Industry Evidence on the Effects of Government Spending

Christopher J. Nekarda
Federal Reserve Board of Governors

Valerie A. Ramey
University of California, San Diego
and NBER

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Abstract

This paper investigates industry-level effects of government purchases 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 labor market equilibrium. We then create a panel data set that matches output and labor variables to shifts in industry-specific government demand. The empirical results indicate that increases in government demand raise output and hours, but have no effect on real product wages, even over a five-year horizon. Government demand also appears to raise productivity and markups when they are measured using gross output. These results are inconsistent with standard neoclassical and New Keynesian models 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, a key difference between the Neoclassical approach and the New Keynesian approach to the effects of government spending is the behavior of real wages. The Neoclassical approach predicts 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 fall in real wages and productivity. In contrast, the standard New Keynesian approach assumes imperfect competition and either sticky prices or price wars during booms. 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, despite a decline in productivity.[2] In alternate versions of this approach, increasing returns can allow an increase in government spending to raise real wage, hours, and productivity.[3]

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 on a panel of industries. As Ramey and Shapiro (1998) point out, an increase in government spending is typically focused on only a few industries. Thus, there is substantial heterogeneity in the experiences of different industries after an increase or decrease in government spending. This heterogeneity allows us to study the partial equilibrium effects of government spending in isolation since our panel data structure permits the use of time fixed effects to net out the aggregate effects. Since the partial equilibrium effects are components of the overall transmission mechanism, it is instructive to study these in isolation.

Building on the ideas of Shea (1993) and Perotti (2008), we use information from input-output data to create industry-specific government demand variables. We then

1. Baxter and King (1993).
2. See, for example, Rotemberg and Woodford (1992).
3. See, for example, Devereux et al. (1996).

merge these variables with the 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 government demand raise output and hours significantly. Gross output measures indicate that labor productivity also rises, though value added measures indicate no change in labor productivity. Real product wages do not change as a result of the increases in government spending, even over the five-year periods we study. Markup measures based on gross output appear to rise when government spending increases; markups based on value added do not change. Both sets of markup results are inconsistent with the standard New Keynesian model, which requires countercyclical markups. The value added results are consistent with the standard neoclassical model, but the gross output results suggest either induced technological change or mild increasing returns to scale.

2 Relationship to the Literature

The existing 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, which was 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 might not properly identify unanticipated shocks to government spending. With their alternative measure, 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.[4] Research that has used the Ramey-Shapiro methodology has tended to find decreases in real wages.[5]

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 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 input-output 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. He conducted no formal statistical analysis, but based on heuristically comparing 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 the key results.

On the other hand, most research tends to find an increase in labor productivity at the aggregate level, although it is not often highlighted.[6] Inspection of most impulse responses reported show that output rises proportionally more than hours after an increase in government spending, irrespective of the identification method. Christiansen and Goudie (2008) are perhaps the only researchers to study the effects of military contracts on firm level productivity. Using data on prime contract awards merged with Compustat, they find that a military contract award leads to an increase

4. See, for example, Fatás and Mihov (2001), Perotti (2004), Pappa (2005), and Galí et al. (2007).

5. See, for example, Burnside et al. (2004), Cavallo (2005), and Ramey (2009b).

6. See, for example, Galí et al. (2007) and Ramey (2009b).

in firm-level productivity, research and development, and patents.

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 real wages and other labor variables in more detail.

3 Industry Labor Market Equilibrium

In this section, we consider how government spending can affect equilibrium employment and wages in an industry under various model assumptions. We then use the theory to derive reduced-form predictions of the various models for the variables of interest.

To begin, consider the first-order condition describing the demand for labor in industry i in year t:

$$A_{it} F_H \left(H_{it}, \mathbf{X}_{it} \right) = Mu_{it} \frac{W_{it}}{P_{it}} \tag{1}$$

The left hand side is the marginal product of labor, with A as technology, H as hours, and $\mathbf{X}$ as a vector of other inputs, including capital. For a neoclassical production function, we require $F_H > 0$ and $F_{HH} < 0$. The right hand side is the markup, Mu, times the real product wage.

The supply of labor to the industry depends on aggregate effects, and potentially on industry-level variables as well. The aggregate Frisch labor supply depends positively on the real consumption wage and the marginal utility of wealth, as in Rotemberg and Woodford (1991). Thus, we can write the Frisch labor supply of labor as:

$$H_{it} = \eta \left(\frac{W_{it}}{P_{it}} \frac{P_{it}}{P_{Ct}}, \lambda_t \right) \tag{2}$$

In this equation, W_i is the wage in industry i, P_C is the consumption goods price deflator and λ is the marginal utility of wealth. Labor supply depends positively on both arguments. The first argument is just the consumption wage, which we have written as the product wage in industry i times the relative price of industry i. Potentially, we could include a third term as well, consisting of the industry relative wage. For example, if the expanding industry must pay an overtime premium, as in one of the models analyzed by Ramey and Shapiro (1998) or if there are adjustment costs of labor across industries, as in Kline (2008), then it is possible that the wage in an expanding industry rises relative to wages in other industries.

Figure 1 combines these supply and demand equations to show equilibrium in the industry's labor market. Panel (a) considers the labor market effects of an increase in government spending in the neoclassical model. The increase in government spending raises the marginal utility of wealth, which shifts the aggregate labor supply curve out. If the industry receives more of the government demand, then the industry price should rise relative to other prices. Thus, P_i/P_C should rise, which also shifts out labor supply to this industry. As a result, equilibrium hours rise and the real product wage and productivity fall.

In contrast, an industry that does not receive any increase in government spending may experience a decline in P_i/P_C that is large enough to counteract the rise in λ. In this case, labor supply curve shifts in. Thus, this industry would experience a decline in hours, an increase in the real product wage and an increase in productivity.

Panel (b) considers the effects of countercyclical markups in the New Keynesian model for an industry receiving part of the increase in government spending. Because the negative wealth effect is still operative in the standard New Keynesian model, the supply curve shifts out, but now the demand curve also shifts out because the markup has fallen. The graph makes clear that the expansionary effect on equilibrium hours is even greater, but that the effect on the real wage is ambiguous. Nevertheless, productivity still falls.

Panel (c) considers the effects of government-spending induced technological change, as in Christiansen and Goudie's (2008) model. They found that military contracts led to firm-level rises in research and development and patents. The graph looks the same as for the countercyclical markup case in panel (b), but the mechanism is different. Here, markups do not necessarily change, but the level of technology changes as a result of the increase in government spending. Equilibrium hours rise. The effect on the real wage and productivity is ambiguous.

Panel (d) considers the increasing returns model of Devereux et al. (1996). In their model, firm-level labor demand curves slope down, but if returns to specialization are sufficiently high, industry-level demand curves can slope upward. In this case, the shift out of labor supply to the industry can lead to a rise in hours, real wages, and productivity.

To summarize, the neoclassical model predicts that an increase in government spending raises an industry's hours, but lowers its real wage and labor productivity. The standard New Keynesian model predicts an increase in hours, a decline in productivity, and an ambiguous effect on real wages. The induced technology model predicts a rise in hours and ambiguous effects on real wages and productivity. The increasing returns model predicts a rise in hours, real wages and productivity.

