Industry Evidence on the Effects of Government Spending

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Abstract

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 begin by highlighting the different theoretical predictions concerning the effects of government spending on industry output and labor market variables. We create a new panel data set that matches output and labor variables to industry-specific shifts in government demand. We find that an increase in government demand raises output and hours, but lowers real product wages and labor productivity slightly in the short-run; the markup does not respond. Our estimates also imply roughly constant returns to scale. The findings are consistent with the neoclassical model of government spending, but they are not consistent with the key mechanism of textbook New Keynesian models of the effects of government spending.

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1 Introduction

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 productivity in a panel of industries. As Ramey and 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 Shea (1993), Perotti (2008), and 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 data set 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. All of the results are consistent with the neoclassical demand curve for labor; they are not consistent with the New Keynesian labor demand curve.

1. For example, Baxter and King (1993) or Rotemberg and Woodford (1992).
2. Devereux, Head and Lapham (1996).

2 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 rises in private hours worked and rises 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 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 argued that the standard types of VARs employed by Rotemberg and Woodford 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]

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

3. See, for example, Fatás and Mihov (2001), Perotti (2004), Pappa (2005), and Galí, López-Salido and Vallés (2007).

4. See, for example, Burnside, Eichenbaum and Fisher (2004), Cavallo (2005), and Ramey (Forthcoming).

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.

3 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:

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

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

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

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, $\mathscr{M}$, 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 $\mathscr{M} = 1$, 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 implies 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 (DSGE) 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 Lucas and Prescott (1974). 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.

4 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 Appendix details how we merged the two data sets.

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. Hall (1980), 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 Bils's (1987) framework. We augment the MID with data on the four-firm concentration ratio from the U.S. Census Bureau and with data on the percent of workers who are unionized from Abowd (1990). The 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 sends 92 percent of its shipments to the government, either directly or indirectly. The average for all manufacturing industries over this time period was only 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.

5 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.

5.1 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 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

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

where Δ_5 denotes the five-year difference and $\bar{\phi}_i$ and $\bar{G}$ 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

$$\Delta g_{it} = \bar{\theta}_i \cdot \Delta \ln G_t, \tag{8}$$

where $\bar{\theta}_i$ 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).

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.

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}.

5.2 Comparison of Government Demand Instruments

We now assess the relevance and exogeneity of the measures on 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 1963–92. 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 output 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: $\bar{\phi}_i \cdot \Delta_5 G_t / S_{i(t-5)}$, where $\bar{\phi}_i$ 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: $\bar{\phi}_i \cdot \Delta_5 G_t / \bar{S}_i$, where $\bar{S}_i$ is the average over

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

7. As we will show in section 6.3, this result is consistent with constant returns to scale because the other inputs rise as well.

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. 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.

6 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 several quarters or year 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:

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

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.

6.1 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 positive and statistically significant for shipments, but very small in magnitude; it is essentially zero for

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.

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 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, particularly at the one year lag, leads to an increase in the relative price of output. 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.

6.2 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 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 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 dos not indicate differences in coefficients for real wages, nominal wages, or output prices.

6.3 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 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 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.

7 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 Basu and Fernald's (1997) framework. The New Keynesian model assumes increasing returns to scale whereas the neoclassical model assumes constant returns to scale.

7.1 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

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

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

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

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

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

$$\Delta\mu_{it}^{\mathrm{PCM}} = \Delta\left[\frac{S_{it} + \Delta I_{it} - \mathrm{payroll}_{it} - \mathrm{material\ cost}_{it}}{S_{it} + \Delta I_{it}}\right], \tag{12}$$

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, Domowitz, Hubbard and 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 marginally 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]

9. We estimate this factor from 2-digit SIC data and apply those estimates to the 4-digit MID data. The Appendix provides details.

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

7.2 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 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 Chang and Hong (2006). This adjustment raises the average labor share in the data set by 4 percentage points. Following Basu, Fernald and 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.

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

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's (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 Δz with our government demand variable, Δg_{it}. 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 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

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

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:

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

where $\bar{\gamma}$ 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

13. See pp. 264–6.

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

factor productivity, it is easy to see how the argument would also extend to labor productivity.

