417)	(0.652)
Observations	12,262	12,536	12,536	12,536	12,262

Notes: Specification is $\Delta z_{it} = \alpha_i + \alpha_t + \rho \Delta z_{i(t-1)} + \Delta g_{it} + \Delta g_{it}\overline{X}_i + \Delta g_{it}\underline{X}_i + \sigma_{it}$, where z is the log of the dependent variable, α_i and α_t are industry- and year-fixed effects, Δg_{it} is the industry-specific change in government demand (equation (8), X is concentration or unionization rate, and σ is the error term. $\overline{X}_i$ is an indicator for the upper tercile of X and $\underline{X}_i$ is an indicator for the lower tercile. Estimated on a panel of 274 industries over 1960–2005; all regressions include industry (α_i) and year (α_t) fixed effects. Standard errors are reported in parentheses.

[a] Uses $\Delta g_{i(t-1)}$ in place of Δg_{it}.

[b] The lower cut-off is 25.8 percent; the upper cut-off is 44.0 percent.

[c] The lower cut-off is 38.6 percent; the upper cut-off is 51.9 percent.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Source: Authors' regressions using data from the NBER-CES MID; BEA NIPA and IO tables; the US Census Bureau; and Abowd (1990).

hours, government spending has the smallest effect for the middle tercile of the unionization rate. The effects are greater for both the upper and lower third, with the lower third having the highest coefficient. Thus, the magnitude of the effects are U-shaped in the unionization rate. As with concentration ratios, the data do not indicate differences in coefficients for real wages, nominal wages, or output prices.

C. *Other Inputs*

We next investigate how other inputs respond to the change in government spending. Table 7 reports estimates of equation (9) for employment, average hours per worker, capital, materials, and energy usage.

The first three rows show the effects of government spending on the labor input. Row 1 reports total production worker hours, reproduced from the fourth column of Table 3. Rows 2 and 3 decompose total hours into employment and the workweek. Coefficients on all three government instruments are positive for total hours and

Table 7—Reduced-Form Regressions of Other Inputs on Government Demand

	Independent variable			
Dependent variable	Lagged dep. var.	$\Delta g_{i(t-1)}$	Δg_{it}	$\Delta g_{i(t+1)}$
1. Production worker total hours	0.024***	0.460**	1.403***	1.039***
	(0.009)	(0.197)	(0.249)	(0.203)
2. Production worker employment	0.026***	0.528***	1.407***	0.880***
	(0.009)	(0.189)	(0.238)	(0.194)
3. Average hours per production worker	−0.280***	−0.088	0.038	0.177**
	(0.009)	(0.071)	(0.090)	(0.073)
4. Nonproduction worker employment	−0.101***	1.598***	0.936***	0.473*
	(0.009)	(0.254)	(0.320)	(0.261)
5. Real capital stock	0.401***	0.378***	−0.014	0.058
	(0.008)	(0.080)	(0.101)	(0.082)
6. Real materials excluding energy	0.000	0.424	1.131***	1.689***
	(0.009)	(0.257)	(0.326)	(0.265)
7. Real energy	−0.087***	0.762***	−0.320	0.683**
	(0.009)	(0.284)	(0.359)	(0.293)

Notes: Dependent variable is annual change in the log of listed variable. Specification is $\Delta z_{it} = \alpha_i + \alpha_t + \rho \Delta z_{i(t-1)} + \kappa_1 \Delta g_{i(t-1)} + \kappa_2 \Delta g_{it} + \kappa_3 \Delta g_{i(t+1)} + \varepsilon_{it}$. Δg_{it} is the industry-specific change in government demand (equation (8)). Estimated on a panel of 274 industries over the period 1960–2005; all regressions include industry (α_i) and year (α_t) fixed effects. Standard errors are reported in parentheses.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Source: Authors' regressions using data from the NBER-CES MID and BEA NIPA, and IO tables.

employment, and are similar in magnitude. The biggest effect is for the contemporaneous change in government spending, and the second biggest is for the future change. The effects are smaller for average hours per worker. It appears that only anticipated future government spending has an effect on average hours. Also, while total hours and employment growth show evidence of small, but statistically significant, positive correlation, the change in average hours per worker shows large, negative correlation with its lagged value. Jointly, the results suggest that most of the response of production worker hours is on the extensive margin rather than the intensive margin. The fourth row shows the results for nonproduction worker employment. All three coefficients on the government demand variables are positive and significant, but the lagged one is the greatest. The coefficient on lagged employment is negative.