All of the analysis so far has assumed that the other factors of production are constant. This is not necessarily a good assumption, particularly for the five-year periods we study. If the other factors adjust completely within the five-year period, then the demand curve will shift out even when markups are constant. To be specific, in the neoclassical case hours can rise and real wages and labor productivity can stay constant if the other inputs rise proportionally. Thus, in our empirical analysis we will also investigate the response of other inputs.

4 Data and Variable Construction

This section describes our data sources and explains how we construct the variables. Throughout the paper, uppercase letters represent real quantities and a tilde indicates a nominal quantity. Lowercase letters indicate the natural logarithm of a variable. The subscript i denotes industry and t denotes year. When possible, these subscripts are omitted in the text; however, they remain in all equations.

4.1 Industry-Specific Government Spending

Our sources for constructing industry-specific government spending are the benchmark input-output (IO) accounts, which are available roughly quinquennially, in 1947, 1958, 1963, 1967, 1972, 1977, 1982, 1987, 1992, 1997 and 2002. The IO accounts for 1947 and 1958 do not contain the industry detail required, so we drop these observations. The last two IO accounts, 1997 and 2002, are based on the North American industrical classification system (NAICS) rather than the Standard Industrial Classification (SIC). Because merging the NAICS with the SIC industries is difficult and fraught with potential error, we also drop 1997 and 2002. Thus, we use information from the 1963, 1967, 1972, 1977, 1982, 1987, and 1992 IO accounts.

By chance, the timing of the input-output data is ideal for studying the effects of military buildups and builddowns. Figure 2 shows real federal spending and real defense spending from 1958 to 1996. The vertical lines indicate the years for which the IO accounts are available. The figure makes clear that almost all fluctuations in federal government purchases are due to defense spending. Defense spending started increasing in 1965 after Johnson sent bombing raids over North Vietnam in February 1965. Defense spending peaked in 1968 at the height of the Vietnam War, and then fell until the mid-1970s. It began to rise in 1979, and then accelerated starting in 1980 after the Soviet Union invaded Afghanistan in December 1979. Spending peaked in 1987, fell gradually until 1990, and then fell more steeply.

We use the IO accounts to compute the sum of direct and indirect government spending. 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. As the previous figure shows, using all federal spending rather than just defense should not be problematic because most of the level and variation in federal government purchases is defense spending. Moreover, some spending not classified as defense, such as that for the National Aeronautics and Space Administration, is often driven by defense considerations.

To compute federal government demand, we use the "Transactions" and "Total Requirements" tables available from the IO accounts. Let $\tilde{T}_{ijt}$ be the nominal value of inputs produced by industry i shipped to industry j in year t, measured in producers' prices. Nominal direct government demand, $\tilde{G}^d$, for industry i in year t is the value of inputs from industry i shipped to the federal government ($j = g$):

$$\tilde{G}^d_{it} = \tilde{T}_{igt}. \tag{3}$$

Indirect government demand, $\tilde{G}^n$, 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:

$$\tilde{G}^n_{it} = \sum_{j=1}^{J_t} \tilde{G}^d_{jt} \times r_{ijt}. \tag{4}$$

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

$$\tilde{G}_{it} = \tilde{G}^d_{it} + \tilde{G}^n_{it}. \tag{5}$$

We define our measure of government demand for an industry as the change in real government purchases relative to the size of the industry. Because the IO data are only available at five year intervals, we consider the annualized five-year change $\Delta_5 \equiv (1 - L^5)/5$, where L is the lag operator.[7] The baseline government demand measure is

$$\Delta_5 GS_{it} = \frac{1}{5} \frac{G_{it} - G_{i(t-5)}}{\left[S_{it} + S_{i(t-5)}\right]/2}, \tag{6}$$

where G is real shipments to the government and S is real total shipments. The nominal series for government shipments and total shipments are calculated from the input-output tables and are deflated using industry-level price indexes from the MID (described in section 4.2).

This definition departs from Perotti's (2008) definition by using the average of output across the two five year periods rather than using just initial output in the denominator. We use this measure for three reasons. First, it is more analogous to the log change measure of the other variables we use. Second, this measure is less likely to be correlated with technological progress, an issue we will discuss below. Third, this measure has more explanatory power than Perotti's measure.

7. This definition is adjusted for the four-year change between 1963 and 1967.

4.2 Variables from the Manufacturing Industry Database

The Manufacturing Industry Database (MID), maintained by the National Bureau of Economic Research (NBER) and Center for Economic Studies (CES), contains annual data for 458 4-digit SIC code manufacturing industries from 1958 to 1996.[8] Most of the information is derived from the Annual Survey of Manufacturers (ASM). Two versions of the database are available, one based on the 1972 SIC codes and one based on the 1987 SIC codes; we use the one based on the 1987 SIC codes.[9]

This database provides information on total employment, as well as employment in the subcategories of production workers and nonproduction workers. It only provides information on hours of 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. This figure 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, so we only report the results using the assumption that nonproduction workers always work 1,960 hours per year. The production worker product wage is the production worker wage bill divided by production worker hours times the shipments deflator.

For one set of results, we construct share-weighted growth of inputs. The payroll data from the MID include only wages and salaries, and do not include payments for social security, health insurance, etc. Thus, labor share estimates from this database are biased downward. Fortunately, Chang and Hong (2006) have compiled annual information for each 2-digit manufacturing industry from the national income and product accounts (NIPA) of the ratio of total compensation to wages and salaries. We merge these factors to our 4-digit data and use them to magnify the payroll data to create more accurate labor shares.

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 in-

8. Bartelsman et al. (2000).

9. Throughout the paper, all SIC codes reported are the 1987 version.

ventories, 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.

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:

$$\tilde{V}_{it}^{\text{MID}} = \tilde{S}_{it} - \tilde{M}_{it} + \Delta \tilde{I}_{it}^{F}, \tag{7}$$

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

Since total inventories is the sum of finished-goods and work-in-process inventories 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

$$Y_{it} \approxeq \frac{\tilde{S}_{it}}{P_{it}} + \left[\frac{\tilde{I}_{it}}{P_{it}} - \frac{\tilde{I}_{i(t-1)}}{P_{i(t-1)}} \right] - \frac{\Delta \tilde{I}_{it}^{M}}{P_{it}}, \tag{8}$$

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

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

where P^M is the price of materials. 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 8 understates production by

$$\frac{\tilde{I}_{i(t-1)}^{M}}{P_{i(t-1)}} \times \frac{P_{it} - P_{i(t-1)}}{P_{it}}, \tag{9}$$

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 Bureau of Economic Analysis (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.