8 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 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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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.

Appendix

Input-Output Data

We use data from the Bureau of Economic Analysis (BEA)'s benchmark input-output (IO) tables to construct measure of industry-level government spending. Benchmark IO tables based on SIC codes are available for 1963, 1967, 1972, 1977, 1982, 1987, 1992. Starting in 1997, the IO tables moved from a SIC-based classification to one based on the North American industrical classification system (NAICS). We do not use the NAICS–based IO tables because we fear merging industries based on NAICS-SIC correspondences may be fraught with additional error.

The IO tables are available on the U.S. Census Bureau's web site.[15] The table below lists the file names for the transactions and total requirements benchmark IO tables.

Year	*Source file*
Transactions	
1963	`1963 Transactions 367-level Data.txt`
1967	`1967 Transactions 367-level Data.txt`
1972	`1972 Transactions 367-level Data.txt`
1977	`1977 Transactions 366-detail Data.txt`
1982	`82-6DT.DAT`
1987	`TBL2-87.DAT`
1992	`SICUSE.TXT`
Total requirements	
1963	`1963 Transactions 367-level Data.txt`
1967	`1967 Transactions 367-level Data.txt`
1972	`1972 Total Requirements 365-level Data.txt`
1977	`1977 Total Req Coeff 366-level Data.txt`
1982	`82CCTR.TXT`
1987	`TBL4-87.DAT`
1992	`CXCTR.TXT`

Except for 1963, the IO data are available at a 6-digit level (537 industries); in 1963, the data are available at 4-digit level (367 industries). All calculations are performed at the most disaggregated level available.

Let S_{ijt} be the value of inputs produced by industry i shipped to industry j in year t, measured in producers' prices. Direct government demand for industry i is the value of inputs from industry i used by the federal government ($j = g$):

$$G^d_{it} = S_{igt}. \tag{A.1}$$

15. http://www.bea.gov/industry/io_benchmark.htm

Although the IO tables distinguish between defense and nondefense federal purchases, we take the sum of both categories. The table below lists the IO codes for the government for each benchmark IO table.

	Industry code	
Year	*Defense*	*Nondefense*
1963	9710	9720
1967	971000	972000
1972	960000	970000
1977	960000	970000
1982	960000	970000
1987	960000	970000
1992	9600I0, 9600C0	9700I0, 9700C0

Indirect government demand is calculated using commodity-by-commodity unit input requirement coefficients. Let r_{ijt} be the commodity i output required per dollar of each commodity j delivered to final demand in year t. The indirect government demand for industry i's output is the direct government purchases from industry j times the unit input requirement of industry i for industry j's output:

$$G_{it}^{n} = \sum_{j=1}^{J_t} G_{jt}^{d} \times r_{ijt}. \tag{A.2}$$

Total government demand for industry i in year t is the sum of direct and indirect demand:

$$G_{it} = G_{it}^{d} + G_{it}^{n}. \tag{A.3}$$

After calculating direct and indirect government shipments, the IO data are aggregated (see below) to merge with the MID data.

Manufacturing Industry Database

Data on manufacturing industries comes from the NBER-CES MID database.[16] The MID database contains annual data on 459 manufacturing industries from 1958 to 2005. The data are compiled from the Annual Survey of Manufacturers and the Census of Manufactures and adjust for changes in industry definitions over time. We use the version based on the 1987 SIC codes.

16. Bartelsman, Becker and Gray (2000). The data are available at http://www.nber.org/nberces/.

We use MID measures of gross shipments; employment, annual hours worked, and the wage bill for production and nonproduction workers; total capital; plant, equipment, investment, materials usage, and energy usage. The MID also includes price indexes for capital, investment, materials, and energy. We create real series from the nominal values by dividing by the appropriate price index. The production worker product wage is the production worker wage bill divided by production worker hours times the shipments deflator.