The fifth row shows that government spending increases lead to a significant rise in the real capital stock after one year. Also, since the coefficient on the lagged change in capital is relatively high, the estimates imply that the effects are long lasting. For an industry that sends 50 percent of its shipments to the government, the coefficients imply that a 10 percent increase in the lagged government instrument leads to a 2.3 percent change in capital this period and a 1 percent change next year. These results are consistent with adjustment costs on capital.

The sixth row shows that real materials usage excluding energy rises in response to an increase in government demand at all horizons. The largest coefficient is on the change in government spending the following year. The sum of the coefficients is greater than the sum for production worker hours. The seventh row shows the effects on real energy usage. The lagged value and future value enter positively and significantly, while the contemporaneous value is estimated to have a negative, but not significant, effect.

In sum, all of the other inputs also increase with an increase in government spending. Some, such as materials, increase proportionally more than hours, others increase less. Moreover, the inputs display a variety of dynamic patterns.

VI. Instrumental Variables Estimates of Markups and Returns to Scale

We now use our government demand instrument to estimate two key parameters that distinguish the New Keynesian from the neoclassical models. First, we estimate the effect of a demand-induced increase in output on the markup. The New Keynesian model predicts that the effect should be negative; the neoclassical model implies no effect. Second, we estimate returns to scale using Susanto Basu and John G. Fernald's (1997) framework. The New Keynesian model assumes increasing returns to scale whereas the neoclassical model assumes constant returns to scale.

A. *Markup*

We consider several possible definitions of the markup. Our baseline measure is that typically used in New Keynesian models. The log change in this measure is given by

$$\Delta\mu_{it}^{A} = \Delta(y_{it} - h_{it}^{p}) - \Delta(w_{it} - p_{it}), \tag{10}$$

where y is the log of real output, h^p is the log of production worker hours, w is the log of the nominal wage, and p is the log of the output price. Because this measure uses the average wage, we call this the "average markup" and denote it with a superscript A.

As first discussed by Bils (1987), the true marginal cost may differ from the average cost because overtime hours often command premium pay, which imparts a procyclical bias in the average markup. Nekarda and Ramey (2010) derive a factor to convert the average markup to the theoretically correct marginal markup. We use the Nekarda-Ramey factors to create a marginal markup and explore its behavior at the industry level.[9] The log change in the marginal markup is

$$\Delta\mu_{it}^{M} = \Delta(y_{it} - h_{it}^{p}) - \Delta(w_{it}^{M} - p_{it}), \tag{11}$$

where w^M is the marginal wage constructed using the Nekarda-Ramey factors.

[9] We estimate this factor from 2-digit SIC data and apply those estimates to the 4-digit MID data. Details are provided in the online Appendix.

The third measure of the markup is the price-cost margin:

$$\Delta\mu_{it}^{PCM} = \Delta\left[\frac{S_{it} + \Delta I_{it} - payroll_{it} - material\ cost_{it}}{S_{it} + \Delta I_{it}}\right], \tag{12}$$

where ΔI is the change in total inventories. This measure, the ratio of price minus variable cost to price, is standard in industrial organization studies. In particular, Ian R. Domowitz, R. Glenn Hubbard, and Bruce C. Petersen (1986) find that this markup is procyclical in 4-digit industry data.

For each of these markup measures, we estimate variations on the following specification:

$$\Delta\mu_{it} = \alpha_i + \alpha_t + \rho\Delta\mu_{i(t-1)} + \beta_1\Delta y_{i(t-1)} + \beta_2\Delta y_{it} + \varepsilon_{it}. \tag{13}$$

In some specifications, we include the lagged values to explore dynamics. We instrument for Δy_{it} and $\Delta y_{i(t-1)}$ with our government demand instruments, so we can determine the response of the markup to *demand-induced* changes in output.