Many studies have used value added measures of output. However, Norrbin (1993) discusses the biases associated with using value added rather than gross output, and Basu and Fernald (1997) argue that value added is only valid with perfect competition and constant markups of unity. For purposes of comparison to the literature, we also consider value added. We use Basu and Fernald's (1997) Divisia measure, which is from equation 4 of their paper. In our case, real value added is calculated as

$$\Delta v_{it} = \Delta y_{it} - \frac{s_{Mit}}{1 - s_{Mit}} \left(\Delta m_{it} - \Delta y_{it} \right), \tag{10}$$

where v is the log of real value added, y is the log of real gross output, s_{Mit} is the share of materials in revenue (calculated as the average of the shares in t and $t-1$), and m is the log of real materials.

We also use MID measures of 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.

4.3 Merging the Data Sets

The key step in merging the two databases is developing a correspondence between the 6-digit IO code–based IO data and the 4-digit SIC code–based MID data. The ultimate correspondence is between 4-digit IO and 4-digit SIC codes, but aggregation is required in both data sets to achieve a one-to-one correspondence. To create a complete correspondence, we occasionally need to assign a 6-digit IO code to a different 4-digit IO code for aggregation. For example, in the 1967 IO table, IO codes 170200 ("felt goods, n.e.c."), 170300 ("lace goods"), 170400 ("paddings & upholstery filling"), and so forth are assigned to 4-digit IO code 1710 ("textile goods, n.e.c.") for final aggregation. This is required because no such industries existed at the 4-digit SIC level. The correspondence tables are available in spreadsheet form (comma separated values) on the authors' web sites. The merged database contains 272 industries at the 4-digit SIC level.

Because some of the industries were combined in the merge, we had to aggregate some variables from the MID. The real quantities were defined at the industry level as the nominal quantities divided by the relevant price index. Because the price indices in this data base are fixed-weight indices, it is possible to sum the real quantities. We then summed nominal and real quantities for the combined industries and used their ratios to construct price indices.

5 Empirical Results

5.1 Properties of Industry-Specific Government Demand

The usefulness of our government demand variable for distinguishing between the various theories depends on two key features. First, in order for it to represent only shifts in industry demand, it must be uncorrelated with technology. Second, it should be *relevant*, in the sense that it adequately predicts changes in industry demand. In this section, we assess how well the government demand variable satisfies these two properties.

At the aggregate level, there is substantial evidence that fluctuations in military spending are mostly driven by geopolitical events and are for the most part exogenous to the current state of the economy.[10] Since most variations in federal purchases are due to military spending, it is unlikely that aggregate shipments to the government are correlated with technology. That said, it is possible that the *distribution* of military spending across industries could be related to technological change. To see why technology might influence government spending at the industry level, consider the following example. Between 1972 and 1977, real federal spending declined by three percent and real defense spending fell by nine percent. In contrast, total real federal purchases of computers (SIC 3571) rose by 219 percent over this period. This increase was 20 percent of the initial value of shipments in 1972, yet the fraction of shipments that went to the government rose only slightly, from 7 percent in 1972 to

10. Ramey (2009a).

9 percent in 1977 because industry shipments to nongovernment destinations also rose dramatically. The story is similar for semiconductors. It is clear that the increase in government spending on computers during this period was not due to a "demand shift," but rather because technological change in the computer industry shifted government demand toward that industry. In other words, it is likely that the rise in government spending was correlated with technology growth.

We try to minimize this potential correlation in several ways. First, our definition of the government spending variable is less prone to this problem than Perotti's (2008) definition. Perotti compared the change in direct plus indirect shipments to the government to the initial total shipments of the industry. In contrast, we compare the change in shipments to the government to the average of shipments at the beginning and end of the five year period, so some overall industry growth is taken into account. Table 1 shows a ranking of the top 30 observations with large changes in government spending relative to average total shipments in our data set.[11] For the most part, the industries are clearly defense industries, such as ammunition and aircraft. Two notable exceptions are semiconductors, which show up twice in the ranking, in 1967 and 1982. Thus, a second way that we try to eliminate this effect is to omit the two computer industries from the sample. A third way we deal with this effect is to include industry fixed effects in the regressions, which control for differing average growth rates of technological change across industries. Finally, we also consider using only direct shipments to the government since it is likely that technological change in an industry is mostly likely to affect indirect shipments. For example, if many products use semiconductors, then indirect shipments of semiconductors to the government would rise significantly.

The second desirable feature for our demand shifter is relevance. Is our government demand variable sufficiently informative about movements in shipments and output? To investigate this feature, table 2 reports regressions of the growth of industry shipments and output on the government demand variable. The first row reports the results of a simple regression of real gross shipments growth on the growth of total government shipments, defined above. According to the estimates, the elasticity of real shipments with respect to total government spending is 1.10 (standard error of

11. The list of industries is similar when considering greatest absolute change.

0.07). Our government shipments variable explains 15 percent of the variation in the growth of shipments. The second row estimates this specification including year and industry fixed effects. The estimate is slightly lower, at 0.95 (0.06), but still highly significant. The third row reports the fixed effects regression of shipments growth on the growth of direct shipments from the government. That is, this measure omits the indirect shipments. The estimated elasticity is somewhat higher, 0.98 (0.07). None of the estimates is significantly different from unity, though.

The fourth row of table 2 shows the fixed effects regression of our measure of output (which includes changes in work-in-process and finished goods inventories) on the growth of total government spending. The coefficient is similar to the corresponding one with shipments, 0.97 (0.06) versus 0.95. Finally, the fifth row shows the fixed effects regression of value added growth on the growth of total government spending. The elasticity is estimated to be 1.00 (0.28) and is statistically significant, although the R^2 is lower than for shipments or gross output. In results without fixed effects (not shown) the R^2 is 0.08. Nevertheless, in every case our government spending variable is highly relevant, as evidenced by the high t statistics (and hence high F statistics).

One might wonder how much the estimates are being driven by just a few industries that are heavily defense-spending dependent. The top panel of figure 3 shows a scatter of the log change in real gross shipments against the change in government spending. There are clearly some potentially influential observations. These observations are not driving the results, however. The lower panel of figure 3 shows the scatter plot for the sample limited to those observations for which the change in government spending was less than five percent of industry shipments (in absolute value). It is evident that there is still a positive relationship.

To investigate more thoroughly the effect of limiting the sample, table 3 shows the results of the fixed-effects specification for four samples: the full sample, the sample in which the change in the government spending variable is less than five percent in absolute value, less than one percent in absolute value, and less than 1/2 percent in absolute value. Interestingly, the elasticities rise as we discard the industries receiving the largest change in government spending. In the full sample, the elasticity for real gross shipments is 0.95. This rises to 3.88 (0.76) in the sample limited to changes of 1/2 percent or less. These results suggest a nonlinearity. When we include a quadratic or cubic in the government variable, however, the additional terms were not statistically significant (results not shown).

To summarize the results of this section, the evidence shows that the new government demand variable we constructed is very informative about shifts in gross output. On the other hand, we have some concerns about a potential correlation between the distribution of government spending and technology for some industries. We have discussed various ways to minimize this correlation.

5.2 Effects of Government Demand on Labor Market Variables

5.2.1 Real Wages and Hours

Table 4 reports the estimated effects of changes in government demand on hours and real wages. All regressions include year and industry fixed effects. Row 1 shows the impact on production worker hours. The elasticity of total production worker hours is 0.84 (0.06). Rows 2 and 3 show that virtually all of the change is due to changes in employment, with only a small part due to an increase in average hours per worker. In every case, the elasticities are precisely estimated.