Total Hours

The database provides information on annual hours only for production workers. We created two measures of total hours using two extreme assumptions: nonproduction workers always work 1,960 hours per year and nonproduction workers always work as much as production workers. The constant-hours value is slightly less than the usual 2000 hours per year because it allows for vacations and holidays, which are not included in production worker hours measures. The results were very similar using both measures, so we only report the results using the conservative assumption that nonproduction workers' hours are constant.

Labor Share

The payroll data from the MID includes only wages and salaries; it does not include payments for benefits, such as Social Security and health insurance. Thus, labor share estimates from the MID are biased downward. Following Chang and Hong (2006), we use NIPA data to compute the ratio of total compensation to wages and salaries for each 2-digit SIC manufacturing industry.[17] When the NIPA data migrate to the NAICS codes in 2001, we adjust the factor shares by the difference in the ratio in 2000.

We merge these factors to our 4-digit data and use them to magnify the payroll data to create more accurate labor shares.

Real Output

We construct real shipments by dividing nominal shipments by the shipments price deflator. However, because firms hold inventories, shipments are not necessarily equal to output. According to the standard inventory identity, real gross output, Y, is equal to real shipments, S, plus the change in real finished-goods and work-in-process inventories, I^F. The MID database reports only the total value of inventories, I, at the end of the year; it does not distinguish inventories by stage of process in the reported stocks.

17. Compensation is from table 6.2; wage and salary accruals are from table 6.3.

Fortunately, we can back out the nominal change in materials inventories from other data in the MID. In particular, the measure of nominal value added, $\tilde{V}$, in the MID is defined as:

$$\tilde{V}_{it}^{\text{MID}} = \tilde{S}_{it} - \tilde{M}_{it} + \Delta\tilde{I}_{it}^{F}, \tag{A.4}$$

where $\tilde{M}$ is nominal materials cost.

Since total inventories is the sum of finished-goods, work-in-process, and materials inventories, I^M, the change in materials inventories can be inferred from the change in total inventories and the change in finished-goods and work-in-process inventories: $\Delta\tilde{I}_{it}^{M} = \Delta\tilde{I}_{it} - \Delta\tilde{I}_{it}^{F}$. Using this inventory relationship, we calculate real gross output as

$$Y_{it} \approxeq \frac{\tilde{S}_{it}}{P_{it}} + \left[\frac{\tilde{I}_{it}}{P_{it}} - \frac{\tilde{I}_{i(t-1)}}{P_{i(t-1)}}\right] - \frac{\Delta\tilde{I}_{it}^{M}}{P_{it}}, \tag{A.5}$$

where P is the price of output. This formulation for gross output is not exact because the last term, the change in real materials inventories, should be

$$\frac{\tilde{I}_{it}^{M}}{P_{it}} - \frac{\tilde{I}_{i(t-1)}^{M}}{P_{i(t-1)}}.$$

Unfortunately the MID does not have data on the stock of materials inventories at each point in time necessary. As a result, our measure of gross real output in equation A.5 understates production by

$$\frac{\tilde{I}_{i(t-1)}^{M}}{P_{i(t-1)}} \times \frac{P_{it} - P_{i(t-1)}}{P_{it}}, \tag{A.6}$$

which is the product of the real initial stock of materials inventories (valued at output prices) and the rate of inflation of output prices. According to BEA estimates of inventories and sales in manufacturing, the real stock of materials inventories is about 50 percent of monthly sales, or about 4 percent of annual sales. Even if annual inflation is as high as 10 percent, the bias would only be −0.4 percent.

Marginal Markup

This section describes how we estimate Nekarda and Ramey's (2010) marginal-average wage adjustment factor for 2-digit SIC manufacturing industries. The adjustment factor (their equation 7) is the ratio of the marginal wage to the average wage:

$$\frac{W_{\mathrm{M}}}{W_{\mathrm{A}}} = \frac{1+\rho\theta\left(\frac{\mathrm{d}v}{\mathrm{d}h}\right)}{1+\rho\theta\left(\frac{v}{h}\right)},$$

where here, h is average hours per worker, v is average overtime hours per worker, ρ is the premium for overtime hours, and θ is the fraction of overtime hours that command a premium.