Table 8 reports the estimated coefficients for all three markup measures. The first column reports a specification with no lagged values of any variables. In every case, β_2 is estimated to be zero, both economically and statistically. We also consider instrumenting for Δy using the lagged, contemporaneous, and future values of our government demand variable and find similar results (column 2). The estimated coefficient of 0.03 implies that a 10 percent increase in output induced by government demand raises the markup by only 0.3 percent. The average markup in the MID is 1.06—that is, price is six percent above cost. A 0.3-percent increase would raise the average markup to 1.063, a trivial change. The third column includes the lagged change in the markup as well as the lagged change in output. The coefficients are all near zero for the average markup measure. For the marginal markup measure, the coefficient on the current change in output is slightly positive, but is offset by the coefficient on the lagged change. For the price-cost margin, the lagged coefficient is negative and the current coefficient is positive, but they also roughly offset. Thus, we find no evidence of countercyclicality of markups.[10]

B. *Estimates of Returns to Scale*

We now estimate the overall returns to scale using the framework pioneered by Hall (1990) and extended by Basu and Fernald (1997). In particular, we estimate returns to scale from the following equation:

$$\Delta y_{it} = \alpha_i + \alpha_t + \gamma\Delta x_{it} + \Delta a_{it}, \tag{14}$$

where y is the log of real gross output, Δx is the share-weighted growth of all inputs, and α_i and α_t are industry and year fixed effects. a is the log of technology, which is

[10] We also investigated (not reported) whether markup cyclicality depended on the concentration ratio. None of the coefficients was statistically significant from zero.

Table 8—Instrumental-Variables Regressions of Markups on Government Demand

100 × coefficient	Instrument for Δy_i		
	Δg_{it}	$\Delta g_{i(t-1)}$, Δg_{it}, and $\Delta g_{i(t+1)}$	
Independent variable	(1)	(2)	(3)
Dependent variable: Average markup			
Lagged dependent variable			−0.060
			(0.039)
$\Delta y_{i(t-1)}$			−0.097
			(0.066)
Δy_{it}	−0.008	0.031	0.102
	(0.053)	(0.047)	(0.065)
Observations	12,536	12,536	12,262
Dependent variable: Marginal markup			
Lagged dependent variable			−0.076**
			(0.037)
$\Delta y_{i(t-1)}$			−0.100
			(0.065)
Δy_{it}	0.001	0.042	0.119*
	(0.053)	(0.048)	(0.064)
Observations	11,735	11,735	11,461
Dependent variable: Price-cost margin			
Lagged dependent variable			−0.245***
			(0.030)
$\Delta y_{i(t-1)}$			−0.089***
			(0.033)
Δy_{it}	−0.021	−0.004	0.067**
	(0.030)	(0.027)	(0.033)
Observations	12,536	12,536	12,262

Notes: Specification is $\Delta\mu_{it} = \alpha_i + \alpha_t + \rho\Delta\mu_{i(t-1)} + \beta_1\Delta y_{i(t-1)} + \beta_2\Delta y_{it} + \varepsilon_{it}$, where markup μ is defined in equations (10)–(12). Δy_{it} is annual growth of log real output in percent. Δg_{it} is the industry-specific change in government demand (equation (8)). Estimated on a panel of 274 industries over the period 1960–2005; all regressions include industry (α_i) and year (α_t) fixed effects. Standard errors are reported in parentheses.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Source: Authors' regressions using data from the NBER-CES MID and BEA NIPA, and IO tables.

unobserved. The coefficient γ measures the returns to scale. If technology is the only source of error in this equation, then one can estimate γ by using a demand instrument that is correlated with input growth but uncorrelated with technology.

We construct share-weighted input growth treating total hours, real capital, real energy, and real materials as separate factors:

$$\Delta x_{it} = s_k \Delta k_{it} + s_h \Delta h_{it} + s_m \Delta m_{it} + s_e \Delta e_{it}, \tag{15}$$

where k is the log of the real capital stock, h is the log of total hours, m is the log of real materials usage excluding energy, e is the log of real energy usage, and s_j is the share of input j.

Total hours is the sum of production workers' hours, which are reported in the MID, and of supervisory and nonproduction workers' hours, which we must impute. We construct the hours of nonproduction workers from their employment totals by assuming that they always work 1,960 hours per year.[11]

The payroll data from the MID include only wages and salaries. They do not include payments for benefits, such as Social Security and health insurance. Thus, labor share estimates from this database are biased downward. We construct the labor share using factors that inflate the observed labor share to account for fringe benefits, as in Yongsung Chang and Jay H. Hong (2006). This adjustment raises the average labor share in the dataset by 4 percentage points. Following Basu, Fernald, and Miles S. Kimball (2006), we calculate the capital share as the residual from labor share and materials share. We also use the average shares over the whole sample.