Rows 4 through 6 show the effects of changes in government spending on product wages, as well as on nominal wages and prices separately. All regressions contain industry and year fixed effects. In every case, the estimate is negative, but is essentially zero, both statistically and economically. Thus, despite their significant positive effects on output and hours, the industry-specific rises in government spending have no impact on wages or prices, or their ratio.

These results stand in contrast to Perotti's (2008) conclusion that government spending raises real wages. Perotti used similar data sources, but based his analysis on ranking the top industries receiving government spending from 1963 to 1967 and from 1977 through 1982. Based on visual inspection of his table, he concluded that "the sectors that experience the largest government spending shocks are also the sectors that experienced the largest positive changes in the real product wage."[12]

12. Perotti (2008), p. 208.

To determine the source of differences in our conclusion, we first substituted Perotti's (2008) definition of government spending changes for ours in the fixed effects regression. Recall that he used only the initial total output in his denominator. When we estimated this regression, the coefficient was -0.0001 (0.015). Thus, changing definitions is not the source of the difference. We then re-estimated the relationship between real wages and Perotti's definition of government spending changes without year and industry fixed effects. In this case, the coefficient rose to 0.039 (0.017). Thus, without fixed effects there is a positive relationship between real wage growth and Perotti's government spending variable. As Ramey (2008) argued in the companion discussion, however, Perotti's results are largely driven by two computer industries, semiconductors (SIC 3674) and computers (SIC 3571). When we estimate the simple regression of real wage growth on Perotti's government variable, with no fixed effects, but excluding the two computer industries, the coefficient falls to 0.019 (0.016). Thus, Perotti's finding of a positive effect of government demand on real wages is due to the unusually fast growth of technology in the computer industries, which also shifted government demand toward those industries. Including full fixed effects to account for different rates of technological change across all industries further reduces the coefficient to zero.

5.2.2 Labor Productivity

Table 5 shows the effect of our government spending growth variable on various measures of the growth in labor productivity. In each case, we divide an output measure by total hours of production workers. The first measure uses real gross shipments, the second uses real gross output (equation 8), and the third measure uses real value added (equation 10). The first row shows the effect of total government spending growth on productivity growth based on real shipments with no fixed effects. The coefficient is 0.21 (0.04) and is statistically significant. Row 2 shows that controlling for fixed effects reduces the coefficient by half, but it is still statistically significant. This result provides support for the importance of including industry fixed effects to control for technology growth differences across industries: the correlation between productivity and government spending is twice as high when we do not control for industry fixed effects. The third row shows the fixed effects results when we instead use only direct government shipments. In this case, the coefficient is slightly higher and still significant. Rows 4 through 6 show slightly higher coefficients for our gross output measure of productivity. We also tried omitting the two computer industries, but it had little effect for the fixed effects regressions. Finally, Rows 7 through 9 show the results with the value added measure of productivity. The coefficients are essentially zero when fixed effects are included.

The difference in the results between gross shipments or gross output on the one hand and value added on the other is perplexing, but not unprecedented.[13] As discussed earlier, there are theoretical reasons to prefer gross output measures to value added. Another reason to prefer gross output to value added is that our value added measure may be subject to more measurement error. One would expect true value added to be more highly correlated than gross output with wages and salaries, since payments to labor constitute such a large part of value added. In fact, the opposite is true in our data set. For example, in the annual data the correlation between real gross output growth and hours growth is 0.75 and between real gross output growth and real payroll growth is 0.84. The correlation of the growth of real value added with hours growth is 0.41, and with real payroll growth is 0.64. This lower correlation could be evidence of measurement error.

5.2.3 Markup

The combination of results for productivity (using gross output) and real wages implies that the countercyclical markup hypothesis is not valid. To see this, consider the definition of the log change in the markup:

$$\Delta_5 \mu_{it} = \Delta_5 \left(y_{it} - h_{it}^{\mathrm{p}} \right) - \Delta_5 \left(w_{it} - p_{it} \right), \tag{11}$$

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.

Table 6 shows the regressions of three versions of the markups on the government spending variable. The three versions of the markup correspond to the three versions of the output measures: gross shipments, gross output, and value added. Consistent

13. See, for example, Basu and Fernald's (1997) discussion of their results.

with the results showing a significant increase in productivity and no change in real wages, the first two measures imply that an increase in government spending raises the markup. In contrast, the value added measure implies that markups are acyclical. Nekarda and Ramey (2009) discuss the cyclicality of markups in much more detail and using other data sources as well. They also conclude that markups are procyclical.

At face value, the productivity results contradict both the standard New Keynesian and Neoclassical approaches, since both rely on production functions with diminishing returns to labor in the short-run. It is important to remember, though, that because of the limited availability of the input-output data, our growth rates are over five-year periods. Thus, it is possible that the other inputs adjusted even more than labor. The next section investigates this possibility.

5.3 Effects of Government Demand on Other Inputs

In this section, we begin by investigating the effects of government spending on several other key inputs. We then construct a share-weighted measure of inputs and estimate the implied returns to scale.

5.3.1 Other Inputs

Table 7 reports the response of various inputs to government spending changes. The first row reproduces the response of production worker hours for comparison. The second row shows the response of supervisory worker employment. This input increases significantly, but the elasticity of 0.77 (0.06) is smaller than for production workers hours, which is 0.84 (0.06). Thus, it is unlikely that an increase in supervisory workers can explain the increase in labor productivity of production workers.

Rows 3 through 5 investigate the response of various measures of capital inputs. Row 3 shows the response of the real capital stock. The response is positive and significant, but with an elasticity of 0.13 (0.03) it is much smaller than for labor. Thus, it is clear that an increase in government spending is leading to a decline in the capital-labor ratio. It is possible, however, that *capital services* could rise by more than the capital stock if capital utilization increases in response to government spending. To investigate this possibility, we consider two measures of capital utilization that have been used in the literature. The first measure is energy usage. Numerous papers have used electricity consumption as an indirect measure of capital utilization.[14] We do not have information in our data set on electricity consumption, but we do have information on overall energy usage. Thus, the fourth row of Table 7 reports the response of real energy usage. The elasticity is 0.27 (0.07). If utilization is proportional to energy usage, then we can combine this estimate with the growth of capital of 0.13, to infer that capital services rise by 0.40. While larger than the basic estimate, it is still far below the rise in production worker hours. The second indicator of capital utilization we consider is Shapiro's (1993) of the workweek of capital, which is utilization we consider is Shapiro's (1993) measure of the workweek of capital, which is based on the Census' Survey of Plant Capacity. This measure counts hours per day and days per week that a plant operates. Shapiro (1993) used this measure to show that the Solow residual was no longer procyclical once this utilization measure was included in the estimation. This measure is only available, however, from 1977 to 1987, and only for a subset of the industries. Row 5 reports the effects of government spending on this measure. The coefficient is 0.14 (0.24) and is not statistically significant. Thus, this alternative source does not raise the estimate of the growth of capital services.