In the Current Employment Statistics (CES) data on production workers in manufacturing, overtime hours are defined as those hours that are paid an premium so $\theta = 1$ by definition. The Fair Labor Standards Act requires that employers pay a 50 percent premium for hours in excess of 40 per week for covered employees. As most workers who earned premium pay received a 50 percent premium, we set $\rho = 0.5$. Thus, to construct the ratio of marginal to average wages we require data on v/h and $\mathrm{d}v/\mathrm{d}h$.

Unfortunately, the MID does not contain information on overtime hours. To obtain estimates of overtime hours, we first regress v on h for each 2-digit industry in the CES data:

$$(v/h)_{it} = \xi_{i0} + \xi_{i1} h_{it} + \omega_{it}. \tag{A.7}$$

The coefficients ξ_{i0} and ξ_{i1}, reported in table A1, are then used with the annual hours data at the 4-digit level in the MID to construct overtime hours. The value of v/h is then directly calculated.

As in Bils (1987) and Nekarda and Ramey (2010), we estimate $\mathrm{d}v/\mathrm{d}h$ using the parametric specification

$$\begin{aligned}\Delta v_{it} = \Big\{ & b_{i0} + b_{i1}t + b_2 t^2 + b_3 t^3 + c_1\left[h_{i(t-1)} - 40\right] + c_2\left[h_{i(t-1)} - 40\right]^2 \\ & + c_3\left[h_{i(t-1)} - 40\right]^3\Big\}\Delta h_{it} + a_{i0} + a_1 t + a_2 t^2 + a_3 t^3 \\ & + d_{i1}\ln\left[N_{it}/N_{i(t-1)}\right] + d_{i2}\Delta\ln\left[N_{it}/N_{i(t-1)}\right] + e_{it},\end{aligned} \tag{A.8}$$

where all parameters listed as a function of i are allowed to differ across industries.[18] We estimate this equation on a panel of 2-digit industries using quarterly data. All hours and employment data are for production and nonsupervisory workers. We seasonally adjust monthly data for each industry, in the process removing outlier observations from holidays, strikes, and bad weather, and then take a quarterly average.

18. See Nekarda and Ramey (2010) for details.

IO-SIC Correspondence

We create a cross-walk between the IO data at various aggregations and years and the 1987 4-digit SIC codes used in the MID data. Some aggregation was required in both data sets to achieve a one-to-one correspondence; this aggregation was made at the most detailed level possible. The ultimate correspondence is between the 6-digit IO code–based IO data and the 4-digit SIC code–based MID data. The merged database contains 274 industries at the 4-digit the SIC level.

The Web Appendix contains the complete correspondence between combined IO and combined SIC codes. It also includes tables detailing how 6-digit IO codes were assigned to a 4-digit IO industry before aggregating to the 4-digit IO level. This assignment changes for each benchmark IO table.

Some SIC codes also required combination. This aggregation occurs mostly at the 3-digit SIC level, which roughly corresponds to the 4-digit IO level, but it was ultimately tailored to preserve the best correspondence with the IO data. A complete list is available in the Web Appendix.

Aggregates are constructed by summing component categories. Because the MID uses fixed-weight deflators, we sum the real quantities and calculate deflators for the combined industries as the ratio of nominal and real quantities.

Other Data Sources

Item	*Source*
Average weekly hours and average weekly overtime hours	BLS Employment, Hours, and Earnings database `ftp.bls.gov/pub/time.series/ee/`
Four-firm concentration rate	U.S. Census Bureau `www.census.gov/epcd/www/concentration92-47.xls`
Unionization rate	Abowd (1990)
Nominal federal spending	NIPA table 1.1.5, lines 22 and 23
Implicit price deflators	NIPA table 1.1.9, lines 22 and 23

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

				Relative[a]			*Unionization rate*	
Rank	*SIC*	*Industry*	θ	*Capital*[b]	*Wages*[c]	C4	*Production workers*	*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

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

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.