In order to facilitate comparison to Basu and Fernald's (1997) results, we show estimates for all of the manufacturing industries in the sample, as well as for durable goods industries and nondurable goods industries. Also, since Basu and Fernald analyze both ordinary least squares (OLS) and instrumental variables (IV) results, we do so as well. They emphasized the OLS results because their instruments were weak.

The upper panel of Table 9 shows estimates of returns to scale for all manufacturing. The first column shows OLS estimates for the basic specification. For the entire manufacturing sector, we estimate γ to be 1.11, statistically different from unity. For durable goods industries the estimate is 1.18, whereas for nondurable goods industries it is 0.94. Thus, the OLS results indicate mild increasing returns to scale for manufacturing as a whole, and particularly for the durable goods industries, and decreasing returns to scale for nondurables. Finding higher returns to scale in durable goods than nondurable goods industries is consistent with Basu and Fernald (1997).

Of course, the OLS estimates of returns to scale will be biased upward if the error term contains technological change. Thus, it is important to instrument for input growth using a demand instrument that is uncorrelated with technology. To this end, we instrument for Δx with our government demand variable, Δg. For the entire manufacturing sector, the first-stage regression of the share-weighted inputs on the lagged, contemporaneous, and future values of the instrument has an F-statistic of 89. The F-statistic is 92 for durable goods industries and only 1 for nondurables. Clearly the instruments are highly relevant for inputs in durable goods industries and for the entire manufacturing sector, but very weak for nondurable goods industries. Column 2 reports the IV estimates. For the entire manufacturing sector, the estimate of γ is 1.16, for durables it is 1.21, and for nondurables it is 0.94. The first two estimates are statistically different from unity. The nondurable estimate is not even statistically different from zero.

These results suggest increasing returns to scale, particularly in durable goods industries. However, as numerous papers have made clear, unobserved variations in capital utilization or labor effort may also contaminate the error term.[12] Because

[11] The results are little changed if we assume nonproduction workers work as many hours a year as production workers.

[12] See, for example, Burnside, Eichenbaum, and Sergio Rebelo (1996) and Basu (1996).

Table 9—Instrumental-Variables Regressions of Output Growth on Input Growth

Independent variable	OLS (1)	IV (2)	OLS (3)	IV (4)
All manufacturing (12,536 observations)				
Δx_{it}	1.112†	1.161†	1.114†	1.059
	(0.007)	(0.049)	(0.007)	(0.102)
$\Delta \overline{h}_{it}$			−0.034**	2.697**
			(0.016)	(1.361)
Durable goods (8,432 observations)				
Δx_{it}	1.181†	1.205†	1.185†	1.140
	(0.008)	(0.044)	(0.008)	(0.099)
$\Delta \overline{h}_{it}$			−0.075***	2.988*
			(0.019)	(1.719)
Nondurable goods (4,104 observations)				
Δx_{it}	0.935†	0.943	0.933†	1.392
	(0.015)	(0.485)	(0.015)	(0.988)
$\Delta \overline{h}_{it}$			0.023	−1.554
			(0.031)	(2.573)

Notes: Specification is $\Delta y_{it} = \alpha_i + \alpha_t + \gamma \Delta x_{it} + \Delta a_{it}$. Δy_{it} is annual change of log real output. Δx_{it} is annual growth of share-weighted log inputs (equation (15)). $\Delta \overline{h}_{it}$ is annual growth of average hours per worker. In IV regressions, both independent variables are instrumented using $\Delta g_{i(t-1)}$, Δg_{it}, and $\Delta g_{i(t+1)}$. Estimated on a panel of 274 industries over the period 1960–2005; all regressions include industry (α_i) and year (α_t) fixed effects. Standard errors are reported in parentheses.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.
†Significantly different from unity at the 10 percent level.

Source: Authors' regressions using data from the NBER-CES MID and BEA NIPA, and IO tables.

these variations are likely to be correlated with any instrument also correlated with observed input growth, estimates of γ are likely to be biased upward. Basu, Fernald, and Kimball (2006) use the theory of the firm to show that, under certain conditions, unobserved variations in capital utilization and labor effort are proportional to the growth in average hours per worker. Thus, they advocate controlling for average hours in the returns to scale regression.