Row 6 shows the response of real materials inputs exlcuding energy. In this case, the response is 1.14 (0.07), larger than that of either output or hours. Row 7 shows the results for the ratio of real materials to output. The elasticity is 0.16 (0.03) and is statistically significant from zero. Thus, the rise in materials usage could potentially explain the rise in labor productivity.

5.3.2 Implications for Returns to Scale

To study the response of other inputs more systematically, we can estimate the overall returns to scale using the framework pioneered by Hall (1990), and extended by Basu and Fernald (1997). In particular, we can estimate overall returns to scale from the following equation:

$$\Delta_5 y_{it} = \gamma \Delta_5 x_{it} + \Delta_5 a_{it} \tag{12}$$

14. See, for example, Jorgenson and Griliches (1967) and Burnside et al. (1996).

where y is the log of real gross output, $\Delta_5 x$ is the share-weighted growth of inputs, and a is the log of technology. 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.

Consider a measure of share-weighted input growth treating energy as an input to production:

$$\Delta_5 x_{it} = s_k \Delta_5 k_{it} + s_h \Delta_5 h_{it} + s_m \Delta_5 m_{it} + s_e \Delta_5 e_{it}, \tag{13}$$

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, e is the log of real energy usage, and s_j is the share of input j. As discussed in section 4.2, we construct the labor share (s_h) using Chang and Hong's (2006) factors to inflate the observed labor share to account for fringe benefits. This raises the average labor share in the data set by 3 percentage points. Following Basu et al. (2006, hereafter BFK), we calculate the capital share as the residual from labor share and materials share and by using shares averaged over the entire sample.

We estimate the return to scale using an instrumental variables (IV) regression of the growth of log gross output on the share-weighted growth of inputs and on year and industry fixed effects. We instrument for $\Delta_5 x$ with our government demand variable ($\Delta_5 GS$). The first-stage regression of the share-weighted inputs on our government variable has an F statistic that exceeds 200, indicating high relevance. The first row of table 8 reports this regression. The estimated coefficient, $\hat{\gamma}$, is 1.23 (0.04), indicating large, statistically significant increasing returns to scale.

However, as numerous papers have made clear, unobserved variations in capital utilization or labor effort may contaminate the error term.[15] Because these variations are likely to be correlated with any instrument that is also correlated with observed input growth, estimates of γ are likely to be biased upward. We attempt to mitigate this bias in two ways. The first is to include a proxy for unobserved utilization. The second is to construct $\Delta_5 x$ treating energy usage as a proxy for capital utilization.

BFK 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

15. See, for example, Burnside et al. (1996) and Basu (1996).

average hours per worker. Row 2 of table 8 adds the growth of average hours per worker ($\Delta_5\bar{h}$) to control for unobserved utilization. The estimate of the returns to scale is little changed. Nevertheless, this specification is probably invalid because $\bar{h}$ is uncorrelated with technology only under restrictive assumptions.

Although $\Delta_5 GS$ is highly relevant for $\Delta_5 x$, it is difficult to find additional relevant instruments for $\Delta_5\bar{h}$. Thus, we use separate measures of direct and indirect government shipment and a quadratic in total government shipments as instruments for both variables. All statistics (such as Shea's partial R^2) suggest the instruments have low relevance for $\Delta_5\bar{h}$ after being used for $\Delta_5 x$.[16] Row 3 of table 8 reports the results of this IV regression. The estimate of returns to scale is again little changed at 1.22 (0.21), but is no longer significantly different from unity. The coefficient on average hours per worker is not significantly different from zero. Nonetheless, we are not very confident of this specification given the weak instruments.

A second approach to mitigate unobserved utilization is to construct $\Delta_5 x$ treating capital utilization as proportional to energy usage. This alternate measure of share-weighted input growth is

$$\Delta_5 x_{it} = s_{ke}\left(\Delta_5 k_{it} + \Delta_5 e_{it}\right) + s_h \Delta_5 h_{it} + s_{m^{\mathrm{xe}}} \Delta_5 m^{\mathrm{xe}}_{it}, \tag{14}$$

where m^{xe} is the log of real materials usage excluding energy. As before, we instrument for $\Delta_5 x$ with $\Delta_5 GS$. Row 4 of table 8 reports the regression using this alternate measure of input growth. The estimate of returns to scale is 1.15 (0.04), lower than the estimate using the input-share measure without accounting for utilization but still statistically greater than unity.

Our results indicate increasing returns to scale, even controlling for unobserved utilization. There are several possible reasons that we find higher returns than BFK, who found a median returns to scale of 1.07. The first possibility could be the instruments. BFK use the standard aggregate instruments, such as oil prices, defense spending, and VAR innovations of money. These instruments potentially have problems of low relevance and correlation with the error term (in the case of oil prices).

A second reason could be the data set used. BFK use the Jorgenson (2007) data

16. Shea (1997).

set consisting of 2-digit industries, whereas we use the 4-digit industry MID data set. As Norrbin (1993) has highlighted, the MID tends to underestimate labor and materials shares because it omits certain components of those costs. Since capital share is estimated as the residual, the capital share might be overestimated. We use Chang and Hong's (2006) factors to upweight the labor share. However, we have not adjusted materials share. To see whether this could account for the difference in results, we used the following approach. We first merged the 2-digit materials shares from BFK to comparable 2-digit materials shares from our database to create ratios of BFK materials shares to MID materials shares, by industry and year. Next, we applied these 2-digit shares to each 4-digit industry within the category to upweight the MID shares.[17] This increases the average materials share from 0.55 to 0.60. Finally we created new residual capital shares using the upweighted materials shares. This regression is reported in row 5 of table 8. Using the materials shares using the BFK weights results in a smaller capital share. The estimate of the returns to scale with this measure is 1.10 (0.04). Although this estimate is slightly lower than that obtained using the MID shares, it is still statistically greater than unity.

In sum, we can explain some, but not all, of the positive effect of government spending on labor productivity with an increase in other inputs. On balance, the estimates suggest some role for increasing returns to scale.

An alternative interpretation of our results is the induced technological change hypothesis of Christiansen and Goudie (2008). They found that an increase in military contracts raises firm-level research and development, patents, and productivity. If this is the case, then our government spending variable induces growth in technology. This means that our instrument is correlated with the error term and is producing an estimate of γ that is upward biased. In this case, though, the correlation occurs because the change in government spending *causes* the change in technology.

17. The Basu et al.'s (2006) data do not separate energy from other materials. However, energy averages only 5 percent of materials cost, so it makes little difference to the calculated shares.

6 Conclusion

In this paper, we have explored the effects of industry-specific changes in government spending on various industry-level output and labor market variables. We have constructed a new panel data set by merging information on government shipments from the input-output accounts with the NBER-CES Manufacturing Industry Database. Our government shipments variable is very informative for variations in industry output and labor variables. We have found that an increase in government shipments raises output, hours, and other inputs. They appear to have no effect on real wages, however. On the other hand, labor productivity, measured using gross output, rises after an increase in government shipments. Labor productivity measured using value added does not change. We find similar results for markups. When we measure overall returns to scale, our results indicate increasing returns to scale.