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)	$\Delta_5 G_{it}/S_{i(t-5)}$	1963–92, 1,630 obs.	1.294^{***} (0.122)	0.196^{***} (0.069)
2. Purged numerator	$\bar{\phi}_i \cdot \Delta_5 G_t/S_{i(t-5)}$	1963–92, 1,630 obs.	0.897^{***} (0.121)	−0.001 (0.067)
3. Purged numerator and denominator	$\bar{\phi}_i \cdot \Delta_5 G_t/\bar{S}_i$	1963–92, 1,643 obs.	1.541^{***} (0.128)	0.056 (0.073)
4. NR w/ average share	$\bar{\theta}_i \cdot \Delta_5 G_t$	1963–92, 1,643 obs.	1.516^{***} (0.129)	0.067 (0.073)
5. NR w/ average share	$\bar{\theta}_i \cdot \Delta_5 \ln G_t^N$	1963–92, 1,643 obs.	1.546^{***} (0.138)	−0.003 (0.078)
6. NR w/ 1963 share	$\theta_{i\,1963} \cdot \Delta_5 \ln G_t^N$	1963–92, 1,643 obs.	1.490^{***} (0.139)	−0.017 (0.078)
Annual changes				
7. NR w/ average share	$\bar{\theta}_i \cdot \Delta \ln G_t^N$	1960–2005, 12,536 obs.	1.475^{***} (0.115)	−0.130 (0.087)
8. NR w/ 1963 share	$\theta_{i\,1963} \cdot \Delta \ln G_t^N$	1960–2005, 12,536 obs.	1.776^{***} (0.139)	−0.156 (0.104)

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

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 regressions include industry (α_i) and year (α_t) fixed effects. Standard errors are reported in parentheses. *** indicates significance at 1-percent, ** at 5-percent, and * at 10-percent level.

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)
Number of obs.	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)
Number of obs.	12,262	12,262	12,262	12,262
F statistic on Δg	173.1^{***}	67.0^{***}	154.8^{***}	66.3^{***}

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

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 1960–2005; all regressions include industry (α_i) and year (α_t) fixed effects. Standard errors are reported in parentheses. *** indicates significance at 1-percent, ** at 5-percent, and * at 10-percent level.

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*** (0.009)	0.027*** (0.009)	0.034*** (0.009)	0.024*** (0.009)
$\Delta g_{i(t-1)}$		1.609*** (0.151)		0.460** (0.197)
Δg_{it}	2.357*** (0.150)			1.403*** (0.249)
$\Delta g_{i(t+1)}$			2.071*** (0.151)	1.039*** (0.203)
Number of obs.	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*** (0.009)	−0.150*** (0.009)	−0.149*** (0.009)	−0.149*** (0.009)
$\Delta g_{i(t-1)}$		−0.286** (0.129)		−0.226 (0.178)
Δg_{it}	−0.175 (0.130)			−0.198 (0.234)
$\Delta g_{i(t+1)}$			0.061 (0.131)	0.255 (0.185)
Number of obs.	12,262	12,262	12,262	12,262
F statistic on Δg	1.8	4.9**	0.2	2.3*

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

Notes: See notes to table 3.

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 (0.009)	−0.012 (0.009)	−0.011 (0.009)	−0.011 (0.009)
$\Delta g_{i(t-1)}$		-0.217^{**} (0.105)		−0.170 (0.139)
Δg_{it}	-0.177^{*} (0.105)			−0.082 (0.176)
$\Delta g_{i(t+1)}$			−0.080 (0.106)	0.020 (0.144)
Number of obs.	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^{***} (0.009)	-0.184^{***} (0.009)	-0.184^{***} (0.009)	-0.184^{***} (0.009)
$\Delta g_{i(t-1)}$		−0.032 (0.065)		0.023 (0.087)
Δg_{it}	−0.083 (0.066)			−0.071 (0.110)
$\Delta g_{i(t+1)}$			−0.082 (0.066)	−0.042 (0.089)
Number of obs.	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^{***} (0.009)	0.111^{***} (0.009)	0.111^{***} (0.009)	0.111^{***} (0.009)
$\Delta g_{i(t-1)}$		0.182^{**} (0.082)		0.167 (0.109)
Δg_{it}	0.109 (0.083)			0.061 (0.138)
$\Delta g_{i(t+1)}$			−0.005 (0.083)	−0.090 (0.113)
Number of obs.	12,536	12,536	12,536	12,536
F statistic on Δg	1.7	4.9^{**}	0.0	1.9

Source: Authors' regressions using data from the NBER-CES MID and BEA NIPA and IO tables.
Notes: See notes to table 3.