The third and fourth columns of Table 9 show the OLS and IV results when the change in average hours per production worker is also included in the regression. In the IV results, we instrument both for the growth of inputs and for average hours using the three timing variations of our government demand instrument. Controlling for average hours has little effect on the OLS estimates of returns to scale but does change the IV estimates. In particular, for the entire manufacturing sector the estimated γ falls to 1.06 and is no longer statistically significant from unity. The estimated γ for durable goods, at 1.14, is slightly higher, but also not statistically different from unity. The estimated γ for nondurable goods is 1.39, but is so imprecisely estimated that it is not statistically different from either unity or zero.

Thus, once we include a proxy for unobserved variation in capital utilization, we find constant returns to scale in manufacturing as a whole. In durable goods industries, the evidence is a bit more suggestive of mild increasing returns to scale, but constant returns cannot be rejected statistically. The estimates for nondurable goods industries are too imprecise to yield meaningful conclusions, although OLS estimates suggest mild decreasing returns.

Despite using different data, levels of aggregation, and instruments, our results are remarkably close to those of Basu and Fernald (1997). Their table 3 reports their reallocation-corrected OLS estimates. They estimate a returns to scale parameter of 1.08 for overall manufacturing, 1.11 for durable goods industries, and 0.96 for nondurable goods industries. Our IV estimates that control for hours are 1.06 for overall manufacturing and 1.14 for durables. The same specification for nondurables yields a higher estimate at 1.39, but these estimates suffer from a weak instrument problem. The other three specifications for nondurables yield estimates of returns to scale parameters of 0.94.

A key question, then, is why the aggregate evidence discussed earlier suggests that increases in government spending raise labor productivity whereas the industry-level evidence presented here implies constant returns to scale on average. Fortunately, Basu and Fernald (1997) also provide an answer to this question.[13] They show that aggregate gross output growth is related to aggregate input growth, technological change, and reallocation of inputs across industries as follows:

$$\Delta y_t = \overline{\gamma}\Delta x_t + \Delta a_{it} + \sum_i \omega_i (\gamma_i - \overline{\gamma}) \Delta x_{it}, \tag{16}$$

where $\overline{\gamma}$ is the weighted average returns to scale across industries, γ_i is returns to scale in industry i, and ω_i is the share of industry i in total output. The last term is what they call the "reallocation" term. If all industries have the same returns to scale, this term is zero. If, however, some industries have higher returns to scale than others, this term is potentially nonzero and correlated with demand instruments. For example, suppose that an increase in government spending raises inputs in all industries, but raises them more in durable goods manufacturing, which has higher returns to scale than other industries. Then an increase in government spending will raise the reallocation term.[14] While this framework applies to total factor productivity, it is easy to see how the argument would also extend to labor productivity.

VII. Conclusion

Our study of the effects of industry-specific changes in government demand indicates that an increase in industry-specific government demand raises relative output and hours in an industry. The increase in government spending is associated with small declines in real product wages and labor productivity, and small increases in industry relative prices. Other inputs, such as capital, energy, and materials, rise as well. Estimates of returns-to-scale parameters are consistent with constant returns to

[13] See Basu and Fernald (1997, 264–266).

[14] As a simple illustration, consider two industries of equal size. Industry A has returns to scale of 1.1, and industry B has returns to scale of 0.9. Suppose that an increase in government spending raises inputs in industry A by 20 percent and raises inputs in industry B by 1 percent. In this situation, we will observe an increase in aggregate inputs of 10.5. However, aggregate output will rise by 11.5 because the reallocation term will be 0.95. Thus, it will appear that there are overall increasing returns to scale, even though the average returns to scale across industries is unity.

scale for all of manufacturing, though the evidence suggests that returns to scale in durable goods industries are somewhat higher than in nondurable goods industries.

We do not find support, however, for the textbook New Keynesian explanation for the effects of government spending. Central to this explanation is the idea that sticky prices and countercyclical markups allow real product wages to rise at the same time that hours increase. We find no evidence for the rising real product wages or declining markups that are at the heart of the New Keynesian explanation for the effects of government spending.

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