These results suggest that neither the neoclassical model nor the standard New Keynesian model may be capturing key elements of the transmission of government spending, since both assume constant returns to scale. Instead, it may be important to consider the possibility of increasing returns to scale, such as in the model analyzed by Devereux et al. (1996), or of induced technological change, as in the model of Christiansen and Goudie (2008).

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Table 1. Observations with the Greatest Increase in Government Spending

Rank	*SIC*	*Industry*	*Year*	$\Delta_5 GS$
1	3483	Ammunition, except for small arms, n.e.c.	1967	0.2619
2	3812	Engineering and scientific instruments	1987	0.2256
3	3482	Small arms ammunition	1967	0.2057
4	3489	Ordnance and accessories, n.e.c.	1967	0.1617
5	3795	Sighting and fire control equip.	1987	0.1336
6	3483	Ammunition, except for small arms, n.e.c.	1987	0.1164
7	3483	Ammunition, except for small arms, n.e.c.	1982	0.0909
8	3672	Other electronic components	1967	0.0613
9	2521	Wood office furniture	1967	0.0608
10	3674	Semiconductors and related devices	1967	0.0604
11	3761	Guided missiles and space vehicles	1987	0.0590
12	3489	Ordnance and accessories, n.e.c.	1982	0.0558
13	3484	Small arms	1967	0.0557
14	3674	Semiconductors and related devices	1982	0.0552
15	2861	Miscellaneous chemical products	1982	0.0531
16	3695	Electrical equipment, n.e.c.	1987	0.0531
17	3728	Aircraft and missile equipment, n.e.c.	1987	0.0529
18	3761	Guided missiles and space vehicles	1982	0.0516
19	3364	Nonferrous castings, n.e.c.	1982	0.0495
20	3724	Aircraft and missile engines and engine parts	1982	0.0483
21	3663	Communication equipment	1982	0.0476
22	3728	Aircraft and missile equipment, n.e.c.	1982	0.0467
23	3873	Watches, clocks, and parts	1967	0.0454
24	3312	Blast furnace and basic steel products	1982	0.0452
25	3843	Dental equipment and supplies	1967	0.0451
26	3724	Aircraft and missile engines and engine parts	1987	0.0443
27	2861	Miscellaneous chemical products	1967	0.0432
28	3674	Semiconductors and related devices	1987	0.0412
29	3731	Ship building and repairing	1967	0.0395
30	3795	Sighting and fire control equip.	1977	0.0383

Source: Author's calculations using data from BEA benchmark IO tables.

Notes: $\Delta_5 GS$ is annualized five-year change in real direct and indirect shipments to government as a share of real total shipments. Calculated from a panel of 274 industries in 1963, 1967, 1972, 1977, 1982, 1987, and 1992 for a total of 1,631 observations.

Table 2. Regressions of Industry Output on Government Demand

Dependent variable	*Independent variable* $\Delta_5 GS_{it}$	$\Delta_5 GS_{it}^d$	*Fixed effects*	R^2
1. Real shipments	1.102*** (0.066)		No	0.145
2. Real shipments	0.948*** (0.061)		Yes	0.494
3. Real shipments		0.982*** (0.070)	Yes	0.477
4. Real gross output	0.969*** (0.062)		Yes	0.493
5. Real value added	1.002*** (0.282)		Yes	0.239

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

Notes: Dependent variable is annualized five-year change in log real shipments ($\Delta_5 s_{it}$), log real gross output ($\Delta_5 y_{it}$), or log real value added ($\Delta_5 v_{it}$). $\Delta_5 GS$ is annualized five-year change in real direct and indirect shipments to government as a share of real total shipments; $\Delta_5 GS^d$ includes only direct shipments to government. Regressions include year and industry fixed effects when indicated. Calculated from a panel of 274 industries in 1963, 1967, 1972, 1977, 1982, 1987, and 1992 for a total of 1,631 observations. Standard errors are reported in parentheses.

Table 3. Regressions of Shipments on Government Demand with Different Samples

	Independent variable		
Sample	$\Delta_5 GS_{it}$	R^2	*No. obs.*
1. Full sample	0.948*** (0.061)	0.494	1,631
2. $\lvert\Delta_5 GS_{it}\rvert \leq 0.05$	1.222*** (0.123)	0.462	1,599
3. $\lvert\Delta_5 GS_{it}\rvert \leq 0.01$	2.337*** (0.362)	0.460	1,333
4. $\lvert\Delta_5 GS_{it}\rvert \leq 0.005$	3.875*** (0.763)	0.467	1,064

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

Notes: Dependent variable is annualized five-year change in log real shipments ($\Delta_5 s_{it}$). $\Delta_5 GS$ is annualized five-year change in real direct and indirect shipments to the government as a share of real total shipments. All regressions include year and industry fixed effects. Calculated on a panel of 274 industries in 1963, 1967, 1972, 1977, 1982, 1987, and 1992. Standard errors are reported in parentheses.

Table 4. Regressions of Hours and Real Wages on Government Demand

Dependent variable	*Independent variable* $\Delta_5 GS_{it}$	R^2
1. Production worker total hours ($\Delta_5 h^p_{it}$)	0.838***	0.427
	(0.057)	
2. Production worker employment ($\Delta_5 n^p_{it}$)	0.799***	0.441
	(0.055)	
3. Average hours of prod. workers ($\Delta_5 \bar{h}^p_{it}$)	0.039***	0.377
	(0.011)	
4. Real wage ($\Delta_5 w_{it}$)	−0.002	0.445
	(0.033)	
5. Nominal wage ($\Delta_5 \tilde{w}_{it}$)	−0.011	0.818
	(0.016)	
5. Price of output ($\Delta_5 p_{it}$)	−0.009	0.716
	(0.031)	

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

Notes: Dependent variable is annualized five-year change of log of indicated variable. $\Delta_5 GS$ is annualized five-year change in real direct and indirect shipments to government as a share of real total shipments. All regressions include year and industry fixed effects. Calculated on a panel of 274 industries in 1963, 1967, 1972, 1977, 1982, 1987, and 1992 for a total of 1,631 observations. Standard errors are reported in parentheses.

Table 5. Regressions of Labor Productivity on Government Demand

	Independent variable			
Output measure	$\Delta_5 GS_{it}$	$\Delta_5 GS^d_{it}$	*Fixed effects*	R^2
1. Real shipments	0.208*** (0.038)		No	0.018
2. Real shipments	0.111*** (0.037)		Yes	0.402
3. Real shipments		0.117*** (0.041)	Yes	0.401
4. Real gross output	0.230*** (0.039)		No	0.021
5. Real gross output	0.132*** (0.036)		Yes	0.411
6. Real gross output		0.142*** (0.041)	Yes	0.410
7. Real value added	0.180** (0.078)		No	0.003
8. Real value added	0.034 (0.082)		Yes	0.232
9. Real value added		0.003 (0.095)	Yes	0.232

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

Notes: Dependent variable is annualized five-year change of log real output per production-worker hour. $\Delta_5 GS$ is annualized five-year change in real direct and indirect shipments to government as a share of real total shipments; $\Delta_5 GS^d$ includes only direct shipments to government. Regressions include year and industry fixed effects when indicated. Calculated on a panel of 274 industries in 1963, 1967, 1972, 1977, 1982, 1987, and 1992 for a total of 1,631 observations. Standard errors are reported in parentheses.