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)
$\Delta g_{it} \times \overline{\text{C4}}_i$	0.991***	1.111***	−0.153	0.054	−0.002
	(0.366)	(0.311)	(0.136)	(0.107)	(0.170)
$\Delta g_{it} \times \underline{\text{C4}}_i$	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)
$\Delta g_{it} \times \overline{\text{UR}}_i$	1.617***	1.445***	0.130	−0.191	−0.031
	(0.353)	(0.300)	(0.212)	(0.166)	(0.261)
$\Delta g_{it} \times \underline{\text{UR}}_i$	2.926***	2.137***	0.059	0.361	0.274
	(0.885)	(0.752)	(0.532)	(0.417)	(0.652)
Number of obs.	12,262	12,536	12,536	12,536	12,262

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

Notes: Specification is $\Delta z_{it} = \alpha_i + \alpha_t + \rho \Delta z_{i(t-1)} + \Delta g_{it} + \Delta g_{it}\overline{\text{X}}_i + \Delta g_{it}\underline{\text{X}}_i + \sigma_{it}$, 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. $\overline{\text{X}}_i$ is an indicator for the upper tercile of X and $\underline{\text{X}}_i$ 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. *** indicates significance at 1-percent, ** at 5-percent, and * at 10-percent level.

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.

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. Avg. 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)

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

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 1960–2005; all regressions include industry (α_i) and year (α_t) fixed effects. Standard errors are reported in parentheses. *** indicates significance at 1-percent, ** at 5-percent, and * at 10-percent level.

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

100 × coefficient

Independent variable	*Instrument for Δy_{it}*: Δg_{it} (1)	$\Delta g_{i(t-1)}$, Δg_{it}, and $\Delta g_{i(t+1)}$ (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 (0.053)	0.031 (0.047)	0.102 (0.065)
Number of obs.	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 (0.053)	0.042 (0.048)	0.119* (0.064)
Number of obs.	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 (0.030)	−0.004 (0.027)	0.067** (0.033)
Number of obs.	12,536	12,536	12,262

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

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 1960–2005; all regressions include industry (α_i) and year (α_t) fixed effects. Standard errors are reported in parentheses. *** indicates significance at 1-percent, ** at 5-percent, and * at 10-percent level.

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

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

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

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). $\Delta \bar{h}_{it}$ 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 1960–2005; all regressions include industry (α_i) and year (α_t) fixed effects. Standard errors are reported in parentheses. *** indicates significance at 1-percent, ** at 5-percent, and * at 10-percent level. † indicates significantly different from unity at the 10-percent level.

Table A1. Regression of Ratio of Overtime Hours to Average Hours on Average Hours

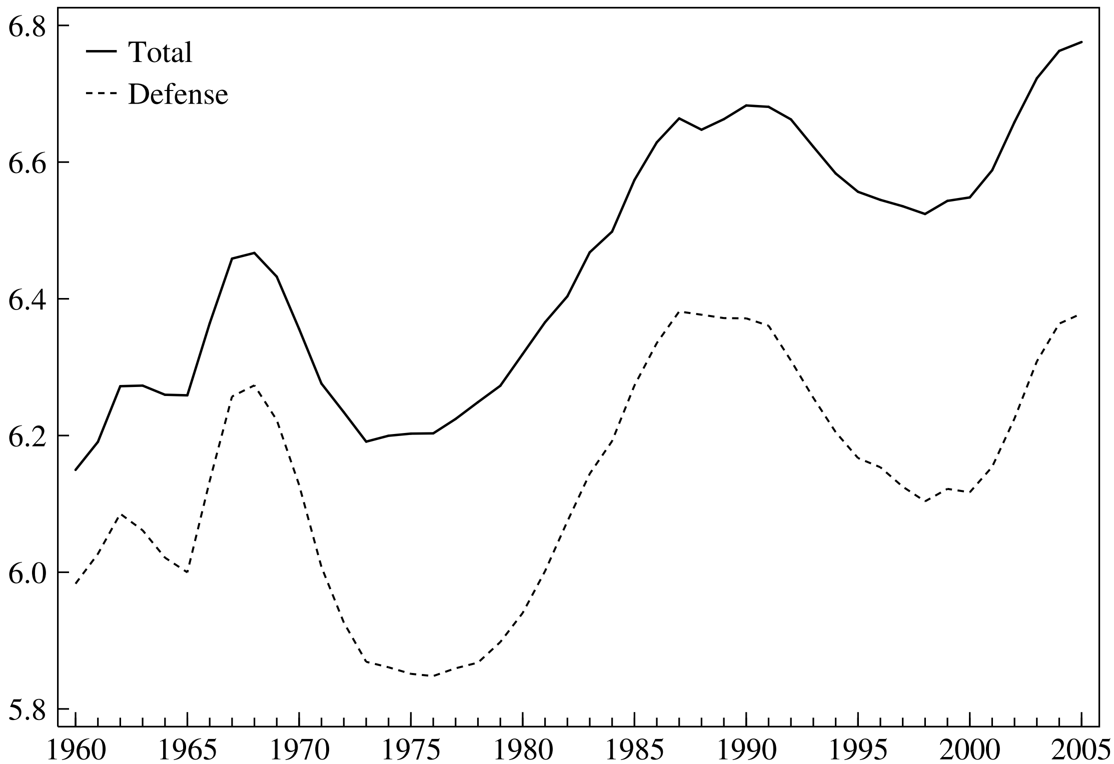
	Constant		*Average hours*		
SIC	$\widehat{\delta}_0$	*Standard error*	$\widehat{\delta}_1$	*Standard error*	R^2
20	-0.377^{***}	0.057	0.012^{***}	0.001	0.297
21	-0.588^{***}	0.056	0.017^{***}	0.001	0.439
22	-0.464^{***}	0.023	0.014^{***}	0.001	0.781
23	-0.362^{***}	0.012	0.011^{***}	0.000	0.864
24	-0.529^{***}	0.031	0.015^{***}	0.001	0.702
25	-0.428^{***}	0.023	0.013^{***}	0.001	0.730
26	-0.304^{***}	0.043	0.010^{***}	0.001	0.363
27	-0.380^{***}	0.030	0.012^{***}	0.001	0.584
28	-1.018^{***}	0.045	0.026^{***}	0.001	0.782
29	-0.698^{***}	0.080	0.019^{***}	0.002	0.372
30	-0.620^{***}	0.031	0.017^{***}	0.001	0.760
31	-0.308^{***}	0.023	0.009^{***}	0.001	0.584
32	-0.634^{***}	0.023	0.018^{***}	0.001	0.856
33	-0.655^{***}	0.014	0.018^{***}	0.000	0.948
34	-0.721^{***}	0.026	0.020^{***}	0.001	0.853
35	-0.629^{***}	0.030	0.017^{***}	0.001	0.776
36	-0.625^{***}	0.032	0.017^{***}	0.001	0.732
37	-0.612^{***}	0.025	0.017^{***}	0.001	0.832
38	-0.683^{***}	0.030	0.018^{***}	0.001	0.780
39	-0.482^{***}	0.033	0.014^{***}	0.001	0.622

Source: Author's regressions using quarterly CES data.

Notes: Regression of $(v/h)_{it} = \xi_{i0} + \xi_{i1} h_{it} + \omega_{it}$ separately for each industry i. Sample contains 20 2-digit SIC industries over 1960:1–2002:4 (172 observations per industry). *** indicates significance at 1-percent, ** at 5-percent, and * at 10-percent level.

Figure 1. U.S. Federal Government Spending, 1960–2005

Natural log of chained 2005 dollars



Source: BEA.