Table 6. Regressions of Price-Cost Markup on Government Demand

	Independent variable	
Output measure	$\Delta_5 GS_{it}$	R^2
1. Real shipments	0.113***	0.259
	(0.032)	
2. Real output	0.134***	0.260
	(0.031)	
3. Real value added	0.036	0.137
	(0.065)	

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

Notes: Dependent variable is annualized five-year change of log markup ($\Delta_5 \mu_{it}$); see equation 11. $\Delta_5 GS$ is annualized five-year change in real direct and indirect shipments to government as a share of real total shipments. All regressions include year and industry fixed effects. Calculated on a panel of 274 industries in 1963, 1967, 1972, 1977, 1982, 1987, and 1992 for a total of 1,631 observations. Standard errors are reported in parentheses.

Table 7. Regressions of Other Production Inputs on Government Demand

Dependent variable	*Independent variable* $\Delta_5 GS_{it}$	R^2
1. Production worker total hours	0.838*** (0.057)	0.427
2. Supervisory worker employment	0.774*** (0.060)	0.362
3. Real capital stock	0.126*** (0.033)	0.614
4. Real energy	0.274*** (0.066)	0.489
5. Workweek of capital	0.138 (0.241)	0.511
6. Real materials excluding energy	1.135 (0.070)	0.436
7. Real materials-output ratio	0.166 (0.034)	0.233

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

Notes: Dependent variable is annualized five-year change of log of indicated variable. $\Delta_5 GS$ is annualized five-year change in real direct and indirect shipments to government as a share of real total shipments. All regressions include year and industry fixed effects. Calculated on a panel of 274 industries in 1963, 1967, 1972, 1977, 1982, 1987, and 1992 for a total of 1,631 observations; regression with workweek of capital (row 5) has 306 observations. Standard errors are reported in parentheses.

Table 8. Instrumental Variables Regression of Shipments Growth on Input Growth

	Independent variable		
Input growth definition	$\Delta_5 x_{it}$	$\Delta_5 \bar{h}_{it}$	R^2
1. Energy as input	1.234*** (0.039)		0.880
2. $\bar{h}$ as proxy for utilization, not instrumented	1.243*** (0.040)	−0.165* (0.087)	0.880
3. $\bar{h}$ as proxy for utilization, instrumented[a]	1.215*** (0.213)	0.401 (4.281)	0.877
4. Energy as proxy for utilization	1.148*** (0.042)		0.839
5. BFK materials share	1.099*** (0.036)		0.866

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

Notes: Dependent variable is annualized five-year change of log real shipments ($\Delta_5 s_{it}$). $\Delta_5 x_{it}$ is annualized five-year growth of share-weighted log inputs; see equations 13 and 14. $\Delta_5 \bar{h}_{it}$ is annualized five-year growth of average hours per worker. Except row 3, $\Delta_5 x_{it}$ instrumented by $\Delta_5 GS_{it}$, the annualized five-year change in real direct and indirect shipments to government as a share of real total shipments. All regressions include year and industry fixed effects. Calculated on a panel of 274 industries in 1963, 1967, 1972, 1977, 1982, 1987, and 1992 for a total of 1,631 observations. Standard errors are reported in parentheses.

a. Both $\Delta_5 x_{it}$ and $\Delta_5 \bar{h}_{it}$ instrumented by direct shipments to government, $\Delta_5 GS^d_{it}$, indirect shipments to government, $\Delta_5 GS^n_{it}$, and total shipments to government squared, $\Delta_5 GS^2_{it}$.

Figure 1. Labor Market Effects of An Increase in Government Spending

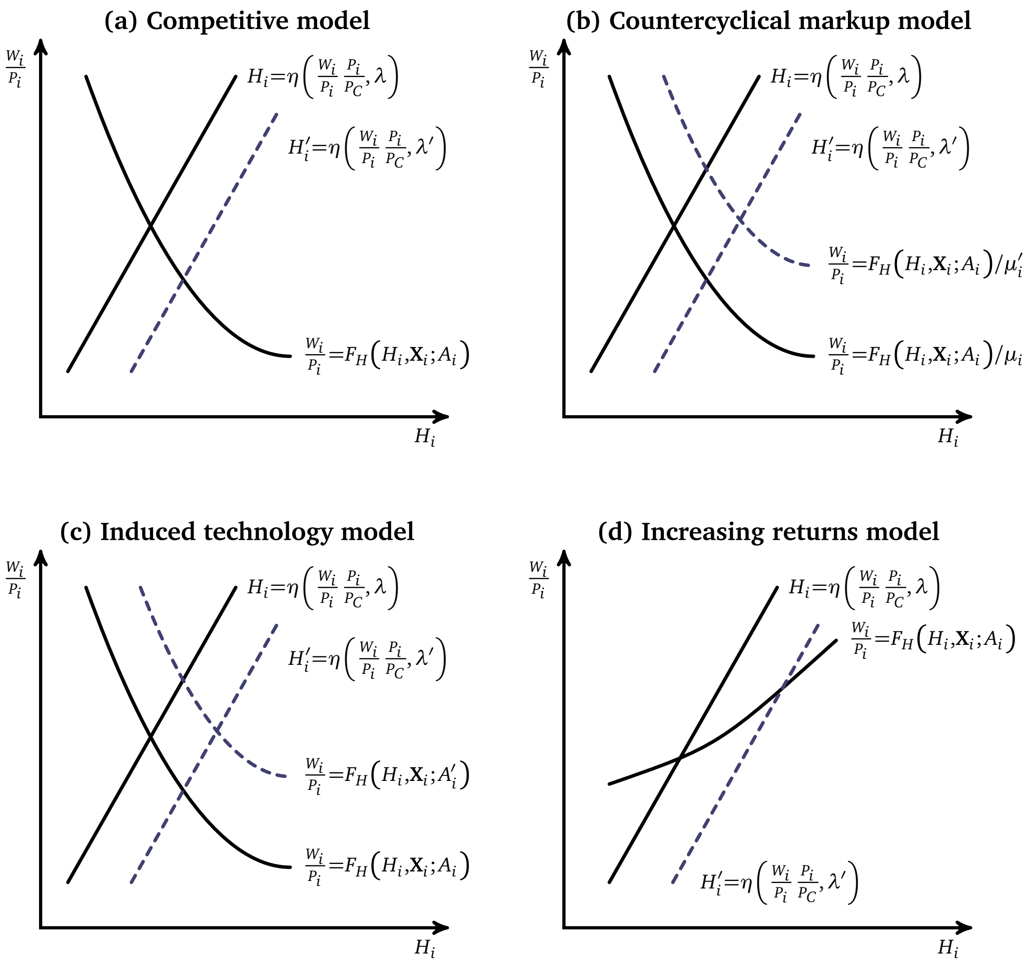
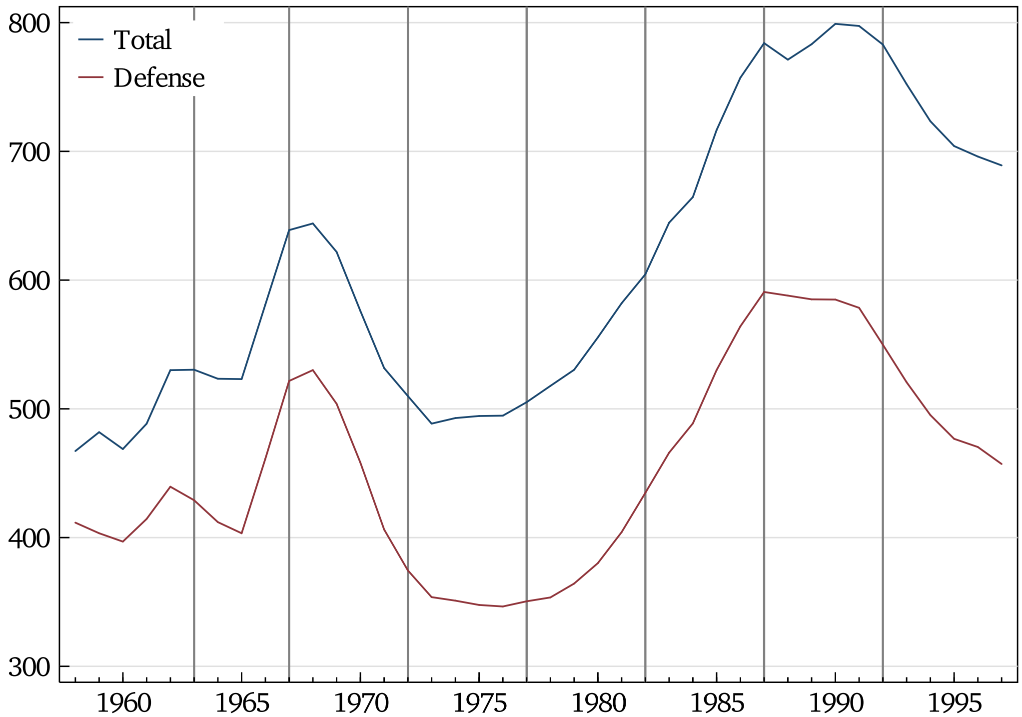


Figure 2. U.S. Federal Government Spending, 1958–1997

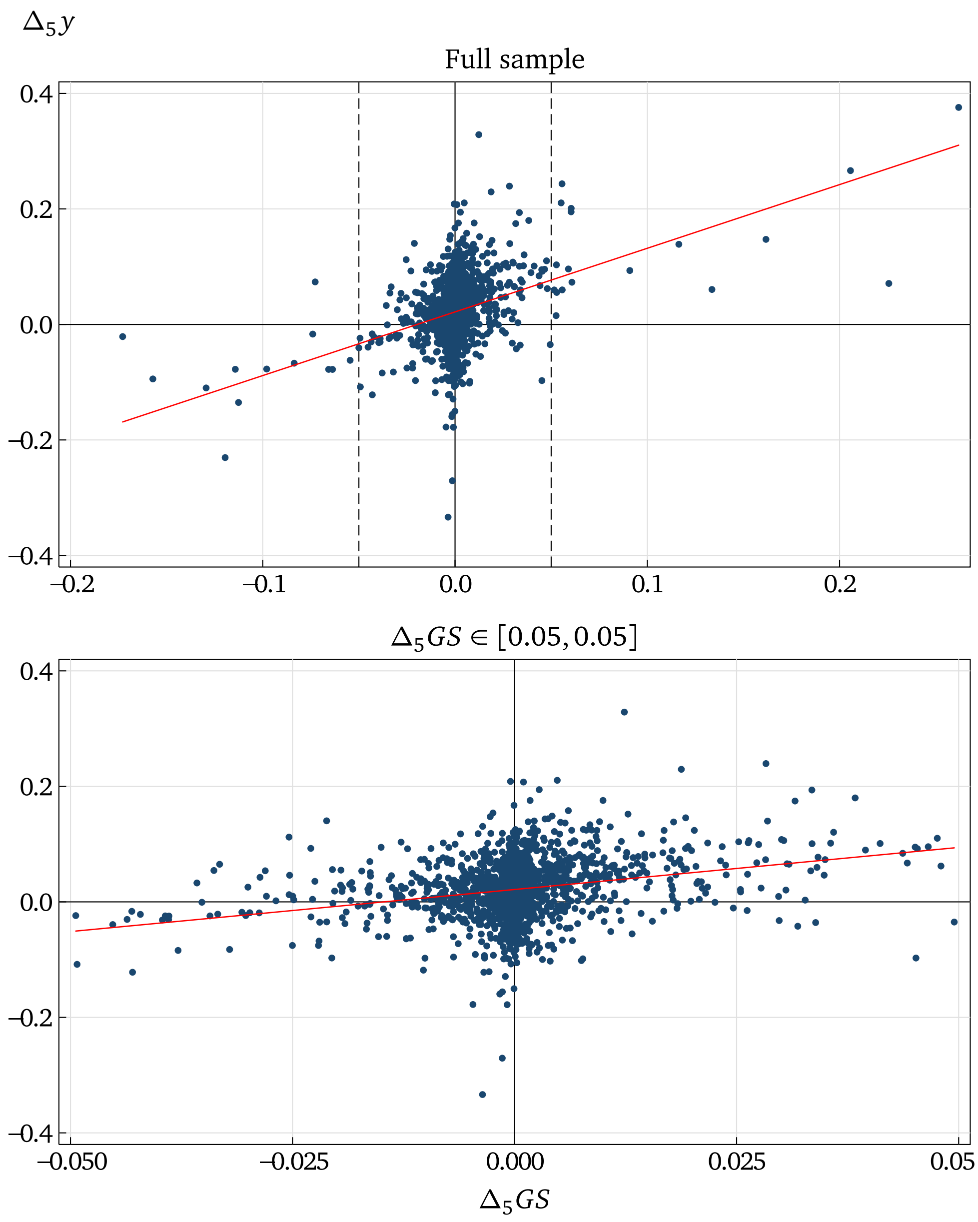
Chained 2005 dollars



Source: BEA.

Notes: Vertical lines indicate years where benchmark input-output data are available.

Figure 3. Output Growth Versus Government Spending Growth



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

Notes: $\Delta_5 y$ is annualized five-year change of log real gross output. $\Delta_5 GS$ is annualized five-year change in real direct and indirect shipments to government as a share of real total shipments. Panel contains 274 industries in 1963, 1967, 1972, 1977, 1982, 1987, and 1992 for a total of 1,631 observations. Red line is linear fit. Dashed lines in upper panel indicate range of $\Delta_5 GS$ shown in lower panel.